CENTER OF ATTENTION

A STUDY OF RETAIL INVESTOR ATTENTION AND IPO PERFORMANCE IN SWEDEN

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Bachelor Thesis

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Abstract:

We test an attention-induced price-pressure hypothesis on Swedish data by replicating and extending the methodology of Da, Engelberg and Gao (2011). Using a sample of 233 IPOs on Nasdaq Stockholm and First North from 2004 to 2019, we examine the relationship between retail investor attention, proxied by Google search data, and IPO performance. We show that aggregate pre-IPO search activity is a significant predictor of first-day IPO returns, but that it does not explain longer-run price reversals. Contrary to previous literature, we observe that attention-grabbing IPOs outperform also in the long run. When studying the two markets separately, we further find that search data predicts first-day IPO returns on First North, where retail investor attention matters the most, while it has virtually no explanatory power on Nasdaq Stockholm, where retail investors are less important.

Keywords:

ipo, underpricing, price-pressure, search data, retail investor attention

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1. INTRODUCTION

Standard asset pricing theories typically assume that all available information is reflected in prices. In reality, the process of incorporating new knowledge requires investors' close attention, and attention is scarce (Kahneman, 1973). Therefore, limited investor attention plays an important role in asset pricing.[1] When studying investor attention, researchers must decide whether to concentrate on individual or institutional investors and what price-setting mechanism to focus on. Many studies point to that initial public offerings (IPOs) experience high first-day returns followed by long-run reversals, and recent publications indicate that these patterns are associated with retail investor behavior.[2]

In this paper, we replicate and extend *In Search of Attention* (2011) by Zhi Da, Joseph Engelberg and Pengjie Gao using Swedish data. Specifically, we examine the relationship between individual retail investor attention and return patterns of Swedish IPOs by testing a price-pressure hypothesis developed by Barber and Odean (2008). We expect attention-grabbing IPOs to have higher first-day returns, but lower long-run returns than comparable IPOs. The reasoning goes as follows. As retail investors cannot spend as much time analyzing information as institutional investors, they are more likely to consider stocks that have recently caught their attention (e.g. stocks featured in the news). Given that retail investors rarely short sell, they will be net buyers of these attention-grabbing stocks. In line with this reasoning, we expect positive first-day price-pressure for attention-grabbing IPOs. Because retail investors only sell what they have previously bought, we further expect negative long-run price-pressure for these IPOs, as excess retail demand fades out.

We also expect attention-induced price-pressure to be more pronounced among IPOs in which individual investor attention *matters the most*. While Da, Engelberg and Gao (2011) prove this relationship for Russell 3000 stocks, they do not study the impact on IPOs. Fortunately, Swedish data offers an excellent opportunity to do exactly this. While Nasdaq Stockholm and Nasdaq First North Growth Market Sweden (hereinafter First North) have both had high IPO-activity in recent years, the two markets differ considerably in terms of investor composition, with retail investors being more important on First North. We therefore hypothesize that attention-induced price-pressure is more articulated on First North than on Nasdaq Stockholm.

When studying investor attention, we need a measure or a proxy, that is as close as possible to the actual attention. Naturally, no trading-related attention measure exists prior to an IPO – but search data does. To approximate investor attention, we use Google search data provided by Google Trends, a publicly available tool displaying what people pay attention to online. The Google Trends data is presented as a Search Volume Index (SVI) ranging from 0 to 100. In the context of our study, search data brings three attractive features. First, it is a *revealed* attention measure. If you search for a specific IPO on Google, you are definitely paying attention to it. Thus, we do not have to rely on the assumption that our measure *generates* attention, like with news coverage or advertising expense for example. Second, Da, Engelberg and Gao (2011) show that search data captures *retail* investor attention, as opposed to institutional investor attention.[3] Third, 95% of Swedish online searches are through Google, making SVI an

[1] See Merton (1987), Huberman & Regev (2001), Hirshleifer & Teoh (2003), Peng & Xiong (2006), Hendershott, Namvar & Blake (2013), Da, Engelberg & Gao (2011), and Ben-Repahael, Da & Israelsen (2017).
[2] See Ritter & Welch (2002), Ljungvist, Nanda & Singh (2006), Cook, Kiescnick & Van Ness (2006), and Neupane & Poshakwale (2012).
[3] Institutional investors use more sophisticated tools. For example, Ben-Repahael, Da & Israelsen (2017) capture institutional investor attention by studying news reading on Bloomberg terminals.

appropriate measure of *aggregate* attention (Tankovska, 2020). Figure 1 provides an SVI example.

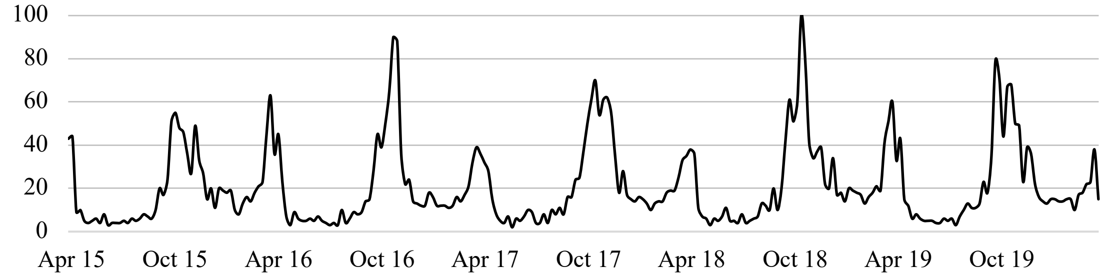

Figure 1: Search Volume Index (SVI) for "dubbdäck"

The figure displays weekly SVI for "dubbdäck" (studded tires) in Sweden between April 2015 and April 2020. We observe a cyclical pattern with SVI spikes in April and October each year. The trend has an intuitive explanation; studded tires are allowed only between the 1st of October and 15th of April and SVI captures the increasing interest for studded tires around these dates through rising search activity.

Google Trends supplies real-time and historical search data, allowing empiricists to observe how search interest varies over time. Interestingly, the application extends to a variety of settings. For example, Ginsberg et al. (2009) find that it is possible to predict influenza outbreaks 1 to 2 weeks before official centers for disease control by *"harnessing the collective intelligence of millions of users"* through search data. Stephens-Davidowitz (2017) highlights another useful feature of SVI in that there is no incentive to lie in a search setting. Through searches, he argues, people share information they would not even tell their doctor, pointing to the usefulness of SVI as a *revealed* measure of attention, as well as a way of understanding human behavior.

We collect SVI for 233 common stock IPOs on Nasdaq Stockholm and First North from January 2004 to April 2019. We are restricted to this time period as Google Trends supplies SVI from 2004 onwards and because we need 52 weeks of stock price data for all observations to evaluate long-run performance. Controlling for a comprehensive set of variables, including both firm-specific and market-level factors, we test the relationship between retail investor attention, proxied by SVI, and first-day IPO returns. By a similar procedure, we test the relationship between SVI and long-run IPO returns. Lastly, we extend the previous research on retail investor attention by studying IPOs on Nasdaq Stockholm and First North separately.

While we find that SVI predicts first-day IPO returns, we find no support for long-run price reversals among Swedish IPOs. Instead, we find that high pre-IPO SVI is linked to long-run *outperformance*. When we study the two markets separately, we find that this "success-feeds-success" pattern holds for First North IPOs, but not on Nasdaq Stockholm, were the fraction of retail investors is relatively low. We conclude that the attention-induced price-pressure hypothesis does not hold for Swedish IPOs, although SVI remains a strong predictor of first-day returns in IPOs where retail investor attention matters the most.

The remainder of this paper is structured as follows. Section 2 provides the theoretical framework and hypotheses. Section 3 describes the data and methodology. Section 4 presents the empirical results. Section 5 concludes with implications and proposals for further research. Section 6 and 7 include references and appendixes.

2. THEORETICAL FRAMEWORK

I. IPO CHARACTERISTICS

When studying the price dynamics of IPOs, there are two stylized facts to consider: underpricing and long-run underperformance. Researchers have long sought to find explanations as to why issuing firms underprice their IPOs, causing a significant jump in share prices during the first day of trading. Since Ibbotson (1975) formalized the presence of underpricing, many researchers have tried to explain the phenomenon. Ritter and Beatty (1986) propose an information asymmetry theory, suggesting that high-uncertainty IPOs will be more underpriced as compensation for investors bearing the ex-ante valuation risk. Rock (1986) too explains underpricing with asymmetric information, but in the sense that issuers will offer their shares at a discount to incentivize uninformed investors to subscribe in the offering. The explanation builds on the assumption that key stakeholders – the offering firm, auditors, underwriters and investors – do not have the same information about the firm, and that informed investors would crowd out uninformed investors if not for the underpricing.

An alternative explanation is put forward by Ibbotson, Sindelar and Ritter (1994). They argue that firms go public in hot IPO markets driven by investor sentiment, thus exploiting *"windows of opportunity"*. This points to high first-day returns being a consequence of overly optimistic investors trading on sentiment, rather than a deliberate pricing mechanism to compensate for uncertainty and asymmetrical information. Ljungvist, Nanda and Singh (2006) support this explanation, and further develop the argument by linking it to the other puzzling IPO characteristic, namely the well-documented tendency to underperform in the long run.[4] Furthermore, Ritter (1991) finds that firms going public in high-volume years fare the worst in the long-run. This is consistent with the explanation of underpricing as a result of overly optimistic investors, where long-run underperformance is a correction for the first-day share price spike. Recent publications indicate that these patterns are also associated with retail investor attention and behavior.[5]

II. ATTENTION-INDUCED PRICE-PRESSURE

Before investors can subscribe to an IPO, they need to allocate sufficient attention to it. Standard asset pricing models typically assume perfect capital markets, and that the diffusion of publicly available information takes place instantaneously. In his paper, Merton (1987) propose a model of capital market equilibrium with incomplete information, where these assumptions are challenged and investors not assumed to act immediately upon new information. Indeed, attention is a scarce cognitive resource (Kahneman, 1973); an increase in attention in one direction inevitably leads to a reduction in another direction. This notion is foundational in investor attention research and points to that, in practice, there are flaws to seemingly efficient markets.

The attention-induced price-pressure hypothesis developed by Barber and Odean (2008) can be considered an example of such a flaw and constitutes the theoretical foundation of this paper. Barber and Odean (2008) argue that retail investors are net buyers of attention-grabbing stocks and that an increase in retail investor attention therefore leads to an upward pressure on share prices (Barber & Odean, 2008). This is the effect of two retail investor characteristics. First, retail investors suffer from an availability bias (Kahneman, 1973). As they cannot spend as much time analyzing information as institutional investors, they are likely to consider stocks that have recently caught their attention. Second, while institutional investors short sell stocks,

[4] See Ritter (1991), Ljunqvist (1997), Barber & Odean (2008), and Da, Engelberg & Gao (2011).
[5] See Ljungvist, Nanda & Singh (2006), Cook, Kiescnick & Van Ness (2006), and Neupane & Poshakwale (2012).

retail investors rarely do, which means that when selling, they only sell what they already own (Barber & Odean, 2008; Odean, 1999). Therefore, retail investors buy positive attention-grabbing stocks but rarely short sell stocks with negative attention-grabbing events.

This price-pressure hypothesis naturally applies to IPOs, as IPO stocks are likely to grab attention at the time of the issuance. An increase in retail investor attention is thus likely to result in higher retail buying pressure in the IPO. As it is generally difficult to short sell IPOs, the retail buying pressure drives first-day returns. When excess retail demand reverts, stock prices will regress, leading to long-run underperformance (Da, Engelberg, & Gao, 2011).

III. INVESTOR ATTENTION PROXIES

When studying attention theories, researchers encounter an empirical obstacle: it is difficult to directly observe attention. Therefore, researches have to rely on proxies. Table 1 presents examples of such proxies used in previous investor attention studies.

Table 1: Examples of Proxies for Investor Attention

Proxy	Market	Author(s)	Findings
Advertising expense	U.S.	(Grullon, 2004)	Increased advertising expenditure makes the firm more visible, leading to more investors in the firm's stock as well as increased stock liquidity
Price limits	China	(Seasholes & Wu, 2007)	Limits on daily stock movements (before trading is suspended) lower investors' search costs and makes active retail investors net buyers of stocks
Trading volume and market state	U.S.	(Hou, Xiong, & Peng, 2009)	Price (earnings) momentum profits are higher (lower) among high (low) volume stocks and in up (down) markets
Trading volume, extreme returns and news coverage	U.S.	(Barber & Odean, 2008)	Retail investors are net buyers of attention-grabbing stocks featured in the news, having abnormal trading volume or extreme one-day returns
State of the business cycle	U.S.	(Kacperczyk, Van Nieuweburgh, & Veldkamp, 2016)	Fund managers add value by allocating attention to important information by optimizing information processing in boom and bust markets
Media attention	U.S.	(Kaniel & Parham, 2017)	Wall Street Journal's "Category Kings" mutual funds experience a 31% increase in quarterly capital flows, compared to funds not making the list
Advertising data	U.S.	(Ungeheuer, Ruenzi, & Focke, 2019)	Advertising impacts attention positively, but has little impact on turnover, stock liquidity and short-term stock returns

While the proxies in Table 1 are useful measures, they do not guarantee attention. Instead, these proxies are assumed to *generate* attention. If, for instance, a stock is featured in the news it could generate attention among investors, but if no investor watches the news it will surely not (Ben-Repahael, Da, & Israelsen, 2017). Reasonably, investors can also direct considerable attention to a stock, without it having to be featured in the news. Thus, news coverage, as every other proxy in Table 1, is imperfect in two dimensions. This poses a challenge to researchers that are trying to distill the relationship between investor attention and stock market movements. While still useful in many contexts, these proxies are not optimal for studying IPOs. In the next section, we explore a more appropriate measure of attention.

