LUISS

Degree Program in Business Administration

Course of Financial Statement Analysis

Predicting IPO Returns in Startup Firms: The Role of Financial Metrics Evidence from U.S. IPOs (2017–2021)

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1 Introduction

1.1 Introduction

Initial public offerings represent an important aspect in the life cycle of startups. An IPO is one of the best ways for a company to rapidly raise capital directly from public investors for growth, operational expansion, and repayment of existing obligations. In addition, IPOs have historically exhibited an extremely interesting and extensively studied phenomenon, known as “IPO underpricing”. This term refers to the consistent observation that shares offered at a specific price during an IPO often close at a price significantly higher than that originally set by the underwriters at the end of the first trading day. This price increase is generally measured as the percentage difference between the offer price and the first-day closing price. Empirically, there is substantial evidence of this. Ritter (1991) documented average first-day returns in the 1980s that already exceeded 15%, and later higher returns were observed in the technology IPO wave of the late 1990s and early 2000s. Different sources often report different numbers, since this phenomenon varies a lot across different regions and periods. Even more recent evidence shows high levels of underpricing during the IPO surge between 2019 and 2021. This suggests that the phenomenon is still relevant and has remained persistent over time, regardless of market evolution.

This trend has some serious implications for issuers, underwriters, and investors. Even though a lot of research has been conducted on this topic, there are not many studies that focus explicitly on analysing this phenomenon in the world of startups. The goal of this thesis is exactly to explore this gap and provide a thorough analysis of the financial statement factors that might influence IPO underpricing, and we will achieve this by focusing on relatively recent IPOs of startups in the U.S. in the years 2017-2021. This could provide a framework to improve our understanding of how investors make decisions, how the market forms expectations, and how offering prices are set.

To do so, we will first conduct a deep literature review. Thanks to this, we will understand the extent of this phenomenon and look at all the possible explanations that have been formulated to explain this peculiar behaviour of firms. We will try to understand what happens to firms after the IPO, looking at both the short term (the first-day returns) as well as the long term (how these returns evolve over the years). We will also look at every specific financial metric that, according to the literature, appears to be playing a significant role in this, understanding how strong its impact is both in the short and in the long term. After this, we will shift our attention to our analysis of startups, clearly identifying which financial metrics play a role for these innovative firms and how they differ from those of more traditional companies.

1.2 Research questions

In this research, the main question we will try to answer is: Can financial metrics help predict IPO underpricing and future stock returns? To answer this question, I will be analysing a sample of 30 startups that went public in the U.S. between 2017 and 2021, and I will test the relationship that exists between their financial indicators and their stock returns over three periods: after 1 day, after 1 month, and after 1 year. I will be looking at the percentage increase between the IPO offer price and the stock prices in those respective time periods. The first-day return will be a proxy for the stock's underpricing, while the 1-month and 1-year returns will be used as proxies for long-term performance.

The financial metrics I will be considering are taken from the company's financial statements the year prior to the one they went public. The metrics I consider are the following. For profitability metrics, I will be looking at EBITDA margin, net profit margin, gross profit margin, and ROE. For leverage, I consider D/A. The liquidity measures I included are current ratio and working capital to total assets. For the size of the firm, I look at the natural logarithm of total assets. I also include R&D/operating expenses, and lastly, I look at gross profit growth, net profit growth, EBITDA growth, and revenue growth for growth measures.

To answer my research question, it is also important to look at the literature that exists around this topic. First, we will explore in depth the phenomenon, understanding why it happens in the first place, by looking at the various theories that have been formulated to explain it. Then we will also explore the literature behind the role of each of the metric categories that I have mentioned and that I will be using in my analysis, both from a short-term and long-term perspective. After that, I will proceed with analysing my sample, looking at what results seem to hold for startups, and which results instead seem to diverge from the classical literature I have analysed. I will mathematically quantify all my results and explain all of them, and I will try to find the best mathematical model, based on my data, to predict underpricing and future price of startups.

1.3 Motivation & contribution

The main contribution I am offering consists of addressing the gap in the predictive role of financial statement metrics on IPO returns in the context of startups. Compared to mature firms, startups represent a distinct class of companies: they are characterized by high uncertainty, more aggressive innovation, and often more volatile financial structures. This means that it might be necessary to formulate a different framework to adapt the existing knowledge to them. It can be of fundamental importance to understand how it might be possible to predict the success of an IPO in the short term and its future performance, and it can be of interest to different parties.

This can be extremely valuable for investors. If it is true that some specific financial ratios can anticipate higher or lower IPO returns, they could use this information to make better investments, being more mindful of potential hidden risks and identifying better opportunities. From an issuer and underwriter perspective, this can help them set adequate prices for their offers. This could mitigate the “money left on the table” phenomenon that often results from excessive underpricing. Overall, this research was conducted with a clear goal in mind and can expand the knowledge we have available today on IPO returns.

2 Literature Review

2.1 IPO Underpricing: Classic Evidence and Theoretical Perspectives

We will start our analysis by looking at how strong IPO returns appear to be, and by looking at the attempts that have been made throughout the years to justify this occurrence. One of the most relevant studies on this topic is Ljungqvist (2004). In this paper, the phenomenon is thoroughly reviewed, and the author reports the existing theories that have been formulated to explain it. Underpricing, historically, has varied greatly. For example, in the United States, the average of this underpricing amounted to 19% from the 1960s to 2000s, but it showed a great variation, reaching, for example, a peak of 71% during the technology-driven market surge in 1999. This raises essential questions about what the underlying causes of this are, and Ljungqvist is responsible for one of the most extensive and influential reviews of IPO underpricing. He categorized all the theories created up to that moment into four broad categories: information theories, institutional theories, control theories, and behavioural theories.

Asymmetric Information Theories

This branch of theories suggests that underpricing primarily arises due to imbalances in information that different parties participating in the IPO process have (issuers, underwriters, institutional investors, and retail investors). An important model in this view is the “winner’s curse” by Rock (1986). This view focuses on the gap that exists between informed investors and uninformed investors. Uninformed investors face a situation in which they disproportionately receive allocations of less attractive IPOs. This is because informed investors tend to bid extensively only on IPOs that are expected to perform well. Thus, underpricing is basically a way to compensate these investors who face the risk of adverse selection.

Another important theory is the one proposed by Beneviste and Spindt (1989), known as the “information revelation” model. According to this view, IPO underpricing acts as an incentive for informed investors to disclose their private valuation during the bookbuilding process. In this way underwriters are able to price stocks more fairly. Empirical evidence shows that indeed underwriters reduce their offer price when they receive negative valuations from investors.

Finally, there is the signalling theory, proposed by Allen and Faulhaber (1989) and Welch (1989). This theory suggests that underpricing is, in reality, encouraged by firms. This is a way for them to send positive signals to the market: a successful IPO could help the firm raise more capital in the future at better terms. Thus, underpricing is used to establish credibility, since low-quality firms would find it too costly to mimic such a behaviour.

An important study by Jegadeesh, Weinstein, and Welch (1993) empirically tested this theory. While they found some support for it, the economic magnitude of the effect appeared to be relatively small. Instead, the authors argue that market feedback appears to play a more important role. According to this view, if the market perceives the firm positively during the first trading day (for example, based on the extent of trading activities, external news, or investor enthusiasm), the price will increase accordingly. Thus, while signalling theory seems to exist, it does not appear to be the dominant factor.

Institutional Theories

Institutional theories find the root cause of underpricing in institutional mechanisms and market practices. One of those comes from litigation risks, analysed by Tinic (1988). Issuers deliberately underprice IPOs to mitigate legal liability. And there is some empirical evidence to back up this claim: IPOs in more litigious jurisdictions typically show higher underpricing.

Another institutional factor is price stabilization, which was extensively analysed by Ruud (1993). It is very common for underwriters to engage in post-IPO stabilization activities, supporting stock prices to minimize negative perceptions. Such practices can thus mask the real price of the firm and lead to observed underpricing. This also seems to be a very common practice: around 50% of the firms engage in some sort of price stabilization activities in the initial trading days.

Finally, there is the underwriter reputation hypothesis, explored by Carter and Manaster (1990). This theory partially counterbalances the other effects previously analysed.

Prestigious underwriters, in fact, want to avoid underpricing, as that would harm their reputation. Consequently, they do their best to limit its extent and try to balance as much as possible the risk of an IPO failure against the harm of excessive underpricing. This is also backed up by empirical evidence: IPOs handled by reputable underwriters show a level of underpricing lower by around 7%. This suggests that these underwriters really have superior market understanding and risk assessment capabilities, leading to more precise pricing.

Control Theories

These theories focus on how IPO pricing strategies can influence ownership structure and corporate control. Brennan and Franks (1997) argue that underpricing is a way for the firm to achieve a wider share distribution. This is particularly appreciated by managers, since through this mechanism they can reduce monitoring by large shareholders and maintain managerial discretion. There is empirical evidence to sustain this theory: IPO underpricing is, in fact, associated with ownership dispersion, and thus lower external control. This theory is supported as well by Zingales (1995), who found that underpricing can help dilute possible problems of managerial control. Therefore, these corporate governance considerations might play an important role in IPO pricing decisions.

Behavioural Theories

The supporters of this last set of theories argue that the causes of IPO underpricing must be found in psychological and cognitive biases. A clear example of this was the dot-com bubble, where valuations and underpricing levels were significantly influenced by investor sentiment. 1999 was, in fact, the year when average underpricing peaked at 71%. The work of Loughran and Ritter examines this phenomenon from the perspective of issuers and underwriters. According to their view, biases like anchoring and mental accounting strongly influence these actors, who end up prioritizing a successful IPO launch rather than maximizing the immediate profit they make from it. Research shows that investor enthusiasm and cognitive biases result in inflated valuations, amplifying IPO underpricing.

Ljungqvist's conclusion is that it is impossible to fully understand IPO underpricing by relying on a single theory. This phenomenon consists of a complex interrelation between all the theories we have analysed. It is therefore fundamental to fully understand this body of theories to gain a more profound comprehension of the phenomenon. In addition, since the focus of my research is on understanding which financial ratios can help predict the success of IPOs, and this alone will probably not suffice to fully predict post-IPO share prices, it is fundamental to be aware of these other mechanisms that also shape IPO outcomes.

