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Information Production, Firm Complexity, and the Underpricing of Initial Public Offerings in Sweden

Master Thesis in Corporate Finance

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Abstract

This paper studies whether the level of IPO underpricing is enforced by increased firm complexity. Evidence from a sample of 215 Swedish IPOs between 2010–2020 suggests that investor's ex-ante uncertainty increases as issuing firms become increasingly complex. As a consequence, firms exhibiting complexity generally experience higher degrees of IPO underpricing. Moreover, we find support for our claim that hiring multiple underwriters reduces underpricing, although with a diminishing effect as companies become more complex. Inconsistent with our expectations, we find that venture capital-backed offerings experience more underpricing compared to their non-backed counterparts.

Keywords: complexity, initial public offerings, underpricing, information production

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1. Introduction

An Initial Public Offering (IPO) is the most common method for private companies to become public (Ritter, 1991). The existing literature finds ample evidence that issuing firms tend to be priced below their intrinsic value, leading to a loss of wealth for the incumbent shareholders (Ritter and Welch, 2002; Loughran and Ritter, 2004; Ljungqvist, 2007). Researchers point to the underpricing phenomenon as one of the best-known anomalies in corporate finance and a clear departure from market efficiency (Abrahamson, De Ridder and Råsbrant, 2011).

Despite that IPO underpricing has been researched from a vast number of angles, little attention has been devoted to investigating how the prevalence of underpricing differs among issuers exhibiting different levels of complexity. Cohen and Lou (2012) argue that increased complexity makes it increasingly difficult to comprehend a firm's true nature and business environment. Loughran and Ritter (2004) and Daily et al. (2005) studied the relationship between firm's exhibiting increased technological advancement and IPO underpricing, finding a significant positive relationship. In line with mentioned literature, this paper studies whether increased ex-ante uncertainty, stemming from firm more complexity, leads to an increased level of IPO underpricing. The research question has previously been studied on the U.S. market but to the best of our knowledge, not in Sweden. Sweden's developed financial system creates a good basis for comparative analysis of empirical evidence from other sophisticated markets.

In a further attempt to examine IPO underpricing related to ex-ante uncertainty, we study how firm characteristics such as the firm's age affect the degree of underpricing. The rationale being that firms of greater age have collected more historical financial- and operational data, which is argued to alleviate ex-ante uncertainty, resulting in investors demanding a lower discount on the firm's shares in the event of an IPO (Ritter, 1991; Chemmanur, 1993; Loughran and Ritter, 2004).

Also, in order to reduce the degree of underpricing, researchers point to a number of mitigating factors, including but not limited to certification, monitoring, and increased information production conducted by the underwriting syndicate (Megginson and Weiss, 1991; Barry et al. 1990; Corwin and Schultz, 2005). Following the line of the certification theory and recognising the monitoring role of an experienced owner, we coincide with Megginson and Weiss (1991) and Barry et al. (1990), arguing that PE- or VC-firms inherent in an issuers list of shareholders serves to reduce ex-ante uncertainty, thus, exhibiting a negative relationship to IPO underpricing. Corwin and Schultz (2005) and Hu and Ritter (2007) recognise information production benefits from hiring additional underwriters. Coinciding with the authors, we intend to study whether a greater number of managing underwriters enhances the ability to produce information, which is assumed to result in a more accurate valuation, thus, less underpricing. The average number of underwriting managers in Swedish IPOs has gradually increased from the 2000s and onwards, making the Swedish market appropriate for this research question (Eikon Refinitiv SCD, 2021). Lastly, this paper studies if the benefit from hiring additional underwriters diminishes when firms become more complex. To our best knowledge, no paper has studied whether the managing underwriters' ability to process information reduces as businesses exhibit increasingly higher complexity.

To enrich the existing literature on IPO underpricing with assumed origins from factors related to information asymmetry, ex-ante uncertainty, and firm complexity, this paper studies 215 IPOs conducted on all five domestic exchanges over 2010–2020. Our main OLS regression finds support for our first proposition, namely that as companies become increasingly more complex, IPO underpricing tend to increase. Also, our results indicate a significant negative relationship between *Firm age* and the degree of underpricing. Concerning PE- and VC-backing of IPOs, we assumed a negative relationship to underpricing. However, we do not find support for this claim, as our coefficient for *VC-backed* IPOs instead came out positive at the one percent level, indicating a converse relation. Lastly, and in line with our intended study on certification and monitoring effects, we find that the assumed benefits of information production (i.e., less underpricing) exhibit a diminishing effect on the relationship as issuing firms become gradually more complex.

The remainder of the paper is structured as follows; *Section 2* will review the key aspects and theories related to initial returns and its links to firm complexity, ex-ante uncertainty, and information production. *Section 3* provides a brief description of the Swedish IPO market and its fundamental characteristics. In *Section 4*, we introduce our hypotheses and their underlying rationale. In *Section 5*, we go through the methodology and include a detailed description of all variables used in the regression. In *Section 6*, we describe our data collection process and present summary statistics. *Section 7* consists of our empirical findings along with discussions following our hypotheses. Lastly, we present our conclusions in *Section 8*.

Figure 3. Aggregate amount left on the table (in billions of USD)

This table plots the aggregate amount of USD foregone by investors on the US market due to underpricing per year between 2010 and 2020

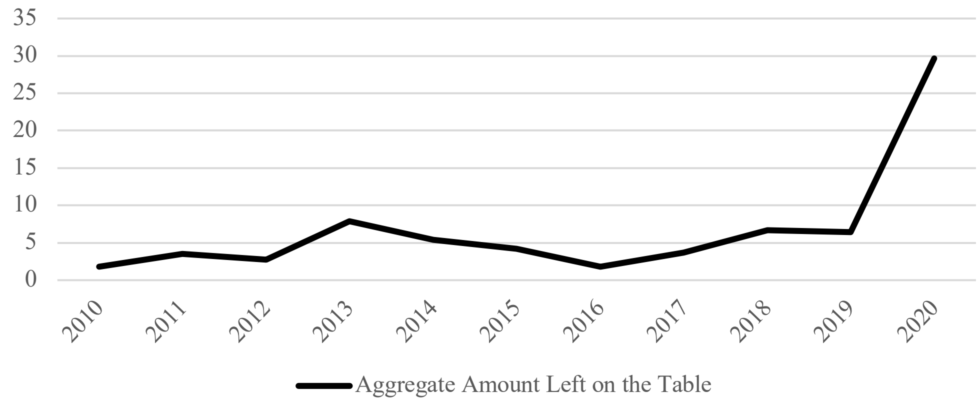

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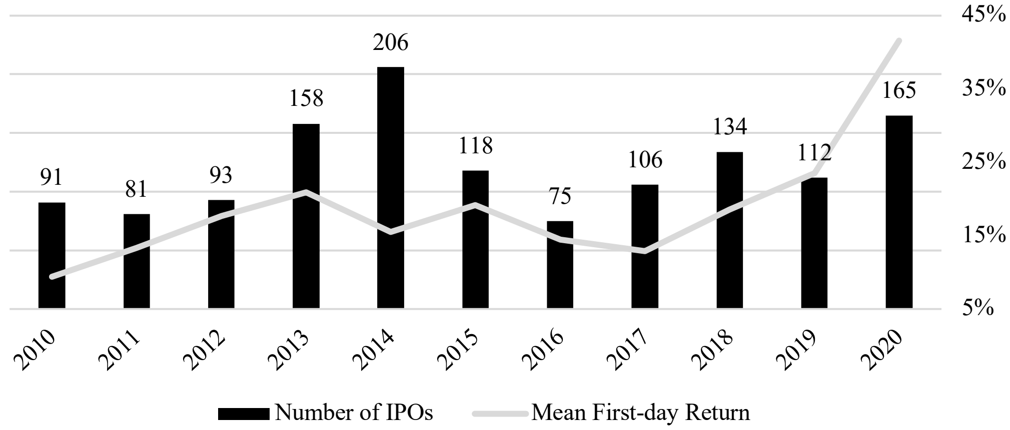
Figure 4. Number of offerings and average first-day returns on US IPOs

This graph plots the overall number of IPOs in the US between 2010 and 2020 along with average first day returns, expressed as a percentage.



[1] Jay Ritter of the University Florida has compiled a comprehensive database of IPO and underpricing related statistics. Jay R. Ritter IPO Data, 2021 https://site.warrington.ufl.edu/ritter/ipo-data/

2. Literature review

2.1 The IPO underpricing phenomenon

Going public can be considered an important step for a firm, allowing the company's equity to be publicly traded on a stock exchange. Upon listing, several direct and indirect costs emerge for the issuing firm. Direct costs consist of listing fees, underwriter fees, and professional fees (e.g., legal fees) (Loughran and Ritter, 2004). The indirect costs associated with IPOs are commonly referred to as the IPO price discount and arise when the offer price for the issuing firm's shares is inferior to the first day closing price.

Previously conducted research has attempted to measure the magnitude that has been forgone by issuing firms. Ritter (2021) estimates the total figure to $201 billion over 1980–2020 (aggregated proceeds of $1001 billion). The degree of underpricing fluctuates over the period, recording its bottom at 3.7 percent in 1984 and the peak at 71.2 percent in 1999. The entire period records an average degree of underpricing at 20.1 percent. Gajewski and Gresse (2006) conducted a study on the European market, studying 15 different countries. With a sample of 2104 IPOs over the years 1995-2004, the authors found all analysed markets underpriced, at an average of 15.6 percent.

A number of studies have been completed on the Swedish market, of which Abrahamsson and De Ridder (2011) approximate the total sum forgone by issuing firms to about SEK 24 billion between 2000-2009. The authors found all Swedish stock exchanges to be underpriced on average, some with double digits (%). Over the studied period, Sweden recorded an average degree of underpricing at 4.5 percent. Additionally, Ritter (2016) studied the Swedish market over the period 1983–2016. The author found the Swedish IPO market to fluctuate over the observed period, recording a bottom average in 1991 (21 percent) and peaking in 1986 at about 60 percent. Over the entire period, Sweden recorded an average degree of underpricing at 6.2 percent.

IPO underpricing arise when the valuation conducted by the underwriting syndicate diverge from that of the aggregated market, once publicly traded. Previous research has developed a number of theories attempting to uncover where the valuation divergence originates from. The remainder of this section describes established theories relating to the underpricing phenomenon, including *information asymmetry, ex-ante uncertainty,* and *firm complexity.*

Additionally, *Section 2* reviews established methods to reduce the degree of underpricing, including *certification, monitoring,* and *information production.*

2.1.1 Information asymmetry

Rock (1986) suggest that underpricing of IPOs stems from the apparent information asymmetry between three involved parties: the issuing firm, the associated underwriter, and the aggregated market (investor base). According to Rock (1986) and supported by Ljungqvist (2007), the issuing firm generally is better informed than both parties about their true value. Ljungqvist (2007) argue that issuers are incentivised not to disclose all negative details on their firm to ensure a higher valuation upon listing, disrupting the valuation process of the firm's true value. Although the managing underwriters have a fiduciary responsibility to compile information on the issuing into a comprehensive information memorandum, Ljungqvist (2007) argue that some information tends to be left out. This leads to a dissimilar amount of information available between the underwriters and the aggregated market. The information asymmetry can result in a pricing error, which translates to an under-or overpriced valuation of the issuing firm's shares (ibid).

Moreover, according to Rock's (1986) *Winner's Curse Model,* IPO underpricing is caused by information asymmetry among investors. The author distinguished investors into two sub-groups. One group being perfectly informed about the offering's true value, while the other group is equally uninformed – causing information asymmetry between the parties. As a result of the information advantage, the informed group only subscribes to issues in which the offer price is inferior to the assumed aftermarket price. On the contrary, uninformed investors subscribe randomly among all issues. The informed group of investors will, as a result, crowd out the uninformed investors from the underpriced issues. Simultaneously, informed investors withdraw their interest from overpriced issues, leaving the uninformed group with disproportional subscription rights to less underpriced issues. The Winner's Curse model has received substantial support from several researchers, e.g., Keloharju (1993) and Koh and Walter (1989).