IV. SEARCH ENGINE DATA AND IPO MARKETS

In addition to being large-scale, search engine data holds a number of advantages over other measures of attention. First, search data is a revealed attention measure. Investors who actively search for an IPO are undeniably paying attention to it. Second, search engines are the main tools used by retail investors when searching for investment information (Da, Engelberg, & Gao, 2011). Third, 95% of Swedish online searches are through Google, making SVI an appropriate measure of aggregate attention (Tankovska, 2020). Lastly, and most critically, search data exists *prior* to the IPO, while commonly used trading-based attention measures do not. For these reasons, search engine data offers a unique opportunity to empirically study the impact of retail investor attention on IPO performance (Da, Engelberg, & Gao, 2011). However, search data is not perfect. For instance, it is not possible to isolate investor attention in search data as it also captures traffic from non-investors. This issue is more pronounced for firms with names with other meanings, like “Midsummer”, or well-known consumer-facing brands, like ”H&M”. As the total internet traffic has increased manyfold over the last two decades, there might also be a problem of comparing search data across years. Despite these imperfections, Da, Engelberg and Gao (2011) show that Google search data, as a measure of investor attention, carries significant predictive power over stock market movements. Specifically, they find that pre-IPO abnormal search volume is a strong predictor of first-day IPO returns and subsequent long-run underperformance, fully in line with Barber and Odean’s (2008) price-pressure hypothesis.

In their paper, Da, Engelberg and Gao (2011) predict stronger price-pressure among stocks in which retail investor attention *matters the most*. Using publicly available market center order execution disclosures, so-called Dash-5 reports, they establish a direct link between SVI and retail investor trading in Russell 3000 stocks. However, they do not investigate this pattern within the context of IPOs. Naturally, Dash-5 or similar order execution reports include only listed and actively traded stocks. Fortunately, Swedish data presents an excellent opportunity to study IPO popularity among retail investors by looking at two different markets, Nasdaq Stockholm and First North. Previous literature that has compared so-called junior markets with main markets have found that firms listing on junior markets tend to be smaller, younger and raise more capital relative to their size than main market IPOs (Ritter, Vismara, & Paleari, 2012). These findings are consistent with our sample.[6] Furthermore, regulatory requirements on First North are lighter than on Nasdaq Stockholm. In accordance with Swedish law, issuers admitted to trading on First North are not subject to, for instance, flagging requirements, IFRS or the Swedish Takeover Act (Nasdaq, 2019).[7] Importantly for this study, First North specifically seems to attract a larger proportion of retail investors than the main market. In 2019, the two largest retail brokerage firms in Sweden, Avanza and Nordnet, alone stood for more than 60% of the volume and 40% of total turnover at First North (Nasdaq OMX Nordic, 2020). The corresponding combined market share on Nasdaq Stockholm was 15% (volume) and 7% (turnover) (Nasdaq OMX Nordic, 2020). Thus, it is interesting to test the validity of the attention-induced price-pressure at First North, where retail investors are proportionally more important, as well as at Nasdaq Stockholm, where retail investors are relatively fewer. In line with Da, Engelberg and Gao (2011), we expect the pattern to be more pronounced where retail investor attention matters the most – that is, in First North IPOs.

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[6] Average asset size, average age and average offering-to-asset ratio on First North (Nasdaq Stockholm) is SEK 0.17 (4.34) billion, ~13 (~24) years and 2.5x (1.3x), respectively.

[7] The First North Premier segment have requirements aligned with those of Nasdaq Stockholm, as it is designed to prepare the company for a main market listing.

V. A BRIEF REVIEW OF THE FIELD

Since *In Search of Attention* (2011), several papers have tested the relationship between search engine data and stock market movements. In Table 2, the studies closest to ours are outlined.

Table 2: Previous Papers Using Google SVI in IPO Research

Title	Author(s)	Market	Years	n	About
Underpricing, Under-performance and Overreaction in Initial Public Offerings	(Vakrman & Kristoufek, 2015)	U.S.	2004-2010	75	Uses SVI to test retail investor attention on IPO performance
Google Searches and IPO Performance	(Krogsrud, Lillefjaere, & Blegen, 2016)	U.S.	2007-2015	810	Uses SVI to test retail investor attention on price revision and IPO performance
Capturing Investor Attention – Do pre-IPO Google Searches Predict Stock Performance?	(Torikka, 2016)	Europe	2004-2015	254	Uses SVI to test retail investor attention on IPO performance
The Relation between Investor Attention and First-Day Returns on IPOs	(Kaukkila & Olofsson Lauri, 2017)	Sweden	2006-2016	96	Uses SVI to test retail investor attention on first-day IPO returns

Building on Da, Engelberg and Gao (2011), our paper is also similar to Vakrman and Kristoufek (2015), Krogsrud, Lillefjaere and Blegen (2016), Torikka (2016), and Kaukkila and Olofsson Lauri (2017). While all test the predictive power of pre-IPO search volume on IPO performance, there are important differences. Vakrman and Kristoufek (2015), as well as Krogsrud, Lillefjaere and Blegen (2016), study only the U.S. market. Torikka (2016) instead looks at Nordic and continental Europe IPOs but has limited representation of Swedish IPOs. In terms of data and geographical focus, Kaukkila and Olofsson Lauri (2017) is closest to our study, focusing on Swedish IPOs on Nasdaq Stockholm and First North. While Kaukkila and Olofsson Lauri (2017) can confirm the predictive power of SVI on first-day returns, they do not study the relationship between SVI and long-run performance. In our paper, we test the *full* price-pressure hypothesis on Swedish IPOs. To further generalize the findings of Kaukkila and Olofsson Lauri (2017) regarding first-day returns, we extend the sample set and control for additional variables. We also test long-run performance. As an extension to Da, Engelberg and Gao (2011), we also study the above patterns on two different markets, with varying degree of retail investor importance, which – to the best of our knowledge – has not been done before.

VI. HYPOTHESES

Based on the reviewed IPO and investor attention literature, we test whether the attention-induced price-pressure hypothesis holds for Swedish IPOs and in different market-settings. Using our main variable, abnormal SVI (ASVI), and a sample of 233 IPOs on Nasdaq Stockholm and First North between 2004 and 2019, we test three hypotheses presented below.

1.	ASVI and first-day return	Swedish IPOs with high ASVI show greater first-day returns than those with low ASVI.
2.	ASVI and long-run return	Swedish IPOs with high first-day return as well as high ASVI show greater long-run underperformance than those with high first-day return and low ASVI.
3.	The price-pressure hypothesis on different markets	The relationship between ASVI and first-day returns as well as long-run underperformance is stronger on First North than on Nasdaq Stockholm.

3. DATA AND METHODOLOGY

I. DATA COLLECTION AND MANAGEMENT

To examine the impact of retail investor attention on IPOs, we need (1) a sample of all common stock IPOs on Nasdaq Stockholm and First North between 2004 and 2019, (2) search volume data for each IPO, (3) firm financials and IPO characteristics, and (4) control variables data.

IPO SAMPLE

We start by collecting all Swedish equity listings between 2004 and 2019 from Thomson-Reuter's Eikon database. We retrieve all deals categorized as "listings" to minimize the risk of missing important observations. Other than regular IPOs, this includes spin-offs, re-listings, secondary offerings and mergers. We note that this dataset excludes firms that have been delisted during the sample period and we therefore cross-check our set of IPOs with corresponding data from SDC Platinum and Nasdaq to reduce survivorship bias.[8] Excluding duplicates, we add 46 equity listings to the sample. Where Eikon, SDC and Nasdaq present insufficient or conflicting information, we collect data from the Swedish Tax Agency. We collect also the name used during the IPO for firms that have changed their name since their listing, as this is essential for gathering the correct SVI data from the time of the IPO. This process generates a sample of 883 equity listings in Sweden between 2004 and 2019.

Table 3: Number of Observations Collected and Eliminated

Reason for elimination	Removed	Remaining
Full sample list	-	883
Not listed on Nasdaq Stockholm or First North Stockholm	312	571
Cancelled or postponed listing	44	527
Originally listed prior to 2004 or with less than 1 year of post-IPO trading	39	488
Non-IPO listings (re-listings, spin-offs, unit emissions, REITs, etc.)	198	290
Lacking sufficient SVI data	28	262
Lacking sufficient financial data	29	233
Final sample of IPOs	650	233

After excluding deals on markets other than Nasdaq Stockholm and First North (312), we remove cancelled listings (44), listings originally conducted prior to 2004 or with less than one year of available share price data (39) and all non-IPO deals (198). Non-IPO deals include re-listings, spin-offs, convertible listings and preferred stock emissions. We also exclude unit emissions as they contain both a share of equity and a warrant, making it difficult to calculate the total IPO return (Da, Engelberg, & Gao, 2011). Also, value weighted returns would change only to a small degree, as unit offering companies tend to be small (Brav & Gompers, 1997). Furthermore, we exclude listings of real estate investment trusts (REITs) and fund-in-funds as they are fundamentally different from industrial IPOs (Chan, Chen, & Wang, 2013). By doing this, we produce a sample of 290 observations that fit our definition of a common stock IPO.

SEARCH VOLUME DATA

For each of the remaining 290 IPOs in our sample, we collect 12 weeks of daily search data from Google Trends using the gtrendsR package in R (Massicotte, 2020). Google Trends calculates SVI from a random subset of the actual historical search data to increase response speed, and thus presents slightly different SVI on the same search term between searches (Rogers, 2016). To adjust for this, we repeat the loop ten times and calculate an average of

[8] We use three sources to cover as many IPOs as possible. Still, there is a risk that our data is not exhaustive. The results of this study are therefore attributable only to our sample of IPOs.

these.[9] We only look at search volume from Swedish users and use adjusted company names as search terms. Out of the 290 IPOs, 7 do not return any SVI due to low search volume. Furthermore, 6 suffered from an obvious noise issue and could not isolate the search volume directed to the IPO. Daily observations are converted to weekly by summing each week and re-indexing the data relative to the maximum SVI observed for each IPO. For each observation, we generate the variable *ASVI.* This is the main variable throughout the paper and is defined as

$$ASVI_i = log(SVI_{IPO}) - log(Med[SVI_{IPO-1}, SVI_{IPO-2}, \ldots, SVI_{IPO-8}]) \qquad \text{(Equation I)}$$

where $\log(SVI_{IPO})$ is the logarithm of the SVI during the IPO week, and $\log(Med[SVI_{IPO-1}, SVI_{IPO-2}, \ldots, SVI_{IPO-8}])$ is the logarithm of the median SVI during the 8 weeks prior to the IPO week. The median captures the "normal" level of attention, robust to run-up increases. The variable definition is in line with Da, Engelberg and Gao (2011). Aggregated SVI for the full sample is presented in Figure 2. Given that ASVI is calculated as the difference between the log of SVI during the IPO week and the log of the median SVI 8 weeks prior, a large positive ASVI indicates a surge in pre-IPO investor attention. This variable is well-suited for comparisons across stocks in our cross-section analysis.

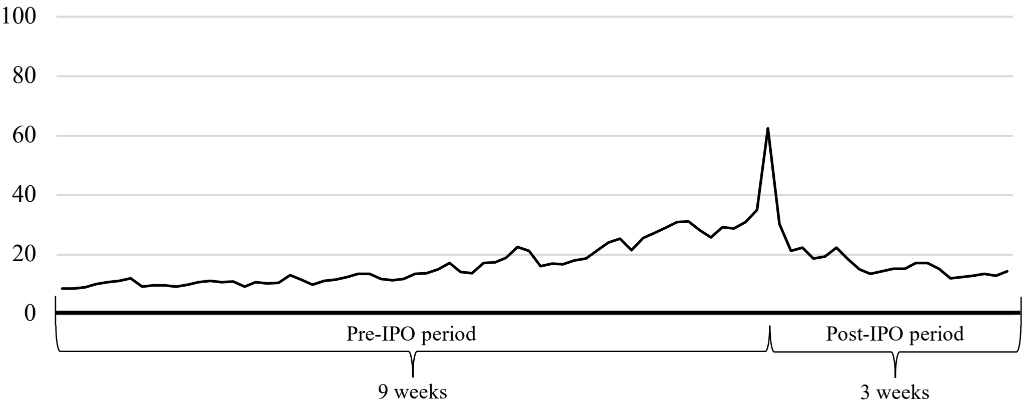

Figure 2: Average Daily Search Volume Index (SVI) around the IPO

The figure presents cross-sectional mean of the SVI before, during and after the IPO. We observe a spike in search volume around the IPO, with a successive increase during the weeks before. This pattern is consistent with Da, Engelberg and Gao (2011) and the literature. For example, Demers and Lewellen (2003) observe a similar increase in investor attention when they study the marketing role of IPOs.

After applying these filters, our SVI dataset includes 3,324 weekly observations covering 277 IPOs. Of these, 15 had a median SVI during the eight weeks prior to the IPO of 0, and thus not enough SVI data for us to be able to generate the ASVI variable for the observation. In the end, this process generates a sample of 262 observations.

FINANCIAL DATA

We collect three categories of financial data for the 262 remaining firms; offer details, firm financials prior to the IPO and stock price data. Offering prices are obtained from the Swedish Tax Agency as they provide the final IPO price, whereas IPO prospectuses can include a price range. First-day, 5-week and 52-week closing prices, used to study the cross-section of returns, are obtained from Nasdaq's website for listed stocks and Nasdaq's historical archive for delisted stocks. These prices are adjusted for corporate events impacting comparability, most notably stock splits. The selected time horizon for evaluating long-run performance is the same

[9] Correlations between outputs are high (97%) and using data from a single download do not change our results.

as in the original study by Da, Engelberg and Gao (2011), in turn inspired by Barber and Odean (2008). Company-specific details (firm founding year, underwriters, total firm assets, shares outstanding before and after the IPO, portion of secondary shares offered and whether the firm is backed by a financial sponsor or not) are collected manually from IPO prospectuses. We exclude 29 observations lacking sufficient data, which generates the final sample of 233 IPOs.[10]

OTHER CONTROL VARIABLES DATA

To control for another attention variable that have previously been shown to have explanatory power over IPO performance, we obtain daily media coverage for each firm over 12 weeks around the IPO. The time horizon and the search terms used are the same as when we collect SVI. We collect the data manually on a per-firm basis from Retriever Research, which covers all major news outlets in Sweden (Retriever Research, 2020). Our media coverage data includes 19,572 daily observations, with a total of 61,428 news articles, covering the 233 IPOs.

