The Hot Tech Issue Market

A Study on Underpricing and Long-Run Post-IPO Performance of Swedish IPOs

ERIC PERSSON

OSKAR JOHNSSON

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Abstract:
We explore the effect on underpricing and long-run post-IPO performance of a firm being classified as high tech or low tech, based on their SIC code. By studying offer prices and post-IPO share prices of a sample of 145 Swedish IPOs between 2004-2017, we do not find support for a difference in long-run post-IPO performance. However, we document that the absolute level of underpricing, and the relative difference in underpricing between high-tech and low-tech companies, increases during the "hot-market" period of 2015-2017. Hence, as previously documented in the 1980s and 2000s, the phenomenon of a general and industry-specific increase in underpricing during hot markets continues to exist.

Keywords:
Underpricing, Long-Run Post-IPO Performance, Initial Public Offering, IPO, Hot Market, High Tech

Authors:
Eric Persson (24226)
Oskar Johnsson (24252)

Tutors:
Anastasia Girshina, Postdoctoral Fellow, Swedish House of Finance

Examiner:
Adrien d´ Avernas, Assistant Professor, Department of Finance, Stockholm School of Economics

Bachelor Thesis in Finance
Bachelor Program in Business and Economics
Stockholm School of Economics

1 Introduction

The number of Initial Public Offerings ("IPOs") has increased in the past decades, causing it to become a well-documented and heavily debated research topic. Previous studies document the level of underpricing to change over time, and find cross-industry differences, particularly during hot markets[1] (Ritter, 1984; Loughran and Ritter 2004). Furthermore, IPOs are documented to exhibit abnormal long-run performance, also demonstrating a difference between industries (Ritter, 1991).

The purpose of this thesis is to explore the effect of a firm being classified as high tech on underpricing and the subsequential post-IPO performance. We contribute to the existing body of research by studying IPOs on the Swedish market during 2004-2017. An examination of the Swedish market during this period is of interest as there is limited previous literature on the topic in the region, but also due to indications of a hot market in Sweden driven by tech IPOs. In our study, we find support for an absolute increase in the level of underpricing across industries during the hot-market period of 2015-2017. Furthermore, we document that the difference between high-tech and low-tech companies increase during the period, with high-tech firms being relatively more underpriced.

In our study companies are classified as high tech by their standard industrial classification ("SIC") code according to a method developed by Kile and Philips (2009). All companies not classified as high-tech are in this thesis referred to as low-tech. Long-run post-IPO performance is, as in previous literature, defined as one-, two-, and three-years relative performance to an industry benchmark, in our case derived from the Capital Asset Pricing Model ("CAPM"). We have constructed this thesis to study the following research question:

Can differences in underpricing and long-run post-IPO performance on the Swedish market be explained by a company being classified as high-tech?

The remainder of this article is organized as follows: Section 2 provides an overview of previous research on underpricing and post-IPO performance. Section 3 presents the data used in our study. Section 4 presents the methodology used to answer our research question. Section 5 presents our main results. Section 6 discusses our findings in relation to the previous body of literature. Finally, our conclusions are presented in section 7.

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[1] Hot markets are periods of high IPO activity and increased level of underpricing (Ritter, 1984; Helwege and Liang, 2004). In this paper, similar to Helwege and Liang (2004), a hot market is defined as years with an IPO count exceeding the upper quartile of our sample.

2 Previous Literature

This section aims to present the existing literature on the relevant topics of this study. Section 2.1 provides a general overview of the topic of IPOs. Previous research on underpricing and post-IPO performance are presented in section 2.2 and 2.3. Section 2.4 continues to discuss the existence of hot markets. Finally, industry and geographical differences are presented in sections 2.5 and 2.6.

2.1 Background

The growing body of research on IPOs has identified three anomalies contradicting the Efficient Market Hypothesis ("EMH") and the theory of investor rationality: the underpricing puzzle, the abnormal post-IPO performance, and the hot-issue market phenomenon (Shiller, 1990; 2003). Underpricing of IPOs occurs when the offer price is below its perceived value by investors, causing the price to rise on the first trading day, resulting in first-day returns above zero percent. The price may however rise above its fair value or vice versa, causing it to revert over time resulting in abnormal post-IPO returns (Shefrin, 2002). Underpricing is a well-documented phenomenon with multiple explanations ranging from information asymmetry and agency problems to traditional economics of supply and demand. In regard to long-run post-IPO performance, Ritter (1991) is the first to prolong the research of IPOs to examine a three-year perspective, where he finds differences in underpricing and post-IPO performance across industries. Furthermore, an increase in underpricing is documented during hot markets, defined as periods with high IPO activity (Ritter, 1984; Ritter and Loughran, 2004; Helwege and Liang, 2004).

In recent years, the tech industry has gained increased attention from investors. A recent report found that between 2015 and 2017 high growth digital tech firms raised over £245 billion globally (Technation, 2019). Some are raising concerns that we are approaching a tech bubble similar to the one of 2000 (Dougherty, 2015; Berocovici, 2015), with one indication being rising valuations of private companies and IPOs in the industry (Maris, 2015). Furthermore, a recent study suggests a technology bias amongst investors, where the participants consistently invested larger amounts in fictive firms labeled as high tech, despite having the same historical and predicted future returns and reputation (Clark et al., 2015).

Sweden has historically been a market characterized by a relatively large proportion of tech companies, having experienced a vast increase in the number of listed companies operating in technology sectors during the early 2000s, compared to other markets (Westerholm, 2006). Technology firms continue to be present as Stockholm is ranked second, only behind Silicon Valley, in the number of tech start-ups per capita (Davidson, 2015).

2.2 Underpricing

The underlying reasons for underpricing have been widely discussed and documented in previous literature. Rock (1982) explains the phenomenon using adverse selection theory, grouping investors into two categories: informed and uninformed. If an issue is priced at its fair value, informed investors will crowd out other investors, and if an issue is overpriced, they will not partake. Uninformed investors face a winner's curse where they receive shares if the issue's offer price is above the fair value but will only want to participate if the expected return is positive. In other words, shares must be underpriced, on average, to attract uninformed investors. Hence, underpricing can be viewed as compensation for investors being uninformed before the company goes public. The greater the risk, the greater the compensation, and thus the level of underpricing (Rock, 1982).

From the underwriter's perspective, Ritter and Loughran (2004) explain underpricing through three underlying questions; (1) Why underwriters want to underprice IPOs, (2) The analyst lust explanation, and (3) The spinning explanation. (1) Underwriters, who advise the issuer on pricing the issue, receive compensation through both the gross spread and underpricing, giving them an incentive to recommend a lower offer price. (2) Regarding the analyst lust explanation of underpricing, Ritter and Loughran hypothesize that issuers choose their underwriter based on expected analyst coverage. The costs for research coverage, which is expensive for the investment banks, are covered through both explicit fees (gross spread) and implicit fees (underpricing). The more that issuing firms see analyst coverage as important, the more they are willing to pay in fees. (3) IPO spinning, where investment banks offer underpriced shares to executives and decision makers of other firms in exchange for future business, shows to be very effective and yields an average first-day return of 23% greater than similar IPOs (Loughran and Ritter, 2004; Liu and Ritter, 2009).

2.3 Post-IPO Performance

Studies prior to 1991 on post-IPO share price performance do not investigate time periods longer than one year. Ritter (1991) is the first to prolong the research of IPOs to examine a long-run three-year perspective. The study of the long-run post-IPO period is of interest for several reasons. Firstly, possible price patterns provide opportunities for active trading strategies to generate superior returns. Secondly, the previously documented abnormal performance of IPOs indicates market inefficiencies. Furthermore, IPO activity and the level of underpricing differ over time, and periods with high activity provide a "window of opportunity" for issuing companies to successfully time their initial public offerings. Ritter (1991) further suggests that underpricing is a short-run phenomenon and that there is a difference in both underpricing and long-run performance between industries. The report is evaluating issuing companies during 1975-1984 and further concludes that these firms significantly underperform a sample of matching firms, from the closing price on the day of the IPO until the day of their third-year trading (Ritter, 1991).

Another study by Krigman et al. (1999) examined a sample of large-cap IPOs between 1988 and 1995 on the U.S. market. In contradiction to Ritter (1991), the study demonstrated a positive relationship between underpricing and long-run post-IPO performance, suggesting that first-day winners continue to be winners, and first-day losers continue to be losers over the one-year post-IPO horizon. (Krigman et al., 1999).

2.4 Hot Markets

The level of underpricing is documented to change over time. Loughran and Ritter (2004) show that the level of underpricing increased from 7 % in 1960 to 65 % during the dot-com bubble years of 1999-2000 and returned to 12 % during 2001-2003. Evidently, the level of underpricing seems to increase during "hot markets" and the phenomena has been given a variety of explanations in previous literature. When studying the 15 months following January 1980, Ritter (1984) finds a positive relationship between the number of initial offerings, and the level underpricing. The initial return averaged 48.4% during the period, compared to 16.3% during the "cold market" of the remainder of 1977-1982. Building on previous research on underpricing by Rock (1982), Ritter (1984) explains how hot markets occur when a large proportion of issues are being viewed as high risk during a given time period, increasing the level of underpricing. Conversely, recent research shows that the difference between hot and cold markets rather exists in the quantity of offerings than the characteristics of the firms going public (Helwege and Liang, 2004). Others attribute the hot market underpricing to a surplus of demand from investors causing initial prices to increase (Shefrin, 2002). From a supply point of view, Ljungqvist instead suggests that the increase in the number of IPOs causes issuers to compete for investors, a resource short in supply, by reducing their offer price (Ljungqvist et al. 2006). In this paper, similar to Helwege and Liang (2004), a hot market is defined as years with an IPO count exceeding the upper quartile of our sample.

