UNIVERSITY OF GOTHENBURG
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UNDERPRICING IN COLD AND HOT ISSUE MARKETS:

Testing the Changing Risk Composition Hypothesis on the Swedish IPO Market

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Abstract

This paper aims to investigate the difference in average first-day return on initial public offerings (IPOs) between the "cold issue" market of 2010-2013 and the "hot issue" market of 2014-2016 on the Swedish IPO market. IPOs during the hot issue market were subject to an average first-day return of 16.57 % compared to 6.02 % during the cold issue market. Among other theories and hypotheses trying to explain such swings in first-day returns over time, the changing risk composition hypothesis has been tested for in this thesis. Our results do not provide evidence that a larger fraction of riskier IPOs can serve as an explanation to the higher average first-day return in the hot issue market. However, looking into alternative potential explanations, we found that IPOs related to the information-technology industry could be central to the difference in average first-day returns.

Keywords: IPO, underpricing, first-day return, changing risk composition hypothesis, hot issue market, cold issue market, going public, risk

Contents

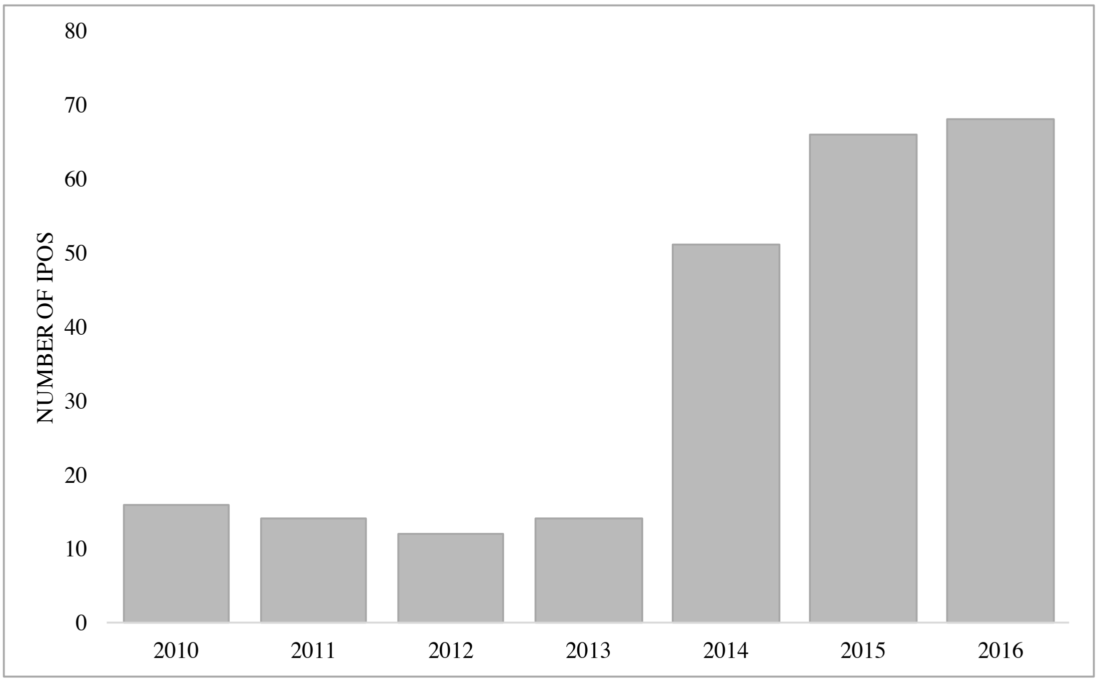
I. Introduction ... **1**
The Underpricing Phenomenon ... 2
Purpose Formulation ... 3
Structure of Paper ... 5
II. Theoretical Framework ... **5**
Asymmetric Information and Winner's Curse ... 5
Ex Ante Uncertainty ... 6
The Changing Risk Composition Hypothesis ... 7
III. Data and Methodology ... **9**
Quantitative Approach ... 9
Delimitations ... 9
Sample Selection and Sample Period ... 10
Variables and Data Sources ... 11
Underpricing ... 12
Assets and Sales ... 12
Age ... 13
Biotech ... 13
Private Equity ... 14
Method of Analysis ... 16
IV. Results and Analysis ... **17**
Cross-Sectional and Longitudinal Patterns ... 17
Regression Analysis ... 24
Another Explanation ... 27
V. Potential Biases and Robustness ... **29**
Sample Size ... 30
"Missing" IPOs ... 30
Outliers ... 32
Omitted Variables ... 33
VI. Conclusions ... **34**
References ... **37**
Appendix ... **41**

I. Introduction

Commencing in January 2014, the number of initial public offerings (IPOs) skyrocketed and the number of firms being floated 2014 beat the old record from 2000 (Affärsvärlden TT, 2014). This record did not hold for long; even more firms decided to go public the following year (Wrede, 2015). The wave continued in 2016, however, no records were broken. Still, in terms of the number of offerings the Swedish marketplaces were the most active in Europe (Cederblad, 2016). Illustrated in Figure 1 below, in comparison to the period between 2010 and 2013, the number of IPOs almost tripled during 2014 to 2016. Moreover, each year in the later period were subject to far more IPOs than each year in the earlier period. Thus, since January 2014 until December 2016, we find ourselves in something that can be described as a *hot issue market*.

Figure 1. Sample-Number of IPOs per Year

The sample includes IPOs listed on *Nasdaq Stockholm, First North* and *Aktietorget*. Listings that are not considered as "real" are excluded: spinoffs, parallel listings, firms that changed list, reverse mergers, mergers and preferred stock IPOs. Unit IPOs, REITs IPOs and IPOs classified as missing (relevant data could not be obtained) are also excluded. The sample size is 241 IPOs for 2010-2016.



Hot issue market refers to certain periods where IPO activity is subject to anomalies, more precisely the IPO market moves in cycles. According to Ibbotson and Jaffe (1975) and Ritter (1984), in comparison to *cold issue markets*, hot issue markets are periods over time with more IPOs and/or higher underpricing (calculated as a percentage change using the offer price of the new issue and the closing price on the initial day of trading). Ritter (1984) also observed that these hot issue markets featured larger proportions of smaller IPOs and concentrations of IPOs in specific sectors. In a more recent study, Ritter (1991) found that these hot issue markets are characterised by overoptimistic investors also, and therefore riskier firms take advantage of these "windows of opportunities." Recognising that the Swedish stock market reached an all-time high in 2015 (Trading Economics, n.d.), this is also coincident with the tendency of the abnormally high floating during market peaks, which was discovered by Loughran, Ritter and Rydqvist (1994).

The Underpricing Phenomenon

The process of going public is mainly about putting a value on the firm, which further implies deciding on the number and setting the price on the shares that will be on issue. Moreover, this evaluation is usually associated with a high level of uncertainty. Once the decision of going public has been made by the firm, the subsequent step is to contact an underwriting firm. This entity will cooperate with the issuing firm which involves the task of valuing the shares that either will be issued or sold by current owners. To determine an appropriate price, the underwriter engages in several activities. The first day of trading, comparing the offer price with the closing price, will reveal if the stock was mispriced or not. It can either be underpriced, overpriced (or remain the same), where the former refers to a positive first-day return and the latter a negative first-day return. A lot of research within the area of IPOs have been conducted on the price of the shares. Research shows that IPOs are underpriced on average and that underpricing fluctuates over time and most of the studies have been conducted on the U.S stock market (Ritter & Welch, 2002).

There are various theories trying to explain the underpricing phenomenon and these theories can be categorised into four branches: asymmetric information models, ownership and control, institutional explanations and behavioural reasons (Ljungqvist, 2007, p. 378). Central to this thesis is Rock's (1986) *winner's curse*. This theory tries to explain underpricing by information asymmetry, and it assumes that underpricing is explained by the investor demand side of the IPO transaction. Briefly, investors are divided into uninformed and informed. Having better information, informed investors only bid on IPOs perceived as attractively priced, conversely, uninformed bid indiscreetly. Therefore, uninformed investors are subject to a winner's curse. And depending on the magnitude, uninformed investors may pull-back from the IPO market and in order to guarantee a well-functioning IPO market, Rock (1986) argues that it relies on the participation of these. Thus, underpricing (in expectation) occurs as an equilibrium condition to elicit the demand of the uninformed investors. An implication of this model, introduced by Ritter (1984) and later formalised by Beatty and Ritter (1986), is the *ex ante* (prior) *uncertainty* regarding the value of an IPO. Ritter (1984) found a positive relation between risk and first-day return. Beatty and Ritter (1986) demonstrated that underpricing is expected to increase the greater is the ex ante uncertainty about the value of the issuing firm. An extension to these theories is the *the changing risk composition hypothesis*. During periods where the proportion of riskier IPOs (IPOs subject to more uncertainty) is larger than in other periods, the changing risk composition hypothesis predicts that average underpricing should increase during these periods (Loughran & Ritter, 2004). In addition, for this hypothesis to hold, the positive relation between risk and first-day return should be stationary (Ritter, 1984) (Loughran & Ritter, 2004).

Investigating why average underpricing has increased over time, Loughran and Ritter (2004) demonstrated that riskier IPOs could account for a small portion of this change. Even though Ritter (1984) could not conclude that the changing risk composition hypothesis could serve as an explanation to the abnormal underpricing during the hot issue market of 1980, Ritter (1984) found some evidence that this hot issue market included more high-risk offerings. Hence, in both papers, the underpricing during the abnormal periods were too high to be explained solely by the changing risk composition hypothesis.

Purpose Formulation

The sample period ranges from 2010 to 2016 and this period is further divided into two sub-periods based on the number of IPOs. The first sub-period covers January 1 2010 to December 31 2013 and is referred to as a cold issue market, whereas the other sub-period comprises January 1 2014 to December 31 2016 and is referred to as a hot issue market. In addition, pursuant to hot issue market characteristics, an assumption that the hot issue market would be subject to higher average underpricing was made. Collecting the necessary data needed to calculate the average level of underpricing, we found that this assumption holds. IPOs in 2014-2016 were underpriced on average by 16.57 % compared to 6.02 % concerning the cold issue market. This comparison in underpricing is not as definite as in other studies, for instance Ritter (1984), nevertheless, the difference is pronounced.

Even though the empirical research and literature on IPO underpricing is now seemingly mature and extensive in general (Ljungqvist, 2007, p. 380), the understanding of the dramatic changes in the extent of underpricing over time is not clear-cut, e.g. Loughran and Ritter (2004) and Ritter and Welch (2002). This may be one reason to why underpricing is still mysterious and referred to as one component of the so-called “IPO puzzle” (Berk & DeMarzo, 2013, p. 820).

Inspired by “*Why Has IPO Underpricing Changed Over Time?*” (Loughran & Ritter, 2004) and “*The Hot Issue Market Of 1980*” (Ritter, 1984), the purpose of this paper is to examine the apparent difference in underpricing between the two sub-periods. In order to do so, the paper will answer to if the higher average IPO underpricing in the hot issue market of 2014-2016 can be attributed to the changing risk composition hypothesis. Thus, the research question is:

- *Using firm characteristics as proxies for ex ante uncertainty, can the changing risk composition hypothesis explain the difference in the level of underpricing between the cold issue market and the hot issue market on the Swedish IPO market?*

If 2014-2016 were subject to a larger fraction of riskier IPOs, then the risk composition of firms going public have changed over time and by theory this may explain the higher underpricing. In order to partially or entirely attribute the higher average underpricing in the hot issue market to the changing risk composition hypothesis, these following criterions should be satisfied:

1. A larger proportion of riskier IPOs in 2014-2016 than in 2010-2013.
2. A positive relation between risk and first-day return in both sub-periods and in the entire sample period.
3. The positive relation between risk and first-day return is stationary at all points in time, i.e. when comparing both sub-periods. By stationary, no fluctuations in this relation are allowed.

Starting off with a cross-sectional and a longitudinal study, and then moving into a regression analysis, we will examine the above criterions. The prediction, in terms of results, is that the difference in average underpricing can be attributed to the changing risk composition hypothesis to some extent. Furthermore, a stationary positive relation between risk and first-day return is expected.