To generate a variable for past industry returns at the time of the IPO and a suitable industry-adjustment for the long-run return evaluation, we collect several Nasdaq Stockholm and First North indexes. In addition to capturing certain industry characteristics related to IPO performance, market-specific indexes help us control for the systematic risk difference between the markets. We collect daily data for all sectors in the sample over the entire sample period. The collected indexes are based on the Industry Classification Benchmark (ICB) standard and all currently listed firms are included in at least one index, based on their industry ICB classification. Firms that have been delisted or listed their shares on another exchange since their IPO are matched with peers and assigned an ICB industry. In total, we collect 17 industry indexes (8 with First North stocks and 9 with Nasdaq Stockholm stocks) covering the 233 IPOs (Nasdaq OMX Nordic, 2020).

We also generate a market sentiment variable to control for deviations in first-day IPO returns generated by sentiment. This is important because IPO intensity and market sentiment varies greatly between years.[11] As a sentiment proxy, we use Statistics Sweden's (SCB) Consumer Confidence Indicator (CCI). CCI is a forward-looking questionnaire-based market-level index tracking Swedish consumer confidence on a monthly basis. We download CCI data directly from SCB (SCB, 2020).

IPOs underwritten by reputable and prestigious underwriters and backed by venture capitalists have been shown to generate greater public interest (Megginson & Weiss, 1991). To control for this, we include two dummy variables: *Multiple Underwriters* and *Sponsor Backing*. When a firm in our sample has more than one global coordinator underwriting the IPO, at least one tends to be a prestigious international bank. We therefore expect a variable for multiple underwriters to carry similar explanatory power as an underwriter ranking variable like the one used in Da, Engelberg and Gao (2011). Furthermore, a considerable portion of our sample (69 IPOs) are backed by financial sponsors. Consistent with Megginson and Weiss (1991), we expect more attention to be generated around issues backed by prestigious owners and therefore include a dummy variable for sponsor backing. The data used for the two dummy variables are collected manually from IPO prospectuses.

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[10] Appendix V contains an exhaustive list of the 233 companies included in the final sample.
[11] See Table 10 in Appendix I for per-year activity.

II. METHODOLOGY

Consistent with our hypotheses, the analytical framework includes three sections; ASVI and first-day return, ASVI and long-run return, and the price-pressure hypothesis on different markets. In Table 4, we present and define the variables used in this paper.

Table 4: Variable Definitions

	Variable	Definition
Dependent Variables	First-day Return	First-day closing price divided by the offering price minus one
	Long-run Return	[IPO+52 week] closing price divided by [IPO+5 week] closing price minus one
	Industry-adjusted Long-run Return	*Long-run Return* adjusted by cumulative corresponding Nasdaq Industry Classification Benchmark index return
Independent Variables	ASVI	Log of SVI during the IPO week minus the log of median SVI during the previous 8 weeks
	Media	Log of the number of news articles recorded by Retriever Research from 8 weeks prior until the day before the IPO
	CCI	Consumer Confidence Indicator the month the firm goes public
Control Variables	Offering Size	Offering price multiplied by the number of shares offered
	Age	Number of years between firm's founding year and the IPO date
	Asset Size	Firm's total assets for the last full year prior to the IPO
	Secondary Share Overhang	Secondary shares offered as a percentage of total shares offered
	Past Industry Return	3-month cumulative Nasdaq Industry Classification Benchmark index return corresponding to the industry identification at the time of the IPO
Dummy Variables	Multiple Underwriters	Dummy variable taking a value of one if the firm has at least two global coordinators, and zero otherwise
	Sponsor Backing	Dummy variable taking a value of one if the firm is backed by a private equity or venture capital firm, and zero otherwise

FIRST-DAY RETURN METHODOLOGY

To test the first hypothesis – that IPOs with high ASVI have greater first-day returns – we split the full sample using median ASVI as the cut-off point. This gives us two subsamples: high ASVI and low ASVI, each consisting of 116 observations.[12] Using an unpaired, one-sided two-sample t-test we test our first-day return hypothesis. Because t-tests assume certain characteristics about the underlying sample distribution, we also run non-parametric Wilcoxon rank sum tests to nuance the significance of the results. We then formalize the analysis by doing cross-sectional regressions on the entire sample with the dependent variable being first-day return. Stepwise, we test the predictive power of ASVI, *Media* and *CCI*, while controlling for *Offering Size, Age, Asset Size, Secondary Share Overhang, Past Industry Returns, Multiple Underwriters* and *Sponsor Backing*. Lastly, we test the full model, presented in Equation II.

[12] Excluding the median value from the sample does not change our results.

$$\begin{aligned}
&\textit{First-day Return}_i = \\
&\quad \beta_0 + \beta_1 * ASVI_i + \beta_2 * Media_i + \beta_3 * CCI_i + \\
&\quad \beta_4 * \log(\textit{Offering Size}_i) + \beta_5 * \log(Age_i) + \beta_6 * \log(\textit{Asset Size}_i) + \\
&\quad \beta_7 * \textit{Secondary Share Overhang}_i + \beta_8 * \textit{Past Industry Returns}_i + \\
&\quad \beta_9 * \textit{Multiple Underwriters}_i + \beta_{10} * \textit{Sponsor Backing}_i + \varepsilon_i
\end{aligned} \qquad \text{(Equation II)}$$

LONG-RUN RETURN METHODOLOGY

To test the second hypothesis – that IPOs with high first-day return *and* high ASVI underperform in the long-run – we exclude IPOs with below-median first-day returns. The remaining IPOs are then again split up in two groups, each with 58 observations, again using median ASVI as the cut-off point. The following statistical procedure is similar to the one described above: we begin with a t-test, nuance the findings with a Wilcoxon test and formalize the analysis with regressions. However, in these regressions we introduce interaction variables, multiplying the attention variables ASVI, *Media* and *CCI* with first-day returns. This adjustment enables us to capture patterns among high first-day return IPOs, while still being able to include 116 observations in the regression. The full model, with unadjusted long-run returns as the dependent variable, is presented in Equation III.[13]

$$\begin{aligned}
&\textit{Long-run Return}_i = \\
&\quad \beta_0 + \beta_1 * ASVI_i + \beta_2 * (ASVI_i \text{ x } \textit{First-day Return}_i) + \\
&\quad \beta_3 * Media_i + \beta_4 * (Media_i \text{ x } \textit{First-day Return}_i) + \\
&\quad \beta_5 * CCI_i + \beta_6 * (CCI_i \text{ x } \textit{First-day Return}_i) + \\
&\quad \beta_7 * \log(\textit{Offering Size}_i) + \beta_8 * \log(Age_i) + \beta_9 * \log(\textit{Asset Size}_i) + \\
&\quad \beta_{10} * \textit{Secondary Share Overhang}_i + \beta_{11} * \textit{Past Industry Returns}_i + \\
&\quad \beta_{12} * \textit{Multiple Underwriters}_i + \beta_{13} * \textit{Sponsor Backing}_i + \varepsilon_i
\end{aligned} \qquad \text{(Equation III)}$$

THE PRICE PRESSURE HYPOTHESIS ON DIFFERENT MARKETS

We test our third hypothesis – that the attention-induced price-pressure is more pronounced on First North than on Nasdaq Stockholm – using similar statistical procedures as the ones above. The key difference is that we, before anything else, split our dataset on listing-exchange. We have 89 IPOs on Nasdaq Stockholm and 144 IPOs on First North. Thereafter, the methodology remains in line with the previous two sections, while performed on the two markets separately.

STATISTICAL MODEL

An important part of our analysis consists of testing differences between groups. To do this, we perform unpaired one-sided two-sample t-tests assuming unequal variances and Wilcoxon rank sum tests. This is in line with the methodology of the original study and a well-suited procedure to test our hypotheses. However, the t-test is parametric and assumes normality and independence. Although the t-test is commonly said to be "robust" against small deviations from these assumptions, this is true only for the significance level of the test; the power is very sensitive even to small deviations from normality (Hampel, 2000). To increase robustness and reduce misguidance in our analysis, we therefore perform non-parametric rank tests as well.

We perform regressions to gain a deeper understanding of the relationship between ASVI and IPO performance. By running a standard OLS regression based on Equation II, we can observe the distribution of residuals. The residuals are tested for heteroskedasticity using the Breusch-Pagan test (Breusch & Pagan, 1979), which rejects the null hypothesis that the residuals have constant variances at the 1% level. Hence, the residuals are heteroskedastic enough to cause

[13] Our findings are not sensitive to the choice of long-run return variable. Because unadjusted numbers are easier to comprehend, we focus on these. The adjusted long-run return analysis is presented in Appendix III and IV.

issues in our regressions. To better understand what generates this variability of the variance, the residuals are plotted against a fitted value line where we can observe that, while the residuals show signs of heteroskedasticity, this comes from a number of extreme values.[14] Heteroskedasticity does not cause bias in the estimations of coefficients but makes them less precise and further away from the actual population value (Williams, 2020). As a consequence, variances are underestimated when calculating t-values, and subsequent p-values, which might lead to misconclusions regarding the statistical significance of our model terms. We test the assumption of normality using the Shapiro-Wilks test (Shapiro & Wilk, 1965), which rejects the null hypothesis that the residuals are normally distributed at the 1% level. We plot the residuals in a histogram and a quantile-quantile plot, both with a fitted line for normality.[15] Much of the normality violation is driven by extreme values, generating a fatter right-side tail in the histogram and a steep increase in the qq-plot towards the higher values. Due to the non-normal and heteroskedastic error terms, the standard OLS regression is unfit as an estimation model (Williams, 2020). Regressions are instead run with robust standard errors, providing more accurate p-values from the test statistics.

While a completely independent sampling model is unrealistic, independent data is a central assumption behind cross-sectional inference (Angrist & Pischke, 2009). Recall that issuers take advantage of *"windows of opportunity"* in hot markets, why the performance of different observations is likely correlated. To adjust for this, regressions are run with clustered robust standard errors per IPO year and quarter. While this is in line with the methodology of the original study, the asymptotic approximation for clustered data in our model relies on large numbers of clusters. Few clusters are likely to underestimate the intra-class correlations (Angrist & Pischke, 2009) and some consensus has been reached that 40 to 50 clusters are desirable to return unbiased standard errors.[16] Clustering per year and quarter of the listing generates regressions with maximum 42 and minimum 17 clusters throughout our analysis.[17]

4. RESULTS

As a starting point for our analysis, we want to understand how the computed variables influence each other. Primarily, we focus on first-day return and ASVI in Table 5.

Table 5: Correlation Matrix

The table shows the correlations between variables defined in Table 4. The sample period is 2004 to 2019.

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.
1. First-day Return	1.000											
2. Long-run Return	0.047	1.000										
3. Long-run Return (adj.)	0.036	0.930	1.000									
4. ASVI	0.162	0.137	0.075	1.000								
5. Media	-0.054	-0.054	-0.010	-0.121	1.000							
6. CCI	0.001	-0.115	-0.019	-0.028	0.107	1.000						
7. log(Offering Size)	-0.080	0.164	0.151	0.150	0.650	0.008	1.000					
8. log(Age)	-0.100	0.134	0.106	-0.079	0.201	-0.060	0.274	1.000				
9. log(Asset Size)	-0.086	0.114	0.098	-0.005	0.661	-0.067	0.845	-0.000	1.000			
10. Secondary Share Overhang	0.023	0.076	0.086	0.048	0.458	0.110	0.587	-0.115	0.585	1.000		
11. Past Industry return	0.106	0.096	0.055	0.054	-0.062	-0.101	0.045	-0.041	0.052	0.038	1.000	
12. Multiple Underwriters	-0.065	0.037	0.033	0.017	0.459	0.006	0.616	-0.098	0.570	0.399	0.058	1.000
13. Sponsor backing	-0.055	0.023	0.054	0.057	0.376	-0.010	0.499	-0.042	0.425	0.339	0.055	0.384

[14] See Figure 7 in Appendix II.
[15] See Figure 8 and 9 in Appendix II.
[16] See, for example, Kézdi (2004), Rogers (1994), Angrist & Pischke (2009), and Cameron & Miller (2015).
[17] This clustering methodology is consistent with Da, Engelberg and Gao (2011). As their sampling period stretches from 2004 to 2007, this method generates a maximum of 16 clusters throughout their analysis.

In general, the correlations between first-day return and the other variables are low. ASVI has the largest correlation at about 16%, followed by *Past Industry Returns* at 10.6%. Seemingly, investors bid up IPOs in hot, attention-grabbing industries, much in line with Barber and Odean's (2008) price-pressure hypothesis. Unexpectedly, first-day return and ASVI both correlate positively with long-run return. This indicates that IPOs enjoying short-term success might also enjoy longer-term success, in contrast with the argument of long-run underperformance being a consequence of an initial overreaction.

Likewise, the correlations between ASVI and the other variables of interest are low. The correlation between ASVI and IPO *Offering Size* is, with exception of first-day return, the largest at 15%. The other retail investor attention proxy, *Media,* has its largest correlation also with *Offering Size* at 65%, consistent with the idea that larger offerings receive more media attention and publicity than smaller offerings (Demers & Lewellen, 2003). Interestingly though, ASVI and *Media* – both showing considerable correlation with *Offering Size* – have a correlation of -12.1%. Intuitively, one would have expected modest positive correlation between these two variables, both being proxies for retail investor attention. However, in accordance with Da, Engelberg and Gao (2011), we see here that ASVI and *Media* captures somewhat different aspects of IPO *Offering Size*. In fact, media coverage does not guarantee attention; even if a surge in search volume is driven solely by a certain news event, ASVI still conveys useful information about how much attention was actually generated through the news (Da, Engelberg, & Gao, 2011). With these observations in mind, we further explore the relationship between ASVI and IPO performance in the following sections.

I. FIRST-DAY RETURN

To confirm the attention-induced price-pressure hypothesis, two patterns must be observed: (1) that ASVI predicts first-day returns and (2) that ASVI predicts long-run underperformance for high first-day return IPOs. In this section we focus on the first pattern: ASVI and first-day return. We begin by splitting our full sample into two groups, high and low ASVI, using the median as the cut-off point. Figure 3 presents first-day returns for both groups, each with 116 observations, as well as the total sample.