2.5 Industry and Market Differences

When studying the hot-issue-market of 1980, Ritter (1984) finds a difference in underpricing between industries, primarily attributable to the high first-day returns of IPOs in the natural resource industry. He attributes this to underwriters exploiting smaller start-up natural resource companies during the 1980s boom. This indicates the existence of a segmented issue market exclusively to one particular industry with firms being subject to exploitive underwriters.

Few previous studies have focused specifically on the difference in underpricing and long-run post-IPO performance between high-tech and low-tech firms. One example is Kim et. al (2008) who finds a difference in underpricing between high-tech and low-tech firms when studying the effect of pre-IPO leverage. Furthermore, Hwang et al. (2012) find a positive relationship between high-tech companies and a higher level of underpricing. This is attributed to the increase in information asymmetries associated with higher research and development ("R&D") expenditures. Further research has documented a relationship between firm age and post-IPO performance present only in the tech industry (Clark, 2002).

The level of underpricing is also documented to differ between exchanges with different firm characteristics. In a study on differences between IPOs on the NYSE and NASDAQ, Loughran (1993) finds that the latter experiences a higher degree of underpricing. The study explains the disparity by the difference in characteristics of the firms listed on the two exchanges, where the majority of firms listed on NASDAQ are growth companies. Furthermore, the companies listed on NASDAQ underperforms, long-run post IPO, in comparison to the ones of similar size on the NYSE (Loughran, 1993).

2.6 Geographical Differences

Previous literature has been conducted in the context of U.S. markets, attributable to the large amount of IPOs compared to other markets and the generally higher global interest for U.S. markets. While underpricing and underperformance of IPOs are well-documented phenomena in the U.S, the results seem to be more conflicted in international markets. For example, studies conducted on the Korean and Singaporean markets found that IPOs outperformed their respective benchmarks (Kim et al., 1995; Lee et al., 1996).

From a Swedish perspective, Loughran et al (1994) find that Swedish IPOs tend to be underpriced at a high level of 36% and suggest that it can be partly attributable to tax avoidance. Furthermore, in contrast to the U.S. market, Swedish IPOs tend to generate high average raw returns in the three years post IPO. In contrast, a study of long-run post-IPO performance on the Nordic markets finds that IPOs in Norway and Denmark outperform their all shares index, while Swedish IPOs underperform. One of the explaining factors in the study is the end of the new-economy tech era of the late 1990s, where Sweden was affected to a larger extent since tech companies were more present (Westerholm, 2006). Our study aims to contribute to the existing literature by focusing on IPOs conducted on the Swedish market, with a specific focus on the high ratio of tech IPOs.

3 Data

The following section critically presents the data sources and variables used in this study. Section 3.1 briefly describes our sample and time period of the study. Section 3.2 to 3.4 summarizes the data points and the corresponding sources that are used as the basis of the study. Lastly, section 3.5 provides a general overview of selected descriptive statistics. Additionally, further descriptive statistics are presented in appendix 1 and 2.

3.1 Sample

The data sample consists of IPOs listed on the Swedish stock exchanges OMX Stockholm, First North, Aktietorget, Nordic Growth Market, and Nordic MTF that went public between the years of 2004-2017. The lower bound of the time period is set to exclude IPOs from the dot-com era, following the economic downturn of the new economy of 1996-2003 (Levis, 2015). 2004 marks the return of the market recovery, and an increase in IPO activity.

3.2 IPO Data

In order to obtain data on IPOs in Sweden during the period, the new issues dataset is collected from the Refinitiv SDC Platinum platform. The database is to our knowledge, regarded as the most complete database for new issues and has been used in previous papers (e.g. Helwege and Liang, 2004). However, the initial dataset includes several duplicates that are excluded. Furthermore, the dataset also includes new issues which were canceled before completion, as well as secondary offerings, which consequently are excluded as well. Finally, observations are omitted where any of the databases are unable to provide crucial data. After excluding these observations, the dataset includes 145 observations. The variables collected for each company are summarized in Table 1.

Table 1: Summary of Variables Collected from SDC Platinum.

Variable	Description
Issue Date	Pricing date of the issue of each company.
Issuer	The name of the issuing company.
Main Sic Code	Main SIC code of the issuing company.
Offer Price	The initial price of a share offered to investors, prior to the open stock market.
ISIN	International Securities Identification Number.
Primary Exchange	The stock exchange where the company's shares were initially listed.

Summary of variables collected from the SDC Platinum New Issues database. The table shows the variable, the name, and a description of each variable.

3.3 Share Price Data

In order to measure the returns following the initial public offerings, data of daily closing prices is obtained from FinBas. FinBas is used as it takes dividends, recapitalization, and splits into consideration when calculating daily share prices, thus facilitating comparability over time. The dataset is obtained by using the ISIN-numbers for each company provided by SDC Platinum. Observations, where the ISIN-numbers are missing or yield no results in the FinBas database, are excluded from the sample. Finally, the datasets are merged by ISIN number. Our trading data ends on 2018-12-31 as FinBas provides daily stock prices until 2019-01-30. Table 2 summarizes the variables collected from FinBas.

Table 2: Summary of Variables Collected from FinBas

Variable	Description
ISIN	International Securities Identification Number.
Name	The name of the company.
LastAd	The closing price of the stock at the end of the trading day, adjusted for corporate actions.
Date	Date corresponding to the closing price.
Currency	Currency corresponding to the closing price.

Summary of variables collected from FinBas. The table shows the variable name and description of each variable.

3.4 CAPM Data

For our benchmark, we used the expected return on an industry basis, calculated using the Capital Asset Pricing Model ("CAPM"). To use the CAPM, we require the risk-free rate, the average levered beta of the industry, and the market return. The formula and methodology of computing the expected return are further illustrated in section 4.3.

3.4.1 Risk-Free Rate

The risk-free rate is defined as the yield of the one-month Swedish treasury bill. The official historical daily yield is obtained from Riksbanken on corresponding trading dates during the period of 2004-2019. Table 3 summarizes the variables collected from Riksbanken's database.

Table 3: Summary of Variables Collected from Riksbanken

Variable	Description
SSVX1M	The yield of the one-month Swedish treasury bill at the corresponding date.
Date	The corresponding date of the treasury bill's yield

Summary of variables collected from Riksbanken's database. The table shows the variable name and description of each variable.

3.4.2 Industry Beta

In order to calculate expected return, we obtain average levered beta per industry for European companies, matching these with corresponding three-digit SIC codes of each company in our sample. Industry average betas are obtained from Professor Damodaran of Stern School of Business's database. These industry betas are constructed from raw data from Capital IQ. The betas are calculated on an average five-year and two-year weekly regression basis, where two thirds are weighted on the last two years. Table 4 summarizes the variables in our dataset from Damodaran's database. A detailed list of average industry betas matched with the SIC codes in our sample is found in appendix 3.

Table 4: Summary of Variables from Damodaran's dataset

Variable	Description
Levered Beta	The average levered industry beta of the corresponding industry.
SIC3	Three-digit SIC code of the corresponding industry.

Summary of variables collected from Damodaran's (Stern School of Business) database. The table shows the variable name and description of each variable.

3.4.3 Market Return

In order to compute the market return, we use the OMXSPI-index as our proxy. Since the IPO dataset includes observations from several stock exchanges with firms of different sizes and market cap, OMXSPI is used as it includes a large number of companies compared to other indices, such as OMXS30 or other industry-specific indices. Since FinBas does not provide historical prices of the index for the entire sample period, we retrieved the data using Thomson Reuters Eikon and collected the daily price of the index on corresponding trading dates. The formula and methodology of computing the market return, from the daily index prices, are illustrated in section 4.3. Table 5 summarizes the variables collected from Thomson Reuters Eikon.

Table 5: Summary of Variables Collected from Thomson Reuters Eikon

Variable	Description
Index price	OMXSPI index daily closing price at the corresponding date.
Date	The corresponding date of the index's closing price.

Summary of variables collected from Thomson Reuters Eikon. The table shows the variable name and description of each variable.

3.5 Descriptive Characteristics

Figure 1 displays the distribution of IPOs in our dataset, both in terms of years and industry classification. Figure 1 shows that IPO activity largely follows the general macroeconomic development. We can observe a decrease in activity following the dot-com bubble, the financial crisis, and the Eurozone debt crisis of 2012. The distribution of IPOs is skewed towards the later years in the period, with 55% of the IPOs in our sample occurring between 2015-2017. Similar to Helwege and Liang (2004), we define a hot market as years with an IPO count exceeding the upper quartile of our sample. Hence, the period between 2015-2017 is considered a hot market. Regarding the difference in industry groups, we can observe that high-tech firms make up for a considerable proportion of the recent increase in IPO activity.

