

Survival of the fittest: The fate of IPOs in the aftermarket

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2024

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Department of: Finance and Economics	**Type of work**: Master's thesis
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Title of thesis:

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Abstract: The purpose of this study is to analyse how changes in issue-, company-, and market-specific characteristics affect the probability that IPOs survive, get acquired, or fail in the aftermarket. Additionally, this thesis aims to identify factors influencing the length of the post-issuance survival period. This thesis contributes to existing literature by retrieving elements from traditional IPO literature and corporate failure prediction studies.

This research combines data from various sources, including LSEG datastream, Jay Ritter's website, Factset, Center for Research on Security Prices (CRSP), Compustat, and IPO prospectuses. The final sample consists of 3038 IPOs listed between January 1st, 1995 and December 31st, 2018 in the U.S. market. The post-issuance tracking period is 5 years, extending the analysis period to December 31st, 2023.

Multinomial logit models are built to determine which characteristics are associated with the probability of transitioning to the general post-IPO states of survival, getting acquired, and failure. The applied post-estimation techniques include Average Marginal Effects and the likelihood ratio Chi-square test. Furthermore, to estimate which factors extend or shorten the survival time in the aftermarket, generalized gamma and log-logistic Accelerated Failure Time models are developed.

The obtained results show that from the IPOs issued between 1995 and 2018, 55% survive, 32% get acquired and 13% fail in the aftermarket over the follow-on period of 5 years. The probability of survival is estimated to increase significantly with offer size, company age, sales, and R&D expenses. In turn, the probability of survival is estimated to decrease significantly with increase in leverage and accumulated deficit, hot market conditions, classification in tech industry, and reported net losses at IPO year. Survival analysis reveals that when examining time-to-delisting due to acquisition or failure, survival time is estimated to extend if a company has low leverage, it is classified in non-tech industry, has positive net income, and is not classified as hot issue.

Keywords: IPO, multinomial logit model, survival analysis, Accelerated Failure Time model

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1 INTRODUCTION

In an Initial Public Offering (IPO), a private company raises capital from investors by offering its shares to the general public for the first time, consequently transforming into a public entity. The event is a pivotal milestone in the company's lifecycle and usually happens only once in its history. Raising funds for future investments and growth is widely recognised as the primary motivation for going public. However, since other sources of funding exist, including retained earnings, debt, and private equity capital, this reasoning by itself is insufficient to explain why companies go public (Brau, 2012). Hence, alternative motives for going public include but are not limited to, improved access to capital, capital structure re-adjustments, improved liquidity of a company's stock, facilitation of future acquisitions or sell-out, and increased visibility. Motives for becoming a listed company vary across geographical areas, legislative frameworks, and individual companies. In fact, some companies may never choose to enter the public market, as an IPO is a choice rather than a mandatory milestone in a company's lifespan.

A successful IPO can unlock significant value for companies and investors, drive innovation, and fuel economic growth. Nevertheless, companies listed on a public stock exchange must comply with stringent requirements, including disclosure obligations, and compliance with certain corporate governance and accounting standards. In the dynamic landscape of the public markets, companies may struggle to maintain their presence on a stock exchange and eventually face the prospect of delisting. This event may take place due to various factors, primarily rooted in poor performance or strategic decisions. If a company delists due to its failure or other negative reasons, investors face a substantial risk of losing their invested capital, also referred to as IPO failure risk. To manage risks related to delisting, this thesis aims to reveal which factors are associated with the probability that IPOs either survive, get acquired, or fail in the aftermarket. Ideally, this study allows issuing companies to make better-informed decisions on entering the public market as well as help investors make better investment decisions.

There are several reasons why the survival of IPOs is of interest. Previous research has captured significant delisting rates three to ten years after the initial offering (Lowry, Michaely and Volkova, 2017) and new issues are continuously challenged to maintain their existence on a stock exchange. By examining the fate of IPOs, the aim is to identify factors that could potentially impact the probability of survival, acquisition, or failure after listing. Generally, the amount of information that is available before or soon after

an IPO is limited, making it difficult to assess the quality of the company and value it at an appropriate level. Therefore, investors should be able to utilise this information as effectively as possible to manage IPO failure risk and mitigate capital losses. Moreover, this analysis is relevant for companies when considering whether they should go public. Lastly, the estimation of the length of time that the stock is expected to remain listed is valuable to those assessing future cash flows of a company and estimating its fair value.

In this thesis, companies listed in the U.S. market between 1995 and 2018 are classified based on their 5-year post-issuance status into categories of (1) survived (2) acquired and (3) failed. When examining the probability of transitioning to the post-IPO states, the aim is to reveal the ideal survival profile of companies listed over the examined period. Multinomial logit models are developed to predict the probability of transitioning to the post-issuance states based on issue-, company-, and market-specific information at the time and soon after an IPO. Moreover, the length of time an IPO remains listed is examined through a survival analysis. Specifically, Accelerated Failure Time (AFT) model which allows to analyse the impact of issue-, company-, and market-specific characteristics on the length of the survival period, is employed in the survival analysis.

1.1 Purpose of the study

The purpose of this study is to analyse how changes in issue-, company-, and market-specific characteristics affect the probability that IPOs survive, get acquired, or fail in the aftermarket. Furthermore, this study aims to identify factors that increase or decrease the survival time after listing.

1.2 Research questions

Related to the purpose of this study, this thesis aims to provide answers to the following research questions:

1. Which issue-, company-, and market-specific characteristics impact the survival of IPOs in the aftermarket?

2. Which issue-, company-, and market-specific characteristics impact the survival time of IPOs in the aftermarket?

1.3 Motivation and contribution

Short- and long-term operational and financial performance of IPOs and hot issue activity have received vast attention in previous literature, while the important concept

of the survival of IPOs has been largely disregarded. In addition, the majority of the previous research on the topic have used data on IPOs that occurred before the early 2000s. Additional research is warranted as there have been notable changes in the trends of the IPO market over the past two decades, one being a declining pattern in the IPO activity. Berk and DeMarzo (2024) argue that this evolution has been mainly driven by two factors. First, companies can remain private longer since they have improved access to large amounts of capital from venture capitalists (VCs) and private equity (PE) firms in private markets. Secondly, rather than going public, small companies are likely to get acquired by others. The proportion of VC-backed companies that have exited the market through an acquisition has increased from below 50% in the 1990s to over 80% in the 2000s (Berk and DeMarzo, 2024). However, even with the reduction in activity, the IPO market remains vibrant, breaking records in the dollar amount of proceeds raised in 2021, at the latest.

In the footsteps of Demers and Joos (2007), this study combines financial literature from two standpoints – by retrieving elements from traditional IPO literature and studies on corporate failure prediction in non-IPO settings. While there are some previous studies on the topic of the survival of IPOs, the majority of earlier research solely considers two possible outcomes, survival and non-survival of new issues in the aftermarket (e.g. Schultz, 1993; Hensler, Rutherford, and Springer, 1997; Demers and Joos, 2007), while neglecting the possibility of an acquisition. Overall, the M&A activity has increased over the past few decades, and especially small public companies may be seen as potential targets. It is interesting to see if other, perhaps not commonly recognised, characteristics are associated with the probability of acquisition. Furthermore, Fama and French (2004) identified diversity of the quality among acquired companies, thus making it valid to examine the topic from all three general post-IPO states and to explore whether the quality of acquired IPOs differ from those delisted due to negative reasons.

1.4 Limitations

The U.S. is selected as the geographical area due to its active IPO market and the lack of data availability on other markets. The sample of IPOs consists of companies that went public between January 1st, 1995 to December 31st, 2018. The start of the examined period is restricted to 1995 to reveal the ideal survival profile of IPOs based on relatively recent data. To ensure a 5-year tracking period following the initial offering, it is mandatory to exclude IPOs that occurred after 2018 from the sample, although the examined follow-on period on delistings extends to December 31st, 2023.

1.5 Structure of the study

The remaining of this thesis consists of eight chapters: introduction to a company's journey from an IPO to a possible delisting, overview of the IPO market dynamics, literature review, data, methodology, results, discussion, and conclusion. The first chapter discusses the motives for going public, the advantages and disadvantages of going public, the IPO process in the U.S., and voluntary and involuntary delisting from a stock exchange. The second chapter provides an overview of the U.S. IPO market, a brief discussion on the underpricing of IPOs, hot issue markets, and long-term underperformance of IPOs, complemented with theories evolved in previous literature to explain the phenomenon. Subsequently, the literature review provides an overview of prior empirical studies on the aftermarket survival of IPOs. In addition, the emphasis is on previous studies on the long-term underperformance of IPOs and corporate failure prediction as those are closely related to the topic of interest. The next chapter presents the data and the sampling process, followed by a chapter on methodologies employed in the empirical study. The results are presented and discussed in the following chapters. Lastly, conclusion summarises the main findings and provides suggestions for further research.

2 FROM AN IPO TO DELISTING

This study focuses on the survival of U.S. IPOs in the aftermarket and factors that potentially influence their long-term post-issuance status. Thus, this chapter introduces a company's journey from going public to its possible delisting from a stock exchange. In addition, previous literature is presented to support the theoretical framework. The following subchapters discuss motives for going public, the advantages and disadvantages of going public, and the IPO process in the U.S. market. Lastly, the subchapter on delisting focuses on the removal of a company's stock from a stock exchange and potential underlying reasons for delisting.

2.1 Why do companies go public?

The decision to go public may be driven by both, pecuniary and non-pecuniary motives. Often primarily considered pecuniary motives are associated with the need to raise capital to fund capital-intensive operations, including the implementation of growth and expansion strategies, research & development (R&D) projects, and debt servicing. A company may also be motivated to go public to obtain a market value for its assets to facilitate future acquisitions or a sell-out. Non-pecuniary motives include but are not limited to, increased visibility and enhanced brand image which can attract and engage stakeholders, including employees and customers. Ritter and Welch (2002) note that it is challenging to test underlying motives for going public empirically as this type of analysis typically considers solely companies that have gone public, thereby excluding those that have chosen not to. Besides internal motives, companies may attempt to time IPOs at periods of high valuations to raise greater amounts of capital, but this strategy does not directly address the question of why a company decides to go public as equity can be issued in private markets as well (Brau, 2012; Lowry, Michaely and Volkova, 2017). However, as many academics, including Ritter and Welch (2002), have perceived that market timing plays a role in the decision to go public, a subchapter is devoted to a discussion on the market timing theory.

2.1.1 Fund investments

Previous research shows indications that companies go public to finance investments and growth. Brau (2012) highlights that it is challenging to separate financial theories to address this motive due to its multifaceted nature. Empirical results supporting this view usually rely on observing financial metrics, such as return on assets or changes in capital expenditures, which may indicate that companies may indeed finance future investments

with proceeds raised at IPO. To illustrate this, Jain and Kini (1994) explored companies before and post-IPO to detect changes in their operating performance after the IPO. Their findings indicate that, on average, the operating performance, measured by operating return on assets and operating cash flows deflated by total assets, of newly listed companies decreased following an IPO. However, the authors note that the companies with declining operating performance demonstrated a simultaneous high growth in sales and capital expenditures. These findings show indications that companies may use the proceeds to fund investments and expansion, although the declining post-issue operating performance could also indicate that companies aim to time IPOs following a period of exceptionally good performance which cannot be sustained in the long run. Mikkelson, Partch and Shah (1997) also documented declining operating return on assets during the first year after the offering among IPOs of U.S. companies between 1980 to 1983. Their findings indicate that compared to seasoned companies, IPOs tend to have higher scaled operating income before the offering. However, after the IPO, the scaled operating income appeared to be lower compared to that of seasoned companies. Kim and Weisbach (2008) shed light on the motives for public equity offerings by estimating the use of proceeds raised through IPOs and Seasoned Equity Offerings (SEOs). They documented that companies' R&D and capital expenditures increased following an equity offering. One year following IPOs and SEOs, R&D expenditures increased by 18.5 cents and 17.8 cents, respectively, for every marginal dollar raised, implying the usage of raised capital for future investments. Bancel and Mittoo (2009) surveyed CFOs of European companies to identify factors that motivate their decision to go public. Their findings suggest that European CFOs consider that funding for growth is one of the primary advantages of an IPO. However, the surveyed CFOs operated across 12 European countries, revealing a wide array of motivating factors that differ significantly between countries, companies, and legal systems.

2.1.2 Facilitate future acquisitions or sell-out

Another motive for companies to go public is the necessity to establish a market value for their assets to either facilitate acquisitions, sell-out, or transfer of control. According to Zingales (1995), companies go public to facilitate the process of future selling of the company by reducing the existing ownership stakes or by facilitating a future acquisition as the company obtains a market value for a its assets. He also argued that acquirers pay higher price for the shares of a publicly traded company since compared to private companies, public companies have more leverage in negotiations with potential

acquirers due to increased transparency and competition among potential acquirers. Brau and Fawcett (2006) conducted a survey for 336 CFOs of U.S. companies to identify factors that affect the decision to go public. Their findings revealed that according to CFOs, the main objective of going public was to facilitate future acquisitions through a creation of public shares. When company's shares are traded publicly, the company can opt to pay for acquisitions with its shares instead of cash.

Early investors, such as VCs, can employ IPO as an exit strategy, although Black and Gilson (1998) found that in the U.S., selling a portfolio company to a larger company seemed to be the dominant exit strategy for VCs. Improved liquidity of shares facilitates the reduction of ownership and insiders can cash out their ownership either at the IPO by selling secondary shares or by reducing their ownership gradually following an IPO. Mikkelson, Partch and Shah (1997) captured a median reduction of 24.2% in the officers' and directors' ownership stakes immediately after the IPO and found that the stake declined over time. Similarly, Pagano, Panetta and Zingales (1998) found that insiders of 14% of Italian IPOs in their sample sold their controlling stake three years preceding the IPO, indicating that insiders may be motivated to conduct an IPO to transfer the controlling stake. However, due to the three-year examination period, it cannot be confirmed that the ownership reduction strategy would have been decided already at the time of an IPO.

2.1.3 Market timing

As discussed earlier, market timing does not directly explain why companies go public but may provide insights into why companies issue equity. Ritter and Welch (2002) concluded that the decision to go public is primarily motivated by internal factors although the timing of the offering may be influenced by market conditions. Pagano, Panetta and Zingales (1998) examined 66 IPOs in the Italian market and the factors associated with the decision to go public. According to their findings, the primary determinant influencing positively on the probability of going public was the market-to-book ratio of companies operating within the same industry. Lowry, Michaely and Volkova (2017) point out that the interpretation of this result is not straightforward as the positive association may reflect two things. First, it may indicate that companies in investment-intensive industries, are more inclined to go public. Alternatively, it may indicate that companies that enter public markets are operating in overvalued industries. This means that companies attempt to optimise the timing of an IPO to benefit from mispricing, which was found to be the primary driver of deciding to go public, as the

companies' investment and profitability decreased following the issuance. Kim and Weisbach (2008) suggest that companies may issue equity to benefit from high valuations. Namely, they found that companies with a high market-to-book ratio were more likely to hold as cash larger proportions of the capital that is raised through an IPO or a SEO. This indicates that at the time of the offering, there was not an immediate need for additional capital to be spent to finance investments. In turn, companies with low valuations used that cash for investments. Furthermore, their findings showed that companies with a high market-to-book value typically sold larger proportions of secondary shares in a SEO, which could indicate that insiders of companies with a high market-to-book ratio aim benefit from high valuations.