2.1.2 Ex-ante uncertainty

Beatty and Ritter (1986) formulated the *uncertainty determinant of underpricing,* arguing that the degree of ex-ante uncertainty surrounding an issue should be compensated with a corresponding discount on the firm's shares. A common denominator among several of the established drivers of IPO underpricing is that they stem from some degree of ex-ante uncertainty. Loughran and Ritter (2004) find significant relationships between several such drivers and underpricing when studying 6391 U.S. IPOs over the period 1980-2003. One being that going public in different stages of a firm's life cycle is associated with different outcomes. The authors outline a rule of thumb, stating that firms of greater age are perceived as less uncertain. Younger firms are consequently associated with increased ex-ante uncertainty, while older firms, on the contrary, are considered to be more dependable and stable. Loughran, Ritter, and Rydkvist (1994) and Chemmanur (1993) explain that younger firms have less financial and operational data presentable to investors. With limited historical data, the firm is unable to communicate sufficient financial figures to support an accurate valuation, with a basis from achieved historical performance. Investors consequentially require a more significant discount on such issues (ibid).

Another factor that is argued to impact ex-ante uncertainty is *industry affiliation* (Loughran and Ritter, 2004). Daily, Carto, and Dalton (2005) performed an IPO underpricing study on the US market, with a sample of 192 IPOs over 1996–1997. The authors divided its sample with a basis from the level of technological advancement inherent within the firm. By creating two sub-groups: high-tech and low-tech, the authors found a significant positive relationship between high-tech firms and IPO underpricing. The rationale being that investors perceive those firms as more complex, causing ex-ante uncertainty and a consequential discount on the firms shares upon listing (ibid).

Moreover, Loughran and Ritter (2004) found a significant negative relationship between *proceeds* (i.e., the amount of capital raised in a share issue) and the level of underpricing. As the issuing firm secures capital by selling secondary shares to the public, they are able to fund firm-specific objectives and expenses, such as retiring existing debt, fund acquisitions or organic growth (ibid). The greater amount of capital that the issuing firm can accumulate, the less uncertain investors will perceive the firm.

Lastly, Loughran and Ritter (2004) state that *leverage* functions as an influencing driver of ex-ante uncertainty and, by extension, IPO underpricing. Cai, Ramchand and Warga (2004) researched the topic, comparing the level of underpricing among two sub-groups: those with issued debt prior to the IPO and those without. The study found an inverse relationship between *leverage* and the degree of underpricing, explained in terms of decreased information asymmetry and ex-ante uncertainty. According to the authors, prior bank loans imply that the issuer has access to the capital markets, which generates a signal of quality for pre-IPO investors.

2.1.3 Firm complexity

The information production hypothesis, initially established by Chemmanur (1993), supported by Corwin and Schultz (2005), explains that the degree of underpricing experienced by an issuing firm is tied to the amount of information that the managing underwriters are able to process, compile, and subsequently translate into a valuation. A more significant number of underwriters should consequentially amplify the ability to process information more efficiently (ibid). However, Cohen and Lou (2012) suggest that comprehending a firm's true nature and environment is related to the firm's degree of complexity. The authors examined the subject in a non-IPO setting, instead in general investment terms on the public equity markets, using a sample of 1056 U.S. based stocks over the period 1977–2009. The paper therefore examines firm-specific characteristics rather than information asymmetry, as in an IPO underpricing case. Cohen and Lou (2012) study market reactions (i.e., share price development) upon corporate events that entail the same type of information (e.g., beating earnings estimates), among two sub-groups: one group that requires straightforward processing to update asset prices, and another group requiring more complicated analyses to incorporate the same piece of information into prices. The authors find that as companies become more complex, investors are less efficient to process and evaluate information related to a company's financial position and operational nature, than when evaluating a less complex company – both in terms of speed and quality of information processing. According to the authors, investor's ability to translate firm-specific information into firm value gradually diminish as the degree of complexity increases. By extension, this leads to an enhanced difficulty to form an opinion on the firm, resulting in a consequent increase in uncertainty. Investors therefore demand and are compensated with a larger pricing discount on the firm's shares as complexity increases.

2.1.4 Internal and external complexity

The assessment of classifying a business as complex is dependent on the information processing ability of every individual stakeholder. However, previous researchers have applied various proxies to assess the degree of complexity embedded within a firm (e.g., R&D intensity, intangible assets relative to total assets). In order to advance the understanding of the complexity and its origins, Markarian and Parbonetti (2007) utilises a sample of 150 firms over 2003–2005, then separates those into two subsets: one set of firms exhibiting internal complexity and another set exhibiting external complexity.

Internal complexity, and its consequential implications, stems from firm-specific characteristics and the sophistication of its internal work processes (Markarian and Parbonetti, 2007). The authors argue that as products, services, and corresponding business models become increasingly more technologically advanced, the difficulty to comprehend and evaluate businesses intensifies, not least from a valuation perspective. Markarian and Parbonetti (2007) also state that firms with such characteristics often are subject to information asymmetry cases, as it becomes difficult to transfer firm-specific information to *outsiders* (i.e., investors). The authors proxy's internal complexity using two measurements: *R&D intensity* (research and development expenditures relative to net sales), and *intangible assets* (relative to total assets).

On the other side of the spectrum, external complexity relates to the outer competitive structure surrounding a business. The environment in which organizations operate today is becoming increasingly complex and unpredictable. The rationale is that the world has become increasingly interconnected due to the acceleration of technological advancement (Dicken, 2007). Firms operating in an interconnected setting, thus different geographical areas, tend to have diversified client bases difficult to assess. According to Dicken (2007), such firms frequently have complex operational- and financial structures, thus being subject to external complexity cases. The ever-changing market landscape gives cause for sophisticated customer bases, making it increasingly difficult to assess whether a firm is able to meet the demands of the market and satisfy its customer base foreseeably (Dicken, 2007).

Internal and external complexity differ in terms of information available to stakeholders. As mentioned, external complexity stems from market conditions and other outside factors. Hence, according to Markarian and Parbonetti (2007), information should exhibit relatively similar availability for all concerned stakeholders. As information is available for both insiders (issuers) and outsiders (underwriting manager and investors), so should the ability to form opinions on such notions. On the contrary, characteristics that give rise to internal complexity are oftentimes only observable by the internal parties, subsequently communicated to the remaining stakeholders. Communicating such information for complex firms might be associated with implications, giving cause to information asymmetry cases (Markarian and

Parbonetti, 2007). Therefore, according to the authors, ex-ante uncertainty is generally higher when measured in terms of internal rather than external complexity.

2.1.5 Certification and monitoring

As mentioned in *Section 2.1.4*, communicating a firm's quality to the public is associated with several challenges. If not done efficiently, it might result in an information asymmetry case where insiders access more information than outsiders on the firm's true value. Previous researchers point to the signalling value of certification and monitoring, and how such effects reduce uncertainty on firm value (Megginson and Weiss, 1991; Barry et al., 1990). Megginson and Weiss (1991) argue that the presence of a private equity-firm (PE) or venture capital-firm (VC) in an issuers list of shareholders can be perceived as a signal of quality. Hence, alleviating ex-ante uncertainty surrounding the issue. According to the authors, the quality signal stems from being perceived as a competent and experienced owner and recognised for its monitoring role. They also act as a third-party certification on the issuing firms' true value, which subsequently reduces information asymmetry (ibid). Barry et al. (1990) elevates the discussion on the monitoring effects of having a VC- or PE-firm inherent as an owner. The authors state that such shareholders exercise considerable influence on the firm throughout its holding period, providing the firm with experience, expertise, and insights. According to the authors, such firms exhibit improvements in their operations, financial structure, as well as human resources related factors.

More recent studies conducted by Gompers (1996) and Lee and Wahal (2004) contradict the above-mentioned authors' conclusions. Hence, stating that VC-backed IPOs, on average, exhibit more underpricing than their non-VC-backed counterparts. The rationale stems from the business model of VCs, where the ability to generate returns and recycle capital onto new funds lies in the ability to exit from current holdings. Since exiting becomes the primary objective, VCs are willing to bear higher degrees of underpricing (Gompers, 1996). Another explanation stems from reputation building of young VC-firms, with little or no proven track record of conducted investments. Due to the signalling of quality taking a firm public, VCs are incentivised to conduct IPOs at an early stage of a holding's lifecycle. As discussed in *Section 2.1.2* and concurred by Gompers (1996), younger firms tend to give rise to higher degrees of ex-ante uncertainty and underpricing. Consequently, leading to VC-backed IPOs, on average, exhibiting more underpricing than non-VC-backed IPOs.

2.1.6 Information production

Prior to an IPO, the issuing firm hires a syndicate of underwriters with the objective to conduct due diligence, compile information to stakeholders, and produce an accurate valuation on the share issue. Corwin and Schultz (2005) have studied information production and its role in setting the final offering price for the firm's shares. The authors argue that market participants influence the underwriting syndicate in the process, and that the level of information received from them impacts the final offering price.

Over the period from IPO filing day until a determined share price has been set (i.e., valuation), the underwriting syndicate engages in discussions with potential investors to determine the share issue's level of demand and interest. In turn, investors express their opinions on what they perceive a reasonable price to be and the amount of shares they are interested in subscribing. Different degrees of information regarding market interest is received depending on the depth of the managing underwriter's client base of potential investors and geographical reach. According to theory, the greater the amount of information received, the more accurate the valuation is (Hu and Ritter, 2007). By including additional underwriters, thus, increasing the size of the underwriting syndicate, the information production process is amplified, with a more diverse range of competencies and attributes, client bases, and market presence. Hence, resulting in a more efficient valuation process (Corwin and Schultz, 2005; Hu and Ritter, 2007).

The required price discount on the offering, stemming from ex-ante uncertainty, could be further alleviated by more efficient information outflows from the underwriting syndicate. In the process of "filling" the offering, managing underwriters presents compiled material on the issuing firm's operations, competitive environment, financial structure, and various risks to potential IPO-investors in a so-called "roadshow". The information produced is likely to be more comprehensive and accurate in the event of additional underwriters (ibid). By creating more comprehensive material, the underwriters are better positioned to convey an equity story that conveys the issuer's true value – as such, lessening the degree of ex-ante uncertainty, which results in a more accurate valuation and decreased discount on the firm's shares (Corwin and Schultz, 2005).

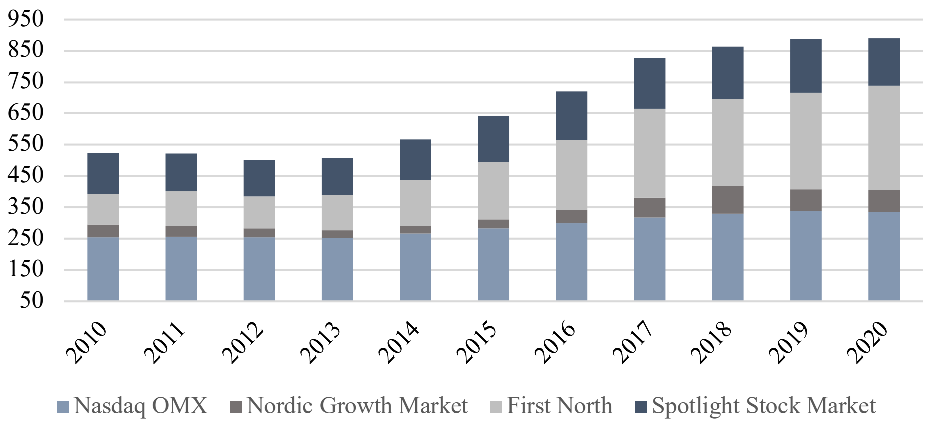
3. The Swedish IPO-market

The Swedish market consists of five different stock exchanges, of which two are regulated: Nasdaq Stockholm and NGM Equity. In addition, there exists three active Multilateral Trading Facilities (MTF): Nasdaq First North, Nordic SME, and Spotlight Stock Market. The regulated market operates in compliance with the legislation of the Swedish Financial Supervisory Authority (the SFSA), in turn, regulated by EU proposed directives (Advokatfirman Hammarskiöld, 2020). Therefore, companies listed on the regulated markets are subject to a higher level (relative to the MTFs) of regulation regarding accounting standards, disclosure of public information, and various admission and trading requirements (ibid). Observing the listing process in Sweden, it differs for every stock exchange. Usually, it takes up to one full year on regulated markets, while it is somewhat faster on MTFs (ibid).

