University of Mannheim

May I Have Your Attention, Please: The Market Microstructure of Investor Attention

- Working Paper -

Authors:

Christopher Fink*[*] and Thomas Johann[†]

This Draft[‡]:

January 18, 2013

JEL Classification: G02; G14

Keywords: Attention; Information Asymmetry; PIN; Liquidity; Market Microstructure

[*]Chair of Finance, University of Mannheim; L5, 2, 68131 Mannheim, Germany; fink@uni-mannheim.de

[†]Chair of Finance, University of Mannheim; L5, 2, 68131 Mannheim, Germany; johann@uni-mannheim.de

[‡]We thank Google for the free and open access to search volume data through Google Insights and Trends. We would like to thank Inga van den Bongard for the provision of the dataset on the ownership structure of German firms and Dr. Christian Westheide for the provision of the DGAP ad-hoc news event dataset. Furthermore, we appreciate the valuable comments of the participants of the University of Mannheim Financial Markets Seminar (2012), the HVB Doctoral Students Seminar (2012), the Auckland Finance Meetings (2012) and WHU Campus for Finance - Research Conference (2013).

Abstract

We analyse whether a stock's liquidity and returns are influenced by short term fluctuations in investor attention attached to the stock. Both returns and liquidity increase in times of high attention. We identify attention grabbing stocks by their Google search volume. In contrast to the existing literature, we measure daily changes in attention and use the category filters offered by Google insights to get a more reliable estimate of investor attention. We correct for possible endogeneity in the relation with the exogenous event of stock index inclusions and deletions and find that the relation is stronger for stocks with a higher proportion of retail trading. We analyse the dynamics of the attention-liquidity relation in an attention-adjusted structural model based on Easley et al. (1996). We find that the liquidity increase on high attention days is due to more overall and less informed trading and particularly strong in small firms.

1 Introduction

This paper studies the impact of investor attention on market liquidity and explains the underlying dynamics in a structural market microstructure model. To motivate the research question of attention-based trading, we give an introductory example about the Korean pop star Psy who broke several records in October 2012. His music video "Gangnam Style" became not just the viral sensation of the year[1] but it also triggered a 500 percent rally in the stock price of DI corp, a company owned by Psy's father producing semiconductor-testing equipment.[2] Several news articles[3] reported about this seemingly coincidental relation and attribute the rise in stock price to investors speculating that the company somehow benefits from the success of Psy. The investors bought the company just because it was owned by Psy's family. The Korean Financial Investment Association released a warning that the company did not release any new development in the last months that could justify the huge increase in stock prices. The sharp increase in the stock price from about 3,000 to 13,100 South Korean Won in September and October 2012 was then followed by a decline in November back to about 3,000 South Korean Won. The story of Psy and his father's company is a text-book example of attention-based trading. Investors buy a stock that attracts their attention, even if there is no new fundamental information about the company. What is more, the public information available might not even speak in favour of the stock[4].

The liquidity of a stock has a distinctive influence on its transaction costs. It has an impact on the expected returns and capital costs of a company (Amihud et al. (2006)). Consequently, it is of great importance to understand this measure and its determinants. The most classical measure of liquidity is the bid-ask spread. In a typical market-maker market, this spread represents the cross-proceeds of the market maker, as he buys stocks at the bid and sells them at the ask price. The higher the bid-ask spread set by the market maker, the bigger the cost of trading. The market microstructure literature has identified three main components of trading costs (see e.g. Johann and Theissen (2012)): Order processing costs, inventory holding costs and adverse selection costs. Adverse selection costs represent the biggest cost component (Stoll (1989); Huang and Stoll (1997)) and stem from the heterogeneity of the investors. As the market maker cannot differentiate between informed and uninformed investors, he will make a loss in expectation when trading with informed investors which have more information than he has about the true value of the stock. Therefore, he will increase the bid-ask spread to compensate these expected losses. This problem of adverse selection was first discussed in the models of Glosten and Milgrom (1985) and Kyle (1985). It seems obvious that the adverse selection is

[1] With over 800m clicks the video was declared the most-watchted video on the video-sharing website Youtube

[2] The South Korean stock exchange ordered a halt in trading of the stock for three days in October, 2012 as is it faced such a high demand and was increasing more than 15% a day.

[3] http://www.reuters.com/article/2012/09/25/entertainment-us-korea-psy-stock-idUSBRE88O03Z20120925, http://www.bloomberg.com/news/2012-10-17/-gangnam-style-link-spurs-di-surge-chart-of-the-day.html

[4] Institutional investors refrained from buying the stock, as it was even loss making.

driven by the proportion of informed and uninformed investors in the market. We show that the attention a stock receives has an influence on the proportion of informed and uninformed investors in the market. This will consequently alter adverse-selection costs and make attention an important determinant of a stock's transaction costs and liquidity.

Attention is a scarce resource and investors have to be selective in their information processing. Merton (1987) finds that if investors' attention is directed to a certain stock it becomes a part of their investment choice set. These "attention-grabbing" stocks will have a higher turnover and volume but perform badly in the long run which is empirically observed by Barber and Odean (2008). Hence, investors will be more prone to buy these "attention-grabbing" stocks than others. The introductory example proposes such a scenario, in which people's attention to a firm's stock is triggered by a non-fundamental and non-informative stimuli. Attention has an influence on stock returns and as exemplary shown could be quite wealth reducing for investors.

In this paper, we shed more light on the attention - liquidity relation in a structural market microstructure model. Based on the theoretical models of Glosten and Milgrom (1985) and Easley et al. (1996), we estimate the arrival rates of informed and uninformed investors on high and low attention days. This allows us to understand the dynamics of informed and uninformed attention-based trading, its influence on the adverse-selection costs and liquidity of a stock. We analyse German stocks from the indices Dax, MDax, SDax and TecDax for the period from 2004 until 2007. We use daily Google search volume of firm names as direct attention measure.[5]

We contribute in several ways to the existing literature: First, we develop a Google Search Volume download methodology that allows us to retrieve a time-series of daily Google Search Volume. We are the first to analyse a large time series of daily search volume from Google Insights. We find that investor attention as measured by Google search volume is very volatile, with a daily volatility of 18%. Second, we refine the Search Volume download in Germany by using the firm names and in addition using the feature offered by Google to filter those searches that are only related to "Finance". Third, we improve the precision of results by consulting intraday data to derive more precise daily liquidity measures. Our measures more accurately reflect the multidimensional character of liquidity. Fourth, we control for possible endogeneity when we empirically test the relationship between attention and liquidity. We use stock index revisions as exogenous event. Furthermore, we find that the relation is stronger for stocks with a higher proportion of retail trading. Finally, we unravel the dynamics of informed and uninformed trading on high attention days and its influence on liquidity in an attention-adjusted structural market microstructure model.

Our analysis contributes to the understanding of heterogeneous investors' decision processes. Furthermore, we describe the price formation process in the presence of attention-driven investors. We argue that a market microstructure model, also incorporating those investors, better reflects market realities. Also, we ameliorate the precision and short term availability of

[5]If we analyse the Google search volume of the DI corp of the introductory example, we see a yearly maximum in October 2012, forecasting the attention-based trading in the stock.

the Google SVI measure. We show that "Finance"-filtered SVI is a better measure of investor attention than unfiltered data or other indirect attention measures. We find that both daily liquidity and returns increase on high attention days. The estimation results of our model show that attention trading by uninformed investors has a positive liquidity effect and that there is no significant negative influence of increased informed trading on high attention days. This relation is particularly strong for small firms.

In the following section 2, an overview of the literature on attention in Finance is given. Section 3 describes our structural market microstructure model of the attention - liquidity relation. In section 4 our hypotheses are derived. Section 5 describes the data focusing on the Google SVI data. In section 6 the estimates of the model estimation are given. In section 7, we first compare the different attention measures. Then, we explain liquidity and returns by investor attention. The thus developed relationship is checked for robustness. In section 8 possible endogeneity issues of the liquidity - attention relation are analysed. Finally, in section 9 we conclude.

2 Related Literature

Attention is a scarce cognitive resource (Kahneman (1973)). Given the amount of information available to investors in the digital age they have to filter and be selective in information processing. With a limited attention span and processing capacity, people make decisions based on simple heuristics (Tversky and Kahneman (1974)). A good example for financial decisions based on heuristics is the home bias as documented by Kang et al. (1997)). Investors tend to choose stocks for their portfolio based on regional criteria and therefore limit their investment horizon. As investors are constrained in their investment decisions to the stocks that capture their attention, not all information is processed and incorporated into stock prices as assumed by the theoretical asset pricing theories e.g. by Sharpe (1964), Lintner (1965) and Merton (1987). In contrast to attention, information is easily and almost freely available in today's digital world. Historic and ad-hoc financial information is instantly provided by companies, financial data providers and discussed in social networks. Today, it is not information which comes at a cost, but rather inattention. DellaVigna and Pollet (2009) find that less investor attention on Fridays leads to lower event responses. Jacobs and Weber (2011) confirm this result for national holidays.Yuan (2011) finds that attention on market-wide attention grabbing events has an effect on investors trading behavior and market price dynamics. Barber and Odean (2008) find that if investors' attention is directed to a certain stock it becomes a part of their choice set. In conclusion these "attention-grabbing" stocks will have a higher turnover and volume but perform badly in the long run which is empirically observed by Barber and Odean (2008).

To measure the attention of a stock, the literature proposes different measures and proxies: Grullon et al. (2004) and Lou (2008) measure the attention a firm receives based on its marketing expenditures and find a relation between marketing expenditures and stock returns. In addition to that, Kent and Allen (1994) test and find a positive relation between brand awareness and stock returns. Kim and Meschke (2011) measure how much attention a company receives by the media by counting the CEO interviews in TV or general news coverage. Barber and Odean (2008) identify attention-grabbing stocks by their news coverage, abnormal returns and abnormal trading volume. All the proposed measures and identification strategies for attention are rather indirect and do not necessarily reflect individual investors' actual attention. Da et al. (2011) propose a direct measure of investor attention using search frequency in Google SVI. Once the investors' interest for a certain stock is raised it becomes part of their choice set and they will directly allocate attention to the stock via an inexpensive Google search request. If someone is googling a term this directly implies that he is interested in it.

SVI has been proven a good proxy for attention in several applications: Da et al. (2011) find that SVI is correlated with and can capture retail investor attention. An increasing SVI can predict higher stock prices in the short run and a return reversal in the medium run (as in Barber and Odean (2008)). Drake et al. (2010) examine investor information demand as measured by Google search frequency around earnings announcements. They find that if investors search more on the pre-event days, the pre-announcement price and volume changes reflect more information and there is less of a price and volume response when earnings are announced. Dimpfl and Jank (2011) measure stock market attention by examining Google queries for a country's leading stock market index. They find in their analysis that there is a strong positive relation between attention and realized volatility. Li et al. (2011) analyse the SVI of small stocks with similar ticker symbols to large stocks that are in the news. They examine how those small stocks perform in terms of trading volume and returns relative to their size quantile peers and find a significant outperformance. Barber and Odean (2008) additionally find an asymmetry in the attention influence on stock returns between buys and sells. They hypothesize that the possible attention effect is much more reinforced in the case of buying stocks as in the selling case, as investors mostly sell the stocks they already own.

The main focus of this paper is on the investor attention - liquidity relation. Compared to the attention - stock return/volatility relation, the liquidity relation is not yet fully researched. Bank et al. (2011) directly address the relationship between SVI and liquidity in a manner which is closest to our research idea. They examine the German market and find that an increase in search volume for a firm's name is positively related to the firm's turnover and liquidity, as measured by the Amihud (2002) illiquidity ratio. In line with Da et al. (2011), they assume that the number of Google search queries measures the interest of uniformed investors rather than informed investors, who trade based on their private information. They further assume that this web search for information by uninformed investors reduces the costs of asymmetric information in the market, as they become more informed, and increases liquidity.

We want to show theoretically and empirically that the second conjecture is not so obvious and needs further consideration. Based on the model ideas of Glosten and Milgrom (1985); Kyle (1985) and Barber and Odean (2008), we expect an informed trader to trade more actively if he can hide his trades in the order flow of uninformed traders on high-attention days. This induces the market maker to increase spreads and decreases liquidity. We describe next the attention-liquidity relation in terms of a structural market microstructure model. In this model we describe uniformed and informed investor arrival as a function of attention. Based on this model, we are able to answer whether uninformed traders really react to increased attention. Furthermore, we can find out if the decision process of informed traders, to match uninformed trading, is influenced by the presence of abnormal attention as measured by Google search frequency.

3 Structural Model of the Investor Attention-Liquidity Relation

In order to describe and test the dynamics and channels of the attention-liquidity relation we develop a structural microstructure model. The model is mainly based on the seminal work of Easley et al. (1996) (EKOP). They develop an empirically testable microstructure model, based on the framework by Glosten and Milgrom (1985), to identify the probability of informed trading (the proportion of informed to uninformed traders on a certain day) in a stock. Our model extends the framework of Easley et al. (1996) by calibrating it for low and high attention days. In the following, we shortly present the Easley et al. (1996) and underlying Glosten and Milgrom (1985) model and comment on our adjustments.

There are three types of market participants in the underlying Glosten and Milgrom (1985) model world: Uninformed traders who randomly buy and sell assets due to some exogenous stimulus; informed traders who receive some signal about the value of an asset and trade based on this information; and finally a competitive market maker that stands ready as a counterparty of trade for the two previously named types. The market maker faces some adverse selection costs due to the chance that the counterparty could be an informed trader. Therefore, he demands a fee (the spread) from anyone who trades with him. We replace the unknown exogenous stimulus that determines the uniformed traders market arrival by his attention towards the asset. While we don't believe that googling will provide the investor with valuable information (in this case he would become an informed trader) we are virtually certain that it will influence his decision making. Easley et al. (1996) take the Glosten and Milgrom (1985) model and formulate it in an empirically testable setting. In their model, every trading day nature decides whether a news event concerning the value of the risky asset happens or not. The probability for a news event is α. The probability that the news is bad is δ and good $(1-\delta)$. The buy and sell trades of the informed and uninformed on days with good, bad and no news follow three mutually independent Poisson processes as in the original model of Easley et al. (1996).