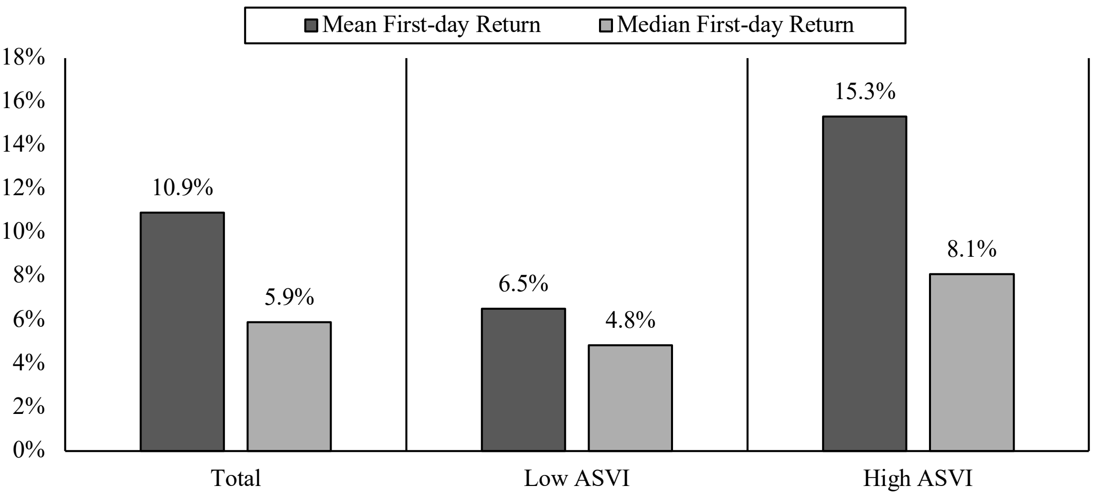

Figure 3: ASVI and First-day Returns

The figure plots mean and median first-day returns for high and low ASVI IPOs, as well as for the total. The sample includes 233 IPOs (with median ASVI observation excluded) on Nasdaq Stockholm and First North between 2004 and 2019.

We find, consistent with the attention-induced price-pressure hypothesis, that attention-grabbing IPOs enjoy considerably higher average first-day returns than IPOs with low pre-IPO attention (15.3% vs. 6.5%). Performing a t-test, we see that the difference is statistically significant at the 1% level. A Wilcoxon rank sum test confirms the significance, albeit at the 5% level. We develop these findings through regressions in Table 6. We begin by regressing the dependent variable first-day return on ASVI (1), *Media* (2) and *CCI* (3), respectively. We then repeat the same procedure through regression 4 to 6 but control for other variables related to first-day IPO returns. Lastly, we run our full model (7), as presented in Equation II.

Table 6: ASVI and First-Day Returns

This table regresses first-day returns on ASVI, Media, CCI and IPO characteristics. All variables are defined in Table 4. The sample includes 233 IPOs on Nasdaq Stockholm and First North from 2004 to 2019 with valid SVI data. Standard errors (in parentheses) are robust and clustered by offering year and quarter. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

	Dependent Variable: First-Day Return						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ASVI	0.096**			0.099**			0.107**
	(0.041)			(0.044)			(0.044)
Media		-0.039			0.016		0.059
		(0.040)			(0.048)		(0.047)
CCI			0.000			-0.001	-0.000
			(0.004)			(0.003)	(0.003)
log(Offering Size)				-0.054	-0.021	-0.018	-0.064*
				(0.038)	(0.035)	(0.035)	(0.038)
log(Age)				-0.058	-0.065	-0.066	-0.056
				(0.045)	(0.042)	(0.042)	(0.045)
log(Asset Size)				0.003	-0.019	-0.017	-0.004
				(0.030)	(0.027)	(0.025)	(0.030)
Secondary Share Overhang				0.087	0.087	0.089	0.084
				(0.063)	(0.058)	(0.057)	(0.061)
Past Industry Returns				0.281*	0.314**	0.306**	0.297**
				(0.140)	(0.138)	(0.143)	(0.143)
Multiple Underwriters				-0.008	-0.019	-0.018	-0.011
				(0.038)	(0.036)	(0.036)	(0.039)
Sponsor Backing				-0.017	-0.020	-0.019	-0.020
				(0.032)	(0.033)	(0.034)	(0.032)
Constant	0.058**	0.187**	0.102	-0.203**	0.207**	0.290	-0.607
	(0.025)	(0.089)	(0.371)	(0.085)	(0.097)	(0.362)	(0.533)
Observations	233	233	233	233	233	233	233
R^2	0.026	0.003	0.000	0.064	0.039	0.038	0.067

Table 6 confirms the patterns seen in Figure 3: ASVI predicts first-day returns, both on a stand-alone basis, as well as when controlling for various variables that by previous literature has shown explanatory power over first-day IPO returns. Regression 1 shows that ASVI has a statistically significant coefficient of 0.096, suggesting that if pre-IPO investor attention, measured by ASVI, increases by one standard deviation (0.473), we expect first-day IPO returns to be 4.5 (= 0.096 $*$ 0.473) pp higher, which is a considerable increase in return. This finding is robust when we control for several firm and industry characteristics (regression 4), as well as *Media* and *CCI,* which are included in the full model (regression 7). Importantly, the coefficients of ASVI are *all* statistically significant at the 5% level and even increases slightly as we include additional variables. *Media*, on the other hand, together with *CCI*, are weak and insignificant predictors of first-day IPO returns.

Being able to establish a significant positive relationship between ASVI and first-day returns, we confirm the first part Barber and Odean's (2008) attention-induced price-pressure hypothesis in a Swedish setting. Next, we turn to the second part: long-run returns.

II. LONG-RUN RETURN

For this section, we focus on the 116 IPOs with highest (above-median) first-day return. We then split these into two groups, high and low ASVI, each with 58 observations. Figure 4 plots 5-to-52-week post-IPO cumulative unadjusted returns for both groups and for the total. Using industry-adjusted long-run returns has hardly any impact on the findings. We refer interested readers to Appendix III for a detailed analysis of industry-adjusted long-run returns.

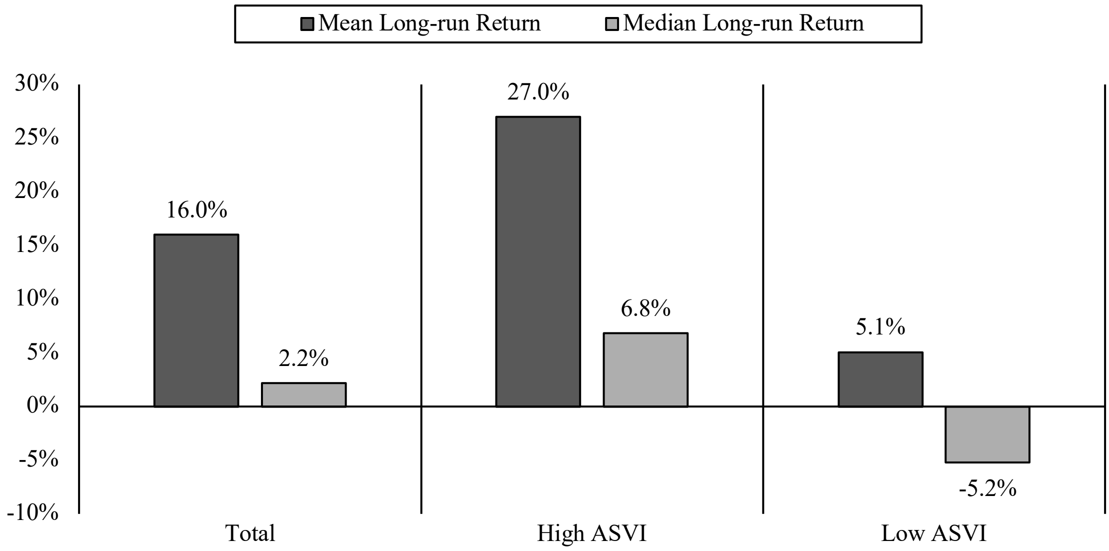

Figure 4: ASVI and Long-run Returns (unadjusted)

The figure plots unadjusted long-run returns for high ASVI IPOs and low ASVI IPOs, as well as for the total. The sample includes 116 IPOs with the highest first-day return on Nasdaq Stockholm and First North between 2004 and 2019.

Figure 4 shows that high ASVI IPOs *outperform* low ASVI IPOs over the one-year post-IPO period by about 22 pp. The results are surprising. In line with the findings of previous studies, we expected the opposite effect; that high ASVI IPOs *underperform* in the long run, as excess retail demand fades out. With a t-test, we find that long-run returns are significantly higher for high ASVI IPOs at the 10% level. However, a Wilcoxon rank sum test cannot confirm the significance, generating a p-value of 0.1185. Despite no test being able to confirm statistical significance at the 5% level, we find the observed relationship aberrant. Therefore, we investigate the full sample of 233 IPOs (i.e. also low first-day return IPOs) to see if the relationship is evident over the entire sample, which it turns out to be.[18] This finding is inconsistent with Da, Engelberg and Gao (2011) and the well-documented pattern of long-run underperformance of IPOs. A possible explanation is that our dataset to 65% consists of 2015-2018 IPOs. This high-intensity IPO market might have fueled returns of hot IPOs, not only in the short-term, but also for the one-year post-IPO period. Indeed, as Ritter and Welch (2002) argue, studies of long-run underperformance are very sensitive to the selection of time periods. As our study aims to test the results of Da, Engelberg and Gao (2011), we keep the 5-to-52-week time window for the long-run performance evaluation.

To better understand this puzzle, we turn to regressions in Table 7. In these regressions, the dependent variable is cumulative unadjusted long-run return. Broadly, we follow the same structure as in Table 6, except that all variables are included throughout the entire table. Instead, we introduce interaction variables and test them stepwise. Regression 1 is performed without

[18] Mean and median unadjusted long-run returns for high (low) ASVI sample is 16.3 (1.1) % and 6.6 (-5.6) %.

any interaction variables; these are added through regression 2 to 4. In regression 5, we run the full model, as presented in Equation III.

Table 7: ASVI and Long-Run Returns (unadjusted)

This table regresses long-run returns on ASVI, Media, CCI and IPO characteristics. All variables are defined in Table 4. The sample includes 116 IPOs on Nasdaq Stockholm and First North from 2004 to 2019 with valid SVI data. Only IPOs with above-median first-day returns are retained in the sample. Standard errors (in parentheses) are robust and clustered by offering year and quarter. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

	Dependent Variable: Long-Run Return (unadjusted)				
	(1)	(2)	(3)	(4)	(5)
ASVI	0.153	0.280	0.155	0.203	0.227
	(0.117)	(0.168)	(0.111)	(0.128)	(0.183)
ASVI x First-Day Return		-0.348			-0.073
		(0.317)			(0.444)
Media	-0.371	-0.362	-0.490	-0.356	-0.459
	(0.266)	(0.270)	(0.355)	(0.272)	(0.357)
Media x First-Day Return			0.503		0.434
			(0.600)		(0.579)
CCI	-0.013	-0.015	-0.012	-0.025	-0.024
	(0.011)	(0.011)	(0.011)	(0.016)	(0.018)
CCI x First-Day Return				0.041	0.036
				(0.033)	(0.046)
First-Day Return	-0.352	-0.130	-1.250	-4.554	-4.822
	(0.247)	(0.274)	(1.030)	(3.531)	(4.972)
log(Offering Size)	0.540***	0.542***	0.534***	0.534***	0.529***
	(0.122)	(0.128)	(0.125)	(0.125)	(0.131)
log(Age)	0.064	0.066	0.664	0.065	0.670
	(0.159)	(0.163)	(0.160)	(0.162)	(0.164)
log(Asset Size)	-0.128	-0.131	-0.121	-0.123	-0.117
	(0.177)	(0.180)	(0.179)	(0.178)	(0.181)
Secondary Share Overhang	-0.025	-0.039	-0.028	-0.039	-0.043
	(0.162)	(0.164)	(0.160)	(0.163)	(0.163)
Past Industry Returns	-0.423	-0.343	-0.435	-0.376	-0.375
	(0.314)	(0.297)	(0.319)	(0.314)	(0.306)
Multiple Underwriters	-0.396***	-0.400***	-0.378***	-0.399***	-0.385***
	(0.121)	(0.118)	(0.123)	(0.120)	(0.122)
Sponsor Backing	-0.107	-0.107	-0.112	-0.116	-0.119
	(0.156)	(0.157)	(0.160)	(0.153)	(0.159)
Constant	1.437	1.591	1.601	2.641	2.683
	(1.260)	(1.275)	(1.258)	(1.512)	(1.783)
Observations	116	116	116	116	116
R^2	0.163	0.167	0.165	0.171	0.172

While ASVI has positive coefficients in all regressions, we cannot confirm that the coefficients are statistically significant. Neither the first-day return coefficients are statistically significant, but consistent with previous literature they are negative. Interaction variables, multiplying first-day return with ASVI (regression 2), *Media* (regression 3) and *CCI* (regression 4), are added stepwise. None of these prove to be statistically significant and we conclude that there is no interaction effect bearing explanatory power over long-run returns. In the end, we observe that only *Offering Size* and *Multiple Underwriters* predict long-run IPO returns, both with large oppositional coefficients statistically significant at the 1% level.

Because ASVI does not predict long-run price reversals, we reject our second hypothesis and thus cannot confirm the full Barber and Odean (2008) price-pressure hypothesis for Swedish IPOs. Instead, we find some evidence of an opposite, “success-feeds-success” pattern, where high ASVI IPOs perform better in the short-term as well as in the long-term perspective. Next, we study the same patterns as in the previous two sections, but on two separate markets.

III. THE PRICE-PRESSURE HYPOTHESIS ON DIFFERENT MARKETS

As our sample includes both Nasdaq Stockholm and First North IPOs, we can test differences in retail investor attention and IPO performance across markets. Since we cannot confirm Barber and Odean's (2008) attention-induced price-pressure hypothesis for the full sample, it is especially interesting to see how well it holds in two systematically different settings. Our hypothesis is that the relationship between pre-IPO retail investor attention and IPO performance is stronger on First North than on Nasdaq Stockholm.