Structure of Paper

The rest of this paper is structured as follows. Section II, Theoretical Framework, presents a theoretical background in the context of this study. Going forward, section III covers data and methodology. In section IV, Results and Analysis, we report and analyse the cross-sectional, longitudinal and regression results. Thereafter, in section V, Potential Biases and Robustness, we address certain issues to our regression model. In the last section VI, Conclusions, we summarise our findings and present our conclusions. References and appendices are provided at the end of the paper.

II. Theoretical Framework

The theoretical framework in this study is introduced by winner's curse. Serving as an implication of winner's curse, the section continues with ex ante uncertainty regarding the value of an IPO, and finally, the section ends with the changing risk composition hypothesis which follows from these theories.

Asymmetric Information and Winner's Curse

In the context of underpricing, asymmetric information refers to a situation in which the parties involved in an IPO transaction possess different knowledge (Ljungqvist, 2007, p. 384). Generally, the three involved parties are the issuing firm, the underwriter and the investors. A well-established model used as an explanation to underpricing within this field is Rock's (1986) winner's curse. Rock (1986) separates investors into two groups, uninformed and informed, where a few informed investors are assumed to have better information about the true value of an IPO than uninformed investors. The issuing firm and its underwriter is also assumed to be uniformed. Investors become informed by investigating the issuing firm's value, and this is costly. If IPOs are underpriced on average, e.g. (Ritter & Welch, 2002), even though a large proportion of IPOs are overpriced, there is an underlying incentive to incur these costs in order to pick out potential underpriced IPOs. However, far from all investors will commit, rather uninformed investors attempt to free ride on behalf of the informed investors (Beatty & Ritter, 1986).

Having superior information, informed investors participate only in IPOs perceived as attractively priced and, in contrast, uninformed investors bid on all IPOs (Rock, 1986). Owing to this, uninformed investors are subject to a winner's curse; in bad offerings, they are allocated the total number of shares they have subscribed for, while in attractive offerings, their allocations become rationed. In other words, if being allocated the total number of requested shares, investors will face a first-day return expected to be below the average underpricing return (Beatty & Ritter, 1986).

In worst case scenario, they are rationed to the extent that they earn breakeven or even experience negative returns. When expected returns are negative on average, uninformed investors will not subscribe to IPOs, resulting in an issue market consisting exclusively of informed investors. Rock (1986) argues that the total demand of the informed investors in the IPO market is insufficient to meet the supply of new shares. Thus, the IPO market relies on the participation of the uninformed demand. This implies that uninformed investors are only willing to bid on IPOs if first-day returns are expected to be non-negative. Therefore, to guarantee the participation of uninformed investors, Rock (1986) concluded that all IPOs must be underpriced (in expectation). Moreover, by incurring the cost related to investigating issuing firms' future prospects, informed investors are compensated for this through underpricing.

Ex Ante Uncertainty

At the heart of Rock's (1986) winner's curse, is the uncertainty about the true value of the issuing firm, where informed investors are more certain about this value than uninformed investors. Since riskier firms are more difficult to evaluate, which in turn makes becoming informed costlier (more thorough investigations), Rock's (1986) model suggests that riskier IPOs should be underpriced more than less risky IPOs. An implication of this model, introduced by Ritter (1984)[1] and later formalized by Beatty and Ritter (1986), is the ex ante (prior) uncertainty regarding the value of an IPO. Trying to explain the occurring hot issue market covering 15 months beginning in January 1980, Ritter (1984) found a positive relation between risk and first-day return. Beatty and Ritter (1986) later conducted a study more specifically focused on the ex ante component as a determent of the level of underpricing. They show that underpricing is expected to increase the greater is the ex ante uncertainty about the value of the issuing firm. This positive relation is formalised and explained by the number of investors who decide to become informed, which consecutively set the required first-day return. Beatty and Ritter (1986) provide the following example. The choice of investing in a call option on the

[1] Notice: the years used in the references are somewhat deceptive here. Just to make clear, Rock's publication in 1986 is based on his earlier unpublished Ph.D. dissertation from 1982 (*Why new issues are underpriced*) which we do not have access to. Ritter (1984) is referring to this paper.

IPO is equal to the decision of becoming informed. The call option is exercised only if the after-market price transcends the strike price (offer price). All else equal, the greater the risk (the ex ante uncertainty), the higher the value of the call option. More fundamentally, the greater the ex ante uncertainty the more investors become informed. However, when the number of informed investors increases, the winner’s curse problem worsens worsens which leads to higher required underpricing. In other words, the greater the risk of the IPO the more is there to lose. Being aware of this and to still participate in the IPO market, uninformed investors require higher levels of underpricing in offers subject to more uncertainty.

In order to test for ex ante uncertainty, adequate proxies for uncertainty (risk) must be used. Common proxies are firm characteristics, offering characteristics, post-IPO variables or information found in prospectuses (Ljungqvist, 2007, p. 387). For instance, Ritter (1984) used the most recent annual sales (firm characteristics) prior to the IPO as well as the standard deviation (post IPO variables) of the first-day returns post IPO. Beatty and Ritter (1986) used number of uses of proceeds given in the prospectus and gross proceeds (offering characteristics).

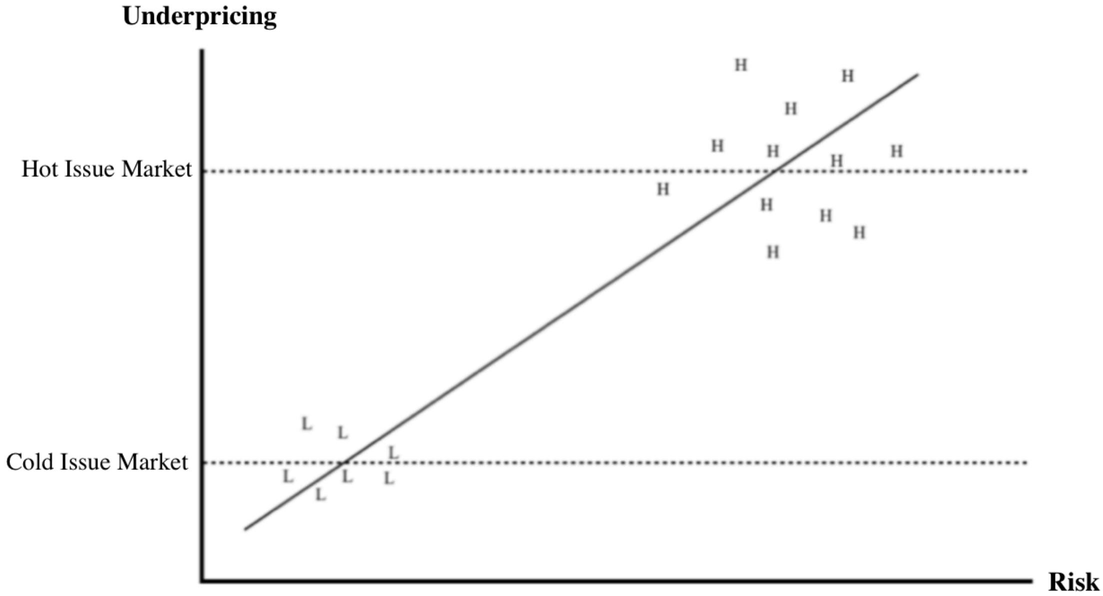
The Changing Risk Composition Hypothesis

This theory is closely related to Rock’s (1986) model and ex ante uncertainty, in that underpricing occurs due to risk. Although, it is different in that it is rather used trying to explain swings over time where underpricing is more severe in some periods than others. Moreover, the changing risk composition hypothesis can be viewed as an extension to the theories mentioned above. Recall that Rock's (1986) winner’s curse and ex ante uncertainty predict that riskier issues are expected to generate higher first-day returns than less risky issues (Ritter, 1984). If there are periods where the proportion of riskier IPOs is greater than in other periods, the changing risk composition hypothesis assumes that the average underpricing should increase during these periods (Loughran & Ritter, 2004).

This can be illustrated in a graph (see Figure 2 below) where the Y-axis represent underpricing and the X-axis represent risk (Ritter, 1984). High-risk offerings are found more to the upper right part of the graph, conversely, low-risk offerings are found to the lower left. The hypothesis argues that both risk categories will be plotted on the same risk-underpricing line. Thus, the positive relation between risk and expected first-day return is shown with an upward sloping line. In other words, as the risk increases the greater is underpricing. This implies that periods consisting of a larger fraction of riskier IPOs should be subject to a higher average level of underpricing, because a larger fraction of the total number of IPOs are clustered more to the right of the risk-return line. Potentially, this could serve as an explanation for higher underpricing in hot issue markets. In addition, the positive relation between risk and first-day return is assumed to be stationary (Ritter, 1984) (Loughran & Ritter, 2004). Hence, if the slope or line shifts over time, the change in underpricing cannot entirely be attributed to the changing risk composition hypothesis.

Figure 2. Illustration of the Changing Risk Composition Hypothesis

H denotes high-risk IPOs and L denotes low-risk IPOs.



In attempt to explain why IPO underpricing has changed over time, Loughran and Ritter (2004) used age, assets, sales and industry (firm characteristics) to measure the significance of the changing risk composition hypothesis. Recognising that this theory coincides with ex ante uncertainty, the proxies used when investigating the latter theory is obviously applicable for the changing risk composition hypothesis as well. As aforementioned in the section covering ex ante uncertainty, Ritter (1984) used sales and standard deviation. Notice that, the higher the value of assets and sales and the older the firm, the less risky is the firm. The same implication applies for standard deviation of first-day returns, where lower standard deviation entails lower risk.

III. Data and Methodology

This section is divided into five parts. It covers the taken approach, descriptions and explanations of made delimitations, how the sample and sample period were selected and constructed and the chosen variables used in our study and which sources that were used to collect the data. Lastly, we present how the study is being conducted, how the results are reported and how the criterions are examined.

Quantitative Approach

The decision to use a quantitative research method is mainly due to the nature of the data that is needed to answer the research question and to fulfil the purpose of this paper. With 493 observations, the collection process was relatively extensive. Adding that this type of data is compatible in statistical sense, this should clearly motivate the choice of a quantitative approach. More general advantages with this method are that it facilitates replication of the study and that the study itself will be based on objective sources.

Delimitations

Listings that are not considered as "real" IPOs are excluded in this study. Such exclusions involve spinoffs, parallel listings, firms that changed list, reverse mergers, mergers and preferred stock IPOs. Spinoffs is the activity of creating a new independent firm through distribution of new shares of a subsidiary from the parent firm (Cusatis, 1993). Parallel listings and change of list is fairly straight forward, the firm is listed on a foreign exchange, or has changed from one list to another. Obviously, these issues are excluded since the firms have been listed prior to the "IPO". It should be mentioned that one spinoff and four firms that changed list were included in the sample. The former issued new shares in conjunction to its listing. The so-called list changers, previously listed on *Alternativa Aktiemarkanden*, (a trading platform for unlisted companies (Alternativa Aktiemarknaden, n.d.)) were still privately held. In addition, they issued new shares in conjunction with their list change. In both cases we were able to obtain a price on the shares being offered, therefore, these firms are treated as "real" IPOs and included in the sample.

Reverse merger refers to the process of when the owners of a privately held company uses its shares in exchange for shares in a public company, which is a way for private firms to go public (U.S. Securities and Exchange Commission [SEC], 2011). We also encountered one firm who went public as part of a merger with one already listed firm. Both types of listings were excluded since these firms can generally go public without resorting to an IPO. Preferred stock IPOs are also excluded in this study. This is due to the different class of ownership imposed on these issues (Berk & DeMarzo, 2013, p. 810) and the lower assumed trading activity.

Consistent with Loughran and Ritter (2004), further exclusions are unit IPOs (offers where a stock and a warrant is combined (Chemmanur & Fulghieri, 1997)) and REITs (real estate investment trusts). They lack an explanation to why they are excluded, however, it should be quite straight forward. Regarding unit offers, the listing price, often seen as the price per share in the unit, may not represent the "real" value due to not accounting for the warrant. Briefly, compared to ordinary firms, REITs serve as an investment vehicle for actual real estate investments and they can be seen more as mutual funds (SEC, 2016). We have also suffered from "missing" IPOs. These observations are classified as missing if they have been delisted, resulting in that trading data no longer is available, or if we could not obtain an offer price. Finally, out of total 493 observations, 218 are excluded given our selection criteria and 34 is missing.

