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Master of Science in Finance

Is There a Negative Relationship Between the Number of Swedish IPOs and the Long-run Performance?

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Spring 2018

UNIVERSITY OF GOTHENBURG
SCHOOL OF BUSINESS, ECONOMICS AND LAW

Abstract

We examine if there is a negative relationship between the number of Swedish IPOs and the long-run performance. In addition, we also investigate what factors that are related to long-run aftermarket performance. The IPOs in our study take place during the period 2004 to 2014 on Nasdaq OMX Stockholm and First North. Previous studies show that firms going public during high volume periods tend to underperform in the long-run. We find a positive and statistically significant relationship between the number of Swedish IPOs and the three-year long-run performance. Our results suggest that firms issuing during high volume periods yield better aftermarket performance compared to those issuing in a low volume period. These results are unexpected and contradict previous studies which have found that firms issuing during a high volume period have a lower cost of equity, reflected in lower aftermarket returns. Further research is needed to help disentangle our contradictory findings to arrive at an unambiguous conclusion, adding support for issuing firms and investors on their decision on when to go public and when to invest in an IPO on the Swedish market, respectively.

Keywords: *IPO*, *BHAR*, *CAR*, *long-run performance*

Acknowledgements

First and foremost, we would like to thank our supervisor, Professor Martin Holmén, for his guidance, support and invaluable inputs throughout this study. Moreover, we would like to thank our fellow students for insightful discussions and for supporting each other to stay motivated throughout the last semester.

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1 Introduction

The aim of this thesis is to examine if there is a negative relationship between the number of Swedish initial public offerings (IPOs) and the long-run performance. We study IPOs taking place during the period 2004 to 2014 on Nasdaq OMX Stockholm and First North. Ritter (1991), Loughran and Ritter (1995) and Lowry (2003) show that firms going public during a high volume period tend to underperform in the long-run.

An IPO is when a firm's shares are sold to the public for the first time. One of the most common reasons for firms choosing to go public is to raise capital for future investments (Ritter & Welch, 2002). Our study seek to provide support to both issuing firms and investors in their decisions on when to go public and when to invest in an IPO, respectively.

Between 2000 to 2012, the number of IPOs have decreased in the U.S. (Gao, Ritter, & Zhu, 2013). The same downward trend has also been experienced among European countries such as Germany and France between 2001 and 2009 (Vismara, Paleari, & Ritter, 2012). On the contrary, there has been an upward trend in the number of IPOs in the Nordic markets. The increased number of listings during the recent years in the Nordics have resulted in 2017 being a record year for listings on Nasdaq Nordic Markets. The amount of listings in 2017 surpassed the previous record of 97 listings in 2015 by 18 listings, mostly driven by IPOs (Nasdaq, 2017; Bloomberg, 2017a). At the same time, the global IPO activity during 2017 reached record levels and has not been this high since the beginning of the recent financial crisis 2007-2008 (EY, 2017). Moreover, conditioned on the fact that the current economic environment remains the same, the SVP and Head of European Listings at Nasdaq believes that the strong IPO activity in the Nordics will continue during the first half of 2018 (Nasdaq, 2017). Furthermore, some experts argue that we are in a ”late-cycle” environment, implying that we will be facing a possible financial downturn in the near future (Bloomberg, 2017b).

Our research question is of interest and importance for both issuing firms and investors. Firstly, a negative relationship suggests that firms time the market, plausibly in an effort to reduce the cost of obtaining external capital. Secondly, it is of importance for investors in terms of when to invest in an IPO and at what costs it may come. For example, the lower cost of external capital for issuers may be at the expense of reduced returns to the investors. In line with this reasoning, knowing what factors that are related to long-run performance may also be of use for both the issuing firm and the investor.

Previous studies on primarily the U.S. market show that there exist a negative relationship between the number of IPOs and the long-run aftermarket performance (Ritter, 1991; Loughran & Ritter, 1995; Lowry, 2003). On the contrary, and in terms of Sweden, Loughran, Ritter, and Rydqvist (1994) find a positive relationship between the number of IPOs and the one-year aftermarket performance when studying a sample of 162 Swedish IPOs between 1972 and 1992. In line with Loughran et al. (1994), Isaksson and Thorsell (2014) also find the same positive relationship when they examine a sample of 122 Swedish IPOs between 1996 and 2006. In regards to the long-run performance, Ibbotson (1975), Ritter (1991) and Loughran and Ritter (1995) find that IPOs tend to have negative three-year aftermarket performance. In fact, Ritter (1991) notes that young and small issues are those with worst aftermarket performance. More recent studies by Ritter and Welch (2002), Schuster (2003) and Gao et al. (2013) also find that IPOs tend to have aftermarket underperformance.

To the best of our knowledge, few similar and recent studies have been done on the Swedish market specifically. In this context, we examine whether there is a relationship between the number of Swedish IPOs and the long-run performance during 2004-2014 using a methodology inspired by Ritter (1991) where he studies the performance of U.S. IPOs. In line with Ritter (1991), we use Buy-and-hold abnormal return (BHAR) and Cumulative abnormal return (CAR) to measure abnormal performance. We conduct cross-sectional regressions using BHARs and CARs as dependent variables to investigate what factors that are related to long-run abnormal performance. Moreover, our study covers a time period which contains the financial crisis of 2007-2008 and its aftermath. The market in general is characterized by periods of large variations in the number of IPOs (Ritter, 1991). Basing this study on a time period containing elements of high market volatility, i.e. the rise, fall and recovery of the market, makes it more likely to capture such market variations. In addition, we contribute to the existing literature by studying a more recent time period compared to much of the previous international studies on IPO performance. Our results will provide support to Swedish issuing firms and investors in their decisions on when to go public and when to invest in an IPO, respectively. Being able to understand and predict such cyclical variations in IPO pricing may also be exploited in active trading strategies by investors (Ritter, 1991).

We find a positive and statistically significant relationship between the number of Swedish IPOs and the long-run aftermarket performance measured as BHAR at the 36 month mark. Our results contradict previous findings by Ritter (1991), Loughran and Ritter (1995), Lowry (2003) who find a negative relationship. It is difficult to find an unambiguous explanation to our contradictory findings. Furthermore, we find a statistically significant median 36 month underperformance measured as BHAR using OMXSPI as benchmark for firms issuing during a low volume period, but we do not find any significant over- or underperformance in any other period making interpretation difficult.

2 Review of Earlier Empirical Literature

The aftermarket performance of IPOs has been studied for decades. More specifically, many researchers have tried to understand and explain the anomalies of IPOs. This section will cover studies that examine the phenomenon of hot issue markets and more specifically the long-run performance of IPOs.

The characteristics of a hot issue market are described as a period of IPOs with high initial returns (Ibbotson & Jaffe, 1975; Ibbotson, Sindelar, & Ritter, 1994). In addition, Ibbotson et al. (1994) and Lowry and Schwert (2002) show that a period of high initial returns is being followed by a large number of IPOs. Studying new issues in the U.S. between 1960 and 1970, Ibbotson and Jaffe (1975) are able to predict hot issue markets. Ritter (1984) examines the hot issue market of 1980 and finds that it can be almost entirely explained by that time's booming natural resource industry. Firms within natural resources going public during 1980 have notably higher average initial returns than those going public in a cold issue market. In comparison, firms in other industries issuing in 1980 had average initial returns not very different from the average initial returns during a cold issue market.

Analyzing a sample of U.S. firms going public during 1975-1984, Ritter (1991) finds the phenomenon of the long-run aftermarket underperformance of new issues. In line with Ibbotson (1975), where he notes that IPOs tend to have positive returns the first and fifth year but a negative return the third year, the findings of Ritter (1991) show that the three-year aftermarket performance of these firms significantly underperforms a set of firms matched by industry and market capitalization. More specifically, young small issues with high adjusted initial returns tend to have the worst aftermarket performance. When comparing the aftermarket performance by industry, Ritter (1991) finds a varying number of new issues as well as varying long-run performance of IPOs in the different industries that the sample covers. The IPOs underperform the matching firms within the same industry in 11 of the 14 industry groups covered by the sample. Moreover, Ritter (1991) finds a negative relationship between the number of issues per year and the aftermarket performance, suggesting that companies time the market and issue shares when they believe investors have high willingness to pay. In line with Ritter (1991), Loughran and Ritter (1995) find evidence on both three- and five-years aftermarket underperformance of the offerings. The five-year aftermarket underperformance holds when comparing with both a set of matching firms by size and by five common market indices. Their study also shows that firms issue shares when valuations are high, in line with Loughran et al. (1994).

Studying international offerings during the period of 1960-1991, Loughran et al. (1994) find tendencies on firms timing the market and go public when valuations are high. They find that GDP growth does not have a large impact on IPO volume but the cost of equity does. Moreover, they also shed light on other international results in which a negative relationship between the number of IPOs and the three-year long-run performance is found. In contrast to these results, Loughran et al. (1994) study a sample of 162 Swedish IPOs between 1972 and 1992 and find a positive relationship between the number of IPOs and the one-year aftermarket returns. The same result was found by Isaksson and Thorsell (2014) when studying a sample of 122 Swedish IPOs between 1996 and 2006.

In a later paper, Ritter and Welch (2002) study the aftermarket performance of U.S. IPOs between January 1973 and September 2001. Their findings are in line with previous studies, where a negative three-year long-run performance is found (Ritter, 1991; Loughran & Ritter, 1995). However, they emphasize the fact that different methods, sample periods and sample selections yield different results. Studying a sample of 99 Swedish IPOs between 1988 to 1998, Schuster (2003) also find a negative three-year aftermarket performance. On the other hand, when he only looks at those who were issued between 1995 to 1998 he finds a positive three-year aftermarket performance. In regards of the IPO volume, Lowry and Schwert (2002) find a positive relationship between high initial returns and the number of issues in the following periods. Their results suggest that other firms' offering decisions and prices are affected by the information announcement of preceding offers. Lowry (2003) finds evidence that firms' capital demands and investor optimism being two of the most important factors explaining the high IPO volume over time. In line with Loughran and Ritter (1995), the findings of Lowry (2003) also suggest that firms issue stocks when valuations are high and that there is a negative relationship between the number of IPOs and the aftermarket raw returns. The IPO volume and the long-run aftermarket performance have also been studied in a more recent paper by Gao et al. (2013). In line with Ritter (1991), among others, the findings of Gao et al. (2013) show that small issues have worse aftermarket performance compared to that of large issues. In addition, they note that the number of U.S. IPOs have decreased over time since the year 2000. They also shed light on a study by Vismara et al. (2012) in which they find that other developed countries such as Germany and France have also experienced a decreasing IPO volume after 2000.

