Complexity, Order and Underpricing

An Empirical Study of Underpricing in Technology IPOs

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Abstract:

Using a sample of IPOs in technology-intensive industries between 1983 and 2022, this paper studies the impact of firm-specific characteristics and actions of prior peers on the initial returns of IPOs. Three types of variables are tested to explain the reasons for the large level and variability of IPO underpricing in the technology sector identified in previous academic studies. The regression analysis is conducted through running an OLS- and a MLE regression, which is extended upon by controlling for a bubble period. The results provide further validity to the explanatory value of previously tested determinants of IPO-underpricing in literature. The study however finds insignificant explanatory power in the effect of relative timing of IPOs on underpricing yet acknowledges that underpricing is more prevalent in the Computer Equipment industry with significance, adding to the scientific discussion of which variables and firm specific characteristics affect the phenomenon.

Keywords:

Common Valuation Factors, Ex-ante Uncertainty, Information Spillover Effects, Initial Public Offerings, Underpricing

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I. Introduction

To list on a public exchange signifies one of the most impactful commitments a company could undertake. An IPO provides apparent benefits for the shareholders of previously private companies through creating liquidity, granting access to public capital and enabling the diversification of assets for equity holders. However, there are also evident disadvantages of becoming a public entity. Increasing public and regulatory scrutiny of business operations and pressure from external investors on maximizing short-term shareholder value can to a great extent influence the strategic direction of any firm. Due to the extent of organizational change that the transaction typically entails, the IPO poses one of the most defining events in the life cycle of a corporation, making it arguably the most critical strategic move to get right.

For that reason, the on-average underpricing of IPOs in the public markets first recognized in (Ibbotson, Jaffe 1975) is intriguing. How come issuers accept losing out on potential gains when initially turning to the public for capital? As a result of the puzzling nature of the on average IPO underpricing, many studies aiming to understand and map the incentives and factors influencing it have emerged within the scope of financial academia. Although various possible explanations have been presented and analyzed, the level of information possessed by investors finds the most empirical support in literature. In an early study on the effects of information asymmetry on underpricing, (Rock 1986) acknowledges that investors differ from each other in terms of what information they possess. This, he suggests, implies the existence of incentives from underwriters to apply underpricing on average in their IPOs to ensure participation from inadequately informed investors. Extending on this notion of underpricing as a mechanism to ensure participation from uninformed investors, (Beatty, Ritter 1986) suggest that the higher the ex-ante uncertainty that is associated with an offering, the greater the need for underpricing in order to compensate uninformed investors. Aiming to test the effect of ex-ante uncertainty on underpricing in IPOs, various studies examine it through creating different proxies and testing them out in empirical studies. Ultimately, evidence that ex-ante uncertainty related to offering characteristics, company characteristics, information disclosed in the IPO prospectus and certain aftermarket variables have explanatory value on the level of underpricing of IPOs has found empirical support.

In addition to this, time period and market sentiment have also shown to play an important role in explaining different levels of IPO-underpricing. (Ibbotson, Jaffe 1975) found that IPO underpricing tends to vary across time, being especially evident during what the authors dub "hot issue" markets. These market periods are defined as intervals in time where many companies choose to go public simultaneously. In a later extension on the article, (Ibbotson, Ritter 1995) adds that the pattern goes back to as far as the 1960's. As to why IPO-clustering can be observed in the markets, (Benveniste, Busaba et al. 2002) presents the notion that aspiring issuers can benefit from prior listings through their revelation of common valuation factors about the industry. This information reveal, they argue, results in more accurate information being publicly available which reduces the need to spend resources on costly information gathering efforts. The authors also theorize that the revelation of common valuation factors has a spillover effect on valuations in that it simplifies subsequent issue pricing. This idea is further supported in (Alti 2005) which finds that outcomes of pioneering firms reflect private information related to common valuation factors facing the industry, making arguably subsequent IPO-pricing efforts increasingly simple and accurate. In a more recent paper (Chemmanur, He 2011) adds that prior listings reduce the informational asymmetry between peers and thus also improve subsequent pricing of IPOs.

(Benveniste, Busaba et al. 2002) also highlights that there is a negative correlation between average initial returns and IPO volume in those cases where firms could be considered to experience common valuation factors. This however could in part be seen to conflict with the general pattern found in empirical studies such as (Ibbotson, Jaffe 1975) that point to that “hot issue” markets, when many firms choose to issue in short succession, tend to entail substantially higher average levels of underpricing. Thus, while information spillover effects and the reveal of common valuation factors provide arguments for why time clustering is preferred by issuers, they fail to explain the counter-intuitive pattern of higher general underpricing in periods when a great deal of information about common valuation factors could be assumed to be publicly available within and between industries. A study adding to the friction is (Benveniste, Ljungqvist et al. 2003) that finds evidence for that information spillover effects in part explain underpricing of new issues, identifying that the initial returns tend to be smaller as the number of firms choosing to go public increases within a narrow timespan within industries. The paper builds on the idea laid out in (Lowry, Schwert 2002), that investment banks, given enough market power, smoothen their offerings across time to combat costs associated with underpricing.

A piece of more recent literature with inspiration partly taken from (Lowry, Schwert 2002) is (Lowry, Officer et al. 2010) that studies underpricing variability through investigating the effects of company specific characteristics on underpricing. One main finding of the study is that the variable “Tech", defined as belonging to SDC’s classification of a “high-tech industry” is a firm- specific characteristic that implies larger initial returns and initial return variability. This finding is in line with (Benveniste, Ljungqvist et al. 2003) who also finds evidence that initial returns are higher for industries that could be considered nascent. Both papers argue that the reason for this is that these industries often consist of firms that in general are more difficult to value due to their future growth prospects being harder to quantify and predict than for incumbent industries. Additionally, the inherent complexity of these firms is assumed to require more extensive underpricing in order to attract investors in line with (Rock 1986).

In general, studies on ex-ante uncertainty related to informational asymmetry suggest that increasing the amount of information available to the public will reduce the ex-ante uncertainty experienced in sequential issues through decreasing the gap between informed and uninformed investors. Previous studies on the topic of peer effects on IPO-underpricing have concentrated on subsequent offerings in aggregate, disregarding relative positioning in these clusters of IPOs due to assumed bundling of offerings by investment banks with market power. Being within a technology intensive industry is found to correlate with high levels of underpricing, which is assumed to be due to high degrees of complexity within the firms and an overall more extensive share of immaterial assets for these types of firms due to them being more heavily valued based on their future growth opportunities.

What previous research fails to account for is how firms in the tech sector differ from each other in terms of operations and complexity and what effect this could have on underpricing and its variability. Furthermore, prior literature does not investigate the immediate peer effects of prior listings on individual offerings underpricing in terms of short-term information spillover effects, as they look at subsequent peer effects on an aggregated cluster level. The argument for not using this methodology, presented in prior research, is the alleged conscious smoothening of offers to spread out implicit costs associated with underpricing from investment banks presented in (Lowry, Schwert 2002). However, this is a strong assumption to make as there are many investment banks in competition globally that could not be assumed to consciously bundle the offerings between themselves to spread out costs. This paper treats industries in a narrower sense to capture for the effects of prior IPOs on individual subsequent listings. Since technology intensive firms are complex and differ greatly from each other, there is an apparent need for more in-depth analysis of the causes behind underpricing in the individual offerings, both in terms of firm and industry characteristics but also regarding the relative timing to peers' financing decisions.