The period 2013–2019 exhibited a notably strong market for Swedish IPOs (Nordnet, 2020). The number of listed companies in Sweden increased from about 500 in December 2013 to approximately 900 in 2019 (ibid). From a historical perspective, the magnitude of this increase can be stated as notable and irregular (Advokatfirman Hammarskiöld, 2020). During 2019, 65 IPOs took place on the Swedish markets, of which 50 were on MTFs and the remaining on regulated markets (ibid). In the light of the coronavirus pandemic, IPO activity decreased in 2020 and recorded the smallest number of IPOs since 2012 (ibid).

Figure 5. Total listed companies on Swedish stock markets

This figure is based on the total number of firms listed on each stock market in Sweden between 2010 and 2020.



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[2] Data collected from the Swedish Statistical Data Base (SCB, 2021) – *Number of quoted companies by Swedish marketplaces*
https://www.statistikdatabasen.scb.se/pxweb/en/ssd/START__FM__FM0201__FM0201D/NoteradeAntalBolag/

4. Hypotheses

4.1 Ex-Ante uncertainty

4.1.1 Firm complexity

More technologically advanced firms are usually characterised as more complex, leading to such firms exhibiting an increased degree of ex-ante uncertainty (Loughran and Ritter, 2004; Daily et al., 2005; Cohen and Lou, 2012). Consequently, investors demand and become compensated with a discount as firms become increasingly complex Loughran and Ritter, 2004; Daily et al., 2005).

In alignment with previous studies, this paper measures complexity using three established proxies: (i) industry affiliation (SIC-codes), (ii) research and development expenditures (relative to net sales), and (iii) intangible assets (relative to net sales) (Kile and Philips, 2009; Markarian and Parbonetti, 2007). Our study expects a positive relationship between the chosen proxies for *complexity* and the degree of IPO underpricing. Our first and foremost hypothesis is formed as follows:

H1: *Increased firm complexity is expected to yield more underpriced issues.*

4.1.2 Firm age

The available historical data on an issue has proven to affect the degree of ex-ante uncertainty surrounding it. Since managing underwriters rely on historical data when evaluating and conducting a valuation on an issue, younger firms tend to be perceived as more uncertain (Loughran and Ritter, 2004). As firms become more established with age, it comes with an increased amount of available historical data, leading to reduced information asymmetry between issuers and investors (Ritter, 1991). Additionally, firms of greater age have had more time to thrive its businesses, oftentimes leading to a defensible position on their respective markets (ibid). Older firms are therefore considered less uncertain, resulting in a reduced degree of IPO underpricing. Simultaneously, younger firms have had less time to alleviate uncertainty concerning their business prospectus and therefore exhibit higher underpricing levels. As such, this paper expects a negative relationship between *Firm Age* and IPO underpricing. Our second hypothesis:

H2: *Younger firms should experience more underpricing than older firms*

4.2 Certification and monitoring

4.2.1 Private equity or venture capital-backed IPOs

The existing literature finds ample evidence that PE- and VC-backed IPOs tend to experience less underpricing than non-backed issues (Barry et al., 1990; Megginson and Weiss, 1991; Vu, Worthington and Laird, 2008). Following the line of certification and recognising the monitoring role of an experienced owner, the presence of a PE- or VC-firm in a list of shareholders should be considered a signal of quality (Barry et al., 1990). Such owners are assumed to have completed thorough due diligence on the issue, indicating a belief in the company's success. As such, they might serve as assurance to potential IPO-investors, signalling that the issuing firm constitutes an attractive investment proposition, hence, reducing the degree of ex-ante uncertainty. Thus, our third hypothesis:

H3: *PE and VC-backed IPOs should experience less underpricing than do unbacked firms.*

4.2.2 Multiple underwriters

As suggested by Corwin and Schultz (2005) and Habib and Ljungqvist (2001), hiring a greater number of underwriters could produce more information and increase the sophistication of the accessible client base of potential investors. Most underwriters have multiple deal-teams specialized in various industries and geographical markets, hence accessing information and evaluating different sorts of businesses more accurately (ibid). Our fourth hypothesis:

H4.1: *Hiring more underwriters is expected to reduce underpricing*

However, this paper argues that more ex-ante uncertainty derived from increased firm complexity inhibits the benefit of hiring multiple underwriters. Consequently, having a reduced effect on the sampled high-tech firms relative to other firms. Therefore, we include an add-on condition to our fourth and final hypothesis:

H4.2: *The effect of hiring multiple underwriters to reduce underpricing is lower among complex firms*

5. Methodology

This paper examines the interaction between information production benefits and ex-ante uncertainty stemming from increased firm complexity. We intend to capture this empirical regularity by testing whether firms characterised as more complex exhibit fewer benefits, in terms of IPO underpricing, by including additional managing underwriters. Furthermore, the study analyses whether information production generates a mitigating effect on IPO underpricing as firms become increasingly complex.

5.1 Multiple regression model

A multiple regression model was derived from the dataset through an OLS regression. The model uses Market Adjusted Initial Return (*MAIR)* as the dependent variable. The explanatory- and control variables applied as regressors are available in detail in *Equation 1* and further elaborated in Section 5.3. To test our main hypotheses, our primary regression is formed as follows:

Equation 1: Ordinary Least Squares Regression

$$\begin{aligned} MAIR = \alpha &+ \beta_1(R\&D\ Intensity_{dummy}) + \beta_2(Intantible\ Assets\ Ratio) \\ &+ \beta_3(SIC11_{dummy}) + \beta_4(Ln\ Proceeds) + \beta_5(Ln\ Total\ Assets) \\ &+ \beta_6(Leverage\ Ratio)\beta_7(Ln\ Firm\ Age) + \beta_8(PE_{dummy}) + \beta_9(VC_{dummy}) \\ &+ \beta_{10}(No.of\ \ Underwriters) + \varepsilon_i \end{aligned}$$

5.2 Dependent variable

The primary target of our study is IPO underpricing. As such, observed underpricing constitutes our dependent variable. Consistent with previous research, we measure IPO underpricing by calculating the difference between the offer price and the first day closing price (Ritter, 1991). By contrast, if a negative percentual difference is retrieved, the issue is classified as overpriced. In order to account for volatile markets conditions and abrupt fluctuations, all observations are adjusted by subtracting the collected first day returns with market movements from the corresponding day from a relevant market index (OMXS30). The approach was initially introduced by Logue (1973) and has been concurred by numerous researchers (e.g., Loughran and Ritter, 2002; Bansal and Khanna, 2012). Going forward with this approach, we end up with the *Market Adjusted Initial Return*, labelled as *MAIR* throughout the paper.

Equation 2: MAIR definition

$$MAIR = \frac{Closing\ price - Offer\ price}{Offer\ price} - \frac{OMXS30\ closing\ value - OMXS30\ opening\ value}{OMXS30\ closing\ value}$$

5.3 Independent variables

We study the relationship between our primary variable (*MAIR*) and ten independent variables used as explanatory- and control variables. The analysis employs these variables as it opts to explain differences in underpricing among the observations.

5.3.1 Main explanatory variables

5.3.1.1 Measures for Ex-ante uncertainty

R&D as a percentage of net sales is used as the primary indicator for complex firms. We argue that the main usage of reported R&D expenditures, in many cases, may be nearly impossible to track by investors. Furthermore, it is considerably difficult to evaluate a firm's pipeline of products in an R&D-phase and their potential to reach the market, even for the firm's management. Outsiders with limited access to information into privately held firms do, as an effect, face even larger difficulty evaluating and forming an opinion on products currently in development. The authors Markarian and Parbonetti (2007) further supports this method, as they found evidence that R&D-related measures function as reasonable proxies for firm complexity. Although, it is important to acknowledge that R&D expenditures are in no way an exhaustive measure for the level of complexity within a firm. Instead, other indicators such as length of management roadshow, or degree of management participation in the roadshow could also be included Although, in this study we do view *R&D Intensity dummy* as straightforward and find it useful for the purpose of the study.

To further target firm complexity, two additional variables are included: (i) intangible assets (relative to total assets) (*Intangible Assets Ratio*), and (ii) industry classification codes (SIC-codes) (*SIC11 dummy*). Kile and Philips (2009) developed a procedure for selecting and portioning samples of complex firms from other firms. The authors identified eleven different SIC-codes suitable for such purposes, of which has been applied in our study. A summary of the SIC-codes is presented in *Table 1* below. Along with our second hypothesis, we also intend to include *Firm Age* as a measure for ex-ante uncertainty, which is defined as total years since firm establishment.

Table 1. 3-digit SIC-codes for sampling complex firms

This table illustrates the eleven 3-digit Standard Industry Classification (SIC) codes used for sampling high-tech firms (Kile and Phillips, 2009)

SIC-Code	Industry name
283	Drugs
357	Computer and office equipment
366	Communication equipment
367	Electronic components and accessories
382	Laboratory, optic, measure, control instruments
384	Surgical, medical, dental instruments
481	Telephone communications
482	Miscellaneous communication services
489	Communication services, NEC
737	Computer programming, data processing, etc.
873	Research, development, testing services

5.3.1.1.1 Detailed description of main explanatory variables used for measures of ex-ante uncertainty

R&D Intensity dummy**:** We apply a dummy approach to test for *R&D intensity*, expressed as the proportion of R&D expenditures relative to net sales. The R&D dummy takes the value of one (1) if the firm has a proportion of R&D expenditures above the median value, otherwise zero (0).

Intangible Assets-Ratio: This variable measure firm complexity, expressed it in terms of intangible assets relative to total assets.

SIC11 dummy**:** As mentioned, Kyle and Phillips (2009) identified eleven SIC-codes for industries optimal for sampling high-tech companies. High-tech firms are targeted due to displaying internal complexity characteristics. Hence, making them difficult to evaluate for outsiders with limited insight (Moornan and Swaminathan, 2003). The *SIC11 dummy* takes the value of one (1) if labelled under one of the eleven SIC-codes, otherwise zero (0).

Ln(Firm Age)**:** We use the natural logarithm of firm age (*Firm Age*), where age is measured as the number of years since establishment, at the time of the IPO. In alignment with previous studies, we argue that the extent of available historical data corresponds to the firm's ex-ante uncertainty. Therefore, an amplified degree of historical data serves to reduce information asymmetry (Lowry et al., 2010; Loughran and Ritter, 2004; Ritter, 1991). Our model uses the variable as a proxy for information asymmetry, as we expect older firms to have provided the market with more information. With this in mind, we expect to yield a negative relationship with underpricing.

5.3.1.2 Measures for certification and monitoring

In line with our third and fourth hypothesis, we use *VC-backed* and *PE-backed* IPOs along with *Number of underwriters* as measures for certification and monitoring, which is argued to affect information production and thus underpricing.

5.3.1.2.1 Detailed description of main explanatory variables used for measures of certification and monitoring

No. of underwriters**:** This variable control for the total number of underwriters included in the underwriting syndicate. In alignment with Corwin and Schultz (2005) and Hu and Ritter (2007), we expect to find comparable evidence that an increased number of underwriters contributes to a decreased level of underpricing.

VC dummy**:** A dummy approach was applied to control correlation between underpricing and VC-backed issuers. The variable takes the value of one (1) if that is the case, otherwise zero (0).

PE dummy**:** A dummy approach was applied to control the correlation between underpricing and PE-backed issuers. The variable takes the value of one (1) if that is the case, otherwise zero (0).

5.3.2 Control variables

To answer our outlined hypotheses, this paper includes the following control variables, customarily included in IPO underpricing studies: firm size (*Ln(Total Assets)*), total proceeds (*Ln(Proceeds)*), leverage-ratio (*(Leverage-Ratio)*).

5.3.2.1 Detailed description control variables used in the regression:

Ln(Total Assets)**:** Analogous to Bansal and Khanna (2012), this paper uses the natural logarithm of total assets, reported on the last day of balance, and applies it as a proxy for firm size. Doing so, we expect a negative relationship to IPO underpricing. Firm size has, in many cases, displayed a negative correlation to underpricing (ibid). According to the authors, smaller and unestablished firms oftentimes cause more uncertainty regarding their prospectuses and valuation (ibid).