FIRST-DAY RETURN

To test our last hypothesis, we repeat the procedure from the previous two sections, but begin with splitting our full dataset on IPO market, generating a sample of 89 observations for Nasdaq Stockholm and 144 for First North. Each of these groups are then split on ASVI, using the median as the cut-off point. Figure 5 plots mean and median first-day returns per market.

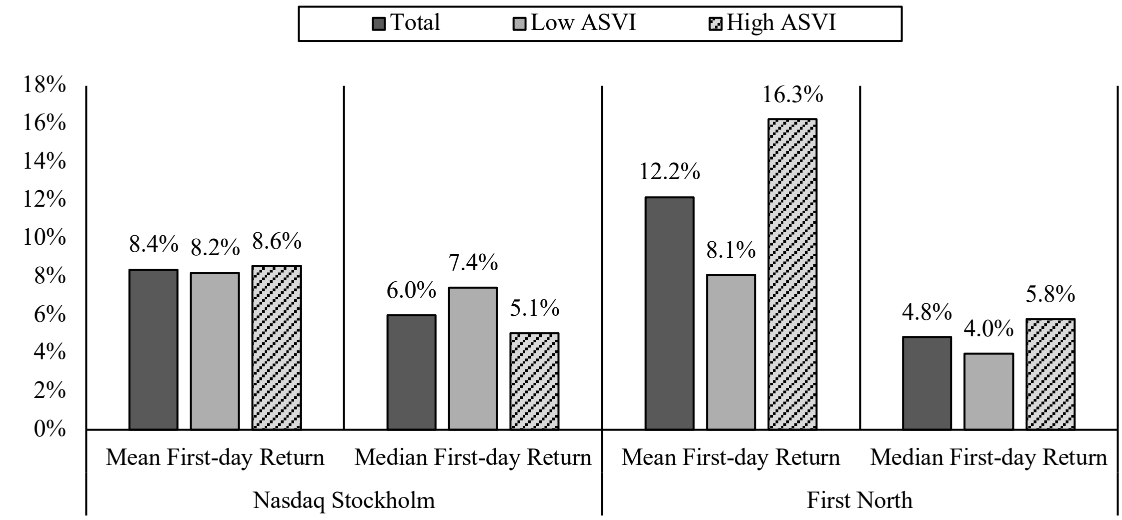

Figure 5: ASVI and First-day Returns per Market

The figure plots mean and median first-day returns for high ASVI IPOs and low ASVI IPOs, as well as for the total, on Nasdaq Stockholm (left) and First North (right). The Nasdaq Stockholm sample includes 89 IPOs (with median ASVI observation excluded) and First North sample includes 144 IPOs, between 2004 and 2019.

Looking at totals in Figure 5, we see that average first-day return is about 3.8 pp higher on First North than on Nasdaq Stockholm. This is in line with the previously discussed theories of underpricing as compensation for IPO uncertainty, as well as the fact the First North firms are generally smaller and considered riskier among investors. However, neither a t-test nor a Wilcoxon test indicate that this difference is significant, the reason likely being that first-day returns are more volatile on First North than on Nasdaq Stockholm.

To better understand retail investor attention and its impact on IPO performance, we focus on the two markets separately. Starting with Nasdaq Stockholm, we see the high ASVI group have average first-day returns of 8.6%, which is only 0.4 pp higher than the average first-day return among low ASVI IPOs of 8.2%. While there is virtually no relationship between ASVI and *average* first-day returns, it is interesting to note that *median* first-day returns show an opposite relationship to what we expected, with the low ASVI median return of 7.4% being higher than the high ASVI median return of 5.1%. Continuing with First North, we observe patterns similar to those of the whole sample: high ASVI IPOs have first-day returns of 16.3%, which is much higher than for low ASVI IPOs, having average first-day returns of 8.1%. This 8.2 pp difference is significant at the 10% level using a t-test, but the more robust Wilcoxon test cannot confirm the significance. Table 8 presents regressions on a per-market basis. We begin by regressing first-day return on ASVI for each exchange. In regression 2 we include control variables and lastly, in regression 3, we run the full model for each market.

Table 8: ASVI and First-Day Returns per Market

This table regresses first-day returns on ASVI and IPO characteristics on two samples based on IPO exchange. Independent variables are defined in Table 4. The sample includes 89 IPOs on Nasdaq Stockholm and 144 on First North from 2004 to 2019 with valid SVI data. Standard errors (in parentheses) are robust and clustered by offering year and quarter. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

	Dependent Variable: First-Day Return					
	Regression 1		Regression 2		Regression 3	
	Nasdaq Stockholm	First North	Nasdaq Stockholm	First North	Nasdaq Stockholm	First North
ASVI	0.031	0.126**	0.065	0.127**	0.073*	0.142**
	(0.035)	(0.060)	(0.039)	(0.059)	(0.039)	(0.061)
Media					0.021	0.102
					(0.055)	(0.084)
CCI					-0.006*	0.002
					(0.003)	(0.005)
log(Offering Size)			-0.057	-0.052	-0.058	-0.071
			(0.039)	(0.047)	(0.041)	(0.047)
log(Age)			0.035	-0.122*	0.045	-0.119*
			(0.039)	(0.026)	(0.033)	(0.065)
log(Asset Size)			0.046**	-0.026	0.038*	-0.028
			(0.022)	(0.043)	(0.020)	(0.044)
Secondary Share			0.025	0.123	0.036	0.109
Overhang			(0.031)	(0.112)	(0.033)	(0.109)
Past Industry Returns			0.055	0.386**	0.064	0.431**
			(0.190)	(0.174)	(0.190)	(0.180)
Multiple Underwriters			-0.005	-0.045	0.000	-0.051
			(0.038)	(0.080)	(0.038)	(0.083)
Sponsor Backing			0.005	-0.057	0.001	-0.061
			(0.023)	(0.057)	(0.021)	(0.073)
Constant	0.069**	0.060	0.012	0.293**	0.590	-0.031
	(0.028)	(0.037)	(0.106)	(0.119)	(0.367)	(0.480)
Observations	89	144	89	144	89	144
R^2	0.009	0.036	0.055	0.096	0.110	0.102

The results are in line with our third hypothesis – that there is a stronger relationship between ASVI and IPO performance on First North than on Nasdaq Stockholm. In all First North regressions, the ASVI coefficient is significant at the 5% level, while for Nasdaq Stockholm the ASVI coefficient is only significant at the 10% level when we run the full model. Importantly, the First North ASVI coefficient is four times larger in regression 1, and almost twice as large as the Nasdaq Stockholm ASVI coefficient in regression 2 and 3. Comparing Nasdaq Stockholm and First North in regression 3, we clearly see this difference, with Nasdaq Stockholm and First North having coefficients of 0.073 and 0.142, respectively. These numbers suggest that if pre-IPO investor attention, measured by ASVI, increases by one standard deviation (0.402 for Nasdaq Stockholm and 0.511 for First North), we expect first-day IPO returns to be 2.9 (= 0.073 $*$ 0.402) pp higher for Nasdaq Stockholm IPOs and 7.3 (= 0.142 $*$ 0.511) pp higher for First North IPOs. Hence, a one-standard-deviation increase in pre-IPO investor attention leads to a 4.4 pp higher first-day return on First North than on Nasdaq Stockholm. This is a meaningful increase in returns.

We can confirm that ASVI carries significant explanatory power over first-day return on First North, and less power for Nasdaq Stockholm IPOs, with ASVI only being significant in one regression and at the 10% level. Importantly, we also find that the changes in underlying investor attention leads to larger first-day return swings on First North, than on Nasdaq Stockholm. Altogether, this analysis confirms the first part of the attention-induced price-pressure hypothesis on First North, but not on Nasdaq Stockholm, in line with our third hypothesis.

LONG-RUN RETURN

In this part, we focus on long-run returns. In line with previous sections we split the full sample based different criteria. First, we split the full dataset on IPO market. Second, we retain only IPOs with above-median first-day return. Last, we split these samples on ASVI, using the median as the cut-off point. This gives us four subsamples that we are interested in; (1) Nasdaq Stockholm with high first-day return and *high* ASVI, (2) Nasdaq Stockholm with high first-day return and *low* ASVI, (3) First North with high first-day return and *high* ASVI and (4) First North with high first-day return and *low* ASVI. The samples from Nasdaq Stockholm each have 22 observations. The samples from First North have 36 observations. We are aware that these sample sets have fewer than optimal observations and we are thus careful when interpreting the results. Figure 6 plots mean and median unadjusted long-run returns. For an illustration of industry-adjusted long-run returns, we refer to Figure 11 in Appendix IV.

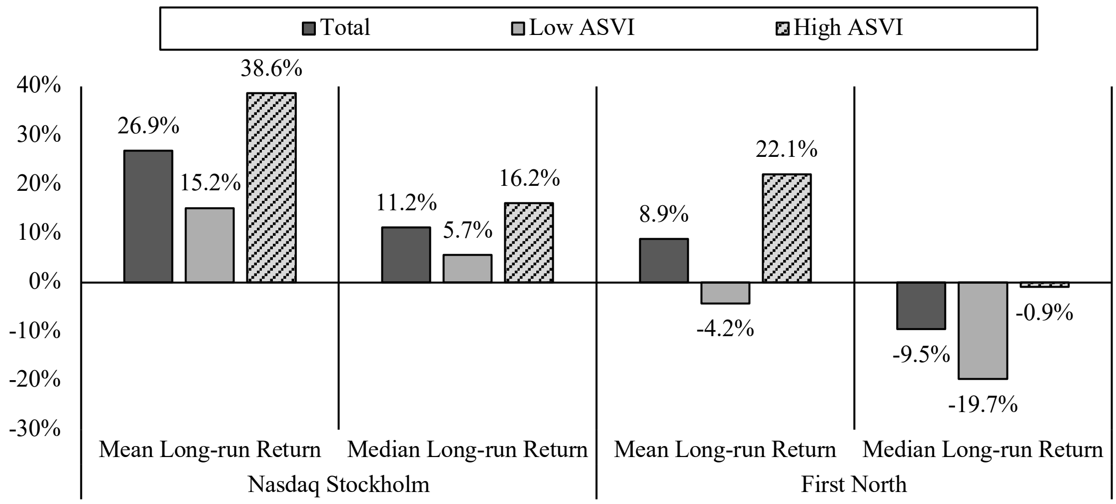

Figure 6: ASVI and Long-run Returns per Market (unadjusted)

The figure plots mean and median unadjusted long-run returns for high ASVI IPOs, low ASVI IPOs and for the total, on Nasdaq Stockholm (left) and First North (right). The samples include the 44 IPOs with the highest first-day return on Nasdaq Stockholm and the 72 IPOs with the highest first-day return on First North between 2004 and 2019.

As in the full sample, we observe that high ASVI is associated with *higher* long-run average returns. Looking at Figure 6, this "success-feeds-success" pattern seems to hold both for Nasdaq Stockholm and First North, with average long-run returns for the high (low) ASVI groups being 38.6% (15.2%) and 22.1% (-4.2%), respectively. We test the differences in average long-run return and only between high and low ASVI IPOs on First North we are able confirm that the difference at the 10% level using a t-test.

To better understand this pattern, we perform regressions which are presented in Table 9. In these regressions, the dependent variable is unadjusted long-run return. Broadly, we follow the same structure as in Table 7, although we perform regressions for Nasdaq Stockholm and First North separately. For an analysis of industry-adjusted long-run returns, we refer interested readers to Table 12 in Appendix IV.

Table 9: ASVI and Long-Run Returns per Market (unadjusted)

This table regresses unadjusted long-run returns on ASVI and IPO characteristics on two samples based on IPO exchange. Independent variables are defined in Table 4. The sample includes 44 IPOs on Nasdaq Stockholm and 72 on First North from 2004 to 2019 with valid SVI data. Only IPOs with above-median first-day returns are retained in the sample. Standard errors (in parentheses) are robust and clustered by offering year and quarter. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

	Dependent Variable: Long-Run Return (unadjusted)					
	Regression 1		Regression 2		Regression 3	
	Nasdaq Stockholm	First North	Nasdaq Stockholm	First North	Nasdaq Stockholm	First North
ASVI	0.173	0.068	0.477	0.202	0.435	0.150
	(0.307)	(0.105)	(0.902)	(0.144)	(0.904)	(0.158)
ASVI x First-Day Return			-1.577	-0.316	-1.334	-0.094
			(4.541)	(0.284)	(4.769)	(0.473)
Media	-0.382	-0.401	-0.405	-0.370	0.047	-0.304
	(0.345)	(0.278)	(0.350)	(0.286)	(0.751)	(0.473)
Media x First-Day Return					-2.425	-0.168
					(3.542)	(0.900)
CCI	-0.007	-0.016	-0.011	-0.018	0.001	-0.030
	(0.022)	(0.017)	(0.019)	(0.017)	(0.058)	(0.028)
CCI x First-Day Return					-0.073	0.036
					(0.434)	(0.056)
First-Day Return	0.731	-0.324	1.634	-0.135	14.657	-3.656
	(1.054)	(0.256)	(3.237)	(0.276)	(44.401)	(5.887)
log(Offering Size)	0.349	0.594***	0.396	0.594***	0.321	0.596***
	(0.435)	(0.159)	(0.447)	(0.165)	(0.457)	(0.166)
log(Age)	0.253	-0.175	0.273	-0.177	0.237	-0.186
	(0.166)	(0.170)	(0.197)	(0.176)	(0.200)	(0.173)
log(Asset Size)	-0.035	-0.111	-0.036	-0.114	0.192	-0.109
	(0.310)	(0.217)	(0.312)	(0.219)	(0.225)	(0.220)
Secondary Share	-0.117	0.111	-0.120	0.091	-0.120	0.073
Overhang	(0.353)	(0.203)	(0.361)	(0.205)	(0.325)	(0.214)
Past Industry Returns	-1.630	-0.036	-1.755	0.066	-1.743	0.028
	(1.283)	(0.433)	(1.300)	(0.424)	(1.285)	(0.441)
Multiple Underwriters	-0.293	-0.255	-0.321	-0.266*	-0.294	-0.278
	(0.277)	(0.158)	(0.297)	(0.154)	(0.315)	(0.166)
Sponsor Backing	-0.384	0.336	-0.377	0.322	-0.343	0.301
	(0.241)	(0.326)	(0.247)	(0.324)	(0.283)	(0.314)
Constant	0.888	1.835	1.062	1.941	-1.163	3.089
	(2.541)	(1.582)	(2.365)	(1.617)	(5.812)	(2.676)
Observations	44	72	44	72	44	72
R^2	0.288	0.206	0.290	0.211	0.298	0.216

Also similar to the full sample long-run analysis presented in Table 7, ASVI has positive coefficients in all Table 9 regressions. None of the coefficients are statistically significant though, but we expected negative coefficients in line with Barber and Odean's (2008) price-pressure hypothesis. Neither first-day return is a significant predictor of long-run returns, but it does have a negative coefficient for First North IPOs, consistent with the literature. The introduction of interaction variables adds almost no insight and the standard errors are much too high for the coefficients to be reliable. In the end, we observe that only *Offering Size* predicts long-run IPO return for First North IPOs at the 1% level with a large coefficient throughout all regressions.