Extending on the model developed in (Lowry, Officer et al. 2010) this paper aims to find explanations for the extensive underpricing, and underpricing variability of technology firms by combining the different findings related to IPO underpricing presented in previous literature. More specifically, the intended scope of this paper is to answer the following research questions:

1. Does technology-intensive sub-industry belonging explain the level and variability of underpricing to different extents?
2. Does having a prior peer go public recently reduce the estimated level of underpricing and its variability in sequential peer IPOs, and does the time between listings influence mispricing?
3. Does IPO-characteristics such as VC backing, the number of shares issued and the exchange the issue is listed on provide explanatory value to underpricing and its dispersion among technology-intensive firms?

To study these questions, data on IPOs in the US has been collected from SDC Platinum. The main dataset consists of a total of 1228 observations (after removal of faulty data) in technology intensive sectors identified as “high-tech” by SDC Platinum. For additional insight, when omitting a bubble period, 1213 of the observations have been analyzed. Following the descriptions of the firms in combination with their four digit SIC codes, the firms were separated into five sub-industries defined by SDC Platinum. The sub-industries were Biotechnology, Computer Equipment, Electronics, Communications, and General Technology. Narrowing down the analysis to these industries allowed for an assessment of whether differences in firms industry-belonging within tech help explain underpricing and its variability, which potentially could point to differences in assumed growth opportunities between the sub-sectors. Another methodological contribution made in this study consists of considering the relative timing of a given issue, in order to analyze theorized information spillover effects of prior peer listings on subsequent IPO's. This was done through analyzing both the monthly position in relation to peers and the time period since the last peer went public. Accompanied with aforementioned factors was firm-specific characteristics previously researched in (Lowry, Officer et al. 2010) such as if the exchange the firm lists on is the Nasdaq stock exchange or not, if the company has previously been backed by venture capital funding and the number of shares listed in the IPO. The reason for why these variables were included despite already being incorporated in previous studies was to analyze whether they have explanatory power in a more recent dataset that consists solely of technology-intensive firms, providing further insight into the variability in between different time periods and technology-intensive industries.

The analysis of the dataset was done through running both an Ordinary Least Square (OLS) and Maximum Likelihood Estimation (MLE) regression, allowing for an estimation of the variables effect on both the level of experienced underpricing and its dispersion. At first, the outcome obtained from the analysis suggests that there is one persistent significant relationship between a firm's sub-industry and initial returns. However, no differences between the sub-industries effect on underpricing, and underpricing volatility were found with statistical significance. Furthermore, this paper finds that the number of shares issued, venture capital funding, company characteristics that provide similar explanatory value to the level of and the dispersion of underpricing as per previous literature on the topic. At last, the article cannot draw consistent conclusions on the effect of prior peer listings on underpricing variability both in terms of time period and relative positioning.

II. Theoretical Framework and Literature Review

To accurately study the potential variables that explain underpricing of technology firms there are many helpful areas of research to emanate from. Of high relevance to this study is prior research conducted on market, offering and firm characteristics' effect on the level of and variability of underpricing in IPOs. Furthermore, literature on information spillover-effects in investment banking processes is of high relevance to our studies. Closely interrelated to the literature on information spillover effects is the concept of common valuation factors and hot-issue markets.

A. Ex-ante Uncertainty's Effect on Underpricing

The literature on what causes underpricing in IPOs is extensive and commonly divided into four subgroups that individually investigate different types of explanatory factors: Information asymmetry models, behavioral theories, institutional factor theories and control theories. The research on information asymmetry investigates the reasons behind different levels of underpricing between firms and market periods in the context of informational differences between issuers, investors and/or underwriters. Many variables that fall within the area are proven to have a first-order effect on underpricing across different time periods.

(Rock 1986) rationalizes underpricing by modeling for informational asymmetry between a company and its prospective investors. Assuming underwriters control price but not allocation of shares, Rock justifies the use of underpricing as a method to attract less informed investors to ensure fully subscribed offerings and continuous participation in an underwriter’s subsequent IPOs. Although Rock's assumption about share-allocation does not accurately describe modern book-building practices and mechanisms in their entirety, his model has received strong empirical support from later studies that have tested it. Building on Rock’s notions, (Beatty, Ritter 1986) theorizes that ex-ante uncertainty should increase the expected level of underpricing in an IPO since difficulties in pricing an issue for potential investors would reduce their willingness to pay a high price for ownership in the company, which essentially makes signaling through underpricing more important in these offerings to attract uninformed investors. In their study, the authors utilized different proxies for measuring the ex-ante uncertainty in offerings such as firm characteristics, time period in which the company chooses to list and pricing volatility with the aim of obtaining a better understanding of the underpricing phenomenon in relation to ex-ante uncertainty.

Since then, many studies have researched ex-ante uncertainty’s effect on underpricing further by extending on different proxies for quantifying and measuring it. In general, these proxies can be divided into four primary categories: Information disclosed in the prospectus, aftermarket variables, company characteristics and offering characteristics. The literature on differences in information presented in the prospectus and entailing underpricing looks at the framing of risks and opportunities in the investment case in relation to the initial return of an IPO. (Beatty, Ritter 1986) approached the informational content of the prospectus by studying the number of mentioned uses of IPO-proceeds in the pre-IPO documents as a proxy for future opportunities. Another study by (Beatty, Welch 1996), utilized a similar methodological approach but instead studied the quantity of mentioned non-legal risk factors. However, the inherent problem when looking at information disclosed in the prospectus is that countries have somewhat different reporting regulation and common practices that affect which risks and opportunities must/should be mentioned in the prospectuses. An approach partly controlling for this was presented by (Hanley, Hoberg 2010), who, by utilizing modern word content analysis, analyzed the summative information disclosed in the prospectus. They found evidence in their study that the more information in the prospectus, the less the underpricing. About after-market variables, measures such as trading volatility and trading volume have been used as proxies for measuring uncertainty in IPO’s. (Ritter 1984) and (Ritter 1987) looks at volatility. (Miller, Reilly 1987) at trading volume. However, the problem with looking at aftermarket variables is that they per definition could be considered to not include ex-ante uncertainty since they focus on market conditions related to the time period after the IPO. Furthermore, since issues that are heavily underpriced in general tend to generate more trading interest it becomes highly difficult to draw conclusions on ex-ante uncertainty based on trading events after an IPO according to (Ljungqvist 2007). Research on underpricing and offering characteristics commonly uses gross proceeds as a proxy for uncertainty in the IPO. There is however great controversy surrounding gross proceeds explanatory value. (Habib, Ljungqvist 1998) highlights evidence that the level underpricing negatively correlates with gross proceeds when uncertainty is held constant, thus a clear connection between gross proceeds and underpricing has not been empirically established. The topic of company specific characteristics is the most widely researched type of variable examined in literature. Different proxies for firm specific variables include age (Ritter 1984) (Megginson, Weiss 1991) (Ljungqvist, Wilhelm Jr. 2003), sales (Ritter 1984) and industry (Ljungqvist, Wilhelm Jr. 2003) (Lowry, Officer et al. 2010). In a study on the variability of underpricing, (Lowry, Officer et al. 2010) researches the explanatory value of both company specific characteristics, market conditions, time period and industry belonging. An important finding of the study was that high-tech industry-belonging had significant explanatory value on underpricing. Applying the SDC Database's classification of high-tech firms, Lowry and Officer points out that underpricing tends to be significantly higher for technology-intensive firms.