2.2 Advantages and disadvantages of going public

An IPO is a significant event in the lifecycle of a company as it provides an opportunity to raise capital from a diverse pool of investors. Public companies enjoy improved liquidity and they can usually get access to larger amounts of capital than private companies. A publicly listed company can raise capital on more favorable terms due to improved liquidity of the stock, whereas a privately owned company must compensate investors for the lack of liquidity, making external funding more expensive. Often at the time of an IPO, companies issue new primary shares while the existing shareholders also have the opportunity to reduce their ownership by selling their existing holdings, referred to as secondary shares (Berk and DeMarzo, 2024). Thus, an IPO always leads to a change in the ownership structure, either through a transition of ownership through selling secondary shares or a reduction in ownership through the issuance of new primary shares. While public companies enjoy major benefits, an IPO is a strategic decision that should involve a thorough consideration of the company's financial health, growth strategy, and ability to meet the requirements of being a publicly listed entity.

Becoming a public company is, without exception, an expensive and exhaustive process. The company must prepare for the increasing reporting requirements set by the stock exchange and pay one-time and continuous fees for listing. Furthermore, following the listing, shareholders and the market must be regularly and timely informed about the operating and financial performance of the company which calls for ongoing additional resources. The reported information is available to all market participants, influencing the competitive landscape in which the company operates. Ritter (1998) categorises the costs associated with an IPO into indirect and direct costs. Legal, auditing, and underwriting fees are classified as direct costs whereas the indirect costs occur from

underpricing the offering and the usage of management's resources, such as time and effort, that are allocated to the execution of the offering. Stock exchanges set prerequisites for listing and ongoing requirements for companies to maintain their existence in the stock exchange. These standards aim to ensure credibility of companies and reduce the information asymmetry between market participants.

2.3 The IPO process

The IPO process varies slightly from one country to another due to differences in regulatory frameworks, market conditions, stock exchanges, and investor preferences. As this study focuses on the U.S. market, the following discussion on the IPO process is given from the U.S. perspective. However, according to Geddes (2002, p.44), regardless of the offering type, its purpose, or geographical area, all successful equity offerings follow a similar structure. He divides the IPO process into five steps: (1) assessment of IPO-readiness and selection of underwriter(s), (2) structuring of the offering, (3) preparation of relevant documentation for investors and regulators (4) marketing, pricing, and allocation (5) listing. These steps are discussed further in this subchapter.

When a company decides to go public, its management structure, financial position, industry dynamics, competitive landscape, and valuation become under scrutiny. To begin with, the competence and profile of the management team play a vital role in successfully implementing the business strategy. The company's management acts as its figurehead when obtaining financing from public markets. After reviewing that a company has a management team with sufficient competence, its historical financial performance becomes of interest. However, even more important are the projected earnings and the potential for growth to become a profitable company accompanied by high cash flows. A company will also be assessed based on its market share and potential to gain a significant foothold in the specific industry. Finally, the shares of the company are valued on an appropriate level through differing valuation techniques (Geddes, 2002).

After the decision to go public is made internally, the company selects at least one underwriter, i.e. an investment bank, to manage and structure the offering. Often, especially in large offerings, a group of underwriters, also known as a syndicate, manages the deal. According to Lowry, Michaely and Volkova (2017), in the 21st century, the average number of underwriters has been 6. The selection of the underwriters, also known as a "bake-off", is usually based on the potential underwriter's reputation and

experience, relationships with potential investors, as well as understanding of the business within a specific industry (Lowry, Michaely and Volkova, 2017). An underwriter assesses the company based on the fundamental factors discussed in the previous paragraph that indicate its IPO readiness. To maintain a solid reputation as an IPO manager, an underwriter may choose not to facilitate an IPO for a company with bad reputation, weak financial position or management team, or a poor business strategy. The responsibilities of the underwriter range from assisting in valuation, regulatory compliance, and preparation of marketing materials for the IPO (Geddes, 2002).

Following the underwriter selection, the investment bank begins to plan the execution of the offering. In this phase, the share type, stock exchange, corporate structure, timing, and mechanisms of the offering will be defined (Geddes, 2002). A firm commitment is the most common method for executing an offering. In this approach, the underwriter buys all the shares offered at a price below the offer price and pledges to sell those to investors at the offer price. The gap between the purchase price and the offering price is referred to as the gross spread, which commonly accounts for 7% of the gross proceeds (Lowry, Michaely and Volkova, 2017). Best-efforts IPO refers to an agreement in which the underwriter commits to try to sell the offering at the best possible price. These types of agreements are more common among small offerings and the risk of the IPO being called off is higher, especially in a case when all the shares are not sold. A third type of offering is an auctioned IPO, in which the shares are directly sold to the public. During a pre-determined period, investors can bid for the number of shares and the price that they are ready to pay for the shares. The offering price is then determined to be the highest price that the number of shares offered and the number of bids at or above that price are equal (Berk and DeMarzo, 2024).

The document requirements are dependent on the structure of the offering and the selected listing venue. In the U.S., all IPO companies must prepare a legal document, called a registration statement, which provides financial and other relevant information regarding the offering and the company to investors. Underwriters assist in preparing the filings and the documentation must be reviewed and approved by the Securities and Exchange Commission (SEC). When disclosure requirements set by the SEC are fulfilled, a company in co-operation with underwriters, prepares a final prospectus which includes the number of shares offered and the offer price (SEC, 2024; Berk and DeMarzo, 2024). During the preparation of the prospectus, underwriters and lawyers conduct due diligence on the company's compliance related to its commercial, financial, and legal

position. The main purpose of due diligence is to mitigate the liability risk of company's executives and intermediaries involved in the transaction. If due diligence uncovers concerning issues, those are reported in the prospectus. The offer price is often determined from a price range which is obtained through varying valuation methods and surveys on investor demand. To advertise the offering and obtain feedback on the offering's pricing from the largest investors, including brokerage firms and institutional investors, who express an interest in purchasing a portion of the shares issued, the underwriters and senior management go on a 'roadshow' to market the offering across the country and, in the case of an international offering, across several countries (Lowry, Michaely and Volkova, 2017; Berk and DeMarzo, 2024).

As a last step before going public, the final price for the issue is determined. Book-building refers to adjusting of the offer price to incorporate the largest investors' insights into the pricing. To reduce the probability of an offering being withdrawn owing to poor demand and to lower the underwriters' risk of suffering losses, the final offer price is frequently set rather low than high. Book-building method is the most typical way to set the price for the offer in the U.S. but other techniques, including the fixed price method and auctioning, exist. In the last step of the IPO process, the company becomes listed on a stock exchange and its shares can be traded publicly (Geddes, 2002).

2.4 Delisting

The opposite event to an IPO is delisting which refers to voluntary or involuntary removal of a stock from public trading on a stock exchange. A company may get, usually voluntarily, delisted from a stock exchange due to merger, acquisition, or privatisation. In practice, companies can self-initiate the delisting process by requesting a removal from a stock exchange. In contrast, the worst performers end up being involuntarily delisted from a stock exchange due to negative reasons, generally related to weak financial performance or inability to meet the listing requirements set by the stock exchange. In this thesis, involuntary delistings include issues that transfer to Over-the-Counter (OTC) trading. Delistings due to negative reasons are often initiated by the stock exchange that the stock is listed on.

2.4.1 Compliance requirements

To maintain an active status on a stock exchange, the company must comply with reporting requirements set by SEC, and continued listing standards set by the specific stock exchange that the company is listed on. These standards are established to

maintain a high level of quality on the listing venue and to enhance the credibility of publicly traded companies. The continued listing standards vary by stock exchange and security type. Regarding the common-stock type of securities, there are often requirements related to the number and market value of shares held by the public, a minimum price of a share and trading volumes, annual listing fees, and corporate governance practices. The two major stock exchanges in the U.S. are NYSE and Nasdaq. As a reference, NYSE requires that the company either has a minimum of 400 shareholders, *or* that the minimum number of total shareholders is 1200 and the minimum average last-twelve-months trading volume is 100,000, *or* that the number of publicly held shares is at least 600,000. If these requirements are not fulfilled, NYSE considers initiation of a delisting process (NYSE, 2024, section 802.00). For all common-stock types of securities, Nasdaq requires a minimum of 400 shareholders and a $1 minimum bid price of a share. Furthermore, it is required that companies' securities fulfil all financial and liquidity criteria from at least one of the set of standards related to Equity, Market Value, or Total Assets/Total Revenue (Nasdaq, 2024, p.3).

In addition to financial and liquidity requirements, there are non-financial continued listing standards in both stock exchanges that must be met. Generally, the non-financial requirements are related to disclosure obligations and corporate governance standards. In the U.S., these standards set by stock exchanges are following the Sarbanes-Oxley Act (SOX) of 2002, a federal act that was established in the early 2000s to mandate corporations to provide detailed and transparent public financial disclosures to protect stakeholders from fraudulent reporting (Sarbanes-Oxley Act, 2002).

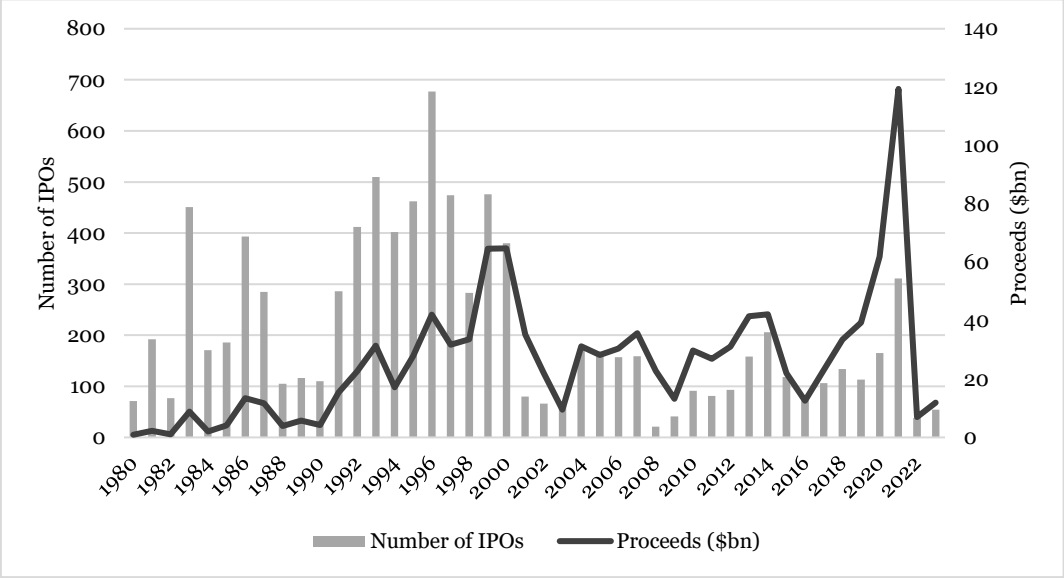
3 IPO MARKET DYNAMICS

To understand the dynamics of the IPO market, it is relevant to explore the characteristics of and prevailing trends of it. Thus, this chapter provides an overview of the U.S. IPO market and its cyclical nature, followed by a brief introduction to the underpricing and the long-run performance of IPOs. Academics globally have discovered that newly listed companies tend to outperform the market shortly after listing, but in the long-run, they demonstrate inferior performance (see summary Loughran, Ritter and Rydqvist, 1994, updated 2024). As this study focuses on the aftermarket survival of IPOs in the long-run, this chapter includes only theories evolved to explain the long-term underperformance of IPOs, leaving out theoretical explanations on the underpricing and short-term performance of IPOs.

3.1 Overview of the U.S. IPO market

Over the decades, the U.S. IPO market has experienced significant fluctuations and fundamental changes mainly driven by shifts in economic conditions, investor sentiment, and technological revolutions. Figure 1 presents the yearly number of IPOs and aggregate proceeds in the U.S. market between 1980 and 2023. The data is collected from Jay Ritter's website. The figure displays the cyclical nature of the IPO market in terms of IPO activity and volume. In addition, there is a clear declining pattern over time in the number of IPOs, while the IPO volume has remained relatively stable. According to Berk and DeMarzo (2024), the size of IPO companies and the popularity of private funding has increased over the years. As companies have access to large amounts of capital from private markets, they can remain private for longer. In addition, they state that early-stage companies get often acquired before exercising the option to go public.

Figure 1 Number of U.S. IPOs and aggregate proceeds 1980-2023 (Jay Ritter's website, 2024)



Clustering in the IPO market is highly driven by economic conditions and investor sentiment. In the late 1990s, speculative internet-based technology companies attracted significant amounts of capital from investors in private and public markets and stock prices of internet-related companies surged rapidly to unsustainable levels. Easy access to capital, coupled with periods of high valuations led to exceptionally high IPO market activity. After the early 2000s, the IPO activity remained relatively low until a record-breaking IPO volume in 2021 which was fueled by low interest rates, investors' appetite for new issues, and slack demand following Covid-19.

The market conditions can also impact IPO market adversely. Namely, the number of IPOs has dropped sharply following economic crises, including the burst of the dot-com bubble in the 2000s and the financial crisis in 2008. From 2022 to 2023, surging inflation, contractionary monetary policy, Russia's invasion of Ukraine, and the backwash of Covid-19 iced the IPO market. During times of uncertainty, investors tend to favor less risky investments which may cause depreciation in the stock market and lead to decreased activity in the IPO market.