Leverage-Ratio**:** This paper measures *Leverage-Ratio* with leverage as a percentage of the firm's total assets, one fiscal year prior to the listing (Leone, Rock, and Willenburg, 2007). A reasonable proportion of debt relative to total assets is, according to the authors, recognised as a signal of quality (ibid). Having issued debt prior to becoming listed is expected to influence the perception of the issuing firm's value. Prior research has found that firm's exhibiting credit relationships in conjunction with their IPO experiences less underpricing, which further indicate an inverse relation between underpricing and leverage (James and Wier, 1990). James and Wier (1990) explain this occurrence by associating information asymmetry, stating that investors perceive prior bank loans as a signal of having access to the capital markets, making investors less uncertain about the firm's true value and its ability to meet its future objectives. Also, prior evidence asserts that the decreased degree of underpricing for firms with issued debt obligations can be explained by the fact such firms often are of greater size oftentimes are older and exhibit less risk by having a more prominent financial- and operational history (Cai et al., 2004). As such, this paper expects a negative relationship between *Leverage-Ratio* and IPO underpricing.

Ln(Proceeds)**:** Proceeds are calculated by taking the issue offer price (measured in USD), then multiplying it with the number of offered shares. Previous research point to a positive correlation between total turnover and the level of IPO underpricing (Loughran and Ritter, 2004). This variable expresses the natural logarithm of the total turnover (proceeds) in the IPO. In our sample, the total turnover differs considerably throughout, resulting in skewness in the dataset. Therefore, a natural logarithmic transformation is performed to create a better fit into a more normalized dataset.

5.4 Interaction between information production and firm complexity

By adding interaction terms to our regression, we intend to expand our understanding of the underwriting syndicate's ability to produce accurate information as firms become increasingly complex. Three variables representing information production and firm complexity are interacted. Information production is proxied by the number of underwriters included in the underwriting syndicate. Firm complexity is proxied by R&D expenditures (relative to net sales), and lastly, our chosen SIC-codes. The regression in an interactive setting will therefore include one additional variable:

***R&D Information Production*:** This variable derives from multiplying the dichotomous variable *R&D intensity dummy* with the continuous variable *No. of underwriters.* By including this variable, the yielded coefficient of the interactive term represents the excelled effect on underpricing achieved by adding additional underwriters, when a firm is considered complex. A winsorized regression is performed in this setting and is formed as follows:

Equation 2: OLS Regression with an interactive term

$$
\begin{aligned}
MAIR\_Win = \alpha &+ \beta_1\left(R\&D\ Intensity_{dummy}\right) + \beta_2(Intangible\ Assets\ Ratio) \\
&+ \beta_3(R\&D\ Info.Prod) + \beta_4\left(SIC11_{dummy}\right) + \beta_5(Ln\ Proceeds) \\
&+ \beta_6(Ln\ Total\ Assets) + \beta_7(Leverage\ Ratio)\beta_8(Ln\ FirmAge) \\
&+ \beta_9\left(PE_{dummy}\right) + \beta_{10}\left(VC_{dummy}\right) + \beta_{11}(No.of\ underwriters) + \varepsilon_i
\end{aligned}
$$

6. Data and summary statistics

6.2 Data collection

The original dataset extracted from Eikon included 234 Swedish IPOs conducted in 2010-2020. Relevant IPO data was regularly absent for IPOs before 2010, thus our motivation for the ten-year period of 2010–2020.

Primary data was collected from Refinitiv Eikon's *Security Data Company Platinum* ("SDC") database on *Equity New Issues Deals Data*. The acquired data includes information on the 234 observation's company name, ticker, date of listing, offer price, issue size, proceeds (turnover), total assets prior to the listing, first-day return, entire underwriter syndicate, as well as each company's Standard Industrial Classification ("SIC") code. In order to market adjust initial returns, market data on OMXS30 was acquired from Nasdaq's web-based database.

Data for a number of variables were collected from Bloomberg, including research and development expenditures (percentage of net sales), intangible assets (percentage of total assets), leverage ratio (total debt over total assets), and incorporation dates (start value in the calculation of firm age). In the event of missing data, information was obtained via the issuing firm's IPO prospectus, which, in turn, was collected from *Börsdata* (Börsdata, 2021).

Data on pre-IPO ownership was acquired from each firm's respective IPO prospectuses. In alignment with Barry et al. (1990) and Ritter (1998), a number of criteria were applied to classify a firm as PE- or VC-backed. Consistent with the authors, lists and journals of active VC- and PE-firms were used to cross-reference against issuing firm's stockholder data. References used in this paper consisted of the *Swedish Private Equity & Venture Capital Association's* (SVCA) members list. Also, the start-up- and VC-oriented news channel Breakit's (*breakit.se)* list of VCs invested in Swedish companies, and *techcrunch.com* list of VCs invested in European companies (Breakit, 2019; Techcrunch, 2021). Concurring with Barry et al. (1990) and Ritter (1998), a minimum pre-IPO ownership stake of ≥ 1% was applied as a threshold.

Out of the original 234 IPOs, five was missing stock price data. Thus, becoming excluded from the final sample. Another 14 observations were excluded as an effect of an inability to obtain various accounting- or firm-specific data (e.g., firm age, assets, R&D expenditures). The final sample applied in our study consisted of 215 Swedish IPOs conducted during 2010-2020.

6.3 Summary statistics

Table 2 below illustrates the number of annual IPOs in Sweden over the researched period 2010-2020, along with a count for the respective stock exchange.

Table 2. Overview of no. of IPOs in Sweden between 2010 and 2020

This table illustrates the number of annual IPOs on the Swedish stock markets; NASDAQ OMX, First North, and Spotlight Stock Market.

Year	No. of IPOs	OMX	First North	Spotlight
2010	**15**	3	2	10
2011	**12**	4	1	1
2012	**3**	2	2	2
2013	**5**	1	1	3
2014	**14**	13	1	2
2015	**32**	18	14	3
2016	**25**	12	15	1
2017	**50**	14	24	12
2018	**24**	8	11	3
2019	**14**	4	7	1
2020	**21**	5	14	1
Total	**215**	**84**	**92**	**39**

Table 4 displays summary statistics for all variables included in the regression models, except for dummies. The average initial return for the 215 sampled firms was 12.7%, with a substantially lower mean at 4.6%. Some outliers are present as the maximum and minimum observed values range between 730.0% (Nordic Iron Ore (FRA:NIO), 2018) and -86.1% (A Group of Retail Asset (FRA:AGORA), 2015). *Table 3* shows that the industries Consumer Goods and Industrials experienced the highest average initial returns at 22.25% and 11.48%, respectively. On the contrary, Telecommunication was the only industry experiencing a negative average initial return at -0.08%. Healthcare was the most active industry on the IPO market with 49 listings, followed by Information Technology with 39 different listings. The industry Oil and Gas was the least active, with a total of five IPOs.

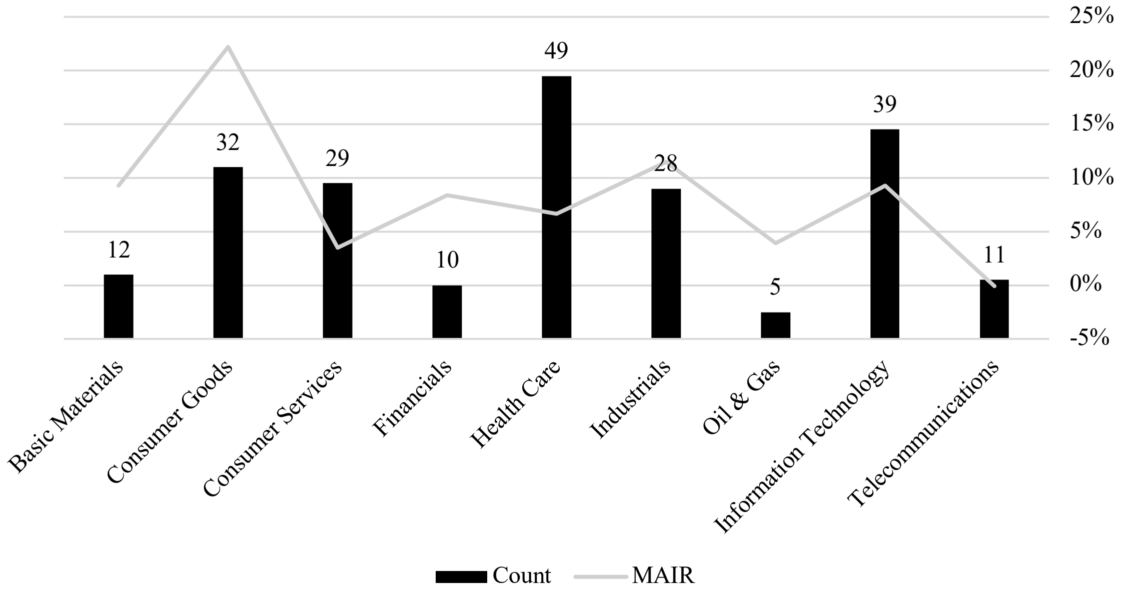
Table 3. Industry statistics for Swedish IPOs

This table presents industry statistics for Swedish IPOs between 2010 and 2020. The count represents the total number of observations. Market Adjusted Initial Return (MAIR) is the mean first day return in the respective industry. Proceeds are average first day return for the respective industry, measured in millions of USD

Industry **n = 215**	Count	MAIR	Proceeds
Basic Materials	12	9.28%	75.75
Consumer Goods	32	22.20%	161.10
Consumer Services	29	3.49%	126.71
Financials	10	8.37%	296.67
Health Care	49	6.63%	59.40
Industrials	28	11.48%	89.78
Oil & Gas	5	3.92%	13.55
Information Technology	39	9.25%	57.22
Telecommunications	11	-0.08%	123.38

Figure 6. Industry statistics and first day returns for Swedish IPOs

This graph plots the total number of offerings per industry between 2010 and 2020 along with the average Market Adjusted Initial Return (MAIR



The average proceeds raised from IPOs was $98 million, with a standard deviation of $191 million. The statistic for the variable indicates large variability in total funds raised across the sampled firms. This can be seen with the maximum proceeds amounting to $1.39 billion, and the minimum is $0.8 million.

The age of the sampled firms varies from newly formed ventures to established companies. The oldest was incorporated 212 years ago, and the youngest was one year old at the time of the IPO. The average *Firm Age* is 22 years throughout the sample, while the median amounts to 12.5 years, entailing potential skewness in the dataset.

The mean and median *Leverage-Ratio* is 22.7 percent and 31.3 percent respectively, with a standard deviation of 14.9 percent. For this control variable, some firms exhibited negative ratios. In this case, it results from a firm having a negative net worth (i.e., total liabilities exceeding total assets).

The mean and median values for *Intangible Assets Ratio* are 22.3 percent and 17.7 percent, respectively, across the sample. The corresponding values for *R&D Intensity* are measured as a percentage relative to net sales, and yield mean and median values of 216.8 percent and 18.7 percent. The maximum values reported for R&D expenditures might strike as extreme at first glance, but after considering the nature and environment of firms exhibiting such figures, it comes off as more reasonable. A significant number of the sampled firms cultivate biotechnology- and medicinal related research, often operating in the early stages of their product development phase at the time of their IPO. Therefore, it is not uncommon for such firms not to have any marketable products to sell (i.e., pre-revenue phase). All products within the medical sector are required to be approved by the respective region's authorities before reaching consumable markets, resulting in neglectable sales and notably high R&D costs.

A majority of the sample hire one single underwriter for their IPO. However, larger firms tend to add additional underwriting managers, increasing the mean of the sample. The largest number of underwriters used in one IPO was ten, and, on these occasions, they play different roles in the IPO process such as coordinator, bookrunner, lead manager etc.

Table 4. Sample descriptive statistics

This table presents sample descriptive statistics for 215 Swedish IPOs between 2010 and 2020. All variables used in the main regression is included in this table, except dummies. The main dependent variable is the Market Adjusted Initial Return (*MAIR*), which is defined as the percentage change in price from the offer price to the first day closing price. *Firm Age* is the age of the firm at the time of the IPO measures in years. *Proceeds* is the dollar value of the total proceeds from the offer. *Total Assets* is the dollar value of total assets on the last balance day before the IPO. Leverage-Ratio measures total long-term debt as a percentage of total assets. *Intangible Assets Ratio* measures the proportion of intangible assets as a percentage of total assets. R&D intensity measures total R&D costs as a percentage of net sales. *No. of underwriters* is the total number of underwriters included in the underwriting syndicate.