In addition to the original model of Easley et al. (1996), we specifically model the behaviour of uninformed and informed traders on high/low attention days. In our model, the uninformed arrival rate may take two states (high attention/low attention) which are determined by the instrument of Google Search Volume. Google Search Volume not only shows passive attention or interest for the stock but also directly measures an active attention effect. A potential investor with no attention towards a stock will certainly not consider to buy it. We thus explain uninformed trader arrival with the Google Search Volume variable. We follow Easley et al. (1996) and differentiate between the uninformed buy arrival ($\varepsilon_t^{b,ha}, \varepsilon_t^{b,la}$) and sell arrival ($\varepsilon_t^{s,ha}, \varepsilon_t^{s,la}$) rates. We estimate the buy and sell arrival rates in their high and low attention states to additionally differentiate between uninformed attention trading and uninformed non-attention trading. The arrival of the informed traders is modelled in terms of μ_t^{ha} and μ_t^{la}. Assuming that the informed traders know the arrival rate of attention based trading at the beginning of the trading day, they can decide if they want to exploit their informational advantage, match the uninformed trades and camouflage behind them. Therefore, the informed arrival rate can also take on a high level μ_t^{ha} and low level μ_t^{la}. Figure 1 exemplifies the whole process.

[**Insert Figure 1 about here**]

The extended model allows us to test if Google search volume describes the arrival rates of the uninformed and informed attention trading by looking at the difference of the EKOP parameters in the low and high attention states.

3.1 Maximum Likelihood Estimation

The trading process is estimated in a maximum likelihood framework. Our data sample ranges from 2004 until 2007 with daily observations of buys, sells and Google search volume of German stocks. We estimate the model parameters per company over the whole time period, on an annual basis. The likelihood function takes the daily buys, sells and Google search volume as input parameters and gives us estimates of $\hat{\theta} = \alpha, \delta, \varepsilon_t^{b,ha}, \varepsilon_t^{b,la}, \varepsilon_t^{s,ha}, \varepsilon_t^{s,la}, \mu_t^{ha}, \mu_t^{la}$ per stock.

As the model is based on the original probability of informed trading model of Easley et al. (1996), we can also derive a PIN measure. This measure can be derived for the high and low attention states as:

$$PIN_t^{low\ attention} = \alpha\mu_t^{la}/(\varepsilon_t^{b,la} + \varepsilon_t^{s,la} + \alpha\mu_t^{la}) \tag{1}$$

$$PIN_t^{high\ attention} = \alpha\mu_t^{ha}/(\varepsilon_t^{b,ha} + \varepsilon_t^{s,ha} + \alpha\mu_t^{ha}) \tag{2}$$

We present the sample likelihood exemplary for the high attention state, with a high arrival rate of uninformed trading and matching of informed trading. In this state, the likelihood to observe B buy trades and S sell trades is

$$a(s_t^{ha}) = (1-\alpha)exp(-\varepsilon_t^{s,ha} - \varepsilon_t^{s,ha})\frac{(\varepsilon_t^{b,ha})^{B_t}}{B_t!}\frac{(\varepsilon_t^{s,ha})^{S_t}}{S_t!} \tag{3}$$

$$+ \alpha\delta exp(-\varepsilon_t^{b,ha} - \varepsilon_t^{s,ha} - \mu_t^h)\frac{(\varepsilon_t^{b,ha})^{B_t}}{B_t!}\frac{(\varepsilon_t^{s,ha} + \mu_t^h)^{S_t}}{S_t!} \tag{4}$$

$$+ \alpha(1-\delta)exp(-\varepsilon_t^{b,ha} - \varepsilon_t^{h,S} - \mu_t^h)\frac{(\varepsilon_t^{b,ha} + \mu_t^h)^{B_t}}{B_t!}\frac{(\varepsilon_t^{s,ha})^{S_t}}{S_t!} \tag{5}$$

The conditional likelihood of the low attention state is calculated analogously. The unconditional likelihood over all states can be computed by taking into account the state probabilities p_t^s as follows

$$L\{(B_t, S_t) \mid \Theta\} = \sum_{k \in ha,la} a(s_t^k) \cdot p(s_t^k) \tag{6}$$

The state probabilities p_t^s are derived by looking at the relative logarithmic Google Search Volume of the day. This Google Search Volume is relative to the maximum search volume over the whole time period.

The likelihood function derived above is not computation-friendly and will potentially cause errors in the numerical optimization process. The factorial and exponential and power functions of buys and sells potentially create infinitely large numbers. As in Duarte and Young (2009), we re-express the conditional state likelihood functions by logarithmizing the factorial terms and adding them in the exponential function.

4 Hypotheses

Our major research goal is to analyse the relation between attention-based trading and liquidity. Previous studies (e.g. Barber and Odean (2008); Da et al. (2011); Bank et al. (2011)) have found that the higher attention for a certain stock, the higher are its short-term returns and liquidity. This relation seems to be robust. Therefore, we want to verify this direct channel in hypothesis 1:

Hypothesis 1a*: High-attention stocks (in terms of daily Google search volume) are more liquid (in terms of intraday liquidity measures).*
Hypothesis 1b*: High-attention stocks (in terms of daily Google search volume) provide higher short-term returns.*

In the model section we indicated two possible outcomes of increased attention. First, we want to show that uninformed traders are influenced in their decision making by their level of attention. Second, we conjecture that informed traders respond to the level of attention attached to a stock. They might camouflage behind uninformed attention traders and increase their information based trading. Based on these ideas, we derive two competing liquidity hypotheses. With increased attention trading more investors are paying the spread to the market maker, while not increasing adverse selection costs. A competitive market maker could therefore reduce the spread demanded from traders. Therefore, we hypothesize:

Hypothesis 2a*: On high-attention days, stocks will be more liquid as the market maker can cover his losses from the informed traders with the spread gains from the uninformed traders.*

However, if more uninformed attention traders are in the market and this is known by insiders, they will camouflage behind uninformed order flow. Consequently, it becomes more difficult for the market maker to detect insider trading. In this scenario, on high attention days, the market maker will increase spreads to protect himself from the information advantage of the informed traders. Therefore, we hypothesize:

Hypothesis 2b*: The market maker protects himself from insiders which hide behind the order flow of uninformed attention traders, therefore the effect from 2a is reduced.*

The structural model offers a tool to quantify both effects by estimating uninformed and informed arrival rates on high and low attention days. Whether hypothesis 2a or 2b prevails and how the probability of informed trading is influenced needs to be tested empirically.

5 Data

Our dataset can be divided into three main sources: Intraday data, daily stock data and Google search query data.

5.1 Intraday and Market Data

To our knowledge we are the first to use intraday data in the context of the application of Google search query data to finance. Former studies (e.g. Bank et al. (2011)) were able to establish a relationship on a weekly basis between Google search frequency and liquidity estimators such as the Amihud (2002) illiquidity ratio. While correlated with actual trading costs (see Goyenko et al. (2009)), these measures are less precise than those derived from intraday data. Additionally they are not available on a daily basis. Investor attention, however, is highly volatile on a day-to-day basis.[6] To compute effective spreads, price impact and market depth, we use millisecond trade and quote data from Xetra. This data is available to us from January 2003 until December 2007 for German stocks.

The relative effective spread for firm i, at day t for trade j is defined as

$$prop\_effective_{itj} = \frac{2 * |P_{itj} - M_{itj}|}{M_{itj}} \tag{7}$$

where P_{itj} is the trading price and M_{itj} is the midpoint between bid B_{itj} and ask A_{itj}.

At each trade *depth* is calculated as

$$d_{itj} = \frac{active\_bid\_quantity_{itj} + active\_ask\_quantity_{itj}}{2}, \tag{8}$$

where *active_*_quantity* is the quantity available for trade at the current bid/ask price.

[6] We identify a daily standard deviation of 18.56 for an Google SVI attention variable scaled between 1 and 100 (see summary statistics, Table 7).

The 5-minute price impact of a trade is defined as

$$PriceImpact_{itj} = \frac{2 * \left| M_{itj}^{5min} - M_{itj} \right|}{M_{itj}}, \tag{9}$$

with M_{itj}^{5min} being the active midpoint five minutes after M_{itj}. These three measure taken together can describe the different dimensions of liquidity.

Daily data (closing prices, daily returns, daily trading volume and number of common stock) is mainly collected from Datastream. We use a return index to measure returns, which artificially reinvests dividends and ignores stock splits.

We collect event data from Deutsche Gesellschaft für ad-hoc Publizität (DGAP[7]). DGAP is a German organization that provides a platform to all German companies to fullfill their disclosure requirements. Those enable us to collect data on a variety of event types: Dividend announcements, quarterly reports, personnel decisions, mergers and acquisitions, etc. We believe that time-stamps are relatively precise (at least on a daily basis) due to the strict disclosure rules. We collect a total of 1722 test events for the total of 239 firms.

Data on the ownership structure of the firm is collected on a yearly basis from the Hoppenstedt database. We consider an owner as blockholder if he owns more than 5% of the stock of a company. The remainder of assets is defined as dispersed ownership.

Finally, we manually collect index changes using information from Deutsche Börse[8]. We note both the date of an index change announcement as well as the date of actual index change.

5.2 Google Search Volume as Measure of Investor Attention

In order to arrive at a direct measure of investor attention we use relative search volume from Google Insights.[9] Google basically offers two different tools to gather search volume data: Google Trends[10] (launched May 2006) and Google Insights (launched August 2008). Both front-end tools are based on the same database, but differ in certain features. Also, both tools do not provide the absolute number of search requests, but only a relative Google Search Volume Index that is scaled by some (unknown) average search volume during that day. Thus we measure relative, rather than absolute attention. The measurement of relative attention ensures a time-series comparability of the data.

The majority of empirical studies (see Da et al. (2011), Drake et al. (2010) , Dimpfl and Jank (2011)) uses Google search volume data from Google Trends. The main advantage of Google Trends compared to Google Insights is that it offers a fixed-scaling option, which basically assures that each index value is expressed relatively to the average search volume during January 2004. This ensures a time-series comparability of different values.

[7] www.dgap.de

[8] Historical Index Composition of the Equity- and Strategy Indices of Deutsche Boerse, Version 3.5, November 2011, http://www.dax-indices.com/EN/MediaLibrary/Document/Historical_Index_Compositions_3_5.pdf

[9] http://www.google.com/insights/search/

[10] http://www.google.com/trends/

Such a fixed-scaling option is not available in Google Insights. However, we found a way to resolve this issue (see later). Meanwhile, Google Insights offers some major advantages compared to Google Trends. First, Google Insights seems to provide more detailed data: If the total number of searches for a specific term is below some unknown threshold both tools return a search volume of zero (due to data privacy protection). Our analysis shows that this threshold seems to be lower for Insights than for Trends. As we are especially interested in low attention levels of stocks, it is very important not to loose this data. Secondly, Google Insights offers the possibility to filter according to categories. The term "adidas" might be entered by someone who wants to invest in the firm, but it is far more likely that this person simply wants to buy new clothes. Data from Google Trends is unable to differentiate between these two types. Da et al. (2011) and Li et al. (2011) avoid this problem by searching for Ticker symbols instead of firm names. However, we believe that this search term is rather atypical and only professional market participants would use ISIN, WKN or other tickers to search for a stock of interest. As in Bank et al. (2011), we agree that one would usually enter the firms name rather than its complex ISIN. Google category filters can ensure a clear separation of different search intentions. Implicitly, Google checks which search queries a specific user started and which links he clicked before and after googling the term of interest. If he googled for "dax" and "stock" this might be a good indicator for his interest in financial information concerning "adidas". By selecting the category filter "Finance" and using firm names instead of tickers we can more precisely capture the direct attention towards the stock. Therefore we search for firm names as provided by Datastream. We manually eliminate corporate form acronyms like "AG". We are relatively certain that the resulting search terms are not ambiguous and reflect investor behavior.

As already mentioned, attention is rather volatile in the short-run. Hence, an observation of monthly or weekly changes in Google SVI might not appropriately capture the dynamics of day-to-day changes in people's attention. We are aiming at a daily measure of investor attention. Except for Drake et al. (2010) who applied a daily attention measure of SVI from Google Trends, researchers so far have only analysed long-term attention changes. Google offers daily SVI values for requests up to a period of 3 months. Requests above this interval only provide results on a weekly or even monthly basis. Due to the fixed-scaling option on Google Trends, one may simply download several 3-month files for the same search term and append those files to arrive at a longer timeseries. This option is not provided by Google Insights: Each inquiry here is standardized to a scale between 0 and 100, where 100 is the day with the maximum relative search volume for the entered time period. A zero search volume does not imply that nobody searched for that specific term on a day but that the number of search requests was below a needed threshold. Google Insights allows to search for 5 different time intervals at the same time. Thus, it is possible to span a time interval of 15 month (five 3-month intervals) all being scaled by the same day of maximum search volume. Unfortunately, it is not directly possible to link two 15-month-intervals, as they are aligned based on unequal reference points. As a longer timeseries permits for more robust analysis, we have developed a 3-step solution algorithm to extract longer periods of daily data:

First, for every company-year combination we search the day with the maximum relative search volume in that specific year[11]. In a second step we compare the identified yearly maxima in one request to determine the global relative search volume maximum. Finally, we again execute yearly requests, but include the found global maximum in any request. Obviously, every search volume will now be scaled by this global maximum and therefore one may append the different firm-years (2004-2007). Table 1 exemplifies this process.

[Insert Table 1 about here]

While this solves the problem of differing reference points, we artificially generate a positively skewed dataset as one extreme attention outlier pushes the rest of the sample to lower SVI levels. Figure 2 shows the resulting SVI distribution for our complete sample without category filter.

[Insert Figure 2 about here]

Note that zero-observations are omitted from the graph as about 46% of all observations are classified as missing. Those include all days where the absolute search volume was too low to be reported. Additionally, it is important to note that the SVI is issued on a discrete scale. This implies some unwanted data aggregation. Also, Google does not search the entire database to produce the outputs, but only a subset of the data. Therefore SVI values might slightly differ for two identical inputs at different points in time.