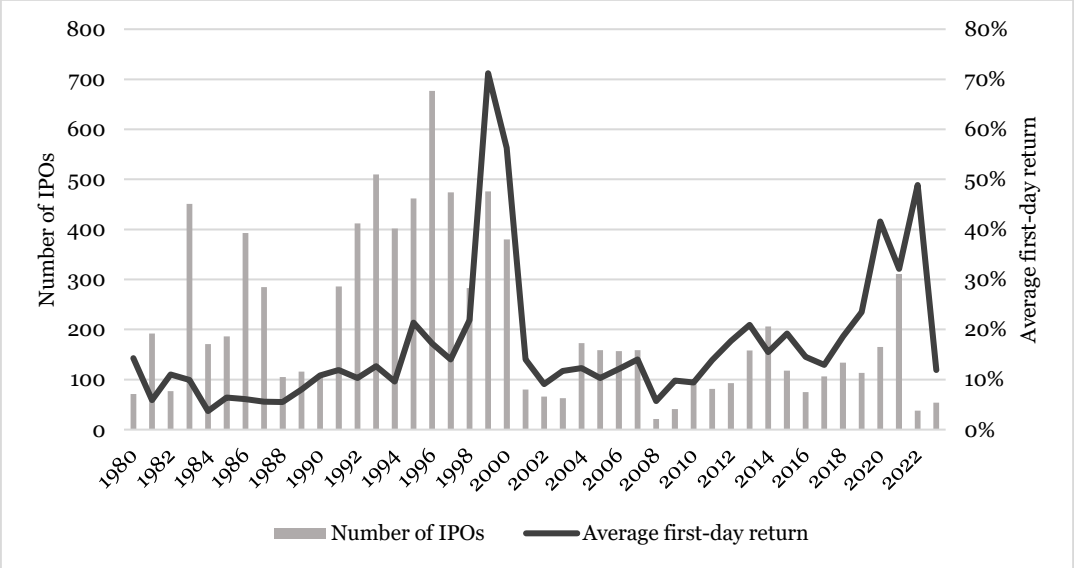
Besides the change in the average size of new listings, WSJ (2018) reported that an expanding group of new lists were making net losses in the U.S. market between 2017 and 2018, reflecting investors' tolerance for loss-making businesses. Although positive earnings can reflect an established market position and good financial health, the proportion of loss-making companies has increased since the dot-com bubble, a period

when many IPOs were unprofitable. The report reveals that the trend is most notably prevalent among newly listed tech companies, where the share of profitable companies pursuing an IPO in 2017 was only 17%. However, these companies were reported to invest heavily in growth which partially explained the reported net losses.

3.2 Underpricing of IPOs

Since early research, including Reilly and Hatfield (1969), Logue (1973) and Ibbotson (1975), academics globally have documented IPO underpricing which refers to a phenomenon in which the offered shares are priced below their market value. Consequently, the first trading day closing price of a share increases above the offer price. Figure 2 displays the yearly number of U.S. IPOs and corresponding average equally-weighted first-day returns between 1980 and 2023. The data is obtained from Jay Ritter's website. The figure shows that the magnitude of underpricing fluctuates significantly from year to year. The average yearly first-day return over the whole period is 7% whereas the maximum and minimum yearly average first-day returns of 71% and 4% were documented in 1999 and 1984, respectively.

Figure 2 Number of U.S. IPOs and average first-day returns 1980-2023 (Jay Ritter's website, 2024)



In financial literature, IPO underpricing remains an unsolved puzzle addressing market inefficiency. Academics have proposed several theories aiming to explain the underlying reasons for abnormally high first-day returns. Ljungqgvist (2007, p.376) divides these theories into four categories: (1) Asymmetric information theories, (2) Institutional theories, (3) Ownership and control theories, and (4) Behavioural theories. As the focus

of this thesis is on the long-term survival of IPOs, these theories are not discussed in detail.

3.3 Hot issue markets

Hot issue markets are characterised as periods when there is excess demand for new issues, and an exceptionally high level of autocorrelated underpricing which is followed by an increase in the IPO volume (Ibbotson and Jaffe, 1975; Ritter, 1998). This pattern suggests that high new issue premiums are a positive signal to companies, prompting them to file offerings more actively. Lowry and Schwert (2002) argue that the root cause for the autocorrelation of new issue premiums is that underwriters fail to fully include all information available, including the appropriate timely valuation insights, into offer prices. On the other hand, Ritter (1998) argues that it is difficult to rationally explain why hot issue markets occur.

The periods of exceptionally high IPO activity have been associated with heated market conditions and overvaluation, most evidently during the internet bubble in the 1990s. During a hot period, the demand for IPOs is higher which allows low-quality companies to complete an IPO and enter the public market (Loughran and Ritter, 2004). Indeed, previous literature has captured higher failure rates among hot issues (Yung, Çolak and Wang, 2008), indicating that the information asymmetry is greater during high activity periods.

3.4 Long-term underperformance of IPOs

Previous studies have systematically documented that IPOs tend to perform poorly in the long run compared to industry and size matched control samples (e.g. Ritter 1991; Ritter and Loughran, 1995). However, authors have noted that the documentation of long-run performance is sensitive to selected methodological approach, geographical area, and examined period, leading occasionally to contradictory results (Loughran, Ritter and Rydqvist, 1994, updated 2024). Although there is much more conflicting evidence on the long-term performance of IPOs than on the underpricing of IPOs, academics have proposed theories to explain the poor long-term aftermarket performance. The following subchapters discuss theories that could potentially explain the weak long-term performance of IPOs. These theories may also provide possible explanations to why IPOs fail in the aftermarket over a long-term tracking period.

3.4.1 The divergence of opinion hypothesis

Miller (1977) proposed a divergence of opinion theory to explain the long-term underperformance of IPOs. According to the theory, in markets, where short selling is restricted, a small group of optimistic investors set the prices for securities. Prior to an IPO, there is a great uncertainty around the fair value of the offering as there is no trading history available, and the amount of financial information is limited compared to seasoned companies. This uncertainty in valuation creates a wide range for the estimated fair value of the stock, optimistic investors valuing the company much higher than pessimistic investors. Optimistic investors are consequently the ones buying the shares at the time of an IPO. Over time, the information asymmetry and valuation uncertainty diminish due to the increasing amount of information available in the market. This leads to a narrowing divergence of opinion between investors, and consequently a corresponding decline in the market price. This theory has been tested by researchers, such as Bradley et al. (2001) who documented that share prices declined dramatically after the expiration of a lockup periods and that the effect was stronger among VC-backed IPOs.

3.4.2 The impresario hypothesis

Academics have proposed that the IPO market is affected by fads which refer to periods when securities are priced irrationally high (Aggarwal and Rivoli, 1990; Shiller, 1990). The impresario hypothesis, also known as the fads hypothesis, suggests that underwriters underprice IPOs to ensure sufficient demand for shares and hype surrounding the offering (Shiller, 1990). Consequently, IPOs experiencing the highest first-day returns should generate the lowest long-term returns as the abnormally high returns are caused by fads (Ritter, 1998).

3.4.3 The windows of opportunity hypothesis

As discussed earlier, IPO activity, volume, and first-day returns appear to be cyclical (see figures 1 and 2). Companies may attempt to time the IPO to benefit from optimistic investor sentiment, leading to a higher number of IPOs in such periods. The windows of opportunity theory suggests that companies aim to time IPOs at periods when IPO volume and valuations are high, consequently leading to low long-term returns as the offerings are subject to over-optimistic valuation at the time of the offering (Ritter, 1998). This hypothesis has also received empirical support from Loughran, Ritter and Rydqvist (1994, updated 2024) and Baker and Wurgler (2002). As discussed in section 2.1.3,

market timing is considered a significant factor affecting the decision to go public because companies can raise more capital during periods when overvaluing of the offering is feasible and the demand for shares is higher.

3.4.4 Earnings management hypothesis

The earnings management hypothesis suggests that companies manage their earnings prior to an IPO to attract investors and create demand for the shares. Earnings management cannot be pursued over long periods, thus leading to weak long-run aftermarket performance of IPOs (Teoh, Welch and Wong, 1998). This hypothesis is closely related to the window dressing hypothesis which suggests that the company's management manipulates financial statements to create an appearance of solid financial performance and health. Before security offerings, managers are tempted to execute window dressing as their compensation and job security may be tied to the company's financial performance. Additionally, by manipulating financial statements, companies may avoid violating contracts with creditors and other stakeholders, avoid regulatory requirements, or obtain regulatory benefits (Healy and Wahlen, 1999).

4 LITERATURE REVIEW

This chapter provides an overview of previous literature that is related to the topic of interest. As stated earlier, this study combines elements from traditional IPO and corporate failure prediction literature. The first subchapter presents findings from previous studies on the IPO failure risk and the survival of IPOs in the aftermarket. The next subchapter presents previous scholarly publications on the aftermarket performance of IPOs, specifically focusing on the long-term underperformance of IPOs as the phenomenon is closely related to the topic of interest. Also, four theories that have evolved in previous literature to explain the long-term underperformance of IPOs are presented. These theories are discussed as they have the potential to explain why IPOs fail in the aftermarket over a long-term tracking period. Lastly, previous literature on corporate failure prediction in non-IPO context is reviewed to gain insights into the potential determinants of failure.

4.1 The survival of IPOs

According to Lowry, Michaely and Volkova (2017), of the companies that went public between 1973 to 2013, 37% delisted from a stock exchange due to acquisition (23%) or poor performance (14%). The frequency of delisting occurrences prompted scholars in the 1990s and early 2000s to examine the survival of IPOs in the aftermarket or the so-called IPO failure risk (e.g. Schultz, 1993; Hensler, Rutherford, and Springer, 1997; Jain and Kini, 1999; Fama and French, 2004; Demers and Joos, 2007; Kooli and Meknassi, 2007). Prior literature has explored the relationship between company-, market-, and offering-specific characteristics and the probability of transitioning to different post-IPO states.

Schultz (1993) carried out one of the first studies on IPO survival, using a sample of 797 U.S. IPOs between 1986 and 1988, including unit and share offerings. He constructed multinomial logit models to estimate the probability of IPO failure one to three years following the offering, based on company and offering specific factors. His findings revealed that one year following the initial offering, companies with high first-day returns were significantly more likely to survive in comparison to failure. In contrast, the probability of failure two and three years after the issuance was negatively related to the offer size, company age, and the underwriter's reputation. This indicates that larger offer size, higher company age and underwriter prestige were associated with survival. In two- and three-year periods, no significant relationship was documented between the probability of failure and initial returns. Additionally, he found that three years following

the IPO, unit offerings which are usually issued by small, young, and risky companies, were more likely to fail compared to common stock offerings.

Hensler, Rutherford, and Springer (1997) studied 741 U.S. IPOs issued between 1974 and 1984 and the determinants of survival by employing an Accelerated Failure Time (AFT) model which enables to examine which characteristics increase and decrease the survival time after issuance. They discovered that the time IPOs survived in the aftermarket increased with the size of the offering, company's age at the offering, level of underpricing, IPO market activity, and percentage of ownership held by insiders. In turn, survival time decreased when market level at the time of the offering (level of S&P 500 common stock index), and the number of risk characteristics identified in the IPO prospectus increased. They also documented that the estimated survival time was affected by industry, survival time increasing if the company operated in the pharmaceutical or optical industry and decreased if the company was classified in the technology, wholesale, restaurant, or airline industry.

By using a sample of 877 newly listed companies between 1977 and 1990, Jain and Kini (1999) estimated multinomial logit models to predict the probability of transitioning to the general post-issuance states 5 years following an IPO. Based on a 5-year post-issuance status, they divided their sample of IPOs into three categories: survivors, those that got acquired, and failures. They integrated several company- and deal-related independent variables into their multinomial logit models to predict the probability of falling into the three post-issuance categories. Their findings suggest that company size, underwriter prestige, pre-IPO operating performance, as measured by operating return on assets and operating cash flows over assets, and R&D intensity within the industry were positively associated with the probability of survival when contrasted to failure. In turn, a risk factor, measured by a standard deviation of post-issuance daily returns, was negatively related to the probability of survival as opposed to failure, meaning that higher risk increased the probability of failure. In addition, they found that company size, R&D intensity within the industry, and the level of industry concentration had a negative relationship with the probability of getting acquired when contrasted to survival. Also, the probability of acquisition as opposed to failure increased with the underwriter's prestige and decreased with the risk factor.

Fama and French (2004) examined 2427 newly listed companies in the U.S. market between 1973 and 2001. Along with surging IPO activity since 1979, they found notable changes in the profitability and total asset growth of IPO companies. According to their

findings, profitability became progressively more left-skewed, indicating that a larger proportion of newly listed companies experienced lower levels of profitability whereas the growth in assets became right-skewed. Simultaneously, they found that the 10-year post-issuance probability to survive declined from 1973 to 1991 from 61.0% cohort to 37.0% cohort. They also documented a 20% 10-year failure rate among 1981-1991 IPOs.

Demers and Joos (2007) examined the survival of 3973 newly listed U.S. companies over a sample period of 1980-2000 by integrating company, issue, and market specific variables into their logistic regression failure prediction model. Their study was developed compared to earlier literature as they included financial accounting information in their models and divided the sample into high-tech and non-tech companies due to fundamental industry-specific differences they captured in the operations, investments in intangible assets, and the level of debt. According to their results, underwriter reputation, offer price, company age, level of debt, SG&A expenditures, and total revenue were statistically significant predictors of IPO failure. Their study also include a section where they estimate the relationship between predicted failure and aftermarket returns.

Kooli and Meknassi (2007) investigated the lifecycle of U.S. IPOs over a period from 1985 to 2005. They utilized multinomial logit and AFT models to investigate which characteristics increased the probability of survival in their sample of 7957 new lists. Their sample was divided into non-survivors, acquired, and non-survived companies. According to their findings, from the selected seven issue and company specific variables, they found that offer size was positively related to the probability of survival, and that an increase in first-day return was associated with a higher probability of failure or getting acquired. They also captured that IPO activity, measured as the quarterly number of IPOs, was positively associated with the probability of acquisition and failure. VC-backing was also documented to be negatively related to the probability of failure as opposed to survival. In a survival analysis, they documented that survival time increased with first-day return and VC-backing but the time-to-delisting was accelerated if a company was classified in the internet sector.

4.1.1 Summary of previous literature

Previous literature on the survival of IPOs is summarised in table 1.

Table 1 Summary of previous research on the survival of IPOs

Authors	Purpose	Time period	Data and Method	Results
Schultz (1993)	Predict the probability of failure contrasted to survival 1-3 years following the offering based on company and issue specific attributes.	1986-1988	Sample of 797 U.S. unit and common stock offerings Binary logit model	1 year following the offering, first-day returns were significantly positively associated with the probability of survival. 2 to 3 years following the offering, offering size, company age, and underwriter ranking were inversely related to the probability of survival. Also, unit offerings which are usually issued by small, risky, and young companies, were less likely to survive than companies issuing common stock.
Hensler, Rutherford, and Springer (1997)	Examine which company and issue specific characteristics increase the survival time after an IPO.	1974-1984	Sample of 741 U.S. IPOs Accelerated Failure Time (AFT) Model	Survival time increased with offering size, company's age at the time of the offering, underpricing, IPO market activity, and the percentage of ownership held by insiders after the offering. Survival time decreased with increase in the prevailing market level, and the number of risk factors identified in the IPO prospectus. In addition, differences in survival times between industries were captured.
Jain and Kini (1999)	Predict the probability of transitioning to post-issuance categories of survived, acquired, and failed five years following IPO by using company and issue specific variables.	1977-1990	Sample of 877 U.S. IPOs Multinomial logit model	Company size, underwriter prestige, pre-IPO operating performance, and industry R&D intensity were positively associated with the probability of survival as opposed to failure. Increase in market risk, measured before an IPO, decreased the probability of survival in contrast to failure. Company size, industry's R&D intensity, and the industry concentration were negatively associated with the probability of getting acquired when contrasted with survival. The probability of acquisition increased with underwriter's prestige and decreased with an increase in the risk factor.
Fama and French (2004)	Examine the changes in characteristics of new lists over time and explore factors associated with the survival of those.	1973-2001	Sample of 2427 U.S. listings Calculation of averages of different factors, observing differences in those over time and comparing those averages to matched seasoned companies.	Along with surging IPO activity since 1980, the profitability of new lists became lower and growth in assets more right-skewed. In addition, increased failure rates over the examined period were captured.