Statistics n = 215	**Mean**	**Median**	**Std. Dev**	**Min.**	**Max.**
MAIR (%)	12.7	4.6	5.8	-86.1	730.0
Firm Age (years)	22.2	12.5	30.5	1.0	212.0
Proceeds (USDm)	98.6	28.8	191.9	0.08	1393.3
Total assets (USDm)	338.5	30.2	1320.3	1.1	16832.4
Leverage-Ratio (%)	22.7	31.3	14.9	-3.4	135.1
Intangible Assets Ratio (% of total assets)	22.3	17.6	2.9	0.0	96.4
R&D intensity (R&D exp. % of Net Sales)	200.2	18.7	61.2	0.0	680.5
No. of underwriters	1.8	1.0	1.4	1.0	10.0

6.4 Sub-groups

To draw further conclusions on the expected effects of information production and its presumed effect on underpricing, our main regression (i.e., *Equation 1*) is divided into two sub-groups. Doing so, we intend to study if the information production benefits alter as firms become increasingly complex. The level of information production in each IPO functions as the determinator for both groups. For this purpose, we use the number of underwriters as a proxy, an approach that finds support from previous studies (e.g., Corwin and Schultz, 2005; Hu and Ritter, 2007). The authors suggest that the depth of information production conducted in connection to an IPO increases as additional underwriters are added to the underwriting syndicate, reducing IPO underpricing. In Group 1, firms with lower information production are included, hence firms with fewer underwriters (less or equal to the 33rd percentile, which in our sample equals two or fewer underwriters). Group 2 includes firms with a higher level of information production (more or equal to the 66th percentile, which in our sample equals four or more underwriters). Summary statistics for the sub-groups are presented in *Table 5* below.

Table 5. Sample subgroup descriptive statistics

This table illustrates the mean, median, standard deviation, minimum- and maximum values of underpricing. Group 1 includes firms with less than or equal to 2 underwriters (33rd percentile), and group two includes firms with four or more hired underwriters in the IPO syndicate (67th percentile).

Group 1 - No. of Underwriters ≤ 2					
n = 127	**Mean**	**Median**	**Std. Dev**	**Min.**	**Max.**
MAIR (%)	10.2	6.9	4.7	-14.4	730.0
Firm Age (years)	12.3	10.7	29.3	1.0	42.2
Proceeds (USDm)	62.2	22.1	118.3	0.07	173.2
Total Assets (USDm)	105.9	66.7	77.3	2.4	1349.6
Leverage-Ratio (%)	32.2	26.6	12.2	-1.5	97.4
Intangible Assets-Ratio (% of total assets)	18.9	14.9	4.8	0.0	105.4
R&D intensity (R&D exp. % of Net Sales)	308.8	155.1	62.4	0.0	578.1
No. of underwriters	1.3	1.0	0.3	1.0	2.0

Group 2 - No. of Underwriters ≥ 4					
n = 34	**Mean**	**Median**	**Std. Dev**	**Min.**	**Max.**
MAIR (%)	15.8	10.6	5.7	-16.1	53.2
Firm Age (years)	25.7	22.5	65.4	12.0	212.0
Proceeds (USDm)	112.3	94.1	202.1	14.8	1393.3
Total Assets (USDm)	462.4	397.8	983.5	88.4	16832.4
Leverage-Ratio (%)	38.6	26.7	13.4	3.8	135.1
Intangible Assets-Ratio (% of total assets)	31.9	24.8	1.8	0.0	96.4
R&D intensity (R&D exp. % of Net Sales)	42.5	12.2	44.3	0.0	341.4
No. of underwriters	6.4	5.0	1.2	4.0	10.0

By dividing our dataset into sub-groups, we attempt to uncover patterns within and between the two groups. In our case, the primary purpose is to find evidence or traits on differences in information production, proxied by the variable *No. of underwriters*, and whether such differences affect the degree of underpricing on firms classified as more complex.

Previously, when researchers have endeavoured studies on plausible correlations between underpricing and underwriter influence, considerable attention has been devoted to the underwriters' reputation (Carter and Dark, 1998; Beatty and Ritter, 1986). Carter and Dark (1998) found that IPOs of which the underwriters were considered prestigious experienced less underpricing than those conducted by less reputable underwriting syndicates. Contradictory, Beatty and Ritter (1986) found empirical evidence that underpricing instead can be enforced by hiring high-status underwriters. The rationale being that such underwriters purposely under-price issues to ensure full subscription, thus, preserve its reputation. Hence, no clear consensus has yet been established on the underpricing effects of underwriter reputation, why we choose to exclude it from this paper. The notion could however be an interesting addition to future research.

7. Results

The following section outlines and discusses findings from the conducted empirical study and then relates the obtained results to the stated hypotheses presented in *Section 4.*

7.1 Diagnostic tests pre-estimation

7.1.2 OLS assumptions

It is necessary to understand underlying OLS assumptions when conducting an OLS regression. A lack of knowledge of OLS assumptions could lead to incorrect results for the econometrics test completed, why it cannot be overemphasized. Since this study is based on a cross-sectional dataset, potential violations of multicollinearity are considered.

7.1.3 Outliers and winsorizing

The dataset can be considered relatively small as it amounts to 215 different observations. As an effect, the sample is somewhat sensitive to inherent outliers. As seen in *Table 6*, the mean and median for *MAIR* is 12.7 and 4.6 percent, respectively, with minimum and maximum values ranging from -86.1 percent to 730.0 percent. We correct these dependencies by winsorizing the dependent variable *MAIR* in the 1st and 99th percentiles, respectively. By doing so, we manage to reduce the impact of spurious outliers in the dataset.

Table 6. Initial Return and Market Adjusted Initial Return (*MAIR*) characteristics

This table illustrates the mean, median, standard deviation, minimum- and maximum value for 215 Swedish IPOs between 2010–2020. Initial Return is the unadjusted first day return, and MAIR is the first day return after adjusting for OMXS30 index movements.

Statistics	n = 215	Mean	Median	Std. Dev	Min.	Max.
Initial Return (%)		13.4	4.7	6.3	-85.9	729.3
MAIR (%)		12.7	4.6	5.8	-86.1	730.0

7.1.4 Multicollinearity

In order to detect multicollinearity, VIF-checks are conducted after each regression. Any sign of correlation between explanatory variables could adversely affect the regression results. Hence, the VIF estimates how much variance of a regression coefficient is inflated due to multicollinearity being present in the model. Although the checks did not give cause for any concerns, we complement the VIF-checks through a correlation matrix, presented in *Table 7*. An interpretation of these numbers reveals a relatively strong correlation between the control variables *Total Assets* and *Proceeds* at approximately 0.81. A correlation coefficient equal to or above 0.80 is used as a cut-off rule, meaning any value above this figure is enough to alter our regression, since the variable might be a subject of the multicollinearity problem. However, some correlation between a firm's assets and total proceeds from the IPO was expected because of similar characteristics. Also, multicollinearity affects only the specific variables correlated, which in our case did not concern any of the main explanatory variables. In *Section 7.4*, we perform a robustness check to see if the quality of the result can be improved.

Table 7. Correlation matrix for independent variables used in the main OLS regression

This table presents any present collinearity between independent variables used in the main regression. A threshold of 0.8 is used as a cut-off rule, meaning any value equal to or above that number will require further investigation. The *R&D intensity dummy* measures total R&D expenses as a percentage of net sales and take the value of one (1) if equal or above the median, and zero (0) otherwise. *Intangible Assets Ratio* measures the proportion of intangible assets as a percentage of total assets. Leverage-Ratio measures total long-term debt as a percentage of total assets. The *SIC11 dummy* takes the value of one (1) if equal to any of the eleven Standard Industry Classification codes used by Kile and Philips (2009) for identifying high-tech firms. *Ln(proceeds)* is the natural logarithm of the dollar value of the total proceeds from the offer. *Ln(Total Assets)* is the natural logarithm of the dollar value of total assets on the last balance day before the IPO. *Ln(Firm Age)* is the natural logarithm of the age of the firm at the time of the IPO measures in years. The *VC dummy* takes the value of one (1) if backed by a venture capital firm at the time of the IPO, and zero (0) otherwise. The *PE dummy* takes the value of one (1) if the firm was backed by a Private Equity firm at the time of the IPO, and zero otherwise. *No. of underwriters* is the total number of underwriters included in the underwriting syndicate.

(obs=215)	R&D dummy	Intangible Assets	Leverage-Ratio	SIC11 dummy	Ln(Proceeds)	Ln(Total Assets)	Ln(Firm Age)	VC dummy	PE dummy	No. of underwriters
R&D Intensity dummy	1.0000									
Intangible Assets-Ratio	-0.2562	1.0000								
Leverage-Ratio	-0.0342	-0.0263	1.0000							
SIC11 dummy	0.6433	-0.1743	-0.0538	1.0000						
Ln(Proceeds)	-0.3234	0.1274	-0.1294	-0.2642	1.0000					
Ln(Total Assets)	-0.5265	0.2642	-0.0634	-0.3973	0.8092	1.0000				
Ln(Firm Age)	0.1632	0.0222	-0.0435	-0.1423	0.1198	0.1523	1.0000			
VC dummy	0.5938	0.2766	-0.0126	0.3984	-0.2674	-0.1766	0.1877	1.0000		
PE dummy	-0.5672	0.2891	-0.0253	0.4024	0.3772	0.5182	-0.0789	-0.5982	1.0000	
No. of underwriters	-0.1892	0.0157	-0.0394	-0.5384	0.5122	0.4781	-0.1283	-0.1244	0.1192	1.0000

7.1.5 Homoskedasticity

Being one of the requirements for statistical analysis, homoscedasticity means that the variance of the error terms is constant. Otherwise, there is a presence of heteroscedasticity which may cause misleading conclusions on the model. We apply *White's Heteroscedasticity Test* to check whether the errors of the variables have constant variance. If the heteroscedasticity is detected, White's heteroscedasticity – consistent standard error estimates can be applied to the model as such modification of the explanatory variables' standard errors alleviates heteroscedasticity problems.

The test output indicates that the null hypothesis of homoscedasticity cannot be rejected – both the F- and X^2 versions of the test exhibit p-values higher than the critical 0.05 value. Therefore, the White's test demonstrates that there is no problem of heteroscedasticity in the dataset.

7.2 Main regression results

7.2.1 Firm complexity effects on underpricing

H1: In *Table 8*, we run an OLS regression as we intend to find statistical evidence for our first hypothesis (H1), presented in *Section 4*. We regress the dependent variable *MAIR* on three proxies for firm complexity *(R&D intensity dummy, Intangible Assets Ratio,* and *SIC11 dummy*), using a sample of 215 Swedish IPOs during 2010-2020. In line with H1, we find statistical evidence supporting our first proposition, namely that increased R&D expenditures (relative to net sales) positively affect underpricing. The coefficient for the *R&D Intensity dummy* yield positive significance at the one percent level. In our second proxy for firm complexity, we regress against a firm's intangible assets (as a percentage of total assets). The results indicate that firms with a higher proportion of intangibles on their balance sheet should exhibit a decreased level of underpricing. Since the coefficient moves in a negative direction, our proposition in H1 is contradicted. However, the coefficient is not significant as it exhibits a P-value of approximately 0.3. As the third proxy for firm complexity, we use SIC-codes (*SIC11 dummy*) to target complexity with a basis from industry affiliation. Similar to our second proxy, the regression results entail a negative slope, which opposes our expectations. Even though the results for this variable were found insignificant, it puzzles the validity of the results as it contradicts prior evidence (Loughran and Ritter, 2004).