2.2 Short- vs. Long-Term IPO Performance: Diverging Outcomes and Empirical Evidence

To fully understand the phenomenon of IPO returns and have a clear and realistic picture of it in mind, it is fundamental to be aware of the difference that exists between short-term and long-term IPO returns. In fact, they tend to significantly diverge, and being able to predict the success of the initial IPO does not necessarily mean one can predict the success of the company in the long term. While earlier studies, like Ritter (1991) and Loughran and Ritter (1995), seem to have documented patterns of long-term underperformance following IPOs, the relationship between short-term and long-term is still extensively debated. A recent thesis by From and Grønkjær (2024) provides an interesting analysis conducted on a sample of 209 IPOs from the Nordic region covering the years 2003-2021. The research was conducted by dividing the sample into underpriced and overpriced IPOs, based on the difference between the offer price and the first-day closing price. The companies were tracked based on their performance over 1-, 2-, and 3-year horizons. This research employed both Buy-and-Hold Abnormal Returns (BHAR) and Cumulative Abnormal Returns (CAR). Buy-and-Hold Abnormal Returns (BHAR) measure how much a firm's IPO returns differ from a benchmark group of comparable companies. Instead, Cumulative Abnormal Returns (CAR) aggregates these differences over time relative to the benchmark's returns. For both, the authors calculated equally-weighted and value-weighted returns, the former giving each IPO equal influence regardless of the size, and the latter accounting for the impact of larger firms more heavily, reflecting more accurately the real monetary returns an investor could expect.

The findings are extremely interesting. Although underpriced IPOs generate positive first-day returns, this advantage does not appear to persist in the long term. The authors were in fact able to prove that over one-, two-, and three-year horizons, there does not seem to be any significant and statistically relevant difference between underpriced and overpriced IPOs. Their bootstrapped analysis reveals that while some individual months may show temporary deviations, in the long term the trend equalizes across the groups. This is already in contrast with one of the theories we have previously analysed, the signalling theory proposed by Faulhaber and Welch, which argued that underpricing is voluntarily incentivized by the firms to signal strong future performance. From and Grønkjær suggest that this lack of long-term performance differences might be attributable to market efficiency: the market rapidly incorporates all the available information, and after some time any pricing inefficiency is corrected. This study also makes use of multivariate regressions to control for other variables, like firm size, sector, and offer year, and it still finds that IPO underpricing does not have significant explanatory power for long-term stock performance.

This research was also able to anticipate some findings about other variables that, instead, hold explanatory power, which we will later explore in more detail. First, it appears that firm size has a positive and statistically significant relationship with long-term returns. Larger firms tend to generate higher BHARs and CARs over time. This directly contradicts what some of the previous literature reports, such as Ritter (1991) and Keloharju (1993), which instead found that smaller firms outperform larger ones. However, this might depend on the context and on the methodology used: the prior literature used equally-weighted returns, which can be heavily biased by outliers, while this thesis, by using value-weighted BHARs and capped weights, avoids these distortions, reaching this conclusion. Another interesting trend concerns the sector classification. In fact, firms in the IT sector show higher long-term returns than industrial firms, even though the results seem to vary significantly between time horizons and measurement methods. For example, looking at 1-year value-weighted BHAR, IPOs in the IT sector ended up outperforming those in the industrial sector by 3.2%, even though this difference lacks strong significance.

In conclusion, it seems possible to say that high first-day returns do not necessarily imply sustainable gains in the future. This also means that a model able to strongly predict first-day post-IPO returns is unlikely to be as effective for predicting prices in the long term, which is something to keep in mind for the analysis I will be conducting later.

2.3 The Predictive Role of Profitability Metrics in Short- and Long-Term IPO Performance

A key contribution to the literature on IPO performance is the study by Abraham, Harris, and Auerbach (2016), titled "IPO performance at announcement and in the aftermarket". This study does something very similar to what I'm trying to do. While it focuses exclusively on profitability metrics, it attempts to predict short-term and long-term IPO performance using pre-IPO financial metrics. The study was conducted on a sample of 468 U.S. IPOs that happened between 2009 and 2014, and it focuses on two performance metrics: announcement-day abnormal returns and holding period returns, the first serving as a proxy for IPO underpricing while the latter represents post-IPO returns from the offer price to subsequent market prices. This distinction is fundamental, since it helps us distinguish immediate IPO returns from medium- to long-term performance.

We will now report the findings emerging from the paper about short-term IPO performance. To conduct the analysis, the authors made use of three different models. They first used the Ibbotson RATS model, which tracks raw market-adjusted performance, and found abnormal returns of 24%, still in line with the broader IPO literature, even if a bit on the higher side. Then, they used two additional models, the market model and the Fama-French three-factor model, which instead account for market risk, and they still found significant abnormal returns. Another interesting aspect reported by this paper is the statistically significant abnormal increase in trading volume during the first day, reaching 233%. In addition to this, it also emerged that offer volume has a negative relationship with day-one abnormal returns, supporting again the idea that large offers tend to exhibit lower first-day returns.

What is important to note is that these short-term returns don't seem to be related to firm fundamentals, but instead, they are driven primarily by trading dynamics. Profitability metrics like profit margin, ROE, and cash flow to assets don't seem to be predicting first-day returns. Even more interesting are the findings about long-term performance, specifically about the stock performance after one year. Those returns seem to be strongly related to a profitability metric: ROE. This proves to be a significant predictor of long-term returns. Since it is strongly related to cash flow to assets and profit margin, these associated metrics also appear to be related to long-term returns. What instead does not seem to be statistically significant is revenue growth, suggesting that not all profitability-related metrics are equally successful in forecasting returns. Another noteworthy finding is the relationship between volatility and ROE. It is significantly positive, indicating that growth-oriented firms may face higher risks, but at the same time, they show greater upside.

To build on this concept, the authors introduced a growth-oriented vs risk-averse categorical variable, classifying firms based on the strategic profile communicated in IPO filings. Firms positioned as aggressive growth seekers on average performed better in the long term compared to more conservative issuers. This is another confirmation of the fact that short-term IPO success and long-term performance stem from different sources. According to this paper, while profitability metrics might not be the best predictor of IPO day-one returns, they seem to be relevant when looking at long-term success.

2.4 Profitability, size, and Post-IPO Dynamics in Emerging Markets: Evidence from Poland

Other important evidence comes from the paper "Performance of Polish IPO Firms: Size and Profitability Effect" by Lizińska and Czapiewski (2014). This paper presents an analysis of 214 Polish IPOs, conducted between 2005 and 2011 on the Warsaw Stock

Exchange. Their study offers valuable insights into the effects of size and profitability on short- and long-term returns.

Focusing on the first-day returns, they documented an 11% increase in price, again well in line with what we have already seen. The key finding from this section comes from the observation that pre-IPO profitability metrics, specifically ROA and ROS, have a statistically significant correlation with underpricing. This seems to be slightly in contrast with the previous paper we have analysed. While the metrics used here are slightly different from the ones used before, they are still a proxy for the profitability of the firm. This shows that this phenomenon still requires a lot of analysis, since the literature seems to show contrasting results concerning whether it is possible to predict first-day returns by looking at profitability-related financial metrics.

Another finding concerns the firm size. Smaller firms, on average, show a higher level of underpricing in the short term, which seems to be coherent with previous studies we have analysed. It is, however, important to mention that they also exhibit a wider range of first-day returns, leading to both more overvalued and undervalued firms. This is also in line with the literature concerning information asymmetry, which increases pricing errors in both directions.

Other relevant information emerges when looking at the phenomenon from a medium-term performance perspective. The authors calculated BHARs for the first month, which resulted in an average of around -4%. This means that very early on, a portion of the rapid price increase is already eroded. It is relevant as well to note the difference that emerged between small and large firms. Small firms showed, on average, a first-month BHAR of 6%, while for large firms it was near zero. This confirms again the pattern that small firms generally tend to be priced differently from their real value during IPOs, which likely stems from information asymmetry. Interestingly, while more profitable firms tend on average to experience less steep corrections, the relationship is not uniform across the sample. It is still common for high-profitability firms to face negative BHAR in the first month, hinting at investor overreaction or even potential window dressing of financial statements prior to the IPO.

The paper also brings forward interesting facts about the three-year time horizon. Here, the initial abnormal return seems to completely adjust. The average BHAR across firms is -7%, indicating long-term underperformance. This decline is even more pronounced for small firms, where it averages at -22%, while for large firms it appears to be +15%, which is in line with the more modern view that large firms tend to outperform in the long run. It is, however, important to note that these results lack strong and consistent statistical significance, so even though they appear to be extremely large, they should be treated with caution.

Also in this paper, the authors looked at whether future success could be predicted by looking at pre-IPO profitability metrics. Contrary to the findings of Abraham et al. (2016), it seems that profitability metrics, while they appear to be positively correlated with first-day returns, lose their predictive power over longer time horizons. There are many cases of high-profitability firms underperforming over three years, once again highlighting the inconsistency in the literature. This reinforces again the view, also supported in Teoh et al. (1998), that before the IPO, earnings may be inflated through earnings management practices to show an artificially positive image of the firm before going public.

Another valuable contribution of this paper lies in the analysis of profitability evolution over time. It seems that large firms see their ROA increase on average by around 49% in the three years preceding their IPO, and then this growth declines slowly after. For small firms, instead, the ROA drops by 78% after going public. This confirms that profitability metrics might not be the best predictors of a firm's success in the long term, especially for small firms, since the initial high ROA seems to be short-lived.

In conclusion, small firms tend to see higher short-term returns than large firms, while this relationship is reversed when looking at the long run. And while profitability metrics seem to aid in predicting those post-IPO returns, they don’t exhibit the same success for long-term predictions, contradicting the previous paper we analysed.

2.5 Short-Term vs. Long-Term IPO Performance: The Role of R&D Intensity

Another topic not yet addressed concerns the impact of R&D intensity in predicting both the short- and long-term returns. This is especially relevant for our analysis, since we are focusing on startups, which tend to have high R&D expenses, making it crucial to understand how this may affect our analysis. In the paper “Explaining the Short- and Long-Term IPO Anomalies in the US” by Re-Jin Guo, Baruch Lev, and Charles Shi (2006), this dynamic is extensivey examined, and it offers yet another crucial perspective on the topic. This research focuses on a sample of 2,696 U.S. IPOs issued during 1980-1995. By dividing the firms into three categories based on their R&D expenditures, the authors were able to show that firms with higher R&D intensity experience greater underpricing on the first day of trading. These results are statistically significant, and they suggest a strong positive relationship between R&D intensity and first-day IPO returns. Firms that invest more aggressively in R&D seem to attract higher investor demand during the first day, and this is once again consistent with the information asymmetry hypothesis: Firms with greater R&D tend to have more uncertain future prospects, leading investors to bid up the price on the first day as a result of speculation and limited available information. This phenomenon was more deeply examined through a regression analysis, which confirms that firms in the high-R&D category tend to experience significantly higher underpricing. Higher R&D signals higher future growth potential, making these IPOs more attractive to investors.