B. Information Revelation Theories and Information Production Costs

Of high relevance to the concept of ex-ante uncertainty and information asymmetry is information revelation theory, information gathering costs and the concept of information spillover effects. A key implication of the (Rock 1986) model of uninformed investors and informed investors is that issuers are incentivized to reveal good information to the public to reduce the information asymmetry between the informed and uninformed investors. (Habib, Ljungqvist 2001) extend on this idea by theorizing that issuers who could take on additional costs to reduce information asymmetry between the two investor groups would do so up to a point where the marginal costs of doing so would equal the marginal benefit. Using a sample dataset of IPOs on the US Nasdaq exchange during the early 1990's the authors found evidence pointing to that an issuer would spend money on revealing more detailed information until the net benefit was statistically zero.

Regarding what could be interpreted to reduce the uncertainty related to an issue, several researchers have theorized and studied the reputation of the facilitators in the transaction. (Carter, Manaster 1990), and (Michaely, Shaw 1994) look at the reputation of the transaction's underwriter. (Titman, Trueman 1986) looks at the auditor. These studies hypothesize that prestigious mediators certify the quality of an offering. Through associating themselves with an issuer's offering, the authors propose that underwriters signal quality to the markets, which reduces the need for conducting proprietary information gathering efforts for potential investors. (Hoffmann-Burchardi 2001) adds support to this idea by finding that information externalities caused by issues reduce the willingness to indulge in expensive information gathering efforts by investors. However, later data on this is ambiguous; while underwriter reputation and underpricing evidently were negatively correlated in datasets used in earlier literature, (Beatty, Welch 1996) found that the relationship had switched and that having a prestigious underwriter was positively correlated with underpricing after the 1990's.

C. Sequential listings, “Hot Issue Markets” and Underpricing

The phrase “hot issue” markets signifying periods of abnormally high initial returns and large volumes of IPOs was coined in (Ibbotson, Jaffe 1975). The authors showcased, using US data, that certain time periods see disproportionate underpricing and IPO volume in relation to others. In an extension of the study (Ibbotson, Ritter 1995) finds that this relationship stems back to 1960. An argument for why IPOs tend to cluster in time was presented in (Alti 2005) that presents a model for information spillover effects in IPO clusters. Essentially, the way the author’s model for information spillovers is by looking at investors' bids as a function of the information they possess. A main finding of the model was that outcomes of pioneering peers reflect private information of common valuation factors, which he argues makes pricing of subsequent issues easier. Additional support for Alti’s notion can be found in (Chemmanur, He 2011) that presents an argument that prior listings reduce the informational asymmetry for investors and peers through reducing the uncertainty regarding firms subject to the same common valuation factors. (Benveniste, Busaba et al. 2002) explores the phenomenon of information externalities further, connecting it to general valuation uncertainty by creating a model that examines new industries entering the public markets. The authors highlight in their study that there is a negative correlation between average initial returns and IPO volume in instances where firms are evidently subjected to the same common valuation factors. (Benveniste, Ljungqvist et al. 2003) find evidence for that information spillover effects in part explain underpricing of new issues, identifying the fact that initial returns tend to be smaller as many firms choose to go public within a narrow timespan. The authors hypothesize that this occurs due to conscious bundling by investment banks in efforts to spread out information gathering costs related to the IPO-process in line with (Lowry, M., Schwert 2002) This finds support in literature on information disclosed in IPO-prospectuses that identifies the fact that firms often are required to conduct expensive information collection relating to their valuations prior to listing (Hanley, Hoberg 2010). Furthermore, this view is additionally supported by (Merton 1987), who argue that the marginal cost of gathering information is lower for investors that have prior knowledge of the industry. The idea that information reveal makes subsequent issues easier finds further evidence in (Aghamolla, Thakor 2022) that find that the propensity to list for firms engaged in the same R&D activities as a peer that recently have conducted an IPO increases significantly in connection to the peer’s IPO.

D. Contributions

Our study contributes to existing research by further examining the impact of technology intensive industry affinity on underpricing and underpricing volatility. This study extends on previous literature by not treating all firms defined as technology intensive similarly. The reason for this extension is that firms in the high-tech sector differ from each other in terms of factors that are both industry- and company-specific. In addition, this paper contributes to prior literature by analyzing whether firm specific characteristics tested in (Lowry, Officer et al. 2010) similarly explain underpricing and its variability in a more recent sample of solely technology intensive firms. Additionally, this study aims to add valuable insight into the effect of information spillover effects on the ex-ante uncertainty and following pricing of subsequent offerings through looking at the relative timing of offerings. By studying both the relative position and the time between issues effect on subsequent peer underpricing the paper provides further intuition on whether underwriter pricing becomes more accurate after information has been revealed through prior offerings in complex industries.

III. Methodology

This section reports the methodology used in order to answer the research questions of this paper. The section is divided into two subsections where ***A.*** describes the collected data, why and how certain demarcations have been made to the sample and how the data has been formatted in order to better fit the intended objective of the paper while ***B.*** showcases and explains the calculations behind measuring the initial returns and their volatility.

A. Data Collection

The data is collected from SDC platinum's transaction database. Information has been gathered on all the issuances made between 1983-2022 in the US by firms that fall within SDC Platinum's classification of high-tech industries. In total, data on 5,995 issuances was initially collected, but in order to find accurate answers to our research questions we have had to remove data from issuances that did not have all necessary information and/or information that was faulty. This was done manually through filtering the data in Excel. The removed data consists of:

1. IPOs without data on the stock's closing price on the first day of trading, as without this information the issue's comparable initial return was not obtainable.
2. Firms listed on an exchange outside of the US misplaced in the dataset, as a result of scope of this paper being IPOs in the US capital markets only.
3. Listings of class A shares to avoid duplicating calculations of the initial return of some IPOs, which could lead to a skewed dataset.
4. Data points containing inaccurate information on the IPOs offer prices that had been mistakenly collected and aggregated by SDC Platinum.

Sorting the data resulted in a dataset containing a total of 1,228 IPOs. The information collected for these IPOs were issue date, offer price of the issue, issuing firm's SIC code, the firm's business description, stock exchange on which the issue was listed, SDC's description of the high-tech industry, and the stock's closing price on its first trading day.

(Lowry, Officer et al. 2010) is the main article that this study draws inspiration from in terms of empirical methodology. The article uses SDCs definition of high-tech firms to identify technology intensive firms. The database's high-tech classifications divide technology-intensive firms into five sub-industries: Biotechnology, Computer Equipment, Electronics, Communications, and General Technology. This paper separates the five sub-industries as opposed to (Lowry, Officer et al. 2010). The rationale behind the separation is to examine differences in initial returns and initial return variability between the sub-industries within the high-tech sector. Additionally, the sub-industries were chosen in order to more accurately analyze the effects of prior closely related offerings. The fragmentation of the firms into the sub-industries was done through filtering in Excel. However, manual adjustments were at times necessary when assigning firms into sub-industries as following SDC Platinum's classifications alone some firms were allocated into multiple sub-industries simultaneously. For example, a firm with activities in manufacturing of telecommunications equipment, and computer related services would for instance be classified as a firm in both the Communications- and Computer Equipment industry. To avoid firms being placed in numerous sub-industries simultaneously, additional information from their 4 digit SIC code and business descriptions were used to categorize the issuer into a sub-industry in line with their primary business operations. This increasingly narrow method is beneficial for the analysis of the firm's industry belonging and the listings effect on subsequent peers as it better ensures firms with proximity in their main operations are classified into the same group. In those rare instances when it was still ambiguous where to assign the firm, manual research was conducted through reading published business descriptions on other public databases to gain valid information of the core activities of the firm at the time of the IPO.