Studying the hot- and cold markets, Helwege and Liang (2004) note that the emergence of a hot market is due to the rise of several industries together rather than due to a rise in a single industry. Also, their result suggests that the firms issuing during cold markets do not show characteristics of being less innovative or have lower expected growth. Jain and Kini (2006) note that new issues tend to cluster in industries with high growth, high R&D and promising industry returns and profitability. However, and in contrast to Lowry (2003), high capital demand do not result in IPO clusters but high demand for R&D investments do. In summary, Jain and Kini (2006) conclude that firms in clustered industries are more inclined to raise higher capital but industry clustering may also result in modest long-run aftermarket performance. In regards of tech companies going public, Clark (2002) note that young technology issues tend to outperform elder technology issues when looking at the average three-year aftermarket excess return.

3 Theoretical Framework

As evident from Section 2, the characteristics of a market with regards to the number of IPOs and their aftermarket performance vary depending on the sample and period studied. Ritter (1984) finds the 1980s hot issue market to be characterized by the rise of a single industry. Helwege and Liang (2004) find that the hot issue markets in their sample is due to the rise of multiple industries rather than a single one. Moreover, Ritter (1991) and Gao et al. (2013) find that small issues have the worst aftermarket performance. This section presents theories relevant for explaining the empirical findings of previous studies.

3.1 Market Timing

Related to market timing is asymmetric information in which one part possesses more information than the other. For example, the management of the issuing firm have naturally better insight and knowledge about the issuing firm than outside investors, so information asymmetry arises (Myers & Majluf, 1984). Thus, given that the issuing firm possesses nonpublic information to their disadvantage, they can benefit from high market valuations and go public during such a market period knowing that their firm is in fact being overvalued. For example, the idea behind the model by Lucas and McDonald (1990) from a perspective of asymmetric information is that firms will postpone their issue if they believe that they are currently undervalued. At the same time, firms believing that they are currently overvalued will issue as soon as possible.

Ritter (1991) finds that companies tend to go public when market valuations are high and their respective industry experiences high capital inflows and favorable deregulations, taking advantage of windows opportunities. During such market conditions investors' willingness to pay is high in general, and for IPOs in particular. Hence, the cost of equity is lower for the issuing firm but the consequence is low aftermarket returns for the investor. In addition, Ritter (1991) argue that the aftermarket underperformance of IPOs are due to ”irrationally overoptimistic forecasts”, ”fads”, or just bad luck. The former is defined as when investors are being periodically overoptimistic about the future of IPO performance. Over time, the disappointment from investors when realized cash flows are lower than expected results in IPOs underperforming (Ritter, 1991). Besides firms taking advantage of windows opportunities and investor overoptimism as explanations for parts of the findings of Ritter (1991), these may also be explained by asymmetric information. For example, in the sense that firms will issue as soon as they believe that they are being overvalued

(Lucas & McDonald, 1990), they will be even more inclined to do so knowing that the market is characterized by investor optimism and overall favorable market conditions. We find some support for our argumentation in the study by Graham and Harvey (2001) in which they ask 392 chief financial officers different questions in order to understand and spread knowledge about how firms operate. One of the questions in the survey is ”Has your firm seriously considered issuing common stock? If ”yes”, what factors affect your firm’s decisions about issuing common stock?”. The results show that more than two-thirds of the respondents answer that ”The amount by which our stock is under or overvalued” is the second most important factor affecting their decision on stock issuance.

Studying the IPO volume during hot- and cold markets Helwege and Liang (2004) find that hot issue markets yield lower industry clusterings since firms from several industries tend to go public during periods with high market valuations. Their findings may be explained by these industries taking advantage of windows opportunities as argued by Ritter (1991).

3.2 Prospect Theory

Ma and Shen (2003) explain the phenomenon of long-run underperformance of IPOs by using prospect theory. They base their study on the exact same data set as Ritter (1991) and offer additional explanations to his findings. In consonance with the prospect theory proposed by Kahneman and Tversky (1979), Ma and Shen (2003) argue that investors tend to overestimate small probabilities and underestimate high probabilities. Furthermore, they state that in comparison with seasoned stocks IPOs are on average underperforming in the long-run. However, IPOs generate positive returns that are more extreme compared to seasoned stocks, but the probability of receiving such high returns is small. Despite the numerous results on IPOs having negative long-run aftermarket returns investors still invest in these issues, overweighting the small probability of achieving high IPO-returns as compensation. Ma and Shen (2003) show that even if investors know that IPOs have lower average returns, they still value these as much as seasoned stocks. The argument regarding investors tendency to overestimate small probabilities is also shared by Loughran and Ritter (1995). They find that investors tend to systematically overestimate their own ability of having identified, and the probability of, an IPO being the next Microsoft. In other words, investors overestimate the probability of an IPO being one of the extreme outliers in terms of long-run performance. Loughran and Ritter (1995) explain this by saying that the high growth of young firms prior to their issuance tend to be the reason for investors overestimation.

4 Method

There are conflicting views on whether CAR or BHAR is the most appropriate measure of IPO long-run performance. For example, Fama (1998) concludes that there is no general consensus regarding which of these two measures that are preferred in general. Barber and Lyon (1997) argue that CAR is less suitable as a long-run measure of portfolio performance and promote the use of BHAR for evaluating long-run abnormal returns. Barber, Lyon, and Tsai (1999) suggest that CAR should be used for analyzing the persistence of monthly abnormal returns rather than actual long-run performance. On the other hand, Fama (1998) highlights that more is known about properties relating to the sample distribution and statistical tests for CAR. As CAR is based on cumulative returns it is less sensitive to outliers and consequently has a lower risk of exhibiting positive skewness bias compared to BHAR (Barber & Lyon, 1997). As argued by Westerholm (2006) however, what BHAR captures is more in line with the returns an actual investor would receive as it better corresponds to real world investing behavior compared to CAR.

This study uses equally weighted BHAR as our main model for evaluating long-run aftermarket IPO performance. To increase the robustness of our results we use CAR as an alternative model. Both measures belong to the event time approach and measure abnormal returns defined as the difference between raw returns and a chosen benchmark. Academic research typically use the event time approach in long-run IPO performance studies, as opposed to the calendar time approach. The latter implies that excess return periods differ in length, in contrast to the event time approach where the time period measured is equal in length for all IPOs (Ritter, 1991). We use two types of benchmarks to evaluate the abnormal long-run return on a monthly basis; a broad market index and industry specific indices where we classify each firm according to the Global Industry Classification Standard (GICS). As stated by Ritter (1991), it may be beneficial to use a small firm index as a benchmark. Using industry specific indices we account for firm specific risks and expected returns to a larger extent compared to using a broad market index. On the other hand, if the industry index is small this may understate the abnormal performance compared to a broader index. The process of measuring IPO long-run performance is sensitive to the chosen benchmark (Ritter, 1991). By using two different benchmarks in our study we increase the robustness of our results. We calculate abnormal returns (Equation 1) from the second day of trading until the 12-, 24- and 36 month mark by subtracting the benchmark return $r_{b,t}$ from the raw return $r_{i,t}$ for each IPO i in month t. A month in the aftermarket period is defined as 21 days, and only contains days where markets are open for trade. In line with Ritter (1991), we also exclude the first day of trading for both measures to not capture effects related to underpricing. Previous studies on IPO long-run performance tend to follow this approach, increasing the comparability of our results.

$$\mathrm{ar}_{i,t} = \mathrm{r}_{i,t} - \mathrm{r}_{b,t} \tag{1}$$

4.1 Buy and Hold Abnormal Returns

BHAR (Equation 2) is defined as the geometric sum from a buy-and-hold strategy using abnormal returns (Equation 1). We calculate BHARs individually for each IPO i where t is the starting month 1 and s is the ending month 36. Additionally, we also calculate BHARs at the 12- and 24 month mark. Individual BHARs are used in cross-sectional regressions as dependent variables to investigate what factors that are related to BHAR aftermarket performance. Moreover, descriptive statistics of BHARs in each period are calculated and interpreted, i.e. mean, median, standard deviation skewness, maximum and minimum values.

$$\mathrm{BHAR}_{i,t} = \prod_{t=1}^{s}[(1 + \mathrm{ar}_{i,t})] - 1 \tag{2}$$

4.2 Cumulative Abnormal Returns

We calculate CAR (Equation 3) as the sum of monthly abnormal returns (Equation 1) for each individual IPO i, where t is the starting month 1 and s is the ending month 36. Following the approach used for BHARs we also calculate CARs for the 12- and 24 month mark. Furthermore, we calculate and interpret the same descriptive statistics as for BHAR and investigate what factors that are related to abnormal IPO aftermarket performance by conducting cross-sectional regressions with CAR as the dependent variable.

$$\mathrm{CAR}_{i,t} = \sum_{t=1}^{s} ar_{i,t} \tag{3}$$

5 Data

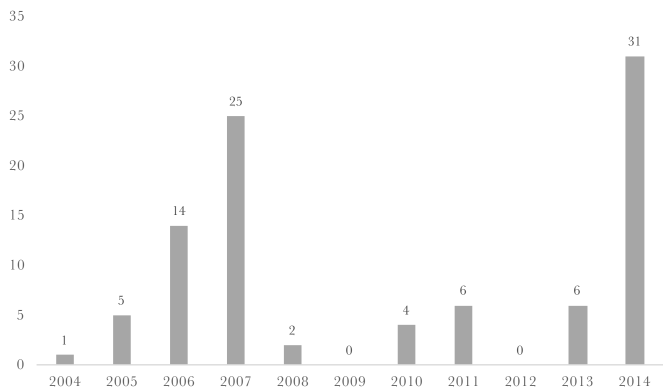
5.1 Sample Selection and IPO Characteristics

Our study includes IPOs of common stock listed on Nasdaq OMX Stockholm and First North during the period of 2004-2014. We choose to include these two exchanges since they are more regulated and have a higher liquidity compared to smaller Swedish exchanges, such as Aktietorget. One can argue that this selection leads to more reliable results since we are studying a more functional market in terms of liquidity. We collect an initial sample of 189 IPOs from Nasdaq (2018). By obtaining company specific information for each IPO from Skatteverket (2018), the Swedish Tax Agency, we exclude switches from other stock exchanges, spin-offs and secondary listings. IPOs that are delisted before the 36 month mark are excluded from our sample. Ritter (1991) includes delistings and sets abnormal returns equal to zero to mitigate potential problems with survivorship bias skewing the results. The number of delistings in our initial sample are relatively few, and hence we find it unlikely that excluding delistings will have a large effect on our results.