Equally interesting is the part of the analysis concerning the long-term prospects. This analysis is not as straightforward as the previous one, and it presents a much more complex picture. Over a period of three years, high-R&D firms tend to outperform the rest. On average, they are reported to have a positive long-term performance. This finding directly challenges what we have discussed up to now and what was reported in papers such as Ritter and Welch (2002). This might mean that firms do not necessarily underperform on average in the long term after the initial IPO, but rather that this situation might be typical exclusively for those firms that do not invest enough in R&D, leading them to be unable to compete with evolving technology due to this underinvestment. The regression results also seem to confirm some other trends we have previously seen: ROE and profit margin seem to be positively associated with holding period returns (HPRs), and this is especially true for high-R&D firms. No-R&D firms show negative excess returns of approximately 6% annually in the three years post-IPO, while for high-R&D firms it is close to 0, being only slightly positive. This is significant evidence of the importance of R&D for firms.

Other important insights that the paper provides concern the role of investor optimism and information disclosure, which we previously mentioned. The authors argue that investor optimism is often the cause of mispricing. Small and low R&D firms tend to be overvalued, while those firms that instead invest a lot in R&D often are undervalued due to information asymmetry concerning their long-term potential. The situation adjusts itself with time, when the market gains more information and realizes the value of R&D projects and the potential of those firms. This leads to a reduction in the initial undervaluation and to improved long-term performance.

Another important finding is that IPO underpricing can be reduced by disclosing information concerning R&D activities, through reducing information asymmetry. In fact, pharmaceutical and biotech firms tend to experience lower underpricing despite the risks often associated with such sectors, as these firms tend to accurately disclose their R&D activities. Thus, transparency is of fundamental importance in ensuring more efficient pricing of IPOs.

2.6 The Impact of Leverage on IPO Pricing: High-Tech vs. Low-Tech

Another important paper for our analysis is the one by Pukthuanthong and Walker (2008). The focus of this research is understanding how leverage can affect IPO returns. To achieve this goal, the authors divided the firms in their sample of 2,391 U.S. IPOs from 1996 to 2002 into two categories: high-tech and low-tech firms, following Loughran and Ritter (2004)'s SIC code classification. The main idea is that leverage can signal financial discipline and lower agency problems in the case of low-tech firms, while for high-tech firms it is the opposite: higher leverage increases perceived risk, amplifying underpricing. This is perfectly in line with capital structure theories like those proposed by Ross (1977) and Myers and Majluf (1984). These theories argue that debt signals quality when there is low risk of financial distress, which is often not the case for high-tech firms.

The research made use of ordinary least squares and two-stage least squares to analyse, as dependent variables, offer price revision (change between the original offer range and final price) and IPO underpricing. The authors were able to find that for low-tech firms leverage is negatively associated with both price revision and underpricing. In fact, higher leverage can reduce information asymmetry, which, as we have already seen, translates into less underpricing. For high-tech IPOs, instead, leverage is positively associated with those variables. In this case, high leverage can signal financial distress, not quality, leading, instead, to initial price discounts, thus higher underpricing. These results appear to be statistically significant even when controlling for industry and year dummies, mispricing relative to comparable firms, institutional holdings, and primary/secondary share sales. These results are even able to hold when adjusting for the dot-com bubble period, meaning that this relationship is structural, and not only a consequence of market exuberance.

2.7 Leverage and Liquidity as Long-Run Predictors: Evidence from the Taiwanese IPO Market

Unfortunately, in the literature, there is a serious lack of papers analysing the effects of liquidity on first-day IPO returns, and the only paper I could find about the impact of such metrics on the long-term performance concerns the Taiwanese market. The paper in question was written by Anlin Chen, Li-Wei Chen, and Lanfeng Kao (2010). The IPOs analysed took place on the Taiwanese OTC market between 1991 and 2002. This research consists of an expansion of the traditional Fama-French three-factor framework, to which the authors added leverage and liquidity factors to obtain a new five-factor model, which they use to explain stock prices movements happening five years after the IPO.

When analysing their results, it is fundamental to keep in mind that the Taiwanese market behaves a bit differently from the U.S. market, and thus the results reported here might not be completely valid for what we are trying to do, but being the only evidence available on long-term effects of liquidity metrics it is still worth analysing. With a sample of 261 IPOs, the authors calculated Buy-and-Hold Abnormal Returns (BHAR) and Cumulative Abnormal Returns (CAR), and found that, unlike the U.S. market, these IPOs outperformed the market by almost 7% over five years instead of underperforming. Even when excluding initial returns the outperformance still amounted to 4%.

Concerning the role of leverage and liquidity, this study found a positive relationship with leverage and a negative one with liquidity, both statistically significant. Thus, while leverage is a positive indicator over the long term, liquid firms tend to earn lower returns in the long run. This intuitively makes sense. In the beginning, liquid IPOs are those that are attracting the most attention from investors, and this may lead to initial overpricing, which erodes in the long-term, leaving illiquid firms as the most profitable. Also, it is likely that for holding illiquid stocks investors may demand a premium in the form of long-term returns. This is not a new idea in the literature. It is a concept that was already analysed by Amihud and Mendelson (1986), who argue that stocks with lower liquidity often deliver higher risk-adjusted returns over time. Merton (1987) argues that stocks not widely recognized by investors require higher expected returns, while Barber and Odean (2007) found that investors are more likely to buy popular and visible stocks, which are as a consequence very liquid and may attract excessive demand early on, leading to initial overpricing that fades in the long-term, resulting in lower returns.

3 Methodology & sample

To conduct this analysis, I collected a sample of 30 startups that went public between the years 2017-2021. These startups are evenly split into 5 different sectors, 6 for each sector: healthcare/biotech, fintech, consumer/retail, software/SaaS, and mobility/energy. The companies were selected randomly to maintain fairness in the analysis and avoid any type of bias. All the financial data and metrics I analyse are obtained by reviewing the financial statements of these companies on Refinitiv. It is important to mention that all the metrics are taken from the financial statements of the year prior to the IPO. For example, for a firm that had its IPO in the year 2021, regardless of the month, I will be looking at the financial statements from 2020. Stock prices across the different time periods I analysed were also collected from Refinitiv. The IPO prices were instead collected from news sources from the relevant period.

I will now proceed to explain in detail all the different metrics I am considering for my analysis. For profitability metrics, I decided to include EBITDA margin, defined as EBITDA divided by total revenues, net profit margin, defined as net income divided by total revenues, gross profit margin, defined as gross profit divided by total revenues, and return on equity pretax (ROE pretax), calculated as pretax income divided by shareholders' equity. This selection was motivated by the diverse findings in the literature. There is mixed evidence on the impact these metrics might have on IPO returns in the short term, while in the long term there seems to be a positive relationship. It might be interesting to see how these results might change with a sample of startups. I include multiple profitability indicators to capture different operational perspectives. Gross profit margin reflects the efficiency of core production before accounting for overhead, EBITDA margin and net margin give us insights into operating profitability, and ROE shows us the return relative to shareholders' capital. By considering all of them, we may better understand which of these metrics are the most relevant when looking at IPO returns.

For leverage, I included a single metric, D/A, defined as the total liabilities of the company over its total assets. While it would have been interesting to include other types of leverage metrics, like net debt/assets, it was unfortunately extremely challenging to find enough information about the amount of net debt the companies held before going public, and considering the already limited sample size of the dataset including a variable with a low number of observations would not have been effective.

I also included liquidity measures, specifically current ratio, defined as current assets over current liabilities, and working capital to total assets, defined as the difference between current assets and current liabilities, divided by total assets. This category of ratios has not been studied extensively in the literature. The only evidence concerning it was the analysis of Chen et al. (2010) about the long-run returns in the Taiwanese markets. We will see in our analysis if these are metrics worth including or if the lack of evidence about it stems from them not being good predictors of IPO returns. Including both will allow us to cover two different angles: the firm's ability to cover short-term obligations, through the current ratio, and the proportion of net liquid resources available in the broader asset base, through the working capital to total assets.

Firm size appears to be the most studied metric when trying to predict IPO returns and future stock prices, and consequently, I included it in my analysis as well. Specifically, I will be looking at the natural logarithm of total assets as a proxy for firm size. The reason why I am choosing to use this measure is to control for scale effects. This is the standard practice in IPO and corporate finance literature, including the ones we have previously analysed. Firm assets tend to be highly right skewed, and applying the logarithm helps in compressing extreme values and linearizing the relationship between size and IPO returns, improving model fit and interpretability. This approach also has another advantage. Doing this, variations in size have a proportionate impact on the regression, avoiding potential distortions caused by extremely large firms.

Since we have previously seen that R&D seems to be relevant to predict the success of the IPO, I also included R&D expenses over operating expenses as a metric. This metric captures how much of a firm's expenditure is devoted to research and development, and the importance of investing in R&D has been shown by the study we previously analysed of Guo, Lev, & Shi (2006). Originally, I also considered using R&D as a percentage of total revenues, however upon further examination I decided to exclude that metric due to the excessively high correlation with the other profitability metrics I analyse. To avoid multicollinearity issues, I opted to use R&D/operating expenses.

To assess whether growth dynamics influence IPO returns and long-term stock prices, I examine the effect of five growth metrics: gross profit growth, net profit growth, EBITDA growth, revenue growth and assets growth. These metrics are all calculated over a 1-year period, and this is because it is difficult to access the financial statements of the firms before they go public, and for many firms I could not really find financial data more than a year prior to the IPO. Notably, I could not find any significant study analysing the direct predictive power of these growth rates, therefore in the analysis we will see whether these metrics can provide novel information in the literature of IPO underpricing and predicting future stock performance. Since I am not able to predict which specific growth metric could have an impact on returns, I decided to include a few of them, all capturing different aspects of a firm's growth.