Demers and Joos (2007)	Predict the probability of failure contrasted with survival 1-3 years following the offering based on company, market and issue specific attributes.	1980-2000	Sample of 3973 U.S. IPOs Binary logit model	Significant determinants of failure included underwriter ranking, market hotness (only tech companies), offer price, age, leverage, R&D expenses (only tech companies), SG&A expenses, gross margin (only non-tech companies), accumulated deficit (only non-tech companies), and sales.
Kooli and Meknassi (2007)	Find out the ideal survival profile of IPOs by exploring issue and company specific characteristics and market activity, and their association with the probability of survival, acquisition, and failure 5 years post-issuance.	1985-2005	Sample of 7957 U.S. IPOs Multinomial logit model, AFT model	The probability of survival increased with offer size. First-day returns and IPO activity were associated with an increased probability of failure and acquisition as opposed to survival. VC-backing decreased the probability of failure in contrast to survival. Survival time increased with first-day returns and VC-backing. Survival time decreased if the IPO was in the internet sector.

4.2 Long-term underperformance of IPOs

While new issues experience high first-day returns, previous literature has documented that IPOs tend to perform poorly in the long run compared to seasoned companies. Aggarwal and Rivoli (1990) studied the long-term performance of 1598 IPOs issued in the U.S. market between 1977 and 1987. They captured an average buy-and-hold return of -13.73% over a tracking period of 250 days, assuming that an investor would purchase shares of a new issue at the closing price of the first trading day, thereby excluding the effect of underpricing. Negative 250-day returns were also documented when the shares were purchased at the offer price. The authors speculated that the abnormal aftermarket returns may be caused by the presence of fads, characterised as temporary overvaluations brought on by excessive investor optimism.

Ritter (1991) extended the examined timeframe by studying a three-year aftermarket performance of 1526 IPOs that occurred between 1975 and 1984 in the U.S. market. He found that IPOs performed poorly compared to a set of companies with comparable sizes and industries. The average three-year monthly buy-and-hold return of IPOs was 34.47%, while the return of the control sample was 61.86%, with IPOs underperforming by 27.39%. The underperformance was especially evident among young companies. In accordance with Aggarwal and Rivoli (1990), the underperformance was explained by the presence of fads in the IPO market. In addition, the author concluded that bad luck and mismeasured risks could partially explain the long-term underperformance.

Loughran and Ritter (1995) conducted long-term performance research on the U.S. IPOs and SEOs and they found that on average, equity issuers tended to significantly underperform their non-issuing peers five years after the offering. The average annual return of newly listed companies was 5% and for SEOs 7%, while the matched companies generated average annual returns of 12% and 15%, respectively. The authors mainly explained weak long-term performance by arguing that the offerings were timed during periods of high valuations. Evidence of long-term underperformance has been documented in several other studies globally, including Levis' (1993) research in the U.K. IPO market and Keloharju's (1993) research in the Finnish IPO market.

4.3 Bankruptcy prediction

Exploring literature on bankruptcy prediction can provide valuable insights and context for understanding the financial health and long-term prospects of newly listed companies. Literature on bankruptcy prediction has evolved since the 1930s (see Bellovary, Giacomino and Akers (2007) for a summary), and early research focused on the identification of significant financial ratios in predicting company failure. Among the first ones, Smith and Winakor (1935) studied the financial ratios of 183 failed companies to shed light on the determinants of company failure. They documented that the financial ratios of failed companies differed significantly from those that survived and their findings suggested that Working Capital to Total Assets and Current Assets to Total Assets, as measures of a company's liquidity and operational efficiency, were the most influential ratios in predicting failure. Later, Merwin (1942) studied small manufacturing companies by comparing failed companies to successful ones. According to his analysis, companies that eventually failed exhibited signs of failure even five years before their collapse. In addition, he documented that financial ratios of Working Capital to Total Assets, the Current Ratio, and Net Worth to Total Debt, describing companies' liquidity, operational efficiency, and solvency, were significant predictors of corporate failure. These prominent early studies laid the foundation for following developed literature, including famous papers of Beaver (1966), Altman (1968), and Ohlson (1980).

Beaver (1966) expanded the literature by comparing the mean of 30 financial ratios of 79 failed and 79 successful companies that represented a variety of industries. By testing the predictive ability of the ratios, he found that several financial ratios had over 90% accuracy in explaining failure one year before the bankruptcy. Furthermore, his suggestion to use multivariate models in further research prompted several academics to examine the topic further. In a groundbreaking piece of research, Altman (1968)

developed a five-factor multivariate discriminant analysis (MDA) model to predict the failure of manufacturing companies. He compared 33 failed companies to an industry and size matched sample of 33 viable companies. From 22 financial ratios, five were selected for the model to function as a measure of a company's liquidity, profitability, leverage, solvency, and activity. This five-factor model, also known as *Altman's Z-score*, became a widely utilised method for predicting bankruptcy.

Since the 1970s, binomial statistical techniques, including logit and probit models that consider the probability that the company will fail, have been applied (e.g. Ohlson, 1980; Zmijewski, 1984). The shift to probabilistic predictive models was mainly due to statistical problems related to the MDA (Bellovary, Giacomino and Akers, 2007). In a frequently cited paper, Ohlson (1980) applied a conditional logit model in which he integrated 9 independent variables to predict the probability that a company will fail within a pre-determined period. The sample consisted of 105 bankrupted and 2058 viable industrial companies. He documented that the one-year probability of failure was significantly influenced by company size, leverage, performance, and current liquidity. Zmijewski (1984) addressed the importance of random sample selection. In total, he examined 800 healthy and 40 bankrupted industrial companies from 1972 to 1978 and estimated the probability of failure based on three financial ratios that measured companies' leverage, liquidity, and performance. His findings suggested that profitability and leverage ratios influenced the probability of company failure. Although Ohlson (1980) and Zmijewski (1984) reported high model accuracies of 96.4% and 98.2%, respectively, the accuracy of the models can be argued to be dependent on the sample period, industries, and financial distress in general (Grice and Dugan, 2003).

Previous research on bankruptcy prediction indicates that variables connected to a company's earnings are good predictors of failure. However, in a more recent study, Wysocki (2007) shows that the informativeness of earnings-based variables in IPO failure prediction has declined over the years. Possible explanations for this could be that previous research has documented decreasing informativeness of accounting earnings among U.S. companies over time (Collins, Maydew, and Weiss, 1997; Francis and Schipper, 1999) and that companies may aim to time IPOs at times of high earnings to attract investors.

5 DATA

This section presents in detail the data used to examine the aftermarket survival of IPOs that occurred in the U.S. market between January 1st, 1995 and December 31st, 2018. This chapter includes a description of the data, sampling process, and a description of the post-issuance categories of survived, acquired, and failed. Furthermore, dependent variables and the expected effects of selected independent variables on the probability of falling into different outcome categories are presented. Lastly, descriptive statistics finalise the chapter.

5.1 Data and sampling

The data for this thesis is combined from multiple sources. Due to restrictions on data collection from LSEG Datastream, the initial list of IPOs taken place between January 1st, 1995 and December 31st, 2018 and their Committee on Uniform Securities Identification Procedures (CUSIP) numbers are collected from Jay Ritter's website. The list consists of 7010 IPOs. Next, a corresponding set of new lists is retrieved from LSEG Datastream, comprising of 6616 IPOs. At this point, the sample size decreases due to missing data on LSEG Datastream, although an exhaustive amount of manual work is devoted to eliminating erroneous matches in the dataset as well as collecting all data available. Next, all non-common stock types of offerings are excluded from the sample, including American Depository Receipts (ADRs), closed-end funds, Real Estate Investment Trusts (REITs), spin-offs, rights issues, and unit offerings. In most cases, IPOs of Special Purpose Acquisition Companies (SPACs) fall into the category of unit offerings and thus, are left out of the sample. This results in 4974 IPOs.

Data on company and deal-specific characteristics are mainly collected from LSEG Datastream. In case of missing data points, LSEG data is complemented with data from Jay Ritter's database, Factset, and IPO prospectuses. First trading day closing prices are collected from the Centre for Research in Security Prices (CRSP) database. Data collected from LSEG Datastream includes offer dates and prices, total gross proceeds raised, total number of shares offered, number of secondary shares, and lead underwriters. Due to changes in dollar value over the years, gross proceeds and offer prices denoted in USD are adjusted to 2018 USD. For this purpose, following Lowry, Michaely and Volkova (2017), GDP Implicit Price Deflator data is obtained from the Federal Reserve Economic Data (FRED) website. GDP Implicit Price Deflator captures changes in prices of goods and services broader in an economic area, including capital goods, government services

and exports, as opposed to the Consumer Price Index (CPI) which tracks the changes over time in the prices paid by households for a fixed basket of goods and services.

Of company specific characteristics, The Refinitiv Business Classification (TRBC) industry classifications are collected from LSEG Datastream. Companies' founding years and lead underwriter reputation rankings are collected from Jay Ritter's database. Underwriter reputation ranking is determined based on Jay Ritter's adjusted Carter-Manaster (1990) and Carter, Dark and Singh (1998) prestige rankings which range from 0 (worst) to 9 (best).

Financial accounting data is collected from Compustat. To examine accounting variables and calculate financial ratios, total liabilities (*lt*), total assets (*at*), selling, general and administrative (SG&A) expenses (*xsga*), sales (*sale*), and retained earnings (*re*) of IPO year are collected from Compustat. In addition, R&D expense (*xrd*), and sales (*sale*) one year prior to IPO are collected. The abbreviations in parentheses assign Compustat's variable codes. Companies' financial data one year before the IPO must be available to be included in the sample. A large number (1859) of observations is eliminated from the sample after applying this criterion. However, it is not discovered that the exclusion would affect some specific type of companies and the proportion of companies in each post-IPO category does not change considerably after the reduction.

The post-IPO states and possible delisting dates between January 1st, 1995 and December 31st, 2023 are collected from the CRSP database. The classification to post-IPO categories of (1) survived (2) acquired and (3) failed companies is executed using CRSP delisting codes assigned based on the status of the stock 5 years following the initial offering. In accordance with prior financial literature, survived companies are those that operate independently over the 5-year tracking period and are listed in a stock exchange to which they were originally listed. In CRSP, the corresponding code for survivors is 100. Companies that delisted after the 5-year follow-up period are also classified as survivors. The category of acquired companies includes those that are merged with or acquired by another public company (codes in the 200 range) during the first 5 years following an IPO. Delistings due to transferring to another stock exchange other than Over-The-Counter (codes in the range of 300) and delistings due to privatisation (code 573) are excluded from the sample as those delistings are not necessarily performance-related. The application of this criterion excludes 13 companies from the sample. The category of failed companies comprises of IPOs that are delisted from a stock exchange due to negative reasons, generally related to poor financial performance or inability to fulfil the

continued listing requirements set by the stock exchange. Following Demers and Joos (2007), this category includes CRSP codes in the 400 and 500 range, assigning "liquidations" or "dropped" companies, respectively.

After matching Jay Ritter's list of IPOs with data on LSEG Datastream, the initial sample consists of 6616 IPOs. When non-common stock types of offerings are excluded, the sample size reduces to 4974 IPOs. After collecting company and issue specific data, and confirming that the company is listed in CRSP, 64 IPOs are excluded due to missing datapoints or CRSP identification code. The main reason for exclusion from the final sample is missing accounting data (1859 companies). Table 2 summarises the sampling process.

Table 2 Sampling process

Criteria	Sample size
List of all new lists between 1995-2018 from Jay Ritter's website	7010
Match Jay Ritter's data with LSEG Datastream	-394
Exclude non-common stock type of offerings	-1642
Exclude IPOs due to missing company or deal specific data or missing CRSP codes	-64
Exclude if CRSP delisting code in the 300 range or 573	-13
Exclude due to missing accounting data on Compustat	-1859
Final sample	**=3038**

5.2 Dependent variables: post-IPO state and survival time

As described in the previous subchapter, IPOs are categorized based on their 5-year post-issuance status to (1) survived (2) acquired and (3) failed companies. These categories are treated as dependent variables when examining the probability of transitioning to the post-IPO states. The length of the follow-on period is chosen following previous studies and Merwin (1942) who specifically proposed that companies may signal upcoming failure already 5 years before the event.

It is valid to acknowledge that the category of acquired IPOs consist of companies with a large dispersion of quality. Namely, the category of acquired companies may include either companies that are so good that the acquirer wants to buy their assets to eliminate competition, or companies that experience a notable decline in the stock price preceding the acquisition as Welbourne and Andrews (1996) suggested. Hence, these companies could practically be integrated into categories of survived and failed companies but as the distinction on the company quality is not straightforward and the number of

observations in this category is notable, the category is classified separately. This choice is additionally supported by Fama and French (2004) who found a great dispersion of quality among companies delisted due to merger or acquisition.

When assessing the survival time of IPOs, the dependent variable is the survival time in months. This is the time before the IPO gets acquired or fails. If a company survives until the end of the survival analysis, the time of survival is the time from the IPO date to the last date of the survival analysis (December 31st, 2023).

5.3 Independent variables

This study considers several issue, company, and market variables to determine which factors are significantly associated with the probability of transitioning to the aforementioned outcome categories over a post-IPO period of five years. The following subchapters present the independent variables and relevant literature related to chosen metrics.

5.3.1 Issue specific variables

The selected issue-specific independent variables are offer size, first-day return, offer price, proportion of secondary shares, underwriter prestige, and presence of VC- and PE-backing.

Several studies have captured a higher risk associated with low-capitalization offerings. Stoll and Curley (1970) were among the first ones that identified high price appreciation among small offerings in the short-run and that these offerings exhibited inferior long-run performance compared to larger offerings. Ritter (1991) and Loughran and Ritter (1995) also found that smaller offerings generated high initial market-adjusted returns but performed the worst in the long-run. Similarly, Mikkelson, Partch and Shah (1997) found declining long-run performance among small offerings. Research on the survival of IPOs have document smaller issues having higher long-term failure rates (Schultz, 1993; Jain and Kini, 1999; Kooli and Meknassi, 2007). Based on previous evidence, it is expected that companies with larger offer sizes survive longer and that offer size has a positive effect on the probability to survive. In turn, offer size is expected to have a negative effect on the probability of acquisition and failure. Offer size is measured as natural logarithm of gross proceeds (*ln_proceeds*). To account for changes in dollar value over time, gross proceeds are adjusted with the GDP price deflator.