Table I: The number of listings in the sample for each sub-industry in the high-tech sector

Table I shows the total number of high-tech IPOs studied in this paper, and how they are distributed across the different sub-industries within the high-tech sector.

	Number of IPOs
Total observations in High-Tech Sector	1228
Biotechnology	671
Computer Equipment	348
Electronics	76
Communications	116
General technology	17

Table I provides insight into the distribution of IPOs in the different sub-industries. Most of the IPOs were observed in the "Biotechnology" industry which includes firms with operations in laboratory-, medical instruments and drug research & development. In the "Computer Equipment" sub-industry firms were foremost conducting software development, data processing and manufacturing of computer equipment. "Electronics" ascribe firms manufacturing semi- or/and superconductors, while "Communications" includes companies with operations relating to telephone-communications and/or communication services. Lastly, "General Technology" refers to firms defined as high-tech yet not included in the other sub-industries. These are mainly firms with operations in defense related activities and/or robotics.

The classification of the firm listing's relative timing to peers in each month was done with excel. Since the firms already were divided into different sub-industries, it was possible to identify the order of listings in an industry within a month by filtering for each industry and month. Furthermore, filtering each sub-industry respectively enabled for a calculation of the number of days between two firms' issues within a sub-industry. This was calculated in order to also analyze whether the time in between listings has significant explanatory value on pricing uncertainty in the high-tech sector. However, for the firms within an industry who constituted the first listing firms in the sample it was not possible to calculate the days since prior listing since we had no previous IPOs to reference. These five firms were treated in the dataset as listing immediately after another firm in order to minimize their effect on the sample, and thus were assigned the value of zero on this variable.

B. Calculation of Underpricing and Underpricing Variability

Using data on the issue's offer price, and the stock's closing price after the first trading day, the underpricing for an IPO, denoted *i*, can be calculated through measuring the percentage difference of these two prices as presented by equation **(a)**. This calculation was done in Excel and assigned each offering. The individual offerings' initial returns were later calculated into monthly averages for each month.

$$(a)\ Initial\ Return_i = \frac{Closing\ price\ 1st\ day\ of\ trading_i - Offer\ price_i}{Offer\ Price_i}$$

As this paper focuses on IPOs in the US, our research method uses the first day closing price to determine the price the market has set for the issue instead of the stock price after 21 days as in (LOWRY, OFFICER et al. 2010). This since the full extent of underpricing can be visible in the US markets on the first day of trading since there are no unique structural limitations in the US capital markets (Ljungqvist 2007). Utilizing the closing price of the first trading day was also done since using the stock price at a later point in time in the underpricing calculation could be considered to increasingly include effects from trading activity and other external events on valuations after an IPO.

$$(b)\ Monthly\ Variability\ of\ Initial\ Returns_t = \frac{(Initial\ Return_i - \overline{Initial\ Return_t})}{n_t - 1}$$

Having data of the listings' underpricing, the variability of the initial returns in month *t* was possible to calculate using equation (b) where n_t stands for the number of IPOs in month *t*.

IV. Empirical Analysis & Findings

This section accounts for the empirical analysis and scientific findings of this paper. The section is divided into two subsections. Part ***A.*** presents the descriptive statistics of the sample and the implications of the dataset's distribution. Part ***B.*** reports the empirical analysis starting with a correlation analysis followed by a cross-sectional regression analysis in part ***B.2.***

A. Descriptive Statistics

Figure 1: Statistics and the distribution of underpricing

Figure 1 shows the distribution of initial returns, and the descriptive statistics for the collected sample. The X-axis represents the initial returns of IPOs, and the Y-axis shows the frequencies of IPOs with a given initial return.

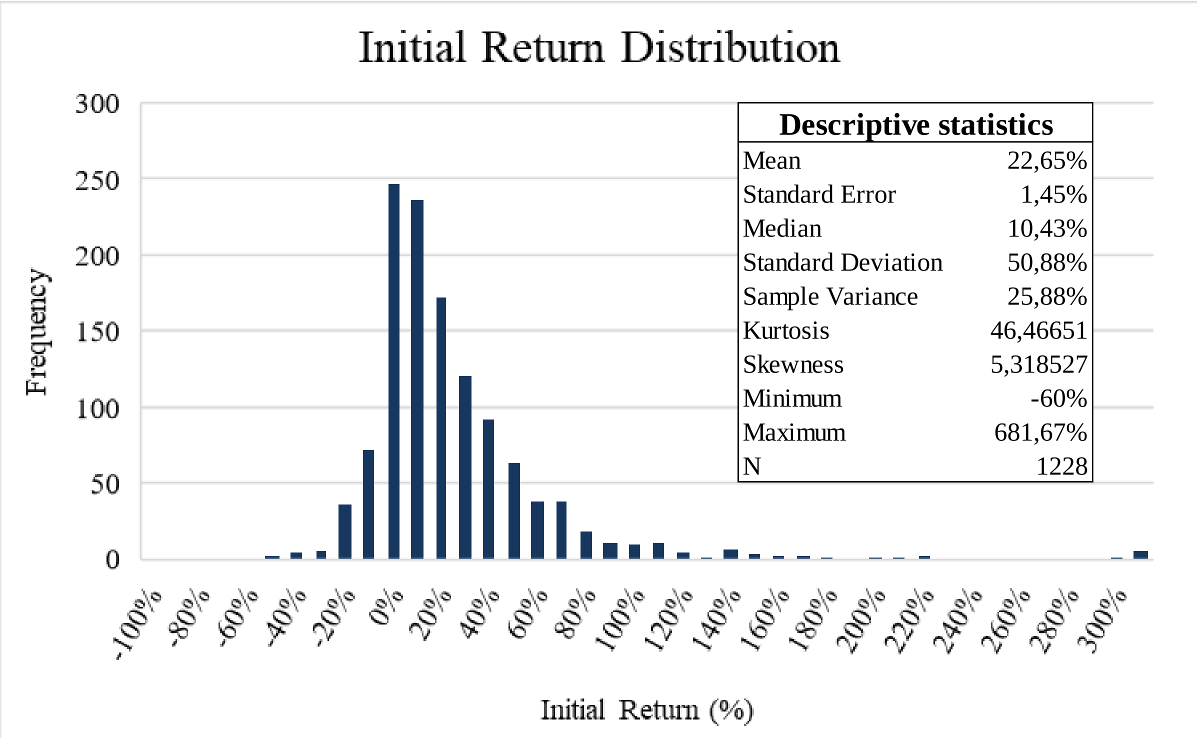
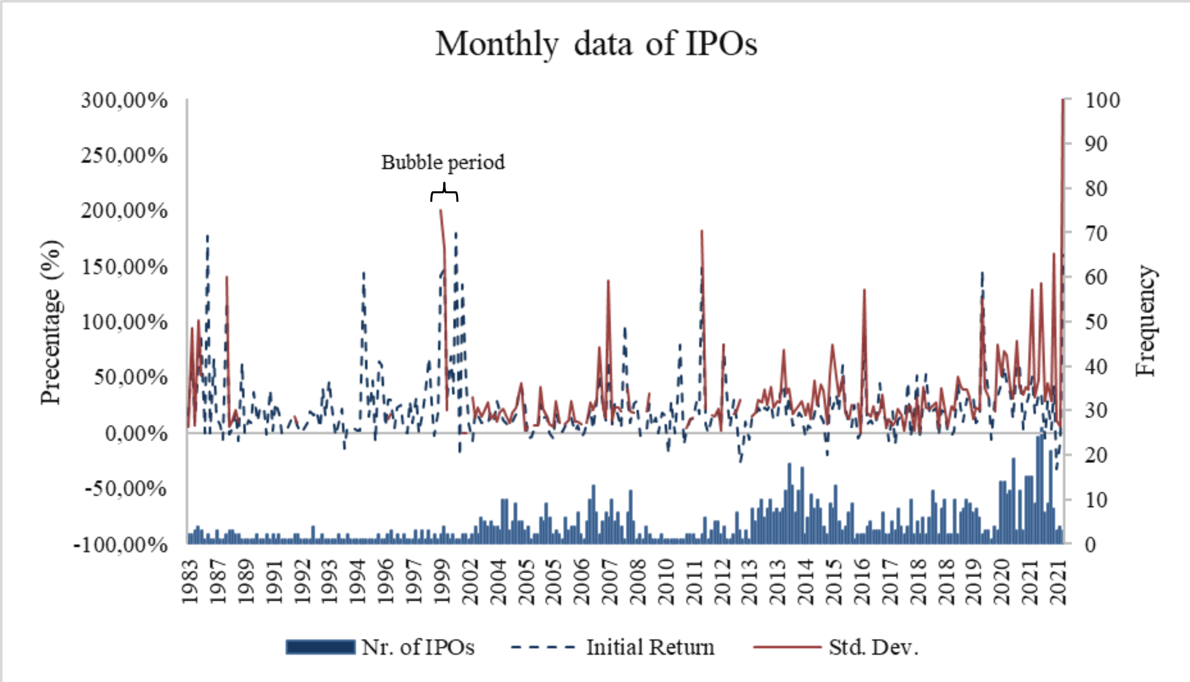