Figure 1: Distribution of IPOs Per Year and Group (2004-2017)

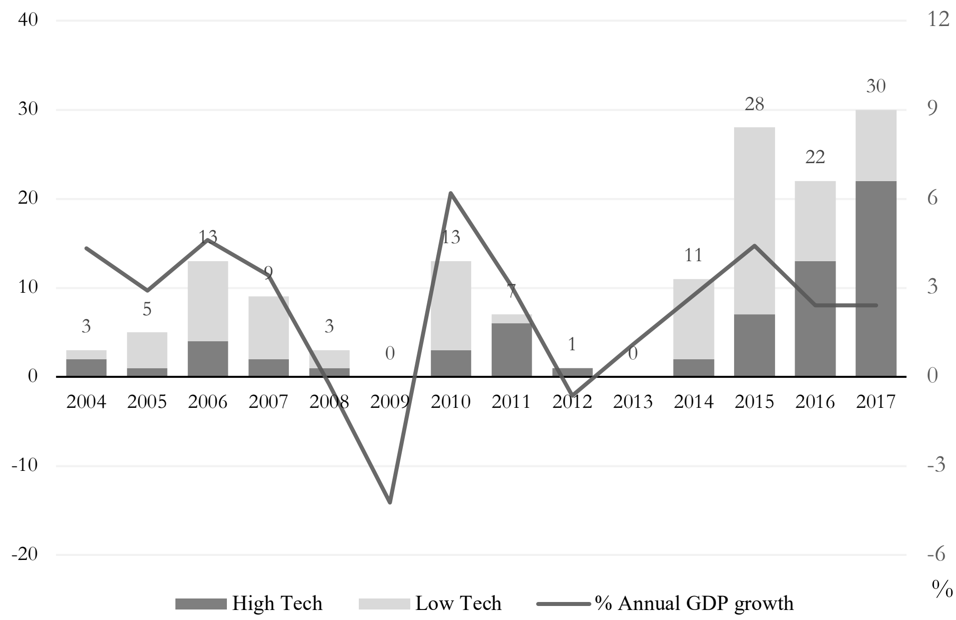

Figure 1 shows the distribution of IPOs per year and industry group for our sample of high-tech and low-tech firms going public on the Swedish stock exchanges between 2004-2017 (left axis), as well as the % Annual GDP growth in Sweden between 2004-2017 (right axis). The bars illustrate the total number of IPOs each year, distributed by high-tech companies (marked in lighter shading) and low-tech companies (marked in darker shading). The line shows the % Annual GDP growth obtained from the World Bank and is indicated on the right axis.

Table 6 shows descriptive statistics of underpricing and long-run post-IPO performance defined as Buy-and-Hold Abnormal Returns ("BHAR") on a one-, two- and three-year basis. The table reports winsorized values of BHAR by the 5th and 95th percentiles. The variables are winsorized as means are sensitive to extreme outliers, which can largely skew the results. When studying returns specifically, there is a limited downside and an unlimited upside, which potentially can bias the mean towards extreme positive outliers. Considering our sample size where e.g. three-year BHAR had 82 observations, a winsorizing of e.g. the 1st and 99th percentiles would not affect the data. Therefore, we apply a winsorizing of the 5th and 95th percentiles. It is important to note that abnormal returns for one, two, and three years are not directly comparable, given that the later period includes the former periods. Lastly, the reduction in the number of observations used to measure BHAR is further described in section 4.3.

Table 6: Sample Descriptive Statistics

Variable	N	mean	min	25th percentile	median	75th percentile	max
BHAR 1 year	144	0.0261	-0.707	-0.256	-0.00740	0.249	1.064
BHAR 2 years	109	0.0862	-0.880	-0.372	0.0367	0.505	1.392
BHAR 3 years	82	0.131	-0.868	-0.438	0.0617	0.458	1.805
Underpricing	145	-0.0873	-0.913	-0.261	-0.0674	0.0839	1.224

Table 6 illustrates the sample size, mean, median, 25th percentile, 75th percentile, as well as maximum and minimum values of underpricing and winsorized Buy-and-Hold Abnormal Returns ("BHAR"). Underpricing is defined as the percentage change from the issuing firm's offer price to the closing price on the first day of trading. BHAR, presented in one, two, and three years, is defined as the difference in return of the security and an industry benchmark over a given period of time.

4 Methodology

The following section explores in detail the methods used in our model to answer our research question. The calculations in focus are underpricing presented in section 4.1 and Buy-and-Hold Abnormal Returns presented in sections 4.2 to 4.3. Section 4.4 presents our methodology of categorizing the companies in our sample as high tech or low tech. Lastly, the regression used to answer our research question is presented and discussed in detail in section 4.5.

4.1 Underpricing

Underpricing is defined as the first-day return, calculated as the change between the offer price of the IPO and the closing price on the first day of trading. The level of underpricing for each security is calculated as follows:

$$Underpricing_i = \frac{P_{i,t=0}}{P_{i,offer}} - 1 \tag{1}$$

where $P_{i,t}$ is the closing price of security i at time $t=0$ and $P_{i,offer}$ is the corresponding security's offer price. According to the efficient market hypothesis, first-day returns greater than zero indicates that a security is listed below its fair value. In general, first-day returns of IPOs are referred to as underpricing. However, an observed first-day return less than zero should be referred to as overpricing.

4.2 Buy-and-Hold Returns

To assess the post-IPO return of each individual firm, we use Buy-and-Hold Returns (BHR). This method is used in several previous studies of post-IPO performance (Ritter 1991; Brav and Gompers 1997). This method reflects the case where an investor buys the security immediately after the company is taken public and holds it until the end of the selected time period, or until the company is delisted if that occurs before the end of the selected time period. The period used is three years post IPO using an event-time approach, as is in line with previous studies (e.g. Ritter 1991).

The daily returns for each security are calculated as the ratio between the daily closing price of day t and day t-1, starting with the closing price of the first trading day. In comparison to using the issue price, the closing price of the first trading day more closely resembles an investor buying the stock post issue and thus provides a better measurement of aftermarket performance. This method is also used in previous studies (e.g. Ritter, 1991). The daily return for each security is calculated as follows:

$$r_{i,t} = \frac{P_{i,t}}{P_{i,t-1}} - 1 \quad (2)$$

where $r_{i,t}$ is the daily return for stock i at time t, and P_{it} is the closing price for stock i at time t. The time period t is measured in daily increments. The BHR for each security is then calculated as follows:

$$BHR_{i,t} = \Pi_{t=1}^{T}[1 + r_{i,t}] \quad (3)$$

where $r_{i,t}$ is the daily return for security i calculated in equation 2 and T denotes the time period studied, which is 1, 2, and 3 years post IPO.

4.3 Abnormal Returns

In order to assess a security's abnormal return, we adjust the BHR of each security by a benchmark. By looking at securities' relative performance to a benchmark, the factor of systematic volatility can be mitigated so that idiosyncratic factors can be investigated to a larger extent. Two common metrics used in the event-time approach to measuring abnormal returns are Cumulative Abnormal Returns ("CAR") and Buy-And-Hold Abnormal Returns ("BHAR"). In a widely cited study, Barber and Lyon (1997) compares the methods and argue for the use of BHAR since CAR leads to biased predictions of abnormal returns, though BHAR also showed negatively biased test statistics (Barber and Lyon 1997). In this paper, we use BHAR to measure abnormal returns.

4.3.1 Industry Benchmark

Previous literature uses different methodologies as their benchmark for calculating BHAR, such as finding matching companies of similar size and industry for each IPO when studying the U.S. market (Ritter 1991). The Swedish stock market is however considerably smaller which makes it difficult to find reference companies for each individual security. Bergström et al. (2006) addressed the importance of finding a benchmark exposed to the same fundamental risks as the IPOs and argues that broad market indices should be used for evaluating active investment strategies. The same method is used in this paper, with one addition: In order to encapsulate systematic risk, we use the expected return based on the Capital Asset Pricing Model ("CAPM") on an industry basis as our benchmark. By using average industry betas, we essentially construct an industry-specific benchmark for each security based on the OMXSPI index, which arguably better captures industry-specific abnormal returns as compared to using raw index returns.

4.3.2 CAPM Expected return

As in section 3.4.3, we define the market return as the daily return of the OMXSPI index, calculated as follows:

$$r_{m,t} = \frac{P_{m,t}}{P_{m,t-1}} - 1 \tag{4}$$

where $r_{m,t}$ is the daily return of the OMXSPI index at time t, and $P_{m,t}$ is the closing price of the index at time t. The time period t is measured in daily increments. The expected return for each industry benchmark is then calculated using the CAPM formula as follows:

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$$E(r_{b,t}) = r_{f,t} + \beta_b(r_{m,t} - r_{f,t}) \tag{5}$$

where $E(r_{b,t})$ is the expected daily return for benchmark industry b at time t. $r_{f,t}$ is the daily risk-free rate based on the yield of the 1-month Swedish treasury bill (SSVX1M) at time t. β_b is the average industry beta of the industry benchmark b, corresponding to the SIC code of security i. $r_{m,t}$ is the daily return of the OMXSPI index at time t.

4.3.3 Buy-and-Hold Abnormal Returns

In order to assess the relative performance of each IPO, the BHR is adjusted by the expected return for each security's industry benchmark to obtain the BHAR. As in 4.3.1, we use the expected return on an industry basis as our benchmark. The BHAR for each security is then calculated as follows:

$$BHAR_{i,t} = \Pi_{t=1}^{T}[1 + r_{i,t}] - \Pi_{t=1}^{T}[1 + E(r_{b,t})] \tag{6}$$

The first part of the equation is the BHR calculated in equation 3 where $r_{i,t}$ is the daily return for security i calculated in equation 2. The second part of the equation is the corresponding expected return for the industry benchmark $E(r_{b,t})$ derived from the CAPM in equation 5. T denotes the time period studied, which is 1, 2, and 3 years post IPO. Finally, the difference between the Buy-and-Hold Return of the security and the industry benchmark is calculated to obtain the BHAR for each security and the corresponding time period. A BHAR greater than zero indicates that the security outperforms the expected returns of its corresponding industry benchmark as predicted by CAPM, and vice versa.

Since the exact corresponding calendar date in the years following the IPO may occur on a non-trading day, i.e. weekends or bank holidays, we define one year ($T=1$) as being 251 trading days. The average trading days per year during the time period are 251.33 (FESE, 2020). While this method results in marginal errors in calendar dates, it ensures that data can be collected and compared in a standardized way for each security.

To limit the effect of survivor bias, companies delisted during the three-year period are included by calculating the return of the security and the benchmark until the year prior to delisting. This approach is in line with previous literature (Ritter, 1991; Loughran and Ritter, 1995).