Previous research has shown that offerings generating high first-day returns demonstrate weak long-term performance one to three years following the offering (Aggarwal and Rivoli, 1990; Ritter, 1991). Schultz (1993) found that higher underpricing was associated with a higher probability of failure one year after an offering. However, the relationship between first-day returns and failure was documented to be insignificant two- and three-years following an IPO. Controversially, Hensler, Rutherford, and Springer's (1997) found that higher underpricing increases the survival time. This finding is consistent with signalling theories, according to which underpricing serves as a signal to investors that the offer is high-quality. By underpricing the IPO, the issuer may be able to sell equity at a higher price at SEO (Allen and Faulhaber 1989; Grinblatt and Hwang, 1989; Welch, 1989). First-day returns are measured as a percentage change between an offer price and first trading day closing price and the variable is winsorized at the 3rd and 97th percentiles to reduce the impact of detected outliers (*return*). The 3rd and 97th percentiles are chosen somewhat arbitrarily, although it is ensured that the majority of the data remains unchanged to maintain reliability in the interpretation of the results. As the evidence of previous research is mixed and the motivation for underpricing remains unclear, it is expected that the relationship between first-day returns and survival or failure can be either positive or negative but is significant. First-day returns are expected to have a positive effect on the probability of acquisition due to the signaling hypothesis.

Logically, the offer price should not impact on the survival of IPOs as it depends on the number of shares offered and it is determined arbitrarily by managers. However, Seguin and Smoller (1997) found that offer price had a significant positive effect on the survival of stocks. Demers and Joos (2007) also documented offer price having a significant negative relationship with IPO failure. Bradley et al. (2006) specifically examined long-run returns of penny stock IPOs by comparing offerings with offer prices equal to or below $5 with other IPOs. Consistently, their findings revealed that penny stocks demonstrated weaker performance as opposed to higher-priced stocks. In accordance with previous studies, the expected relationship between offer price and the probability of failure and acquisition is negative. In turn, it is expected that offer price has a positive effect on the probability of survival. Offer price is calculated as a natural logarithm of offer price and the variable is GDP Implicit Price Deflator adjusted (*ln_offerprice*).

Ritter (1991) and Loughran and Ritter (1995) argued that existing shareholders may be willing to reduce their ownership of the company at the time of an IPO if they believe

that the shares are overvalued. Intuitively, a high proportion of secondary shares could indicate that insiders are willing to cash out their investment and potential investors may interpret this as a lack of growth potential or stability in a company. Jain and Kini (1994) captured a positive association between the post-issuance operating performance and the share of ownership retained by the founding shareholders. Kim and Weisbach (2005) found that companies issuing primary shares exhibited surging cash reserves and increased debt servicing following an IPO, indicating a better financial position. Thus, it is expected that the proportion of secondary shares of the total number of shares has an inverse effect on the probability of survival and a positive effect on the probability of failure. Furthermore, as discussed earlier, for some companies, IPO is the first stage in preparing the company for a sell-out. Therefore, the effect on the probability of acquisition is expected to be positive. The proportion of secondary shares is calculated as number of secondary shares offered divided by the total number of shares offered (*sec_shares*).

The underwriter has a significant role in managing the IPO and completing the offering successfully. In previous literature, scholars have developed varying proxies to examine the influence of the underwriter's reputation on the short- and long-term performance of IPOs. Generally, the proxies are related to deal amount, market share and cumulative proceeds raised. Findings of previous research indicate that first-day returns of IPOs with more prestigious underwriters are lower, implying that there is less valuation uncertainty present at the time of the offering (Carter and Manaster, 1990; Megginson and Weiss, 1991). In addition, previous studies have documented underwriter's prestige being positively related with long-term returns of IPOs. By using the leading underwriter's capital as a proxy for the underwriter's prestige, Michaely and Shaw (1994) document that IPOs managed by prestigious underwriters experienced less underpricing and in the long term, they performed better than IPOs managed by less prestigious underwriters. Carter, Dark and Singh (1998) extended previous literature by using various proxies for underwriter reputation. They found that IPOs with a prestigious underwriter experienced less severe underperformance than other IPOs. Schultz's (1993) and Demers and Joos' (2007) findings indicate that the probability of firm failure has an inverse relationship with the underwriter's prestige. Following Demers and Joos (2007), modified Carter-Manaster (CM) rankings collected from Jay Ritter's website, are used as a proxy to measure the underwriter's prestige (*UW_rank*). It is expected that the underwriter's prestige has a positive effect on the probability of survival and acquisition and a negative effect on the probability of failure.

VC- and PE-backed IPOs refer to those companies that preceding the initial offering were financed by VCs or PE firms. IPO allows VCs and PE firms to cash out all or part of their investment. Brav and Gompers (1997) examined the long-run performance of IPOs and the effect of VC-backing on the performance. Their results revealed that five years after the initial offering, VC-backed IPOs performed significantly better compared to non-backed offerings. Megginson and Weiss' (1991) found that VC involvement in the IPO process attracted high-profile investors to invest in an IPO during a roadshow. Jain and Kini (2000) found that the presence of VC-backing decreases the probability of IPO failure and increases the survival time. Similarly, Kooli and Meknassi (2007) discovered that VC involvement increased the probability of survival as well as acquisition when contrasted to the probability of failure. Based on previous literature, the expected outcome is that the presence of VC- or PE-backing decreases the probability of failure. Also, these firms are expected to be viewed as potential acquisition targets so the expected effect on the probability of acquisition is positive. A dummy variable gets a value of 1 if the offering is VC-backed and is otherwise 0 (*VC_dummy*). Correspondingly, a dummy variable gets a value of 1 if the offering is PE-backed, otherwise 0 (*PE_dummy*).

5.3.2 Company specific variables

The selected company specific independent variables are company age, technology industry, leverage, accumulated deficit, R&D expenses, SG&A expenses, sales, and net income.

Ritter (1991) reported that the underperformance of IPOs over long term was especially evident among young growth-oriented companies. Consistently, company age at the time of an IPO has been documented to have a positive effect on the probability of survival as well as on the length of the survival time (e.g. Hensler, Rutherford, and Springer, 1997; Demers and Joos 2007). Older companies are considered more stable compared to young companies and they can provide investors with more information on their historical performance, thus leaving less room for speculations regarding the true value of the offering and their ability to survive through varying economic conditions (Demers and Joos, 2007). Thus, it is expected that company age has a positive effect on the probability of survival and an inverse effect on the probability of acquisition and failure. Company age at the time of the offering is measured as a natural logarithm of one plus company age (*ln_age*). The number one is added to the value to ensure that the logarithm is defined for all non-negative values of age on the data set, including zeros.

Ritter (1991) documented differences in the long-run performance of IPOs by industry. He found that, on average, IPOs of financial institutions, airlines and pharmaceutical companies outperformed a set of seasoned companies matched by size and industry. In turn, oil and gas IPOs performed the worst. In a study on the survival of IPOs, Hensler, Rutherford, and Springer (1997) found that survival time decreased if the company operated in the computer and data, wholesale, restaurant, or airline industry and increased if the company was classified in the optical or pharmaceuticals industry. In addition, Demers and Joos (2007) created separate samples for high-tech companies and non-tech companies, identifying industry-related differences. Over the study period of this thesis, a substantial proportion of companies are in the technology industry (see table 9). Especially during the dot-com bubble, a large proportion of technology companies went public and ended up failing in the aftermarket. Hence, it is expected that tech industry classification has a negative effect on the probability of survival and a positive relationship with acquisition and failure. A dummy variable gets a value of 1 if an IPO is classified in technology industry and otherwise 0 (*tech*).

As discussed in the literature review, in non-IPO settings, accounting-based metrics have been commonly integrated into corporate failure prediction models as they provide valuable insights on companies' operating financial performance. In traditional failure prediction models, different ratios measuring, for example, company's leverage, profitability, and liquidity have been applied. Demers and Joos (2007) include a range of accounting-based variables in their IPO failure prediction model and a selected set of these variables are integrated into the models of this study, too.

In studies on general corporate failure, leverage has been an important determinant of failure (e.g. Altman, 1968; Ohlson, 1980; Zmijewski, 1984). In the context of IPO survival, Demers and Joos (2007) also documented a positive relationship between leverage and the probability of failure. Different measures of leverage may provide insights into a company's financial health and indicate its prospects of survival. Financially distressed companies with high levels of leverage could also be considered easier targets due to a lack of bargaining power in price negotiations of M&A transactions. Leverage is calculated as total liabilities divided by total assets at IPO year (*leverage*). It is expected that leverage has a positive effect on failure and acquisition and a negative effect on the probability of survival.

R&D investments can serve as a proxy of the aim for technological advancements, implementation of product differentiation strategy, and unlocked opportunities in a

specific area of business. Demers and Joos (2007) documented that pre-IPO R&D expenses reduce the probability of failure but the impact was significant only among high-tech companies. It is expected that R&D expenses have a positive effect on the probability of survival and acquisition as companies are expected to have more growth opportunities. In turn, the expected effect on the probability of failure is negative. R&D expenses are measured as a natural logarithm of one plus R&D expenses one year before IPO (*ln_rd*).

Some companies do not generate sales before they start trading in a public market, which could indicate risk associated with the business. Although several companies with high grow potential experience net losses at the time of IPO, the absence of sustainable revenue streams could be a sign of the immatureness of a company (WSJ, 2018). In accordance with Demers and Joos (2007), it can be argued that companies with higher revenues are more likely to gain a foothold in the market and are considered less likely to fail. Also, sales can serve as a proxy for company size, indicating that companies with high sales have a more stable position in the market and are less likely to fail. High revenues bring flexibility to cost coverage and reduce the risk of discontinuation of the business. Thus, sales are expected to have a negative effect on the probability of failure and acquisition. Sales are measured as a natural logarithm of one plus sales one year prior to IPO (*ln_sales*).

SG&A expenses include operational expenses, such as marketing and advertising costs, which are not directly related to the production of goods and services. Demers and Joos (2007) argue that SG&A expenses may provide insights into company's ability to control costs associated with its operations or measure a company's investments in intangible assets. Their findings reveal that SG&A expenses are positively related to the probability of failure, implying that the variable is more strongly related to inefficient cost management rather than investments in intangible assets. It is expected that SG&A expenses have a positive effect on the probability of failure and acquisition and a negative effect on the probability of survival. SG&A expenses are measured as a natural logarithm of one plus SG&A expenses at IPO year (*ln_sga*).

Net income dummy gets a value of 1 if company's earnings are negative at IPO year, otherwise 0 (*NI_dummy*). It is expected that companies with negative earnings are less likely to survive, although WSJ (2018) reported that several IPOs that could be profitable are reporting net losses due to massive investments in growth. Growth-oriented

companies often pose more risk but could also be viewed as fruitful acquisitions. Thus, the expected effect of *NI_dummy* on the probability of failure and acquisition is positive.

Negative retained earnings, called an accumulated deficit, refer to an inability to cover net losses occurred previously. Retained earnings can be reinvested in business to fuel growth and expansion. Thus, the accumulated deficit may raise concerns about the company's financial health, especially as it indicates reoccurrence of net losses. In accordance with Demers and Joos (2007), accumulated deficit is defined as being 0 if no accumulated deficit is reported, otherwise as a negative natural logarithm of the absolute value of accumulated deficit (*accumdeficit*). The expected effect of accumulated deficit on failure and acquisition (survival) is negative (positive).

5.3.3 Market heat

Market heat can be measured through varying proxies. In accordance with Yung, Çolak and Wang (2008), each IPO is classified as (1) hot (2) normal or (3) cold issue based on the moving average MA(4) of the number of IPOs at the specific quarter and three previous quarters compared to the historical average of the quarterly number of IPOs. If MA(4) is 50% above (below) the historical average, the issue is categorised as a hot (cold) issue. The observations that do not fall into either hot or cold categories are classified as neutral issues. The heat variable is categorical and the neutral category is captured by intercept, leaving *hot* and *cold* categories for further analysis. Monthly data on the number of IPOs between 1960 to 2018 is collected from Jay Ritter's website. By calculating the moving average of IPOs in a specific quarter, the seasonality effect can be reduced. Seasonality effect refers to systematic differences in the number of IPOs occurring by quarter. In the sample, the number of IPOs occurring in the first quarter is 7% lower than the number of IPOs occurring in the second and fourth quarters. It is expected that hot market conditions decrease the probability of survival and increase the probability of failure and acquisition, whereas cold market conditions are expected to have the opposite effects.

5.3.4 Control variables

Control variables can be used to account for potential factors that may influence the relationship between independent variables and the dependent variable. To control for time and industry effects, year (*year*) and industry (*industry*) dummies are integrated into the models. Each newly listed company is classified based on The Refinitiv Business Classification (TRBC) classification system. A dummy variable gets a value of 1 if the

company belongs to a specific industry (other than technology, see description of *tech* variable above) and otherwise 0. As the number of IPOs fluctuates every year and prevailing economic conditions differ, year dummies are indicated based on the IPO year to control for time specific effects.

5.4 Summary of variables

Table 3 shows a summary of all variables, their descriptions, definitions and the expected signs of effects on the probability of survival, acquisition, and failure.

Table 3 Variables and definitions

Variable	Description	Definition	Sign of expected effect		
Dependent variables			**Survival**	**Acquisition**	**Failure**
IPO_state	5-year post-issuance status	Survived, acquired, failed			
survival_time	Survival time	Survival time in months before IPO gets acquired or fails			
Issue specific variables					
ln_proceeds	Issue size, million USD	ln(total gross proceeds) (GDP Implicit Price Deflator adjusted)	+	-	-
return	First trading day return (underpricing)	(First trading day closing price – Offering price) / Offering price x 100, winsorized at the 3rd and 97th percentiles	+/-	+	+/-
sec_shares	Proportion of secondary shares	Number of secondary shares offered / Total number of shares offered	-	+	+
UW_rank	Underwriter ranking	Reputation ranking of the main underwriter ranging from 0 (worst) to 9 (best), data obtained from Jay Ritter's website	+	+	-
ln_offerprice	Offer price	ln(offer price) (GDP Implicit Price Deflator adjusted)	+	-	-
VC_dummy	Offer VC-backed	Dummy variable, 1=VC-backed, otherwise 0	+	+	-
PE_dummy	Offer PE-backed	Dummy variable, 1=PE-backed, otherwise 0	+	+	-
Company specific variables					
ln_age	Company age at the time of an IPO	ln(1+company age)	+	-	-
tech	Technology industry	Dummy variable, 1=technology industry, otherwise 0	-	+	+
leverage	Leverage at IPO year	Total Liabilities / Total Assets	-	+	+
ln_sales	Pre-IPO sales	Natural logarithm of one plus sales one year prior to IPO	+	-	-

		ln(1+sales)			
NI_dummy	Net income (loss) at IPO year	Dummy variable, 1=net loss, 0 otherwise	-	+	+
accumdeficit	Accumulated deficit at IPO year	For companies with accumulated deficit at the IPO year -ln(absolute value of retained earnings if negative), otherwise 0	+	-	-
ln_rd	Pre-IPO R&D expenses	Natural logarithm of one plus R&D expenses one year before IPO ln(1+R&D expenses)	+	+	-
ln_sga	Selling, general and administrative (SG&A) expenses at IPO year	Natural logarithm of one plus SG&A expenses at IPO year ln(1+SG&A expenses)	-	+	+
Market variable					
heat	Market heat at the time of the offering (hot, neutral, or cold issue)	Moving average MA(4) of the number of IPOs in current and three previous quarters / historic average number of IPOs in a specific quarter Data on the quarterly number of IPOs starting from 1960 is retrieved from Jay Ritter's website. The quarter is classified as hot (cold) if the moving average is 50% higher (lower) than the historical average, otherwise neutral	Cold: + Hot: -	Cold: - Hot: +	Cold: - Hot: +
Control variables					
year	IPO year	Categorical variable, 1=IPO year, otherwise 0.			
industry	Industry	Industry classification based on The Refinitiv Business Classification (TRBC), categorical variable, 1=belongs to a specific industry (other than technology, see *tech* variable above) group, otherwise=0.			