Table 8. Ordinary Least Squares Regression

This table present main OLS regression with robust standard errors. The main dependent variable is the Market Adjusted Initial Return (MAIR), which is defined as the percentage change in price from the offer price to the first day closing price. The R&D Intensity dummy measures total R&D expenses as a percentage of net sales and takes the value of one (1) if equal or above the median, and zero (0) otherwise. Intangible Assets-Ratio measures the proportion of intangible assets as a percentage of total assets. Leverage-Ratio measures total long-term debt as a percentage of total assets. The SIC11 dummy takes the value of one (1) if equal to any of the eleven Standard Industry Classification codes used by Kile and Philips (2009) for identifying high-tech firms. Ln(proceeds) is the natural logarithm of the dollar value of the total proceeds from the offer. Ln(Total Assets) is the natural logarithm of the dollar value of total assets on the last balance day before the IPO. Ln(Firm Age) is the natural logarithm of the age of the firm at the time of the IPO measures in years. The VC dummy takes the value of one (1) if backed by a venture capital firm at the time of the IPO, and zero (0) otherwise. The PE dummy takes the value of one (1) if the firm was backed by a Private Equity firm at the time of the IPO, and zero otherwise. No. of underwriters is the total number underwriters included in the underwriting syndicate.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	**MAIR**	**MAIR**	**MAIR**	**MAIR**	**MAIR**
R&D Intensity dummy	14.73***	13.94***	12.43***	12.22***	10.93***
	(2.985)	(2.732)	(2.734)	(2.569)	(2.734)
Intangible Assets-Ratio	-0.0731*	-0.0475	-0.0462	-0.0454	-0.0425
	(0.0452)	(0.0432)	(0.0458)	(0.0462)	(0.0483)
Leverage-Ratio	-0.532***	-0.512***	-0.511***	-0.509***	-0.511***
	(0.0947)	(0.0857)	(0.0865)	(0.0873)	(0.0879)
SIC11 dummy	-3.843	-3.851	-3.832	-3.863	-3.877
	(3.147)	(3.116)	(3.237)	(3.121)	(3.153)
Ln(Proceeds)	7.214**	7.219**	7.224**	6.316**	6.212**
	(3.114)	(3.121)	(3.119)	(3.102)	(3.104)
Ln(Total Assets)	-2.007	-2.012	-2.017	-2.002	-2.021
	(1.632)	(1.5129)	(1.622)	(1.641)	(1.629)
Ln(Firm Age)		-0.0312	-0.0291	-0.0335	-0.0322
		(0.0458)	(0.0422)	(0.0426)	(0.0431)
VC dummy			7.491**	9.932**	10.042**
			(3.156)	(3.242)	(3.361)
PE dummy				5.103*	4.231
				(3.017)	(2.984)
No. of underwriters					-0.916**
					(0.377)
Constant	-10.41	-1.214**	-1.343	-1.411***	-1.727**
	(8.873)	(521.4)	(525.9)	(518.8)	(534.1)
Observations	215	215	215	215	215
R-squared	0.078	0.112	0.138	0.158	0.198

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

7.2.2 Firm age effects on underpricing

H2: In our second hypothesis (H2), our proposition suggests that younger firms should experience more underpricing due to less time to alleviate ex-ante uncertainty regarding their business prospectuses. Following previous research (e.g., Ljungqvist, 2007), we tested this proposition by regressing against firm age (*Firm Age*), expecting a negative coefficient for the variable, which was also obtained. A negative slope suggests that older, more established firms should experience less underpricing. Although the results were found insignificant, the findings show similarities to previous studies and established theory. Namely, that uncertainty regarding firm value is negatively correlated to firm age. The rationale is that the amount of historical data available increases with age, which increases the outsider's ability to assess firm value and quality.

7.2.3 Private equity and venture capital-backed IPOs

H3: In our third hypothesis, we argue that PE- and VC-backed IPOs should experience less underpricing compared to non-backed firms due to the assumed benefits of certification and monitoring. Hence, we expect to yield a negative relationship with our dependent variable *MAIR*. The proposition for this hypothesis is derived from previous research declared by Megginson and Weiss (1990), finding a negative relationship between VC-backed IPOs and underpricing. However, an interpretation of the regression results contradicts our expectations as we observe a positive coefficient for the *VC dummy*, significant at the five percent level. Hence, the results contradict our hypothesis, as the slope came out positive.

Though, there are more recent research findings supporting such results. Gompers (1996) and Lee and Wahal (2004) examined the role of VC-backing in IPO underpricing. Similar to our research, the authors found VC-backed IPOs to exhibit larger first-day returns than non-backed IPOs. Gompers (1996) substantiates these findings with two explanations. Firstly, reputation building influences the IPO timing decisions of young VCs. The establishment of reputation is important to access funding for subsequent funds. Gompers (1996) argue that young VCs are incentivised to bring portfolio companies public at an early stage, as IPOs communicate a signal of the fund's quality. Consequently, less mature firms become listed, causing VC-backed IPOs to exhibit more underpricing. Secondly, VCs revenue model typically surrounds an annual fixed fee, based on the fund's assets under management (~2 percent). In addition to that, the fund receives ~20 percent of the fund's investment profits. By taking its holdings public, VCs realises gains, which in turn can be returned to investors. Theory states that such investors are incentivised to invest in subsequent and larger follow-on funds, which in turn grows total assets under management for the VC (ibid).

As stated in H3, we expect a negative relationship between the dependent variable *MAIR* and the *PE dummy*. However, the results were inconsistent with our expectations as the relationship turned out positive, although not significant. A positive slope contradicts our hypothesis as well as established theories on certification and monitoring. Similar to VC-firms, PE-firms are incentivised by reputation building. Hence, persist strong incentives to exit portfolio companies through a successful IPO. Gompers (1996) also found the underpricing-PE-backed relationship is positive, suggesting a plausible explanation for the output similar to the one exhibited by VC-firms.

Furthermore, we conduct a T-test on mean differences between: (i) VC-backed and non-backed IPOs, and (ii) PE-backed and non-backed IPOs. The purpose is to examine if there exist differences in underpricing between the sub-groups. Obtained results are similar to our OLS regression. Hence, detecting no significant difference for the dependent variable *MAIR* between VC- and PE-backed IPOs. However, the sampled PE-backed IPOs exhibit more underpricing compared to non-backed IPOs. The T-test output for VC-backed IPOs also aligns with the OLS regression. On average, VC-backed IPOs were underpriced 19.7 percent, and non-backed IPOs 10.2 percent. Significance at the one percent level is obtained for these results, corresponding to similar findings by Gompers (1996), and Lee and Wahal (2004). The T-test output is presented in *Table 9* below.

Table 9. T-test

This table illustrates differences in means of underpricing between VC backed IPOs and non-backed IPOs, as well as the differences in means of underpricing between PE backed IPOs and non-backed IPOs.

VC-backed IPOs						**H0: Mean (Non-backed) - Mean (VC-backed) = Diff = 0**		
	Mean	**Std. Error**	**Std.Dev.**	**[95% Conf.Intervall]**		**Ha: diff < 0**	**Ha: diff != 0**	**Ha: diff > 0**
Non-backed IPOs	10.23	2.44	25.73	5.13	15.98	Pr(T < t) = 0.0003	Pr(|T| > |t|) = 0.0006	Pr(T > t) = 0.9997
VC-backed IPOs	19.78	2.67	34.15	19.39	29.14			
Combined	20.83	2.03	32.18	17.06	23.76			
Difference	**-9.55**	**4.11**		**-22.42**	**-5.89**			

PE-backed IPOs						**H0: Mean (Non-backed) - Mean (PE-backed) = Diff = 0**		
	Mean	**Std. Error**	**Std.Dev.**	**[95% Conf.Intervall]**		**Ha: diff < 0**	**Ha: diff != 0**	**Ha: diff > 0**
Non-backed IPOs	10.23	2.44	25.73	5.13	15.98	Pr(T < t) = 0.1721	Pr(|T| > |t|) = 0.3443	Pr(T > t) = 0.8279
PE-backed IPOs	13.24	1.42	22.13	10.89	16.87			
Combined	13.02	1.29	23.11	10.39	15.52			
Difference	-3.01	2.78		-8.03	2.75			

7.2.4 Firm complexity and information production

H4: The fourth and final proposition tests whether the assumed benefits from information production, achieved by hiring additional underwriters, has a diminishing effect as firm's become gradually more complex. The proposition intends to contribute to the existing empirical evidence from Corwin and Schultz (2005) and Hu and Ritter (2007), with a different angle on the relationship. In *Table 10*, an OLS regression with an interactive term between firm complexity and information production is illustrated. Information production is proxied by the total number of underwriters included in the issuing firm's underwriting syndicate. An interpretation of the regression results entails a negative relationship between information production and the level of underpricing, significant at the one percent level. Thus, similar to Corwin and Schultz (2005) and Hu and Ritter (2007), hiring multiple underwriters tend to decrease ex-ante uncertainty, hence, reducing the level of underpricing. However, the interactive term yielded a positive coefficient, though not significant, indicating a somewhat reduced net effect which aligns with the proposition in H4. Interpreting the effect of the interactive term on information production, we conclude that hiring more underwriters reduces the level of underpricing. Nevertheless, the benefit of hiring multiple underwriters turned out to have a diminishing effect as firms become increasingly complex, supporting our proposition.

Table 10. Ordinary Least Squares Regression of Market Adjusted Initial Returns (*MAIR*) With Interactive Term Included

This table presents the main OLS regression with robust standard errors and interactive term between the R&D Intensity dummy and the No. of underwriters. The main dependent variable is the Market Adjusted Initial Return (*MAIR*), which is defined as the percentage change in price from the offer price to the first day closing price. The *R&D Intensity dummy* measures total R&D expenses as a percentage of net sales and takes the value of one (1) if equal or above the median, and zero (0) otherwise. *Intangible Assets Ratio* measures the proportion of intangible assets as a percentage of total assets. *Leverage-Ratio* measures total long-term debt as a percentage of total assets. The *SIC11 dummy* takes the value of one (1) if equal to any of the eleven Standard Industry Classification codes used by Kile and Philips (2009) for identifying high-tech firms. *Ln(proceeds)* is the natural logarithm of the dollar value of the total proceeds from the offer. *Ln(Total Assets)* is the natural logarithm of the dollar value of total assets on the last balance day before the IPO. *Ln(Firm Age)* is the natural logarithm of the age of the firm at the time of the IPO measures in years. The *VC dummy* takes the value of one (1) if backed by a venture capital firm at the time of the IPO, and zero (0) otherwise. The *PE dummy* takes the value of one (1) if the firm was backed by a Private Equity firm at the time of the IPO, and zero otherwise. *No. of underwriters* is the total number underwriters included in the underwriting syndicate.

VARIABLES	(1) MAIR
R&D Intensity dummy	10.02*
	(2.353)
No. of underwriters	-0.923**
	(0.341)
Interaction term (R&D dummy and information production)	0.421
	(0.661)
Intangible Assets-Ratio	-0.031
	(0.042)
Leverage-Ratio	-0.514***
	(0.089)
SIC11 dummy	-3.822
	(3.223)
Ln(Proceeds)	7.113**
	(3.404)
Ln(Total Assets)	-2.121
	(1.629)
Ln(Firm Age)	-0.053
	(0.028)
Constant	-1.021*
	(547.3)
Observations	215
R-squared	0.189

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Two additional OLS regressions are conducted to examine the underpricing benefits of information production when firm complexity increases. In the regression, we use two sub-groups: (i) IPOs with a low degree of information production (Group 1), and (ii) IPOs with a high degree of information production (Group 2). Firms are distributed according to the number of underwriters included in the underwriting syndicate. Group 1 represents less than or equal to the 33rd percentile, and Group 2 is equal or greater than the 67th percentile.

In Group 1, the *R&D Intensity dummy* exhibit a positive correlation and a slope of 11.23 at the one percent level, which compared to the total sample is slightly higher. For Group 2, the coefficient drops to 6.02. Thus, insignificant but nevertheless in line with the information production hypothesis. The output indicates similarities to previous findings, namely that underpricing tend to decrease as additional underwriters are added (Corwin and Schultz, 2005). Increased firm complexity therefore indicate a mitigating effect on IPO underpricing. The results align with the information production hypothesis (ibid).