Figure 1 presents the distribution of underpricing in IPOs from 1983 to 2022. The sample of 1228 high-tech IPOs have an observed mean of 22,65% indicating that the first day closing price of an issue averages well above the offer price. A standard deviation of 50,88% further indicates the large variability of initial returns. Additionally, a skewness of 5,319 and a kurtosis of 46,467 demonstrate that the initial return distribution is asymmetric towards a positive return, with more heavy tails than what is suggested by a normal distribution.

Figure 2: Monthly listings, Average Initial returns and initial return volatility

The figure shows the average initial return, initial return variability[1], and number of IPOs each month between 1983 and 2022 in the high-tech sector as defined by SDC Platinum. The dotted blue line represents the monthly average initial returns of IPOs, and the solid red line represents the initial returns' standard deviation each month. Both mentioned measures are in percentage terms (%) as shown on the left Y-axis. The blue bars represent the monthly number of IPOs as shown on the right Y-axis. The horizontal bracket depicts the identified bubble period.



From **figure 2** it is possible to observe a cyclical behavior in the initial returns, their variability and the number of IPOs each month. Particularly, the relationship between the three measures illustrate that periods of high initial return frequently are accompanied by a high variability and large number of issues. This could further explain the skewness in the set of observations presented in **figure 1**.

In the sample, one bubble period was identified in the dataset following the distinction made in (LOWRY, OFFICER et al. 2010), which is observable in **figure 2**. IPOs conducted during the period May 1999 to July 2000 averaged a monthly initial return of 89,23%, and a monthly initial return volatility of 78,86%.

[1] For a number of months the standard deviation of initial returns was not possible to calculate as there were only one IPO in that particular month.

B. The Effect of Firm Characteristics & Relative IPO Timing on Underpricing and Underpricing Variability

Table II presents the variables that form the basis of the analysis. The variables in the table will be studied in terms of whether they provide explanatory power to the level of, and volatility of initial returns. In other words, the variables will be studied regarding whether they can separately help explain the previously mentioned positive skewness in the distribution of initial returns in the sample.

Table II: Definition of variables

Table II reports the firm-specific variables used in the empirical analysis. The brackets divide the variables into three different categories; **(1)** denotes the variables identifying which industry an issuing firm belongs to in the high-tech sector. **(2)** are variables previously tested in (Lowry, Officer et al. 2010). **(3)** represents variables identifying a firm's relative timing in relation to prior listings in the industry. Lastly, we add a dummy variable identifying a bubble period (May 1999 to July 2000).

(1) Sub-Industries in High-Tech	***BioTech***	Dummy variable equal to one if firm is in the Biotechology industry, and zero if not
	CompEq	Dummy variable equal to one if firm is in the Computer Equipment industry, and zero if not
	Elec	Dummy variable equal to one if firm is in the Electronics industry, and zero if not
	Comm	Dummy variable equal to one if firm is in the Communications industry, and zero if not
	GenTech	Dummy variable equal to one if firm is in the General Technology industry, and zero if not
(2) Prior Literature Variables	***VC***	Dummy variable equal to one if firm has recieved funds from venture capitalists prior to listing, zero if not
	LogShares	Variable with the value of the logarithm of the amount of share the IPO firm is issuing
	Nasdaq	Dummy variable equal to one if firm is being listed on Nasdaq, and zero if not
(3) IPO Spillover Effects	***LogDays***	Variable with the value of the logarithm of the amount of days since the previous IPO in an industry
	LogOrder	Variable with the value of the logarithm of the order an IPO has within an industry, within a month
	Bubble	Dummy variable equal to one during the identified bubble periods, and zero if not

Three types of variables are tested in the analysis. These are variables identifying which of the five sub-industries in the high-tech sector a firm belongs to, previously tested in (Lowry, Officer et al. 2010) and variables catching a firm's relative timing when listing on the public markets. Included is also a dummy variable intended to study a bubble's effect on pricing uncertainty.

Firstly, the "Sub-Industries in High-Tech"-variables classify the issues based on the specific industry the firms are part of in the high-tech sector as defined by SDC Platinum. Being a firm in the high-tech sector is thought to impose uncertainty in the book-building process mainly due to the underwriter's estimation of the offer price could be dependent on the growth opportunities of significantly complex activities, in line with (Lowry, Officer et al. 2010). As these sub-industries are treated separately, the analysis will be able to capture their unique effect on the mispricing of different technology-intensive industry IPOs. The prediction is that industry belonging will impact the ex-ante uncertainty differently. *BioTech* refers to the dummy variable signaling whether the firm's primary operations are in Biotechnology or not. *CompEq* denotes the firms with main operations in Computer Equipment and *Elec* firms manufacturing Electronics, mainly semi- and superconductors. *Comm* and *GenTech* are firms with foremost activities in Communications and General Technology that refer to other technology-intensive operations not included in previously mentioned industries, for example defense and robotics.