Because ASVI does not predict long-run reversals for neither Nasdaq Stockholm nor First North, we cannot confirm the second pattern of the price-pressure hypothesis for any separate market. As shown, not even the initial upward price pattern of the attention-induced price-pressure hypothesis is very outspoken on Nasdaq Stockholm. For First North, however, we find that ASVI is an important and significant variable in explaining first-day IPO returns. Thus, we can at least partly confirm our third hypothesis, that the price-pressure hypothesis is more pronounced where retail investor attention matters the most, that being on First North.

IV. ROBUSTNESS AND MODEL LIMITATIONS

POST-HOC ROBUSTNESS CHECKS

Recall from the methodology section that our sample includes some extreme first-day return and long-run performance observations. To get a sense of how robust our findings are, we conduct two data manipulations. These are summarized below.

First, we winsorize first-day and long-run returns at the 5% and 95% level to examine the impact of extreme values on our results. ASVI remains a significant predictor of first-day returns at the 5% level when testing the difference in returns between high and low ASVI groups and when we run regressions with ASVI as independent variable. However, the ASVI coefficients are approximately 25% smaller compared to the unmanipulated model. The surprising long-run performance trend remains visible, where the difference in both unadjusted and industry-adjusted long-run returns is significant at the 10% level with t-tests but not with rank sum tests. All IPOs affected by the winsorizing are from First North. Neither the t-test nor the rank sum test can reject the hypothesis that first-day returns on Nasdaq Stockholm and First North are equal, and the difference in first-day returns between high and low ASVI is no longer significant on First North.

Second, we log-transform first-day and long-run returns to examine whether re-scaling our dependent variables impacts the robustness of our findings. The difference in first-day returns between the high and low ASVI groups remains significant at the 1% (t-test) and 5% (rank sum test) level. Similar to when winsorized, ASVI remains significant at 5% level in all regressions, but with an even smaller coefficient at approximately 33% of those in the unmanipulated model. We observe the same long-run trend as previously, however, neither the unadjusted nor the industry-adjusted long-run performance is significantly different between the high first-day return high ASVI sample and the high first-day return low ASVI sample. When separating the First North and Nasdaq Stockholm IPOs, the difference in first-day returns between the two markets is no longer significant and neither is the difference in first-day returns between the high and low ASVI samples on each market.

LIMITATIONS OF THE ORIGINAL MODEL

As we set out to understand how investor attention impacts stock prices, we would ideally have been able to observe many investors' attention directly. Unfortunately, we must rely on proxies of attention and while search engine data is a good proxy, as previously discussed, it is not perfect. SVI does a good job capturing changes in search volume, but it is not a measure of magnitude since all search data is indexed. Thus, ASVI is a measure of abnormality in search volume relative to its own history and does not allow for comparisons in absolute numbers. Actual search volume, as opposed to an indexed frequency, would therefore have been better.

Long-run performance is evaluated at the one-year mark from the IPO. As the aim of this paper is to replicate and extend Da, Engelberg and Gao (2011), we stick to their selected one-year evaluation period. However, Ritter and Welch (2002) show that long-run IPO performance is very sensitive to the methodology, sample set as well as the time period studied. For example, Ljungqvist (1997) and Ritter (1991), study long-run IPO performance using a three-year evaluation period and although our sample would have been smaller with this time horizon, adjusting the evaluation period could improve the validity of our results.

LIMITATIONS IN RELATION TO THE ORIGINAL MODEL

Our model differs from Da, Engelberg and Gao (2011) in three main aspects. First, we do not include the variable *Price Revision,* defined as the ratio of the offering price divided by the median of the filing price, found to be a strong predictor for first-day IPO returns. A corresponding measure in a Swedish setting would be the price range provided in some IPO prospectuses. However, the offering price to retail investors will not be greater than that provided in the prospectuses in Sweden. This is not the case in the U.S. where firms can offer their shares above the filing price (Hanley, 1993), which gives the measure different characteristics and likely larger predictive power over first-day IPO returns. Nonetheless, there is a risk of an omitted variable bias in our replicated model, where the effect of *Price Revision* is attributed to the estimated effects of the included variables instead (Wooldridge, 89-93).

Second, we use a different market sentiment variable. Da, Engelberg and Gao (2011) use *DSENT*, an index building on six proxies for investor sentiment (Wurgler & Baker, 2006). There are two reasons why *DSENT* is not a suitable variable for our study. First, *DSENT* is a U.S. market sentiment measure that cannot effectively reflect Swedish sentiment. Second, it stretches only to 2018. In our analysis, we find that *CCI* carries very little predictive power over IPO performance, which could be due to it not being a market-based sentiment index, but a survey-based one.

Third, we adjust long-run returns using only one method, while Da, Engelberg and Gao (2011) adjust long-run returns twice. We benchmark the long-run unadjusted return against sector-specific indexes, but the original study first adjust for Fama-French 48-industry returns (French, 2020) and then for size- and book-to-market portfolio weights. To some extent, our industry adjustment captures size as well, as the indexes used are both sector- and exchange-specific. For instance, this means that a First North healthcare IPOs will be benchmarked to an index including only other First North healthcare firms. However, we expect that a more similar size- and book-to-market-adjustment would further suppress long-run returns, but not change any price dynamics found in our study.

5. CONCLUSION

In this paper we test the attention-induced price-pressure hypothesis by Barber and Odean (2008) by replicating and extending the methodology of Da, Engelberg and Gao (2011). Specifically, we investigate the impact of retail investor attention, measured by aggregate search engine data, on IPO performance. While we find a significant positive relationship between ASVI and first-day returns, ASVI does not predict long-run price reversals. Instead, we observe that attention-grabbing IPOs tend to outperform also in the long run, contrary to the price-pressure hypothesis. This pattern is robust to controlling for industry returns. As an extension, we find that aggregate search engine data predicts first-day IPO returns on First North, where retail investor attention *matters the most*, while it has virtually no explanatory power on Nasdaq Stockholm, where retail investors are much less important.

These results are robust to controlling for market sentiment, media coverage and several firm characteristics. However, our market-specific findings underline the fact that the results are sensitive to research setting, time frame as well as extreme values. Therefore, it could prove fruitful to further research the relationship between search engine data, retail investor attention and stock market movements in different settings. Specifically, it would be interesting to examine the underlying mechanism behind the market-specific IPO-patterns highlighted in this paper. We leave that for future research.

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7. APPENDIX

APPENDIX I – IPO CHARACTERISTICS PER YEAR

Table 10: IPO Characteristics Per Year

The table presents the number of IPOs per year and their respective average, median, lowest and highest first-day return as well as the standard deviation.

Year	# of IPOs	First-day return (%)				
		Average	Median	Min	Max	Std. dev.
2004	1	-8.0	-8.0	-8.0	-8.0	n.m.
2005	4	4.6	2.9	0.0	12.7	6.0
2006	8	1.7	1.9	-12.0	13.2	8.6
2007	14	10.3	0.8	-37.3	119.3	37.3
2008	3	7.9	8.4	-1.9	16.6	8.1
2009	0	n.m.	n.m.	n.m.	n.m.	n.m.
2010	4	1.1	1.6	-8.6	10.0	8.2
2011	6	-2.7	-0.8	-13.1	2.8	5.6
2012	2	-7.8	-7.8	-32.4	16.7	34.7
2013	5	19.3	6.2	5.3	72.7	29.9
2014	22	3.2	6.2	-21.7	32.3	13.6
2015	39	16.3	9.3	-24.0	94.1	28.1
2016	43	14.8	13.1	-39.2	147.3	34.7
2017	54	14.4	12.2	-34.8	123.2	25.1
2018	21	-0.6	-0.1	-30.3	77.1	23.2
2019	6	24.9	17.8	-52.5	117.0	57.1
Full sample	233	10.8	5.8	-52.5	147.3	27.9

APPENDIX II – RESIDUAL PLOTS

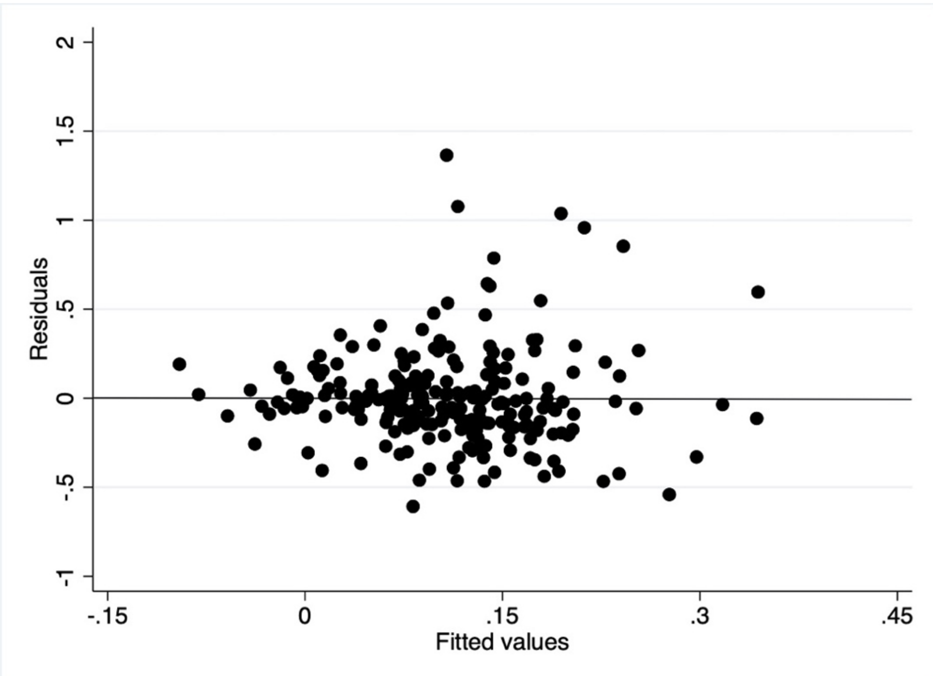

Figure 7: Residual Scatterplot

The figure contains a visual representation of the residuals from Equation I against a fitted values line. The original regression is run with first-day return as dependent variable on the full sample of 233 IPOs on Nasdaq Stockholm and First North between 2004 and 2019.

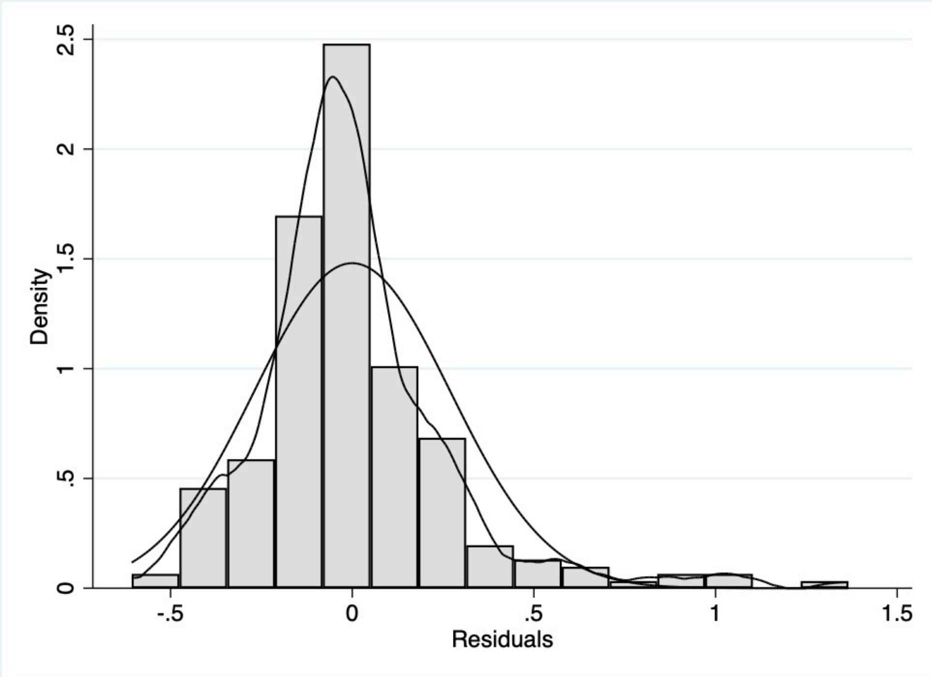

Figure 8: Residual Histogram

The figure contains a visual representation of the residuals from Equation I against an imposed normal line. The original regression is run with first-day return as dependent variable on the full sample of 233 IPOs on Nasdaq Stockholm and First North between 2004 and 2019.