Sample Selection and Sample Period

The sample includes IPOs listed on *Nasdaq Stockholm, First North* and *Aktietorget* which are the three larger exchanges in Sweden, with *Nasdaq Stockholm* being the largest. Even though these are the larger exchanges, the firms being listed differs significantly, for instance, in terms of size and risk. Therefore, by selecting all three exchanges, our sample consists of a variety of IPOs in terms of firm characteristics. Adjusted for our selection criteria and IPOs classified as missing, we are left with a sample of 241 IPOs. The sum of the sample (241), unit IPOs (24), REITs (9) and the IPOs classified as missing (34), 308, are somewhat deceptively referred to as the "real" number of IPOs. Thus, the "loss" of data, i.e. unit IPOs, REITs and IPOs classified as missing, 67, make up to 22 % of the number of "real" IPOs.

The sample period, January 1 2010 to December 31 2016, is divided into two sub-periods. The first sub-period ranges from January 1 2010 to December 31 2013 and the second ranges from January 1 2014 to December 31 2016. These periods were determined using the principals of cold and hot issue markets by looking at the number of new offerings for each year between 2010 and 2016 (Ritter, 1984) (Ibbotson & Jaffe, 1975). Observing this data, we found that the number of issues are relatively low between 2010 and 2013, and then more than tripled between 2013 and 2014. This number increased even further throughout 2015 and 2016 which is consistent with the market swings referred to as cold and hot issue markets. Therefore, the earlier sub-period, 2010-2013, represents a cold issue market and the later sub-period, 2014-2016, represents a hot issue market. Of the total sample size, 56 and 185 IPOs originate from, respectively, 2010-2013 and 2014-2016.

Regarding the sample period, the years prior to 2010 have been excluded from the years observed. This exclusion was not intended, rather it had to be made due to the difficulty getting hold of the data needed to conduct this study.

Variables and Data Sources

Pursuant to the presented theory, we have used assets, sales and age as proxies for ex ante uncertainty (risk) and as measures for the changing risk composition hypothesis. These firm characteristics were also recognised to be used by Loughran and Ritter (2004). We will also look closer at an industry-related variable, biotechnological firms (biotech), which is added to the set of measures of the changing risk composition hypothesis. Lastly, data has been collected on all sorts of private equity (PE) ownership (investments into private companies characterised by active ownership (Invest Europe, n.d.)) at the time of going public. This variable is referred to as a control variable. More information is given below.

Our primary source for finding IPO data was *nyemissioner.se*. This database was mainly used to track the firms that went public in first place. It also showed the year of the IPO and offer prices. Then, this data was double-checked by comparing it to the *Swedish Tax Agency's* (*Skatteverket*) corporate history database and prospectuses. Moreover, the data was complemented by information from *nasdaqomxnordic.com* and *aktietorget.se* which are the official websites for *Nasdaq Stockholm*, *First North* and *Aktietorget*. For a few number of IPOs where information was missing or inconsistent, we collected data from various sources, including prospectuses.

Underpricing

The level of underpricing is calculated as a percentage return using the offer price of the new issue and the closing price on the initial day of trading:

$$\frac{Initial\ Day\ of\ Trading\ Closing\ Price - Offer\ Price}{Offer\ Price}$$

The closing price was collected from *avanza.se* (*Avanza Holding AB*). This is a raw figure and it has not been adjusted for market movements which sometimes has been made in previous studies on underpricing, e.g. Bergström, Nilsson and Wahlberg (2006).

Assets and Sales

Our source for asset and sales mainly comes from *Retriever Business*' database, and all data is based on December 31 the year prior to going public. Assets and annual sales should be adequate proxies for risk, where firms with substantially lower assets and annual sales levels are considered riskier than firms with higher levels of assets and annual sales. When assets and sales are reported in a currency other than SEK, we used the cross-rate December 31 the year prior to the IPO obtained from *Bloomberg Terminal* to estimate assets and sales in SEK.

When figures were missing, we used data from either the firms' annual reports or prospectuses. When firms have a fiscal year other than calendar year, the assumption was that the change in assets and sales the coming fiscal year will be linear (and constant each month) to the difference between previous two fiscal years. Thus, our data of assets and sales are adjusted to December 31 the year prior to going public. However, one implication with this approach is, opposed to assets that is measured at a certain point in time, that sales starts over from zero each year. Thus, compared to the true sales levels for the year we are interested in, our calculated figures should deviate.

In the case of firms reporting on calendar year basis and having sales previous years but no sales in the latest year prior to the IPO, we reported sales as zero. Another minor issue is when firms had sales in the months prior to going public but annual sales were reported as zero in the latest annual report. Furthermore, for firms that were founded the same year as the IPO, we reported assets and sales as zero. Consequently, in all three cases it would appear as the firm had no assets and/or sales experience which would not be true. Thus, there are pitfalls in which our data could be perceived as misleading and to some extent bias the results. Nevertheless, we did only encounter a few of these situations, and therefore, the effect should be minor. More importantly is that this approach caused our data to be consistent, with assets and sales based on December 31.

Lastly, it should be noted that the different sets of principles, guidelines and standards available and accepted in accounting entails a homogenous error in this study. Moreover, since these sets differ and adding the fact that the practice of these allow for interpretations, financial information is not absolute which could lead to inconsistent data when comparing firms.

Age

Information on founding year comes from various sources. Founding year is defined as the year of incorporation of the original firm (Loughran & Ritter, 2004). This information is generally provided on the firm's website. When this information is missing the founding year can usually be found in the corporate description in *Bloomberg Terminal* or in the prospectus. Age is also used as a risk measure, where younger implies more risk. It is calculated using the year of the IPO and the founding year:

$$Year\ of\ the\ IPO - Founding\ Year$$

Biotech

Each firm in our analysis is categorised by industry and by sub-industry in accordance to *Thomson Financial Securities Data* under Business Info. Approaches have been made to account for industries with an expected high level of uncertainty. For instance, Loughran and Ritter (2004) categorised firms into tech- and internet-related owing to the Internet Bubble during 1999-2000 and used these, among assets, sales and age, as measures for the changing risk composition hypothesis. In addition, Ritter (1984) demonstrated that the high average underpricing during the hot issue market of 1980 substantially was attributed to the natural resources industry.

Biotech firms are often heavily research and development (R&D) intensive firms which contribute to information asymmetry between the issuing firm and the investors. This is due to the absence of timely information on R&D activities and the high intangible assets relative to tangible, and therefore, R&D-intensive firms tend to get systematically mispriced (Guo, Lev & Shi, 2006). This is particularly attributed to inadequate disclosure of R&D activities, presumably favoured by insiders, e.g. management and large shareholders, usually to not benefit competitors (Aboody & Lev, 2000). Thereby, heavily spending on R&D implicitly mean less disclosure, which would increase the uncertainty about an issue. Consistent with Ritter (1984), this implies that these issues may be more subject to underpricing since uncertainty and underpricing are expected to be positively related. Moreover, biotech firms are largely high-risk ventures and at the time of the IPO, they consist predominantly of a bundle of intellectual property and with usually no sales (Stephan, Higgins & Thursby, 2004). Therefore, we conjecture that, in line with the prediction from the ex ante uncertainty theory, R&D-intensive firms are more likely to be underpriced than non-R&D-intensive firms due to less disclosure and the inherent risk associated with these issues. In other words, we suspect that biotech firms will be more underpriced on average than non-biotech firms. In addition, the assumption is also that biotech firms are younger and have lower assets and sales than average.

Therefore, along with assets, sales and age as measures for the changing risk composition, we add the variable biotech which accounts for all biotech IPOs. Given recent hype in the biotech industry, e.g. Strandberg (2015), we predict an increased fraction of biotech companies going public during the hot issue market. Thus, by adding this variable, we want to examine the effect on underpricing of this line of business more thoroughly.

Private Equity

Regarding PE, we could not obtain any single source showing which IPOs were being backed. Rather, prospectuses and some supplemental information given on *nyemissioner.se* were used. Discovering that these prospectuses only showed the name of the owners and not the type of business, we manually looked up all owners with names[2] that could indicate some sort of PE. Furthermore, the analysis was not restricted by any predetermined ownership share. Based on that premise, simply, if the issuing firm were subject to some sort of PE ownership, regardless of the extent, the firm is considered backed in our study.

As noticed in other studies concerning underpricing, for instance Loughran and Ritter (2004), venture capital (VC) backing (private equity invested into young start-up firms (Invest Europe,

[2] Names that included, for instance: ”investment”, ”capital”, ”kapital” (Swedish for capital), ”equity” and/or ”venture”.

n.d.)) is used as a control variable. However, they lack a detailed explanation to why it is included in the regression and an exact specification of what type of ownership it covers. Although, this is not to be interpreted as a shortage in their models. Firstly, pursuant to recent research, VC backing is known to have impact on underpricing, e.g. Megginson and Weiss (1991) and Lee and Wahal (2004). If the level of underpricing is lower for VC backed IPOs compared to non-VC backed IPOs, however, this is not completely clear-cut. Secondly, Loughran and Ritter (2004) among others used *Thomson Financial* (as of 2008 *Thomson Reuters*) as the main source to collect data on VC. This database for financial information should be trustworthy, wherein its classification of VC would not need further specifications.

In addition to VC having impact on underpricing, such backing may as well be correlated to the other variables used in our setting, and by controlling for it, the risk of an omitted variable bias[3] may be reduced (Clarke, 2005). However, as aforementioned, we could not find any source showing which IPOs that were backed by VC particularly. Recognising that prospectuses only showed the name of the owners (not the type of business) and in order to distinguish VC, we manually looked up all owners with names that could be related to PE. By doing this, another problem was encountered. For the greater part of firms (owners) found to operate with some sort of PE, and knowing that PE include VC among other subsets (Invest Europe, n.d.), the information given were insufficient to correctly classify the type of PE as VC. Consequently, the PE variable controls for all sorts of PE. Furthermore, regarding the collection process of the data, a minor issue with the somewhat constrained approach is that there is a possibility that a few IPOs have been reported as non-backed even though they were backed.

Speaking in terms of firms rather than capital, a PE firm and a VC firm are similar in many aspects. However, while both types of firms provide growth capital, VC firms usually invest in earlier stages of the private-company-life-cycle, in contrast, PE firms generally buy larger stakes in later stages (Berk & DeMarzo, 2013, p. 809). Furthermore, involvement of a PE firm or VC firm in an IPO may result in different effects in the level of underpricing compared to non-backed offerings, e.g. Mogilevsky and Murgulov (2012). Owing to this, it should be clarified that when controlling for all subsets of PE, this may be a minor shortcoming in our investigation. However, opposed to excluding it, we argue that it is more reasonable to control for it.

[3] A bias created by leaving out a variable that is relevant to the dependent variable and are correlated with at least one of the explanatory variables (Clarke, 2005).

Method of Analysis

In order to analyse the data and to examine the criterions concerning the changing risk composition hypothesis, we will first report our results with panels. These panels will show both cross-sectional and longitudinal patterns. The former refers to comparing the same set of variables in a specific point in time, while the latter refers to comparisons over time. In these panels, however, the variables are not independent of each other. Taking this into consideration, and to examine causal effects more correctly, a regression analysis will be conducted.

The first panel, Panel A, reports the average and the median values of first-day return, assets, sales and age for each year, the sub-periods and for the entire sample period. In addition, it will show the proportion of IPOs that are operating in the biotech sub-industry and which are backed by PE. Panel A also reports the total number of observations, sample size, excluded listings and excluded "real" IPOs where IPOs classified as missing are included. In the second panel, Panel B, each variable used as measure for risk are segmented into two risk categories. Assets and sales are divided by percentiles and age by median. Since we encountered a handful of firms that were very old, we argue that the median, rather than percentiles, is more suitable when segmenting the IPOs by age. Below the 25th-percentile and above the 75th-percentile denotes high and low risk, accordingly, below median age represents high risk and equal to and above represent low risk. In addition, average first-day return and the number of IPOs in each category is given. Panel B will also show IPOs classified as biotech and non-biotech, PE backing and non-PE backing and IPOs segmented by exchange.