5.5 Descriptive statistics

This section presents the descriptive statistics of the data. First, figure 3 presents the distribution of delistings due to both acquisition and failure. The figure includes all delistings, despite delistings >5 years following the IPO (grey bars) are classified as survivors in the study. Year 1 includes delistings that occurred ≤1 year after listing, year 2 those that delisted >1 and ≤2 years after an IPO, and year 3 those that delisted >2 and ≤3 years after an IPO, and so on. Thus, years 1-5 on the x-axis (green bars) assign the proportion of delistings that occurred 0-5 years after an IPO. The figure shows that 45% of all delistings are classified as acquisitions or failures and the remaining 55% as survivors since delisting occurs after the tracking period of 5 years. The figure also shows

that the frequency of delistings is the highest 3 years following the initial offering (14%) and that 58 (2%) companies got acquired or failed during the first year after the offering. Starting from year 3 following the listing, the number of yearly delistings starts to diminish.

Figure 3 Distribution of delistings across the total sample

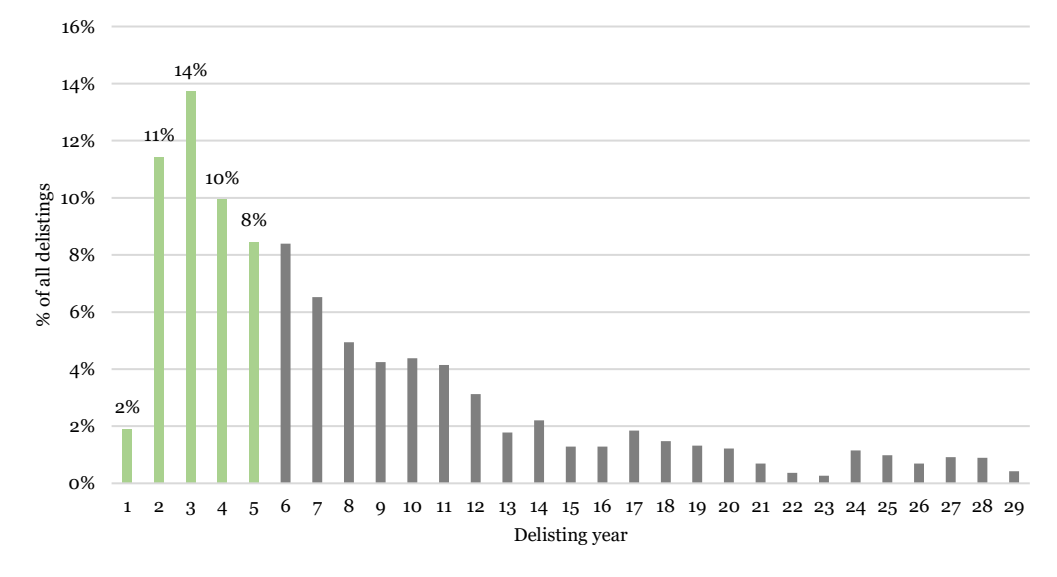


Table 4 presents the yearly number of IPOs. The table shows the number of companies acquired and failed as well as the proportion of IPOs that got acquired or failed in a specific year. From the total sample of 3038 IPOs, 1657 (55%) companies fall into the category of survivors, 980 (32%) to acquired, and 401 (13%) to failures. A significant proportion of delistings due to acquisition (65%) and failure (81%) are covered by IPOs that occurred prior to 2001.

Table 4 Number of IPOs by year

Year	Number of IPOs	Number of Acquired	Number of Failed	% of Acquired	% of Failed
1995	279	122	34	12.45	8.48
1996	431	179	81	18.27	20.20
1997	306	116	67	11.84	16.71
1998	190	49	43	5.00	10.72
1999	282	107	65	10.92	16.21
2000	211	66	34	6.73	8.48
2001	12	2	1	0.20	0.25
2002	18	5	1	0.51	0.25
2003	52	18	6	1.84	1.50
2004	133	44	7	4.49	1.75
2005	105	25	7	2.55	1.75
2006	119	31	10	3.16	2.49
2007	118	32	8	3.27	2.00
2008	13	2	1	0.20	0.25
2009	32	9	3	0.92	0.75
2010	56	9	5	0.92	1.25
2011	58	12	2	1.22	0.50
2012	78	23	5	2.35	1.25
2013	117	37	5	3.78	1.25
2014	127	33	5	3.37	1.25
2015	78	22	4	2.24	1.00
2016	60	11	0	1.12	0.00
2017	77	13	2	1.33	0.50
2018	86	13	5	1.33	1.25
Total	**3038**	**980**	**401**	**100.00**	**100.00**

Table 5 presents the sample categorised according to CRSP codes and presents detailed descriptions of reasons for delisting. Codes 231 (merged, shareholders receive common stock or ADRs), 233 (merged, shareholders receive cash payments), and 241 (merged, shareholders receive common stock and cash) cover the largest proportions of acquired companies whereas codes 552 (stock price fell below acceptable level), 561 (insufficient float or assets), and 574 (bankruptcy, declared insolvent) cover the largest shares of failures.

Table 5 Sample grouped by CRSP delisting codes

Category	CRSP Code	Number of companies	% of total sample	Description
Survived	100	1657	54.54	Issue trading actively
Acquired	231	345	11.36	When merged, shareholders primarily receive common stock or ADRs
Acquired	232	1	0.03	When merged, shareholders primarily receive common stock or ADRs.
Acquired	233	538	17.71	When merged, shareholders receive cash payments.
Acquired	234	1	0.03	When merged, shareholders primarily receive preferred stock, bundled units, warrants, or rights, or debentures, or notes, or bundled units.

Acquired	241	81	2.67	When merged, shareholders primarily receive common stock and cash.
Acquired	242	8	0.26	When merged, shareholders primarily receive common stock and preferred stock or warrants or rights or debentures or notes.
Acquired	243	1	0.03	When merged, shareholders primarily receive common stock.
Acquired	244	1	0.03	When merged, shareholders primarily receive common stock or ADR, and cash and preferred stock or warrants or rights or debentures or notes.
Acquired	251	1	0.03	When merged, shareholders primarily receive common stock or ADRs and cash.
Acquired	261	3	0.10	When merged, shareholders primarily receive cash and preferred stock, or warrants, or rights, or debentures, or notes.
Failure	450	3	0.10	Issue liquidated, final distribution verified, issue closed to further research.
Failure	470	1	0.03	Issue liquidated, no final distribution is verified, issue pending further research.
Failure	490	1	0.03	Issue liquidated, no distributions are to be paid, issue closed to further research.
Failure	520	6	0.20	Issue stopped trading current exchange - trading Over-the-Counter (OTC).
Failure	551	2	0.07	Delisted by current exchange - insufficient number of shareholders.
Failure	552	83	2.73	Delisted by current exchange - price fell below acceptable level.
Failure	560	31	1.02	Delisted by current exchange - insufficient capital, surplus, and/or equity.
Failure	561	64	2.11	Delisted by current exchange - insufficient (or non-compliance with rules of) float or assets.
Failure	570	27	0.89	Delisted by current exchange - company request (no reason given).
Failure	574	56	1.84	Delisted by current exchange - bankruptcy, declared insolvent.
Failure	575	1	0.03	Delisted by current exchange - company request, offer rescinded, issue withdrawn by underwriter.
Failure	580	47	1.55	Delisted by current exchange - delinquent in filing, non-payment of fees
Failure	581	1	0.03	Delisted by current exchange - failure to register under 12G of Securities Exchange Act.
Failure	582	11	0.36	Delisted by current exchange - failure to meet exception or equity requirements.
Failure	583	2	0.07	Delisted by current exchange - denied temporary exception requirement.
Failure	584	47	1.55	Delisted by current exchange - does not meet exchange's financial guidelines for continued listing.
Failure	585	15	0.49	Delisted by current exchange - protection of investors and the public interest.
Failure	587	1	0.03	Delisted by current exchange - corporate governance violation.
Failure	591	2	0.07	Delisted by current exchange - delist required by Securities Exchange Commission (SEC).
Total		**3038**	**100**	

Table 6 presents descriptive statistics of continuous variables of the total sample. Due to differing statistical properties, indicator variables are not included. The table shows

mean, median, standard deviation, kurtosis, skewness, minimum, and maximum values. Mean, median, minimum, and maximum values of first-day returns (*return*) and the proportion of secondary shares (*sec_shares*) are transformed into percentages for a meaningful interpretation. From the viewpoint of statistical efficiency, normally distributed data is desirable. A variable is normally distributed when skewness is equal to 0 and kurtosis is equal to 3. From continuous variables, *return* is winsorised at the 3rd and 97th percentiles to reduce the right-skewness of the variable. Furthermore, several log-transformations are executed due to high skewness (see table 2). The skewness of *sec_shares* 2.28 and *leverage* 1.91 deviate most from 0 but this is considered acceptable as financial data is rarely normally distributed.

On the first row, the mean (median) survival time is 91.19 (66.08) months, which is equivalent to approximately 7.6 (5.5) years. The minimum survival time is only 3.72 months, whereas the maximum survival time is 347.38 (28.9) months (years), meaning that some company in the sample has remained listed for nearly the entire study period. *ln_proceeds* are reported on a logarithmic scale, minimum proceeds of 0.51 being equivalent to proceeds of approximately $1.67 million and maximum proceeds of 10.04 being equivalent to approximately $23 billion. The average (median) first-day return of 21.56% (11.74%) demonstrates that the widely documented phenomenon of IPO underpricing is prevalent in the U.S. market over the examined period. It is also interesting that the mean of 7.75 and median of 8.5 of underwriter ranking (*UW_rank*) are quite high as the maximum ranking is 9. On a logarithmic scale, the mean company age is 2.42 which is equivalent to approximately 11.25 years. Minimum *ln_age* of 0 indicates that some company have gone public in less than a year since the establishment of the company. In turn, maximum company *ln_age* of 5.17 is equivalent to approximately 177 years.

Table 6 Descriptive statistics of continuous variables

Variable	Mean	Median	St Dev	Kurtosis	Skewness	Min	Max	N
survival_time	91.19	66.08	76.42	1.40	1.40	3.72	347.38	3038
ln_proceeds	4.61	4.56	1.10	1.11	0.36	0.51	10.04	3038
UW_rank	7.75	8.50	1.84	2.80	-1.87	1.00	9.00	3038
ln_offerprice	2.84	2.87	0.41	1.68	-0.18	1.22	5.91	3038
sec_shares	12.19 %	0.00 %	0.23	4.87	2.28	0 %	100 %	3038
return	21.56 %	11.74 %	0.30	3.29	1.86	-10.55 %	124.95 %	3038
ln_age	2.42	2.30	0.95	0.12	0.35	0.00	5.17	3038
leverage	0.43	0.36	0.31	9.74	1.91	0.00	3.41	3038
ln_sales	3.79	3.79	2.07	-0.25	0.13	0.00	10.33	3038
ln_rd	1.03	0.22	1.29	0.57	1.09	0.00	7.90	3038
accumdeficit	-2.23	-2.20	2.21	-1.00	-0.34	-9.44	3.77	3038
ln_sga	2.98	3.17	1.77	-0.40	-0.16	0.00	8.71	3038

As the post-IPO status is a categorical dependent variable, it is perhaps more interesting to observe descriptive statistics grouped by the outcome categories. Thus, table 7 gives insights into the differences between the descriptive statistics of dependent variable groups. In the table, the mean and median values of independent variables are categorised by post-IPO status. Indicator variables are excluded from the table due to differing statistical properties. Independent samples t-test is performed to test whether the observed differences in means of different groups are statistically significant. The following statistical hypotheses are tested:

$$H_0: \mu_1 = \mu_2$$
$$H_1: \mu_1 \neq \mu_2$$

where: μ_1 is the mean of the first group and μ_2 is the mean of the other group.

To test the significance of differences in median values between different groups, The Wilcoxon rank-sum test, also known as the Mann-Whitney U-test, is performed. The null and alternative statistical hypotheses are as follows:

$$H_0: \tilde{x}_1 = \tilde{x}_2$$
$$H_1: \tilde{x}_1 \neq \tilde{x}_2$$

where: $\tilde{x}_1$ is the median of the first group and $\tilde{x}_2$ is the median of the other group.