I will now go over the metrics I will try to predict with my analysis. There are three which I will consider: first-day returns, 1-month returns and 1-year returns. First-day returns are calculated as:

$$(1) First\ day\ returns = \frac{first\ day\ closing\ price - IPO\ price}{IPO\ price}$$

In the same way, substituting first day closing price with the closing price after 1-month and after 1 year, I have calculated, respectively, 1-month and 1-year returns, as:

$$(2) First\ month\ returns = \frac{first\ month\ closing\ price - IPO\ price}{IPO\ price}$$

$$(3) First\ year\ returns = \frac{first\ year\ closing\ price - IPO\ price}{IPO\ price}$$

This will give us a perspective on the short-, medium- and long-term performance of the firm. I have stopped at 1-year returns since this time horizon captures the most critical early performance window, which is the focus of most IPO studies. While we could gain additional insights from extending this analysis further, we would also introduce confounding effects unrelated to IPO fundamentals, and the relationship with per-IPO financial data would probably become less relevant.

In this analysis, I use a wide variety of statistical methods. Firstly, I addressed the outliers in my sample. To handle the extreme values I found in many of my metrics, I decided to winsorize all the variables at the 1^{st} and 99^{th} percentiles. This means that for all my variables any observation falling below the 1^{st} percentile was set equal to the 1^{st} percentile, while any value above the 99^{th} percentile was capped at the 99^{th} percentile. I decided to take this approach due to the limited sample size I am working with: dropping the outliers would have strongly compromised the quality of my analysis by leaving me with too few observations. Winsorization is a common practice in empirical financial research, and the rest of the values I will be reporting in my analysis are based on the winsorized sample. However, even with this method, I was not able to effectively deal with outliers for the following metrics: EBITDA margin, net profit margin, revenue growth, assets growth, gross profit growth and net profit growth. The reason for this is that the distribution of these variables was excessively skewed, either to the right or the left (Figure 1). For those variables I had to take a more arbitrary approach: I capped their values between -1 and 1. This was the only way I could find to preserve enough observations and at the same time avoid that the outliers in my dataset played an excessively important role. I made sure to report (Table 1) the means, median, 25th and 75th percentiles, and standard deviation of all the winsorized variables I analyse, as well as the return metrics I am trying to predict. I will not go over all the single variables, but it is especially important to be aware of their volatility when discussing the results.

Now I will move to the core of my analysis. Firstly, I computed correlation matrices to get a general feeling of which variables appear to be most correlated with post-IPO returns (Figure 2). Then, I employed ordinary least squares (OLS) regression to quantify how pre-IPO metrics relate to IPO returns. I ran a series of simple linear regressions, regressing each predictor individually to see which ones were the most statistically relevant. The general form of each univariate model is:

(4) $R_{it} = \beta_0 + \beta_1 X_i + \varepsilon_i$

Where R_{it} is the IPO return for firm i at time horizon t (with t varying based on whether we are looking at 1-day, 1-month or 1-year returns), and X_i being one of the financial predictors previously discussed. We run Equation (4) for each of the variables we are analysing, and the results are summarized for the different time periods, respectively in Table 2, Table 3 and Table 4. Next, the multivariate OLS regressions I include follow the general specification:

(5) $R_{it} = \beta_0 + \beta_1 X_{i,t} + \beta_2 X_{2,t} + \cdots + \beta_k X_{k,t} + \varepsilon_i$

Where $X_{j,i}$ denotes the jth selected explanatory variable for firm I, and K is the number of regressors. All these models include an intercept β_0 and an error term ε_i. The coefficient β measures the effect of a one-unit change in the associated predictor on the IPO return (in percentage points). The multivariate regressions I will explain in detail are

(6)$R_{i,1d} = \beta_0 + \beta_1(\mathrm{D/A})_i + \beta_2 \ln(\mathrm{assets}_i) + \beta_3(\text{gross profit margin})_i + \beta_4(\text{R\&D/operating expenses}) + \varepsilon_i$

(7)$R_{i,1y} = \beta_0 + \beta_1(\mathrm{D/A})_i + \beta_2(\text{current ratio})_i + \beta_3(\text{gross profit margin})_i + \beta_4(\text{ROE pretax})_i + \varepsilon_i$

(8)$R_{i,1y} = \beta_0 + \beta_1(\mathrm{D/A})_i + \beta_2(\text{current ratio})_i + \beta_3(\text{gross profit margin})_i + \beta_4(\text{R\&D/operating expenses}) + \beta_5(\text{ROE pretax})_i + \varepsilon_i$

Equation 6 refers to the best model I could find to predict first-day returns, while Equation 7 refers to the one concerning 1-year returns. I will be also explaining a competitor to the best model I found for 1-year returns, described by Equation 8. The reason why I did not report any equation for the 1-month return is that I could not produce any model which held sufficiently strong predictive power. These models were created by comparing all the possible models that could be created using all the variables we have seen. To select these models, I chose among them the one that showed the best combination of a high Adjusted R-squared and the lowest Akaike (AIC) and Bayesian (BIC) scores. In Table 5 I show the five best models that could be fitted for first-day returns ordered firstly by the AIC score, then by the BIC and lastly by the adjusted R-squared. The same thing was done for 1-month and 1-year returns, respectively in Table 6 and Table 7. I also made sure to check for collinearity in my models using variance inflation factors (VIFs). The full regressions for the 1-day, 1-month and 1-year time periods together with the VIFs are in Table 8, Table 9, and Table 10.

4 Results

4.1 Overview of Post-IPO returns in the Startup Sample

Firstly, I analysed the post-IPO returns. Since this is a sample of exclusively startups, I was expecting more volatility compared to classic firms, and this is indeed the result I got. Across all 30 firms, the average first-day return was a remarkably high 29.95%. However, based on what we have previously analysed in the literature review, this is not completely a surprise. We have seen repeatedly that uncertainty and risk tend to be associated with higher underpricing. And startups, more than any other type of firm, are generally considered risky, and their future is often uncertain, which makes this result very reasonable.

The first month's results are not much different. We are still in a very early phase for firms, and it seems that prices have not yet adjusted. In fact, the returns here amount to 43.35%, considerably higher than before. It is important to mention that this is largely due to three specific firms, which experienced incredible success after 1 month, exhibiting 1-month returns of 152%, 131%, and even 242%. These numbers can, of course, significantly influence a sample size of only 30 firms.

When calculating 1-year returns we start to observe the classic phenomenon of IPO underperformance over the long run. Compared to the offer price, the price of the shares appears to have declined by 2.82%. Most of the firms in this phase show a significant price decline, and this is compensated by a handful of survivors that instead show extremely high returns. Most firms at this stage show a significant price drop, which is offset by a few high performers with exceptional returns of 221%, 187% or 169%. Notably, these top performers are not the same firms that showed the very high 1-month returns we previously discussed, and this highlights how unstable startups can be in this phase, and how it might be very hard to find some consistent patterns in predicting their returns.

4.2 Profitability Metrics and Their Predictive Power

After analysing the returns, I started to look at their correlations with the other variables (Figure 2). First, I will be looking at what resulted from my analysis of profitability metrics. As I mentioned, I decided to focus on ROE pretax, EBITDA margin, net profit margin, and gross profit margin. Looking at the correlation with the IPO returns, when analysing the matrix, EBITDA margin and net margin seem strongly correlated to the first-day IPO returns, with a coefficient of 0.25 and 0.17, respectively. ROE also shows a certain degree of correlation, amounting to 0.10, while gross profit margin instead seems to be the weakest predictor among these, with a correlation of only -0.02.

Despite the decent correlation with some of these profitability metrics, when I tried to fit a univariate regression model with these variables the results did not seem too convincing. All the results for the metrics I discuss from this point on concerning 1-day, 1-month and 1-year returns are contained, respectively, in Table 2, Table 3 and Table 4. All the profitability variables show negative adjusted R-squared values, except for net profit margin, which was the one exhibiting the highest correlation. But even then, it amounts to only 2.8%, and the p-value shows that this relationship might not be very convincing, since it amounts to 19%. These results are however perfectly in line with the literature we have previously analysed. While some works, like the one by Lizińska & Czapiewski (2014), found a positive relationship between underpricing and profitability, since high profitability might attract demand during the IPO, others, like Abraham et al. (2016), did not find any significant predictive power. This divergence in findings might stem from both methodological and contextual differences.

Focusing on the long-term perspective, some very interesting results emerge. The farther we move in time, the more the role of these metrics shifts. For the 1-month returns, the correlation for all the metrics significantly diminishes, showing a general move toward a negative relationship. ROE shows a correlation of -0.06, net margin of 0.11, EBITDA margin of 0.04, and gross profit margin of -0.01. For all these metrics, the correlation is extremely low, and in fact, when running the regression, not even one of them exhibits a positive adjusted R-squared. This trend continues and culminates in the 1-year returns. Here, all the profitability metrics have negative coefficients. ROE shows the most significant one at -0.52, but it is extremely high also for the other metrics: For net margin it is -0.27, for EBITDA margin -0.23, and for gross profit margin -0.31. This time these results are well supported by the regression analysis. All these metrics show positive adjusted R-squared, even though for most of them the p-value is not excessively convincing. However, there is an exception: ROE, which shows significantly strong predictive power. With an adjusted R-squared of 23.8% and a p-value of 0.6%, there appears to be plenty of evidence that it might play an important role in predicting long-term stock prices. The surprising fact is that this result is explicitly in contrast with what was found in the papers by Abraham et al. (2016) and Guo et al. (2006). While it is true that they found a correlation with long-term performance, the correlation was positive. There is a possible explanation for this, which stems from the fact that our sample consists of startups. These firms operate in highly dynamic environments where financial performance can fluctuate dramatically. In this context, high pre-IPO profitability may reflect short-term financial engineering or window dressing, as was studied by Teoh et al. (1998). It is also possible that underwriters may anchor the IPO price to strong financial performance, leading to a high price that reflects overly optimistic growth assumptions. The profitability of the firms before the IPO might not be the best predictor of long-term success, leading to this negative relationship stemming from the original overpricing. This is intensified by the startup's environment, where uncertainty is higher, business models are unproven and financial performance is volatile, making it even more likely that those firms might not meet the original expectations.