These panels will be used to examine all three criterions, primarily the first criterion. Regarding criterion two and three, however, we cannot draw valid conclusions from these panels since the variables are not independent of each other. Nevertheless, they may illustrate patterns which to some extent could reveal something about the changing risk composition hypothesis.

Therefore, in order to examine criterion two and three we run three identical regressions, one for each sub-period and one for the entire sample period. Consistent with previous research, e.g. Loughran and Ritter (2004), first-day returns are used as the dependent variable. We include assets, sales, age and biotech as explanatory variables to test the changing risk composition hypothesis. We specify assets, sales and age as natural logarithms. Since the natural logarithm of zero is undefined, firms with zero assets or sales the year prior to going public are assigned SEK 1. Consequently, age is added with the value of 1 due to some firms going public the same year they are founded. Biotech and PE are dummy variables that take the value of one (zero otherwise) for, respectively, biotech IPOs and some sort of PE backing. Moreover, the PE dummy is included as a control variable. The regression is:

$$\begin{aligned} \textit{First-Day Return}_i \\ &= \beta_0 + \beta_1 \ln(Assets)_i + \beta_2 \ln(Sales)_i + \beta_3 \ln(1 + Age)_i + \beta_4 Biotech\ Dummy_i \\ &+ \beta_5 PE\ Dummy_i + \varepsilon_i \end{aligned}$$

where i denotes IPO. Generally, this regression tests whether risk (our risk proxies) can predict first-day returns. Particularly, criterion two is tested for by examining the signs on the estimated coefficients on the risk measurements in all three regressions. Criterion three is tested for by comparing the estimated coefficients given by the regression results in both sub-periods. Lastly, regarding the results, we will report significance levels of 1 %, 5 % and 10 %, however, we will only accept at the 5 % level in our analysis since we do not want to exert data mining.

IV. Results and Analysis

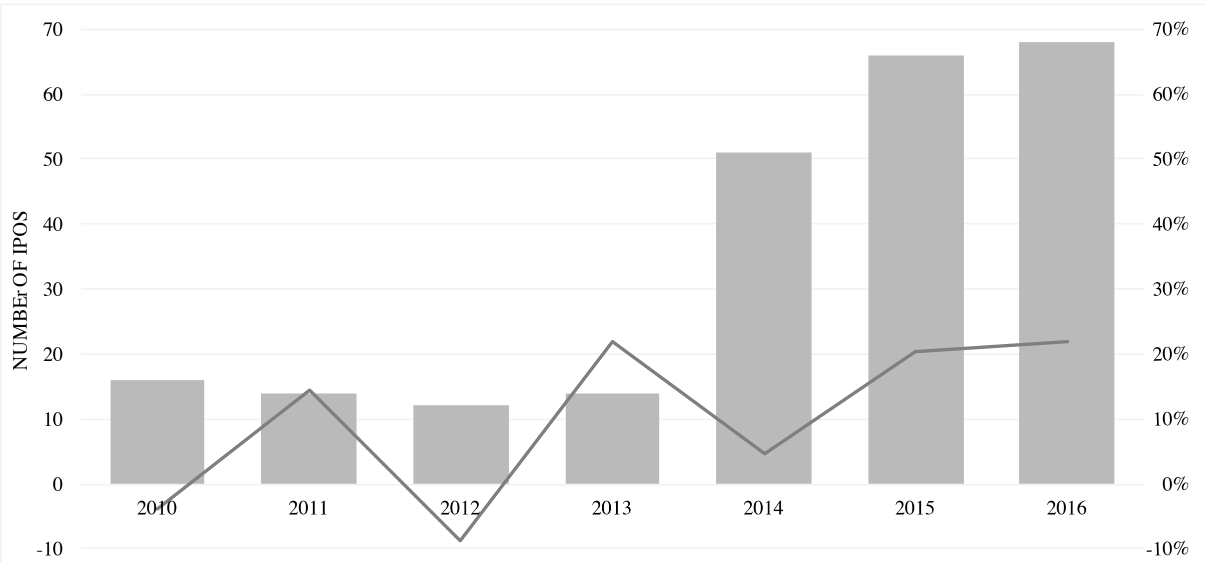
In this section, the results are reported and analysed. We begin by presenting cross-sectional and longitudinal patterns, followed by a regression analysis in which we will examine the explanatory variables' effect on first-day returns. Because of the findings, this section ends with a presentation of another factor that could be central to the higher underpricing in the hot issue market.

Cross-Sectional and Longitudinal Patterns

Referring to Panel A and Figure 3 below, clearly, each year in the later sub-period contains far more IPOs than each year in the previous sub-period. This was known from the beginning of this study. Moreover, these figures are in line with the sectioning of the two sub-periods, where 2010-2013 is referred to as a cold issue market and 2014-2016 as a hot issue market. Based on hot issue market characteristics, knowing that the number of IPOs almost tripled during 2014-2016 compared to 2010-2013, the assumption was that each year and all years in 2014-2016 should be subject to higher average underpricing than each year and all years in 2010-2013. However, as shown in the panel, 2014 had lower average first-day return than both 2011 and 2013. To our surprise, 2013 was the year with the highest average first-day return during the entire sample period. Observing the sample size and the data input for each year, this finding can be quite misleading; both 2011 and 2013 had low IPO activity, and therefore, offerings subject to very high first-day returns (also the case for very low or negative first-day returns) will have major impact when calculating the average first-day return. This is also the case, in 2011 and 2013 two IPOs in each year can be seen as outliers due to their stock surging more than, respectively, 100 % and 70 % the initial day of trading. Hence, a more appropriate measurement might be the median. Comparing all years, still, 2013 had the highest first-day return, but the median return for 2014 exceeds the return reported for 2011. Notice that, if found and included in the calculations, "missing" IPOs could potentially have great effect on average first-day return for each year in 2010-2013. In contrast, comparing the sub-periods, the average underpricing for the hot issue market was 16.57 %, close to three times the average first-day return (6.02 %) for the cold issue market. Thus, the volume of IPOs especially and the higher underpricing should justify current sectioning of the sub-periods.

Figure 3. Sample-Number of IPOs per Year (bars) and Average First-Day return per Year (line)

The sample includes IPOs listed on *Nasdaq Stockholm, First North* and *Aktietorget*. Listings that are not considered as "real" are excluded: spinoffs, parallel listings, firms that changed list, reverse mergers, mergers and preferred stock IPOs. Unit IPOs, REIT IPOs and IPOs classified as missing are also excluded. The sample size is 241 IPOs for 2010-2016.



Panel A. Number of IPOs, First-Day Return, Assets, Sales, Age, Biotech and PE

PANEL A

	NUMBER OF IPOS				FIRST-DAY RETURN		ASSETS (Thousands of SEK)		SALES (Thousands of SEK)		AGE		OTHER	
Year	**Sample**	**Excluded**	**Excluded "real" IPOs**	**Total observations**	**Average**	**Median**	**Average**	**Median**	**Average**	**Median**	**Average**	**Median**	**Biotech**	**PE**
2010	**16**	20	14	50	**-3.97%**	-1.45%	318,103	10,750	277,602	13,210	11.3	8.5	12.5%	56.3%
2011	**14**	29	5	48	**14.38%**	0.00%	300,555	17,144	215,479	6,121	16.6	5.0	35.7%	35.7%
2012	**12**	16	2	30	**-8.84%**	-1.17%	735,423	15,118	54,434	3,200	8.5	6.0	16.7%	50.0%
2013	**14**	27	6	47	**21.82%**	13.13%	463,525	11,750	40,477	4,928	11.6	7.0	21.4%	42.9%
2014	**51**	32	17	100	**4.54%**	4.84%	1,436,035	26,964	755,268	16,555	23.0	10.0	11.8%	45.1%
2015	**66**	34	15	115	**20.48%**	11.09%	2,394,007	47,868	1,505,811	26,808	15.4	9.5	15.2%	56.1%
2016	**68**	27	8	103	**21.81%**	7.22%	1,046,106	23,438	747,933	12,032	14.3	9.0	10.3%	50.0%
SUB-PERIODS														
2010-2013	**56**	92	27	175	**6.02%**	0.00%	439,497	14,309	154,968	6,922	12.1	6.5	23.2%	46.4%
2014-2016	**185**	93	40	318	**16.57%**	6.83%	1,634,473	33,961	1,020,334	16,555	17.1	9.0	12.4%	51.9%
SAMPLE PERIOD														
2010-2016	**241**	185	67	493	**14.12%**	5.00%	1,356,802	23,436	819,253	12,009	15.9	9.0	14.9%	50.6%

Moving on to the variables used as measurement for the changing risk composition hypothesis, do the simple average and median figures reveal that more high-risk IPOs can explain the higher underpricing in 2014-2016? Eyeballing Panel A, the reported values do not support such predictions from theory. Recall that the premise of the changing risk composition hypothesis follows from high-risk issues being underpriced more than low-risk issues. Therefore, if there are periods where the fraction of riskier IPOs is greater than in other periods, the average underpricing should increase during these periods. We find that IPOs in 2014-2016 have higher assets and sales, both by average and median, and are older than offerings in the earlier period. In other words, offerings are less risky during this hot issue market. Hence, by only observing average and median values, there is in fact a negative relation between risk and first-day return and the changing risk composition hypothesis may not explain the difference in underpricing. However, for instance, this panel does not show the fraction of riskier IPOs, and therefore, we cannot draw any valid conclusions.

The proportion biotech-related IPOs in the hot issue market was lower than in the cold issue market. Remember that the initial assumption was that a greater proportion of biotech IPOs would be observed in 2014-2016 and that these issues were subject to higher uncertainty, and therefore higher expected underpricing according to theory. The difference between the sub-periods speaks against that an increase in the fraction of riskier IPOs should explain the higher average first-day return for 2014-2016. Lastly, not as important in this setting, is the control variable. Offerings with some sort of PE ownership were fewer by the number in 2010-2013. Although PE, especially the subcategory VC, somewhat signals more risk in this context, the small difference in the proportion backed IPOs between the sub-periods do not alter the patterns outlined above.

Panel B. Average First-Day Returns on IPOs Segmented by Assets, Sales, Age, Industry, Private Equity and Exchange

PANEL B				
	2010-2013		2014-2016	
Segmented by	**Return**	**N**	**Return**	**N**
ASSETS				
Small	11.92%	15	19.98%	45
Large	3.25%	8	12.33%	53
SALES				
Small	-3.22%	15	18.64%	46
Large	2.67%	8	11.11%	52
AGE				
Young (0-8)	8.41%	34	24.53%	82
Old (>8)	2.33%	22	10.24%	103
INDUSTRY				
Biotech	4.31%	13	3.19%	23
Non-Biotech	6.54%	43	18.47%	162
PRIVATE EQUITY				
PE Backed	4.86%	26	16.80%	96
Non-PE Backed	7.03%	30	16.33%	89
EXCHANGE				
Nasdaq Stockholm	0.10%	8	11.62%	42
First North	-2.15%	14	15.52%	85
Aktietorget	10.78%	34	21.71%	58

To examine the changing risk composition hypothesis more thoroughly, in Panel B, the IPOs are segmented into two risk categories where the average first-day return and the number of IPOs in each category is given. Then, we investigate if the average first-day return is higher for firms in higher risk categories and if the proportion of high-risk IPOs are different between the sub-periods. Lastly, we attempt to make more valid conclusions about whether the changing risk composition hypothesis can explain the observed average underpricing between the sub-periods. In addition, this panel also shows offerings classified as biotech, having PE backing and exchanges.

Consistent with Rock's (1986) winner's curse and the implication ex ante uncertainty, there is an overall positive relation between risk and first-day return for both sub-periods, except for sales 2010-2013. Therefore, especially assets and age could be seen as adequate risk proxies, where sales is less solid. This finding is contradicting to the overall negative relation between risk and first-day return seen in Panel A. In a demonstrative purpose, this positive relation between risk and first-day return is also shown in the last row. Segmented by exchange, even though IPOs on *First North* 2010-2013 are subject to lower first-day returns than IPOs on *Nasdaq Stockholm*, the figures illustrate an overall trend towards offerings being underpriced more on the exchanges designed for smaller growth companies, i.e. *Aktietorget* and *First North*.