We test he applied algorithm by checking whether changes in the SVI (ΔSVI) are systematically different for request jumps[12] compared to other monthly jumps. We hereby drop event dates as those would falsify the comparison. We apply a stock-wise mean-comparison t-test and find that the null hypothesis of equal mean ΔSVI can not be refused in 98% of the cases at 99% significance[13].

[Insert Figure 3 about here]

Figure 3 shows the timeseries development of equally-weighted Google SVI over all sample stocks. One may already note that the average SVI is below 50 which is due to the few extreme attention events in the sample. Also, even on this aggregated scale one may see that SVI is very volatile. We identify a decreasing pattern in average SVI over time. This pattern is less present in category-filtered SVI. SVIs are generally lower around Christmas, which is intuitively explained by the dominance of other stimuli over financial news during that time.

The SVI from Google Insights with a finance-category filter seems to be the best way to measure attention in financial assets. However, we are well aware of its shortcomings. We also

[11] Per year, one needs to inquire four 3-month intervals: January-March, April-June, July-September and October-December

[12] first days of January, April, July, October

[13] 92% for 95% significance and 85% for 90% significance level

include the SVI from Insights without category filter as it has less missing values due to a higher absolute search volume. Finally, the SVI from Google Trends is downloaded as its fixed-scaling option might offer some advantages over the described algorithm. Table 2 describes the three different attention measures across years.

[Insert Table 2 about here]

First, note that the use of a category filter and the data from Google Trends significantly reduce the sample size to 23% and 56% of the Insights sample. A value of 113,675 daily observations over a sample of 150 stocks that contain at least one non-missing information on Google SVI means that those firms on average contain information on 758 trading days (74% of 1021 trading days). In contrast, we only have information for 68% of trading days per stock for category-filtered data with a significantly reduced number of 37 firms.

Generally, category filtered data seems to have a significantly higher average SVI than non-filtered data, while having a lower variance. This can be understood as first indication for the usefulness of a category filter: the two measures measure something different. Skewness and kurtosis are nearly normal. However, tests for normality (Shapiro-Wilk, Shapiro-Francia) are generally refused at 1% significance over all indices and SVI measures. Google Trends can not be easily compared to the two datasets due to the different scaling of the variable.[14] However, we observe a left-skewed sample with excess kurtosis. Across time we observe a decrease in relative attention for the stocks in our sample measured by unfiltered SVI. This does not necessarily mean that absolute search volume decreased but rather that it did not grow as fast as the average search term on Google. Applying the finance category filter we observe the opposite development. Also the volatility of attention in the financial assets seems to increase over time.

Table 3 describes the three different attention measures across indices. SVI values are largest for Dax followed by TecDax, MDax and SDax. While our query algorithm does not allow for cross-sectional comparisons, this indicates that attention in large companies from the technical sector is generally higher as, the average attention level is closer to the highest level of 100. Standard deviation is relatively stable across indices and the high skewness encountered in the trends data seems to be mainly attributable to smaller companies from MDax and SDax.

[Insert Table 3 about here]

5.3 Sample Selection

We include all stocks that were listed in one of the four indices (Dax, MDax, SDax and TecDax) during the time from January 1^{st} 2003 until December 31^{st} 2007. This includes firms that went bankrupt during that time as well as firms that newly became part of the index. We drop all

[14]Opposed to SVI from Insights, search volume indices from Google Trends are not scaled between 1 and 100. The average SVI in January 2004 is set to 1.0. All other search volumes are aligned to this reference point. Thus the variable basically may take any positive value.

non-trading days. While we also have information on Google SVI on those days, we could not analyse stock price or liquidity reactions. Daily data is matched with intraday data based on ISIN.[15] For 32 of the 239 companies that were part of the four major German stock indices during the analysed period no intraday data is available.

In total we generate 211,813 firmday observations across all 4 indices. However, we do not have information on all variables of interest, e.g. Google SVI, for all those firms. As we perform separate analyses on the time-series behaviour of returns and liquidity respectively, we refuse to artificially reduce our sample to a state where all information is available for each company, as this would bias our sample towards large, liquid firms with high absolute levels of Google search volume. To evaluate the data availability, Table 4 summarises the different sample sizes across all variables. It can be seen that the number of firms, that do jointly provide price, intraday and Google information amounts to roughly 50% of the total sample. The data quality is increasing over time which is mainly due to an increased usage of search engines and an increased popularity of the internet over time.

[Insert Table 4 about here]

6 Estimation Results of the Structural Model

In table 5, we find the estimation results of the of the Maximum Likelihood estimation of the attention-adjusted microstructure model as described in section 3. The microstructure model is estimated for 90 stocks out of the total sample for which Google Search Volume is available. The companies are sorted into size terciles and parameter estimates are shown for the respective tercile.

[Insert Table 5 about here]

Overall, we can see that the α estimates seem to be quite stable around 36%, only the large firms seem to have slightly more information event days. The probability of a bad-news event δ is gradually increasing with firm size and is on average around 50%. The daily arrival rates of uninformed and informed trades (ε, μ) are strongly increasing from the small company tercile to the large company tercile. Furthermore, the arrival rates differ for low attention and high attention days, as measured with Google Search Volume. However, from all terciles, only the small size tercile shows significance in the parameter estimates. In the small company tercile, both informed and uninformed investors seem to trade relatively more on high attention days. For the medium and large tercile companies this trading behaviour is reversed. In these companies, there is only about half of the trading of informed and uninformed investors on high attention days.

In table 6, we analyse the probability of informed trading as determined in section 3. We can see that it is about twice as high for small firms than for large firms. The PIN seems to be

[15] We hereby control for ISIN changes during that time period.

slightly lower for small firms on high attention days and slightly lower for medium-sized firms on high attention days. Attention does not seem to have an effect on the PIN in large firms.

[Insert Table 6 about here]

Overall, we can say that there is more trading of informed and uninformed investors on high attention days in small firms. The relative proportion of informed to uninformed traders in small firms, the probability of informed trading, seems to be slightly lower in small firms. This is an indication, that the spreads will be lower on high attention days, due to more overall trading and relatively less insider trading, reducing the adverse-selection costs and increasing liquidity. This result supports hypothesis 1, that attention increases liquidity and hypothesis 2a that adverse-selection costs are reduced on high-attention days. It does not support hypothesis 2b, that insiders hide behind the order flow of uninformed traders on high attention days. In medium-sized firms, there is slightly more informed trading on high attention days and less overall trading on high attention days. This speaks for a negative influence of attention on the liquidity of these firms. For large firms the probability of informed trading seems to be unchanged between low and high attention days. Attention seems to have a significant positive effect on the liquidity in small firms due to increased general trading and less informed trading. The results for medium and large firms are not significant and less obvious.

7 Empirical Analysis of the Attention - Liquidity Relation

7.1 Summary Statistics

In table 7 we provide summary statistics of all variables used in the study. The variables are shown for the four indices Dax, MDax, SDax, TecDax and aggregated over the full time period. In the last row of table 7 we see the number of firms included in the respective index from 2004 to 2007. The 41 firms included in the Dax during this period imply that 11 firms must have been dropped from the index and have been replaced by other companies during this period.

[Insert Table 7 about here]

In terms of market value and the number of daily trades, buys and sells, the four indices show the expected ordering among each other. Dax index stocks are on average the most traded and have the highest market value, followed by MDax, TecDax, and SDax. The liquidity measures effective spread, market depth and price impact show a similar ordering. In some cases the ordering between TecDax and SDax is reversed. It is not surprising that Dax is the most liquid among the four indices.

The proportion of small buys (which we understand as proxy for retail trader presence) is highest for Dax and TecDax companies. Dax companies due to their size and TecDax companies due to their appealing business model are generally more attractive to retail traders. The share of blockholders is larger in the smaller SDax and MDax companies.

Next we examine the direct and indirect attention measures. Trading volume from Datastream shows the expected ordering. It is by far highest for Dax companies followed by MDax and TecDax. Average daily squared returns are highest for TecDax followed by SDax and MDax. Events happen most often for Dax companies but across all indices events occur only at about 1% of the days in our sample. If we analyse the time-series attention measures Trends SVI, Insights SVI and Insights Finance SVI (as already done in table 3), we see that Insights SVI and Insights Finance SVI have a higher mean and median value for the bigger indices and a higher standard deviation for smaller indices. For Trends SVI we cannot confirm this pattern.

We not only apply the algorithm described in the data section to arrive at an unbiased within-company timeseries of data, but also transform the procedure to infer a cross-sectional ordering. We here do not identify the maximum attention quarter for one company, but search for the maximum attention firm for each quarter.[16] Within one quarter, we thus are able to order firms by their cross-sectional attention. Therefore this data might not be compared across indices as the reference point is index specific, namely the company with the highest attention within the respective index. Across all indices we find that average Finance SVIs are larger than unfiltered SVIs. This implies that the firm with the maximal search volume is less of an outlier in the Insights Finance data. This is another evidence in favour of the use of the Finance filter as attention measure.

7.2 Correlation Analysis

Table 8 shows the correlations between different attention measures. Correlations are calculated for each of the stocks separately and then averaged across the total sample. The indirect attention measures trading volume, squared returns and events were already used in previous studies (e.g. Barber and Odean (2008)). We call those measures indirect as they are only a possible consequence/trigger of increased attention and may therefore (opposed to Google SVI) be noisy, due to other factors that simultaneously influence those measures. Squared returns for example will be large for volatile stocks, while volatility not necessarily implies attention. The correlation among these indirect measures is significantly positive as expected. Only the correlation among the event dummy and lagged squared returns is insignificant and small.

[Insert Table 8 about here]

The attention measures Insights SVI, Insights Finance SVI and Trends SVI show a much higher significantly positive correlation among each other. Google Insights SVI and Trends SVI are almost perfectly correlated, whereas Insights Finance SVI seems to measure something slightly different. Insights SVI shows a significantly positive correlation with all the traditional attention measures, whereas the other Google measures only show a significant relation with

[16]This is achieved by a stepwise comparison of sets of five companies. The one company with the highest search volume in each of these sets "survives". The remainder of companies then again is compared in sets of five against each other. This procedure is repeated until the maximum attention company is identified.

the Volume measure. An unexpected result is the negative but insignificant relation between Trends SVI and squared returns. Generally one can note that the Google attention measures are significantly positive correlated with the measures trading volume, squared returns and event dummy. However, as correlation is not perfect, SVI seems to measure an additional dimension. While the indirect attention measures might be influenced by other factors, Google SVI is a clean measure of investor attention.
In line with Da et al. (2010), we believe that Google SVI is a more direct measure of actual investor attention. Among the different Google measures, we conjecture that Insights Finance SVI is more connected to actual investor attention while the other two measures are influenced by the general attention towards the products and non-financial news of a firm. Nevertheless, we test our hypotheses with both Insights SVI and Insights Finance SVI data, due to the higher number of observations in Insights SVI.
Next we further elaborate on the difference between direct and indirect attention measures by observing their response time to attention triggering events in a simple crosscorrelation analysis. We hypothesize that SVI reacts more speedily to such events as it is positioned at the beginning of the decision process: The person observes the stimuli, then gathers information and finally trades, which might generate extreme stock returns or abnormal trading volume. In this line of argument another weakness of the indirect attention measures becomes obvious: They might be stimulus and consequence of attention at the same time. This endogeneity issue is less pronounced for Google SVI. Figure 4 plots the average stock-by-stock crosscorrelations between Insights SVI and the three indirect attention measures. Hereby, SVI is kept fixed, while the other measures are shifted by up to 20 leads and lags. Red bars indicate a significance at the 99% level. Results for SVI Finance and Trends SVI are similar, but omitted here.

[**Insert Figure 4 about here**]

First, its important to notice that correlations for the 0-lag are different from those in Table 8. This is due to the fact that we only include stocks for which a timeseries of at least 100 days was available, such that crosscorrelations for high leads and lags can be measured.
Generally we observe that correlations are highest for the 0-lag day which means that SVI and indirect attention measures seem to be high at the same days. Interestingly, the distribution of cross-correlations is asymmetrical for lags and leads (especially for squared returns and the event dummy). Correlations are higher and more often significant for leads than for lags. The relatively high and significant lead-1 relation (compared to the lag-1 relation) indicates that Google SVI sometimes is frontrunning squared returns or even events like mergers or dividend announcements. We believe that this is rather natural as attention might rise in anticipation of events. However, one can also observe significantly positive correlations in lags especially for trading volume and squared returns. This might be due to the fact that high trading volume and extreme returns of the previous day trigger the attention of investors e.g. by appearing in top/flop-lists of online trading platforms.

7.3 Relations between Attention Measures

In table 9 we provide six regressions to explain the *direct* Google attention measures Insights SVI, Insights Finance SVI and Trends SVI by the *indirect* measures Trading Volume, Event Dummy and Squared Return and their lags. Firm clustered robust standard errors are given in parentheses. All variables (except the Event Dummy) are standardized to make coefficients comparable.

[Insert Table 9 about here]

In regression (1)-(2) we explain Insights SVI without use of a category filter. As can be seen in regression (1), all three indirect measures have a significant positive influence on Insights SVI. The effects of Trading Volume and Squared Returns on daily SVI are in the same range. Remembering that variables are standardized, this implies that a σ-change in trading volume (which means that about 3000 more shares are traded, see Table 7) triggers a 6% standard deviation change in Insights SVI (a change of 1 in SVI). The Event Dummy coefficient must be interpreted differently as it is not standardized. In case of an Event occurring SVI is higher by 3.4 points ($0.18 * 18, 56$). If we additionally analyse the lagged indirect measures in regression (2) we see that all lagged coefficients are positive. However, only the Event Dummy has a positive significant influence. The lagged coefficients of Trading Volume and Squared Returns show minor statistical and economical significance. This result is intuitive: First it shows that indirect and direct attention measures co-move (a result that is also in line with Figure 4). Second, it indicates that yesterday's events trigger today's attention, e.g. via news paper articles. In regression (3)-(4) the SVI from Google Insights with category filter Finance is explained. In these regressions only Trading Volume and lagged Trading Volume can explain the Insights Finance SVI. The Event Dummy and Squared Return variables show no significance and in case of the Squared Return variable even show a negative influence. These results might be due to the low number of firm observations for the Insights Finance category. In regression (5)-(6), the results for the SVI from Google Trends are shown. The results are in line with those in regression (1)-(2) for the Insights SVI variable, only that the Trading Volume variable has no significant influence anymore. Overall, we see that the *direct* Google attention measures can be explained by the same or previous day *indirect* attention measures. This supports the hypothesis that the measures are closely related.