Furthermore, as trading data is obtained until the 31st of December 2018, three-year returns will be missing for IPOs during 2016, and two- and three-year returns will be missing for IPOs during 2017. Due to the vast increase in IPO activity during 2015, 2016, and 2017, constituting 55% of our sample, we chose to include IPOs from that period in our sample in order to be able to investigate the effect of a hot market on underpricing and post-IPO performance. This results in a smaller sample of IPOs included in the later time periods of BHAR. Hence, the periods should be analyzed independently. However, given that the focus of this study is in the difference between high-tech and low-tech firms within the same measurement periods, rather than the relationship between different periods, this does not interfere with our analysis.

4.4 Industry Classification

To determine if the IPOs would be considered as high-tech or low-tech, we use the SIC codes provided by SDC. Kile and Philips (2009) use SIC codes to find the optimal categorization of codes to reduce sampling errors when matching their defined benchmark sample of high-tech companies. Their results provide three-digit combination SIC codes, categorized into eleven different high-tech industry groups. By applying the same methodology to our data sample, we receive the categorization presented in Table 7. The IPOs are then categorized into two main groups: high-tech if their SIC code is one of the eleven presented by Kile and Philips (2009), and low-tech otherwise. However, since SIC codes are based on traditional industries prior to the rise of tech companies in recent years, they may fail to capture what today is commonly referred to as tech companies. While this issue exists, this approach secures a standardized and unbiased methodology of classifying companies.

Table 7: Distribution of IPOs by three-digit SIC-Code Category

SIC	Industry Name	Frequency	%	Cumulative %
–	Low Tech	81	55.86	55.86
283	Drugs	19	13.10	68-97
366	Computer and Office Equipment	3	2.07	71.03
367	Communication Equipment	3	2.07	73.10
384	Electric Components and Accessories	8	5.52	78.62
481	Laboratory, Optic, Measure and Control Instruments	2	1.38	80.00
489	Surgical, Medical and Dental Instruments	1	0.69	80.69
737	Computer Programming, Data Processing etc.	25	17.24	97.93
873	Miscellaneous Communication Services	3	2.07	100.00

Distribution of IPOs per high-tech SIC-code category. The classification for high-tech companies, developed by Kile and Philips (2009) divides the original SIC codes into eleven high-tech industries, whereof we have obsevations for eight. There are two dominant categories; Drugs (283) and Computer Programming, Data Processing (737), with the eleven high-tech categories constituting 44% of total IPOs in the sample. Companies with other SIC codes are considered low tech, constituting 56% of the sample.

4.5 Ordinary Least Squares Regression

To examine differences in underpricing and long-run post-IPO performance of classifying a company as high-tech, we apply multiple ordinary least squares ("OLS") regression models. This method enables us to include control variables in order to truly understand the effect of classifying a company as high-tech. We perform multiple regressions for four dependent variables; Underpricing, and BHAR for each time period: $BHAR_{1\ year}$, $BHAR_{2\ years}$, and $BHAR_{3\ years}$. The following independent variables are included in our regression:

$High\_Tech_i$ is a dummy variable taking a value of 1 if the company is classified as a high-tech company based on the three-digit SIC-code classification developed by Kile and Philips (2009), and 0 otherwise. Given our research question, this will be the variable of focus. A positive coefficient (β_1) can be interpreted as high-tech companies being relatively more underpriced or having a relatively higher BHAR than low-tech companies. The method of using SIC codes to classify industries and then including them as an independent variable in a regression is similar to the method used by Ritter (1991) and Loughran and Ritter (2004).

$Exchange_i$ is a dummy variable taking a value of 1 if the company was listed on OMX Stockholm at the time of the IPO and 0 if the company was listed on either First North, Aktietorget, Nordic Growth Market and Nordic MTF. OMX Stockholm is the exchange where larger companies most commonly get listed (large- and mid-cap) while smaller companies, typically growth companies (small- and micro-cap), are usually listed on the other exchanges. The use of this control variable is supported by the results of Loughran (1993), showing that securities listed on NYSE, typically characterized as larger value companies, outperformed securities listed on NASDAQ, typically characterized as smaller growth companies, during the 1973-1988 period (Loughran, 1993). Similarly, smaller growth firms could be present to a larger extent on the small- and micro-cap markets in Sweden.

Hot_Market_i is a dummy variable taking a value of 1 if the company's shares were initially offered after 2014, and 0 if initially offered prior to or during 2014. The hot IPO market in Sweden is identified as 2015 and onwards, as we define hot markets as years with IPO count exceeding the upper quartile of our sample. As illustrated by figure 1, 80 out of 145 IPOs in our sample occurred during the defined hot market. The use of this control variable is supported by the results of Ritter (1984), showing that periods with a high number of IPOs tend to be associated with high average initial returns (Ritter, 1984). Furthermore, an increase in underpricing was previously observed during the dot-com era (Loughran and Ritter, 2004), which may suggest a similar increase in recent years due to indications of an approaching tech-boom (Maris, 2015).

$Financial\_Crisis_i$ is a dummy variable taking a value of 1 if the company's shares were initially offered during the 2007-2008 financial crisis, defined as between September 2007 and June 2009, and 0 otherwise. September

2007 marks the beginning of broader market indices declining globally as well as the beginning of the Federal Reserve's large interest rate cuts from 5.25% to 0.00-0.25% conducted over the 15 months from September 2007 to December 2008 (Federal Reserve, 2020). June 2009 marks the end of the great recession (National Bureau of Economic Research, 2020). In Figure 1, we can observe a macroeconomic downturn associated with a following decline in IPO activity, which can be expected to impact the performance of IPOs during this period. Furthermore, by including another time-based variable, we can further control for the financial crisis' effect on the non-hot market, as well as the impact of the largest macroeconomic event in our sample period.

Rather than including our event variables for the hot market and the financial crisis, we could instead control for year fixed effects. However, due to our small sample size with an uneven distribution of the number of IPOs per year, with some years exhibiting zero observations, we don't have the statistical power to run a fixed year effects regression. Therefore, we decided to run our regressions with the event variables to control for time-varying effects. For illustrative purposes, fixed year effect regressions can be found in Appendix 10.

The regressions are done in multiple steps, adding the control variables sequentially. Firstly, the regression only includes our focus variable **High_Tech$_i$.** Secondly, the robustness is tested by including the **Exchange$_i$** variable to account for the previously observed relationship between exchanges and the dependent variables. Thirdly, the robustness is further tested by including the **Hot_Market$_i$** variable in order to account for the previously observed effect of hot issue markets. Lastly, we include the **Financial_Crisis$_i$** variable to account for yet another time period with observed effects on IPO activity. The following regressions will be executed:

$$Underpricing_i = \alpha_i + \beta_1(High\_Tech_i) + \beta_2\,(Exchange_i) + \beta_3(Hot\_Market_i\,) + \beta_4(Financial\_Crisis_i)$$

$$BHAR_{1\,year,i} = \alpha_i + \beta_1(High\_Tech_i) + \beta_2\,(Exchange_i) + \beta_3(Hot\_Market_i\,) + \beta_4(Financial\_Crisis_i)$$

$$BHAR_{2\,years,i} = \alpha_i + \beta_1(High\_Tech_i) + \beta_2\,(Exchange_i) + \beta_3(Hot\_Market_i\,) + \beta_4(Financial\_Crisis_i)$$

$$BHAR_{3\,years,i} = \alpha_i + \beta_1(High\_Tech_i) + \beta_2\,(Exchange_i) + \beta_3(Hot\_Market_i\,) + \beta_4(Financial\_Crisis_i)$$

where β_n represents the regression coefficients and α_i represents the model's intercept.

Based on the results of the above regressions, which are in focus to answer our research question, there will be further regressions and tests performed.

5 Results

The following section presents the empirical results from our OLS regressions described in section 4.5 in relation to our research question. Initially, section 5.1 presents the results of our first regression and discusses the observed positive relationship between high-tech firms and the level of underpricing. Section 5.2. presents the obtained results from the second regression focusing on the relationship between post-IPO performance, measured by BHAR, and high-tech firms. Finally, an additional regression is performed focusing on the observed difference in underpricing during the hot market period of 2015-2017 presented in section 5.3.

5.1 Underpricing

To answer the first part of our research question, we run an ordinary least squares regression to examine the relationship between the level of underpricing and the independent variables defined in section 4.5. Initially, the regression is run using only our variable of focus, the dummy variable for high-tech firms, and grows to include further control variables. The results are shown in Table 8.

Table 8: Regression of Underpricing on Several Variables

Underpricing	1	2	3	4
High_Tech	0.119* (0.060)	0.121** (0.060)	0.085 (0.057)	0.085 (0.057)
Exchange		0.010 (0.056)	0.034 (0.053)	0.034 (0.053)
Hot_Market			0.228*** (0.054)	0.228*** (0.060)
Financial_ Crisis				-0.001 (0.067)
Intercept	-0.140*** (0.030)	-0.146*** (0.049)	-0.267*** (0.057)	-0.267*** (0.062)
Obs.	145	145	145	145
R-squared	0.029	0.029	0.132	0.132

***** p<0.01, ** p<0.05, * p<0.1**

Table 8 shows the results for the multiple OLS regression analysis of the dependent variable "Underpricing" for our sample of high-tech and low-tech firms going public on the Swedish stock exchanges between 2004-2017. The dependent variable "Underpricing" is defined as the first-day return calculated as the ratio between the closing price on the first day of trading and the offer price of the IPO. The variable "High_Tech" is a dummy variable taking a value of 1 if the company is classified as a high tech based on the three-digit SIC-code classification developed by Kile and Philips (2009), and 0 otherwise. The variable "Exchange" is a dummy variable taking a value of 1 if the company was listed on OMX Stockholm at the time of the IPO and 0 otherwise. The variable "Hot_Market" is a dummy variable taking a value of 1 if the company's shares were initially offered post 2014, and 0 otherwise. The variable "Financial_Crisis" is a dummy variable taking a value of 1 if the company's shares were initially offered during the 2007-2008 financial crisis, defined as between September 2007 and June 2009, and 0 otherwise. "Intercept" is the mean of the dependent variable when all other variables are 0. "Obs" shows the number of observations in the regression. "R-squared" represents the proportion of the variance for the dependent variable that is explained by the independent variables. The results show estimates for the β_n coefficients and can be interpreted as the change in the dependent variable if the corresponding independent variable increases by 1, holding the other independent variables constant. The asterisks indicate the significance level as stated above. The parentheses show corresponding robust standard errors.