We use Bloomberg (2018) to gather all data necessary for this study. Where data from Bloomberg (2018) is unavailable we use relevant online resources, e.g. prospectuses and press releases. We also use Thomson Reuters Eikon (2018) to gather data in cases where it cannot be found in Bloomberg (2018). Daily closing price data on our sample IPOs and our benchmark indices are collected for two periods; (1) the initial period (month 0), defined as the first trading day and (2) the aftermarket period consisting of the 36 months following the initial period. The IPOs in our sample are gathered between the time period 2004-2014 while the daily closing price data is gathered between the time period 2004-2017, in order to allow for examination of the 36 month aftermarket performance of firms going public in 2014. If there are less than, or equal to, ten days of missing price data we replace the missing data with the previously recorded data point otherwise these are excluded. After exclusion according to these criteria our final data sample consists of 94 Swedish IPOs issued during the time period between 2004 to 2014.

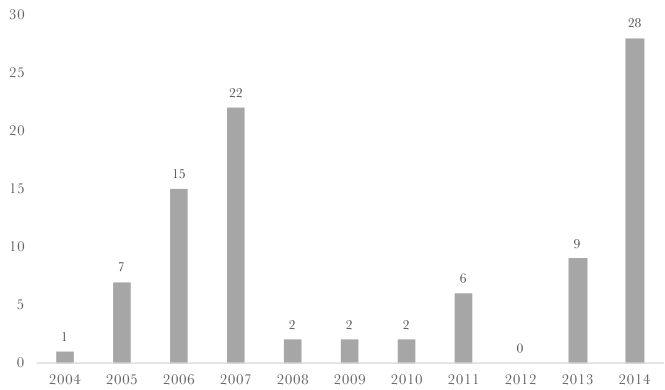
As Figure 1 demonstrates, the number of IPOs over our examination period is not evenly distributed. The number of IPOs fluctuates over time in which it increases between 2004-2007, decreases after the crisis and slowly increases after 2009-2010. Our findings of varying number of IPOs over time are in line with Ritter (1991).

Figure 1: The number of IPOs between 2004-2014



In practice, a firm cannot decide to do an IPO one day and go public the day after. For this reason, we argue that the announcement date is of greater importance than the offer date for defining a high- or low volume period. We construct an approximate announcement date due to faulty or missing data for the actual announcement date for a large part of our sample. The average time between announcement- and offer date for the IPOs in which we have data for is three months. Hence, we define our approximate IPO announcement date as three calendar months before the offer date. Figure 2 illustrates the number of approximate IPO announcement dates.

Figure 2: The number of approximate IPO announcements between 2004-2014



5.2 Data- and Variable Characteristics

To answer our research question we have one main variable. In addition, we have four control variables to investigate what factors that are related to long-run performance. The continuous variables are transformed by taking the natural log. We do this for two reasons: (1) it makes interpretation of the regressions more convenient as our dependent variables are in decimal form, (2) it alters the scale of variables with positive skewness, improving the fit of our linear regressions.

5.2.1 Main Variable

5.2.1.1 High Volume

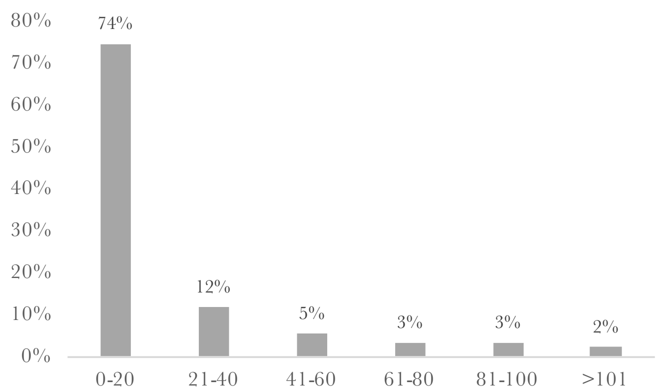
To examine the relationship between the number of Swedish IPOs and the long-run performance we include the variable *High volume*. This is the main variable in our regressions and takes on the value one if the IPO is issued during a high volume IPO period and zero otherwise. In general, we define a high volume period as a market where a large number of IPOs are taking place. Previous studies show that firms tend to go public when market valuations are high (Loughran et al., 1994; Loughran & Ritter, 1995; Lowry, 2003). As mentioned in section 5.1, we have missing or faulty data for a large part of our IPOs' announcement dates. When calculating the time between the announcement- and offer date for the IPOs we have data for we can see that it is on average approximately three months. Therefore, as a proxy we use an approximate IPO announcement date defined as three calender months before the offer date. The dummy variable *High volume* equals one if more than three IPOs have taken place in the month of the approximate announcement date for each IPO and zero otherwise. This threshold corresponds to the 95th percentile of monthly IPO approximate announcement dates frequency. Using a moving measure of IPO volume ensures we capture all relevant periods. In total, 37 of our IPOs belong to a high volume period according to our definition. Out of these, 21 have an approximate announcement date during 2014, 12 during 2007 and 4 during 2006.

5.2.2 Control Variables

5.2.2.1 Ln Firm Age

The variable *Ln Firm age* is constructed by subtracting the year the firm goes public by the year it was founded. We add a value of one to each data point before conducting a natural log transformation. This mitigates the problem with taking natural logs of firms younger than one year old since we measure it in integers. By including this variable we are able to investigate possible age relation on aftermarket performance. The average age among the firms included in our sample is 20 years with a median of 19 years. The youngest company went public the same year as they were founded while the oldest company went public at the age of 138. As seen in Figure 3, 74% of the IPOs in our sample are between 0-20 years old when going public. This variable is of interest since there has been shown that young firms, with small offer sizes, tend to have the worst thee-year aftermarket performance (Ritter, 1991).

Figure 3: Age distribution of the IPOs between 2004-2014



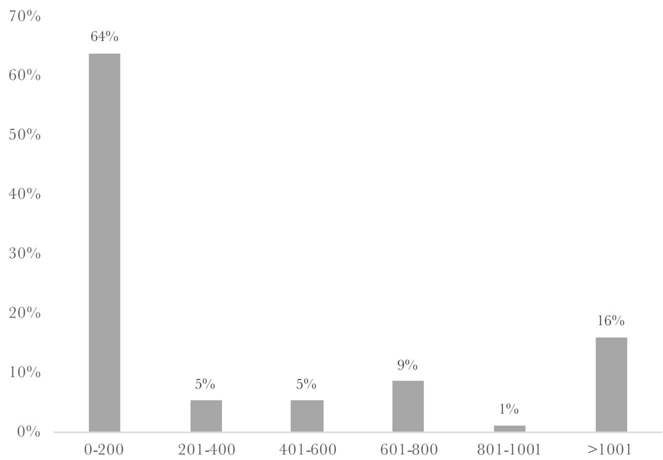
5.2.2.2 Crisis 080910

The variable *Crisis 080910* is a dummy variable that takes on the value one if the IPO is issued between 2008 and 2010, i.e. the crisis years and its aftermath, and zero otherwise. Since our examination period spans over the years 2004-2014 this allow us to study whether economic upturns and downturns have an impact on the aftermarket performance. According to Gao et al. (2013), the number of U.S. IPOs have decreased between the years 2000 to 2012. In addition, the same trend has also been shown in Germany and France between the years 2001 to 2009 (Vismara et al., 2012). At the same time, some argue that the strong IPO activity in the Nordics will continue during the first half of 2018 (Nasdaq, 2017) while others argue that we are in a ”late-cycle” business environment where we may eventually face a possible financial downturn in the near future (Bloomberg, 2017b).

5.2.2.3 Ln Offer Size

The variable *Ln Offer size* represents the total size of the IPO offer of each company which we conduct a natural log transformation on. The data for this variable is obtained from the IPO prospectuses. Ritter (1991) notes that young and small issues tend to result in the worst three-year aftermarket performance. By including this variable we are able to study whether there is a positive- or negative relationship between the Swedish IPOs' offer sizes and the aftermarket performance. As shown in Figure 4, 64% of the issues between 2004 and 2014 are between 0-200 MSEK which is in the lower range of the total offer size interval in our sample. This implies that our data sample consist of mostly small IPO offers.

Figure 4: Offer size distributions of the IPOs between 2004-2014 in MSEK



5.2.2.4 Technology

The IPOs are categorized into eight different industries according to the GICS. The GICS industries that the companies in our data sample operate in are; basic materials, communications, consumer cyclical, consumer non-cyclical, energy, financial, industrial and technology. Industry benchmarks are manually matched with their corresponding GICS. In cases where there is no Swedish index matching the corresponding GICS we use a Nordic- or European index. The variable *Technology* is highly correlated with the technology industry index we use as a benchmark in $BHAR_{Industry}$ and $CAR_{Industry}$ for firms operating within technology. Thus, we exclude *Technology* in these regressions. In regards of $BHAR_{OMXSPI}$ and CAR_{OMXSPI}, we only include the variable *Technology* because when adding the remaining seven industry variables one by one, only the *Technology* industry variable is significant. Moreover, in the recent years increased IPO activity both globally and in the Nordics, technology has shown to be one of the industries with highest number of issues (EY, 2017; Bloomberg, 2017a). Thus, we only take into account whether a firm is operating within the technology industry or not. The variable *Technology* takes the value one if the issuing firm is operating within technology and zero otherwise.