Nevertheless, in terms of explaining the higher underpricing in the hot issue market, this evidence is not persuading enough. Going back to the risk proxies, for both low-risk and high-risk IPOs, the average underpricing is more severe in the hot issue market than in the cold issue market. This is not consistent with a stationary relation between risk and first-day return, which assumes that the relationship between the variables and average underpricing should be the same at all points in time. In other words, when risk is held constant the average underpricing should stay the same, and not increase, for each risk category. However, risk may not be held constant within each risk category. Furthermore, observing the number of IPOs in the high-risk categories, the proportion of high-risk firms going public during the hot issue market is less than in the cold issue market. In fact, the cold issue market was subject to more high than low-risk offerings. Even if there is an overall positive relation between risk and first-day return, the higher average underpricing in the hot issue market may not be attributed to the changing risk composition of firms going public, because the relationship is nonstationary and neither did the fraction of high-risk IPOs increase.

Surprisingly, firms related to the biotech line of business had lower average first-day return in both sub-periods than non-biotech firms. The largest difference can be seen for the hot issue market. In addition, biotech IPOs generate on average a weak positive average first-day return. Looking closer at the data input, the median age for all biotech IPOs is 6 years, which is lower than the median age 9 for all IPOs. Thus, our prediction that biotech firms are younger by median holds. Furthermore, these companies also have lower assets and sales on average that again justifies our assumption. Pursuant to a positive relation between risk and first-day return, this should imply a higher level of underpricing than the average underpricing of 14.12 % for the entire sample period, which evidently is not the case. Comparing biotech to non-biotech IPOs in both sub-periods and in the entire sample period, the same characteristics and results are seen and obtained. This may imply that assets, sales and age, are inadequate measures of risk in this setting or that other factors outdo the effect of risk.

Thus, rather than using firm characteristics, we further investigated this by using a post-IPO variable as a proxy for risk. Previous research suggest that risky industries are characterised by both higher levels of underpricing and greater variability (standard deviation) of first-day returns, e.g. Ritter (1984). Using the same proxy for measuring risk and based on our initial assumptions, we presumably should obtain higher standard deviation of first-day returns for biotech firms relative to non-biotech firms in both sub-periods, as a positive relation between risk and first-day return is expected. In the cold issue market, a higher standard deviation of first-day returns is obtained for biotech IPOs compared to non-biotech IPOs. Conversely, in the hot issue market, standard deviation of first-day return is significantly lower for biotech firms. These results are contradicting since risk and return are assumed to be positively related. This is violated in the first sub-period in which first-day returns are lower while the risk is higher relative to non-biotech issues. Moreover, using data from the entire sample period, we obtain that biotech firms have significantly lower standard deviations of first-day returns relative to non-biotech firms. As concluded above, this is in line with biotech firms being underpriced less than non-biotech firms on average. The cross-sectional pattern seen in 2010-2013, however, is contradicting. Also, comparing both sub-periods, the average underpricing on biotech firms has remained fairly constant, even though the relation between risk and first-day return has not based on standard deviation. As for biotech IPOs, neither does the positive relation between risk and first-day return seem to hold, nor is it stationary.

Another explanation for this aberration might be the potential effect of PE backing. By assumption, the nature of this business is to generate the highest return on investment as possible. In other words, PE capitalists want to leave as little money on the table as possible when exiting an investment. Examining the data, more than 50 % of the biotech companies are backed with some sort of PE. Adding to this, there is a small difference in the average underpricing of biotech backed IPOs (4.9 %) compared to non-backed (5.9 %). This is in line with some previous mentioned studies suggesting that IPOs being backed by PE exhibits lower underpricing than non-backed. However, recall that all sorts of PE is included in this variable and that these sorts might have opposing effects, also between themselves, on the level of underpricing compared to non-backed IPOs. Hence, we are not in the position to completely propose that this difference in underpricing is consistent with theory. Nevertheless, both the proportion of backed biotech IPOs and the difference in underpricing (4.9 % compared to 5.9 %) are too small to account for the difference in underpricing between biotech and non-biotech IPOs in both sub-periods and to outdo any positive relation between risk and first-day return in 2010-2013. In addition, eyeballing the next row in Panel B, there is only weak evidence that an IPO backed by some sort of PE matters in terms of underpricing.

Regression Analysis

As seen above, the cross-sectional pattern between assets and first-day return in Panel B can be perceived as a positive relation between risk and first-day return. The negative relation between age and first-day return also displays this pattern, where older firms are subject to lower underpricing. Surprisingly though is that biotech IPOs did not illustrate such pronounced relationship. However, the variables are not independent of each other. As an example, a younger firm is more likely to have lower assets. Accounting for this, we have conducted a regression analysis; one for each sub-period and one for the entire sample period. However, we do not expect that using this type of statistical model would alter the patterns that negates the changing risk composition hypothesis seen in Panel A and B.

To understand the regression outputs and before analysing them, defining what the changing risk composition hypothesis predicts in terms of the coefficients on the explanatory variables is required. Recall that the explanatory variables are proxies for risk. Based on the assumption that 2014-2016 was subject to riskier IPOs (was not the case, referring to Panel A and B), if the risk composition of firms going public changes over time the variables will change, and by theory this will explain the higher underpricing. This also means that the estimated coefficients should remain approximately the same in both sub-periods, unless some source of endogeneity problem[4] has different effects in each sub-period. In other words, if exogeneity[5] holds, the hypothesis predicts a stationary relation between risk and first-day return. In contrast, if the coefficients changes over time, referring to section II Theoretical Framework and Figure 2 illustrating the changing risk composition, this would affect the slope and result in a nonstationary relationship. Lastly, the sign on the coefficients for assets, sales, age and biotech must be consistent with a positive relation between risk and first-day return. Hence, assets, sales and age should have negative coefficients (the higher and older, the lower the risk), whereas

[4] This problem arises when an explanatory variable is endogenous, meaning that it is correlated with the error term (Wooldridge, 2013, p. 848).
[5] Exogeneity means that the explanatory variables are uncorrelated with the error term (Wooldridge, 2013, p. 848).

biotech should have a positive coefficient given the initial assumption that these are high-risk issues. If the variables are significant and if these factors hold, then confidently, we could attribute some part of the higher underpricing in the hot issue market to the changing risk composition hypothesis.

Table 1. Regressions on First-Day Returns for each Sub-Period and for the Entire Sample Period

The table shows the regression results where first-day returns are used as the dependent variable. T-statistics are given in the parentheses. Significance level 1 % is denoted by ***, 5 % is denoted by ** and 10 % is denoted by *. The regressions are run with robust standard errors.

	SUB-PERIODS		SAMPLE PERIOD
Variables	**2010-2013**	**2014-2016**	**2010-2016**
ln(*Assets*)	-3.16618	0.1232655	-0.2417959
	(-1.44)*	(0.17)	(-0.35)
ln(*Sales*)	0.4817679	-0.0244648	0.0473289
	(1.00)	(-0.08)	(0.18)
ln(1 + *Age*)	2.3777	-5.032181	-2.762418
	(0.39)	(-1.99)**	(-1.18)
Biotech	-3.983565	-17.07889	-13.27841
	(-0.29)	(-2.57)***	(-2.00)**
PE	-2.990083	2.664853	1.076222
	(-0.3)	(0.39)	(0.19)
Constant	50.72334	27.37351	25.40295
	(1.37)*	(2.31)**	(2.25)**
R^2	0.025	0.024	0.0157

The regression results do not speak in favour of the changing risk composition hypothesis. Starting with regression for the entire sample period, even though the negative sign on the coefficients on $\ln(Assets)$ and $\ln(1 + Age)$ are consistent with the hypothesis, all variables (except for the $Biotech\ Dummy$) are insignificant. Thus, we cannot provide evidence showing that these variables have an effect on first-day returns. In other words, assets, sales and age could be irrelevant to the level of underpricing during 2010-2016. This may be consistent with the fact that the offerings in the later sub-period were less risky offerings but had higher average first-day return, and vice versa for 2010-2013. Hence, we cannot conclude a positive relation between risk and first-day return. Furthermore, the $Biotech\ Dummy$ is significant and has a negative coefficient, suggesting that biotech IPOs are negatively related to first-day returns.

This result is not in line with our assumptions nor is it with the finding that these IPOs were younger and had lower assets and sales than non-biotech IPOs. Nevertheless, it is consistent with the overall lower standard deviation of first-day returns than for non-biotech and the cross-sectional patterns where these types of firms were subject to lower average underpricing than non-biotech firms.

Overall, the regression results for the sub-periods do not alter the results reported for the entire sample period. The statistical insignificance of all variables in the earlier sub-period suggests that risk and some sort of PE backing are likely irrelevant to underpricing. In contrast, during 2014-2016, both $\ln(1 + Age)$ and the $Biotech\ Dummy$ have a significant effect on first-day returns. The negative coefficient on the former is consistent with a positive relation between risk and first-day return and thus the changing risk composition hypothesis, whereas the negative coefficient on the latter is consistent with the observed substantial lower first-day return on biotech IPOs than non-biotech. However, by only having significant variables being negative related to first-day returns, there might be other components included in the error term which have opposing effects on the average underpricing during the sub-period.

Due to the insignificance of all variables in the cold issue market, we cannot make valid comparisons between the sub-periods to further investigate criterion three concerning the stationary component. Even if all variables were to be statistically relevant to first-day returns in both sub-periods, all coefficients have changed over time. Moreover, all explanatory variables except for the biotech dummy have opposing signs in each sub-period. This nonstationary implies that the changing risk composition would fail to explain the higher average underpricing in the hot issue market.

Even though $\ln(1 + Age)$ in 2014-2016 and the $Biotech\ Dummy$ in, respectively, 2014-2016 and the entire sample period have a significant effect on average underpricing, if our variables are adequate measures of risk, the overall insignificance of the variables suggest that risk is likely irrelevant to underpricing over the entire sample period and in each sub-period. Hence, the regression analysis does not change the inference made from Panel A and B, where we could not see patterns of that the difference in underpricing could be attributed to the changing risk composition hypothesis.

Another Explanation

As last resort, we have looked closer at our data set for other potential explanations to the higher average underpricing in the hot issue market. By looking closer at industries, the higher underpricing in 2014-2016 seems to be associated with IPOs within the information technology (info-tech) industry primarily. While most industries have first-day returns consistent with average for the entire sample period (14.02 %), with relatively small deviations, we found that IPOs related to info-tech are significantly more underpriced on average (32.98 %). Referring to Panel C below, adding up the other industries, these non-info-tech IPOs were underpriced on average with 10.92 %; being even lower than the average for the sample period. What is even more interesting is that, comparing the sub-periods, the proportion of info-tech related firms were not only substantially greater in the hot issue market they were also much more underpriced than in the cold issue market. In comparison to non-info-tech IPOs, the difference in first-day returns is almost absent in 2010-2013 (6.87 % compared to 5.96 %), whereas in the later sub-period first-day returns for info-tech firms are significantly higher (36.35 % compared to 12.59 %).

Panel C. Information Technology IPOs Comparison

PANEL C						
				Thousands of SEK		
SUB-PERIODS		**FIRST-DAY-RETUI**		**ASSETS**	**SALES**	**AGE**
2010-2013	**Sample**	**Average**	**Median**	**Average**	**Average**	**Median**
Information Technology	**4**	**6.87%**	13.08%	12,619	17,569	9.5
Non-Information Technology	**52**	**5.96%**	0.00%	472,334	165,537	6.0
2014-2016						
Information Technology	**31**	**36.35%**	13.53%	101,137	144,849	10.0
Non-Information Technology	**154**	**12.59%**	6.73%	1,943,131	1,196,567	9.0
SAMPLE PERIOD						
2010-2016						
Information Technology	**35**	**32.98%**	13.53%	91,020	130,303	10.0
Non-Information Technology	**206**	**10.92%**	3.62%	1,571,862	936,307	9.0

Nevertheless, yet again, we cannot ensure that this finding can be attributed to the changing risk composition hypothesis. Although info-tech IPOs are riskier than non-info-tech IPOs and there is a positive relation between risk and first-day return supported by the lower average assets and sales and that the hot issue market saw a larger fraction of these, the positive relation between risk and first-day return is not supported entirely and the relation being stationary is not evident.