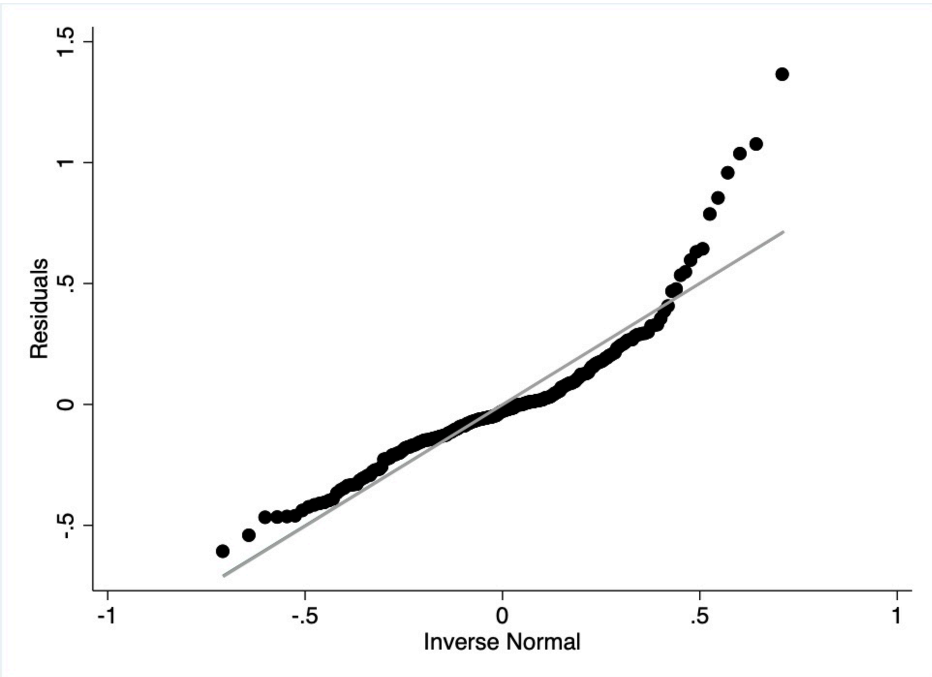

Figure 9: Residual QQ-plot

The figure contains a visual representation of the residuals from Equation I in a quantile-quantile plot against an inverse normal curve. The original regression is run with first-day return as dependent variable on the full sample of 233 IPOs on Nasdaq Stockholm and First North between 2004 and 2019.

APPENDIX III – ADJUSTED LONG-RUN PERFOMANCE (FULL SAMPLE)

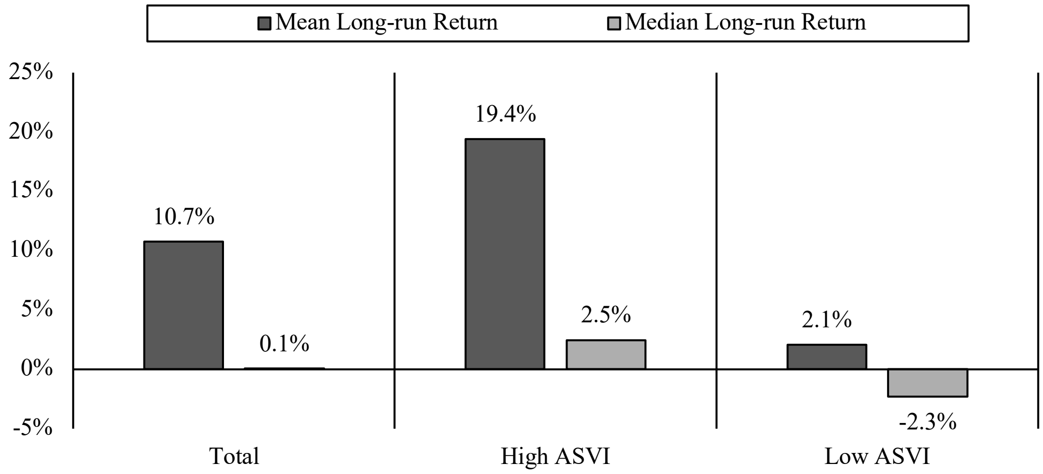

Figure 10: ASVI and Long-run Returns (adjusted)
The figure plots industry-adjusted long-run returns for high ASVI IPOs and low ASVI IPOs, as well as for the total. The sample includes 116 IPOs with the highest first-day return on Nasdaq Stockholm and First North between 2004 and 2019.

Table 11: ASVI and Long-Run Returns (adjusted)
This table regresses industry-adjusted long-run returns on ASVI, Media, CCI and IPO characteristics. All variables are defined in Table 4. The sample includes 116 IPOs on Nasdaq Stockholm and First North from 2004 to 2019 with valid SVI data. Only IPOs with above-median first-day returns are retained in the sample. Standard errors (in parentheses) are robust and clustered by offering year and quarter. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

	Dependent Variable: Long-Run IPO Returns (adjusted)				
	(1)	(2)	(3)	(4)	(5)
ASVI	0.059	0.150	0.063	0.100	0.095
	(0.102)	(0.156)	(0.094)	(0.114)	(0.180)
ASVI x First-Day Return		-0.249			0.022
		(0.301)			(0.466)
Media	-0.338	-0.332	-0.498	-0.326	-0.482
	(0.284)	(0.011)	(0.376)	(0.290)	(0.384)
Media x First-Day Return			0.676		0.654
			(0.628)		(0.634)
CCI	-0.002	-0.003	-0.001	-0.011	-0.011
	(0.010)	(0.011)	(0.010)	(0.014)	(0.016)
CCI x First-Day Return				0.033	0.033
				(0.028)	(0.043)
First-Day Return	-0.262	-0.102	-1.475	-3.621	-4.813
	(0.223)	(0.288)	(1.070)	(2.999)	(4.803)
log(Offering Size)	0.489***	0.490***	0.481***	0.483***	0.475***
	(0.138)	(0.143)	(0.140)	(0.143)	(0.147)
log(Age)	0.027	0.028	0.030	0.278	0.030
	(0.138)	(0.141)	(0.139)	(0.141)	(0.142)
log(Asset Size)	-0.086	-0.088	-0.076	-0.081	-0.071
	(0.180)	(0.184)	(0.182)	(0.181)	(0.186)
Secondary Share Overhang	-0.029	-0.036	-0.034	-0.041	-0.044
	(0.168)	(0.170)	(0.166)	(0.170)	(0.169)
Past Industry Returns	-0.376	-0.319	-0.392	-0.339	-0.359
	(0.328)	(0.317)	(0.327)	(0.335)	(0.326)
Multiple Underwriters	-0.417***	-0.420***	-0.393***	-0.419***	-0.396***
	(0.121)	(0.119)	(0.128)	(0.120)	(0.127)
Sponsor Backing	-0.036	-0.036	-0.042	-0.043	-0.049
	(0.169)	(0.171)	(0.172)	(0.166)	(0.172)
Constant	0.237	0.348	0.458	1.200	1.405
	(1.262)	(1.288)	(1.304)	(1.462)	(1.683)
Observations	116	116	116	116	116
R^2	0.131	0.133	0.135	0.136	0.140

APPENDIX IV – ADJUSTED LONG-RUN PERFOMANCE (PER MARKET)

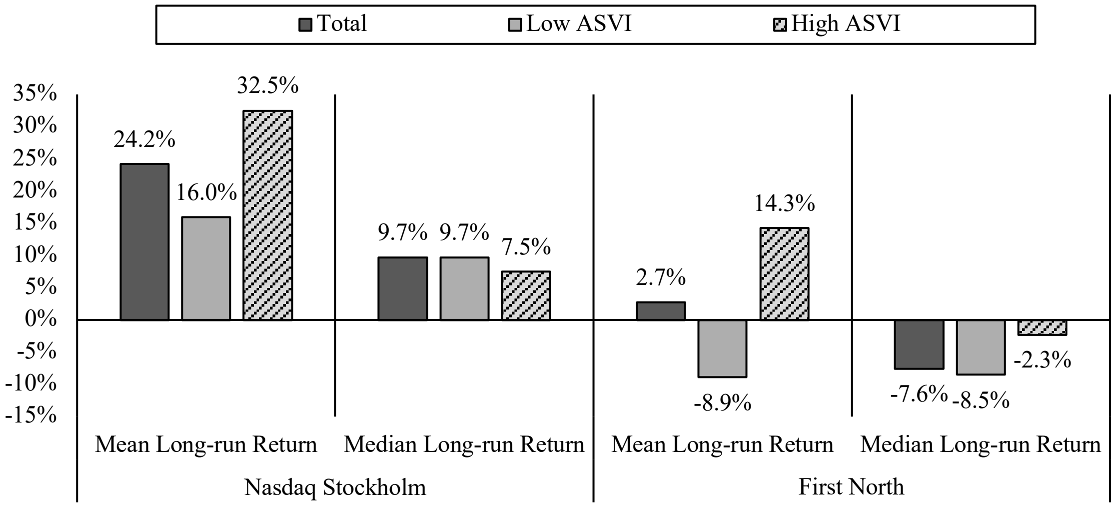

Figure 11: ASVI and Long-run Returns per Market (adjusted)

The figure plots ASVI and mean and median industry-adjusted long-run returns for IPOs on Nasdaq Stockholm (left) and on First North (right). The samples include IPOs with high first-day returns (44 on Nasdaq Stockholm and 72 on First North) between 2004 and 2019. Only IPOs with valid SVI data is included in the sample.

Table 12: ASVI and Long-Run Returns per Market (adjusted)

This table regresses industry-adjusted long-run returns on ASVI and IPO characteristics. The dependent variable is the individual IPO's adjusted long-run return. Independent variables are defined in Table 4. The sample includes 44 regular and common equity IPOs on Nasdaq Stockholm and 72 on First North from 2004 to 2019. Only IPOs with above median first-day returns and valid SVI (searched using firm names) are retained in the sample. Regressions are run with CRSE and standard errors (in parentheses) are clustered by offering year and quarter. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

	Dependent Variable: Long-Run IPO Returns (adjusted)					
	Regression 1		Regression 2		Regression 3	
	Nasdaq Stockholm	First North	Nasdaq Stockholm	First North	Nasdaq Stockholm	First North
ASVI	-0.033	0.010	0.304	0.049	0.219	0.031
	(0.291)	(0.097)	(0.889)	(0.142)	(0.918)	(0.161)
ASVI x First-Day Return			-1.751	-0.092	-1.245	-0.027
			(4.349)	(0.266)	(4.767)	(0.487)
Media	-0.273	-0.464	-0.298	-0.455	0.082	-0.487
	(0.362)	(0.282)	(0.371)	(0.288)	(0.643)	(0.475)
Media x First-Day Return					-2.059	0.134
					(2.902)	(1.043)
CCI	-0.004	0.006	-0.009	0.006	-0.010	0.003
	(0.021)	(0.017)	(0.019)	(0.017)	(0.053)	(0.027)
CCI x First-Day Return					0.015	0.008
					(0.409)	(0.055)
First-Day Return	0.992	-0.245	1.995	-0.195	5.202	-1.292
	(0.936)	(0.238)	(2.923)	(0.282)	(41.024)	(6.014)
log(Offering Size)	0.501	0.509**	0.554	0.509**	0.499	0.507**
	(0.395)	(0.192)	(0.413)	(0.196)	(0.418)	(0.196)
log(Age)	0.158	-0.208	0.180	-0.208	0.126	-0.209
	(0.156)	(0.167)	(0.185)	(0.169)	(0.208)	(0.171)
log(Asset Size)	-0.216	-0.057	-0.217	-0.058	-0.180	-0.052
	(0.276)	(0.228)	(0.278)	(0.231)	(0.260)	(0.233)
Secondary Share Overhang	-0.198	0.122	-0.202	0.116	-0.189	0.110
	(0.316)	(0.225)	(0.323)	(0.233)	(0.287)	(0.242)
Past Industry Returns	-0.900	-0.102	-1.039	-0.072	-0.953	-0.097
	(1.272)	(0.433)	(1.345)	(0.430)	(1.381)	(0.483)
Multiple Underwriters	-0.398	-0.236	-0.429	-0.239	-0.406	-0.238
	(0.272)	(0.157)	(0.298)	(0.156)	(0.307)	(0.161)
Sponsor Backing	-0.293	0.399	-0.285	0.395	-0.268	0.393
	(0.245)	(0.369)	(0.251)	(0.371)	(0.277)	(0.367)
Constant	0.676	-0.317	0.871	-0.286	0.243	0.026
	(2.486)	(1.585)	(2.348)	(1.625)	(5.391)	(2.603)
Observations	44	72	44	72	44	72
R^2	0.285	0.186	0.287	0.186	0.296	0.187