5.3 Model Specification

The regression in our study is inspired by Ritter (1991) where he studies the long-run performance of U.S. IPOs in which he runs a regression on raw three-year return from the first aftermarket closing price to the earlier of the IPOs' three-year anniversary or their delisting date. The variables Ritter (1991) takes into account in his regression are; market-adjusted initial return, firm age, value-weighted market return for the same return interval as the dependent variable and the annual IPO volume. In addition, he also has two dummy variables to distinguish if the issuing firm is operating withing the oil- and gas industry or in the bank industry. Ritter (1991) takes these two industries into account because during his examination period the oil prices decreased substantially resulting in many issuing firms operating within oil- and gas industry substantially underperformed the market. At the same time, the interest rates also decreased substantially, resulting in bank issues having the best long-run performances.

In our study we run regressions on our 12-, 24- and 36 month BHARs and CARs in order to examine the relationship between the number of Swedish IPOs and the long-run aftermarket performance, and what factors that are related to long-run aftermarket performance. The main regression in our study is the one stated below and is run on both BHAR (Equation 4) and CAR (Equation 5), where t is either 12-, 24- or 36 month mark and b is the benchmark, either OMXSPI or corresponding industry index depending on which industry each issuing firm i operates in.

$$\mathrm{BHAR}_{t,b} = \beta_0 + \beta_1 \mathrm{Highvolume}_i + \beta_2 \mathrm{LnFirmage}_i + \beta_3 \mathrm{Crisis080910}_i + \beta_4 \mathrm{LnOffersize}_i + \mathrm{u}_i \tag{4}$$

$$\mathrm{CAR}_{t,b} = \beta_0 + \beta_1 \mathrm{Highvolume}_i + \beta_2 \mathrm{LnFirmage}_i + \beta_3 \mathrm{Crisis080910}_i + \beta_4 \mathrm{LnOffersize}_i + \mathrm{u}_i \tag{5}$$

To correct for heteroskedasticity we use White robust standard errors. In addition, to control for potential multicollinearity we generate a correlation matrix (Appendix Table A1). From the table it is evident that there is no considerable risk of multicollinearity among our independent variables.

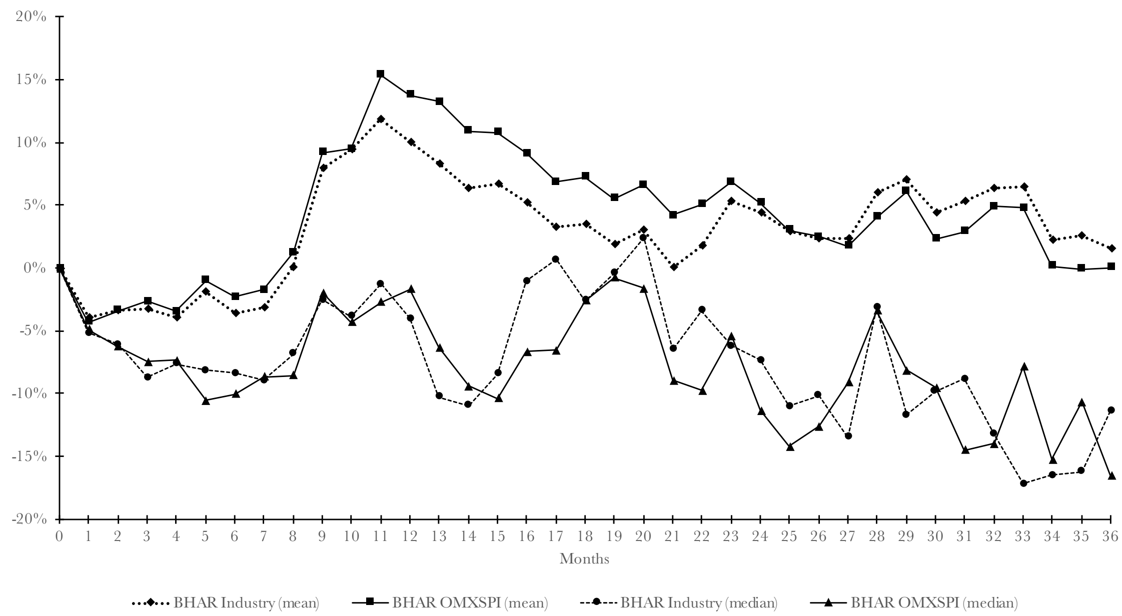
6 Results

In this section we present descriptive statistics on our sample of BHARs and CARs and also conduct relevant statistical tests. The first subsection is dedicated to our sample of BHARs and the second to our sample of CARs.

6.1 Distribution and Summary Statistics of BHARs

In Figure 5 we observe the median and mean of both BHAR measures for each corresponding month during the whole 36 month period. Average BHARs remain negative up until month 8 where the mean value of both measures turn positive for the rest of the period. From month 8 there is a rapid increase in BHARs until month 11. From month 11 the overall trend is decreasing, although average BHARs for both benchmarks are positive in each of the following months.

Figure 5: BHAR mean and median for all 36 months



As evident from Table 1 both benchmarks used in BHAR result in positive 12 month mean returns. $BHAR_{OMXSPI}$ yields higher return in all periods except at the 36 month mark, compared to $BHAR_{Industry}$. The mean and median differs a lot at the 12 month mark with Appendix Figure A1a and A1b indicating a positive skew. This is confirmed when observing the calculated skewness in Table 1, as $BHAR_{12,Industry}$ and $BHAR_{12,OMXSPI}$ are severely positively skewed. $BHAR_{Industry}$ is less skewed in all periods compared to $BHAR_{OMXSPI}$. This is likely due to the fact that the IPO more closely follows each corresponding industry benchmark, correcting for risk and size to a higher degree compared to the broad index benchmark.

Table 1: Descriptive statistics of BHARs for the whole sample of IPOs

	BHAR OMXSPI	BHAR Industry	BHAR OMXSPI	BHAR Industry	BHAR OMXSPI	BHAR Industry
	12 month		24 month		36 month	
Mean	13.764%	10.034%	5.209%	4.382%	0.030%	1.574%
Median	-1.651%	-4.010%	-11.360%	-7.369%	-16.550%	-11.329%
Std. Dev.	0.967	0.869	0.766	0.741	0.888	0.795
Min	-85.776%	-87.273%	-93.131%	-94.606%	-97.232%	-96.583%
Max	500.629%	520.143%	365.545%	203.548%	584.947%	287.440%
Skewness	3.505	3.292	1.526	0.936	3.401	1.397

At the 24 month mark, BHARs have decreased but are still showing an average overperformance in our sample. The distribution is positively skewed, but to a lesser extent compared to the 12 month measure as shown in Table 1 and in Appendix Figure A2a and A2b. One year later mean BHARs have decreased even more, where $BHAR_{36,OMXSPI}$ is close to zero and $BHAR_{36,Industry}$ is approximately 1.6%. At the 36 month mark, the sample is severely positively skewed for $BHAR_{OMXSPI}$ while $BHAR_{Industry}$ shows a moderate positive skewness as evident from Table 1 and Appendix Figure A3a and A3b. BHAR as a measure in general suffers from skewness due to the compounding effect (Barber & Lyon, 1997). The less severe skewness of the industry benchmark suggests the ability to correct for industry specific risk to a higher degree compared to the OMXSPI benchmark.

We conduct t-tests testing whether the mean of BHAR for each of the three time periods and both benchmarks are significantly different from zero. From these test statistics we are not able to conclude if mean BHARs are significantly different from zero in any of the time periods or for any of the benchmarks. T-tests depend on the assumption of normal distribution. However, as shown in Table 1 our BHARs are severely skewed. Winsorising by replacing the values outside the 5th and 95th percentile with their closest inner values did not lead to better test statistics. Furthermore, a closer examination of the individual data points reveal that no extreme values are due to invalid data and that all values appear to be actual market movements in share price. As an alternative to testing the mean of BHARs with t-tests we conduct Wilcoxon signed-rank tests, testing whether the median is significantly different from zero. The Wilcoxon signed-rank test is more suitable as a significance test when the sample can be assumed not to be normally distributed. However, we are not able to reject the null hypothesis in any of the three time periods for any of the two benchmarks.

Since our findings of general IPO long-run performance are not statistically significant we cannot draw any definite conclusions that applies to the population as a whole. Looking at Figure 5, one might interpret the overall negative trend starting in month 11 as a point in which new- and negative information about the firms in our sample has reached the investors. Furthermore, it is worth to emphasize that we observe an average three-year aftermarket overperformance in our sample, although it is not statistically significant. Other studies, such as Loughran and Ritter (1995) and Lowry (2003), find that IPOs underperform in the long-run.

Additionally, we divide the sample of 94 IPOs into high- and low volume periods depending on the time of issue as defined by the variable *High volume* in Section 5.2.1.1. This allows us to investigate if there is any difference in BHAR-characteristics between IPOs issued in high- and low volume environments respectively. A total of 37 IPOs are issued during high volume periods and 57 during low volume periods. As shown in Table 2, IPOs issued during high volume periods have substantially higher mean values of BHARs in all three periods for both benchmarks compared to the low volume sample in Table 3. We observe the largest mean $BHAR_{12,OMXSPI}$ of 28.524% in the high volume sample, which is also the largest mean BHAR overall in the whole sample. The median is positive in all instances of the high volume sample except for $BHAR_{36,OMXSPI}$. IPOs issued during low volume periods exhibit modest positive average BHARs at the 12 month mark as shown in Table 3, with negative mean BHARs in the remaining two periods. In the same table, we observe the most negative mean and median BHARs in the 36 month period for both benchmarks. The median is negative in all three time periods and for both benchmarks of low volume period issues.