Regarding the cold issue market, given the difference in assets and sales between info-tech and non-info-tech IPOs, this should imply a higher expected difference in average underpricing. In other words, the relation between risk and first-day return is positive indeed, however, almost non-existent. In addition, contradicting to assets and sales, if age is an adequate risk proxy, this variable does not support the overall underpricing difference between info-tech and non-info-tech IPOs since the median age of info-tech IPOs are more or less consistent with the age of non-info-tech IPOs. Owing to this, consistent to when we investigated the biotech variable in Panel B, we looked at the standard deviation of first-day returns. Using this variable as a proxy for risk, the underpricing difference between info-tech and non-info-tech IPOs for each sub-period and the entire sample period becomes more explainable. Regarding the entire sample period, info-tech IPOs are subject to much higher variability in first-day return than non-info-tech IPOs. Furthermore, while there is little deviation in the first sub-period there is a huge difference in the second sub-period. This is more consistent with the difference in average underpricing between info-tech and non-info-tech IPOs, with a very small difference in the cold issue market and a much greater difference in the hot issue market. However, for instance, the variability in the first sub-period for info-tech IPOs are lower than for non-info-tech IPOs while info-tech IPOs are subject to higher underpricing than non-info-tech IPOs. Thus, the positive relation between risk and first-day return is still not completely distinct.

Comparing the cold issue market to the hot issue market for both info-tech and non-info-tech IPOs, if assets, sales and age are adequate risk proxies, the risk has decreased but the return has increased. This is also seen based on standard deviation of first-day returns for non-info-tech IPOs. If standard deviation is an appropriate risk measure, this pattern is not seen for info-tech IPOs where the risk has increased and so the return. Thus, these longitudinal patterns are negating the changing risk composition hypothesis, due to the confusing relation between risk and first-day return but also the tendency of the relation being nonstationary since both info-tech and non-info-tech IPOs are underpriced more in the hot issue market. Regarding nonstationary, however, risk is not held constant within the info-tech and non-info-tech categories. Lastly, to righteously reject the changing risk composition though, a regression analysis must be conducted.

Even if the changing risk composition may not explain this finding, the fact that info-tech IPOs in the hot issue market were both greater by the proportion and subject to significantly higher underpricing are in it itself interesting. IPOs related to this kind of business could actually be central to the higher underpricing witnessed during the hot issue market – but most likely in obedience to other underpricing theories. Furthermore, referring to a hot issue market based on underpricing, there seems to be that no such occurred for non-info-tech IPOs pursuant to the average underpricing of these. This finding is similar to Ritter's finding (1984) where he demonstrated that the abnormal underpricing during the hot issue market of 1980 largely was attributed to the natural resources industry. In addition, the relation between risk and first-day return was nonstationary for IPOs related to this industry, however, opposed to our finding the relation was still pronouncedly positive. Finally, we will not proceed investigating this finding by testing for other theories. But, as outlined in this section, info-tech IPOs seems to be of importance with respect to the higher average underpricing during the hot issue market.

V. Potential Biases and Robustness

The regression results and the overall insignificance, especially regarding the cold issue market, could be affected by or the result of potential biases. Such potential biases could possibly arise from, for instance, most likely a small sample size and/or omitted variables.

The sample includes 241 IPOs, and in comparison to earlier studies, e.g. Loughran and Ritter (2004) and Ritter (1984), the sample size is very small. Furthermore, we are missing data on 30 % of the "real" number of IPOs from 2010-2013. Another potential issue, to especially a small sample size, is extreme values, i.e. outliers or leverage points, in terms of first-day return or the independent variables. Not only will these have a large effect on the reported results in the panels, the regression estimates can be very sensitive to these as well (Rousseeuw, Peter & Annick, 2005, p. 8). Finally, there is the possibility of the regression model being subject to some source of endogeneity problem. Primarily, in our regression specification, this problem can arise as a result of omitted variables. If these left out variables are relevant to first-day returns and are correlated with at least one of the explanatory variables, then by not controlling for them the regression coefficients will be biased (Clarke, 2005). Therefore, we have four potential issues to deal with; a relatively small sample size, "missing" IPOs, outliers and omitted variables. Each issue is addressed below.

Sample Size

By extending our sample period, the samples size would increase which in turn might change our results. However, as mentioned in section III, Data and Methodology, we have excluded the years prior to 2010. This exclusion was not intended, rather it had to be made due to the difficulty getting hold of the data needed to conduct this study. In addition, the data required could only be collected manually. Therefore, extending the sample period to reduce the possibility of any biases as well as robust testing our regression model would be close to insurmountable, and thus, this robust test will not be conducted. Even if we would proceed with collecting data from previous years, our results may be even more misleading (if they are now) owing to, for instance, the international financial crisis. Since we aim to test the changing risk composition hypothesis using "normal" years, the IPO market during 2007 to 2008 is not assumed to be representative and neither is 2009 which presumably was affected and still recovering from the crisis (Statistiska Centralbyrån [SCB], 2010).

"Missing" IPOs

One way to increase our sample without extending the sample period is to include IPOs that are classified as missing. Recall that these IPOs were ignored since offer price and/or initial day of trading closing price could not be obtained and, therefore, first-day returns could not be calculated. Moreover, 30 % of the "real" number of IPOs for 2010-2013 is missing. If calculated as a proportion of our sample size for this sub-period, these make up to 45 %. Considering this loss, the analysis and particularly the regression results reported for 2010-2013 may not be representative. A technique used to deal with missing data is imputation where missing data is replaced (Enders, 2010, p. 42). It should be clarified that excluding missing IPOs (listwise deletion), which have been done thus far, is also a technique to deal with missing data (Enders, 2010, p. 39). As mentioned, however, this decreases the sample size and in turn most likely weakens the statistical power of the analysis. In contrast, imputation gives a complete data set. Thus, rather than deletion, we experimented with mean substitution where "missing" IPOs are imputed with the sub-period average underpricing. Among other imputation techniques, the choice of mean imputation was based mainly on the simplicity of using this method. In addition, offer price and/or initial day of trading closing price are assumed to be missing completely at random (MCAR) (Enders, 2010, p. 7). In other words, the missingness is not conditional on first-day return and it is plausible to assume that the missingness are independent of assets, sales, age, biotech and PE.

“Missing” IPOs in 2010-2013 are assigned with the average first-day return of 6.02 %. Consequently, 16.57 % will be used as first-day return for the “missing” IPOs in 2014-2016. In addition, consistent with our selection criteria, any “missing” IPOs being unit offerings or REITs are removed. The regression results are presented in Table 2 which can be found in the Appendix.

Regarding the entire sample period, compared to the original regression, all variables become insignificant. Regarding the cold issue market, all independent variables are still insignificant. Recall that $\ln(1 + Age)$ and the $Biotech\ Dummy$ were negative related to first-day return in the original regression for the hot issue market, this is also the result when using mean imputation. Moreover, the coefficient on $\ln(1 + Age)$ is less negative whereas the coefficient on the $Biotech\ Dummy$ is more negative. Although mean imputation caused one more variable ($Biotech\ Dummy$) to be insignificant, the overall regression results did hardly change.

Interpreting the results, we cannot tell whether the results are more valid with mean substitution than using deletion. Furthermore, previous research and literature, e.g. Scheffer (2002), Donders, van der Heijden, Stijnen and Moons (2006) and Enders (2010, p. 43), demonstrates that using mean imputation causes more biasedness than other missing data handling methods, even when the data is MCAR. Pursuant to this and by not considering other imputation methods, adhering to listwise deletion of “missing” IPOs should generate more valid results.

It should be clarified, however, that when first-day closing price could not be obtained due to the firm being delisted, this could be the result of the firm declaring bankruptcy. In turn, bankruptcy can be conditional on, e.g. assets and/or sales, thus, the data is not MCAR; rather the data is missing at random (MAR) (Scheffer, 2002). In this case, listwise deletion of “missing” IPOs may no longer be an appropriate method. Thus, in both situations, whether the missing data are MCAR or MAR, recent research suggest using a multiple imputation approach, e.g. Scheffer (2002) and Donders et al. (2006). This approach will not be tested since we lack the knowledge needed.

Outliers

This section will cover outliers in first-day return, i.e. in the dependent variable. Examining the data, some IPOs have experienced extreme underpricing, both negative and positive. By assumption, due to the relatively small sample in 2010-2013, these IPOs will presumably have immense impact on the results in this sub-period. As aforementioned, regression coefficients are usually very sensitive to outliers, not to mention the panel results. Thus, we have used two similar methods to robust test our original model. The first method is called winsorization and the second is called trimming. The former is used to replace unusually large outliers with less large values and unusually small outliers with less small values, while the latter refers to eliminating outliers (Ghosh & Vogt, 2012). In other words, rather than dropping the outlier from the sample resulting in a smaller sample, winsorization downgrades the weight of the outlier. For both methods, we have used the 5th and 95th-percentile to classify outliers with respect to underpricing. IPOs subject to extreme underpricing, i.e. above the 95th-percentile of the sample, are assigned with the 95th-percentile first-day return or eliminated. Consequently, IPOs subject to extreme overpricing, i.e. below the 5th-percentile of the sample, are replaced with the 5th-percentile first-day return or eliminated. Lastly, regarding both methods, the calculation of percentiles is either based on the entire sample period, test 1, or the sub-periods, test 2. This generates two different samples, respectively, for the winsorization and the trimming treatment. The regression results are presented in Table 3, 4, 5 and 6 which can be found in the Appendix.

When using winsorization for test 1, $\ln(Assets)$ becomes significant for 2010-2013. The negative sign on the coefficient is consistent with a positive relation between risk and first-day return. Regarding the regression results for the later sub-period, the $Biotech\ Dummy$ variable stays significant but the causal effect is less negative. However, $\ln(1+Age)$ is no longer relevant. Lastly, no variable is significant when running the regression on the entire sample period. Moving on to the regression results when trimming is used. Compared to the original regression model, $\ln(Assets)$ and $\ln(Sales)$ are now significant for the cold issue market. The negative sign on the coefficient on $\ln(Assets)$ is consistent with a positive relation between risk and first-day return, however, the positive sign on the coefficient on $\ln(Sales)$ is not. Furthermore, the R^2 value of 0.1842 is substantially higher than in the original model (0.025). Regarding the regression results for the hot issue market, there have been a shift in significance between the variables. Rather than $\ln(1+Age)$ and the $Biotech\ Dummy$ as in the original model, $\ln(Assets)$ and $\ln(Sales)$ are significantly related to first-day return. The former being negatively related and the latter being positively related. In this case, when the same set of variables are significant in both sub-periods, we can examine criterion three and say something about stationarity. First, the coefficients have changed over time, which indicate a nonstationary relation between risk and first-day return. In addition, the sign on $\ln(Sales)$ in 2010-2013 and $\ln(Assets)$ in 2014-2016 is not consistent with a positive relation between risk and first-day return. Moreover, the signs are opposing in each sub-period. Hence, pursuant to these variables, the changing risk composition hypothesis cannot explain the higher average underpricing observed in 2014-2016. Lastly, as with winsorization, trimming caused insignificance of all variables when running the regression on the entire sample period.

When percentiles are calculated on the sub-periods (test 2) rather than the entire sample period (test 1), winsorizing the outliers leads to more insignificant variables. The only relevant variable in all three period-wise regressions is the $Biotech\ Dummy$ for 2014-2016. The coefficient has a negative sign and it is less negative than in the original model. Furthermore, dropping outliers from the sample also caused more insignificance, however, instead of $\ln(1 + Age)$ and the $Biotech\ Dummy$, $\ln(Assets)$ and $\ln(Sales)$ are relevant to underpricing in 2014-2016. The sign on the latter is consistent with a positive relation between risk and first-day return.