In Table 8, the initial results presented in columns 1 and 2 show that high-tech firms' initial offerings were relatively more underpriced than low-tech firms at a significance level of 5 %. The positive coefficient implies a firm being categorized as high-tech increases the level of underpricing by 12.1% on average. However, when adding our control variable for the hot market period, the coefficient for high-tech firms loses its statistical significance[2]. The results imply that the initially observed difference between high-tech and low-tech firms is rather explained by the hot-market period. These results will be further examined in section 5.3.

The results further show that companies going public during the hot-market period exhibits a higher degree of underpricing. The positive coefficient is significant at a 1% significance level and is still robust after controlling for the other event effect, the financial crisis. This indicates that firms going public between the years of 2015-2017 were relatively more underpriced in comparison to firms going public during the remainder of the studied period. A noteworthy observation is a vast increase in the R-squared values when the hot-market variable is included, indicating a strong explanatory power in relation to other variables. Furthermore, the relatively low R-squared value of 0.132 is not surprising given the specification of our model and the huge number of possible explanatory variables affecting public share price data.

To conclude, while we do not find robust support for that categorizing a company as high tech affects underpricing, we will further investigate the hot market phenomenon in section 5.3.

5.2 Post-IPO Performance

In order to test the second part of our research question, we run ordinary least squares regressions to examine the relationship between post-IPO performance, measured by BHAR on a one, two, and three-year basis, and the independent variables defined in section 4.5. Following the same procedure as in the previous section, the regression is run using our variable of focus and our control variables. The results are presented in Table 9, with a more detailed stepwise regression for each period presented in appendix 4.

Table 9 shows that classifying a company as high tech, although not significant, has a negative effect on BHAR. When adding our control variables for the exchange, the hot market period, and the financial crisis period, the high-tech coefficient is still not significant. The results further show that companies going public during the hot-market period exhibits higher two-year abnormal returns. The positive coefficient is significant at a 1% significance level, after including all control variables. This indicates that firms going public in 2015 and 2016 outperformed the OMXSPI benchmark at a higher level than firms going public during the remainder of the studied period. A noteworthy observation is

[2] When including all control variables, the coefficient of the High_Tech variable is showing a p-value of 0.139 presented in appendix 11.

that when adding the hot market dummy, the R-squared value does not increase at the same magnitude as in Table 8 when using underpricing as our dependent variable. This suggests that IPOs during hot markets do not explain abnormal returns to the same degree as it explains underpricing. One should however note that abnormal returns, unlike underpricing, are already adjusted by the OMXSPI index and thus encapsulate some macroeconomic impact on the financial markets. Furthermore, when comparing Tables 8 and 9 we can observe an inverse sign of the high-tech variable's coefficient, which may suggest an indication of an inverse relationship between underpricing and BHAR for high-tech firms.

To conclude, we do not find support for that categorizing a company as high tech affects long-run post-IPO performance on either a one-, two-, or three-year basis.

Table 9: Regression of BHAR on Several Variables and Time Periods

BHAR	BHAR 1 year	BHAR 2 years	BHAR 3 years
High_Tech	-0.073	-0.092	-0.143
	(0.087)	(0.126)	(0.175)
Exchange	0.041	0.058	-0.036
	(0.084)	(0.122)	(0.171)
Hot_Market	0.091	0.246**	0.129
	(0.078)	(0.120)	(0.174)
Financial_Crisis	-0.043	0.061	-0.171
	(0.123)	(0.211)	(0.200)
Intercept	-0.010	-0.029	0.174
	(0.085)	(0.130)	(0.170)
Obs.	144	109	82
R-squared	0.018	0.042	0.029
	***** p<0.01, ** p<0.05, * p<0.1**		

Table 9 shows the results for the multiple OLS regression of the dependent variable "Buy-and-Hold Abnormal Returns" ("BHAR") on a one-, two-, and three-year basis for our sample of high-tech and low-tech firms going public on the Swedish stock exchanges between 2004-2017. The dependent variable "BHAR" is defined as the Buy-and-Hold Return of a security less the expected return of its corresponding industry benchmark. The variable "High_Tech" is a dummy variable taking a value of 1 if the company is classified as a high tech based on the three-digit SIC-code classification developed by Kile and Philips (2009), and 0 otherwise. The variable "Exchange" is a dummy variable taking a value of 1 if the company was listed on OMX Stockholm at the time of the IPO and 0 otherwise. The variable "Hot_Market" is a dummy variable taking a value of 1 if the company's shares were initially offered post 2014, and 0 otherwise. The variable "Financial_Crisis" is a dummy variable taking a value of 1 if the company's shares were initially offered during the 2007-2008 financial crisis, defined as between September 2007 and June 2009, and 0 otherwise. "Intercept" is the mean of the dependent variable when all other variables are 0. "Obs" shows the number of observations in the regression. "R-squared" represents the proportion of the variance for the dependent variable that is explained by the independent variables. The results show estimates for the β_n coefficients and can be interpreted as the change in the dependent variable if the corresponding independent variable increases by 1, holding the other independent variables constant. The asterisks indicate the significance level as stated above. The parentheses show corresponding robust standard errors.

5.3 Hot-Market Effect on Underpricing

As presented in section 5.1, we observe a higher degree of underpricing during the hot-market period of 2015-2017 in relation to the preceding period of 2004-2014. This section aims to further investigate these findings by running an additional regression including an interaction term of the hot market and high-tech variables.

Figure 2: Distribution of Underpricing per Year and Industry Category

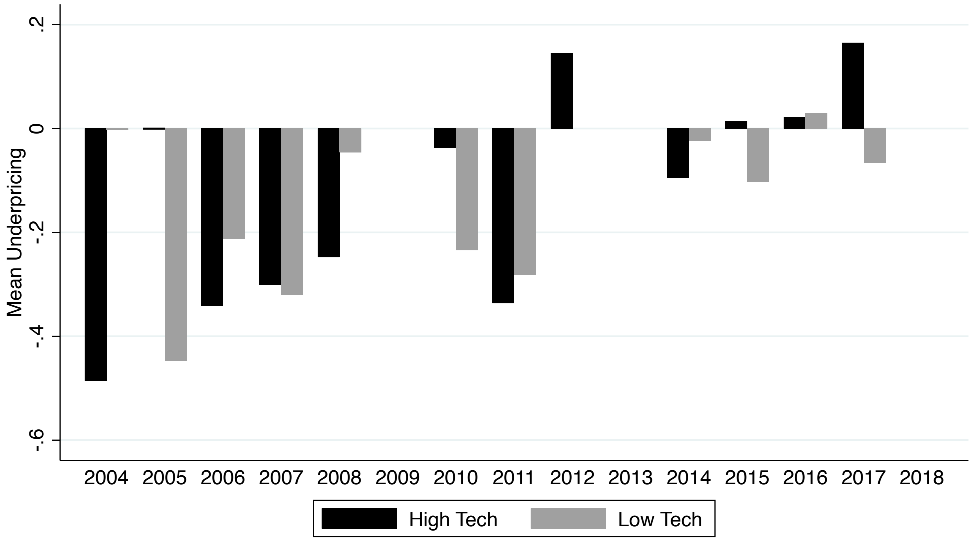

Figure 2 shows the distribution of the mean level of underpricing per year and industry group for our sample of high-tech and low-tech firms going public on the Swedish stock exchanges between 2004-2017.

As illustrated in figure 2, we can see indications of an increase in the mean level of underpricing over time, moving from overpricing, validated in appendix 10, to underpricing in the later years. Furthermore, as observed in section 5.1, the results imply that the initially observed difference between high-tech and low-tech firms is rather explained by the hot-market period. To examine whether a firm being categorized as high-tech explains the observed increase in underpricing during the hot-market period we included an interaction term in our regression:

$$Interaction_i = (High\_Tech_i \times Hot\_Market_i\ )$$

$$Underpricing_i = \alpha + \beta_1(High\_Tech_i) + \beta_2\,(Exchange_i) + \beta_3(Hot\_Market_i\ ) + \beta_4(Financia\_Crisis_i) + \beta_5(Interaction_i)$$

In column 5 in the regression presented in Table 10, the coefficient of the interaction variable illustrates the difference in the level of underpricing between high-tech and low-tech companies during the hot-market period. The coefficient of our high-tech variable now illustrates the effect on the level of underpricing of a company being classified as high-tech before 2015. Likewise, the coefficient of the hot-market variable illustrates the effect on the level of underpricing of a company being classified as low tech during the hot-market period.