Table 2: Descriptive statistics of BHARs for the sample of high volume IPOs

	BHAR OMXSPI	BHAR Industry	BHAR OMXSPI	BHAR Industry	BHAR OMXSPI	BHAR Industry
	12 month		24 month		36 month	
Mean	28.524%	19.081%	19.126%	14.284%	16.396%	14.805%
Median	8.213%	3.961%	4.316%	13.688%	-0.236%	10.795%
Std. Dev.	1.208	0.961	0.954	0.834	1.239	0.991
Min	-85.776%	-87.273%	-93.131%	-94.606%	-97.232%	-96.583%
Max	500.629%	330.281%	365.545%	200.908%	584.947%	287.440%
Skewness	2.613	1.891	1.273	0.473	2.831	1.194

Table 3: Descriptive statistics of BHARs for the sample of low volume IPOs

	BHAR OMXSPI	BHAR Industry	BHAR OMXSPI	BHAR Industry	BHAR OMXSPI	BHAR Industry
	12 month		24 month		36 month	
Mean	4.183%	4.162%	-3.825%	-2.046%	-10.597%	-7.015%
Median	-4.860%	-6.148%	-18.770%	-18.932%	-19.465%	-25.851%
Std. Dev.	0.769	0.807	0.606	0.674	0.542	0.632
Min	-80.982%	-77.895%	-84.843%	-90.872%	-85.444%	-91.710%
Max	492.820%	520.143%	207.888%	230.548%	181.292%	188.211%
Skewness	4.589	4.716	1.291	1.351	0.827	1.097

We apply the same testing procedure as for the whole sample, using t-tests and Wilcoxon signed-rank tests to investigate if what we observe is statistically significant. More precisely, we are testing if mean- and median values for high- and low volume periods are statistically different from zero. The Wilcoxon signed-rank test reveals that the median of $BHAR_{36,OMXSPI}$ is significantly different from zero at the 10% level for IPOs issued during low volume periods as evident from Table 4. Hence, we can conclude that we have significant BHAR median underperformance at the 10% level in the sample of IPOs issued during low volume periods for $BHAR_{36,OMXSPI}$.

Table 4: Test statistics for BHAR OMXSPI 36 month

	BHAR OMXSPI 36 month		
	High volume	Low volume	Difference
Mean	16.396%	-10.597%	26.993%
T-test	(0.426)	(0.146)	(0.151)
Median	-0.236%	-19.465%	19.229%
Wilcoxon signed-rank test	(0.780)	(0.059)*	
Wilcoxon rank-sum test			(0.623)

Table 4. T-tests, Wilcoxon signed-rank tests and Wilcoxon rank-sum test. The difference is the absolute value calculated as the subtraction of High- and Low volume for mean and median respectively. P-values are in parentheses and the significance level is given by *** p<0.01, ** p<0.05 and * p<0.1

Our finding that low volume issues underperform is unexpected as Loughran and Ritter (1995) and Lowry (2003) find that there is a negative relationship between the number of IPOs and the long-run aftermarket performance. They also find that firms tend to time the market and issue shares when valuations are high in periods of increased IPO activity which is reflected in low aftermarket returns. However, we do not observe any statistically significant over- or underperformance in any of the other periods for any of the two benchmarks, hence we cannot draw any inferences from this that apply to the general population.

Additionally, we test if mean BHARs are significantly different from each other for the two samples of high- and low volume issues using two-sided two-sample t-tests. We also conduct two-sample Wilcoxon rank-sum tests to test if the median of the high- and low volume samples are significantly different from each other. As shown in Table 4, the tests do not yield any significant results and thus we are not able to conclude that the mean or median of the two samples are significantly different from each other. Applying the same testing procedure for 24- and 12 month $BHAR_{OMXSPI}$ and all three periods of $BHAR_{Industry}$ do not yield any significant results and are therefore not presented.

Briefly summarizing our findings so far, our mean BHARs are not statistically different from zero and we cannot conclude whether there has been any mean underperformance or overperformance during our 10 year examination period. We find median $BHAR_{36,OMXSPI}$ to be negative and significant at the 10% level during low volume periods. Moreover, the observed skewness varies but generally our sample of BHARs exhibit a positive skewness bias. This is in line with Barber and Lyon (1997) who argue that BHARs in general have a positive skewness bias due to the compounding effect.

6.2 Distribution and Summary Statistics of CARs

The CARs in our sample exhibit less skewness for both benchmarks in all three time periods compared to our BHARs as shown in Table 5. This is expected as Barber and Lyon (1997) argue that CARs are less skewed due to its cumulative nature. As can be seen in Table 5, at the 12 month mark CAR_{OMXSPI} and $CAR_{Industry}$ show positive returns and a positive skewness. From Table 5 we see that CARs after 24 months show slightly lower returns for both benchmarks and a much smaller degree of positive skewness compared to 12 month CARs. $CAR_{24,Industry}$ is almost normally distributed, and the corresponding $CAR_{24,OMXSPI}$ is slightly more skewed in comparison. The decrease in skewness implies that some of the right hand side outliers have performed worse between month 12 and 24 as CAR is a cumulative measure.

At the 36 month mark CARs have increased and the two benchmarks are showing the highest mean and median returns for the three time periods in our sample. As shown in Table 5, the positive skewness of $CAR_{36,Industry}$ have decreased further while $CAR_{36,OMXSPI}$ has an almost unchanged skewness when comparing with their respective 24 month skewness. Moreover, we use the same procedure as for BHARs when investigating statistical significance. T-tests and Wilcoxon signed-rank tests yield no significant over- or underperformance in mean or median CARs in any of the three time periods for any of the two benchmarks. Previous studies find negative long-run IPO performance measured as CAR, for instance Ritter (1991) and Lowry (2003).

Table 5: Descriptive statistics of CARs for the whole sample of IPOs

	CAR OMXSPI	CAR Industry	CAR OMXSPI	CAR Industry	CAR OMXSPI	CAR Industry
	12 month		24 month		36 month	
Mean	8.406%	6.903%	6.736%	5.834%	8.944%	10.972%
Median	3.430%	1.359%	7.124%	6.069%	21.028%	21.500%
Std. Dev.	0.802	0.791	0.929	0.946	0.986	1.009
Min	-162.804%	-168.923%	-205.225%	-225.708%	-256.757%	-278.018%
Max	412.452%	376.118%	392.720%	342.722%	464.344%	407.670%
Skewness	1.765	1.537	0.625	0.319	0.640	0.226

Continuing with the identical approach to that used for our BHARs, we divide the sample of CARs into high- and low volume issue periods according to the variable *High volume* in Section 5.2.1.1. In Table 6 we observe positive mean and median CARs in all three periods of high volume issues. Compared to the mean and median returns we observe in the low volume period in Table 7, the returns are much higher in the high volume period. Our sample of CARs exhibits the same mean and median return patterns for high- and low volume periods as our sample of BHARs. T-tests and Wilcoxon signed-rank tests result in no statistically significant over- or underperformance. Additionally, we test if there is any significant difference in mean or median CARs between the high- and low volume samples in all three time periods using t-tests and Wilcoxon rank-sum tests. The tests reveal that there is no statistically significant difference in mean or median CARs between the two samples in any of the three time periods.

Summarizing our findings regarding CARs we find no statistical significant over- or underperformance in any period or for any benchmark. Thus, we cannot make any inferences that applies to the population as a whole.

Table 6: Descriptive statistics of CARs for the sample of high volume IPOs

	CAR OMXSPI	CAR Industry	CAR OMXSPI	CAR Industry	CAR OMXSPI	CAR Industry
	12 month		24 month		36 month	
Mean	20.971%	17.058%	15.812%	13.703%	20.241%	21.627%
Median	12.096%	8.665%	29.170%	29.957%	29.946%	36.461%
Std. Dev.	1.058	1.036	1.207	1.197	1.296	1.294
Min	-162.804%	-168.923%	-205.225%	-225.708%	-256.757%	-278.018%
Max	412.452%	376.118%	392.720%	342.722%	464.344%	407.670%
Skewness	1.494	1.239	0.381	0.039	0.497	0.018

Table 7: Descriptive statistics of CARs for the sample of low volume IPOs

	CAR OMXSPI	CAR Industry	CAR OMXSPI	CAR Industry	CAR OMXSPI	CAR Industry
	12 month		24 month		36 month	
Mean	0.250%	0.310%	0.845%	0.726%	1.610%	4.055%
Median	1.513%	-3.362%	-0.271%	-0.101%	3.612%	10.119%
Std. Dev.	0.575	0.581	0.699	0.747	0.721	0.775
Min	-137.850%	-122.808%	-130.553%	-134.341%	-176.048%	-170.953%
Max	212.700%	218.286%	232.049%	237.391%	227.966%	229.404%
Skewness	1.003	1.226	0.694	0.657	0.198	0.299

6.3 Regression Results

In this section we continue our study by running regressions on BHARs and CARs in order to examine what factors that are related to the long-run performance of Swedish IPOs, regardless of whether they have under- or overperformed. We run regressions on both benchmarks at the 12-, 24- and 36 month mark. The first subsection is dedicated to $BHAR_{36,OMXSPI}$, the second subsection to $BHAR_{36,Industry}$ and the third subsection to the shorter time periods, 12- and 24 months.