Table 11. Ordinary Least Squares Regression comparing two groups with different Information Production

The main dependent variable is the Market Adjusted Initial Return (MAIR), which is defined as the percentage change in price from the offer price to the first day closing price. The R&D Intensity dummy measures total R&D expenses as a percentage of net sales and takes the value of one (1) if equal or above the median, and zero (0) otherwise. Intangible Assets Ratio measures the proportion of intangible assets as a percentage of total assets. Leverage-Ratio measures total long-term debt as a percentage of total assets. The SIC11 dummy takes the value of one (1) if equal to any of the eleven Standard Industry Classification codes used by Kile and Philips (2009) for identifying high-tech firms. Ln(proceeds) is the natural logarithm of the dollar value of the total proceeds from the offer. Ln(Total Assets) is the natural logarithm of the dollar value of total assets on the last balance day before the IPO. Ln(Firm Age) is the natural logarithm of the age of the firm at the time of the IPO measures in years.

VARIABLES	(1) **MAIR**	(2) **MAIR**
R&D Intensity dummy	11.23***	6.024
	(4.435)	(7.451)
Intangible Assets-Ratio	-0.025	-0.053
	(0.035)	(0.059)
Leverage-ratio	-0.498***	-0.343*
	(0.029)	(0.099)
SIC11 dummy	-9.452*	3.422
	(2.563)	(6.343)
Ln(Proceeds)	7.561*	6.143
	(2.905)	(5.426)
Ln(Total Assets)	-1.151	-2.643
	(1.738)	(1.711)
Ln(Firm Age)	1.033*	-0.254
	(1.045)	(0.063)
Constant	-1.044	-3.021*
	(614.5)	(547.3)
Observations	127	34
R-squared	0.143	0.174

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

7.3 Regression results for other control variables

7.3.1 Leverage ratio

In line with expectations, we found a significant negative relationship between *Leverage-Ratio* and IPO underpricing at the one percent level. As prior research is typically focused on the US market, our results imply that similarities also exist in Sweden, since similar empirical evidence are found.

7.3.2 Proceeds

Based on (Loughran and Ritter (2004) and Yüksel and Yüksel (2006), a positive relationship to underpricing is expected. Yüksel and Yüksel (2006) refer to the positive relationship as an indicator of trading activity, arguing that informational frictions between market participants serve to positively influence underpricing as *Proceeds* increase. The results for the variable are consistent with our expectations and in line with prior research. The slope of the coefficients is positive, and the relationship to underpricing is significant at the five percent level.

7.3.3 Total assets

Total assets are used in the regression as a proxy for firm size. In line with Loughran and Ritter (2004), we expected a negative relationship to occur. Our received results entail a negative relationship to underpricing, although insignificant. The negative relationship can be explained by investors being less uncertain about investing in firms that have reached more mature stages. Greater age has allowed them to accumulate more capital, consequently signalling higher quality.

7.4 OLS regression with robustness checks

Due to high correlations between the two control variables *Total Assets* and *Proceeds*, we perform a robustness check on the regression. Observable in *Table 12*, we decided to drop *Total Assets* as it was insignificant in the main regression. Doing so, the coefficients change somewhat in magnitude, however, not enough to affect our overall findings. Hence, we conclude our regression to be robust.

In *Table 12*, we also include the *Hot market dummy*. The variable takes the value of one (1) if the IPO was conducted during a year with equal to, or more than the yearly mean of IPOs (19). According to Dimovski and Brooks (2003), hot IPO markets appear at the peak of market expansion, while cold markets are associated with market contractions. Additionally, the authors suggest that hot markets tend to attract low quality firms to go public for opportunistic reasons, which might cause the average degree of underpricing to increase. Inclusion of such a variable does however only impact our findings marginally. Nevertheless, the variable turned out positive, aligning with prior findings (Alti, 2005).

Table 12. Robustness check of Ordinary Least Squares Regression by dropping *Total Assets* and including a *Hot market dummy*

This table present a robustness check of the main OLS regression by dropping the variable Total Assets due to high correlation with the variable proceeds. The main dependent variable is the Market Adjusted Initial Return (MAIR), which is defined as the percentage change in price from the offer price to the first day closing price. The R&D Intensity dummy measures total R&D expenses as a percentage of net sales and takes the value of one (1) if equal or above the median, and zero (0) otherwise. Intangible Assets-Ratio measures the proportion of intangible assets as a percentage of total assets. Leverage-Ratio measures total long-term debt as a percentage of total assets. The SIC11 dummy takes the value of one (1) if equal to any of the eleven Standard Industry Classification codes used by Kile and Philips (2009) for identifying high-tech firms. Ln(proceeds) is the natural logarithm of the dollar value of the total proceeds from the offer. Ln(FirmAge) is the natural logarithm of the age of the firm at the time of the IPO measures in years. The VC dummy takes the value of one (1) if backed by a venture capital firm at the time of the IPO, and zero (0) otherwise. The PE dummy takes the value of one (1) if the firm was backed by a Private Equity firm at the time of the IPO, and zero otherwise. No. of underwriters is the total number underwriters included in the underwriting syndicate. The Hot market dummy takes the value of one (1) if the issue was conducted during a year with equal or more than the mean total yearly listings.

VARIABLES	(1) MAIR	(2) MAIR	(3) MAIR	(4) MAIR	(5) MAIR
R&D Intensity dummy	14.30***	13.72***	12.42***	12.62***	10.38***
	(2.923)	(2.832)	(2.365)	(2.547)	(2.794)
Intangible Assets-Ratio	-0.0691*	-0.0425	-0.0412	-0.0435	-0.0435
	(0.0522)	(0.0436)	(0.0454)	(0.0496)	(0.0433)
Leverage-Ratio	-0.552***	-0.503***	-0.554***	-0.587***	-0.587***
	(0.0915)	(0.0843)	(0.0856)	(0.0836)	(0.0899)
SIC11 dummy	-3.816	-3.782	-3.865	-3.898	-3.801
	(3.139)	(3.119)	(3.224)	(3.124)	(3.145)
Ln(Proceeds)	7.312**	7.202**	7.285**	6.387**	6.276**
	(3.523)	(3.193)	(3.196)	(3.135)	(3.112)
Ln(Firm Age)		-0.0304	-0.0273	-0.0324	-0.0354
		(0.0458)	(0.0499)	(0.0497)	(0.0465)
VC dummy			7.454**	9.923***	10.065**
			(3.176)	(3.255)	(3.323)
PE dummy				5.154*	4.255
				(3.076)	(2.964)
No. of underwriters					-0.954**
					(0.365)
Hot market dummy	2.412	2.305	3.185	3.327	3.376
	(1.553)	(1.192)	(1.199)	(1.135)	(1.112)
Constant	-10.25	-1.232**	-1.354	-1.423***	-1.765**
	(8.854)	(529.2)	(522.4)	(515.4)	(524.3)
Observations	215	215	215	215	215
R-squared	0.070	0.933	0.112	0.134	0.169

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

7.5 Research limitations and future research recommendations

For the purpose of this thesis, we have devoted our research towards the Swedish market over a specific period (i.e., 2010–2020). This naturally limits the study to a rather small number of observations (215), something that might work unfavourably for the empirical results. The chosen period was decided upon the availability of required data – both regarding explanatory variables and other control variables. However, when collecting secondary data, a proportion of the conducted IPOs had to be omitted, mainly due to a lack of historical data. Compared to similar studies performed in the U.S., our relatively small sample might limit the validity of the empirical results. A potential follow-up paper would benefit from including and comparing received results with other Nordic markets to increase the sampled target markets. Also, this paper has focused on uncovering the relationship that firm complexity has with IPO underpricing, although only using indicators of internal complexity. To contribute with further empirical evidence on the topic, future studies would benefit from including assumed indicators of external complexity. Such research could compare results and consequential impact on underpricing between both complexity measures, to efficiently add empirical evidence on its link to underpricing. Further indicators of firm complexity, such as length of management roadshow, and management participation on roadshows could also contribute valuable insights. Nevertheless, this paper's applied proxies for complexity are well-recognized and supported by previously established research.

Moreover, Habib and Ljungqvist (2001) suggested that the extent of the issuing firm's promotion (marketing) of the issue can have a strong influence on first day returns, hence, that there exists a trade-off between underpricing and the promotion. Assuming there is a trade-off, a possibility occurs that the optimal allocation of promotion costs and costs incurred due to underpricing results in a level of underpricing which is above that of less complex firms. Given this is the case, it could serve as an additional explanation to our findings, stating that firms exhibiting higher levels of complexity, in general, experiences more underpricing. At this stage, we do however not yet have any empirical support for this claim. Therefore, it could be an interesting angle for future research to examine the optimal allocation of promotion costs following the trade-off theory. It could provide additional explanations to the IPO underpricing phenomenon of complex firms.

8. Conclusion

We investigate the effects of information production on IPO underpricing in the Swedish market between 2010–2020. Prior evidence suggests a negative relationship between information production benefits and IPO underpricing (Corwin and Schultz, 2005; Hu and Ritter, 2007). Hence, hiring additional underwriters is argued to reduce underpricing. This paper intends to contribute to the academic literature and further investigate this relationship by including an additional factor: firm complexity. This paper argues that the benefits received from adding additional underwriters in an IPOs underwriting syndicate (i.e., less underpricing) gradually diminishes as firms become more complex. By applying three proxies from firm complexity, this paper finds empirical evidence to support this claim. Coinciding with Cohen and Lou (2012), we argue that firm complexity makes it increasingly difficult to comprehend a firm's true nature and business environment. Consequently, these information frictions increase the firm's ex-ante uncertainty, which in turn cause higher degrees of IPO underpricing. Thus, the underpricing of such issues is an indirect effect of investors requiring and being compensated, with a discount corresponding to the firm's level of complexity.

The study found empirical evidence also for this proposition, as some firm characteristics tend to reduce underpricing (e.g., *Firm Age*). Prior research (e.g., Ljungqvist, 2007; Chemmanur, 1993) found similar evidence, namely that an increased *Firm Age* function as a mitigating factor for underpricing. Our received results entail that firms of greater age tend to experience less underpricing relative to younger firms. The rationale being the reduced level of ex-ante uncertainty inherent in more established firms. Our second proposition is thus confirmed.

In our third proposition, we test the effect of having private equity- and venture capital-firms in an issuing firms list of shareholders. The proposition relates to the certification and monitoring effect such ownership is assumed to signal to outside investors. The signal of quality is as assumed to decrease underpricing. Our propositions find support in prior research, whereas Megginson and Weiss (1990) discovered a negative relationship between VC-backed IPOs and first day returns. In this paper, we do not find support for this claim, as our coefficient for VC-backed IPOs instead came out contradicting, being positive at the one percent level. This implies a positive relationship between VC-sponsorship and IPO underpricing, which align with Gompers (1996), and Lee and Wahal (2004), whose findings indicate similar tendencies. A theoretical explanation for these results is that VCs are incentivised to take their portfolio companies to market early, as such, returning capital to investors that can be recycled into subsequent funds. As PE-firms operate on a comparable basis, a similar explanation could be applied for firms with PE-sponsorship. However, this paper did not find statistical support for this claim in our regression model.

Finally, the fourth and final proposition tests whether the assumed benefits of information production (i.e., less underpricing), achieved by hiring additional underwriters, has a diminishing effect on the relationship when issuing firms become increasingly more complex. As prior research suggests, a negative relationship appears. In line with the fourth hypothesis, we find a negative relationship between *Number of Underwriters* and IPO underpricing, and that firm complexity indeed causes a diminishing effect, significant at the one percent level.

9. References

Abrahamson, M., de Ridder, A. & Råsbrant, J. (2011). "Information Asymmetries among European Investors: Evidence from Swedish IPOs", Kungliga Tekniska Högskolan

Advokatfirman Hammarskiöld, (2020). Available online: https://www.lexology.com/library/detail.aspx?g=db230b5a-f261-4a52-9198-9adc4d0048fa

Altı, A. (2005). IPO Market Timing. Review Of Financial Studies, 18(3), 1105-1138. doi:10.1093/rfs/hhi022

Bansal, R. and Khanna, A. (2012). Determinants of IPOs Initial Return: Extreme Analysis of Indian Market, Journal of Financial Risk Management, 1(4), pp. 68-74.

Barry, C.B., Muscarella, C.J., Peavy, J.W. & Vetsuypens, M.R. (1990). The role of venture capital in the creation of public companies. Journal of Financial Economics, vol. 27, ss. 447–471

Breakit. (2019). Available online: https://www.breakit.se/how-to/6893/lista-fran-a-till-o-harar-riskkapitalbolagen-som-investerar-i-startups-och-tech-i-sverige

Cai, N., Ramchand, L. & Warga, A. (2004). The Pricing of Equity IPOs That Follow Public Debt Offerings, Financial Management, vol. 33, no. 4, pp. 5-26

Carter, R B. Dark, F H. & Singh, A K. (1998). Underwriter reputation, initial returns and the long-run performance of IPO Stocks. The Journal of Finance. Vol 53, No. 1. pp. 285-311.