In comparison to the original model, using either winsorization or trimming results in higher R^2. Generally, this means that treating outliers improves our regression model since it better predicts first-day returns. In contrast, overall, these methods caused more insignificant variables. Lastly, being subject to a relative small sample size, it does not come as a surprise that 2010-2013 were most affected by outliers. In conclusion, the regression results suggest that our original model is sensitive to outliers, hence, it is not robust to outliers in first-day returns.

Omitted Variables

Having intercepts above the average IPO underpricing, we suspect that our original model is not perfect. It is plausible to assume that not all components trying to explain underpricing are negatively related to underpricing. Thus, the error term may include components which have positive effect on first-day returns. These omitted variables might as well be correlated to our variables used in the regression, if so, we are subject to biases and the reported coefficients do not estimate true marginal effects and the intercepts would be inaccurate. This may also be a potential reason to the overall insignificance.

Recall that the literature offers many theories and models to why underpricing occurs. Thus, in order to model an optimal regression, we need to control for these when testing the changing risk composition hypothesis, and most importantly, if they also affect our explanatory variables. In our original regressions, the relatively low R^2 values imply that our model does a poor job to explain underpricing. Thus, adding any possible omitted variables may increase the R^2, and therefore, improve the model's fitting to the data. However, due to the time constraint imposed on this study and the fact that such data requires to be collected manually, we have not proceeded with this robust test. Nevertheless, we believe that adding variables would only increase or decrease the estimated parameters and change the intercepts, but not the overall results. Even though panel data in general are not fully reliable to measure true relationships between variables, we argue that the patterns provided by Panel A and B are far too strong showing that the changing risk composition hypothesis is likely irrelevant to the higher average underpricing in the hot issue market.

Finally, given all the theories being provided in previous research and current literature on the underpricing phenomenon, we believe that modelling a regression with a high R^2 is nearly impossible. In addition, recognizing that the theories being provided are either similar, based on each other and/or extensions, researchers would find it difficult satisfying the exogeneity assumption in the first place. A solution to this is indeed a two-stage least squares regression, seen to be used by e.g. Loughran and Ritter (2004). However, sorting out the endogenous variable(s) ought to be too complex and too time consuming to resolve with in this study – not to mention to claim for its endogeneity among other variables. Thus, even though our original regression model is far from perfect, the results were consistent with the cross-sectional and longitudinal patterns.

VI. Conclusions

First and foremost, consistent with previous research, this study shows that IPOs are underpriced on average. During the entire sample period, 2010-2016, IPOs on the Swedish stock market saw their shares surge on average 14.12 % at the initial day of trading. Moreover, IPOs during the hot issue market of 2014-2016 were subject to pronouncedly higher average first-day returns than the four-year period prior to this period, where the difference was more than 10 percentage points.

The purpose of this paper was to investigate this difference in underpricing between the cold issue market of 2010-2013 and the hot issue market of 2014-2016. Among other theories and hypotheses trying to explain swings in underpricing over time, the changing risk composition hypothesis was tested for in this paper. Having surveyed previous research and conducted this study, it does not come as a surprise that IPO underpricing is still mysterious. In a broader viewpoint, our results do to some extent amplify this puzzling phenomenon.

Although the reported results, mainly in Panel B, showed some tendencies of a positive relation between risk and first-day return, which must be satisfied in first place in order to some extent attribute the higher underpricing in 2014-2016 to the changing risk composition hypothesis, the relation was nonstationary. Furthermore, if our risk proxies are adequate risk measures, the overall insignificance of these indicate that risk is likely irrelevant to underpricing in our regression model. More precisely, the regression results could not ensure a distinct relation between risk and first-day return. In addition, a larger proportion of riskier IPOs in the hot issue market than in the cold issue market was not seen, and therefore, the first criterion was neither satisfied. Thus, our results do not provide evidence that the changing risk composition hypothesis can serve as an explanation to the higher average underpricing in the hot issue market.

However, to some degree, the results can be biased. Even if they are biased, we argue that this would not change the outcome. Moreover, the cross-sectional and longitudinal patterns shown were too strong providing evidence against the changing risk composition hypothesis. Nevertheless, opposed to Ritter (1984) and Loughran and Ritter (2004), we are not in the position to neither conclude that risk has effect on underpricing nor that it has no effect, and in turn either linking it to the changing risk composition hypothesis or rejecting it to the average higher underpricing in the hot issue market.

Therefore, we looked for other potential factors in our data set and we found a component that could be central to the higher underpricing in 2014-2016; IPOs related to the info-tech line of business. In general, IPOs in this industry were subject to evidently higher average first-day returns than the other industries during the entire sample period. Adding the other industries together, the average first-day return for info-tech IPOs was relatively consistent with the average (14.12 %) for the entire sample period. In addition, the proportion of info-tech related firms was not only substantially greater in the hot issue market they were also much more underpriced than in the cold issue market. Thus, referring to a hot issue market based on underpricing, there seems to be that no such occurred for non-info-tech IPOs. In other words, the higher average underpricing during 2014-2016 may be attributed to info-tech IPOs – but pursuant to some other underpricing theories rather than the changing risk composition hypothesis. This is only a vague inference, however, since it must be investigated more thoroughly. As such, an idea for further research would be to examine this factor.

If the missing data on the "missing" IPOs could be obtained, it would be interesting to see whether adding these IPOs to the sample would have any implications in terms of results for this study, especially regarding the cold issue market where an abundance of IPOs were reported as "missing". However, shown by the various robustness tests, the higher underpricing in 2014-2016 is still not likely to be attributed to the changing risk composition hypothesis. Regardless, we would still see this test made since it would increase the validity of this study and we could only hope for such further research to be made in the future. In addition, in order to obtain more valid results, we suggest that data on other underpricing theories and hypotheses should be collected and controlled for.

Given the overall insignificance of our proxies for ex ante uncertainty, for further research on why IPO underpricing fluctuates over time it would be appropriate to challenge these proxies when testing for the changing risk composition hypothesis. Thus, it would be interesting to see if other common proxies for risk, for instance related to information found in prospectuses such as risk factors (Beatty & Welch, 1996) and/or how the IPO proceeds will be used (Beatty & Ritter, 1986), could be more adequate and in turn alter any results. Finally, a more general suggestion for studying the distinct difference in average underpricing examined in this thesis would be to test for other underpricing theories, but rather where adequate risk proxies are used as control variables.

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Appendix

Table 2. "Missing" IPOs

The table shows the regression results where first-day returns are used as the dependent variable. "Missing" IPOs are included through imputation. T-statistics are given in the parentheses. Significance level 1 % is denoted by ***, 5 % is denoted by ** and 10 % is denoted by *. The regressions are run with robust standard errors.

	SUB-PERIODS		SAMPLE PERIOD
Variables	**2010-2013**	**2014-2016**	**2010-2016**
ln(*Assets*)	-2.552684	0.1545201	-0.0712786
	(-1.65)*	(0.41)	(-0.21)
ln(*Sales*)	0.4347833	0.0123423	0.0603196
	(1.27)	(0.04)	(0.25)
ln(1 +*Age*)	1.579119	-4.895775	-2.712613
	(0.37)	(-2.08)**	(-1.38)*
Biotech	-2.645092	-17.35475	-12.1196
	(-0.23)	(-2.50)***	(-1.89)*
PE	-4.871736	2.71574	0.0945625
	(-0.65)	(0.41)	(0.02)
Constant	42.78601	26.02479	21.55975
	(1.61)*	(2.89)***	(2.78)***
R^2	0.0241	0.0235	0.0130

Table 3. Winsorization Test 1

The table shows the regression results where first-day returns are used as the dependent variable. Based on the entire sample period, an IPO is classified as an outlier if it had a first-day return below the 5th-percentile or above 95th-percentile. Outliers are replaced with either the 5th-percentile or the 95th-percentile first-day return. T-statistics are given in the parentheses. Significance level 1 % is denoted by ***, 5 % is denoted by ** and 10 % is denoted by *. The regressions are run with robust standard errors.

	SUB-PERIODS		SAMPLE PERIOD
Variables	**2010-2013**	**2014-2016**	**2010-2016**
ln(*Assets*)	-3.568143	0.3515613	-0.0010426
	(-2.01)**	(0.66)	(-0.00)
ln(*Sales*)	0.5646198	-0.1020271	-0.00071163
	(1.42)*	-0.36	(-0.00)
ln(1 +*Age*)	1.927257	-3.880818	-2.1781
	(0.42)	(-1.84)*	(-1.12)
Biotech	-5.17151	-11.92309	-9.127158
	(-0.50)	(-2.11)**	(-1.77)*
PE	-5.917241	2.65421	0.4994992
	(-0.75)	(0.63)	(0.14)
Constant	59.76264	17.30209	17.45566
	(1.99)*	(2.06)**	(2.12)**
R^2	0.0567	0.0318	0.0167

Table 4. Winsorization Test 2

The table shows the regression results where first-day returns are used as the dependent variable. Based on the sub-periods, an IPO is classified as an outlier if it had a first-day return below the 5th-percentile or above the 95th-percentile. Outliers are replaced with either the 5th-percentile or the 95th-percentile first-day return. T-statistics are given in the parentheses. Significance level 1 % is denoted by ***, 5 % is denoted by ** and 10 % is denoted by *. The regressions are run with robust standard errors.

	SUB-PERIODS		**SAMPLE PERIOD**
Variables	**2010-2013**	**2014-2016**	**2010-2016**
ln(*Assets*)	-3.010863	0.3565547	0.0420794
	(-1.58)*	(0.69)	(0.08)
ln(*Sales*)	0.4882466	-0.1356668	-0.0517142
	(1.15)	(-051)	(-0.22)
ln(1 +*Age*)	0.8389657	-3.844115	-2.276331
	(0.17)	(-1.85)*	(-1.16)
Biotech	-7.261034	-12.04766	-10.48415
	(-0.63)	(-2.18)**	(-1.94)*
PE	-4.072999	2.517134	0.9649929
	(-0.49)	(0.61)	(0.26)
Constant	51.41327	17.87513	17.32971
	(1.58)*	(2.20)**	(2.17)**
R^2	0.0369	0.0337	0.0208

Table 5. Trimming Test 1

The table shows the regression results where first-day returns are used as the dependent variable. Based on the entire sample period, an IPO is classified as an outlier if it had a first-day return below the 5th-percentile or above the 95th-percentile. Outliers are dropped from the sample. T-statistics are given in the parentheses. Significance level 1 % is denoted by ***, 5 % is denoted by ** and 10 % is denoted by *. The regressions are run with robust standard errors.

	SUB-PERIODS		**SAMPLE PERIOD**
Variables	**2010-2013**	**2014-2016**	**2010-2016**
ln(*Assets*)	-4.193463	1.104229	0.7014707
	(-2.90)***	(2.92)***	(1.91)*
ln(*Sales*)	0.8613153	-0.586105	-0.3077285
	(2.19)**	(-2.49)***	(-1.47)*
ln(1 +*Age*)	0.468675	-2.23804	-1.791627
	(0.19)	(-1.20)	(-1.08)
Biotech	-1.541458	-9.214828	-5.684015
	(-0.20)	(-1.69)*	(-1.21)
PE	-11.04795	3.706232	0.3962572
	(-1.65)*	(1.03)	(0.12)
Constant	74.84152	3.866562	6.842298
	(2.91)***	(0.67)	(1.18)
R^2	0.1842	0.0649	0.0230

Table 6. Trimming Test 2

The table shows the regression results where first-day returns are used as the dependent variable. Based on the sub-periods, an IPO is classified as an outlier if it had a first-day return below the 5th-percentile or above the 95th-percentile. Outliers are dropped from the sample. T-statistics are given in the parentheses. Significance level 1 % is denoted by ***, 5 % is denoted by ** and 10 % is denoted by *. The regressions are run with robust standard errors.