Secondly, this study includes variables in the analysis tested in previous literature denoted "Prior Literature Variables" in **table II**. The empirical value of including the variables in this paper is that they help to analyze whether they have predictable explanatory power of the dependent variables in a sample of firms already instituting a significant effect on the pricing uncertainty. The predictions for these variables are as follows; The variable identifying firms with venture capital backing *(VC)* is expected to reduce the pricing uncertainty as the venture investor could provide increasingly accurate information about the issuing firm to the underwriters prior to the listing. Similar effect is predicted for the logarithm of the shares issued in a firm's IPO *(LogShares)*. This due to the larger an offering is, the more information tends to be available on the firm implying less ex-ante uncertainty. Contrasting effects are however hypothesized for the variable indicating a firm's listing on the Nasdaq stock exchange *(Nasdaq)*. The rationale behind this prediction is that young and less established firms in nascent industries tend to list on Nasdaq implying less information being available of these firms prior to the listing.

Thirdly, to analyze potential informational spillover effects on underpricing and the volatility of initial returns, two new variables are introduced in this paper. Firstly, the variable *LogDays* is the logarithm of the number of days since the last IPO was conducted in a particular industry in the US plus one. The reason for why the number of days is added with one is due to the logarithm of zero being undefined, and if not done the variable's effect would not be as accurately measured. The prediction for this variable is that firms issuing shortly after another firm within the same industry should expect less pricing uncertainty, while more days should entail increased uncertainty. This idea follows the theories presented in (Benveniste, Ljungqvist et al. 2003) where it was found that initial returns were lower for firms in aggregate who issued close in time to a peer. Secondly, *LogOrder* is a variable catching the order of a firm's listing in a month relative to the other firms' issues in its sub-industry. Following the research in (Alti 2005), and (Chemmanur, He 2011) our prediction for this variable is that firms issuing earlier in a month will experience more uncertainty in the pricing process compared to firms in the same sub-industry that issues later in the month.

Lastly, a dummy variable is included in order to control for the potential effect of bubble periods. All listings in the period May 1999 to July 2000 will be assigned the value of 1, and the remaining issues in the sample 0.

Table III: Correlations between Initial Returns and Firm Characteristics

The table presents the Spearman correlations of the monthly initial returns and their variability with the monthly proportion of each variable. **Section 1** of the table presents the outcome when the entire sample is included. **(1)** shows the correlations between the monthly average initial return and the monthly fraction of each variable. Column **(1.1)** presents the variables that correlation has been tested for, **(1.2)** shows the spearman correlations, and **(1.3)** the p-values where *, **, and *** specify significance on a 10%, 5%, and 1% level. **(2)** Presents the correlations between the monthly portion of each variable and the monthly variability of initial returns. **Section 2** of the table presents the correlations when the bubble period has been omitted from the sample.

Section 1: Entire sample

(1) Initial Return			(2) Standard Deviation		
(1.1) Variables:	**(1.2) Correlation:**	**(1.3) P-value:**	**(2.1) Variables:**	**(2.2) Correlation:**	**(2.3) P-value:**
IR & BioTech	-0,106	0,075*	*Std. Dev. & BioTech*	-0,007	0,922
IR & CompEq	0,118	0,047**	*Std. Dev. & CompEq*	0,055	0,439
IR & Elec	-0,002	0,976	*Std. Dev. & Elec*	-0,129	0,067*
IR & Comm	-0,014	0,812	*Std. Dev. & Comm*	0,005	0,942
IR & GenTech	0,018	0,769	*Std. Dev. & GenTech*	0,162	0,021**
IR & VC	0,048	0,425	*Std. Dev. & VC*	-0,115	0,105
IR & LogShares	-0,097	0,103	*Std. Dev. & LogShares*	-0,158	0,025**
IR & Nasdaq	0,007	0,903	*Std. Dev. & Nasdaq*	-0,077	0,274
IR & LogDays	0,004	0,952	*Std. Dev & LogDays*	-0,024	0,7372
IR & LogOrder	0,030	0,611	*Std. Dev & LogOrder*	0,086	0,223
* if p-value ≤ 0,1 ** if p-value ≤ 0,05 *** if p-value ≤ 0,01	**Sample size:** 284 months		**Sample size:** 284 months		

Section 2: Omitting bubble periods from sample

(3) Initial Return			(4) Standard Deviation		
(3.1) Variables:	**(3.2) Correlation:**	**(3.3) P-value:**	**(4.1) Variables:**	**(4.2) Correlation:**	**(4.3) P-value:**
IR & BioTech	-0,040	0,511	*Std. Dev. & BioTech*	0,041	0,568
IR & CompEq	0,089	0,141	*Std. Dev. & CompEq*	0,023	0,744
IR & Elec	-0,080	0,188	*Std. Dev. & Elec*	-0,117	0,102
IR & Comm	-0,010	0,872	*Std. Dev. & Comm*	-0,059	0,410
IR & GenTech	0,032	0,598	*Std. Dev. & GenTech*	0,181	0,011**
IR & VC	0,003	0,954	*Std. Dev. & VC*	-0,150	0,035**
IR & LogShares	-0,090	0,134	*Std. Dev. & LogShares*	-0,159	0,025**
IR & Nasdaq	-0,033	0,591	*Std. Dev. & Nasdaq*	-0,101	0,157
IR & LogDays	-0,026	0,664	*Std. Dev & LogDays*	-0,081	0,257
IR & LogOrder	0,065	0,280	*Std. Dev & LogOrder*	0,119	0,096*
* if p-value ≤ 0,1 ** if p-value ≤ 0,05 *** if p-value ≤ 0,01	**Sample size:** 276 months		**Sample size:** 276 months		

Table III gives an insight into the co-movement of underpricing and variability with the monthly proportion of industry variables. The table is divided into two separate sections labeled **section 1**, and **2**. **Section 1** of the table presents the results of the correlations when the whole sample is included. **Section 2** of the table shows the results when the bubble period has been omitted from the sample.

The presentation of the results will start with **section 1** in **table III** where the whole sample is included in the tests. Firstly, interpreting the industry-based variables one can expect that in months with large proportions of *BioTech* firms going public, the average underpricing of the listings decreases. For the variability of initial returns in months with a large fraction of the listings being *BioTech* firms there seems to be no significant co-dependence. In months where a large share of firms going public are in the *CompEq* industry the initial returns, contrary to the *BioTech* case, increase significantly. However, for months with a high frequency *CompEq* listings there is no significance in the interrelation to the dispersion of initial return. The monthly proportion of *Elec* firms seem to have no evident co-movement with the Initial Returns as opposed to the two previously mentioned industries. Nonetheless, months with larger fractions of Electronics firms have lower underpricing variability. In months with high volumes of *Comm* firms, the correlation with the monthly average and dispersion of underpricing has no significant explanatory power. When it comes to *GenTech*, the monthly proportion's correlations to the average and variability of initial returns there are only significant results for the positive relationship with the dispersion of initial returns.

Regarding timing effect on underpricing and initial return dispersion it is not possible to observe a significant effect. Months where there were many sequential movers in a sub-industry seem to have no statistically significant correlation with underpricing. Similarly, the variable capturing the days between two listings within an industry lacks in providing significant evidence as well.

Regarding the remaining variables, **section 1** of **table III** suggests that months with a high percentage of firms with backing from venture capitalist do not correlate on a 10% significance level, with neither the monthly average nor the variability of initial returns. The same argument follows for months with a high percentage of listings on the Nasdaq exchange. However, an increased monthly value of the logarithm of shares issued seem to only significantly correlate with the standard deviation of underpricing and not the average of initial returns.