Table 10: Regression of Underpricing with Interaction Term

Underpricing	1	2	3	4	5
High_Tech	0.119*	0.121**	0.085	0.085	-0.035
	(0.060)	(0.060)	(0.057)	(0.057)	(0.092)
Exchange		0.010	0.034	0.034	0.050
		(0.056)	(0.053)	(0.053)	(0.053)
Hot_Market			0.228***	0.228***	0.140**
			(0.054)	(0.060)	(0.062)
Financial_Crisis				-0.001	-0.007
				(0.067)	(0.062)
Interaction term					0.213*
					(0.118)
Intercept	-0.140***	-0.146***	-0.267***	-0.267**	-0.236***
	(0.030)	(0.049)	(0.057)	(0.062)	(0.062)
Obs.	145	145	145	145	145
R-squared	0.029	0.029	0.132	0.132	0.154

***** p<0.01, ** p<0.05, * p<0.1**

Table 10 shows the results for the multiple OLS regression analysis of the dependent variable Underpricing" for our sample of high-tech and low-tech firms going public on the Swedish stock exchanges between 2004-2017. The dependent variable "Underpricing" is defined as the first-day return calculated as the ratio between the closing price on the first day of trading and the offer price of the IPO. The variable "High_Tech" is a dummy variable taking a value of 1 if the company is classified as a high tech based on the three-digit SIC-code classification developed by Kile and Philips (2009), and 0 otherwise. The variable "Exchange" is a dummy variable taking a value of 1 if the company was listed on OMX Stockholm at the time of the IPO and 0 otherwise. The variable "Hot_Market" is a dummy variable taking a value of 1 if the company's shares were initially offered post 2014, and 0 otherwise. The variable "Financial_Crisis" is a dummy variable taking a value of 1 if the company's shares were initially offered during the 2007-2008 financial crisis, defined as between September 2007 and June 2009, and 0 otherwise. The variable "Interaction" is an interaction variable of the High_Tech and Hot_Market variables, taking a value of 1 if the company was classified as high tech and went public during the hot-market period post 2014, and 0 otherwise. "Intercept" is the mean of the dependent variable when all other variables are 0. "Obs" shows the number of observations in the regression. "R-squared" represents the proportion of the variance for the dependent variable that is explained by the independent variables. The results show estimates for the β_n coefficients and can be interpreted as the change in the dependent variable if the corresponding independent variable increases by 1, holding the other independent variables constant. The asterisks indicate the significance level as stated above. The parentheses show corresponding robust standard errors.

Table 10 indicates that a difference between the two groups only exists during the hot-market period at a significance level of 10%. During the hot-market period of 2015-2017, high-tech firms' initial offerings are relatively more underpriced. The positive coefficient of the hot-market variable in columns 3 and 4 shows that the hot-market period alone has a positive effect on the level of underpricing at a 1% significance level. When adding the interaction term in column 5, the coefficient of the hot-market variable is still robust at a 5% significance level, implying that the level of underpricing for low-tech firms increases by 14.0% during the hot-market period. Furthermore, the interaction term shows that the level of underpricing of high-tech firms increases even more. The positive coefficient of the interaction term implies that firms being categorized as high tech increases the level of underpricing by an additional 21.3% during the hot-market period compared to low-tech firms.

To conclude, we find that the hot-market period alone increases the level of underpricing, and that categorizing a company as high tech further increases the level of underpricing during the hot-market period.

6 Discussion

This section discusses our main findings, presented in section 5, in relation to the body of previous literature. Section 6.1 discusses potential explanations for the observed increase in underpricing for high-tech companies during hot markets. Section 6.2 addresses the observed overpricing and outperformance of Swedish IPOs. Finally, section 6.3 discusses future research and limitations.

6.1 Why Does Underpricing Increase for Tech-IPOs During Hot Markets?

Our results do not support a difference in long-run post-IPO performance between high-tech and low-tech firms, but they do support an increase in underpricing during the hot market period of 2015-2017. More specifically, our findings show an absolute increase in underpricing for both groups during this period and a relatively larger increase for high-tech firms.

Out initial results presented in Table 8 show a general increase in the level of underpricing for both high-tech and low-tech companies during the hot-market period. When including the interaction term presented in Table 10 we confirmed the general increase but more interestingly observed an increased difference between high-tech and low-tech IPOs during the hot market. More specifically, high-tech companies showed a larger increase in underpricing and were more underpriced relative to low-tech companies during the hot-market period.

The phenomenon of an increase in underpricing during hot markets was initially found by Ritter (1984) and was further confirmed by Loughran and Ritter (2004) and Helwege and Liang (2004). The relatively larger observed increase in underpricing for high-tech companies during a hot market period can also be considered to be in accordance with previous findings, where a cross-industry difference in the level of underpricing was found during the hot market of 1980 (Ritter, 1984). Since similar differences are found across time and markets, we can conclude that these results are not unique to our study.

The observed increase in the number of IPOs during the hot market, as illustrated in figure 1, may be an explanation of the general and tech-specific increase in underpricing. Recent research argues that the difference between hot and cold markets mainly exists in the quantity of offerings, rather than the characteristics of the firms going public (Helwege and Liang, 2004). Hence, with the large quantity and high ratio of high-tech IPOs during the hot-market period, one could expect high-tech offerings to exhibit an even larger increase in underpricing. A hot market driven by tech-companies could also imply the existence of a segmented issue market where firms in a booming industry are being subject to exploitive underwriters, as documented by Ritter (1984).

Hot markets have also been explained as a period where issuing firms are predominately high-risk companies (Ritter 1984). High-tech companies are generally associated with higher risk, as appendix 8 supports, which causes investors to require higher expected first-day returns (Rock, 1982). As an investment associated with higher risk implies a higher required return, the higher risk from high-tech companies can explain the increase in underpricing during the hot market period. However, further research needs to be conducted before this hypothesis can be validated.

As outlined in more recent research, there may be several other explanations of the increase in IPO activity and underpricing of high-tech firms during the hot-market period. For example, previous authors have explained the phenomena using traditional theories of supply and demand. On the supply side, Ljungqvist (2006) suggests that issuers are forced to lower their offer price during hot markets, causing an increase in underpricing. As volume increases, a higher number of issuers compete for investor sentiment, a resource short in supply. Hence, issuing tech companies must lower their offer price to a greater extent in order to compete for investor attention in an increasingly more saturated market of tech firms. On the demand side, hot markets have been explained as periods with especially high investor demand (Shefrin, 2002). The recent tech-bias amongst investors increase demand(Clark, 2015) and could explain the increase in underpricing concentrated to tech-companies during the hot market period, as it pushes first-day trading prices above its fair value.

6.2 Why does Sweden Demonstrate Overpricing and Outperformance?

As presented in Table 6 and validated in appendix 9, our results show that on average, the IPOs in our sample exhibited negative underpricing, i.e. overpricing, and outperformance on a two- and three-year basis, as defined by BHAR. In comparison with most previous research on the topic of IPOs, our findings may at first seem surprising. However, the studied time period begins after the dot-com era, where the majority of existing research ends. Compared to examinations including the dot-com era Swedish tech issues, as illustrated by figure 2, demonstrated poor first-day returns following the dot-com era. Furthermore, underpricing on the U.S. market has been documented to change over time, showing an increase until the peak of the dot-com bubble, and a decline in the following period (Loughran and Ritter, 2004). Following Westerholm's results (2006), our findings seem to follow a similar trend of a low level of underpricing following the dot-com bubble, which could be expected on the Swedish market due to its high ratio of tech IPOs. Hence, one could speculate that investors were more reluctant to invest in new tech issues after the dot-com bubble. The fact that investors are reluctant towards new initial offerings may cause them to not take part in IPOs despite offer prices being set below fair value. This could potentially explain the negative first-day returns, and the long-run post-IPO overperformance as prices revert to fair value.

6.3 Limitations and Future Research

Since IPOs on the Swedish market are less frequent than on the U.S market, the methods that we are able to use are affected. Hence, we are unable to include year fixed effects which otherwise is important to control for since previous studies show that underpricing and long-run post-IPO performance varies over time. The primary underlying reason for us being unable to include year fixed effects is that there are many years with very few observations, causing us to run out of statistical power. Although some of the time-varying effects are captured by including the hot-market and financial-crisis variables we may miss to control for other time-varying effects. Given a larger sample, our model would most likely benefit from including year fixed effects.

Furthermore, our method of classifying high-tech companies by SIC codes may not perfectly reflect what is commonly referred to as tech since SIC was initially developed for traditional industries. While classifying companies using their SIC codes allows for a structured and coherent way of categorizing companies with limited bias, another approach could be more efficient in correctly categorizing companies as high tech. For example, we could instead use R&D expenditures as a proxy.

As we currently cannot collect three-year data for companies listed in 2016 and two-year data for companies listed in 2017, we do not receive perfectly paired samples. Therefore, we are unable to investigate relationships between underpricing and long-run post-IPO performance, solely looking at the different periods independently. Future research would be able to investigate the two- and three-year BHAR of IPOs during the hot market period of 2015-2017 and would thus be able to investigate a potential relationship between underpricing and long-run post-IPO performance.

Finally, the indications of overpricing and outperformance may be explained by the sample size and the distribution of IPOs. As we present in figure 1, we have very few companies going public at the beginning of the period, which may skew the results. The later years of our sample period show that the level of overpricing decreases, eventually leading to underpricing, especially for high-tech companies during the observed hot-market period. Further research could study other geographical markets during the hot-market period to investigate whether a similar hot-market phenomenon can be found, either within tech or within another industry more frequent in that market.

7 Conclusions

This study examines whether categorizing a company as high tech can explain differences in long-run post-IPO performance and underpricing of companies listed on Swedish stock exchanges during the period of 2004-2017. We do not find support for a difference in long-run post-IPO performance. However, we document a difference in underpricing during the hot-market period of 2015-2017. Hence, as documented in the 1980s and 2000s, the phenomenon of a general increase in underpricing during hot markets continues to exist. Furthermore, in line with Ritter (1984), we find a cross-industry difference in the level of underpricing, with our hot-market increase being predominant to high-tech companies.

To conclude, the increase in underpricing during the hot-market period, particularly for high-tech companies, may have several explanations. While it is difficult to determine the best explanation in our case, we believe our findings to be a combination of two: Generally, the increased level of underpricing across the market may be the result of an increased quantity of offerings, forcing underwriters to set offer prices below fair value to compete for investors. For high-tech companies specifically, tech-biased investors increase demand causing first-day closing prices to rise above fair value, resulting in even higher first-day returns.