6.3.1 Regression Results of 36 Month BHAR OMXSPI

Table 8: Regressions on 36 month BHAR with OMXSPI as benchmark

Variables	(1) BHAR OMXSPI	(2) BHAR OMXSPI	(3) BHAR OMXSPI	(4) BHAR OMXSPI	(5) BHAR OMXSPI	(6) BHAR OMXSPI
	36 month					
High volume	0.270	0.370	0.336	0.354	0.363	0.421
	(0.213)	(0.077)*	(0.113)	(0.099)*	(0.092)*	(0.034)**
Ln Firm age		0.184	0.189	0.143	0.155	0.155
		(0.001)***	(0.000)***	(0.011)**	(0.006)***	(0.028)**
Crisis 080910			-0.350	-0.359	-0.379	Omitted
			(0.093)*	(0.109)	(0.092)*	
Ln Offer size				0.072	0.063	0.089
				(0.054)*	(0.098)*	(0.030)**
Technology					-0.516	-0.567
					(0.038)**	(0.068)*
Year dummies						Yes
Constant	-0.106	-0.600	-0.577	-1.809	-1.645	-2.240
Observations	94	94	94	94	94	94
F-statistic	1.570	8.850	8.110	6.270	6.400	-
Adj. R-squared	0.012	0.043	0.042	0.049	0.053	0.015
R-squared	0.022	0.064	0.073	0.090	0.104	0.153

Table 8. BHAR OMXSPI 36 month is the three-year buy-and-hold abnormal return measured from the second day of trading until the 36 month mark with OMXSPI as benchmark. High volume equals one if more than three IPOs have taken place in the month of the approximate announcement date for each IPO. This threshold corresponds to the 95th percentile of monthly IPO approximate announcement dates frequency. Ln Firm age is the natural logarithm of one plus the difference between the year the firm goes going public and the year it was founded. Crisis 080910 equals one if the IPO is issued between 2008 and 2010, i.e. the crisis years and its aftermath, and zero otherwise. Ln Offer size is the natural logarithm of the total size of the IPO offer of each firm. Technology equals one if the issuing firm is operating within technology and zero otherwise. Year dummies include the years 2004 to 2014. P-values are in parentheses and the significance level is given by *** p<0.01, ** p<0.05 and * p<0.1.

In Table 8 we observe the regression outputs of $BHAR_{36,OMXSPI}$. In our main regression (4), the main variable *High volume* is significant at the 10% level in which the positive coefficient of 0.354 indicates that firms issuing during a high volume period have a 35.4% higher $BHAR_{36,OMXSPI}$ than those issuing during a low volume period. As for our control variables in our main regression (4), the positive coefficient of *Ln Firm age* is statistically significant at the 5% level suggesting that the older the firm is the higher is the $BHAR_{36,OMXSPI}$. Thus, a 1% increase in *Ln Firm age* results in a 0.143% increase in $BHAR_{36,OMXSPI}$. In terms of the control variable *Crisis 080910*, our results show that this variable is not statistically significant in our main regression (4). When analyzing the control variable *Ln Offer size* we can see that it has a positive coefficient of 0.072 that is statistically significant at the 10% level. This result implies that the larger the offer size, the higher the $BHAR_{36,OMXSPI}$. Thus, a 1% increase in *Ln Offer size* results in a 0.072% higher $BHAR_{36,OMXSPI}$.

As shown in Table 8, our main variable *High volume* is significant in regression (2), (4), (5) and (6). What can be emphasized is that the significant coefficients are positive and have an increasing trend in magnitude as more variables are controlled for in these four regressions. The positive and statistically significant coefficients of *High volume* in these regressions suggest that there is a positive relationship between the number of Swedish IPOs and the three-year aftermarket performance, $BHAR_{36,OMXSPI}$. Our results contradict the findings of Ritter (1991), Loughran and Ritter (1995) and Lowry (2003) in which they find a negative relationship. The same relationship as in the mentioned studies have also been found in different international results that are highlighted by Loughran et al. (1994) in their study. One possible and simple explanation to the contradiction may partly be due to the fact that these studies examine IPOs in other markets and during different time periods compared to us. A similar explanation is presented by Ritter and Welch (2002) regarding the results in their study, where they emphasize the fact that different methods, sample periods and sample selection yield different results. Another plausible explanation to our contradictory results may be due to the recent years increasing number of IPOs in the Nordics that can be interpreted as the market being in a ”fads” period as explained by Ritter (1991). This argument is further strengthened when looking at Figure 2 in Section 5.1 where 39% of the IPOs within our sample had an approximate announcement date during the years 2013 and 2014. Given the recent three years IPO boom it is possible that the market is still in a ”fads” period in which investors willingness to pay and market valuations, for IPOs in particular, are high. Thus, this may explain why our results show a positive relationship between the variable *High volume* and $BHAR_{36,OMXSPI}$ contradicting previous studies. At the same time, some experts argue that we are currently in a ”late-cycle” environment where we may face a possible financial downturn in the near future (Bloomberg, 2017b). Hence, further research stretching our examination period with one year, including IPOs during 2015, and studying their three-year aftermarket performance may result in other findings given that the market may be facing a financial downturn in the near future. However, we do find some support for our findings in a study by Loughran et al. (1994). In their study they also examine the same relationship as we do but on IPO data for 14 different countries. Their findings show that 4 of the 14 countries have a positive relationship between the IPO volume and one-year aftermarket performance. Among those four countries in which they note a positive relationship, Sweden is one of them. Another study offering some support to our findings is Isaksson and Thorsell (2014) in which they note a positive relationship between the number of Swedish IPOs and the one-year aftermarket performance. As noted, the positive relationship in these two studies are found for one-year aftermarket performance and not three-year aftermarket performance as in our study.

In regards of our control variables, the positive and statistically significant coefficients of *Ln Firm age* and *Ln Offer size* in regression (4), in Table 8, support the findings of Ritter (1991) where he notes that young and small issues tend to be those with worst three-year aftermarket performance. One possible explanation to this may be that the older the firms are, the more stable they are both financially and operationally. Experienced business leaders may be better at running their firms and therefore also able to yield higher returns in the long-run. This is partly supported by Gao et al. (2013) in which they note a negative relationship between the size of the offer and the aftermarket performance. They explain this by arguing that small issues do not tend to grow and become as highly profitable and returning high returns in the same extent as larger issues do.

In terms of the two control variables *Crisis 080910* and *Technology* in regression (5) in Table 8, both are negative and statistically significant. The coefficient of *Crisis 080910* is negative and significant at the 10% level. The negative sign is unexpected and if we are to speculate, a positive coefficient may be interpreted as firms issuing during crisis years are valued at lower prices and as the market recovers these firms will yield higher $BHAR_{36,OMXSPI}$. However, the negative impact on $BHAR_{36,OMXSPI}$ of issuing in crisis years and its aftermath does not completely rule out lower valuations during these years. It may be that they are valued at lower prices but it takes more than 36 months before the market recovers from the downturn. The coefficient of *Technology* is negative and significant at the 5% level in regression (5), showing that issuing technology firms tend to yield 51.6% lower $BHAR_{36,OMXSPI}$ compared to issuing firms operating in other industries. Our results showing a negative coefficient of *Technology* in regression (5) are in contrast to the findings of Clark (2002) in which he notes that younger technology issues outperform elder technology issues in terms of average three-year holding period excess returns. One possible explanation to this contradiction in our findings may be due to the fact that Clark (2002) studies technology issues during the 1990's, a period where the market for technology firms was on the rise.

6.3.2 Regression Results of 36 Month BHAR Industry

Table 9: Regressions on 36 month BHAR with Industry as benchmark

	(1)	(2)	(3)	(4)	(5)	(6)
	BHAR Industry	BHAR Industry	BHAR Industry	BHAR Industry	BHAR Industry	BHAR Industry
Variables	36 month					
High volume	0.218	0.317	0.284	0.298		0.367
	(0.236)	(0.081)*	(0.127)	(0.112)		(0.070)*
Ln Firm age		0.182	0.187	0.152		0.146
		(0.004)***	(0.002)***	(0.018)**		(0.023)**
Crisis 080910			-0.345	-0.351		Omitted
			(0.166)	(0.180)		
Ln Offer size				0.055		0.094
				(0.175)		(0.021)**
Technology						Not included
Year dummies						Yes
Constant	-0.070	-0.561	-0.537	-1.483		-2.289
Observations	94	94	94	94		94
F-statistic	1.430	5.170	4.810	3.740		-
Adj. R-squared	0.008	0.049	0.050	0.052		0.055
R-squared	0.018	0.069	0.080	0.093		0.177

Table 9. BHAR Industry 36 month is the three-year buy-and-hold abnormal return measured from the second day of trading until the 36 month mark with different industry indices as benchmark. High volume equals one if more than three IPOs have taken place in the month of the approximate announcement date for each IPO. This threshold corresponds to the 95th percentile of monthly IPO approximate announcement dates frequency. Ln Firm age is the natural logarithm of one plus the difference between the year the firm goes going public and the year it was founded. Crisis 080910 equals one if the IPO is issued between 2008 and 2010, i.e. the crisis years and its aftermath, and zero otherwise. Ln Offer size is the natural logarithm of the total size of the IPO offer of each firm Technology equals one if the issuing firm is operating within technology and zero otherwise. Because Technology is highly correlated with the technology industry index used in BHAR Industry and CAR Industry for firms operating within technology, we exclude the variable Technology in these regressions. Thus we do not run regression (5). Year dummies include the years 2004 to 2014. P-values are in parentheses and the significance level is given by *** p<0.01, ** p<0.05 and * p<0.1.

Table 9 displays the regression outputs for $BHAR_{36,Industry}$. In contrast to the findings regarding $BHAR_{36,OMXSPI}$, the main variable *High volume* is not statistically significant in our main regression (4) on $BHAR_{36,Industry}$. In regards of our main variable *High volume*, we can see that it is positive and statistically significant at the 10% level only in regression (2) and (6) suggesting a positive relationship between the number of Swedish IPOs and the three-year aftermarket performance. The coefficient of *High volume* increases in magnitude between regression (2) and (6) as additional variables are controlled for. However, the coefficients of *High volume* in regression (2) and (6) for $BHAR_{36,Industry}$ in Table 9 have lower magnitudes than the coefficients of *High volume* in the corresponding two regressions for $BHAR_{36,OMXSPI}$ in Table 8. Moreover, the only significant variable in our main regression (4) is the control variable *Ln Firm age* that is positive and significant at the 5% level.