Chemmanur, T.J. 1993, "The Pricing of Initial Public Offerings: A Dynamic Model with Information Production", The Journal of Finance, vol. 48, no. 1, pp. 285-304.

Cohen, L. & Lou, D. 2012, "Complicated firms", Journal of Financial Economics, vol. 104, no. 2, pp. 383-400.

Corwin, S. & Schultz, P. 2005, "The Role of IPO Underwriting Syndicates: Pricing, Information Production, and Underwriter Competition", The Journal of Finance, vol. 60, no. 1, pp. 443-486.

Daily, C. M., Certo, S. T., Dalton, D. R. (2005). ‘Investment bankers and IPO pricing: does prospectus information matter?, Journal of Business Venturing, 20(1), pp. 93–111.

Dicken, Peter (2007). Global shift: Mapping the changing contours of the world economy. 5th edition. London: Sage.

Gajewski J. F. & Gresse, C. (2006). A Survey of the European IPO Market, working paper, no. 2, European Capital Markets Institute

Dimovski, W., & Brooks, R. (2004). Do you really want to ask an underwriter how much money you should leave on the table?. Journal Of International Financial Markets, Institutions & Money, 14(3), 267. doi:10.1016/j.intfin.2003.11.001

Gompers, P. 1996, "Grandstanding in the Venture Capital Industry", Journal of Financial Economics, vol. 42, no. 1, pp. 133-156.

Habib, M. & Ljungqvist, A. 2001, "Underpricing and Entrepreneurial Wealth Losses in IPOs: Theory and Evidence", The Review of Financial Studies, vol. 14, no. 2, pp. 433-458.

Hu, W. & Ritter, J. 2007, Multiple Bookrunners in IPOs, UFRGP

James, C. & Wier, P. (1990). Borrowing Relationships, Intermediation and the Cost of Issuing Public Securities, Journal of Financial Economics, vol. 28, pp. 149-171

Keloharju, M. 1993, "The winner's curse, legal liability and the long-run price performance of initial public offerings in Finland", Journal of Financial Economics, vol. 34, no. 2, pp. 251-277.

Kile, C. & Phillips, M. 2009, "Using Industry Classification Codes to Sample High-Technology Firms: Analysis and Recommendations", Journal of Accounting, Auditing and Finance, vol. 24, no. 1, pp. 35-58.

Koh F & Walter T 1989, "A direct test of Rock's model of pricing of unseasoned issues", Journal of Financial Economics, vol. 23, no. 2, pp. 251-272.

Lee, P.M. & Wahal, S. 2004, "Grandstanding, Certification and the Underpricing of Venture Capital Backed IPOs", Journal of Financial Economics, vol. 73, no. 2, pp. 375-407.
Ljungqvist, A. (2007). IPO Underpricing. Handbook Of Corporate Finance, Vol. 1, Ch. 7, pp. 482- 506.

Logue, D.E. The American Economic Review (1973). Vol. 63, No. 2, Papers and Proceedings of the Eighty-fifth Annual Meeting of the American Economic Association pp. 134-139

Loughran, T., Ritter, J. R. & Rydqvist, K. (1994). Initial Public Offering: International Insights, Pacific-Basin Finance Journal, vol. 2, pp. 165-199

Loughran, Tim & Ritter, Jay R. (2004). Why Has IPO Underpricing Changed Over Time? Financial Management, Vol. 33, No. 3, pp. 5-37

Lowry, M., Officer, M. & Schwert, W. (2010). The Variability of IPO Initial Returns. The Journal of Finance Vol. 65, No. 2, pp. 425-465.

Markarian, G. & Parbonetti, A. 2007, "Firm Complexity and Board of Director Composition.", Corporate Governance: An International Review, vol. 15, no. 6, pp. 1224-1243.

Markarian, G. & Parbonetti, A. 2007, "Firm Complexity and Board of Director Composition.", Corporate Governance: An International Review, vol. 15, no. 6, pp. 1224-1243

Megginson, W. & Weiss, K. (1991). "Venture Capital Certification in Initial Public Offerings", The Journal of Finance, vol. 46, no. 3, pp. 879-903.

Nordnet (2021). Available online:
https://www.nordnet.se/blogg/ipo/

Ritter (2021). Available online:
https://site.warrington.ufl.edu/ritter/files/IPOs-Underpricing.pdf

Ritter, J. R. (1991). The Long-run Performance of Initial Public Offerings, Journal of Finance, vol. 46, no. 1, pp. 3-27

Ritter, J.R. (2016). ”Initial Public Offerings” Homepage of University of Florida.
Rock, K. (1986). "Why new issues are underpriced", Journal of Financial Economics, vol. 15, no. 1, pp. 187-212.

Swedish Private Equity & Venture Capital Association (SVCA). (2019). Available online: https://www.svca.se/

Techcrunch (2021). Available online: https://techcrunch.com/the-techcrunch-list/

Vu, N., Worthington, A. & Laird, P. (2008). The Pricing and Performance of Initial Public Offerings in Australia, 1996-2007: A Comparison of Ordinary, Venture Capital and Private Equity-Backed Issues.

Yüksel, A. & Yüksel, A. (2006). The Link Between IPO Underpricing and Trading Volume: Evidence from the Istanbul Stock Exchange, Journal of Entrepreneurial Finance, vol. 11, no. 3, pp. 57-66

10. APPENDIX

10.1 Calculations of Independent Variables

$$R\&D\ Intensity_{\ dummy} = \frac{Total\ R\&D\ expenses}{Net\ Sales}$$

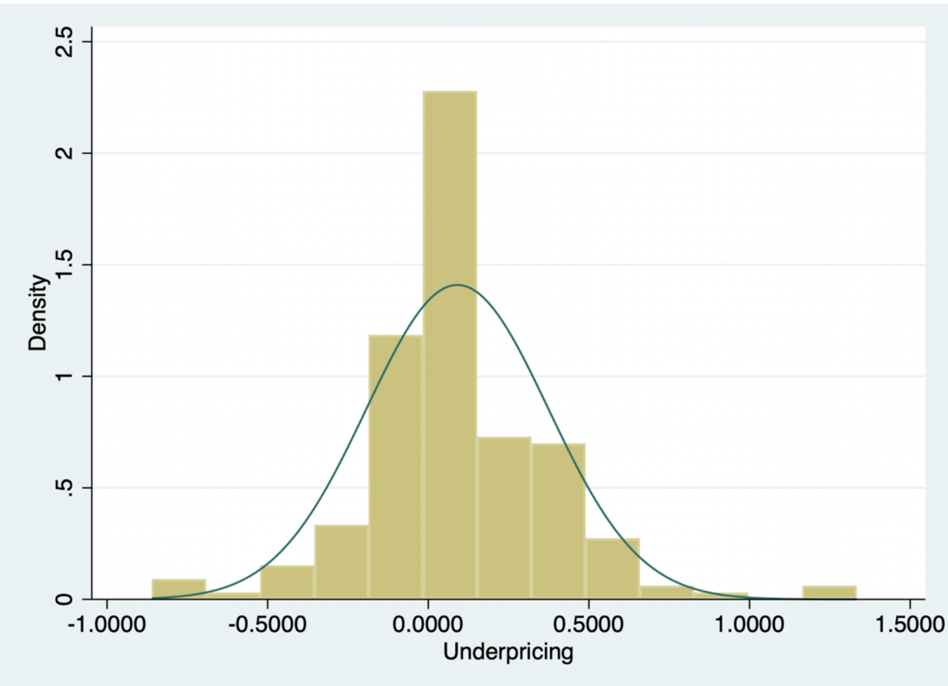
$$Intangible\ Assets\ Ratio = \frac{Total\ Intangible\ Assets}{Total\ Assets}$$

$$Firm\ Age = \ln\left(1 + (Year_{IPO} - Year_0)\right)$$

$$Leverage\ Ratio = \frac{PreIPO\ long\ term\ debt}{PreIPO\ Total\ Assets}$$

$$Proceeds = Offer\ price\ \times No.of\ offered\ shares$$

10.2 Histogram of continuous variable (underpricing) with frequencies and overlaid normal density curve



10.3 Variance Inflation Factor (VIF) output

VIF output from regression in Table 8 (Main regression)

Variable	VIF	1/VIF
R&D Intensity dummy	3.84	0.2604167
Intangible Assets-Ratio	3.16	0.3164557
Leverage-Ratio	2.47	0.4048583
SIC11 dummy	1.26	0.7936508
Ln(Proceeds)	1.11	0.9009009
Ln(Total Assets)	1.24	0.8064516
Ln(Firm Age)	1.1	0.9090909
VC dummy	2.54	0.3937008
PE dummy	1.95	0.5128205
No. of underwriters	2.14	0.4672897
Mean VIF	**2.08**	

VIF output from regression in Table 10 (Regression with interactive term)

Variable	VIF	1/VIF
R&D Intensity dummy	3.82	0.2617801
No. of underwriters	3.13	0.3194888
Interaction term (RD dummy and information production)	2.42	0.4132231
Intangible Assets-Ratio	1.24	0.8064516
Leverage-Ratio	1.12	0.8928571
Ln(Proceeds)	1.09	0.9174312
Ln(Total Assets)	2.51	0.3984064
Ln(Firm Age)	1.91	0.5235602
Mean VIF	**2.15**	

VIF output from regression in Table 11 (Regression comparing two groups)

Variable	VIF	1/VIF
R&D Intensity dummy	3.74	0.2673797
Intangible Assets-Ratio	3.12	0.3205128
Leverage-Ratio	2.84	0.3521127
SIC11 dummy	1.28	0.7812500
Ln(Proceeds)	1.19	0.8403361
Ln(Total Assets)	2.74	0.3649635
Ln(Firm Age)	1.14	0.8771930
Mean VIF	**2.29**	

VIF output from regression in Table 12 (Regression with Robust check)

Variable	VIF	1/VIF
R&D Intensity dummy	3.83	0.2610966
Intangible Assets-Ratio	3.17	0.3154574
Leverage-Ratio	2.45	0.4081633
SIC11 dummy	1.22	0.8196721
Ln(Proceeds)	1.11	0.9009009
Ln(Firm Age)	1.16	0.8620690
VC dummy	2.52	0.3968254
PE dummy	1.92	0.5208333
No. of underwriters	2.16	0.4629630
Hot market dummy	1.19	0.8403361
Mean VIF	**2.07**	

10.4 Industry Classification Benchmark

Industry	Sub-Sector	Sector
Oil & Gas	Oil & Gas	Oil & Gas Producers
		Oil Equipment, Services & Distribution
		Alternative energy
Basic Materials	Chemicals	Chemicals
	Basic Resources	Forestry & Paper
		Industrials Metals & Mining
		Mining
Industruals	Construction & Materials	Construction & Materials
	Industrials Goods & Services	Aerospace & Defence
		General Industrials
		Electronic & Electrical Equipment
		Industrial Engineering
		Industrial Transportation
		Support Services
Consumer Goods	Automobile & Parts	Automobile & Parts
	Food & Beverage	Beverages
		Food Producers
	Personal & Household Goods	Household Goods & Home Construction
		Leisure Goods
		Personal Goods
		Tobacco
Health Care	Health Care	Health Care Equipment & Services
		Pharmaceuticals & Biotechnology
Consumer Services	Retail	Food & Drug Retailers
		General Retailers
	Media	Media
	Travel & Leisure	Travel & Leisure
Telecommunications	Telecommunications	Fixed Line Telecommunications
		Mobile Telecommunications
Utilities	Utilities	Electricity
		Gas, Water & Multiutilities
Financials	Banks	Banks
	Insurance	Non-Life Insurance
		Life Insurance
	Real Estate	Real Estate Investments & Services
		Real Estate Investment Trusts
	Financial Services	Financial Services
		Equity Investment Instruments
		Non-Equity Investment Instruments
Technology	Technology	Software & Computer Services
		Technology Hardware & Equipment