In table 10 we provide additional regressions to explain the *indirect* measures Trading Volume, Event Dummy and Squared Return with the *direct* Google attention measures Insights SVI and Insights Finance SVI. As causality is not obvious here it makes sense to simply revert the regression equation.

[Insert Table 10 about here]

In regression (1)-(3), we explain the Trading Volume measure with SVI from Google Insights, with and without category filter Finance. In regression (1), we see that Google SVI significantly explains Trading Volume. However, in regression (2), as we also add the Insights Finance SVI variable, the Insights variable loses its significance. This is some indication for the dominance of Finance SVI over non-filtered data in the Finance applications. The lagged variables have a negative insignificant influence. In regression (4)-(6) the Event Dummy is explained in a Probit regression. In these regressions the only statistically significant influence comes from the Insights SVI variable. This result supports the strong correlations found between the Event Dummy and Google Insights SVI. In the last set of regressions we explain the Squared Return variable with the Insights SVI measures. As in the Trading Volume case, the Insights Finance SVI has the most significant influence on the Squared Return variable. Additionally, in this regression specification the lags of the Insights Finance variable have a significant influence. Overall, Insights Finance SVI seems to be the more precise measure with the most explanatory power in explaining the indirect attention measures.

7.4 Liquidity, Stock Returns and Attention

In this section we turn towards the relationship between short term liquidity, returns and the attention of retail investors. In the hypothesis section we showed that it is not straightforward how market liquidity is affected by higher investor attention. We found from the structural model estimation that the relation should be positive. Liquidity is a multidimensional and rather volatile variable. Previous studies, like Bank et al. (2011) only use the Amihud (2002) illiquidity ratio, turnover, volume and closing spreads as liquidity measure. While a relationship between those proxies and intraday measures is documented in the literature (see e.g. Goyenko et al. (2009)) it is far from being perfect. In the following regressions, we try to account for the multidimensionality of liquidity by using three different intraday measures of liquidity, namely Relative Effective Spreads, Market Depth and Price Impact.

We run the following fixed-effect regression:

$$\begin{aligned} liq_{i,t} = \alpha &+ \beta_1 SVI_{i,t} + \beta_2 SVI_{i,t-1} + \beta_3 Vol_{i,t} + \beta_4 Vol_{i,t-1} \\ &+ \beta_5 r^2_{i,t} + \beta_6 r^2_{i,t-1} + MV_{i,t} + Firm_i + \epsilon_{i,t} \end{aligned} \tag{10}$$

where $liq_{i,t}$ is the respective liquidity measure of firm i at day t, SVI is the applied attention measure (we here use Insights SVI and Insights Finance SVI) and Vol, r^2, MV are control variables for Trading Volume, Squared Return and Market Value that potentially could also explain the stock's liquidity. $Firm_i$ is a dummy variable which is 1 for firm i. The inclusion of firm-fixed effects is necessary due to possible omitted variables and the firm-dependent level of Google SVI which we describe in Section 5. Table 11 summarizes the results. We are mainly interested in the relationship between SVI and the dependent variable. Our sample includes 132 stocks for Insights SVI and 31 for Insights Finance SVI.

[Insert Table 11 about here]

The negative coefficient for Google SVI in regressions (1) and (2) implies smaller relative effective spreads for higher levels of attention in a firm's stock, meaning the stock becomes more liquid. We therefore find evidence in favour of Hypothesis 1. This effect is consistent between Insights SVI and Insights Finance SVI: For Finance SVI, which we believe to be the more appropriate but less available measure, it is confirmed with 99% significance. Also, search volumes seem to be related to liquidity improvements on the following day.

As another liquidity dimension, market depth measures the available quantity for trade at the current bid-ask spread. The larger the market depth, the larger is the quantity one may trade without influencing the market price. Therefore market depth is large in liquid markets. Results for market depth as second liquidity measure are counter-intuitive for Insights SVI. A rise in Insights SVI seems to reduce market depth and thus liquidity. This effect however is only significant in lagged SVIs.[17] Regarding the search volume within the finance category, we observe the expected positive relationship (although it is not significant).

Price Impact is an interesting measure of liquidity as it measures the response of market prices to trading. Market prices should only react to trades if those might be informative (see Kyle (1985)). Thus, the Price Impact of a stock is important as it is strongly related to informed trading. We observe, both for general as well as for category sorted search volume indices, a reduced price impact of trades on high attention days. Presuming that the behaviour of attention traders is unaffected, increased attention trading implies a higher arrival rate of uninformed traders and thus a lower probability of informed trading. Market makers should then become less sensitive to trades and liquidity increases.

Generally one may therefore confirm Hypothesis 1, while keeping in mind possible endogeneity issues that potentially harm the reliability of the described results. We document first evidence that increased attention leads to higher liquidity.

In addition to the analysis of liquidity we also elaborate on the relationship between attention and stock prices. Most attention-related studies in finance primarily investigate this relationship (see e.g. Barber and Odean (2008), Da et al. (2011) or Drake et al. (2010)). In line with the named studies we find a positive relationship between attention and returns. Yet, this relationship is not significant. The differences to the results of Da et al. (2011) or Bank et al. (2011) can be explained by the different time horizons of our studies: While those studies regard average weekly SVI changes and their influence on weekly returns, we regard daily changes. Therefore the results are not contradictory.

7.5 Small Trade Quintiles and the Liquidity Attention Relation

For this analysis we use the same fixed-effect regression as in equation 10. However, we run those regressions only for chosen subsamples of our data. Those subsamples are constructed as quintiles of the proportion of small trades. We classify a trade as small if the trade size in euro terms

[17] Yesterday's attention might trigger so many trades that market depth is reduced. This would be the case if no new liquidity is provided to the market.

is among the smallest 10% of all trades within a year. Other classification algorithms generate similar orderings.[18] We calculate the proportion of small trades for each stock-day. Finally, stocks are sorted into quintiles on a yearly basis according to their average proportion of small trades.[19] We generally assume that small trades are usually conducted by retail traders (see e.g. Kumar and Lee (2006)). We are well aware of possible biases to this measure: algorithmic trading also uses small and frequent trades (see e.g. Chordia et al. (2011)). Also, retail traders might trade via their broker who might aggregate trades from different entities. Still, we believe that a higher proportion of small trades in a stock is the best available indicator of a higher proportion of retail trading. If this conjecture is correct, the effects found in Table 11 should be more pronounced for stocks that are traded relatively more often by retail traders. Table 12 provides evidence on this hypothesis for Insights Finance SVI as attention measure.[20]

[Insert Table 12 about here]

In Panel (a) the results are shown for effective spreads as dependent variable. First, note that the general negative relationship across all quintiles between attention and effective spreads confirms the results from column (2) in Table 11. Second, this relationship gets stronger for higher proportions of small trades (exception: quintile (4)). This indicates that Google SVI actually measures retail trader attention. Attention should affect equilibrium outcomes stronger in a market where more participants are exposed to attention. Market makers can reduce spreads as they know that the already large fraction of retail traders collectively is more prone to trade due to increased attention. This is evidence in favour of Hypothesis 2a. The positive effects from more uninformed trading seem to outweigh those of more informed trading.

In Panel (b) we only observe that the weak results for market depth are confirmed across all quintiles. All coefficients for Insights Finance SVI are insignificant and one cannot identify a clear pattern across quintiles.

Panel (c) shows the result for Price Impact as dependent variable and confirms the findings for effective spreads in the sense that we find a negative relationship between SVI and Price Impact across all quintiles except for quintile (4). However, this relationship is only significant for quintile (3) and we are unable to establish any ordering of coefficients across quintiles.

Finally, Panel (d) shows the results for returns as dependent variable. We encounter that the expected positive relationship between returns and attention only holds for quintiles (3) to (5). For higher proportions of small trades the effect generally gets more positive. Barber and Odean (2008) argue that attention is more relevant for buying than for selling decisions as

[18] We also classify trades as small relative to the average trade size within the respective firm or relative to a fixed euro amount, e.g. 10,000 Euro.

[19] Quintile (1) holds stocks with the smallest proportion of small trades, quintile (5) stocks with the highest proportion of small trades.

[20] One may note that the number of firms included in the quintiles is unbalanced. To arrive at unbiased results we did the previously described quintile sorting for all stocks of our sample. However, some of the stocks might have no SVI data available, which is why they are dropped from the final regressions.

only in the case of a buying situation investors are exposed to a large universe of investment alternatives. Therefore, high attention should trigger higher buying pressure and therefore (at least short term) positive returns. It is logical that a higher proportion of retail traders in a market will reinforce this effect.

8 Endogeneity

If we want to test the attention - liquidity relation, we face some endogeneity issues. It is not entirely clear if attention-trading has an influence on a stock's liquidity or if there is reverse causality in a sense that very liquid stocks lead to increased attention of investors. In order to circumvent the endogeneity problem we need to find an exogenous event that moves liquidity but not attention or an event that changes the level of attention but is not related to liquidity.

We use stock index changes and re-changes as exogenous events to control for reverse causality. The data sample of our study consists of German stocks that are constituents of either the Dax, MDax, SDax or TecDax index. Germany has 4 major stock indices. Those are disjoint by definition and have different sizes. Dax and TecDax contain 30 companies while MDax and SDax contain 50 constituents respectively. Ordering among the three indices Dax, MDax and SDax is based on a joint assessment of trading volume and (dispersed) market capitalization of the stock. Dax contains the 30 largest companies followed by MDax and SDax. TecDax takes a special position here as it contains the technology stocks that do not qualify for a Dax inclusion. This implies, that technology stocks that could be part of both MDax/SDax and TecDax will always be included in the TecDax. Regular changes in the composition of indices may happen every quarter.

An index change is distinct from the fundamentals of the firm, as no new information is revealed (see e.g. Hegde and McDermott (2003) and Wurgler (2010)). However, if a stock moves into an index, out of an index, or changes between indices, this causes two effects. Take for example the scenario that a company moves from the MDax to the Dax index. The announcement of this event increases investor attention and can consequently invoke a positive liquidity effect (as hypothesized). Furthermore, this index change might not only induce liquidity effects from attention traders but also other liquidity effects for simple supply and demand reasons. For example, consider the buying pressure of financial institutions that have to hold same part of the new Dax index company. A re-change, i.e. a downgrading from the Dax to MDax will cause the same liquidity effects (due to selling pressure) but less attention-based trading. Index inclusion is positive news to the attention trader and will create more attention-based trading than an exclusion (Barber and Odean (2008)). This is due to the fact that in the exclusion case, the investor can only sell the stocks he already has in his portfolio. By looking at the difference of the pre- and post index change periods, we can clearly identify an attention-based trading effect on liquidity.

8.1 Index Changes and the Liquidity Attention Relation

In order to confirm the results found about the relation between liquidity measures and direct Google attention variables and to solve the problem of possible endogeneity as explained in section 8, we have a detailed look at index inclusion and deletion effects of stocks. We use stock index increases and drops as exogenous event to control for reverse causality in the liquidity - attention relation. As explained, the specific characteristics of the German stock indices allow for a differentiation between index rise and index drop. By rise we not only mean the inclusion of stocks that were not constituent of one of the indices before, but also an index change from SDax to MDax/Dax or from MDax to Dax. All those events imply an increase in recognition and reputation. Index drops are defined conversely. We analyse both the date of an index change announcement and the actual date of index change. In total we identify 71 up- and 71 down-events. In a first step, we analyse the influence the announcement and actual index increase/decrease has on attention measures. The results are depicted in figure 5.

[Insert Figure 5 about here]

In Panel (a) of figure 5 we see the average effect of an index increase of a stock on the equally-weighted Google Insights SVI. On the announcement as well as on the actual event day the average standardized SVI increases by 0.3 points. The same effect can be identified for an index descent. On the announcement day of the drop the Google SVI increases by 0.4 points from a below average value and continues to increase the next day. The index deletion effect on the actual event day is somewhat weaker. Overall, index changes seem to raise attention as measured by Google SVI.

We analyse how those attention rises translate into liquidity effects. We therefore reconsider the liquidity - attention regression 10 but control for the possible endogeneity by including index rise/drop dummies[21] as well as interaction terms between SVI and index dummies. Table 13 shows the regression results.

[Insert Table 13 about here]

In regression (1)-(4), we regress the effective spread on the Google Insights measures as well as on announcement/actual day index increase/decrease dummies. Furthermore, we analyse the interaction effect between the Google attention measure and index increase / decrease on announcement and actual days. In regression (1)-(2), in which we analyse the influence of Insights SVI on Effective Spread, we do not find significant results for the Insights variable. However, a negative relationship between attention and liquidity is suggested. Only the lagged Insights variable has a negative significant influence on the Effective Spread. Furthermore, we find that on announcement days of an index drop, the effective spread is lower. All the other index dummies as well as interaction terms have no significant coefficients. The more interesting

[21] The dummy takes value 1 only for the day of an actual index increase/drop.

results can be found in regression (3)-(4). We analyse the influence of Insights Finance SVI, which we believe to be the more suitable measure of investor attention. The Insights Finance as well as the lagged Insights Finance measure have a strong significant negative influence on the effective spread. This means the higher the attention, the higher the liquidity of a stock. Furthermore, we find that on index decline days the liquidity of a stock is significantly reduced and on inclusion days the liquidity is (not significantly) increased. Note that by construction this is the clean index inclusion effect given no attention-level changes. Next, we analyse the interaction terms of the announcement and actual index changes combined with the attention measure. Those provide the attention on liquidity effect given that we observe an index change. We find that on these days the Effective Spread increases for index drops. In case of index inclusion the effective spread decreases (announcement day) or increases much less (actual day) than in the exclusion case. The negative effect of attention on liquidity at index change events is not expected.