4.3 Leverage Effects: Insights from the Debt-to-Assets Ratio

It is now time to explore the findings about leverage. As a measure of that, I focused on a single metric: D/A. By first looking at the correlations, we can see that, concerning first-day returns, it seems to be negatively correlated, with a coefficient of -0.27. This trend reverses already in the first month, where we have a correlation of 0.09, culminating in the 1-year return, where it is 0.23. Once again, this is not fully in line with the trends we have analysed, so we will try to explain this. The evidence we have for the first-day returns comes from Pukthuanthong and Walker (2008). They found that for high-tech firms, like our sample of startups should be, higher leverage means higher underpricing due to higher uncertainty. However, they also found that for lower tech firms debt might make them more credible and instead reduce underpricing. It might be, then, that our firms behave more similarly to low-tech firms. It appears that the main factor affecting lerverage's impact on IPO returns is credibility. In the startup environment, obtaining funds to finance the firm can be extremely challenging. Thus, the credibility a startup gains when receiving a good portion of money from an investor might offset the risk that comes from the high-tech environment in which it operates, leading to this result. In the long term, instead, the only evidence we have is that from the Taiwan market by Chen et al. (2010), where high-leverage IPOs outperformed the rest over a 5-year period. However, it seems that this works in the same way for U.S. firms, as this is what this positive long-term correlation seems to indicate.

However, the statistical analysis is not particularly convincing. For 1-day returns, D/A has an adjusted R-squared of 3.8%. However, the p-value for this metric is 15.4%. A p-value like this would generally indicate that the results are not statistically significant. It is, however, not an excessively high value, which indicates that these observations should not be completely disregarded, but rather that they should be approached with a certain degree of caution. The regression for the 1-month period appears to be very far from being statistically significant, and this trend continues for the 1-year period. With a p-value of 21.3% and an adjusted R-squared of 2.1%, it becomes hard to draw solid conclusions from the analysis. Even though the data still suggests that there is some kind of long-term positive correlation, it does not appear to be excessively significant. However, it is definitely possible to see a trend over these periods, with D/A becoming more and more positively correlated to returns after each period, and even though it is for the moment impossible to confirm the evidence from the Taiwan market for certain, taking into consideration that the data were analysed over a period of 5 years and not a single one, it definitely cannot be excluded that, over a longer period of time, this trend might continue and it might be possible to find significance in the long run.

4.4 Liquidity Indicators and Their Relevance

Concerning liquidity, we will be analysing the current ratio and working capital/total assets. These ratios behave quite similarly. For 1-day returns, they have a similar correlation of 0.29 for current ratio and 0.26 for working capital/total assets. The main difference arises in the 1-month returns, which, as we have seen up to now, appear to be the hardest to predict. While for the current ratio the correlation is -0.15, for working capital/total assets it is close to zero. For the 1-year returns, in contrast with what the literature tells us, there appears to be a very low correlation of -0.03 for the current ratio and -0.07 for working capital/total assets, indicating that, for startups, pre-IPO liquidity seems to have very little impact on long-term performance.

For the regressions, I will be looking exclusively at the 1-day returns, since the others exhibit a negative adjusted R-squared. I will focus on the current ratio, because between the two predictors, it seems to be the most solid one. With an adjusted R-squared of 5.3% and a p-value of 11.5%, the results are not completely convincing. The p-value is once again higher than 5%. It is, however, not too distant from that threshold. In the literature, it appears that the relationship between short-term returns and liquidity has rarely been analysed, but this evidence, even if not completely statistically significant, could mean that there might be an incentive in exploring it more extensively, since a correlation appears to be present. This relationship might be interpreted through the signalling theory by Allen (1989) and Welch (1989). More liquidity can be a signal of operational strength, and firms like these can be more willing to tolerate underpricing to attract investor interest and establish credibility, leading to this positive relationship.

4.5 Firm Size and Its Impact on IPO Returns

To measure firm size, I analysed the natural logarithm of total assets. My findings appear to be coherent with the old literature, such as Ritter (1991). The size of a firm is inversely correlated with the returns. The correlation is -0.12 for 1-day, -0.32 for 1-month, and -0.12 for 1-year. This finding contrasts with more recent studies, like From and Grønkjær (2024), but this is probably due to our use of an equally weighted sample, where outliers among small firms disproportionately influence the results. The reasoning for this negative correlation stems from asymmetric information theory: since smaller firms are less reliable, investors demand higher returns, which is achieved through initial underpricing. This time, the only results that appear to be noteworthy in the regressions are those concerning the 1-month period. With an adjusted R-squared of 6.7%, even though the p-value is 9.0%, once again a bit higher than the conventional thresholdthe result can still be considered relevant. However, it is interesting to note that this is, for now, the only metric that has an almost significant relationship with 1-month returns. It is not a coincidence that the impact of firm size on stock prices is probably the most extensively studied phenomenon among the metrics we are analysing. Even though for the other time periods there does not appear to be statistical significance, these results may change once other factors are accounted for in the multivariate regression.

4.6 The Role of R&D Intensity

To understand the impact of R&D expenditure, examining R&D as a share of operating expenses is particularly insightful. In this dataset, the 1-day correlation is negative, with a value of -0.16. This is yet another result that clearly contrasts with the literature we have analysed. There still might be some explanation for this discrepancy. Since we are analysing startups, which are already inherently associated with strong risks, R&D expenditure might be interpreted positively, as a signal of long-term growth potential. What startups need to do in their early phase is focus on innovation to grow in the future; thus, specifically for these types of firms, this might reduce underpricing, as it could be in line with what investors expect from firms at this stage.

This pattern changes when looking at the long run, where both the 1-month and 1-year correlations are 0.15 and 0.17, respectively. This is very logical as well. Since for startups innovation is the main performance driver, it makes perfect sense that those firms that invest more in it outperform the others. Despite the moderate correlation, when running the regression model, it seems to be impossible to draw solid conclusions with our dataset. The linear regression shows no significance for this variable. However, it is important to mention that this is the variable that, from our sample, is missing the greatest amount of information. 8 of the firms in this sample did not have data about their R&D expenditures, and with already such a small sample size to start with, it is not surprising that it becomes harder to find statistical significance for this metric.

4.7 Exploring Growth Metrics

The last metrics I analysed were growth metrics. These were by far the hardest metrics to analyse. Most of them are extremely unstable, and the lack of literature covering this topic does not help. The fact that they were collected over a single year may also make them less reliable. For the sake of simplicity, I will not be using these metrics in the multivariate regression model. There is just not enough literature to support their inclusion, and their intrinsic instability also discourages me from using them. However, they can still be interesting to analyse, and I will try to explain what they reveal looking at their correlations and the univariate regressions.

Looking at the first-day returns, only two of them appear to show some solid correlations: EBITDA growth and net profit growth. They amount respectively to 0.25 and 0.11. However, neither shows significant statistical relevance. The best one, EBITDA growth, has an adjusted R-squared of 3.0% and a p-value of 18.4%. Still, the positive correlation we observe can be justified. Firms exhibiting strong recent growth in their profitability metrics may attract higher investor demand, leading to higher underpricing. Especially for startups, where profitability in the early stages is extremely limited, an early increase in it before going public could be a reason why an investor decides to buy the stock. In addition, in startups, investors tend to consider more narrative-driven projections rather than hard fundamentals.

The analysis of the long-term gives us a very coherent picture. All metrics related to the firm’s profits show high positive correlations both for the 1-month and the 1-year returns. While EBITDA growth, gross profit growth and net profit growth are all around 0.20 for both periods, the most interesting metric is surely revenue growth. With a correlation of 0.31 for the 1-month period and 0.37 for the 1-year period, there seems to be strong evidence that it might play a significant role in predicting long-term stock prices. The analysis of the regression is extremely solid as well. I will focus on the results of revenue growth, since it is the only one to exhibit convincing regressions. For the 1-month period, the adjusted R-squared is 6.0% and the p-value is 10.6%. Even though this is not exactly statistically significant, considering it is about the 1-month period, which is the period that, throughout the analysis, gave us the most problems with finding consistent results, this p-value is quite solid. For the 1-year returns we have even better results: with an adjusted R-squared of 10.2% and a p-value of 5.0%, this is, once again, one of the best results we have obtained so far. Theoretically, this might mean that revenue growth signals real business momentum. In early-stage companies, where profitability tends to be extremely limited, revenue expansion is often one of the best and most credible indicators of scalability and product-market fit. A startup whose revenue is growing is probably starting to find its market, which is key for startups, and an early expansion might be a sign that the core idea of the business is working. In addition to this, revenue growth is less prone to accounting manipulation compared to earnings metrics, explaining why it might have this higher correlation. The last metric left to analyse is assets growth. It does not exhibit the highest correlations, being -0.10 for the 1-month period and -0.09 for the 1-year period, and the regression analysis does not find any statistical significance. However, the fact that it is negative is coherent with the analysis we have done on the natural logarithm of assets, and the theoretical explanation for that would be the same.

4.8 Multivariate Model for First-Day IPO Returns

After having explored individually how each variable was related to IPO returns, I started to look at which multivariate regression model could better explain the movements of those percentages, to determine whether it was possible to create a model capable of at least partially predicting them using exclusively financial metrics. Running all the possible combinations of the variables of my sample, I ordered the best models I could find for 1-day, 1-month and 1-year returns by AIC, BIC and adjusted R-squared, to see which one performed the best.

The first model I analyse is the one about first-day returns, and the results were promising. After comparing the best models in Table 5, the best one I found includes the following variables: D/A, log assets, gross profit margin, and R&D/operating expenses. This is the model that possesses the lowest AIC, and compared to the model with the lowest BIC, it exhibits a higher adjusted R-squared. A very close second was the model including all the previous variables plus current ratio. While that is the model with the highest adjusted R-squared, the improvement was marginal, and the additional complexity did not justify its inclusion.

The selected multiple linear regression (Table 8) has an adjusted R-squared of 19.7%. Given that IPO returns are very noisy and influenced by many factors, this number is very acceptable. The F-statistic is 2.289, which corresponds to a p-value of 10.2%. This makes the model not significant at the 5% level, but it is reasonably close. This should not come as a surprise due to the small sample size and the volatility of IPO data. However, it is still fair to say that the model shows some meaningful explanatory power.

The choice of these variables is not only appropriate for our sample. They reflect structural dimensions of financial health, market uncertainty and innovation intensity, which are all very relevant in the startup context. These four dimensions capture those aspects that the literature has explored as potential drivers of IPO performance: we have a metric for the firm's size (log assets), one for leverage (D/A), one for profitability (gross profit margin) and one for R&D expenditures (R&D/operating expenses). What has been excluded is a metric that captures the liquidity of the firm, but, at least for 1-day returns, adding such a metric did not add significant explanatory power to our model. Its lack of relevance here might stem from the fact that at the time of the IPO investors anticipate an immediate cash infusion, and solvency concerns may be deferred, especially in high-growth firms like startups, where risk is already priced in. The choice of gross profit margin over the other profitability metrics has a theoretical explanation. Compared to EBITDA margin and net profit margin, it is the most stable predictor. It did not require manual capping during the winsorization process thanks to its relatively low variance compared to these other two profitability metrics. Instead, ROE was excluded because it represents profitability from the perspective of equity holders: investors, in the beginning, are more likely to look at fundamentals that better reflect the firm's core offering, and gross profit margin serves this purpose by isolating product-level efficiency.