On the right-hand side of table 7, t-statistics and z-scores indicate whether the differences in mean and median values of one outcome group contrasted with another group are statistically significant. The average survival times (*survival_time*) of

acquired (33.03) and failed (33.31) companies are relatively similar, with failed companies having slightly longer mean survival times. In terms of offer size (*ln_proceeds),* the average and median offer size are the highest among survivors. Failed IPOs have the lowest average and median offer size. T- and Wilcoxon rank-sum test statistics indicate that mean and median offer sizes differ significantly in all cases when comparing one outcome category with another. The average and median underwriter rankings (*UW_rank*) are significantly lower among failed IPOs as opposed to survivors and those getting acquired. There is no significant difference between the mean underwriter rankings in survived and acquired groups, although according to obtained z-scores, medians of underwriter rankings among those groups are different at a 10% level of significance. Failed IPOs have the lowest mean and median offer prices (*ln_offerprice*) whereas the acquired group has the highest mean and median offer prices. The mean and median proportion of secondary shares offered (*sec_shares*) are the lowest (highest) among failed (survived) IPOs. The median proportion of secondary shares offered is 0% in all groups, suggesting that at least 50% of the companies in each outcome group did not offer any secondary shares at the IPO. Positive mean and median first-day returns (*return*) in all outcome categories indicate presence of underpricing in the U.S. IPO market over the examined period. In all outcome categories, the average returns are higher compared to medians, suggesting right-skewed data. Mean first-day return is the highest in the acquired group and the lowest median return is in the failed group. Mean and median company ages (*ln_age*) are the lowest in the failed category and the highest among survivors, and the differences in means and medians between those groups are statistically significant. Mean and median leverage (*leverage*) is the highest among failed companies. Average and median sales (*ln_sales*) are the lowest in the failed group, suggesting higher failure rates among companies with lower sales. In turn, survived companies have the highest average and median sales. The differences in means and medians of sales in all groups are significant at a 1% level. Average and median R&D expenses (*ln_rd*) are significantly lower among failed companies as contrasted to survivors and those getting acquired. The median R&D expenses is 0.00, suggesting that at least 50% of failed companies did not make any investments in R&D a year before an IPO. Mean and median accumulated deficits (*accumdeficit*) are negative in all groups due to the calculation method (see section 5.3.2). However, according to the t-test and Wilcoxon rank-sum test, there are surprisingly no differences in means or medians of the accumulated deficit when comparing one outcome category with another. Average and median SG&A expenses (*ln_sga*) are the lowest in the failed group, indicating that survivors and those getting acquired have greater SG&A expenses in the

IPO year. This suggests that those companies use more capital for expenses that arise from running the business, excluding expenses related to the production of goods and services sold.

Table 7 Average and median of continuous variables by outcome category

Variable	Survivors	Acquired	Failures	Survivors vs. Acquired	Survivors vs. Failures	Acquired vs. Failures
	Mean (Median)	Mean (Median)	Mean (Median)	t-statistic (Wilcoxon-z)	t-statistic (Wilcoxon-z)	t-statistic (Wilcoxon-z)
survival_time	139.59	33.03	33.31	57.35***	55.40***	-0.35
	(116.71)	(31.92)	(32.15)	(42.97)***	(31.12)***	(-0.39)
ln_proceeds	4.78	4.60	3.92	4.43***	13.66***	10.63***
	(4.69)	(4.53)	(4.04)	(4.35)***	(12.23)***	(9.58)***
UW_rank	7.97	7.97	6.34	0.04	8.17***	11.66***
	(9.00)	(8.00)	(7.50)	(1.72)*	(12.16)***	(10.73)***
ln_offerprice	2.85	2.90	2.64	-3.11**	8.17***	9.75***
	(2.87)	(2.93)	(2.69)	(-3.30)***	(7.41)***	(8.95)***
sec_shares	14.20 %	11.96 %	4.45 %	2.38**	11.25***	8.04***
	(0.00 %)	(0.00 %)	(0.00 %)	(1.37)	(7.19)***	(6.17)***
return	20.59 %	22.98 %	22.14 %	-1.93**	-0.86	0.43
	(11.46 %)	(12.50 %)	(10.53 %)	(-1.26)	(0.72)	(1.48)
ln_age	2.57	2.35	1.98	5.86***	12.34***	7.13***
	(2.48)	(2.30)	(1.95)	(5.81)***	(11.07)***	(6.52)***
leverage	0.42	0.42	0.46	0.67	-1.69*	-1.98**
	(0.36)	(0.34)	(0.37)	(1.37)	(-0.52)	(-1.29)
ln_sales	4.17	3.66	2.54	6.18***	16.26***	10.58***
	(4.18)	(3.63)	(2.57)	(6.23)***	(13.97)***	(9.54)***
ln_rd	1.16	1.03	0.54	2.62***	10.85***	8.07***
	(0.55)	(0.47)	(0.00)	(1.64)*	(7.81)***	(6.69)***
accumdeficit	-2.21	-2.28	-2.14	0.76	-0.65	-1.17
	(-2.16)	(-2.36)	(-2.11)	(1.03)	(0.12)	(-0.75)
ln_sga	3.14	2.99	2.29	2.10**	9.62***	7.67***
	(3.34)	(3.17)	(2.48)	(2.51)**	(8.87)***	(7.39)***

***, **, * indicate statistically significant t-statistic and Wilcoxon z-score at 1%, 5%, and 10% levels respectively

Table 8 presents the frequency distribution of indicator variables across the whole sample. According to the table, 45.5% and 19.2% of all offerings are VC-backed and PE-backed, respectively. Hot issues cover 42.7% of the sample, while 49.5% are classified as neutral issues and 7.6% as cold issues. This implies that over the examined period, the majority of issues have been timed during hot and neutral periods. 45.2% of IPOs record net losses at the IPO year, suggesting that a large proportion of companies are not profitable when entering public markets. Even 65.3% of failed companies recorded net losses at the IPO year whereas 39.2% of survivors experienced net losses. Only 3.5% of failed companies were issued during a cold period, whereas 61.6% of those were issued during a hot period.

Table 8 Frequency distribution of indicator variables

			Dummy=1					
Indicator Variable	**Total sample**	**% of total sample**	**Survived**	**% of survived**	**Acquired**	**% of acquired**	**Failures**	**% of failures**
VC_dummy	1381	45.5	743	44.8	501	51.1	137	34.2
PE_dummy	582	19.2	362	21.8	184	18.8	36	9.0
hot	1298	42.7	527	31.8	524	53.5	247	61.6
neutral	1508	49.6	965	58.2	403	41.1	140	34.9
cold	232	7.6	165	10.0	53	5.4	14	3.5
tech	1012	33.3	497	30.0	391	39.9	124	30.9
NI_dummy	1372	45.2	650	39.2	460	46.9	262	65.3

Table 9 presents the total sample grouped by TBRC industry groups. The table shows that 1012 (33.3%) of IPOs that occurred between 1995 to 2018 were technology companies. In addition, companies in the technology sector comprise 39.9% and 30.9% of the acquired and failed companies, respectively. IPOs in the healthcare sector cover 17.0% of the total sample and 15.0% and 15.5% of the companies in the acquired and failed categories respectively. One company fell under the industry classification of Government Activity. However, this observation was moved to the Utilities industry due to the description of core business activities.

Table 9 Sample grouped by industry

Industry (TRBC)	**N**	**% of total sample**	**Number of acquired**	**Number of failures**	**% of acquired**	**% of failures**
Technology	1012	33.3	391	124	39.9	30.9
Healthcare	517	17.0	147	62	15.0	15.5
Consumer Cyclicals	437	14.4	122	64	12.5	16.0
Industrials	416	13.7	132	67	13.5	16.7
Financials	276	9.1	77	40	7.9	10.0
Consumer Non-Cyclicals	110	3.6	37	15	3.8	3.7
Energy	106	3.5	28	9	2.9	2.2
Basic Materials	89	2.9	26	14	2.7	3.5
Real Estate	40	1.3	6	3	0.6	0.8
Academic & Educational Services	20	0.7	6	2	0.6	0.5
Utilities	15	0.5	8	1	0.8	0.3
Total	**3038**	**100**	**980**	**401**	**100.00**	**100.00**

6 METHODOLOGY

This chapter presents the methodologies employed in this thesis to analyse the data described in previous section. The dependent and independent variables presented in previous chapter are integrated into multinomial logit and Accelerated Failure Time (AFT) models which are described in detail in the following sub-chapters. These methodologies are selected as they have been most commonly utilised in studies on the survival of IPOs or IPO failure risk (see section 4.1). Data processing and analysis is conducted in Stata software.

6.1 Multinominal logit model

In financial literature, different variations of logit models are perhaps most commonly used to predict the probability of bankruptcy (e.g. Martin, 1977; Gilbert, Menon and Schwartz, 1990). Schultz (1993) conducted one of the first studies on predicting the survival of newly listed companies in the aftermarket by using a binary logit model. Later, Jain and Kini (1999) as well as Kooli and Meknassi (2007), utilised multinomial logit models, also known as a multinomial logistic regressions, to predict the probability of IPOs transitioning to pre-determined post-issuance categories in the aftermarket. In this study, company, market, and issue-specific information available before and soon after an IPO are integrated into multinomial logit models to predict the probability of transitioning into the three post-issuance states.

Whereas binary logit models can be employed when the dependent variable has two categories, the multinomial logit model allows the usage of more than two unordered categories as a dependent variable. The model inputs are dependent and independent variables, and parameters are estimated with a maximum likelihood technique to maximise a log-likelihood function (Brooks, 2008, p.518). In this study, the dependent variable, also known as the outcome, is the post-issuance status of a company: (1) survived (2) acquired or (3) failed. The multinomial logit model estimates how changes in the independent variables are related to the probability of falling into each outcome category, along with comparing one category of the dependent variable (reference class) with the category of interest (Brooks, 2008). In this study, the survived category is designated to be the reference class, against which failures and acquired categories are compared. Survival as an independent business is the desired and most common outcome, thus representing the reference category.

Company and issue-specific information available before and soon after an IPO are integrated into the multinomial logit model as independent variables to predict how changes in independent variables impact the probability of falling into a specific outcome category. The subchapter under section 5.3 describes the chosen issue, company, and market specific independent variables. For a dependent variable with n categories, the calculation requires n-1 equations, one for each category compared to the reference category (Brooks, 2008). Thus, the probability of transitioning to one of the post-issue states is estimated as follows (Jain and Kini, 1999):

$$log_e(P_A/P_S) = \beta_{11} + \beta_{12}X_1 + \beta_{13}X_2 + \beta_{14}X_3 + \cdots + \beta_{1n}X_n \quad (1)$$
$$log_e(P_F/P_S) = \beta_{21} + \beta_{22}X_1 + \beta_{23}X_2 + \beta_{24}X_3 + \cdots + \beta_{2n}X_n \quad (2)$$

where: P_S = probability of survival, P_A= probability of getting acquired, P_F= probability of failure, and X_1through X_n represent the independent variables described in section 5.3.

To compare acquired and failed companies, the third equation is derived from equations (1) and (2) as follows (Jain and Kini, 1999):

$$log_e(P_A/P_F) = log_e(P_A/P_S) - log_e(P_F/P_S) \quad (3)$$
$$= \beta_{31} + \beta_{32}X_1 + \beta_{33}X_2 + \beta_{34}X_3 + \cdots + \beta_{3n}X_n \quad (3) = (2) - (1)$$

The multinomial logit model can predict the general probability of transitioning to a specific outcome category, but it does not provide a time estimate on when the transitioning occurs, meaning that companies failing after one year and five years are categorised similarly.

6.1.1 Assumptions and model diagnostics

Certain statistical assumptions regarding the underlying data must be met to produce accurate results with a multinomial logit model. These assumptions include nominal dependent variable, independence of irrelevant alternatives (IIA), and absence of multicollinearity. To ensure that the underlying data is appropriate for estimating multinomial logit regressions and to enhance the validity and interpretation of results, it is checked that the assumptions hold sufficiently, and potential negative effects are mitigated through remedial statistical procedures.

6.1.1.1 Nominal dependent variable

A prerequisite for selecting a multinomial logit model as an appropriate method is that the dependent variable is categorical and in the case of a multinomial model, there must be more than two unordered categories (Brooks, 2008). As the dependent variable is the post-IPO status of (1) survived (2) acquired and (3) failed, this assumption is met.

6.1.1.2 Independence of Irrelevant Alternatives (IIA)

The relative probability of falling in one category of dependent variable compared to the reference class should not be dependent on the presence or absence of other dependent variable categories. This means that the probability of getting acquired in relation to survival and the probability of failure in relation to survival should not change if other dependent variable categories are introduced (Brooks, 2008, p.524). There is no confidential statistical test to observe whether this assumption is met but often the violation of this assumption is related to an outcome category that represents a set of choices which is not comparable to the case of the post-IPO state.

6.1.1.3 Multicollinearity

Multicollinearity refers to a situation in which two or more of the independent variables in a statistical model are highly correlated. The multinomial logit model assumes that there is no multicollinearity among the independent variables (Hosmer and Lemeshow, 2000). The presence of multicollinearity leads to severe statistical issues and prohibits a reliable interpretation of the results. Correlation matrix and variance inflation factors (VIFs) can detect the presence of multicollinearity. However, there are no universally accepted thresholds of correlation or VIF that definitely determine the existence of multicollinearity. Nevertheless, if the correlation between some independent variables is greater than 0.80 or lower than -0.80, multicollinearity is likely a concern. VIF > 10 indicates issues with multicollinearity and VIF > 5 should be investigated further (Shrestha, 2020). It is discovered, that when including *year* and *heat* variables in the same regression, VIF of *hot* indicator variable exceeds the threshold of 10. Thus, *year* and *heat* variables are run in separate models. Otherwise, a correlation matrix and VIF values are checked (see Appendix 1), and no critical signs of multicollinearity was detected among independent variables.

6.1.2 Interpretation of the model output

When interpreting the output of a multinomial logit model, three different types of coefficients and statistics are presented: log-odds, relative risk ratios (RRRs), and

average marginal effects (AMEs). These are discussed briefly to ease the interpretation of the results of the multinomial logistic regression.

6.1.2.1 Log-odds

First, log-odds, which represent the standard output coefficient, describe the relative log-odds of falling into a specific outcome category when contrasted to a reference category. As presented in the previous subchapter, acquired, and failed IPOs are contrasted with a reference category of survivors and acquired IPOs with failures. Then, one-unit change in the independent variable is associated with a positive (negative) change in the log-odds of falling into a specific outcome category in contrast to the reference category (Stata, 2023a). Apart from their sign, the estimated parameters are difficult to interpret as they are on a log-odds scale.

6.1.2.2 Relative risk ratios (RRRs)

Secondly, relative risk ratios (RRRs) measure the relative risk of falling into a category of interest in comparison to the reference category. RRRs are exponentiated values (e^{β}) of log-odds. Often, these are mistakenly referred to as odds ratios as in binary models, but these terms cannot be used interchangeably in case of a multinomial model due to technical differences (Stata, 2023a). When interpreting RRRs, a one-unit change in the independent variable is associated with a positive or negative change in the relative risk of falling into a specific category when contrasted to a reference class. Specifically, RRR above 1 indicates that the risk of being in a specific category compared to the reference class is higher for larger values of the independent variable whereas RRR below 1 indicates lowering risk.

6.1.2.3 Average Marginal Effects (AMEs)

Several studies utilising multinomial logistic regression report the log-odds but those are difficult to interpret. Thus, this study presents Average Marginal Effects (AMEs) which provide the estimated average change in the probability of each dependent variable category, when the focal independent variable changes by one small unit and other variables are held constant. Instead of one-unit change, AMEs of indicator variables are captured when their value changes from 0 to 1. After a multinomial logit model is fitted, AMEs, also referred to as margins of derivatives of responses, can be calculated. AMEs provide insights into how changes in independent variables are related to the probability of falling into different outcome categories across the whole sample and the strength of the relationship. Positive AMEs indicate that the probability of falling into the outcome

category is higher with an increase in the independent variable, while negative effects indicate a decrease in the probability.