In **section 2** of **table III** when the bubble periods have been omitted from the sample significance in some of the correlations disappear. More specifically, with the bubble period removed from the sample both the monthly fractions of *BioTech*, and *CompEq* firms' correlations with monthly initial returns lose significance. The reason for this change could be that the IPO bubble period explains the significant correlations these variables show when the entire sample is included. Similar explanation follows for *Elec's* loss of significance in the correlations with monthly standard deviation of underpricing. However, in contrast to the disappearance of significance in the mentioned correlations, we see that the correlation between monthly proportion of listings in *Gentech*, and monthly initial return dispersion gain significance. In months with large fractions of Nasdaq listings the standard deviation of underpricing tends to decrease. Gaining significance also follows for the positive correlation between months with a large proportion of later movers, and the volatility of initial returns. Specifically, in months where there are many later movers, the monthly standard deviation of initial returns decreases.

In conclusion, the output of **table III** suggests that there are predictive relationships present between some of the variables, and either the level, or dispersion of underpricing. However, the general level of significance in the output is insufficient for making claims on the factors' impact on uncertainty. This is due to factors increasing the difficulty for an underwriter to accurately price an IPO should have a significant positive correlation with both the monthly level, and volatility of initial returns (Lowry, Officer et al. 2010). This is not persistent with the results presented in **table III** and a more thorough cross-sectional analysis will follow in **section B.2**. which will form the basis of the discussion in **section V**.

B.2. Cross-Sectional Regression Analysis

In this subsubsection a regression analysis is made of the variables' effect on initial returns and initial return dispersion through running an OLS, and a MLE. Running both an OLS, and a MLE allows for a comparison of the explanatory strength of the regressions. Additionally, running a MLE is beneficial for the scope of this paper as it estimates the proxies' individual effect on the initial returns and their variability simultaneously. The OLS is run directly from equation **(c)** which is the function of initial returns described by the variables presented in **table II**. When it comes to the execution of a MLE regression, this paper follows the methodology in (Lowry, Officer et al. 2010) where the logarithm of the error terms' variance is assumed to be linearly explained by the variables shown in **(c)**. This allows for the MLE to be run on both **(c)** and **(d)**. Note that one of the variables has been omitted from the regression equations due to multicollinearity concerns. This was the explanatory variable *BioTech.*

$$(c)\ IR_i = \beta_0 + \beta_1 CompEq_i + \beta_2 Elec_i + \beta_3 Comm_i + \beta_4 GenTech_i + \beta_5 VC_i + \beta_6 LogShares_i + \beta_7 Nasdaq_i + \beta_8 LogDays_i + \beta_9 LogOrder_i + \beta_{10} Bubble_i + \varepsilon_i$$

$$(d)\ Ln(\sigma^2(\varepsilon_i)) = \gamma_0 + \gamma_1 CompEq_i + \gamma_2 Elec_i + \gamma_3 Comm_i + \gamma_4 GenTech_i + \gamma_5 VC_i + \gamma_6 LogShares_i + \gamma_7 Nasdaq_i + \gamma_8 LogDays_i + \gamma_9 LogOrder_i + \gamma_{10} Bubble_i + \varepsilon_i$$

Table IV: Cross-sectional regressions of Underpricing and its Variability

The table shows the results of the cross-sectional regressions run using equation **(c)**, and **(d)**. **Section 1** of the table presents the regressions of the entire sample of 1228 observations. Part (1) reports the results of the OLS regression equation **(c)**. Column **(1.1)** presents the independent variables tested in the regressions, **(1.2)** reports the variables' coefficients, and **(1.3)** the p-values. Part **(2)** reports the results of the MLE regression of equation **(c)** and **(d)**. Specification **(2.1)** presents the output from the MLE regression of equation **(c)** where column **(2.1.1)** reports the variables' estimators, and Column **(2.1.2)** the p-values. Specification **(2.2)** presents columns with the results from the MLE of equation **(d)**. Column **(2.2.1)** shows the estimators, and **(2.2.2)** their p-values. **Section 2** of the table reports the output of the OLS, and MLE regression of equation **(c)**, and **(d)** when the identified bubble periods have been removed from the sample. The Log-likelihood estimators presented in the table are used to study the eventual enhancement in the model when running a MLE as it accounts for heteroskedasticity. All p-values presented use robust standard errors (HC1) where *****, ******, and ******* indicate 10%, 5%, and 1% significance.

Section 1: Entire sample

	(1) OLS		(2) MLE			
			(2.1) IR		(2.2) LN(Variance)	
(1.1) Variables:	**(1.2) Coefficient:**	**(1.3) P-value:**	**(2.1.1) Coefficient:**	**(2.1.2) P-value:**	**(2.2.1) Coefficient:**	**(2.2.2) P-value:**
Intercept	0,349	0,380	-0,303	0,421	6,375	0,018**
CompEq	0,115	0,002***	0,066	0,050*	0,311	0,339
Elec	0,092	0,325	-0,009	0,906	1,302	0,131
Comm	0,102	0,065*	0,073	0,175	0,683	0,145
GenTech	0,154	0,117	0,015	0,836	-0,382	0,507
VC	0,062	0,039**	0,099	0,001***	-0,250	0,452
LogShares	-0,032	0,561	0,059	0,276	-1,215	0,003***
Nasdaq	0,022	0,552	0,047	0,128	0,271	0,315
LogDays	-0,020	0,479	-0,003	0,895	-0,109	0,609
LogOrder	0,002	0,963	-0,016	0,778	-0,004	0,991
Bubble	0,725	0,009***	0,783	0,016**	1,311	0,002***
* if p-value ≤ 0,1	**R^2** 0,039					
** if p-value ≤ 0,05	**Log-likelihood:** -887,700		**Log-Likelihood:** -724,112			
*** if p-value ≤ 0,01	**Sample size:** 1228		**Sample size:** 1228			

Secion 2: Omitting bubble periods from the sample

	(3) OLS		(4) MLE			
			(4.1) IR		(4.2) LN(Variance)	
(3.1) Variables:	**(3.2) Coefficient:**	**(3.3) P-value:**	**(4.1.1) Coefficient:**	**(4.1.2) P-value:**	**(4.2.1) Coefficient:**	**(4.2.2) P-value:**
Intercept	0,322	0,531	-0,305	0,423	6,430	0,019**
CompEq	0,103	0,005***	0,064	0,055*	0,298	0,363
Elec	0,089	0,344	-0,007	0,926	1,342	0,125
Comm	0,109	0,044**	0,073	0,173	0,661	0,165
GenTech	0,143	0,145	0,014	0,839	-0,374	0,519
VC	0,049	0,098*	0,098	0,001***	-0,258	0,440
LogShares	-0,026	0,635	0,059	0,275	-1,217	0,003***
Nasdaq	0,017	0,647	0,046	0,131	0,255	0,342
LogDays	-0,018	0,504	-0,004	0,877	-0,126	0,564
LogOrder	-0,002	0,962	-0,017	0,757	-0,031	0,937
* if p-value ≤ 0,1	**R^2** 0,009					
** if p-value ≤ 0,05	**Log-likelihood:** -849,195		**Log-Likelihood:** -700,751			
*** if p-value ≤ 0,01	**Sample size:** 1213		**Sample size:** 1213			

Table IV provides the results of the OLS, and MLE regressions which show the characteristics' individual explanatory power on both the level of underpricing and its dispersion. The table is divided into two sections, the first one includes the bubble period in the sample, and the second section excludes it. The presentation of the results below will first be of **section 1** of **table IV,** the regressions when the whole sample period is included. Subsequently will follow the presentation of **section 2** of **table IV** when the regression results when the bubble periods have been excluded. Additionally, as the log likelihood of the MLE is larger than the equivalent measure for the OLS, it implies that the model predicted by the MLE is a better fit for the sample compared to the OLS. Thus, the result presentation will mainly be based on the outcome from the MLE. However, the OLS will be a benchmark intended for comparisons with the results provided by the MLE regression of initial returns.