We will now examine the single variables. D/A has a negative coefficient of -0.83, and it appears to be statistically significant with a p-value of 2.5%. This means that when D/A increases by 1%, making the firm more leveraged, the return decreases by 0.83% on average. When looking at the multiple linear regression, thus accounting for other variables to explain some of the variance of the data, the natural logarithm of total assets finally becomes statistically significant, as the literature predicts. With a p-value of 11% and a coefficient of -0.18, each increase of 1 unit in the logarithm of the assets of a firm leads to a 0.18% decrease in the post-IPO returns. The most dubious yet intriguing metric of this model is gross profit margin. As we have seen, the literature presents contrasting views concerning the role of profitability metrics in IPO returns. When we analysed the impact of profitability metrics on first-day returns this metric performed the worst. It seems that this variable can capture unique variance in IPO performance when combined with other controls. Though the p-value for this variable is 9.5%, not reaching the threshold of 5%, it is still sufficiently low. The coefficient amounts to -0.43, so for each increase of 1% in gross profit margin, there is a decrease of 0.43% in IPO returns. Last, R&D/operating expenses also appears to be playing a significant role. It exhibits a low p-value of 2%, and a quite high coefficient of -1.20. Even though we had to sacrifice a bit of our sample to include this variable, due to the presence of many null values, it seems to be well worth it. An increase of 1% in this metric leads to a significant decrease of 1.20% in returns. The overall model was also checked for multicollinearity. When controlling for VIFs, all the variables showed a value lower than 5, meaning that this model seems to be safe under this aspect. Log of assets exhibited a somewhat higher value, amounting to 4.95, which makes sense, since size often correlates with many other metrics, but the value is just under the typical threshold of concern.

4.9 Multivariate Model for One-Year Post-IPO Performance

For 1-month returns it was completely impossible to find a good enough model, since none of them had a significant enough adjusted R-squared (Table 6). The highest possible value one of these models reached 7%, which is too small to consider analysing.

For the 1-year period, it is instead possible to find a model, even though finding the best one is not easy. In fact, we get different results based on the criteria we want to use to choose the model (Table 7). The lowest possible BIC model has an Adjusted R-squared of 27%, while for the lowest possible AIC model this value is 36%. When choosing between these two, the decision is obvious and, looking only at those values, I would have chosen the model with the highest adjusted R-squared. However, when we look at the models ordered by the Adjusted R-squared, we see a model that almost reaches 50% in that value, which is extremely high. Moreover, when looking at the AIC and BIC scores, they are not that far from the best AIC model, since they amount to, respectively, 57.47 and 63.95 against 53.16 and 59.43. In these situations, it is still generally better to take the model with the lowest AIC or BIC score, since it is typically more robust. However, upon closer inspection, we can see that this highest R-squared model is exactly the highest-AIC model but with one less variable. The former, in fact, includes ROE (pretax), D/A, current ratio, Gross profit margin, while the latter includes the same plus R&D/operating expenses. Since it is generally considered better to take the simplest possible model, I decided to run the regression for both models to compare more deeply the results (Table 9 and Table 10). And the result is that the highest R-squared model clearly outperforms the other one. The F-statistic for it is 7.4, compared to the other model's 3.3. In addition to this, the additional metric (R&D/operating expenses) exhibits a p-value of 88%. With a significantly higher R-squared, more statistical significance and a lower number of predictors used, the choice was clear.

The model I will be analysing is therefore the one including only D/A, current ratio, gross profit margin and ROE (pretax). The choice of these metrics, together with leading mathematically to the best model we can have with our sample, also has a theoretical foundation. Compared to the 1-day model, a few changes stand out: size and R&D metrics have been replaced with a liquidity metric (current ratio) and a shareholder profitability metric, ROE. Concerning the exclusion of log assets, this may be due to multicollinearity issues. This problem already emerged with 1-day returns. In Table 8 we can see that log assets has a VIF of 4.95, approaching the threshold that indicates multicollinearity. This is a well-known phenomenon in the literature: Some of the studies we previously analysed, like Ritter (1991) and Loughran & Ritter (1995), acknowledge that multicollinearity exists between size and risk proxies. The work by Teoh et al. (1998) instead mentions how earnings management and firm size often travel together. Pukthuanthong & Walker (2008) point out that capital structure variables interact with size in IPO settings, especially in tech firms. Our own correlation matrix shows that log assets exhibits high correlation with most of the other metrics we are using. While this problem was not marked enough for the metrics we were using in the first-day returns model, it might have become important for the combination of metrics we are using for the 1-year model. The other variable that was excluded is R&D/operating expenses. This might be because a 1-year time horizon might still be too early for R&D projects to start producing significant returns, thus it might be possible that its effect would be more preponderant when looking at longer time periods. The inclusion of ROE is interesting as well. While it did not appear relevant in the 1-day model, in the 1-year period it seems to start becoming important. We will later see that this is not a metric that alone seems to directly drive higher returns, but it captures a dimension that, when interacting with other variables, gives the model higher explanatory power. It is also the preferred metric that was used by Abraham et al. (2016) when analysing profitability effects in the long-term.

Also, a liquidity metric like current ratio finally becomes relevant in the 1-year period: firms that maintained good liquidity ratios pre-IPO might probably show a certain degree of skill in managing their position and might be better prepared to deploy capital efficiently post-IPO, leading in the long-term to higher returns.

To be precise, our model achieves an adjusted R-squared of 49.6% and an F-statistic of 7.394 which leads to a p-value of 0.06%, extremely low. This level of explanatory power is extremely solid, especially for such a small sample size. I will once again go through each single variable, starting with ROE (pretax). We previously saw that it appeared to be an extremely solid predictor when considered singularly. However, when accounting for other variables, a different trend emerges. ROE has a coefficient of -0.08 and a p-value of 62.5%, which makes it seem non-statistically significant. However, its inclusion in the model significantly improves its explanatory power. Thus, ROE acts as a suppressor variable. Even though its direct contribution is weak, it indirectly enhances the model. In the simple model, ROE absorbed variation from multiple profitability-related characteristics, but when accounting for other factors, and those other factors capture more specific aspects of capital structure and operational health, ROE loses its significance. However, it still improves the model by controlling for unobserved profitability dimensions that are otherwise dispersed across liquidity and leverage measures. The other variables appear all to be extremely relevant. D/A has a coefficient of 3.04 and a p-value of 0.6%, very significant. Liquidity also appears to be important, with the current ratio having a coefficient of 0.2 and a p-value of 2%, extremely significant. Once again, gross profit margin seems to be the best profitability metric. Its impact appears to be even stronger than in first-day returns, with a coefficient of -1.03, and a p-value of 1.7%.

5 Conclusion

The goal of this thesis is to examine whether pre-IPO financial metrics can help predict IPO underpricing and post-IPO stock performance for U.S. startups between 2017 and 2021. Through our regression analysis, we found some very interesting results. While first-day returns exhibit significant underpricing, financial data can only partially explain this phenomenon. With an adjusted R-squared of 20%, even though our best model, which includes D/A, log assets, gross profit margin, and R&D/operating expenses, is not fully statistically significant, it is still possible to say that it holds a certain amount of explanatory power. We also observed how financial metrics may behave differently for startups compared to classic firms. For startups, for example, high R&D and strong gross profit margins are associated with lower underpricing, while leverage plays a credibility-signaling role, diverging from the high-tech skepticism shown in classic literature.

Our results are even more fascinating for long-term returns. While returns at 1 month are too volatile and largely unpredictable, since we can neither observe the phenomenon of first-day IPO returns nor count on having a stable enough firm like after 1 year, for the 1-year period we can get some solid results. Our model, with D/A, current ratio, gross profit margin, and ROE, achieved a significant adjusted R-squared of 50%. Here as well, there are some patterns that diverge from the classic literature. While ROE in our model primarily acts as a suppressor variable, it still presents a negative correlation with returns, in contrast to what we found analysing the literature.

This thesis can also act as a starting point for considering more growth metrics in these types of analysis: while calculating these metrics in an IPO environment can be tricky due to the lack of financial data, they seem to be worth analysing further. Our univariate regression analysis showed that most of the growth metrics appeared to have a significant correlation with both short- and long-term returns. While it is not certain that this correlation can also be found in classic firms, it is something that could be tested, possibly with methods that are able to handle volatile and extreme values more effectively.

Our findings suggest that startups may require a different interpretative framework compared to classic firms, as we have seen that many variables we analysed showed some differences from what the literature predicted. Despite the multiple insights gained, it is important to be aware of the major limitations of our analysis, which are the limited sample size, the missing data (especially for R&D), and the volatile nature of startup financials. It is also fundamental to remember that, for the sake of simplicity, this analysis only considered financial metrics: in reality, there are many other factors that can influence IPO returns and long-term stock prices, and, if we wanted to find the best models for predicting these outcomes, we would have to include those factors as well. Another direction a possible expansion this model could take would be to consider even longer time-horizons: while, as discussed, for the most part, 1 year is enough for understanding the long-term direction of a firm, looking at later years, even if, probably, the correlation with pre-IPO metrics would inevitably go down, we could still get some additional insights. Still, this thesis shows that financial metrics, when carefully selected and interpreted, can provide valuable signals in the chaotic landscape of startup IPOs. This analysis can encourage additional research and provide a framework for investors, issuers and analysts to look at when dealing with startups' IPOs.

5 Tables and Figures

Table 1 Descriptive statistics of all variables (predictors and predicted outcomes). Mean, median, interquartile range (25th and 75th percentiles), and standard deviation for all financial metrics used in the analysis. Pre-IPO variables are winsorized; return variables are reported as is.