However, in this test we are more interested in the difference in coefficients on inclusion ant exclusion event days. This difference is significant. From this result we can confirm that attention has a positive effect on liquidity, even if we control for endogeneity. This is due to the idea that on index change days no new information is generated and the liquidity effects that are not attributable to attention changes are captured by the dummy variables. The additional effects from an attention increase due to an index increase and decrease should be symmetrical in rises and drops. As we can derive from the interaction terms in equation (4), given an index change, liquidity is reduced significantly more by drops than by increases. The gap may only be explained by the exogeneous effect of attention on effective spreads. Therefore and due to the negative sign of Insights SVI on days of no index change we confirm Hypothesis 1. The results from this endogeneity tests are not yet particularly strong and require further verification.

In regressions (5)-(8), we analyse the depth dimension of liquidity. We again focus on regressions (7)-(8) as the Insights Finance variable is more appropriate. Insights Finance has a negative impact on the depth, therefore reducing liquidity. Index changes in general seem to improve liquidity as the coefficients are positive but insignificant. The additional attention on index change announcement and actual days seems to reduce depth and therefore liquidity. However, all these coefficients are insignificant.

In regression (9)-(12), the analysis of the price impact liquidity dimension is performed. The Insights measure seems to have a negative influence on liquidity as the price impact increases. Coefficients for index dummies are insignificant. Regarding the interaction terms, we observe the opposite pattern as for effective spreads: The attention on index increase days has a negative and the attention on index decrease days a positive but insignificant influence on the price impact. This implies a positive influence of attention on price impact. While coefficients are insignificant, this finding raises doubts concerning the positive attention-liquidity relation. We earlier discussed the different dimensions of liquidity. We document in this analysis that it might be that the different dimensions are affected in opposed ways.

In the last set of regressions (13)-(16), we analyse the influence of attention on the return of a stock. We find that both attention measures have a positive significant influence on returns. Announcement days of index increases seem to have a strong positive effect on returns whereas the actual event days show a negative but insignificant relation. For exclusion days we only find a positive effect for actual index drops. While insignificant, the interaction terms for index drops are negative.

Overall, we find that attention has a negative effect on Effective Spreads increasing liquidity. However, the Depth and Price Impact dimension of liquidity seem to suffer from an increase in attention, even if we control for reverse causality. Returns seem to increase with attention. Furthermore, additional attention on bad news days (index deletions) seems to decrease returns and on good news days increase returns. The endogeneity tests need further refinement and will be extended with cumulative abnormal attention measures (over several days) to find significant changes in liquidity measures.

9 Conclusion

The research aim of this paper was to describe the relation between attention-driven trading and the liquidity of a stock. We hypothesize that this relation is not just direct but influenced by the strategic decision making of all market participants. We develop an attention-based structural microstructure model that allows for an empirical analysis of those different channels. Our findings have implications for the market microstructure and asset pricing literature and contribute to the understanding of retail investor decision making. We show that daily changes in the Google Search Volume Index are related to liquidity in its different dimensions. This relation seems robust to endogeneity and stronger for stocks with a higher proportion of retail trading. Further research has to explain why the different liquidity dimensions are not influenced in equal measure. Also, we find evidence that high attention triggers positive short term returns. To our knowledge, we are the first to show these relationships based on daily Google Search Volume Data. We find that Google Insights is correlated with the existing indirect attention measures but has additional explanatory power. By filtering for finance-related searches we extend recent studies using Google search data. The estimation results of our attention-adjusted microstructure model show that attention has a particularly strong and significant effect on the liquidity of small firms. This liquidity improvement is due to more overall trading and less informed trading on high attention days. This implies that trading in small stocks is relatively cheap on high attention days.

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10 Figures and Tables

Figure 1: Structural Market Microstructure Model based on Easley et al. (1996)
This figure shows the extended structural microstructure model. Every trading day it its determined if it is a high or low attention day based on the relative Google Search Volume for the respective day. On the beginning of every trading day, nature decides if it is a news or no news day. The probability for a news event on trading day t is depicted as α. The probability of bad news is δ and good news $(1-\delta)$. The buy and sell trades of the informed and uninformed on no news, good and bad news days follow three mutually independent Poisson processes as in the original model of Easley et al. (1996) (EKOP). The EKOP model is then estimated for high and low attention days (ha/la). This allows to derive a probability of informed trading for high and low attention days

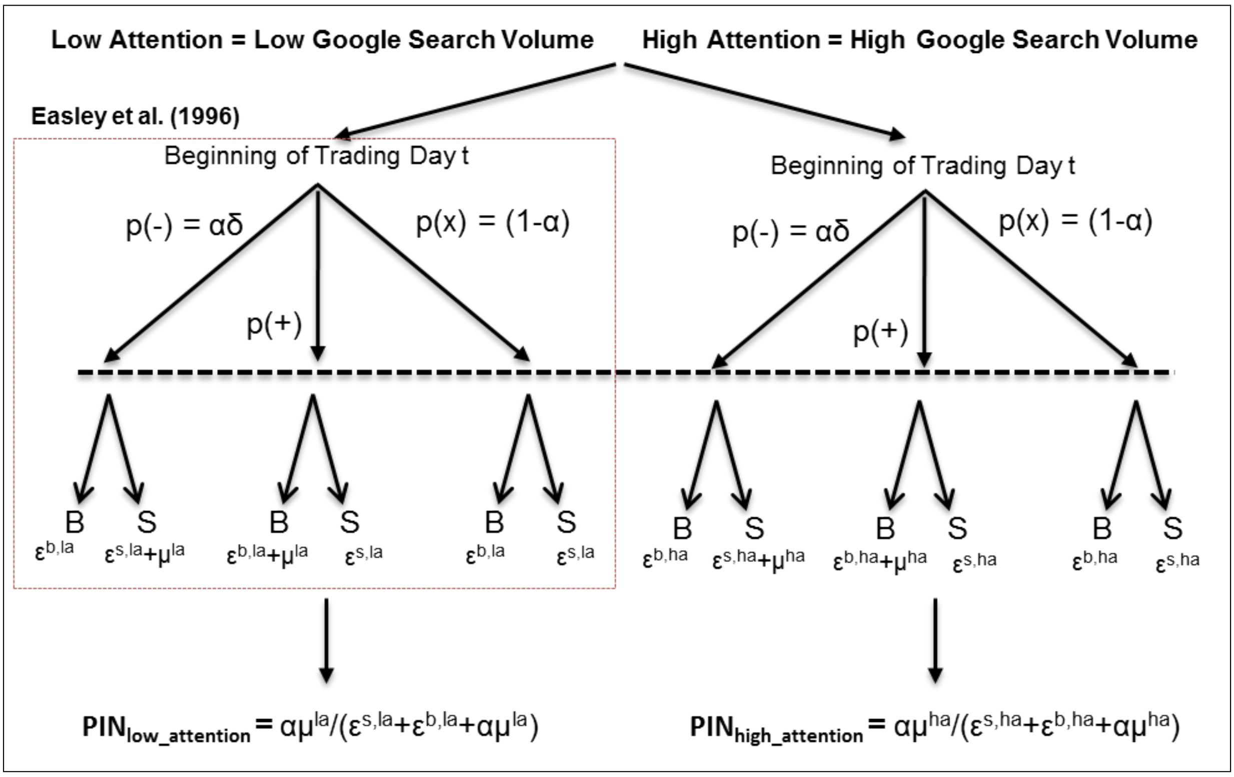


Figure 2: Density Distribution of SVI from Google Insights

This figure shows aggregated SVI (Google Search Volume Index) for all constituents of Dax, MDax, SDax and TecDax during 2004 to 2007, searched by adjusted Datastream firm names. Zero-SVIs are eliminated. Stocks are equally weighted.

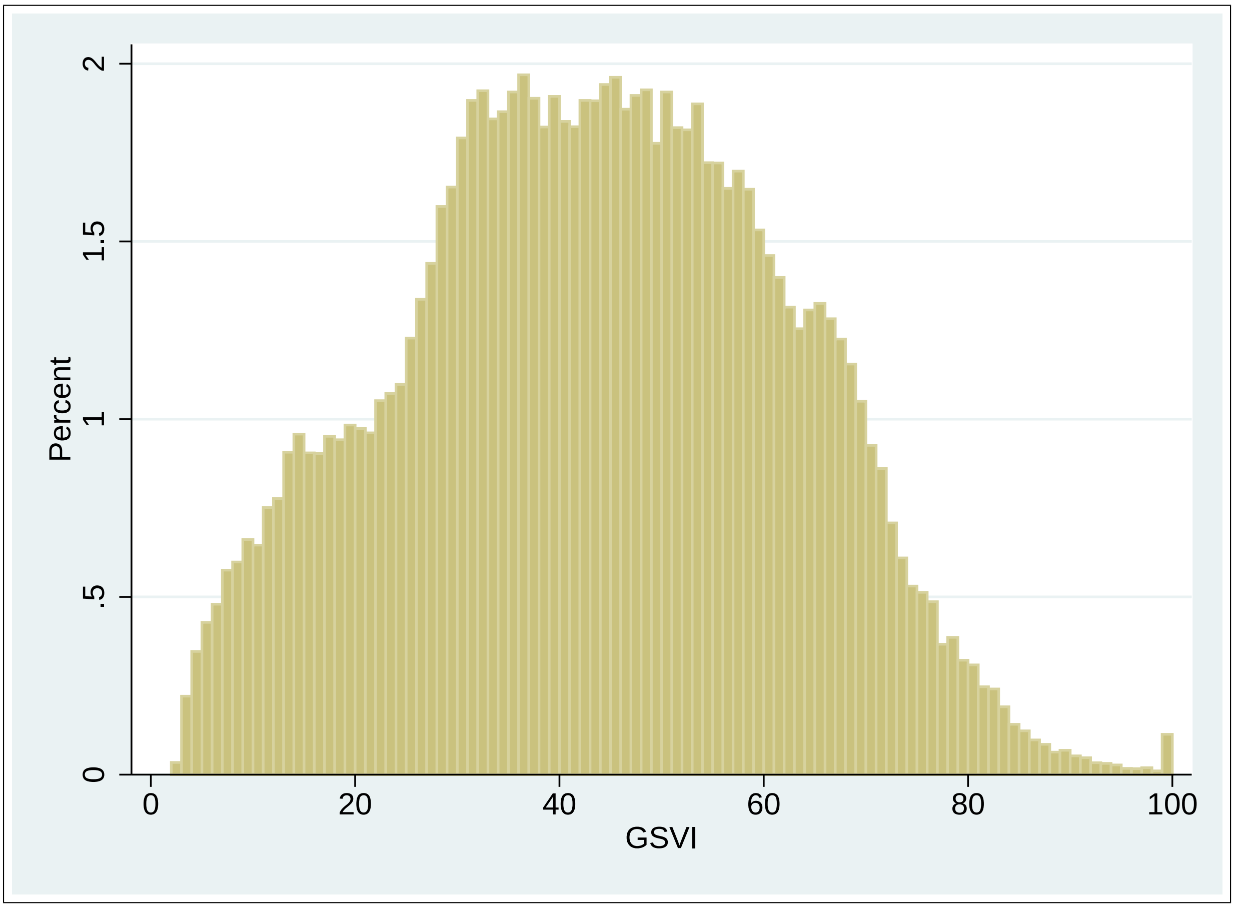
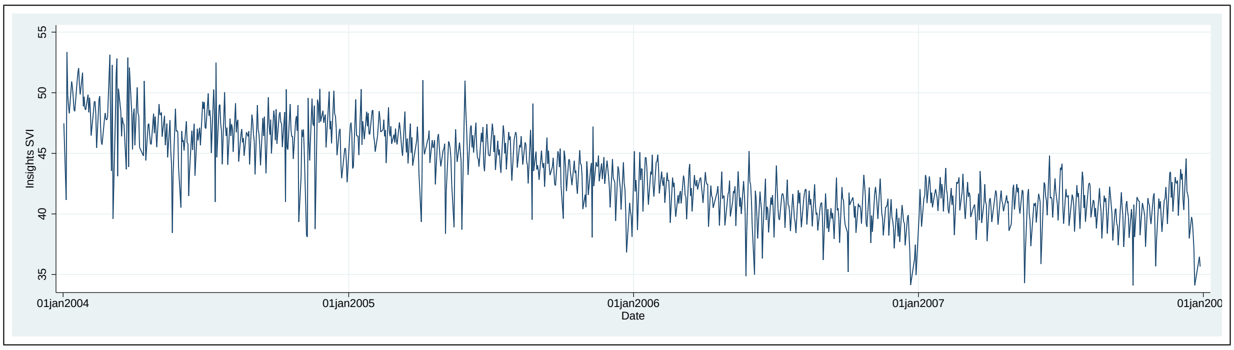


Figure 3: Average Timeseries SVI from Google Insights

This figure shows the timeseries of equally-weighted SVI for all constituents of Dax, MDax, SDax and TecDax during 2004 to 2007, searched by adjusted Datastream firm names. Zero-SVIs are eliminated.

Panel (a) shows this plot for SVI from Google Insights without use of a category filter (Insights SVI), Panel (b) for SVI from Google Insights with category filter Finance (Insights Finance SVI).