Given our results, a potential investment strategy would be to subscribe to high-tech IPOs during hot markets and sell the security at the closing price of the first day of trading. More specifically, when investors recognize an increase in the quantity of high-tech initial offerings, they should be more willing to take part in the IPOs, as offer prices are lower and first-day demand is higher.

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Appendix

Appendix 1: Detailed Descriptive Statistics of Underpricing and BHAR per Industry Group

Variable	mean	standard deviation	25th percentile	median	75th percentile
Underpricing $_{High\_Tech}$	-0.0210	0.415	-0.253	-0.0524	0.172
Underpricing $_{Low\_Tech}$	-0.140	0.273	-0.281	-0.0751	-0.00216
BHAR 1 year $_{High\_Tech}$	-0.0102	0.506	-0.345	-0.0913	0.210
BHAR 1 year $_{Low\_Tech}$	0.0551	0.408	-0.210	0.0527	0.259
BHAR 2 years $_{High\_Tech}$	0.0320	0.677	-0.531	-0.0987	0.496
BHAR 2 years $_{Low\_Tech}$	0.118	0.581	-0.333	0.0565	0.505
BHAR 3 years $_{High\_Tech}$	0.0252	0.795	-0.592	-0.149	0.446
BHAR 3 years $_{Low\_Tech}$	0.179	0.639	-0.262	0.125	0.480

Appendix 1 illustrates the sample size, mean, median, 25th percentile, 75th percentile, as well as maximum and minimum values of underpricing and winsorized values for Buy-and-Hold Abnormal Returns (BHAR), for the two groups of firms in our sample: high-tech and low-tech firms. Underpricing is defined as the first-day return calculated as the ratio between the closing price on the first day of trading and the offer price of the IPO. BHAR, presented on a one-, two-, and three-year basis, is defined as the Buy-and-Hold Return of a security less the expected return of its corresponding industry benchmark.

Appendix 2: Descriptive Statistics for Control Variables

Variable	Obs
High_Tech=1	64
High_Tech=0	81
Exchange=1	73
Exchange=0	72
Financial_Crisis=1	10
Financial_Crisis=0	135
Hot_Market=1	80
Hot_Market=0	65

Appendix 2 illustrates the number of observations for each value of each control variable. The variable "High_Tech" is a dummy variable taking a value of 1 if the company is classified as a high tech based on the three-digit SIC-code classification developed by Kile and Philips (2009), and 0 otherwise. The variable "Exchange" is a dummy variable taking a value of 1 if the company was listed on OMX Stockholm at the time of the IPO and 0 otherwise. The variable "Hot_Market" is a dummy variable taking a value of 1 if the company's shares were initially offered post 2014, and 0 otherwise. The variable "Financial_Crisis" is a dummy variable taking a value of 1 if the company's shares were initially offered during the 2007-2008 financial crisis, defined as between September 2007 and June 2009, and 0 otherwise.

Appendix 3: SIC Codes and Average Industry Betas

SIC	Beta	SIC	Beta	SIC	Beta
1522	0.79	3751	0.82	6722	1.00
1531	0.79	3841	1.12	6726	1.00
1711	0.79	3842	1.12	6799	0.56
1731	0.79	3845	1.12	7011	0.97
2015	0.71	3949	0.85	7311	0.90
2099	0.71	4724	0.96	7312	0.90
2331	0.85	4731	0.96	7319	0.90
2676	1.07	4812	0.90	7361	1.04
2834	0.92	4813	0.90	7371	1.05
2835	0.92	4841	1.19	7372	1.05
2836	0.92	4899	1.23	7374	1.05
2861	1.22	5045	1.20	7375	1.05
3069	1.26	5047	1.20	7376	1.05
3365	1.01	5074	1.20	7379	1.05
3442	1.39	5082	1.20	7382	1.06
3446	1.39	5085	1.20	7389	1.06
3448	1.39	5211	1.01	7991	0.83
3511	1.70	5611	0.85	7999	0.83
3559	1.31	5621	0.85	8051	0.75
3564	1.31	5712	1.08	8059	0.75
3634	0.86	5714	1.08	8062	0.75
3646	1.34	6000	0.50	8069	0.75
3663	1.36	6282	0.84	8299	1.31
3674	1.29	6289	0.84	8711	1.13
3678	1.29	6311	1.20	8731	1.12
3679	1.29	6512	0.49	8744	1.04
3711	1.55	6531	0.72	8748	1.04
3714	1.55	6552	0.79		

Appendix 3 shows SIC codes and corresponding European average industry betas in our sample of IPOs. The industry betas were obtained from Professor Damodaran of Stern School of Business's database. These industry betas are constructed from raw data from Capital IQ. The betas are conducted on an average five-year and two-year weekly regression basis, where two thirds are weighted on the last two years.

*Please note that Beta was matched with the first three digits of the SIC codes. Hence, some four-digit SIC codes in our sample will have the same industry beta.

Appendix 4: Stepwise Regression for BHAR with Several Variabels

BHAR 1 year	(1)	(2)	(3)	(4)
High_Tech	-0.065	-0.057	-0.072	-0.073
	(0.078)	(0.087)	(0.087)	(0.087)
Exchange		0.032	0.041	0.041
		(0.085)	(0.084)	(0.084)
Hot_Market			0.098	0.091
			(0.074)	(0.078)
Financial_Crisis				-0.043
				(0.123)
Intercept	0.055	0.036	-0.017	-0.010
	(0.046)	(0.081)	(0.083)	(0.085)
Obs.	144	144	144	144
R-squared	0.005	0.006	0.017	0.018
BHAR 2 years	(1)	(2)	(3)	(4)
High_Tech	-0.086	-0.081	-0.093	-0.092
	(0.128)	(0.131)	(0.125)	(0.126)
Exchange		0.032	0.057	0.058
		(0.127)	(0.122)	(0.122)
Hot_Market			0.237**	0.246**
			(0.116)	(0.120)
Financial_Crisis				0.061
				(0.211)
Intercept	0.118*	0.099	-0.019	-0.029
	(0.070)	(0.124)	(0.130)	(0.130)
Obs.	109	109	109	109
R-squared	0.005	0.005	0.042	0.042
BHAR 3 years	(1)	(2)	(3)	(4)
High_Tech	-0.154	-0.156	-0.141	-0.143
	(0.177)	(0.176)	(0.175)	(0.175)
Exchange		-0.047	-0.030	-0.036
		(0.173)	(0.170)	(0.171)
Hot_Market			0.158	0.129
			(0.166)	(0.174)
Financial_Crisis				-0.171
				(0.200)
Intercept	0.179**	0.208	0.141	0.174
	(0.086)	(0.159)	(0.160)	(0.170)
Obs.	82	82	82	82
R-squared	0.011	0.012	0.023	0.029

****** p<0.01, ** p<0.05, * p<0.1***

Appendix 4 shows the results for the multiple OLS regression for "Buy-and-Hold Abnormal Return" ("BHAR") on a one-, two-, and three-year basis for our sample of high-tech and low-tech firms going public on Swedish stock exchanges between 2004-2017. The dependent variable BHAR is defined as the Buy-and-Hold Return of a security less the expected return of its corresponding industry benchmark. The variable "High_Tech" is a dummy variable taking a value of 1 if the company is classified as a high tech based on the three-digit SIC-code classification developed by Kile and Philips (2009), and 0 otherwise. The variable "Exchange" is a dummy variable taking a value of 1 if the company was listed on OMX Stockholm at the time of the IPO and 0 otherwise. The variable "Hot_Market" is a dummy variable taking a value of 1 if the company's shares were initially offered post 2014, and 0 otherwise. The variable "Financial_Crisis" is a dummy variable taking a value of 1 if the company's shares were initially offered during the 2007-2008 financial crisis, defined as between September 2007 and June 2009, and 0 otherwise. "Obs" shows the number of observations in the regression. "R-squared" represents the proportion of the variance for the dependent variable that is explained by the independent variables. The results show estimates for the β_n coefficients and can be interpreted as the percentage change in the dependent variable if the corresponding independent variable increases by 1, holding the other independent variables constant. The asterisks indicate the significance level as stated above. The parentheses show corresponding robust standard errors.

Appendix 5: VIF - Underpricing Regression

Underpricing	VIF	1/VIF
Hot_Market	1.145	.873
Financial_Crisis	1.101	.908
High_Tech	1.097	.911
Exchange	1.082	.924
Mean VIF	1.106	.

Appendix 5 illustrates the Variance Inflation Factor ("VIF") value of a regression with "Underpricing" as the dependent variables and the following independent variables: The variable "High_Tech" is a dummy variable taking a value of 1 if the company is classified as a high tech based on the three-digit SIC-code classification developed by Kile and Philips (2009), and 0 otherwise. The variable "Exchange" is a dummy variable taking a value of 1 if the company was listed on OMX Stockholm at the time of the IPO and 0 otherwise. The variable "Hot_Market**"** is a dummy variable taking a value of 1 if the company's shares were initially offered post 2014, and 0 otherwise. The variable "Financial_Crisis" is a dummy variable taking a value of 1 if the company's shares were initially offered during the 2007-2008 financial crisis, defined as between September 2007 and June 2009, and 0 otherwise. The VIF values correspond to the regression illustrated in Table 8.

Appendix 6: VIF - BHAR Regressions

BHAR 1 year	VIF	1/VIF
Hot_Market	1.144	.874
Financial_Crisis	1.104	.906
High_Tech	1.094	.914
Exchange	1.078	.928
Mean VIF	1.105	.
BHAR 2 years	VIF	1/VIF
Hot_Market	1.099	.91
Financial_Crisis	1.083	.923
High_Tech	1.032	.969
Exchange	1.022	.978
Mean VIF	1.059	.
BHAR 3 years	VIF	1/VIF
Hot_Market	1.09	.917
Financial_Crisis	1.068	.936
High_Tech	1.018	.982
Exchange	1.009	.991
Mean VIF	1.047	.