	SUB-PERIODS		SAMPLE PERIOD
Variables	**2010-2013**	**2014-2016**	**2010-2016**
ln(*Assets*)	-3.04089	0.8563912	0.4981492
	(-1.80)*	(2.41)**	(1.42)*
ln(*Sales*)	0.5961939	-0.4846301	-0.3040959
	(1.51)*	(-2.09)**	(-1.44)*
ln(1 + *Age*)	-1.732643	-2.877334	-2.06573
	(-0.49)	(-1.59)	(-1.22)
Biotech	-8.937058	-10.20013	-9.459169
	(-0.88)	(1.90)*	(-1.90)*
PE	-3.833795	2.504	1.132903
	(-0.51)	(0.70)	(0.35)
Constant	55.68888	10.17551	10.87794
	(1.85)*	(1.92)*	(1.99)**
R^2	0.0674	0.0606	0.0328

Table 7. Sample

Issuer	Issue year	Exchange
Arise Windpower AB	2010	Nasdaq Stockholm
Byggmax Group AB	2010	Nasdaq Stockholm
Challenger Mobile AB	2010	Aktietorget
EcoRub AB	2010	Aktietorget
Episurf Medical AB	2010	Aktietorget
Genesis IT AB	2010	Aktietorget
Jays AB	2010	Aktietorget
MQ Holding AB	2010	Nasdaq Stockholm
Pallas Group AB	2010	First North
Parans Solar Lightning AB	2010	Aktietorget
PharmaLundensis AB	2010	Aktietorget
ScandBook Holding AB	2010	First North
True Heading AB	2010	Aktietorget
Vendator AB (Hubbr AB)	2010	Aktietorget
WntResearch AB	2010	Aktietorget
ZinZino AB	2010	Aktietorget
5050 Poker Holding AB	2011	First North
Arocell AB	2011	Aktietorget
Boule Diagnostics AB	2011	Nasdaq Stockholm
Cefour Wine & Beverage Partihandel AB	2011	Aktietorget
Ecomb AB	2011	Aktietorget
Enzymatica AB	2011	Aktietorget
Finnvedenbulten AB	2011	Nasdaq Stockholm
FX International AB	2011	Aktietorget
Kancera AB	2011	Aktietorget
Karolinska Development AB	2011	Nasdaq Stockholm
Mackmyra Svensk Whiskey AB	2011	First North
MediRätt AB	2011	Aktietorget
Moberg Pharma AB	2011	Nasdaq Stockholm
ZetaDisplay AB	2011	First North
ALM Equity AB	2012	First North
AVTECH SWEDEN AB	2012	First North
Brighter AB	2012	Aktietorget
Creades AB	2012	First North
Gullberg & Jansson AB	2012	Aktietorget
Latvian Forest Company AB	2012	Aktietorget
Medfield Diagnostics AB	2012	Aktietorget
PlayHippo AB	2012	Aktietorget
Respiratorius AB	2012	Aktietorget
RLS Global AB	2012	Aktietorget
Spago Nano Medical AB	2012	Aktietorget
Sportamore AB	2012	First North
A1M Pharma AB	2013	Aktietorget
Arc Aroma Pure AB	2013	Aktietorget
Emotra AB	2013	Aktietorget
Immunicum AB	2013	First North
Kentima Holding AB	2013	First North
Mindmancer AB	2013	First North
North Chemical AB	2013	First North
Platzer Fastigheter AB	2013	Nasdaq Stockholm
ProstaLund AB	2013	Aktietorget
Recyctec Holding AB	2013	Aktietorget
Serstech AB	2013	Aktietorget
SyntheticMr AB	2013	Aktietorget
TiksPac AB	2013	Aktietorget
Tourn International AB	2013	Aktietorget
Absolent Group AB	2014	First North
Advenica AB	2014	First North
Aha World AB	2014	Aktietorget
Alteco Medical AB	2014	Aktietorget
Arcoma AB	2014	First North
Axon Kids AB	2014	Aktietorget
Bactiguard Holding AB	2014	Nasdaq Stockholm
Besqab AB	2014	Nasdaq Stockholm
Braincool AB	2014	Aktietorget
Bufab Holding AB	2014	Nasdaq Stockholm
Byggmästare Anders J Ahlström Holding AB	2014	First North
C Security Systems AB	2014	Aktietorget
Christian Berner Tech Trade AB	2014	First North
Clavister Holding AB	2014	First North
Com Hem AB	2014	Nasdaq Stockholm
D. Carnegie & Co AB	2014	First North
DDM Holding AG	2014	First North
Dentware AB	2014	Aktietorget
Dextech Medical AB	2014	Aktietorget
Ecoclime Comfort Ceilings AB	2014	Aktietorget
Envirologic AB	2014	Aktietorget
Greater Than AB	2014	Aktietorget
Gränges AB	2014	Nasdaq Stockholm
Hanza AB	2014	First North
Hemfosa Fastigheter AB	2014	Nasdaq Stockholm
Igrene AB	2014	Aktietorget
Inwido AB	2014	Nasdaq Stockholm
Lifco AB	2014	Nasdaq Stockholm
Motion Display Scandinavia AB	2014	Aktietorget
Nexstim Oyj	2014	First North
NP3 Fastigheter AB	2014	Nasdaq Stockholm
Oboya Horticulture Industries AB	2014	Aktietorget
Optifreeze AB	2014	Aktietorget
Oscar Properties Holding AB	2014	First North
Papilly AB	2014	First North
Peptonic Medical AB	2014	Aktietorget
Phase Holographic Imaging Phi AB	2014	Aktietorget
PromikBook AB	2014	Aktietorget
Recipharm AB	2014	Nasdaq Stockholm
Rootfruit Scandinavia AB	2014	Aktietorget
Saniona AB	2014	Aktietorget
Scandi Standard AB	2014	Nasdaq Stockholm
Scandidos AB	2014	First North
Scandinavian Enviro Systems AB	2014	First North
Scandinavian Real Heart AB	2014	Aktietorget
Sealwacs AB	2014	Aktietorget
Sprint Bioscience AB	2014	First North
Thule Group AB	2014	Nasdaq Stockholm
VA Automotive i Hässleholm AB	2014	First North
Verisec AB	2014	First North
Zenicor Medical Systems AB	2014	Aktietorget
A City Media AB	2015	First North
A Group of Retail Assets Sweden AB	2015	First North
Alimak Group AB	2015	Nasdaq Stockholm
Attendo AB	2015	Nasdaq Stockholm
Bravida AB	2015	Nasdaq Stockholm
Camurus AB	2015	Nasdaq Stockholm
Cantargia AB	2015	First North
Capacent Holding AB	2015	First North
Capio AB	2015	Nasdaq Stockholm
Cline Scientific AB	2015	Aktietorget
CLX Communications AB	2015	Nasdaq Stockholm
Collector AB	2015	Nasdaq Stockholm
Coor Service Management Group AB	2015	Nasdaq Stockholm
Corline Biomedicial AB	2015	First North
Dalsspira Mejeri AB	2015	Aktietorget
Dometic Group AB	2015	Nasdaq Stockholm
Double Bond Pharmaceutical International AB	2015	Aktietorget
Dustin Group AB	2015	Nasdaq Stockholm
Eltel AB	2015	Nasdaq Stockholm
Evolution Gaming Group AB	2015	First North
Gaming Corps AB	2015	First North
Hoist Finance AB	2015	Nasdaq Stockholm
Hybricon Bus Systems AB	2015	Aktietorget
Hövding Sverige AB	2015	First North
Imint Image Intelligence AB	2015	Aktietorget
Immunovia AB	2015	First North
Inission AB	2015	First North
Insplorion AB	2015	Aktietorget
Ivisys AB	2015	First North
Karessa Pharma Holding AB	2015	First North
Kontigo Care AB	2015	First North
Magnolia Bostad AB	2015	First North
Maxkompetens Sverige AB	2015	First North
Minesto AB	2015	First North
Nanexa AB	2015	Aktietorget
Nanologica AB	2015	Aktietorget
Nilsson Special Vehicles AB	2015	First North
Nilörn Gruppen AB	2015	First North
Nobina AB	2015	Nasdaq Stockholm
Nordax Bank AB	2015	Nasdaq Stockholm
Nuevolution AB	2015	First North
Oncology Venture Sweden AB	2015	Aktietorget
Organoclick AB	2015	First North
Pandox Holdings AB	2015	Nasdaq Stockholm
Pexa AB	2015	Aktietorget
Pharmacolog i Uppsala AB	2015	Aktietorget
Photocat AB	2015	First North
Prebona AB	2015	Aktietorget
Prime Living AB	2015	First North
Quickcool AB	2015	Aktietorget
Saltx Technology Holding AB	2015	First North
Savo-Solar Oyj	2015	First North
Scandic Hotels Group AB	2015	Nasdaq Stockholm
Scibase AB	2015	First North
Soltech Energy Sweden AB	2015	First North
Spectracure AB	2015	Aktietorget
Stillfront Group AB	2015	First North
TC Tech Sweden AB	2015	First North
The Lexington Company AB	2015	First North
Tobii Technology AB	2015	Nasdaq Stockholm
Transtema Group AB	2015	Aktietorget
Troax Group AB	2015	Nasdaq Stockholm
Vibrosense Dynamics AB	2015	Aktietorget
Vicore Pharma Holding AB	2015	First North
Waystream Holding AB	2015	First North
Zenergy AB	2015	Aktietorget
Absolicon Solar Collector AB	2016	Aktietorget
Academedia AB	2016	Nasdaq Stockholm
Acarix AB	2016	First North
Adderacare AB	2016	First North
Ahlsell AB	2016	Nasdaq Stockholm
Aino Health AB	2016	First North
Alelion Batteries AB	2016	First North
Alligator Bioscience AB	2016	Nasdaq Stockholm
Appspotr AB	2016	Aktietorget
B3IT Management AB	2016	First North
Brinova Fastigheter AB	2016	First North
Bygg Partner I Dalarna Holding AB	2016	First North
Catena Media P.L.C	2016	First North
Cellink AB	2016	First North
Cereno Scientific AB	2016	Aktietorget
Clean Motion AB	2016	First North
Cognosec AB	2016	First North
Crowdsoft Technology AB	2016	Aktietorget
Crunchfish AB	2016	First North
Cyxone AB	2016	First North
Dignita Systems AB	2016	Aktietorget
Edgeware AB	2016	Nasdaq Stockholm
Enorama Pharma AB	2016	First North
Expres2ion Biotech Holding AB	2016	First North
Fastout Int. AB	2016	Aktietorget
Finepart Sweden AB	2016	Aktietorget
Gapwaves AB	2016	First North
Garo AB	2016	Nasdaq Stockholm
Gasporox AB	2016	First North
GS Sweden AB	2016	First North
Humana AB	2016	Nasdaq Stockholm
Index Pharmaceuticals AB	2016	First North
Internationella Engelska Skolan i Sverige AB	2016	Nasdaq Stockholm
Invent Medic Sweden AB	2016	Aktietorget
Lauritz.com Group A/S	2016	First North
LeoVegas AB	2016	First North
Litium AB	2016	Aktietorget
Maxfast Properties AB	2016	First North
Nepa AB	2016	First North
Nordic Water Proofing Holding A/S	2016	Nasdaq Stockholm
Paradox Interractive AB	2016	First North
PEN Concept Group AB	2016	Aktietorget
PiezoMotor Uppsala AB	2016	First North
Plejd AB	2016	Aktietorget
Polygiene AB	2016	First North
Provide IT Sweden AB	2016	Aktietorget
Raybased AB	2016	Aktietorget
Redwood Pharma AB	2016	Aktietorget
Resurs Holding AB	2016	Nasdaq Stockholm
Rethinking Care Sweden AB	2016	First North
Scandinavian Chemotech AB	2016	First North
Seatwirl AB	2016	First North
Serneke Group AB	2016	Nasdaq Stockholm
Shortcut Media AB	2016	Aktietorget
Simris Alg AB	2016	First North
Sjöstrand Coffee Int AB	2016	Aktietorget
Sleepo AB	2016	Aktietorget
Smart Eye AB	2016	First North
Sweden Care AB	2016	First North
Talkpool AG	2016	First North
The Marketing Group P.L.C	2016	First North
THQ Nordic AB	2016	First North
Vadsbo SwitchTech Group AB	2016	Aktietorget
Videobur Sthlm Int AB	2016	Aktietorget
Volati AB	2016	Nasdaq Stockholm
Wilson Therapeutics AB	2016	Nasdaq Stockholm
Xbrane Biopharma AB	2016	First North
Åacmicrotec AB	2016	First North