(a) Average Insights SVI



(b) Average Insights Finance SVI

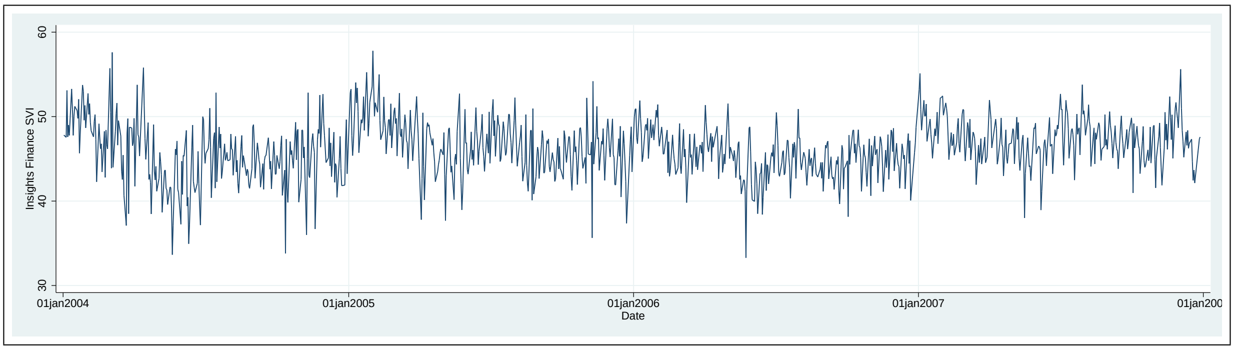
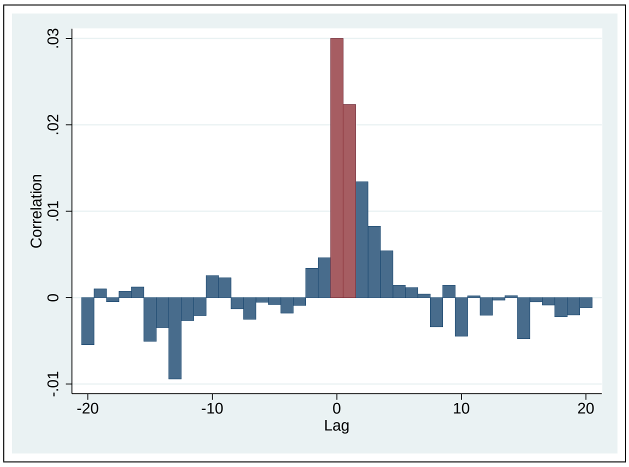


Figure 4: Time Series Cross-Correlations

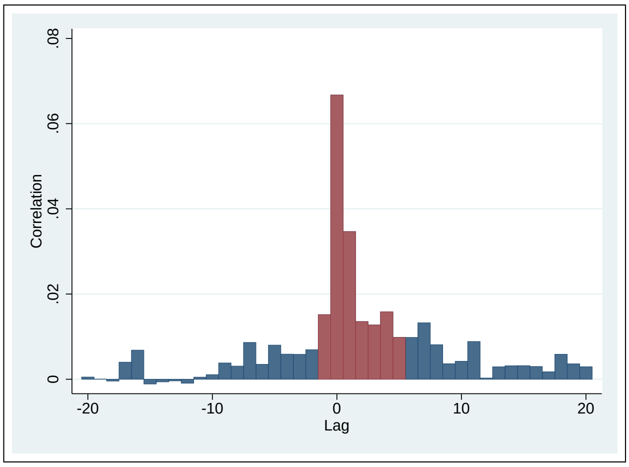
This figures show the time series cross-correlations between the equally-weighted Insights SVI for all constituents of Dax, MDax, SDax and TecDax during 2004 to 2007 with the Events, Squared Returns and Trading Volume of the corresponding companies over time.

Panel (a) shows the cross correlation between Google SVI and the Event dummy. The Google SVI is fixed the Event dummy lagged. Panel (b) shows the cross correlation between Google SVI and the Squared-Returns variable. The Google SVI is fixed the Squared-Returns variable lagged, and Panel (c) shows the cross correlation between Google SVI and Trading Volume variable. The Google SVI is fixed the Trading Volume variable lagged.

(a) Cross-Correlation Google SVI - Event Dummy



(b) Cross-Correlation Google SVI - Squared Returns



(c) Cross-Correlation Google SVI - Trading Volume

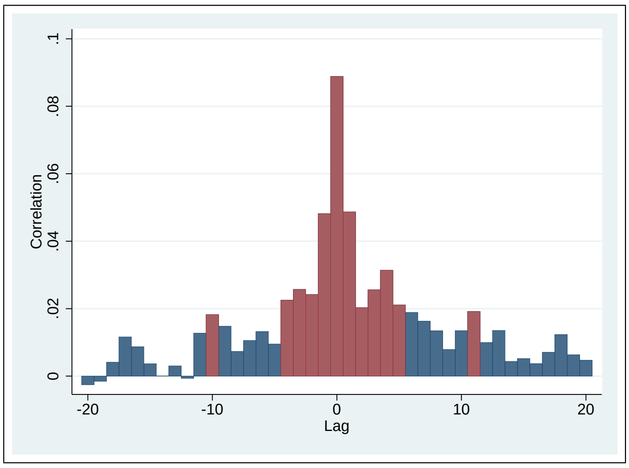
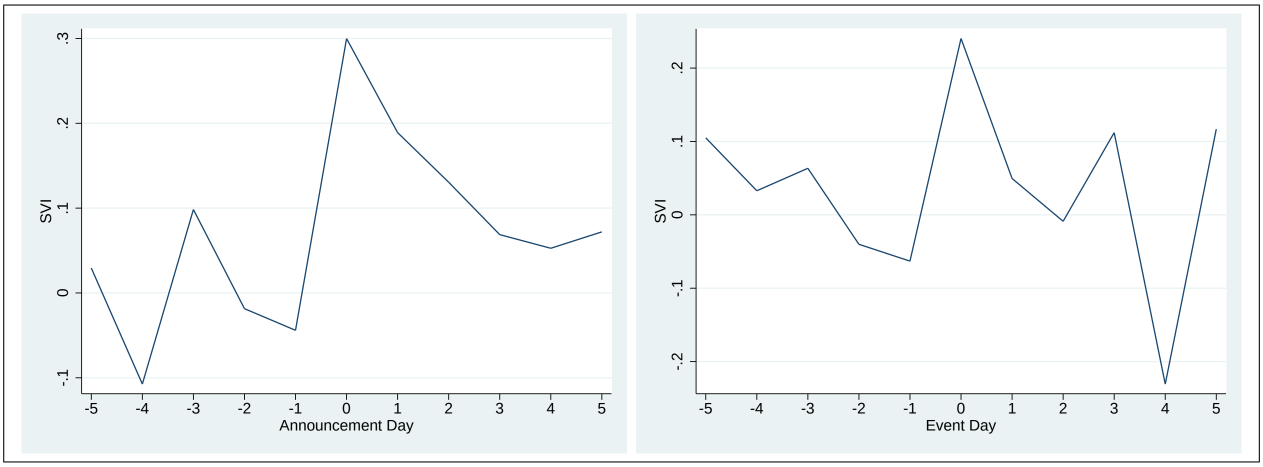


Figure 5: Attention and Index Changes

This figure shows the daily average equally-weighted SVI five days before and after an index change announcement or actual change. Zero-SVIs are eliminated. Panel (a) shows this plot for index inclusions, Panel (b) for index deletions.

(a) Index Increase



(b) Index Decrease

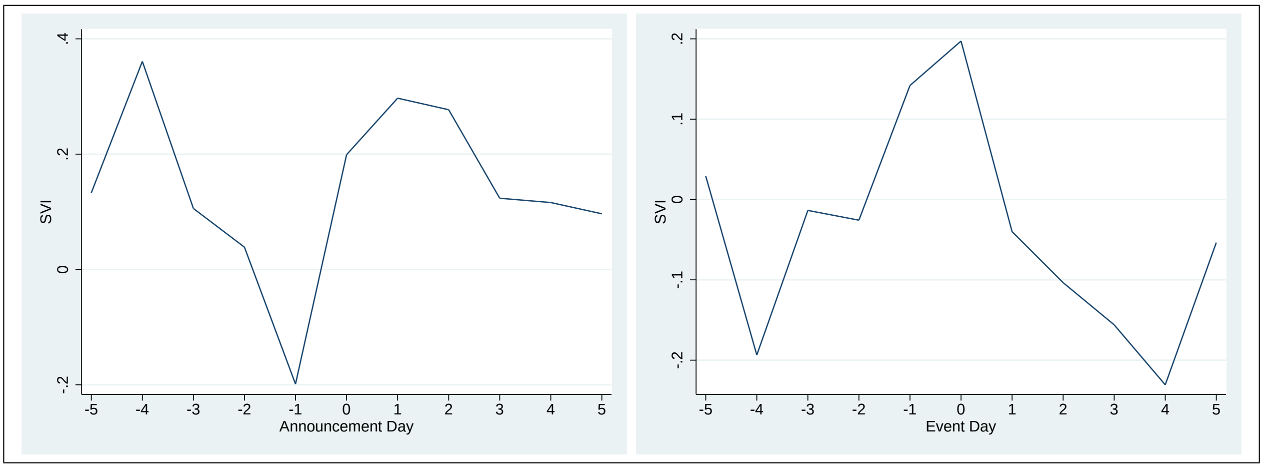


Table 1: Example of the Google Insights Solution Algorithm

This example demonstrates how one might generate a timeseries of daily *SVI* data for a time interval of more than 15 month from *Google Insights*.

(a) Step 1: Find yearly maxima

Year	Q1	Q2	Q3	Q4
2004		x		
2005	x			
2006			x	
2007			x	

(b) Step 2: Find global maximum

2004 Q2	2005 Q1	2006 Q3	2007 Q3
		x	

(c) Step 3: Include global maximum in yearly requests

		2004		
2006 Q3	Q1	Q2	Q3	Q4
		2005		
2006 Q3	Q1	Q2	Q3	Q4
		2006		
2006 Q3	Q1	Q2	Q3	Q4
		2007		
2006 Q3	Q1	Q2	Q3	Q4

Table 2: ***Summary Statistics Google SVI across years***

The table provides summary statistics for equally-weighted *SVI* across the years 2004 to 2007 for constituents of the 4 major German stock indices Dax, MDax, SDax, TecDax. We differentiate between SVI from Google Insights without use of a category filter (*Insights SVI*), SVI from Google Insights with category filter Finance (*Insights Finance SVI*) and SVI from Google Trends (*Trends SVI*).

N provides the total number of non-missing daily observations. Additionally *Mean, Median, Standard Deviation, Skewness* and *Kurtosis* are provided.

year	**SVI variable**	**N**	**Mean**	**Median**	**Std.Dev.**	**Skewness**	**Kurtosis**
2004	Insights SVI	22612	47.19	48.00	17.68	-0.07	2.65
	Insights Finance SVI	4441	45.64	46.00	14.30	0.10	2.99
	Trends SVI	11600	1.04	1.03	0.20	2.35	31.95
2005	Insights SVI	26970	44.82	45.00	17.70	-0.07	2.52
	Insights Finance SVI	6005	46.91	48.00	14.62	-0.25	3.55
	Trends SVI	15053	1.05	1.02	0.29	4.48	73.71
2006	Insights SVI	30777	40.87	41.00	18.37	0.06	2.38
	Insights Finance SVI	7371	45.37	46.00	15.48	-0.30	3.05
	Trends SVI	17660	1.03	0.99	0.43	13.16	504.19
2007	Insights SVI	33316	40.76	40.00	19.34	0.21	2.42
	Insights Finance SVI	8240	47.47	47.00	18.56	0.05	2.84
	Trends SVI	19542	1.04	0.98	0.53	11.38	500.39
Total	Insights SVI	113675	43.03	43.00	18.56	0.03	2.44
	Insights Finance SVI	26057	46.43	47.00	16.17	-0.05	3.18
	Trends SVI	63855	1.04	1.00	0.41	12.45	621.26

Table 3: ***Summary Statistics Google SVI across indices***

The table provides summary statistics for equally-weighted *SVI* across the four German stock indices Dax, MDax, SDax and TecDax. A stock is considered part of the index if it at least once was listed in the respective index during 2004 to 2007. We differentiate SVI from Google Insights without use of a category filter (*Insights SVI*), SVI from Google Insights with category filter Finance (*Insights Finance SVI*) and SVI from Google Trends (*Trends SVI*).

N provides the total number of non-missing daily observations. Additionally *Mean, Median, Standard Deviation, Skewness* and *Kurtosis* are provided.

year	**SVI variable**	**N**	**Mean**	**Median**	**St.Dev.**	**Skewness**	**Kurtosis**
Dax	Insights SVI	35445	47.92	48.00	18.24	-0.09	2.22
	Insights Finance SVI	15090	49.55	49.00	13.39	0.24	3.14
	Trends SVI	27655	1.05	1.03	0.32	2.23	22.20
MDax	Insights SVI	44268	41.19	41.00	18.11	0.11	2.39
	Insights Finance SVI	9122	46.24	47.00	16.84	0.15	2.70
	Trends SVI	21493	1.08	1.03	0.48	17.36	832.69
SDax	Insights SVI	41741	40.64	41.00	18.51	0.02	2.45
	Insights Finance SVI	5678	40.73	40.00	20.25	0.21	2.70
	Trends SVI	21382	0.97	0.92	0.43	6.52	146.93
TecDax	Insights SVI	17614	42.72	43.00	18.94	0.01	2.68
	Insights Finance SVI	2021	47.22	46.00	11.80	0.85	3.80
	Trends SVI	6623	1.08	0.99	0.40	1.58	8.43

Table 4: ***Sample Size per Index and Year***

The number of firms included in the sample year that were listed in the respective index, that at least once contain information on prices, effective spreads and timeseries search volume from Google Insights. *TOTAL* gives the same information over the whole sample. $TOTAL^{\star}$ gives the same information for all firms, including those that lack joint information on all three dimensions (Prices, Spreads and *Insights SVI*).

Index	**2004**	**2005**	**2006**	**2007**	**TOTAL**	$TOTAL^{\star}$
All Indices	90	105	119	126	132	239
Dax	28	30	31	32	32	41
MDax	37	47	51	53	55	86
SDax	36	42	47	50	53	104
TecDax	11	12	18	20	21	51

Table 5: This table shows the estimation results $\hat{\theta} = \alpha, \delta, \varepsilon_t^{b,ha}, \varepsilon_t^{b,la}, \varepsilon_t^{s,ha}, \varepsilon_t^{s,la}, \mu_t^{ha}, \mu_t^{la}$ of the Maximum Likelihood estimation of the attention-adjusted structural microstructure model as described in section 3. The microstructure model is estimated for 90 stocks out of the total sample for which Google Search Volume is available. The companies are sorted into size terciles and parameters estimates are shown for the respective tercile. The p-values are given in brackets. ***, ** and * indicate that the parameter estimate across all stocks is significant at a 1%, 5% and 10% significance level, respectively.