6.3.3 Regression Results of Shorter Time Periods

To examine whether we observe the same results in shorter time periods we run the same regressions as in Section 6.3.1 and 6.3.2 but for 12- and 24 month $BHAR_{OMXSPI}$ and $BHAR_{Industry}$. The main variable *High volume* is not significant in our main regression (4) for neither $BHAR_{24,OMXSPI}$ nor $BHAR_{24,Industry}$ as shown in Appendix Table A2 and A3. However, when including the control variable *Technology* in regression (5), our main variable *High volume* is significant at the 10% level for $BHAR_{24,OMXSPI}$ as shown in Appendix Table A2. Altogether, the significant variables are lower in magnitude and fewer variables are significant when studying the 24 month periods for both BHAR measures. Regressions on 12 month $BHAR_{OMXSPI}$ and $BHAR_{Industry}$ only result in a few significant year dummies in regression (6) for both $BHAR_{12,OMXSPI}$ and $BHAR_{12,Industry}$. These results are not presented since interpretation is difficult and may be inaccurate.

6.4 Robustness

To test the robustness of our results we use CAR as an alternative model and run the same regressions as for $BHAR_{OMXSPI}$ and $BHAR_{Industry}$ on the 12-, 24- and 36 month marks of CAR_{OMXSPI} and $CAR_{Industry}$. Appendix Table A4 and A5 illustrate the regression results on the 36 month CARs. The coefficient for our main variable *High volume* is not statistically significant in any of the regressions for neither $CAR_{36,OMXSPI}$ nor $CAR_{36,Industry}$. Thus, we cannot draw any conclusions regarding the relationship between the number of IPOs and the three-year aftermarket performance when using our alternative model CAR.

The regression results on 24 month CARs are not presented in tables since these regressions do not yield any significant results in our main regression (4). In addition, neither are the regression results on 12 month CARs presented since the only significant variables are a few year dummies in regression (6). In summary, the significant variables in the CAR-regressions follow the same pattern as in our BHAR-regressions however, fewer variables are significant in the CAR-regressions. The latter implies that our results and analysis of BHARs should be interpreted with caution.

7 Summary and Concluding Discussion

This study examines if there is a negative relationship between the number of Swedish IPOs and the long-run performance, and what factors that are related to the long-run performance. The methodology we use is inspired by Ritter (1991), where we measure abnormal returns as BHARs and CARs. We examine IPOs issued on Nasdaq OMX Stockholm and First North during 2004 to 2014, a time period spanning over the recent financial crisis and its aftermath. To the best of our knowledge few recent studies examine this relationship during this particular period on the Swedish market, this differentiates our study from previous research.

We find a positive and significant relationship between the number of Swedish IPOs and the long-run performance measured as 36 month BHAR using OMXSPI as benchmark in our main regression (4). Our results are not in line with previous studies in which a negative relationship is found (Ritter, 1991; Loughran & Ritter, 1995; Lowry, 2003). However, Loughran et al. (1994) and Isaksson and Thorsell (2014) find a positive correlation at the 12 month mark when studying Swedish IPOs, offering some support for our findings. When conducting the same regressions on our alternative model CAR, we do not find any significant relationship between the number of IPOs and long-run returns. In general, fewer variables are significant in the CAR-regressions implying that our results and analysis of BHARs should be interpreted with caution.

As neither of our BHARs or CARs for any time period or benchmark have a mean that is statistically different from zero, we cannot conclude whether there has been any mean underperformance or overperformance in our sample during our examination period. However, we do find a statistically significant median underperformance measured as 36 month BHAR using OMXSPI as benchmark for IPOs issued during low volume periods. Other studies find that IPOs in general have a negative three-year aftermarket performance (Ritter, 1991; Ibbotson, 1975; Loughran & Ritter, 1995; Ritter & Welch, 2002; Schuster, 2003). Without a significant median for the high volume sample it is not possible to interpret this in relation to a difference in performance between the two periods. The expected finding would be that the high volume sample have even worse long-run median performance compared to the low volume sample. As evident from previous studies, if our results were significant we would have expected long-run aftermarket underperformance for both BHARs and CARs. If we are to speculate further, the decreasing but not statistically significant trend for mean BHARs and CARs in our sample may be at least partially explained by asymmetric information. As argued by Ritter (1991), when an increasing amount of negative information becomes available to investors for each month that passes by, the disappointment of reality results in lower aftermarket performance. As previously mentioned, this is only speculations due to our insignificant results.

Our finding of a positive relationship in regards to our research question suggests that issuing in a high volume period results in better aftermarket performance compared to issuing in a low volume period. This implies that firms have a higher cost of equity when issuing in a high volume period. These results are unexpected and contradict previous studies which have found that firms issuing during a high volume period have a lower cost of equity. The lower cost of equity for high volume issues is in turn reflected in lower aftermarket returns, compared to those issuing in low volume periods.

Several explanations to our unexpected results may exist. For instance, the recent years increasing number of IPOs in the Nordics can be interpreted as the market being in a "fads" period, overvaluing IPOs, as explained by Ritter (1991). Inspecting our data set we see that 39% of the IPOs have an approximate announcement date during 2013 and 2014. Thus, given the recent years increasing number of IPOs it is possible that the market is still in a "fads" period in which investors willingness to pay, and market valuations of IPOs in particular, are high. On the other hand, there are experts claiming that we are in a "late-cycle" environment with an imminent threat of a financial downturn occurring (Bloomberg, 2017b). If this is the case, extending the time period of our study may capture IPOs that are not within such a "fads" period. This could yield a negative relationship between the number of IPOs and the long-run performance, as would be expected. In addition, extending the time period would also expand the number of observations in our sample, mitigating potential problems of making inferences using small sample sizes in general.

Another explanation to our contradictory results may be the definition and setup of our models, and in particular the variable *High volume*. It may be possible that our *High volume* variable not accurately captures what is studied in earlier empirical literature. According to Ibbotson and Jaffe (1975), a hot issue market is defined as a period of high initial returns, which is followed by a high volume of IPOs (Ibbotson et al., 1994; Lowry & Schwert, 2002). For example, Ritter (1991), among others, study the hot issue markets which involves underpricing, i.e. when the first closing price exceeds the offer price. Our study focuses on the volume of IPOs, which is a phenomenon closely related to hot issue markets. Thus, an approach where factors of initial returns and the volume of IPOs are incorporated in the definition of the variable *High Volume* may yield different results. Additionally, studies on IPO performance are also dependent upon using a correct benchmark (Ritter, 1991). We use a broad index benchmark as well as different industry indices to calculate two alternatives of abnormal returns for our BHARs and CARs. These two benchmarks might not be accurate enough. In contrast, Ritter (1991) uses a matched portfolio of firms when calculating abnormal returns in addition to different indices.

Concluding our discussion, it is hard to arrive at an unambiguous conclusion that explains our findings of a positive relationship between the number of Swedish IPOs and the long-run performance. Further research is needed, perhaps by extending the period studied, rethinking the definition of what constitutes a high volume period and using portfolios of matched firms as benchmarks. Improving our study with the recommended suggestions may help disentangle our findings, adding support for issuing firms and investors in their decision on when to go public and when to invest in an IPO on the Swedish market, respectively.

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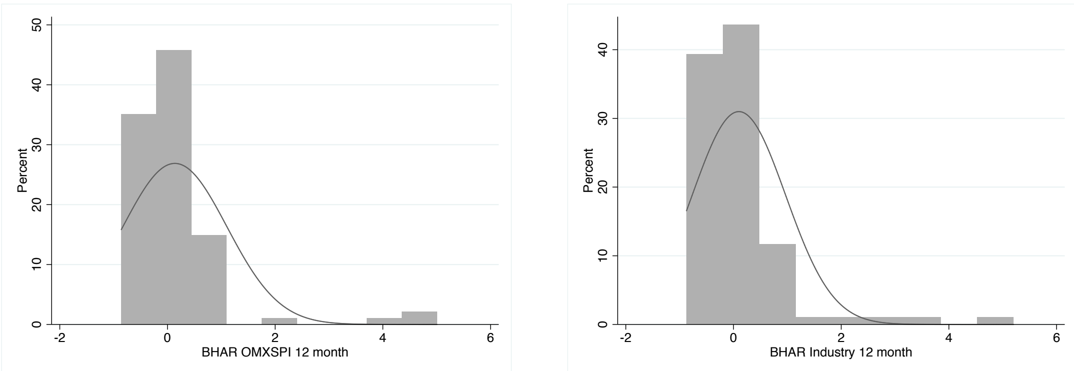
Appendix

Table A1: Correlation Matrix

	High volume	Ln Firm age	Crisis 080910	Ln Offer size	Technology
High volume	1.000				
Ln Firm age	-0.261	1.000			
Crisis 080910	-0.210	0.109	1.000		
Ln Offer size	-0.172	0.390	0.071	1.000	
Technology	0.046	0.041	-0.055	-0.122	1.000