APPENDIX V – LIST OF SAMPLE OBSERVATIONS

Company name	Exchange	IPO date	Search term
2cureX AB	First North	2017-11-24	2curex
AcadeMedia AB	Nasdaq Stockholm	2016-06-15	academedia
Acarix AB	First North	2016-12-19	acarix
Acconeer AB	First North	2017-12-11	acconeer
Actic Group AB	Nasdaq Stockholm	2017-04-07	actic
AdderaCare AB	First North	2016-12-01	adderacare
Advenica AB	First North	2014-09-18	advenica
Agellis Group AB	First North	2007-12-07	agellis
Ahlsell AB	Nasdaq Stockholm	2016-10-28	ahlsell
Aino Health AB	First North	2016-12-16	aino health
Alimak Group AB	Nasdaq Stockholm	2015-06-17	alimak
Alligator Bioscience AB	Nasdaq Stockholm	2016-11-23	alligator bioscience
AlzeCure Pharma AB	First North	2018-11-28	alzecure
Ambea AB	Nasdaq Stockholm	2017-03-31	ambea
Arise Windpower AB (Arise AB)	Nasdaq Stockholm	2010-03-24	arise
Asarina Pharma AB	First North	2018-09-24	asarina
Ascelia Pharma AB	Nasdaq Stockholm	2019-03-13	ascelia
Aspire Global PLC	First North	2017-07-11	aspire
Attendo AB	Nasdaq Stockholm	2015-11-30	attendo
Atvexa AB	First North	2017-12-13	atvexa
Avega AB	First North	2007-11-01	avega
Avtech Sweden AB	First North	2012-02-20	avtech
Awardit AB	First North	2017-12-05	awardit
Azelio AB	First North	2018-12-10	azelio
B3IT Management AB (B3 Consulting Group AB)	First North	2016-06-13	b3it
Bactiguard Holding AB	Nasdaq Stockholm	2014-06-19	bactiguard
Balco Group AB	Nasdaq Stockholm	2017-10-06	balco
Bambuser AB	First North	2017-05-05	bambuser
Besqab AB	Nasdaq Stockholm	2014-06-12	besqab
Better Collective A/S	Nasdaq Stockholm	2018-06-08	better collective
Bio-Works Technologies AB	First North	2017-12-14	bioworks
BioArctic AB	Nasdaq Stockholm	2017-10-12	bioarctic
Bioservo Technologies AB	First North	2017-05-22	bioservo
Biovica International AB	First North	2017-03-29	biovica
Biovitrum AB (Swedish Orphan Biovitrum AB)	Nasdaq Stockholm	2006-09-15	biovitrum
Boozt AB	Nasdaq Stockholm	2017-05-31	boozt
Boule Diagnostics AB	Nasdaq Stockholm	2011-06-27	boule diagnostics
Bravida Holding AB	Nasdaq Stockholm	2015-10-16	bravida
Bufab AB	Nasdaq Stockholm	2014-02-21	bufab
Bygghemma Group First AB	Nasdaq Stockholm	2018-03-27	bygghemma
Byggmax Group AB	Nasdaq Stockholm	2010-06-02	byggmax
ByggPartner i Dalarna Holding AB	First North	2016-12-05	byggpartner
CAG Group AB	First North	2018-12-12	cag
Camurus AB	Nasdaq Stockholm	2015-12-03	camurus
Capacent Holding AB	First North	2015-10-02	capacent
Capio AB	Nasdaq Stockholm	2015-06-30	capio
Catena Media PLC	First North	2016-02-11	catena media
Cellink AB	First North	2016-11-03	cellink
Christian Berner Tech Trade AB	First North	2014-10-20	christian berner
Cimco Marine AB (Oxe Marine AB)	First North	2017-07-04	cimco
Clean Motion AB	First North	2016-05-26	clean motion
Climeon AB	First North	2017-10-13	climeon
CLX Communications AB (Sinch AB)	Nasdaq Stockholm	2015-10-08	clx
Cognosec AB (Cyber Security 1 AB)	First North	2016-09-22	cognosec
Collector AB	Nasdaq Stockholm	2015-06-10	collector
Com Hem Holding AB	Nasdaq Stockholm	2014-06-17	com hem
Coor Service Management Holding AB	Nasdaq Stockholm	2015-06-16	coor
Corline Biomedical AB	First North	2015-06-03	corline
Crunchfish AB	First North	2016-11-11	crunchfish
CybAero AB	First North	2007-06-13	cybaero
Dannemora Mineral AB	First North	2007-05-25	dannemora mineral
DevPort AB	First North	2017-12-07	devport
DGC One AB	Nasdaq Stockholm	2008-06-16	dgc
Diadrom Holding AB	First North	2007-06-01	diadrom
DIBS A/S	First North	2007-06-18	dibs
Diös Fastigheter AB	Nasdaq Stockholm	2006-05-22	diös
Dometic Group AB	Nasdaq Stockholm	2015-11-25	dometic
Duni AB	Nasdaq Stockholm	2007-11-14	duni
Dustin Group AB	Nasdaq Stockholm	2015-02-13	dustin

Edgeware AB	Nasdaq Stockholm	2016-12-09	edgeware
Eltel AB	Nasdaq Stockholm	2015-02-06	eltel
Enersize Oyj	First North	2017-06-15	enersize
Enorama Pharma AB	First North	2016-06-10	enorama
Evolution Gaming Group AB	First North	2015-03-20	evolution gaming
eWork Group AB	Nasdaq Stockholm	2008-05-22	ework
ExpreS2ion Biotech Holding AB	First North	2016-07-29	expres2ion
Fastighets AB Trianon	First North	2017-06-21	trianon
Ferronordic AB	Nasdaq Stockholm	2017-10-27	ferronordic
FlexQube AB	First North	2017-12-14	flexqube
Fluicell AB	First North	2018-04-18	fluicell
FM Mattsson Mora Group AB	Nasdaq Stockholm	2017-04-10	fm mattsson
Gaming Corps AB	First North	2015-06-04	gaming corps
Garo AB	Nasdaq Stockholm	2016-03-16	garo
Gasporox AB	First North	2016-10-25	gasporox
Global Gaming 555 AB	First North	2017-10-19	global gaming
Gränges AB	Nasdaq Stockholm	2014-10-10	gränges
Green Landscaping Group AB	First North	2018-03-23	green landscaping
GS Sweden AB (GomSpace Group AB)	First North	2016-06-16	gs sweden
Gymgrossisten Nordic AB	First North	2006-12-07	gymgrossisten
Hakon Invest AB (ICA Gruppen AB)	Nasdaq Stockholm	2005-12-08	hakon invest
Handicare Group AB	Nasdaq Stockholm	2017-10-10	handicare
Hanza Holding	First North	2014-06-19	hanza
Hemfosa Fastigheter AB	Nasdaq Stockholm	2014-03-21	hemfosa
Hoist Finance AB	Nasdaq Stockholm	2015-03-25	hoist
Hövding Sverige AB	First North	2015-06-16	hövding
Humana AB	Nasdaq Stockholm	2016-03-22	humana
Iconovo AB	First North	2018-04-06	iconovo
Immunicum AB	First North	2013-04-22	immunicum
Immunovia AB	First North	2015-12-01	immunovia
InCoax Networks AB	First North	2019-01-03	incoax
InDex Pharmaceuticals Holding AB	First North	2016-10-11	index pharmaceuticals
Indutrade AB	Nasdaq Stockholm	2005-10-05	indutrade
Infrea AB	First North	2018-04-20	infrea
Inission AB	First North	2015-06-10	inission
Insplanet AB	First North	2006-06-07	insplanet
Instalco AB	Nasdaq Stockholm	2017-05-11	instalco
Integrum AB	First North	2017-05-15	integrum
Internationella Engelska Skolan I Sverige Holdings II AB	Nasdaq Stockholm	2016-09-29	engelska skolan
Inwido AB	Nasdaq Stockholm	2014-09-26	inwido
IRLAB Therapeutics AB	First North	2017-02-28	irlab
Irras AB	First North	2017-11-22	irras
Isconova AB	First North	2010-11-10	isconova
Jetpak Top Holding AB	First North	2018-12-05	jetpak
JonDeTech Sensors AB	First North	2018-05-25	jondetech
Kancera AB	First North	2011-02-25	kancera
KappAhl AB	Nasdaq Stockholm	2006-02-23	kappahl
Karnov Group AB	Nasdaq Stockholm	2019-04-11	karnov group
Karolinska Development AB	Nasdaq Stockholm	2011-04-15	karolinska development
Kentima Holding AB	First North	2013-06-19	kentima
Lauritz.com Group A/S	First North	2016-06-22	lauritz
LeoVegas AB	First North	2016-03-17	leovegas
Lifco AB	Nasdaq Stockholm	2014-11-21	lifco
Lime Technologies AB	Nasdaq Stockholm	2018-12-06	lime technologies
Lindab International AB	Nasdaq Stockholm	2006-12-01	lindab
Liv ihop AB	First North	2018-02-23	livihop
Lyko Group AB	First North	2017-12-12	lyko
Mackmyra Svensk Whisky AB	First North	2011-12-16	mackmyra
MAG Interactive AB	Nasdaq Stockholm	2017-12-08	mag interactive
Magnolia Bostad AB	First North	2015-06-09	magnolia bostad
Maxkompetens Sverige AB (MoxieTech Group AB)	First North	2015-11-23	maxkompetens
Medicover AB	Nasdaq Stockholm	2017-05-23	medicover
Mindmancer AB (Irisity AB)	First North	2013-10-23	mindmancer
MIPS AB	Nasdaq Stockholm	2017-03-23	mips
Moberg Derma AB (Moberg Pharma AB)	Nasdaq Stockholm	2011-05-26	moberg derma
Munters Group AB	Nasdaq Stockholm	2017-05-19	munters
NCAB Group AB	Nasdaq Stockholm	2018-06-05	ncab
Nepa AB	First North	2016-04-26	nepa
Nexstim Oy	First North	2014-11-14	nexstim
Nilorngruppen AB	First North	2015-06-12	nilörngruppen

Nilsson Special Vehicles AB	First North	2015-12-11	nilsson special vehicles
Nitro Games Oyj	First North	2017-06-16	nitro games
Nobina AB	Nasdaq Stockholm	2015-06-18	nobina
Nordax Group AB	Nasdaq Stockholm	2015-06-17	nordax
Nordic Waterproofing Holding A/S	Nasdaq Stockholm	2016-06-10	nordic waterproofing
Note AB	Nasdaq Stockholm	2004-06-23	note
NP3 Fastigheter AB	Nasdaq Stockholm	2014-12-04	np3
Nuevolution AB	First North	2015-12-17	nuevolution
Odd Molly International AB	First North	2007-06-18	odd molly
Oncopeptides AB	Nasdaq Stockholm	2017-02-22	oncopeptides
Orexo AB	Nasdaq Stockholm	2005-11-09	orexo
Oscar Properties Holding AB	First North	2014-02-17	oscar properties
Pallas Group AB	First North	2010-07-07	pallas
Pandox Holding AB	Nasdaq Stockholm	2015-06-18	pandox
Paradox Interactive AB	First North	2016-05-31	paradox interactive
Paxman AB	First North	2017-06-12	paxman
Phone Family AB	First North	2014-06-09	phone family
Photocat A/S	First North	2015-11-20	photocat
Platzer Fastigheter Holding AB	Nasdaq Stockholm	2013-11-29	platzer
Prime Living AB	First North	2015-06-12	prime living
Projektengagemang Sweden AB	Nasdaq Stockholm	2018-06-19	projektengagemang
Q-Linea AB	Nasdaq Stockholm	2018-12-07	q-linea
Raketech Group Holding PLC	First North	2018-06-29	raketech
Ranplan Group Ab	First North	2018-06-28	ranplan
Realfiction Holding AB	First North	2017-07-14	realfiction
Recipharm AB	Nasdaq Stockholm	2014-04-03	recipharm
Resurs Holding AB	Nasdaq Stockholm	2016-04-29	resurs bank
Rethinking Care Sweden AB (Curando Nordic AB)	First North	2016-12-22	rethinking care
Rezidor Hotel Group (Radisson Hospitality AB)	Nasdaq Stockholm	2006-11-28	rezidor
S2Medical AB	First North	2018-11-28	s2medical
Sanitec Oyj	Nasdaq Stockholm	2013-12-10	sanitec
Scandi Standard AB	Nasdaq Stockholm	2014-06-27	scandi standard
Scandic Hotels Group AB	Nasdaq Stockholm	2015-12-02	scandic hotels
ScandiDos AB	First North	2014-04-11	scandidos
Scandinavian ChemoTech AB	First North	2016-12-06	scandinavian chemotech
SciBase Holding AB	First North	2015-06-02	scibase
Scout Gaming Group AB	First North	2017-12-11	scout gaming
Sdiptech AB	First North	2017-05-12	sdiptech
Seamless Distribution Systems AB	First North	2017-07-21	seamless distribution
Seanet Maritime Communications AB	First North	2007-06-28	seanet
SeaTwirl AB	First North	2016-12-22	seatwirl
SECITS Holding AB	First North	2017-05-11	secits
Sedana Medical AB	First North	2017-06-21	sedana
SenzaGen AB	First North	2017-09-21	senzagen
SERNEKE Group AB	Nasdaq Stockholm	2016-11-24	serneke
Simris Alg AB	First North	2016-04-22	simris alg
SJR in Scandinavia AB	First North	2007-03-06	sjr
Smart Eye AB	First North	2016-12-07	smart eye
SolTech Energy Sweden AB	First North	2015-06-25	soltech
Sportamore AB	First North	2012-10-25	sportamore
Sprint Bioscience AB	First North	2014-11-07	sprint bioscience
SSM Holding AB	Nasdaq Stockholm	2017-04-06	ssm
Stillfront Group AB	First North	2015-12-08	stillfront
Surgical Science Sweden AB	First North	2017-06-19	surgical science
Svenska Capital Oil AB (Misen Energy AB)	First North	2007-06-12	capital oil
Swedencare AB	First North	2016-06-14	swedencare
Systemair AB	Nasdaq Stockholm	2007-10-12	systemair
TalkPool AG	First North	2016-05-24	talkpool
Tangiamo Touch Technology AB	First North	2017-04-06	tangiamo
TC Connect AB (TCECUR Sweden AB)	First North	2017-06-09	tc connect
TC TECH Sweden AB	First North	2015-11-30	tc tech
Tempest Security AB	First North	2017-12-06	tempest security
Teqnion AB	First North	2019-04-04	teqnion
TerraNet Holding AB	First North	2017-05-30	terranet
TF Bank AB	Nasdaq Stockholm	2016-06-14	tf bank
The Lexington Company AB	First North	2015-02-18	lexington
The Marketing Group PLC	First North	2016-06-09	the marketing group
THQ Nordic AB (Embracer Group AB)	First North	2016-11-22	thq
Thule Group AB	Nasdaq Stockholm	2014-11-26	thule
Tilgin AB	Nasdaq Stockholm	2006-12-14	tilgin
Tobii AB	Nasdaq Stockholm	2015-04-24	tobii
Tobin Properties AB	First North	2016-10-28	tobin

TradeDoubler AB	Nasdaq Stockholm	2005-11-08	tradedoubler
Transmode Holding AB	Nasdaq Stockholm	2011-05-27	transmode
Triboron International AB	First North	2019-04-08	triboron
Troax Group AB	Nasdaq Stockholm	2015-03-27	troax
Trygga Hem Skandinavien AB	First North	2008-05-27	trygga hem
Unibap AB	First North	2017-03-27	unibap
Upsales Technology AB	First North	2019-04-24	upsales
Urb-it AB	First North	2017-07-07	urb-it
VA Automotive i Hässleholm	First North	2014-12-01	va automotive
Verisec AB	First North	2014-12-18	verisec
Vicore Pharma Holding AB	Nasdaq Stockholm	2015-12-10	vicore
Vinovo AB (Nordic Flanges Group AB)	First North	2007-11-22	vinovo
Volati AB	First North	2016-11-30	volati
Waystream Holding AB	First North	2015-11-12	waystream
WeSC AB	First North	2008-05-19	wesc
West International AB (Westpay AB)	First North	2007-10-26	west international
Wilson Therapeutics AB	Nasdaq Stockholm	2016-05-12	wilson therapeutics
Xbrane Biopharma AB	First North	2016-02-03	xbrane
XMReality AB	First North	2017-04-26	xmreality
XSpray Pharma AB	First North	2017-09-28	xspray
Zaplox AB	First North	2017-06-08	zaplox
Zutec Holding AB	First North	2018-03-15	zutec