	Small		Large
α	0.36*	0.36	0.40
	(0.07)	(0.23)	(0.28)
δ	0.45*	0.49	0.53
	(0.07)	(0.23)	(0.30)
$\varepsilon_t^{b,ha}$	68*	129	835
	(0.08)	(0.28)	(0.42)
$\varepsilon_t^{b,la}$	46*	206	1467
	(0.08)	(0.30)	(0.38)
$\varepsilon_t^{s,ha}$	72*	130	891
	(0.09)	(0.29)	(0.47)
$\varepsilon_t^{s,la}$	44*	209	1571
	(0.07)	(0.39)	(0.42)
μ_t^{ha}	93*	142	484
	(0.10)	(0.30)	(0.42)
μ_t^{la}	67*	201	866
	(0.10)	(0.33)	(0.38)

Table 6: This table shows the Probability of Informed trading derived from estimation results of the attention-adjusted structural microstructure model in table 5. The probability of informed trading for the high and low attention states is calculated as $PIN_t^{low\ attention} = \alpha\mu_t^{la}/(\varepsilon_t^{b,la} + \varepsilon_t^{s,la} + \alpha\mu_t^{la})$ and $PIN_t^{high\ attention} = \alpha\mu_t^{ha}/(\varepsilon_t^{b,ha} + \varepsilon_t^{s,ha} + \alpha\mu_t^{ha})$ as described in section 3.The PIN is shown for the respective size terciles.

	Small		Large
$PIN_t^{high\ attention}$	0.19	0.17	0.10
$PIN_t^{low\ attention}$	0.21	0.15	0.10

Table 7: Descriptive Statistics

The table provides daily *Mean* (equally-weighted), *Median* and *Standard Deviation* of several variables for the four markets *Dax, MDax, SDax, TecDax* as well as for our total sample from 2003 to 2007. Additionaly the number of daily observations (N) and the number of firms for which this field is filled (*Firms*) is provided.

Daily Stock Return is the daily stock return. *Market Value* is the daily Market Value calculated as Price times Shares Outstanding. *No of. Trades* is the total number of daily trades and *No. of Buys/Sells* is the daily number of buyer-/seller-initiated trades. *Prop of Small Buys/Sells* gives the proportion of daily trades that were among the smallest 10% of all buys/sells. *Relative Effective Spread* is twice the relative absolute difference between trading price and midpoint during a day. *Market Depth* is the average quantity available for trade at the best bid/ask. *Price Impact* is the equally-/dollar-volume-weighted relative difference between the midpoint and the midpoint 5 minutes later. *Squared Return* is the stocks' squared return. *Trading Volume* is the number of shares traded per day. *Event Dummy* is a dummy variable, which takes value 1 if an event happens at a specific day. We differentiate between SVI from Google Insights without use of a category filter (*Insights SVI*), SVI from Google Insights with category filter Finance (*Insights Finance SVI*) and SVI from Google Trends (*Trends SVI*). For SVI data retrieved for crosssectional comparisons we add a *(cs)*. *Share Blockholders* is the percentage of the stock that is held by parties that own more than 5% of the company. *No. of firms* finally provides the total number of firms that were part of the respective index during 2003 to 2007.

Daily Stock Return, Prop of Small Buys/Sells, Relative Effective Spread, Price Impact, Squared Return, Event Dummy and Share Blockholders are given in percentage terms.

	Dax					MDax					SDax					TecDax					Total				
	Mean	*Median*	*Std.Dev.*	*N*	*Firms*	*Mean*	*Median*	*Std.Dev.*	*N*	*Firms*	*Mean*	*Median*	*Std.Dev.*	*N*	*Firms*	*Mean*	*Median*	*Std.Dev.*	*N*	*Firms*	*Mean*	*Median*	*Std.Dev.*	*N*	*Firms*
Daily Stock Return	0.10	0.06	1.54	41422	41	0.09	0.00	2.06	75248	86	0.07	0.00	2.76	89385	104	0.10	0.00	2.91	45016	51	0.08	0.00	2.46	211574	239
Market Value	18650696	10329350	18733080	41463	41	2580061	1469660	3354527	73051	83	501466	309040	603723	83591	96	707192	315000	1462057	40912	45	4607352	681585	11202196	200498	223
No. of Trades	2223.32	1597	2137.83	35621	36	475.01	251	641.10	68690	81	108.27	43	193.26	72483	93	249.36	114	430.13	33057	38	635.53	144	1305.04	173692	207
No. of Buys	1075.14	772	1044.11	35621	36	235.74	124	320.92	68690	81	54.55	21	99.35	72483	93	122.93	54	218.88	33057	38	310.12	70	635.71	173692	207
No. of Sells	1142.82	820	1106.74	35621	36	238.56	123	327.35	68690	81	53.63	20	97.51	72483	93	126.17	57	217.80	33057	38	324.12	71	673.73	173692	207
Prop. of Small Buys	1.31	0.92	2.46	35606	36	0.10	0.00	1.60	67768	81	0.28	0.00	3.13	69238	93	9.00	5.41	11.69	32535	38	2.08	0.00	6.49	169396	207
Prop. of Small Sells	1.13	0.68	1.84	35615	36	2.26	0.91	5.74	67974	81	5.11	0.00	11.89	69939	93	4.39	2.00	7.71	32671	38	3.48	0.85	8.75	170487	207
Relative Effective Spread	0.09	0.07	0.13	35621	36	0.50	0.21	4.52	68690	81	1.30	0.64	8.03	72483	93	0.71	0.43	2.04	33057	38	0.75	0.32	5.41	173692	207
Market Depth	4616.75	1308.06	14591.73	35621	36	4210.87	707.89	46222.07	68690	81	4233.07	640.75	45066.53	72483	93	1745.22	843.54	21831.02	33057	38	3219.31	790.14	31384.83	173692	207
Price Impact	0.21	0.19	0.11	35621	36	0.27	0.22	0.33	68690	81	0.30	0.22	0.70	72483	93	0.35	0.28	0.32	33057	38	0.28	0.22	0.51	173692	207
Squared Return	2.37	0.63	13.06	41381	41	4.25	0.84	25.09	75162	86	7.65	1.07	60.60	89281	104	8.48	1.58	35.85	44965	51	6.06	0.97	43.39	211335	239
Trading Volume	3578.16	1792.40	5905.07	41463	41	436.68	152.20	1201.83	75334	86	104.02	27.10	397.74	89489	104	246.04	85.20	583.50	45067	51	857.19	90.00	2978.31	211813	239
Event Dummy	0.95	0	9.69	41463	41	0.83	0	9.08	75334	86	0.85	0	9.19	89489	104	0.77	0	8.74	45067	51	0.81	0	8.98	211813	239
Insights SVI	47.92	48	18.24	35445	37	41.19	41	18.11	44268	58	40.64	41	18.51	41741	57	42.72	43	18.94	17614	28	43.03	43	18.56	113675	150
Insights Finance SVI	49.55	49	13.39	15090	20	46.24	47	16.84	9122	13	40.73	40	20.25	5678	9	47.22	46	11.80	2021	3	46.43	47	16.17	26057	37
Trends SVI	1.05	1.03	0.32	27655	35	1.08	1.03	0.48	21493	48	0.97	0.92	0.43	21382	44	1.08	0.99	0.40	6623	22	1.04	1.00	0.41	63855	123
Insights SVI (cs)	9.91	2	14.40	24122	32	6.73	2	12.69	17348	33	7.04	1	18.31	16695	34	19.38	3	33.28	5000	11	9.42	2	18.25	52044	89
Insights Finance SVI (cs)	15.66	8	19.55	14940	22	13.91	7	19.78	9523	16	10.94	3	18.54	6666	12	21.06	3	24.90	2137	5	13.65	6	18.96	27371	45
Trends SVI (cs)	0.06	0.01	0.09	26070	32	0.03	0.01	0.04	19605	38	0.02	0.01	0.02	18186	35	0.14	0.02	0.26	5518	14	0.05	0.01	0.11	57625	99
Share Blockholders	44.23	38.02	26.81	38405	39	51.07	52.32	24.28	68467	82	55.10	54.40	23.49	57100	84	43.76	43.58	21.05	26923	37	49.75	50.43	24.79	154071	199
No. of Firms			41					86					104					51					239		

Table 8: Attention Measure Correlations

This table provides average stock-by-stock correlations between different attention variables for a sample of all Dax, MDax, SDax and TecDax stocks between 2003 and 2007.

Event is a dummy variable, which takes value 1 if an event happens at a specific day. *Volume* is the number of shares traded per day. *sq. ret.* is the squared stock return lagged by one day. We differentiate between SVI from Google Insights without use of a category filter (*Insights SVI*), SVI from Google Insights with category filter Finance (*Insights Fin. SVI*) and SVI from Google Trends (*Trends SVI*).

***, ** and * indicate that the mean correlation coefficient across all stocks is significant at a 1%, 5% and 10% significance level, respectively.

	Event	**Volume**	**sq. ret.**	**Insights SVI**	**Insights Fin. SVI**	**Trends SVI**
Event	100.00%	11.13% ***	0.19%	3.03% ***	1.86%	3.42%
Volume		100.00%	23.63% ***	8.00% ***	9.58% ***	7.72% **
sq. ret.			100.00%	3.40% ***	1.13%	-2.47%
Insights SVI				100.00%	45.58% ***	86.97% ***
Insights Fin. SVI					100.00%	39.68% ***
Trends SVI						100.00%

Table 9: Google SVI and Indirect Attention Measures: Regression Results

This table provides regression results for *Google SVI* as dependent variables for the sample of all Dax, MDax, SDax and TecDax firms from 2003 to 2007. We differentiate between SVI from Google Insights without use of a category filter (*Insights SVI*), SVI from Google Insights with category filter Finance (*Insights Finance SVI*) and SVI from Google Trends (*Trends SVI*). *Trading Volume* is the number of shares traded per day. *Event Dummy* is a dummy variable, which takes value 1 if an event happens at a specific day. *Squared Return* is the squared stock return.

All variables are standardized ($\frac{x-mean_x}{\sigma_x}$). Lagged variables are lagged by one day. Robust standard errors are clustered by firm and shown in parentheses. ***, ** and * indicate significance at a 1%, 5% and 10% significance level, respectively.

	(1) Insights SVI	(2) Insights SVI	(3) Insights Finance SVI	(4) Insights Finance SVI	(5) Trends SVI	(6) Trends SVI
Trading Volume	0.0564***	0.0437***	0.109***	0.0858***	0.00342	0.00436
	(0.0162)	(0.0122)	(0.0299)	(0.0242)	(0.0188)	(0.0145)
Event Dummy	0.184***	0.195***	0.0482	0.0707	0.171**	0.172**
	(0.0526)	(0.0525)	(0.105)	(0.105)	(0.0696)	(0.0697)
Squared Return	0.0386***	0.0404***	-0.000488	0.00634	0.0308***	0.0302***
	(0.00812)	(0.00783)	(0.0180)	(0.0169)	(0.00942)	(0.00880)
Lagged Trading Volume		0.0200*		0.0610***		-0.00663
		(0.0114)		(0.0206)		(0.0139)
Lagged Event Dummy		0.129***		0.0279		0.140**
		(0.0460)		(0.0718)		(0.0626)
Lagged Squared Return		0.00758		-0.0246		0.00718
		(0.00669)		(0.0163)		(0.00903)
Constant	-0.00384***	-0.00495***	-0.00497***	-0.00679***	-0.00232**	-0.00318**
	(0.000850)	(0.00117)	(0.00172)	(0.00247)	(0.000978)	(0.00144)
Observations	113,583	113,511	26,038	26,026	63,799	63,756
Cluster(Firms)	149	149	37	37	113	112
R-squared	0.007	0.008	0.013	0.016	0.002	0.002

Table 10: Indirect Attention Measures and Google SVI: Regression Results

This table provides regression results for indirect attention measures as dependent variables for the sample of all Dax, MDax, SDax and TecDax firms from 2003 to 2007. *Trading Volume* is the number of shares traded per day. *Event Dummy* is a dummy variable, which takes value 1 if an event happens at a specific day. *Squared Return* is the squared stock return. We differentiate between SVI from Google Insights without use of a category filter (*Insights SVI*) and SVI from Google Insights with category filter Finance (*Insights Finance SVI*).

All variables are standardized ($\frac{x-mean_x}{\sigma_x}$). Lagged variables are lagged by one day. Robust standard errors are clustered by firm and shown in parentheses. ***, ** and * indicate significance at a 1%, 5% and 10% significance level, respectively.

	(1) Volume	(2) Volume	(3) Volume	(4) Event Dummy	(5) Event Dummy	(6) Event Dummy	(7) Squared Return	(8) Squared Return	(9) Squared Return
Insights SVI	0.0645***	0.0117	0.0220	0.0839***	0.0622	0.0585	0.0797***	0.0388	0.0202
	(0.0102)	(0.0152)	(0.0134)	(0.0132)	(0.0418)	(0.0476)	(0.0170)	(0.0320)	(0.0217)
Insights Finance SVI		0.0440***	0.0527***		0.0298	0.0450		0.0947***	0.0796***
		(0.0156)	(0.0175)		(0.0382)	(0.0466)		(0.0226)	(0.0181)
Lagged Insights SVI			-0.0139			-0.00490			0.00406
			(0.0119)			(0.0410)			(0.0223)
Lagged Insights Finance SVI			-0.0165			-0.0444			0.0603***
			(0.0114)			(0.0343)			(0.0183)
Constant	0.00509**	0.00181	0.00164	-2.422***	-2.418***	-2.418***	0.0336***	0.0442***	0.0459***
	(0.00197)	(0.00540)	(0.00555)	(0.0340)	(0.0608)	(0.0619)	(0.00655)	(0.0149)	(0.0154)
Observations	113,583	25,996	25,342	113,583	25,996	25,342	113,674	26,015	25,342
Cluster(Firms)	149	37	37	149	37	37	149	37	37
R-squared	0.004	0.003	0.003	0.006	0.005	0.005	0.006	0.014	0.017

Table 11: Liquidity and Return: Regression Results

This table provides firm-fixed effects regression results for liquidity measures and returns as dependent variables for the sample of all Dax, MDax, SDax and TecDax firms from 2003 to 2007. *Effective Spread* is the relative absolute difference between trading price and midpoint during a day. *Market Depth* is the average quantity available for trade at the best bid/ask. *Price Impact* is the equally-weighted relative difference between the midpoint and the midpoint 5 minutes later. As control variables we use Trading Volume, Squared Return and Market Value (lagged and unlagged) that potentially could also explain the stock's liquidity. We differentiate between SVI from Google Insights without use of a category filter (*Insights SVI*)and SVI from Google Insights with category filter Finance (*Insights Finance SVI*).
All variables are standardized ($\frac{x-mean_x}{\sigma_x}$). Lagged variables are lagged by one day. Robust standard errors are shown in parentheses. ***, ** and * indicate significance at a 1%, 5% and 10% significance level, respectively.