Starting the interpretation of the results from the MLE regression on the initial returns in specification **(2.1)**, certain findings show significant explanatory power. Firstly, consistent with the output of the OLS, IPOs of firms in the *CompEq* have a positive effect on the level of initial return. Similarly, also consistent with the results of the OLS regression, venture capital funding has a positive effect on underpricing. The firms funded by venture capital additionally have the highest initial return in the regression apart from the *Bubble* dummy. With reference to the

OLS regression, *Comm* firms increase the level of initial returns. The explanatory effect on underpricing of firms with activities in the communications sub-industry however lose significance in the MLE regression. Lastly, both regressions on underpricing fail to provide significant evidence on the effect of the relative timing of an IPO.

Next, interpreting the results from MLE regression on the natural logarithm of the variance we find that issuing many shares in an IPO negatively affects the volatility of underpricing. This negative effect is consistent with the output of the monthly data presented in **section 1** of **table III.** However, contrasting the correlation output is that no sub-industry has significance in their effect on the dispersion of underpricing in the MLE. In addition, regarding the sequential listing variables there seems to be no predictable pattern in their ability to explain the volatility of underpricing either.

Regarding the bubble dummy variable, IPOs between May 1999 to July 2000 have the largest significant positive effect on both the level of initial return, and the measure's dispersion. However, when the IPO bubble period is removed from the sample in **section 2** of **table IV** we see little change in terms of the variables' explanation of initial returns, and its variability. More specifically, the only change appearing is that most of the variables' p-values slightly increase in combination with a marginal change in the value of their coefficients. Apart from that, we see no changes of the coefficient signs, and small differences in terms of the value of the coefficients. Thus, the results from the regressions when removing the bubble periods closely follow the output in **section 1** of **table IV**

V. Discussion

In this section there will be a discussion of the results presented in the cross-sectional analysis. This section will mainly discuss the implications of the results in **table IV,** and how well it follows the predictions of this paper. Any deviation from the predictions is monitored, highlighted and discussed. Lastly, this section will mention potential reasons why some results are insignificant in the cross-sectional analysis.

Firstly, with respect to the sub-industry characteristics, one objective of this paper is to compare the relative effects that the variables have on the initial returns, and their variability. In the OLS, two sub-industry variables have positive significant effect on initial returns, suggesting that *CompEq* has a larger effect on underpricing than *Comm.* In contrast, when the bubble period has been omitted from the sample the situation is reversed, consistent with the outcome in the MLE. Nonetheless, in a linear hypothesis test the differences between the coefficients of the two variables cannot be discerned with statistical certainty (See **table AI** in the appendix).

Secondly, venture capital backing induces a positive effect on underpricing which is the opposite of the predictions in this paper. The positive effect venture capital backing has on underpricing is evident in both the OLS-, and the MLE regression, which could be explained by VC-backing causing the listing to catch risky industry effects in line with (LOWRY, OFFICER et al. 2010). In contrast, the negative effect the number of shares issued has on underpricing dispersion, accurately follows the predictions of this paper.

*CompEq, VC***,** *LogShares* persistently show a significant effect on either the level of underpricing, or its variability. Nonetheless, as stated before, only having explanatory power for one of them makes it insufficient to claim the variables' effect on the difficulty of the underwriter's book-building process with certainty (Lowry, Officer et al. 2010).

The difference between the results presented in **section 1**, and **section 2** in **table IV** is small in terms of the coefficient significance despite the bubble period showcasing a large positive effect on both the level, and variability of initial returns. A possible explanation for this is that the bubble period only concerned a small number of observations in the sample (15 IPOs). Consequently, the IPO bubble's effect in this study did not change the other variables' explanatory value notably when the period was omitted from the sample.

Finally, the insignificant results in this article for some variables could have several explanations. Firstly, the necessary removals of data points heavily reduced the theoretical sample size which could have affected the results. Conducting the same analysis on a larger sample might provide significantly different results. However, with limited access to additional data sources to complement SDC Platinum, a more extensive dataset was not obtainable. In particular, the size of the dataset assumingly had a large effect on the explanatory power of the variables intended to examine the informational spillover effects**.** This due to the informational spillover effects is dependent on the previous listings. With insufficient information of all listings within a given time period, these effects are more difficult to accurately discern. On a similar note, the sub-industry separation could be considered too broad for accurate analysis of the effect of common valuation factors due to the inherent complexity within tech. A narrower definition of sub-industries could have positively contributed to the results of this study.

VI. Conclusion

This paper studies the impact of various factors influencing the mispricing of IPOs in the technology sector. Three types of categories that follow previous literature's rationales are tested in a model inspired by (Lowry, Officer et al. 2010)) on a sample of 1228 IPOs conducted between 1983 to 2022 in the US public markets. The model allows for an accurate analysis of the variables' impact on the level, and volatility of underpricing. The three types of variables tested are, (1) the firm's sub-industry belonging within the high-tech sector, (2) variables tested in (Lowry, Officer et al. 2010), and (3) variables identifying the relative timing of IPOs. Additionally, a bubble period is identified, intended to study whether the factors' effect on the level, and variability of initial returns is persistent in a sample when the period has been omitted.

This article finds that only the computer equipment sub-industry significantly helps to explain underpricing in the high-tech sector consistently. Thus, the article does not accurately determine differences between the sub-industries in their impact on underpricing, and its variability.

For the variables tested in previous literature, this paper highlights that venture capital backing positively affects underpricing in a sample of technology firms. Additionally, issuing many shares reduces the dispersion of underpricing on a significant level. These findings validate the outcome of previous literature as the ex-ante uncertainty proxies' effect on either the level of underpricing or the underpricing's standard deviation are persistent in a sample solely of technology firms where uncertainty in the pricing process is already found to be extensive.

Furthermore, this paper does not find significance in the effect of recent listings in the same industry, nor the order of a firm issue relative to peers, and volatility on underpricing. This further validates the difficulty in measuring informational spillover effects highlighted in previous studies.

In terms of directions for future research on the topic of underpricing determinants, this paper paves the way for more detailed analysis regarding the effect of peer listings on subsequent IPOs. Additionally, a narrower definition of the sub-industries based on operations, products and services could spawn a more nuanced and complete overview of the phenomenon within the technology sector.

Furthermore, an analysis of a firm's sub-industry effect on pricing uncertainty could be extended with additional variables catching the firm's relative operational characteristics such as R&D expenditure, immaterial assets and product/service assortment.

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VIII. Appendix

Table AI: Linear Hypothesis Test of OLS result

The table show the results from linear hypothesis test of the difference between the beta coefficients of *CompEq,* and *Comm* in the OLS output. **(1)** presents the results of the hypothesis test of the results in the OLS when the entire sample is included. **(2)** depicts the result of the test of the output in the OLS when the bubble period has been omitted from the sample.

(1) Entire sample:
Hypothesis: β(*CompEq)* = β(*Comm)*
p-value: 0,814
(2) Bubble omitted:
Hypothesis: β(CompEq) = β(Comm)
p-value: 0,911