	Mean	**Median**	**25th Percentile**	**75th Percentile**	**Std Dev**
ROE (pretax)	-0,6858	-0,3398	-0,9346	-0,1289	1,0949
net profit margin %	-0,5294	-0,6181	-1	-0,1239	0,4491
D/A	0,5274	0,4778	0,2793	0,7031	0,3121
current ratio	3,119	2,5752	1,7411	3,6423	2,1946
log Assets	19,9828	19,5611	18,9349	20,1039	2,0008
EBITDA margin %	-0,467	-0,4136	-0,9947	-0,0962	0,4532
gross profit margin %	0,497	0,5455	0,1916	0,7451	0,3388
working capital/total assets	0,4059	0,4288	0,2411	0,6275	0,2574
R&D/operating expenses	0,2993	0,2635	0,1444	0,3661	0,2252
assets growth	0,45	0,5125	-0,0306	1	0,4846
revenue growth	0,6256	0,8735	0,2672	1	0,4291
EBITDA Growth	0,2214	0,392	-0,4341	1	0,7144
gross profit growth	0,553	0,874	0,1407	1	0,5799
net profit growth	0,2862	0,4328	-0,1081	0,9708	0,6641
1-day returns	0,2995	0,2503	0,0595	0,4109	0,3341
1-month returns	0,4335	0,2921	-0,0041	0,689	0,6303
1-year returns	-0,0282	-0,3929	-0,6348	0,4881	0,8857

Figure 1 Distribution and skewness of highly skewed pre-IPO financial variables. This figure presents the distribution and skewness of the most highly skewed pre-IPO financial variables used in the regression models. Each subplot displays a histogram with a fitted density curve, along with the skewness statistic to indicate the degree and direction of asymmetry.

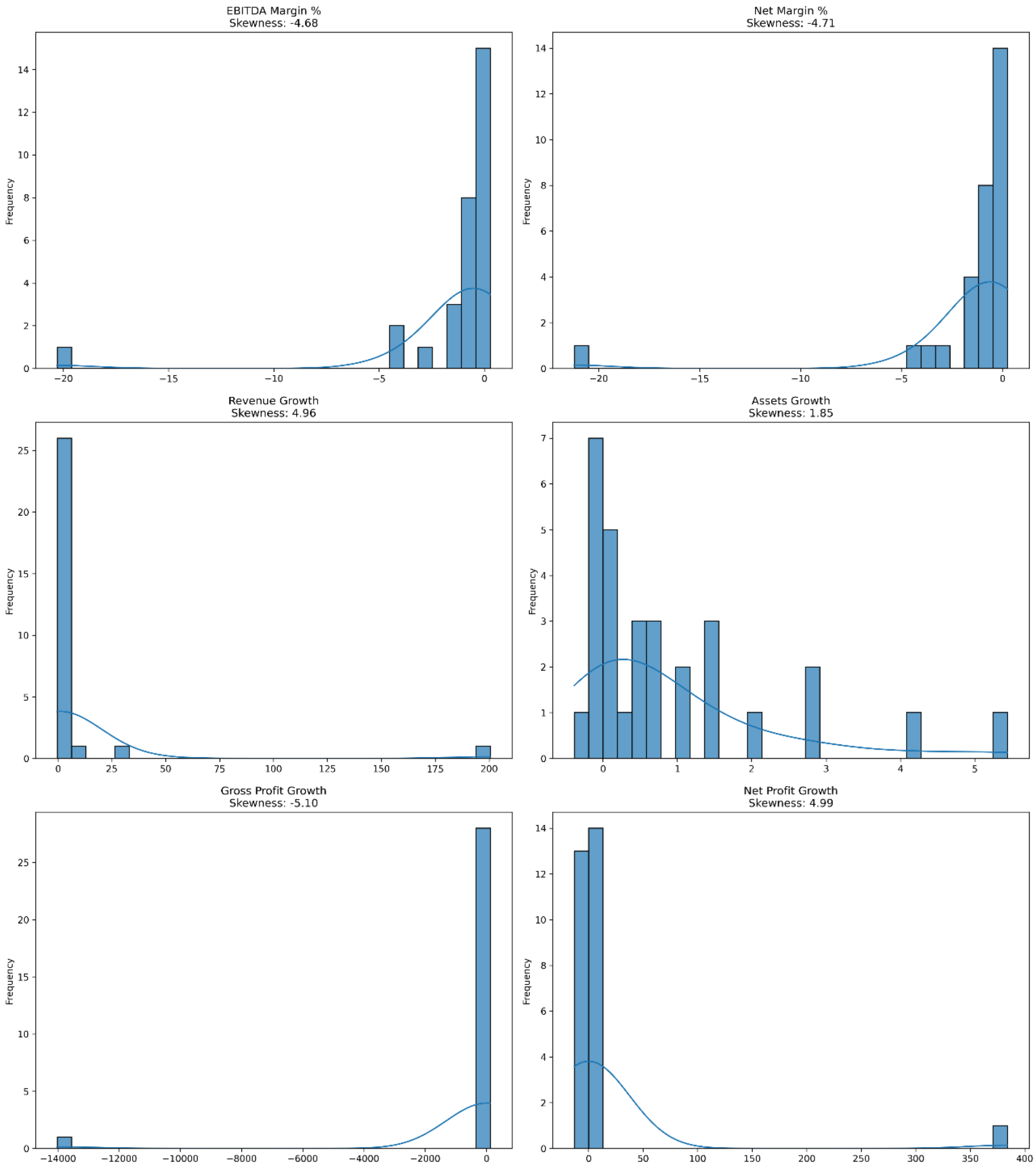

Figure 2 Correlation matrix of pre-IPO metrics and IPO returns. Heatmap of Pearson correlation coefficients among all financial predictors and first-day, one-month and one-year returns

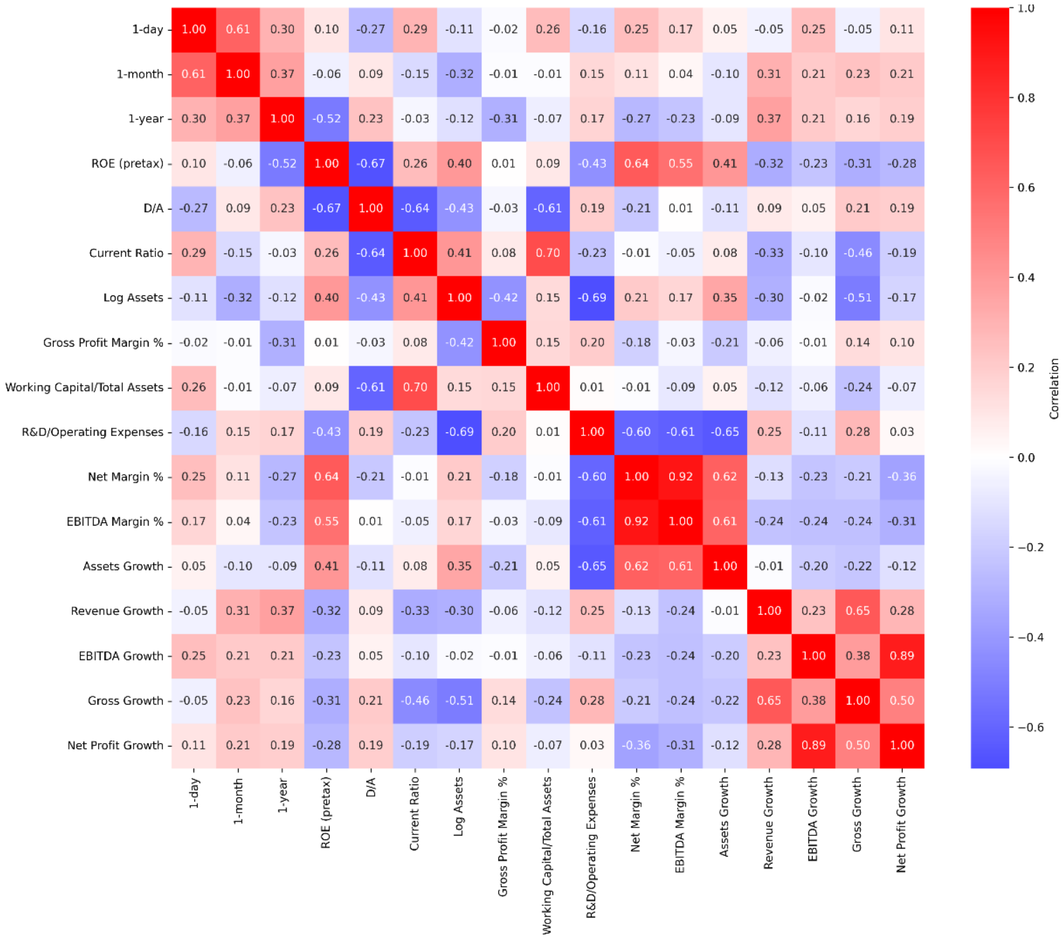

Table 2 Univariate OLS results for first-day returns. Regression coefficients (β), p-values, adjusted R^2, and number of observations for each predictor

Predictor	**Coefficient**	**p-value**	**Adj. R-squared**	**N_obs**
ROE (pretax)	0,029922	0,629577	-0,03017	27
net profit margin %	0,185576	0,183697	0,028742	30
D/A	-0,28582	0,153768	0,038123	30
current ratio	0,044684	0,115438	0,053511	30
log Assets	-0,01862	0,557464	-0,02284	30
EBITDA margin %	0,122986	0,378227	-0,00689	30
gross profit margin %	-0,02122	0,91013	-0,03523	30
working capital/total assets	0,337557	0,165219	0,034316	30
R&D/operating expenses	-0,23288	0,489856	-0,02464	22
assets growth	0,037566	0,774913	-0,03264	30
revenue growth	-0,03495	0,809184	-0,03476	29
EBITDA Growth	0,113624	0,184085	0,029741	29
gross profit growth	-0,02993	0,779839	-0,03398	29
net profit growth	0,052824	0,58535	-0,02641	28

Table 3 Univariate OLS results for one-month returns. Regression coefficients (β), p-values, adjusted R², and number of observations for each predictor

Predictor	**Coefficient**	**p-value**	**Adj. R-squared**	**N_obs**
ROE (pretax)	-0,03783	0,752263	-0,03578	27
net profit margin %	0,155412	0,560198	-0,02301	30
D/A	0,183632	0,632757	-0,02715	30
current ratio	-0,04229	0,437506	-0,01326	30
log Assets	-0,09936	0,089583	0,067298	30
EBITDA margin %	0,055472	0,834241	-0,03407	30
gross profit margin %	-0,02244	0,949557	-0,03556	30
working capital/total assets	-0,02613	0,955383	-0,0356	30
R&D/operating expenses	0,445999	0,504148	-0,02626	22
assets growth	-0,12427	0,615532	-0,02626	30
revenue growth	0,448475	0,105852	0,060382	29
EBITDA Growth	0,181236	0,283166	0,007062	29
gross profit growth	0,253517	0,221494	0,019821	29
net profit growth	0,205042	0,276334	0,008681	28