Appendix 6 illustrates the Variance Inflation Factor ("VIF") value of a regression with "BHAR" as the dependent variable and the following independent variables: The variable "High_Tech" is a dummy variable taking a value of 1 if the company is classified as a high tech based on the three-digit SIC-code classification developed by Kile and Philips (2009), and 0 otherwise. The variable "Exchange" is a dummy variable taking a value of 1 if the company was listed on OMX Stockholm at the time of the IPO and 0 otherwise. The variable "Hot_Market**"** is a dummy variable taking a value of 1 if the company's shares were initially offered post 2014, and 0 otherwise. The variable "Financial_Crisis" is a dummy variable taking a value of 1 if the company's shares were initially offered during the 2007-2008 financial crisis, defined as between September 2007 and June 2009, and 0 otherwise. The VIF values correspond to the regressions illustrated in Table 9.

Appendix 7: VIF – Underpricing (incl. interaction term) regression

Underpricing	VIF	1/VIF
Interaction	3.636	.275
High_Tech	2.463	.406
Hot_Market	1.891	.529
Exchange	1.109	.902
Financial_Crisis	1.102	.908
Mean VIF	2.04	.

Appendix 7 illustrates the Variance Inflation Factor ("VIF") value of a regression with "Underpricing" as the dependent variable and the following independent variables: The variable "High_Tech" is a dummy variable taking a value of 1 if the company is classified as a high tech based on the three-digit SIC-code classification developed by Kile and Philips (2009), and 0 otherwise. The variable "Exchange" is a dummy variable taking a value of 1 if the company was listed on OMX Stockholm at the time of the IPO and 0 otherwise. The variable "Hot_Market**"** is a dummy variable taking a value of 1 if the company's shares were initially offered post 2014, and 0 otherwise. The variable "Financial_Crisis" is a dummy variable taking a value of 1 if the company's shares were initially offered during the 2007-2008 financial crisis, defined as between September 2007 and June 2009, and 0 otherwise. The variable "Interaction" is an interaction variable of the High_Tech and Hot_Market variables, taking a value of 1 if the company was classified as high tech and went public during the hot-market period post 2014, and 0 otherwise. The VIF values correspond to the regressions illustrated in Table 10.

Appendix 8: standard deviation

Annual standard deviation	mean	median
High-tech companies	0.702	0.504
Low-tech companies	0.560	0.360

Appendix 8 illustrates the annual mean and median standard deviation of high-tech and low-tech companies in our sample.

Appendix 9: T-tests

One-sample t-test for Underpricing

	obs	Mean	St_Err	t_value
Underpricing	145	-.087	.029	-3.05
Ha: mean < 0		Ha: mean != 0	Ha: mean > 0	
Pr(T < t) = 0.0015		Pr(|T| > |t|) = 0.0029	Pr(T > t) = 0.9985	

One-sample t-test for BHAR 1 year

	obs	Mean	St_Err	t_value
BHAR1	144	.026	.038	.7
Ha: mean < 0		Ha: mean != 0	Ha: mean > 0	
Pr(T < t) = 0.7540		Pr(|T| > |t|) = 0.4920	Pr(T > t) = 0.2460	

One-sample t-test for BHAR 2 years

	obs	Mean	St_Err	t_value
BHAR2	109	.086	.059	1.45
Ha: mean < 0		Ha: mean != 0	Ha: mean > 0	
Pr(T < t) = 0.9264		Pr(|T| > |t|) = 0.1472	Pr(T > t) = 0.0736	

One-sample t -test for BHAR 3 years

	obs	Mean	St_Err	t_value
BHAR3	82	.131	.076	1.7
Ha: mean < 0		Ha: mean != 0	Ha: mean > 0	
Pr(T < t) = 0. 9545		Pr(|T| > |t|) = 0. 0910	Pr(T > t) = 0. 0455	

Appendix 9 shows T-tests for underpricing and BHAR. Underpricing is defined as the first-day return calculated as the ratio between the closing price on the first day of trading and the offer price of the IPO. BHAR is defined as the Buy-and-Hold Return of a security less the expected return of its corresponding industry benchmark. The table shows the number of observations, mean, standard error, and t statistic. In the fourth row of the table, p-values of three alternative hypotheses are illustrated. Row 3, furthest to the left shows the hypothesis of the mean of the variable being less than zero, the middle shows the hypothesis of the mean deviating from zero and furthest to the right shows the hypothesis of the mean being greater than zero.

Appendix 10: Fixed Effects Regressions

The table below illustrates regressions run with year fixed effects. In columns 3 and 4 where N_{year} (number of IPOs in a calendar year) is higher than 15.25 (the upper quartile of all the years with observations higher than zero). This demonstrates the effect of running regressions with year fixed effects if we would have had a larger number of observations per year. Although, we cannot draw any conclusions from these regressions, they illustrate that when a fixed year regression is performed with N_{year}>15.25 we see a significant effect of all variables. This could imply that with our small sample size, we have less statistical power and run a higher risk of type II errors.

	"As-is" (N_{year}>0)		If N_{year}>15.25	
	(1) BHAR3	(2) Underpricing	(3) BHAR3	(4) Underpricing
High_Tech	-0.098	0.080	0.239	0.168*
	(0.183)	(0.064)	(0.334)	(0.085)
Exchange	-0.117	0.057	-0.014	0.134*
	(0.174)	(0.062)	(0.293)	(0.079)
Intercept	0.231	-0.152***	0.192	-0.127*
	(0.145)	(0.054)	(0.233)	(0.074)
Obs.	82	144	27	80
R-squared	0.127	0.203	0.022	0.112

****** p<0.01, ** p<0.05, * p<0.1***

Appendix 10 shows the results for the fixed year effects multiple OLS regression for "Underpricing" and "BHAR3" for our sample of high-tech and low-tech firms going public on the Swedish stock exchanges between 2004-2017. Underpricing is defined as the first-day return calculated as the ratio between the closing price on the first day of trading and the offer price of the IPO. BHAR is defined as the Buy-and-Hold Return of a security less the expected return of its corresponding industry benchmark. Columns 1 and 2 illustrate the "as-is" scenario where all years with more than zero observations are included in the regression. Columns 3 and 4 illustrate the scenario where only the upper quartile of N_{year} (number of observations per year) is included, which corresponds to more than 15.25 IPOs. The variable "High_Tech" is a dummy variable taking a value of 1 if the company is classified as a high-tech based on the three-digit SIC-code classification developed by Kile and Philips (2009), and 0 otherwise. The variable "Exchange" is a dummy variable taking a value of 1 if the company was listed on OMX Stockholm at the time of the IPO and 0 otherwise. The results show estimates for the βn coefficients and can be interpreted as the percentage change in the dependent variable if the corresponding independent variable increases by 1, holding the other independent variables constant. The asterisks indicate the significance level as stated above. The parentheses show corresponding robust standard errors. The regression is performed using year fixed effects.

Appendix 11: P-Values for Regressions of Underpricing and BHAR with Several Variables

Underpricing	(1)	(2)
Variable	Coefficient	P-value
High_Tech	0.0845	0.139
Exchange	0.0336	0.527
Hot_Market	0.228	0.000201
Financial_Crisis	-0.00126	0.985

BHAR1	(1)	(2)
Variable	Coefficient	P-value
High_Tech	-0.0730	0.405
Exchange	0.0415	0.622
Hot_Market	0.0910	0.245
Financial_Crisis	-0.0431	0.727

BHAR2	(1)	(2)
Variable	Coefficient	P-value
High_Tech	-0.0924	0.463
Exchange	0.0581	0.636
Hot_Market	0.246	0.0427
Financial_Crisis	0.0614	0.772

BHAR3	(1)	(2)
Variable	Coefficient	P-value
High_Tech	-0.143	0.419
Exchange	-0.0361	0.833
Hot_Market	0.129	0.460
Financial_Crisis	-0.171	0.395

Underpricing	(1)	(2)
Variable	Coefficient	P-value
High_Tech	-0.0346	0.708
Exchange	0.0502	0.341
Hot_Market	0.140	0.0248
Financial_Crisis	-0.00698	0.911
Interaction	0.213	0.0742

Appendix 11 shows the coefficients and p-values of multiple OLS regressions for underpricing and $BHAR_t$ for our sample of high-tech and low-tech firms going public on the Swedish stock exchanges between 2004-2017. Underpricing is defined as the first-day return calculated as the ratio between the closing price on the first day of trading and the offer price of the IPO. BHAR is defined as the Buy-and-Hold Return of a security less the expected return of its corresponding industry benchmark. The variable "High_Tech" is a dummy variable taking a value of 1 if the company is classified as a high tech based on the three-digit SIC-code classification developed by Kile and Philips (2009), and 0 otherwise. The variable "Exchange" is a dummy variable taking a value of 1 if the company was listed on OMX Stockholm at the time of the IPO and 0 otherwise. The variable "Hot_Market" is a dummy variable taking a value of 1 if the company's shares were initially offered post 2014, and 0 otherwise. The variable "Financial_Crisis" is a dummy variable taking a value of 1 if the company's shares were initially offered during the 2007-2008 financial crisis, defined as between September 2007 and June 2009, and 0 otherwise. The variable "Interaction" is an interaction variable of the High_Tech and Hot_Market variables, taking a value of 1 if the company was classified as high tech and went public during the hot-market period post 2014, and 0 otherwise. The coefficients show estimates for the βn coefficients and can be interpreted as the percentage change in the dependent variable if the corresponding independent variable increases by 1

These coefficients and p-values correspond to the regressions illustrated in Tables 8, 9, and 10.