	(1) Effective Spread	(2) Effective Spread	(3) Market Depth	(4) Market Depth	(5) Price Impact	(6) Price Impact	(7) Return	(8) Return
Insights SVI	-0.00420		-0.00479		-0.0139***		0.00426	
	(0.00338)		(0.00363)		(0.00334)		(0.00361)	
Lagged Insights SVI	-0.00635*		-0.0104***		-0.00629*		-0.00472	
	(0.00338)		(0.00363)		(0.00334)		(0.00361)	
Insights Finance SVI		-0.0224***		0.00515		-0.0354***		0.00893
		(0.00674)		(0.00681)		(0.00649)		(0.00703)
Lagged Insights Finance SVI		-0.0202***		0.00452		-0.0139**		-0.00744
		(0.00674)		(0.00682)		(0.00649)		(0.00702)
Constant	12.65***	12.93***	10.91***	15.41***	-0.450***	0.788***	-0.740***	-0.893***
	(0.110)	(0.254)	(0.118)	(0.257)	(0.108)	(0.245)	(0.117)	(0.268)
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Observations	94,229	21,580	94,229	21,580	94,229	21,580	109,675	25,404
Firms	132	31	132	31	132	31	145	37
R-squared	0.168	0.160	0.112	0.190	0.259	0.280	0.022	0.021

Table 12: Trade Size Sort: Liquidity and Return - Regression Results (I/II)

This table provides firm-fixed effects regression results for liquidity measures and returns as dependent variables for the sample of all Dax, MDax, SDax and TecDax firms from 2003 to 2007 (as in Table 11). However, regressions are done for small-trade-size quintiles separately. Each year firms are sorted according to their average trade size (in euro terms) into quintiles. A trade is labelled small if it is among the smallest ten percent of all trades during that year. Stocks here are sorted into quintiles according to the proportion of small trades in this stock during a year. (1) means a low proportion of small trades, thus many high trades.

Effective Spread is the relative absolute difference between trading price and midpoint during a day. *Market Depth* is the average quantity available for trade at the best bid/ask. *Price Impact* is the equally-weighted relative difference between the midpoint and the midpoint 5 minutes later. As control variables we use Trading Volume, Squared Return and Market Value (lagged and unlagged) that potentially could also explain the stock's liquidity. We differentiate between SVI from Google Insights without use of a category filter (*Insights SVI*) and SVI from Google Insights with category filter Finance (*Insights Finance SVI*).

All variables are standardized ($\frac{x-mean_x}{\sigma_x}$). Lagged variables are lagged by one day. Robust standard errors are clustered by firm and shown in parentheses. ***, ** and * indicate significance at a 1%, 5% and 10% significance level, respectively.

(a) Dependent variable: Effective Spread

Quintile	(1)	(2)	(3)	(4)	(5)
	Effective Spread	Effective Spread	Effective Spread	Effective Spread	Effective Spread
Insights Finance SVI	-0.0215	-0.0380***	-0.0383***	-0.00546	-0.117***
	(0.0161)	(0.0116)	(0.00955)	(0.0113)	(0.0444)
Lagged Insights Finance SVI	-0.0159	-0.0359***	-0.0256***	-0.0155	-0.0182
	(0.0161)	(0.0117)	(0.00956)	(0.0113)	(0.0444)
Lagged Effective Spread	0.530***	0.404***	0.425***	0.406***	0.414***
	(0.0173)	(0.0121)	(0.00971)	(0.0120)	(0.0390)
Constant	6.921***	5.266***	15.81***	10.49***	32.08***
	(0.772)	(0.357)	(0.879)	(0.570)	(6.202)
Controls	yes	yes	yes	yes	yes
Observations	2,552	5,545	7,963	4,801	564
Firms	6	12	16	12	2
R-squared	0.365	0.365	0.307	0.346	0.324

(b) Dependent variable: Depth

Quintile	(1)	(2)	(3)	(4)	(5)
	Depth	Depth	Depth	Depth	Depth
Insights Finance SVI	-0.0100	-0.00371	0.0120	-0.00372	0.00183
	(0.0206)	(0.0116)	(0.0100)	(0.0126)	(0.0469)
Lagged Insights Finance SVI	-0.0456**	-0.0122	0.0175*	0.00652	-0.0310
	(0.0206)	(0.0116)	(0.0100)	(0.0126)	(0.0467)
Lagged Market Depth	0.505***	0.375***	0.287***	0.356***	0.349***
	(0.0170)	(0.0123)	(0.0107)	(0.0136)	(0.0398)
Constant	3.795***	6.002***	8.768***	13.87***	11.79*
	(0.948)	(0.360)	(0.887)	(0.660)	(6.307)
Controls	yes	yes	yes	yes	yes
Observations	2,552	5,545	7,963	4,801	564
Firms	6	12	16	12	2
R-squared	0.316	0.338	0.146	0.342	0.356

Table 12: Trade Size Sort: Liquidity and Return - Regression Results (II/II)

Table 12 continued. Effective Spread is the relative absolute difference between trading price and midpoint during a day. *Market Depth* is the average quantity available for trade at the best bid/ask. *Price Impact* is the equally-/dollar-volume-weighted relative difference between the midpoint and the midpoint 5 minutes later. *Return* is the daily stock return. As control variables we use Trading Volume, Squared Return and Market Value (lagged and unlagged) that potentially could also explain the stock's liquidity. We differentiate between SVI from Google Insights without use of a category filter (*Insights SVI*)and SVI from Google Insights with category filter Finance (*Insights Finance SVI*).

All variables are standardized ($\frac{x-mean_x}{\sigma_x}$). Lagged variables are lagged by one day. Robust standard errors are clustered by firm and shown in parentheses. ***, ** and * indicate significance at a 1%, 5% and 10% significance level, respectively.

(c) Dependent variable: Price Impact

Quintile	(1)	(2)	(3)	(4)	(5)
	Price Impact	Price Impact	Price Impact	Price Impact	Price Impact
Insights Finance SVI	-0.0102	-0.000610	-0.0667***	0.00173	-0.0103
	(0.0201)	(0.0126)	(0.00981)	(0.0136)	(0.0422)
Lagged Insights Finance SVI	0.0396**	-0.00743	-0.00393	-0.0219	-0.0552
	(0.0201)	(0.0126)	(0.00982)	(0.0135)	(0.0419)
Lagged Price Impact	0.169***	0.285***	0.363***	0.278***	0.146***
	(0.0193)	(0.0127)	(0.0103)	(0.0137)	(0.0411)
Constant	-0.625	1.356***	5.405***	-0.239	15.84***
	(0.915)	(0.369)	(0.861)	(0.637)	(5.654)
Controls	yes	yes	yes	yes	yes
Observations	2,552	5,545	7,963	4,801	564
Firms	6	12	16	12	2
R-squared	0.238	0.328	0.403	0.343	0.280

(d) Dependent variable: Return

Quintile	(1)	(2)	(3)	(4)	(5)
	Return	Return	Return	Return	Return
Insights Finance SVI	-0.0131	-0.00260	0.0327***	0.0117	0.109**
	(0.0206)	(0.0156)	(0.0124)	(0.0168)	(0.0478)
Lagged Insights Finance SVI	0.0410**	-0.0110	-0.0233*	0.0150	-0.000446
	(0.0205)	(0.0157)	(0.0124)	(0.0167)	(0.0475)
Lagged Return	-0.00329	0.00705	-0.00402	-0.0400***	-0.0671
	(0.0179)	(0.0134)	(0.0112)	(0.0143)	(0.0421)
Constant	-1.552	-0.602	-5.331***	-1.965**	-19.00***
	(1.001)	(0.458)	(1.093)	(0.787)	(6.398)
Controls	yes	yes	yes	yes	yes
Observations	3,145	5,622	8,050	4,850	570
Firms	6	12	16	12	2
R-squared	0.009	0.016	0.050	0.026	0.134

Table 13: Attention and Index Changes: Regression Results

This table provides firm-fixed effects regression results for liquidity measures and returns as dependent variables for the sample of all Dax, MDax, SDax and TecDax firms from 2003 to 2007. *Effective Spread* is the relative absolute difference between trading price and midpoint during a day. *Market Depth* is the average quantity available for trade at the best bid/ask. *Price Impact* is the equally-/dollar-volume-weighted relative difference between the midpoint and the midpoint 5 minutes later. *Return* is the daily stock return. We differentiate between SVI from Google Insights without use of a category filter (*Insights SVI*)and SVI from Google Insights with category filter Finance (*Insights Finance SVI*). *Index Up/Down (Announced/Actual)* is a dummy variable which is 1 for the day of announced/actual change of a stock into a higher/lower index. The remaining variables are interaction terms.

All variables are standardized ($\frac{x-mean_x}{\sigma_x}$). Lagged variables are lagged by one day. Robust standard errors are shown in parentheses. ***, ** and * indicate significance at a 1%, 5% and 10% significance level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Effective Spread	Effective Spread	Effective Spread	Effective Spread	Depth	Depth	Depth	Depth	Price Impact	Price Impact	Price Impact	Price Impact	Return	Return	Return	Return
Insights SVI	-0.00591	-0.00576			0.000753	0.000760			0.0231***	0.0235***			0.0148***	0.0149***		
	(0.00369)	(0.00369)			(0.00384)	(0.00384)			(0.00386)	(0.00386)			(0.00360)	(0.00360)		
Lagged Insights SVI	-0.0112***	-0.0112***			-0.00702*	-0.00708*			0.00282	0.00272			-0.00865**	-0.00869**		
	(0.00368)	(0.00368)			(0.00383)	(0.00383)			(0.00385)	(0.00385)			(0.00359)	(0.00359)		
Insights Finance SVI			-0.0628***	-0.0634***			-0.0197***	-0.0197***			0.00431	0.00452			0.0198***	0.0198***
			(0.00723)	(0.00723)			(0.00750)	(0.00750)			(0.00757)	(0.00757)			(0.00702)	(0.00702)
Lagged Insights Finance SVI			-0.0656***	-0.0655***			-0.0225***	-0.0223***			0.00296	0.00289			-0.00852	-0.00854
			(0.00723)	(0.00723)			(0.00751)	(0.00751)			(0.00757)	(0.00757)			(0.00702)	(0.00702)
Index Up (Announced)	0.289		-0.0623		-0.102		0.118		0.259		0.371		0.348*		0.834**	
	(0.193)		(0.424)		(0.200)		(0.440)		(0.202)		(0.444)		(0.188)		(0.411)	
Index Down (Announced)	-0.411**		-0.333		0.436**		0.623		-0.00282		-0.0797		-0.221		0.0563	
	(0.177)		(0.391)		(0.184)		(0.406)		(0.185)		(0.409)		(0.186)		(0.412)	
Index Up (Actual)		-0.0982		-0.113		-0.00522		0.105		0.0468		-0.0183		-0.216		-0.587
		(0.190)		(0.447)		(0.198)		(0.464)		(0.199)		(0.468)		(0.187)		(0.457)
Index Down (Actual)		0.281		1.277***		0.258		0.641		0.0986		-0.307		0.138		0.785*
		(0.184)		(0.409)		(0.191)		(0.425)		(0.192)		(0.429)		(0.189)		(0.432)
Index Up (Announced)∗Insights SVI	0.158				-0.0581				0.383***				0.0550			
	(0.129)				(0.134)				(0.135)				(0.135)			
Index Down (Announced)∗Insights SVI	0.0867				-0.119				0.0415				-0.158			
	(0.268)				(0.279)				(0.281)				(0.270)			
Index Up (Actual)∗Insights SVI		-0.107				-0.125				0.0486				-0.0846		
		(0.185)				(0.192)				(0.193)				(0.153)		
Index Down (Actual)∗Insights SVI		0.0136				0.0580				-0.349*				-0.165		
		(0.203)				(0.211)				(0.212)				(0.188)		
Index Up (Announced)∗Insights SVI Finance			-0.0325				-0.155				0.203				0.187	
			(0.347)				(0.360)				(0.363)				(0.363)	
Index Down (Announced)∗Insights SVI Finance			0.225				0.360				0.148				-0.615	
			(0.392)				(0.407)				(0.411)				(0.414)	
Index Up (Actual)∗Insights SVI Finance				0.376				-0.337				0.357				-0.00384
				(0.650)				(0.674)				(0.680)				(0.641)
Index Down (Actual)∗Insights SVI Finance				1.232***				-0.106				-0.260				-0.581
				(0.381)				(0.396)				(0.399)				(0.402)
Constant	-0.0576***	-0.0577***	-0.0782***	-0.0788***	-0.00236	-0.00233	-0.0267***	-0.0267***	0.0160***	0.0161***	0.00656	0.00675	-0.00114	-0.00108	-5.43e-05	0.000169
	(0.00310)	(0.00310)	(0.00644)	(0.00644)	(0.00323)	(0.00323)	(0.00668)	(0.00668)	(0.00324)	(0.00324)	(0.00674)	(0.00674)	(0.00301)	(0.00301)	(0.00626)	(0.00626)
Observations	94,283	94,283	21,590	21,590	94,283	94,283	21,590	21,590	94,283	94,283	21,590	21,590	111,783	111,783	25,416	25,416
Firms	132	132	31	31	132	132	31	31	132	132	31	31	149	149	37	37
R-squared	0.000	0.000	0.013	0.014	0.000	0.000	0.001	0.001	0.001	0.001	0.000	0.000	0.000	0.000	0.001	0.001