Table 4 Univariate OLS results for one-year returns. Regression coefficients (β), p-values, adjusted R^2, and number of observations for each predictor

Predictor	**Coefficient**	**p-value**	**Adj. R-squared**	**N_obs**
ROE (pretax)	-0,42952	0,005744	0,238095	27
net profit margin %	-0,53887	0,144026	0,041611	30
D/A	0,664872	0,212731	0,021131	30
current ratio	-0,01401	0,855501	-0,03447	30
log assets	-0,05391	0,521515	-0,02036	30
EBITDA margin %	-0,44674	0,224365	0,018405	30
gross profit margin %	-0,80363	0,098467	0,062143	30
working capital/total assets	-0,23566	0,719194	-0,03086	30
R&D/operating expenses	0,715675	0,446559	-0,01927	22
assets growth	-0,17272	0,619433	-0,02647	30
revenue growth	0,760506	0,050407	0,102392	29
EBITDA Growth	0,262173	0,273171	0,008893	29
gross profit growth	0,246934	0,404381	-0,01019	29
net profit growth	0,259652	0,327535	-0,00016	28

Table 5 Top 5 model specifications for first-day returns. Model regressors, AIC, BIC, and adjusted R^2 (ordered by AIC, then BIC, then Adj R^2)

Ordered by AIC			
predictors	**AIC**	**BIC**	**AdjR2**
D/A, log Assets, gross profit margin %, R&D/operating expenses	14,13	19,59	0,20
Current ratio, log Assets, gross profit margin %, R&D/operating expenses	14,71	20,17	0,18
current ratio, log Assets, R&D/operating expenses	14,73	19,10	0,15
D/A, Current ratio, log Assets, gross profit margin %, R&D/operating expenses	14,77	21,32	0,20
D/A, log assets, gross profit margin %, working capital/total assets, R&D/operating expenses	15,63	22,17	0,17
Ordered by BIC			
predictors	**AIC**	**BIC**	**AdjR2**
current ratio, log assets, R&D/operating expenses	14,73	19,10	0,15
D/A, log assets, gross profit margin %, R&D/operating expenses	14,13	19,59	0,20
current ratio, log assets, gross profit margin %, R&D/operating expenses	14,71	20,17	0,18
D/A, log assets, R&D/operating expenses	15,84	20,20	0,10
log Assets, R&D/operating expenses	17,02	20,30	0,02
Ordered by AdjR2			
predictors	**AIC**	**BIC**	**AdjR2**
D/A, current ratio, log assets, gross profit margin %, R&D/operating expenses	14,77	21,32	0,20
D/A, log assets, gross profit margin %, R&D/operating expenses	14,13	19,59	0,20
current ratio, log assets, gross profit margin %, R&D/operating expenses	14,71	20,17	0,18
ROE (pretax), current ratio, log assets, gross profit margin %, R&D/operating expenses	16,03	22,30	0,17
net profit margin %, current ratio, log assets, gross profit margin %	18,38	25,38	0,17

Table 6 Top 5 model specifications for one-month returns. Model regressors, AIC, BIC, and adjusted R^2 (ordered by AIC, then BIC, then Adj R^2)

Ordered by AIC			
predictors	**AIC**	**BIC**	**AdjR2**
log Assets, R&D/operating expenses	46,67	49,94	0,03
ROE (pretax), log assets, R&D/operating expenses	47,41	51,59	-0,02
ROE (pretax), R&D/operating expenses	48,04	51,17	-0,09
net margin %, log assets, R&D/operating expenses	48,07	52,44	0,01
ROE (pretax), log Assets, gross profit margin %, R&D/operating expenses	48,21	53,43	-0,02
Ordered by BIC			
predictors	**AIC**	**BIC**	**AdjR2**
log Assets, R&D/operating expenses	46,67	49,94	0,03
ROE (pretax), R&D/operating expenses	48,04	51,17	-0,09
ROE (pretax), log assets, R&D/operating expenses	47,41	51,59	-0,02
net profit margin %, R&D/operating expenses	48,39	51,67	-0,04
EBITDA margin %, R&D/operating expenses	48,44	51,71	-0,05
Ordered by AdjR2			
predictors	**AIC**	**BIC**	**AdjR2**
net profit margin %, log Assets	58,19	62,39	0,07
log Assets, gross profit margin %	58,42	62,63	0,06
net profit margin %, log Assets, gross profit margin %	59,48	65,09	0,05
ROE (pretax), D/A, log Assets	55,73	60,91	0,05
log Assets, EBITDA margin %	58,99	63,20	0,04

Table 7 Top 5 model specifications for one-year returns. Model regressors, AIC, BIC, and adjusted R^2 (ordered by AIC, then BIC, then Adj R^2)

Ordered by AIC			
predictors	**AIC**	**BIC**	**AdjR2**
ROE (pretax), D/A, current ratio, gross profit margin %, R&D/operating expenses	53,16	59,43	0,36
ROE (pretax), gross profit margin %, R&D/operating expenses	54,61	58,78	0,27
ROE (pretax), log Assets, gross profit margin %, R&D/operating expenses	54,94	60,16	0,28
ROE (pretax), EBITDA margin %, gross profit margin %, R&D/operating expenses	55,12	60,34	0,28
ROE (pretax), D/A, gross profit margin %, R&D/operating expenses	55,32	60,54	0,27
Ordered by BIC			
predictors	**AIC**	**BIC**	**AdjR2**
ROE (pretax), gross profit margin %, R&D/operating expenses	54,61	58,78	0,27
ROE (pretax), D/A, current ratio, gross profit margin %, R&D/operating expenses	53,16	59,43	0,36
ROE (pretax), R&D/operating expenses	56,59	59,73	0,17
ROE (pretax), log assets, gross profit margin %, R&D/operating expenses	54,94	60,16	0,28
ROE (pretax), EBITDA margin %, gross profit margin %, R&D/operating expenses	55,12	60,34	0,28
Ordered by AdjR2			
predictors	**AIC**	**BIC**	**AdjR2**
ROE (pretax), D/A, current ratio, gross profit margin %	57,47	63,95	0,50
ROE (pretax), D/A, current ratio, gross profit margin %, working capital/total assets	58,95	66,72	0,48
ROE (pretax), D/A, current ratio, EBITDA margin %, gross profit margin %	59,23	67,01	0,48
ROE (pretax), net profit margin %, D/A, current ratio, gross profit margin %	59,36	67,14	0,47
ROE (pretax), D/A, current ratio, log assets, gross profit margin %	59,37	67,15	0,47

Table 8 Multivariate OLS regression and VIFs: first-day returns. Full β estimates, standard errors, t-stats, p-values and variance-inflation factors for the best 1-day model: $R_{i,1d} = \beta_0 + \beta_1(\mathrm{D/A})_\mathrm{i} + \beta_2 \ln(\mathrm{assets_i}) + \beta_3(\text{gross profit margin})_\mathrm{i} + \beta_4(\text{R\&D/operating expenses}) + \varepsilon_\mathrm{i}$

Model	**N observations**	**Adj R² (%)**	**F-statistic**	**Prob (F)**
D/A + log assets + gross profit margin % + R&D/operating expenses	22	19.7	2.289	0.102091
Variable	**Coefficient**	**Std. Err.**	**t**	**p-value**
const	4,9323	1,588	3,105	0,006
D/A	-0,8337	0,34	-2,454	0,025
log assets	-0,1809	0,063	-2,856	0,011
gross profit margin %	-0,4311	0,244	-1,766	0,095
R&D/operating expenses	-1,1761	0,457	-2,573	0,02
Variable	**VIF**			
D/A	2.237054			
log assets	4.952051			
gross profit margin %	1.858396			
R&D/operating expenses	2.432659			

Table 9 Multivariate OLS regression and VIFs: one-year returns. Full β estimates, standard errors, t-stats, p-values and variance-inflation factors for the best 1-year model:

$$R_{i,1y} = \beta_0 + \beta_1(\mathrm{D/A})_\mathrm{i} + \beta_2(\text{current ratio})_\mathrm{i} + \beta_3(\text{gross profit margin})_\mathrm{i} + \beta_4(\text{ROE pretax})_\mathrm{i} + \varepsilon_\mathrm{i}$$

Model	**N observations**	**Adj R^2 (%)**	**F-statistic**	**Prob (F)**
ROE (pretax) + D/A + current ratio + gross profit margin %	27	49.6	7.394	0.000622
Variable	**Coefficient**	**Std. Err.**	**t**	**p-value**
const	-1,6079	0,676	-2,379	0,026
ROE (pretax)	-0,0835	0,169	-0,496	0,625
D/A	3,0355	1,004	3,022	0,006
current ratio	0,2168	0,086	2,517	0,02
gross profit margin %	-1,0319	0,402	-2,57	0,017
Variable	**VIF**			
ROE (pretax)	2.122768			
D/A	3.921038			
current ratio	2.341674			
gross profit margin %	1.000184			

Table 10 Multivariate OLS regression and VIFs: one-year returns – alternative model. Full β estimates, standard errors, t-stats, p-values and variance-inflation factors for the best 1-year model: $R_{i,1y} = \beta_0 + \beta_1(\mathrm{D/A})_i + \beta_2(\text{current ratio})_i + \beta_3(\text{gross profit margin})_i + \beta_4(\text{R\&D/operating expenses}) + \beta_5(\text{ROE pretax})_i + \varepsilon_i$

Model	**N observations**	**Adj R^2 (%)**	**F-statistic**	**Prob (F)**
ROE (pretax) + D/A + current ratio + gross profit margin % + R&D/operating expenses	21	36.1	3.261	0.034343
Variable	**Coefficient**	**Std. Err.**	**t**	**p-value**
const	-1,5018	0,978	-1,536	0,145
ROE (pretax)	-0,1149	0,234	-0,49	0,631
D/A	2,8335	1,366	2,074	0,056
current ratio	0,213	0,118	1,811	0,09
gross profit margin %	-1,0627	0,489	-2,175	0,046
R&D/operating expenses	0,0278	0,876	0,032	0,975
Variable	**VIF**			
ROE (pretax)	2.497931			
D/A	4.604262			
current ratio	2.794561			
gross profit margin %	1.019943			
R&D/operating expenses	1.301779			

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