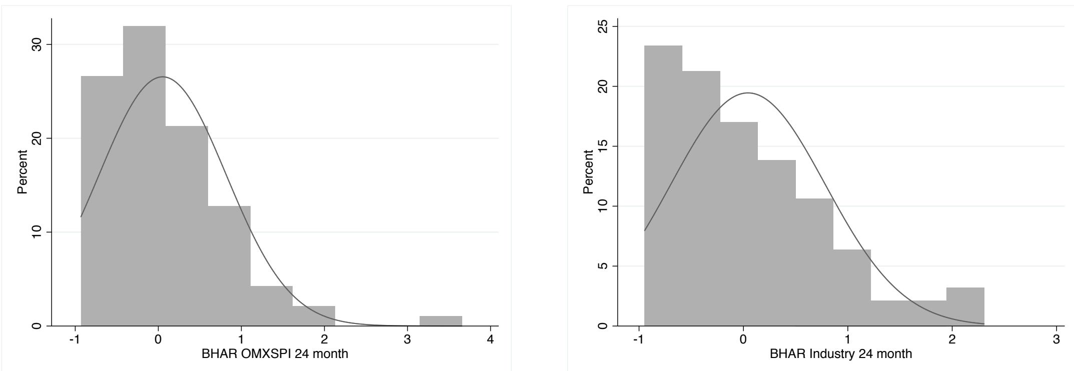
Figure A1: Histograms of 12 month BHARs



(a) Histogram of 12 month BHAR OMXSPI

(b) Histogram of 12 month BHAR Industry

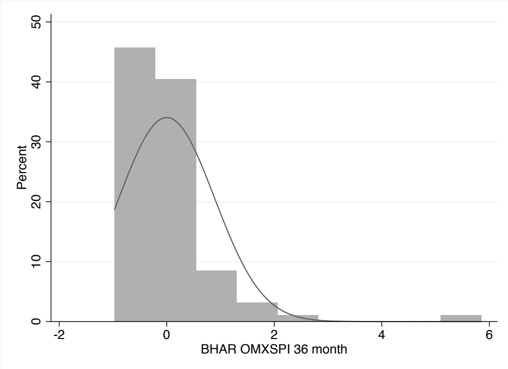
Figure A2: Histograms of 24 month BHARs



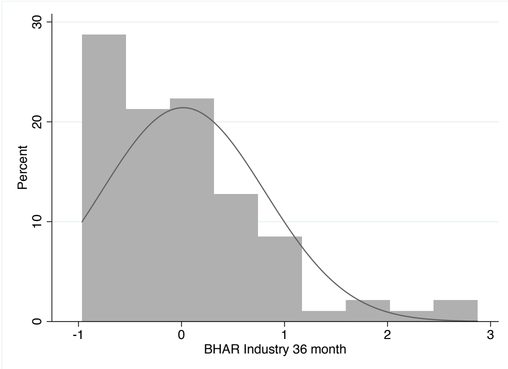
(a) Histogram of 24 month BHAR OMXSPI

(b) Histogram of 24 month BHAR Industry

Figure A3: Histograms of 36 month BHARs



(a) Histogram of 36 month BHAR OMXSPI



(b) Histogram of 36 month BHAR Industry

Table A2: Regressions on 24 month BHAR with OMXSPI as benchmark

Variables	(1) BHAR OMXSPI	(2) BHAR OMXSPI	(3) BHAR OMXSPI 24 month	(4) BHAR OMXSPI	(5) BHAR OMXSPI	(6) BHAR OMXSPI
High volume	0.230	0.306	0.292	0.298	0.308	0.337
	(0.195)	(0.081)*	(0.103)	(0.101)	(0.089)*	(0.084)*
Ln Firm age		0.141	0.143	0.127	0.140	0.116
		(0.012)**	(0.010)**	(0.037)**	(0.023)**	(0.081)*
Crisis 080910			-0.149	-0.152	-0.175	Omitted
			(0.558)	(0.562)	(0.506)	
Ln Offer size				0.026	0.015	0.048
				(0.539)	(0.719)	(0.258)
Technology					-0.569	-0.495
					(0.051)*	(0.110)
Year dummies						Yes
Constant	-0.038	-0.418	-0.408	-0.847	-0.666	-1.494
Observations	94	94	94	94	94	94
F-statistic	1.700	4.420	3.160	2.300	2.740	-
Adj. R-squared	0.011	0.034	0.026	0.018	0.030	0.011
R-squared	0.022	0.055	0.057	0.060	0.082	0.149

Table 10. BHAR OMXSPI 24 month is the two-year buy-and-hold abnormal return measured from the second day of trading until the 24 month mark with OMXSPI as benchmark. High volume equals one if more than three IPOs have taken place in the month of the approximate announcement date for each IPO. This threshold corresponds to the 95th percentile of monthly IPO approximate announcement dates frequency. Ln Firm age is the natural logarithm of one plus the difference between the year the firm goes going public and the year it was founded. Crisis 080910 equals one if the IPO is issued between 2008 and 2010, i.e. the crisis years and its aftermath, and zero otherwise. Ln Offer size is the natural logarithm of the total size of the IPO offer of each firm. Technology equals one if the issuing firm is operating within technology and zero otherwise. Year dummies include the years 2004 to 2014. P-values are in parentheses and the significance level is given by *** p<0.01, ** p<0.05 and * p<0.1.

Table A3: Regressions on 24 month BHAR with Industry as benchmark

Variables	(1) BHAR Industry	(2) BHAR Industry	(3) BHAR Industry	(4) BHAR Industry	(5) BHAR Industry	(6) BHAR Industry
	24 month					
High volume	0.163	0.249	0.233	0.238		0.240
	(0.320)	(0.130)	(0.166)	(0.163)		(0.228)
Ln Firm age		0.157	0.159	0.147		0.131
		(0.009)***	(0.007)***	(0.023)**		(0.041)**
Crisis 080910			-0.160	-0.162		Omitted
			(0.584)	(0.587)		
Ln Offer size				0.019		0.045
				(0.663)		(0.301)
Technology						Not included
Year dummies						Yes
Constant	-0.020	-0.442	-0.431	-0.763		-1.415
Observations	94	94	94	94		94
F-statistic	1.000	4.120	2.930	2.170		-
Adj. R-squared	0.001	0.034	0.027	0.017		0.027
R-squared	0.012	0.055	0.058	0.060		0.163

Table 11. BHAR Industry 24 month is the two-year buy-and-hold abnormal return measured from the second day of trading until the 24 month mark with different industry indices as benchmark. High volume equals one if more than three IPOs have taken place in the month of the approximate announcement date for each IPO. This threshold corresponds to the 95th percentile of monthly IPO approximate announcement dates frequency. Ln Firm age is the natural logarithm of one plus the difference between the year the firm goes going public and the year it was founded. Crisis 080910 equals one if the IPO is issued between 2008 and 2010, i.e. the crisis years and its aftermath, and zero otherwise. Ln Offer size is the natural logarithm of the total size of the IPO offer of each firm Technology equals one if the issuing firm is operating within technology and zero otherwise. Because Technology is highly correlated with the technology industry index used in BHAR Industry and CAR Industry for firms operating within technology, we exclude the variable Technology in these regressions. Thus we do not run regression (5). Year dummies include the years 2004 to 2014. P-values are in parentheses and the significance level is given by *** p<0.01, ** p<0.05 and * p<0.1.

Table A4: Regressions on 36 month CAR with OMXSPI as benchmark

Variables	(1) CAR OMXSPI	(2) CAR OMXSPI	(3) CAR OMXSPI	(4) CAR OMXSPI	(5) CAR OMXSPI	(6) CAR OMXSPI
	36 month					
High volume	0.186	0.258	0.203	0.209	0.211	0.251
	(0.426)	(0.254)	(0.378)	(0.372)	(0.373)	(0.332)
Ln Firm age		0.132	0.139	0.125	0.129	0.100
		(0.074)*	(0.043)**	(0.095)*	(0.084)*	(0.188)
Crisis 080910			-0.557	-0.560	-0.565	Omitted
			(0.034)**	(0.036)**	(0.035)**	
Ln Offer size				0.022	0.019	0.060
				(0.632)	(0.677)	(0.214)
Technology					-0.140	-0.048
					(0.757)	(0.925)
Year dummies						Yes
Constant	0.016	-0.337	-0.300	-0.671	-0.627	-1.517
Observations	94	94	94	94	94	94
F-statistic	0.640	2.570	4.260	3.110	2.540	-
Adj. R-squared	-0.002	0.005	0.012	0.003	-0.008	-0.030
R-squared	0.009	0.026	0.044	0.046	0.046	0.114

Table 12. CAR OMXSPI 36 month is the three-year cumulative abnormal return measured from the second day of trading until the 36 month mark with OMXSPI as benchmark. High volume equals one if more than three IPOs have taken place in the month of the approximate announcement date for each IPO. This threshold corresponds to the 95th percentile of monthly IPO approximate announcement dates frequency. Ln Firm age is the natural logarithm of one plus the difference between the year the firm goes going public and the year it was founded. Crisis 080910 equals one if the IPO is issued between 2008 and 2010, i.e. the crisis years and its aftermath, and zero otherwise. Ln Offer size is the natural logarithm of the total size of the IPO offer of each firm. Technology equals one if the issuing firm is operating within technology and zero otherwise. Year dummies include the years 2004 to 2014. P-values are in parentheses and the significance level is given by *** p<0.01, ** p<0.05 and * p<0.1.

Table A5: Regressions on 36 month CAR with Industry as benchmark

	(1)	(2)	(3)	(4)	(5)	(6)
	CAR Industry	CAR Industry	CAR Industry	CAR Industry	CAR Industry	CAR Industry
Variables	36 month					
High volume	0.176	0.247	0.191	0.195		0.230
	(0.458)	(0.282)	(0.416)	(0.412)		(0.380)
Ln Firm age		0.131	0.139	0.129		0.101
		(0.108)	(0.071)*	(0.118)		(0.221)
Crisis 080910			-0.572	-0.574		Omitted
			(0.067)*	(0.069)*		
Ln Offer size				0.015		0.063
				(0.747)		(0.196)
Technology						Not included
Year dummies						Yes
Constant	0.041	-0.311	-0.272	-0.537		-1.476
Observations	94	94	94	94		94
F-statistic	0.560	2.010	3.150	2.320		-
Adj. R-squared	-0.003	0.002	0.010	-0.000		-0.008
R-squared	0.007	0.024	0.042	0.043		0.122

Table 13. CAR Industry 36 month is the three-year cumulative abnormal return measured from the second day of trading until the 36 month mark with different industry indices as benchmark. High volume equals one if more than three IPOs have taken place in the month of the approximate announcement date for each IPO. This threshold corresponds to the 95th percentile of monthly IPO approximate announcement dates frequency. Ln Firm age is the natural logarithm of one plus the difference between the year the firm goes going public and the year it was founded. Crisis 080910 equals one if the IPO is issued between 2008 and 2010, i.e. the crisis years and its aftermath, and zero otherwise. Ln Offer size is the natural logarithm of the total size of the IPO offer of each firm Technology equals one if the issuing firm is operating within technology and zero otherwise. Because Technology is highly correlated with the technology industry index used in BHAR Industry and CAR Industry for firms operating within technology, we exclude the variable Technology in these regressions. Thus we do not run regression (5). Year dummies include the years 2004 to 2014. P-values are in parentheses and the significance level is given by *** p<0.01, ** p<0.05 and * p<0.1.