In accordance with Stata (2023b, p.26), the following formula of derivatives of responses, i.e. AMEs is:

$$dydx = dy/dx \quad (4)$$

where: d = derivative; y = linear predictions from the fitted model; x = independent variable, and it is interpreted so that "*a change in y for a change in x*" (Stata, 2023b, p.26).

In the margins manual of Stata (2023b, p.26), the interpretation of AMEs is illustrated with the following example: *"If* $dydx = 0.5$*, y increases with x at a rate such that, if the rate were constant, y would increase by 0.5 if x increased by 1*".

6.1.3 Measure of the goodness of fit

In a regression model, R-squared (R^2) often measures model's accuracy. In practice, R^2 describes how successfully the chosen independent variables explain the variation in the dependent variable. This measure can only be applied in the case of a continuous dependent variable. Since the multinomial logit model has a categorial dependent variable, pseudo-R^2 is an appropriate measure of the model's accuracy. The following equation represents McFadden's pseudo-R^2 (Brooks, 2008):

$$Pseudo\ R^2 = 1 - \frac{LLF}{LLF_0} \quad (5)$$

where: LLF = maximised value of the log-likelihood function for a full model with predictors; LLF_0 = value of the log-likelihood function for a model without predictors.

Pseudo-R^2 takes a value ranging from 0 to 1. However, the interpretation of pseudo-R^2 is incomparable to R^2 obtained from OLS estimation models (Brooks, 2008). The exact interpretation is arduous, but when comparing pseudo-R^2's of two models with the same underlying data, higher pseudo-R^2 indicates better predictive capabilities of the model. According to Hensher and Stophe (2021, p.308), pseudo-R^2 of 0.2 to 0.4 indicates an excellent fit of a model.

6.1.4 Testing the significance of independent variables

To test the significance of individual independent variables in a multinomial logit model, a likelihood ratio Chi-square test is performed. In the multinomial logit models, three equations assign specific relative log-odds of falling into one outcome category compared to a reference class. The models produce coefficients assigning the effect of each independent variable on the log-odds of the dependent variable category. A likelihood ratio Chi-Square test allows to evaluate a null hypothesis stating that all the coefficients across equations of the multinomial logit model are simultaneously equal to zero (Chatterjee and Simonoff, 2013). In turn, the alternative hypothesis suggests that one or more of the coefficients are not equal to zero. The null and alternative hypotheses are stated as follows:

$$H_0: All\ coefficients\ associated\ with\ independent\ variable(s)\ are\ equal\ to\ 0$$
$$H_1: At\ least\ one\ coefficient\ is\ not\ equal\ to\ 0$$

If a p-value of the Chi-square test statistic is <0.05, the null hypothesis is rejected. This test enables to determine whether an independent variable has a significant effect on the outcome of an IPO in the model. If the null hypothesis is rejected, the independent variable is assumed to have a significant relationship with the probability of falling at least into one of the outcome categories.

6.2 Survival analysis

Generally, the purpose of a survival analysis is to analyse time until an event of interest occurs (time-to-event). As stated previously, the cross-sectional multinomial logit model considers whether an event will occur, not the time when it will occur. Since the length of survival after an IPO varies and a set of companies remain listed on a stock exchange at the end of the follow-on period, it is of interest to conduct a more detailed analysis of the time-to-acquisition or -failure and the survival time.

Different types of survival models, also known as hazard models, are suitable for analysing situations that involve time durations, such as the survival of companies. In financial literature, these models have been utilised to examine bank failure (Lane, Looney, and Wansley, 1986), corporate failures in the newspaper industry (Carroll and Delacroix, 1982), and corporate failure in general (Freeman, Carroll, and Hannan, 1983; Carroll, 1983). In addition, Hensler, Rutherford, and Springer (1997), Jain and Kini (2000) and Kooli and Meknassi (2007) analysed the outcome of IPOs by applying a

hazard model, which enables to assess the probability of delisting under specific conditions, considering that the company has continued to exist until the current time. This probability is often referred to as a hazard rate or the probability of failure.

Survival analysis is a beneficial approach when analysing the lifecycle of IPOs as it allows to consider censored data which is prevalent when the event of interest has not occurred yet (Kalbfleisch and Prentice, 2011, p.12). In other words, IPO data is "right censored", meaning that at any given time, there are many IPOs that are trading actively on a stock exchange and their full history will not be observed over the examined period. In this thesis, right censored data includes companies that go public during the examined period but do not delist during the tracking period of 5 years. In addition, the observation period is different between companies as it depends on the time when they got listed on a stock exchange and survival analysis can take this into account. In essence, the risk of failure (or delisting due to acquisition) may vary on the basis of the duration of time after the company goes public.

Cox (1972) developed a proportional hazard model which describes the relationship between the probability of an event at a given time and the covariates of interest. The hazard rate refers to the risk of event at time t, given that the company has remained listed up to t. The hazard function is defined in the following way (Kalbfleisch and Prentice, 2011; Hensler, Rutherford, and Springer, 1997):

$$h(t) = f(t, X_j) / \left(1 - F(t, X_j)\right) \quad (6)$$

where $h(t)$ = hazard function; $F(t, X_j)$ = survivor function denoting the probability that an IPO issued at time $t = 0$ with characteristics of X_j has failed or acquired before time t; and $f(t, X_j)$ = the probability density. The hazard rate enables to define the association between the density of failure times, and the survivor function simultaneously.

To define the hazard rate for each company j, the generalized Cox (1972) proportional hazard model takes the following form (Kalbfleisch and Prentice, 2011; Hensler, Rutherford, and Springer, 1997):

$$h(t_j) = h_0(t) \exp(X_j \beta) \quad (7)$$

where: $h(t_j)$ = hazard function, $h_0(t)$ = baseline hazard which describes the hazard probability distribution for IPOs delisting due to negative reasons under similar average conditions; X_j= vector of covariates; β= vector of regression coefficients.

As equation (7) above displays, the hazard function is determined by a set of covariates which act multiplicatively on the baseline. Thus, the generalized hazard model can be viewed as a multivariate regression where log of failure rate is modelled based on the explanatory variables with the baseline hazard serving as a time-varying intercept term. The generalized model specifies that log of hazard rate represents a linear function of covariate X.

6.2.1 Accelerated Failure Time (AFT) model

The coefficients produced by the generalized model (7) are difficult to interpret (Kalbfleisch and Prentice, 2011, p.44). To overcome this limitation, the survivor function defining the effect of covariates is adjusted through a parametric Accelerated Failure Time (AFT) model. The AFT model enables to examine the effect of issue, company, and market specific characteristics on the survival time of IPOs. The model considers survival time after issuance while estimating the effect of independent variables on the hazard probability.

The generalized model (7) serves as a base for building the AFT model (Kalbfleisch and Prentice, 2011, p.42). In the model, the dependent variable is a logarithm of the number of months t that a company has survived following the IPO up to the end of 2023. The model then identifies which independent variables accelerate or decelerate the time-to-event and the effect may vary depending on the time that the company has remained listed. Estimated coefficients that are positive (negative) indicate that a one-unit increase in the covariate increases (decreases) the survival time. In accordance with Jain and Kini (2000) and Kooli and Meknassi (2007), two types of AFT models are developed for the survival analysis. The first model considers survivors against acquired and the second model survivors against failures. Stata (2023c, p.5) presents the AFT model as follows:

$$\log t_j = X_j\beta + z_j \quad (8)$$

where $\log t_j$ = a natural logarithm of survival time in months; X_j = vector of covariates; β = vector of regression coefficients; z_j = error with specific continuous density $f(\cdot)$. The error term is determined to follow a specified distribution which defines the model's

functional form. In the AFT model, a one-unit change in covariates changes the time scale by exp($-X_j\beta$) factor (Stata, 2023c, p.5). If the factor is greater (lower) than 1, the covariate is estimated to decelerate (accelerate) the time-to-event.

6.2.1.1 Functional form of the AFT model

In section 5.5, figure 3 displays the shape of the distribution of yearly delistings, indicating that in year 3, the number of delistings peaks and decreases thereafter. Hensler, Rutherford, and Springer (1997) argue that after a company can survive through a certain threshold, in this case over 3 years, the number of delistings should decrease, indicating increasing hazard probability until 3 years and decreasing probability thereafter. Finding similar patterns in their data, Jain and Kini (2000), and Kooli and Meknassi (2007) developed log-logistic AFT models based on the assumed distribution of the hazard risk. Additionally, Blossfeld, Hamerle and Mayer (2014, p.250) suggest that a log-logistic model can be appropriate choice for this type of non-monotonic distribution where the risk of the event occurring is assumed to first increase up to a certain point and decrease thereafter. Although the log-logistic model is flexible (Stata, 2023c, pp.9-10), and could potentially fit the underlying data, Akaike Information Criterions (AICs) are obtained to find best-fitted distribution among the log-logistic, log-normal, exponential, generalized gamma, and Weibull distributions, as suggested by Stata (2023c, p.16). In previous studies using log-logistic form of the AFT model (Hensler, Rutherford, and Springer, 1997; Jain and Kini, 2000; Kooli and Meknassi, 2007), model fit statistics have not been compared when selecting the best-fitted model.

The functional form of AFT models is specified through the evaluation of AICs. Obtained AICs in table 10 show that generalized gamma and log-linear distributions get the lowest AICs, suggesting a better fit than a log-logistic model which has been employed in previous studies. However, in addition to best-fitted generalized gamma distribution, log-logistic models are also built in accordance with previous literature.

Table 10 Testing AFT model fit

	Survival vs. Acquisition	**Survival vs. Failure**
Distribution	**AIC**	**AIC**
Generalized gamma	5237.92	2498.23
Log-normal	5678.97	2518.91
Log-logistic	5787.16	2547.13
Weibull	5954.95	2608.12
Exponential	6067.72	2635.11

Table 11 presents the parametrizations and ancillary scale parameters for log-logistic and generalized gamma distributions.

Table 11 AFT model distributions (Stata, 2023c, pp.6-7)

Distribution	Survivor function	Parameterization	Ancillary scale parameters
Log-logistic	$\left\{1+(\lambda_j t_j)^{1/\gamma}\right\}^{-1}$	$\lambda_j = \exp(-X_j\beta)$	γ
Generalized gamma			
If $\kappa > 0$	$1 - I(\gamma, u)$	$\mu_j = X_j\beta$	σ, κ
If $\kappa = 0$	$1 - \phi(z)$	$\mu_j = X_j\beta$	σ, κ
If $\kappa < 0$	$I(\gamma, u)$	$\mu_j = X_j\beta$	σ, κ

where $\phi(z)$ = standard normal cumulative distribution;
for generalized gamma: $\gamma = |\kappa|^{-2}, u = \gamma \exp(|\kappa|z)$, $I(a,x)$ is the incomplete gamma function,
and $z = sign(\kappa)\left\{log_{(t_j)-\mu_j}\right\}/\sigma$ (Stata, 2023c, p.7).

The log-logistic model assumes that z_j follows logistic density. The survivor and density functions of log-logistic regression are presented as follows (Stata, 2023c, p.9):

$$F(t) = \left\{1 + (\lambda t^{1/\gamma}\right\}^{-1} \quad (9)$$

$$f(t) = \frac{\lambda^{1/\gamma} t^{1/\gamma - 1}}{\gamma\left\{1+(\lambda t)^{1/\gamma}\right\}^2} \quad (10)$$

where: $\phi(z)$ = standard normal cumulative distribution function; γ = ancillary scale parameter estimated from underlying data.

Generalized gamma model has three-parameter survivor and density functions (Stata, 2023c, p.10):

$$F(t) = \begin{cases} 1 - I(\gamma, u) & \text{if } \kappa > 0 \\ 1 - \phi(z) & \text{if } \kappa = 0 \\ I(\gamma, u) & \text{if } \kappa < 0 \end{cases} \quad (11)$$

$$f(t) = \begin{cases} \frac{\gamma^\gamma}{\sigma t\sqrt{\gamma\Gamma(\gamma)}} \exp(z\sqrt{\gamma} - u) & \text{if } \kappa \neq 0 \\ \frac{1}{\sigma t\sqrt{2\pi}} \exp(-z^2/2) & \text{if } \kappa = 0 \end{cases} \quad (12)$$

where: $\gamma = |\kappa|^{-2}; z = sign(\kappa)\{log(t) - \mu\}/\sigma;\ u = \gamma exp(|\kappa|z);\ \phi(z) =$ standard normal cumulative distribution function; $I(a,x) =$ incomplete gamma function. Parameters κ

and σ are ancillary scale parameters that are estimated from the underlying data through parameterising $\mu_j = X_j\beta$.

The parameters of the AFT model are estimated through a maximum likelihood estimation technique. This procedure requires additional censoring indicator to account for the right-censored observations (Blossfeld, Hamerle and Mayer, 2014, pp.69-71), which occur when the company has remained listed over a tracking period of five years, and theoretically, the survival could exceed that period by an infinite period. This indicator variable is the post-IPO status (survived or acquired and survived or failed).

6.2.1.2 Dependent variable and covariates

In the AFT model, the dependent variable is a natural logarithm of survival time in months (*survival_time*). Independent variables presented in section 5.3 are integrated into AFT models as covariates. The *year* variable is not considered due to detected multicollinearity and hence, only *heat* indicators are included in the models. In addition, models include indicator variable of *IPO_state* which assigns the right-censored data as described in section 6.2.1.1.

6.2.1.3 Assumptions of the AFT model

As specified above, survival times are assumed to follow a specific distribution and the model requires this specification, often through the lowest AIC (Stata, 2023c, p.15-16). Common functional forms of the AFT model include log-logistic, log-normal, generalized gamma, exponential, and Weibull distributions. Secondly, the effect of covariates is expected to be constant, and they should act multiplicatively on the survival time (Bradburn et al., 2003).

6.2.1.4 Interpretation of the model output

AFT model's coefficient describes a situation in which a one-unit increase (decrease) in a covariate is associated with an increase (decrease) in the average survival time. In other words, positive (negative) coefficients imply that a specific covariate decelerates (accelerates) the time-to-event. In addition to estimated coefficients, time ratios are displayed to ease the interpretation of the results. Time ratios, also known as accelerating factors, are obtained by exponentiating the logarithmic coefficients. If the time ratio is greater (less) than 1, the time-to-event decelerates (accelerates) indicating extended (shorter) survival time. As an example, a time ratio of 1.1 (0.9) would imply a 10% increase (decrease) in the average survival time.

7 RESULTS

This chapter introduces the results of the multinomial logit and AFT models. Throughout the chapter, the interest lies in statistically significant relationships due to large sizes of the models. Table 12 shows the variables that are integrated into multinomial logit and AFT models. In total, 4 different multinomial logit models are built. Multinomial logit models 1 and 2 do not include accounting variables to test if model fit improves when adding financial information into it. Due to detected multicollinearity among *year* and *heat* dummies, two reduced and extended models are built. However, as the main interest relies on the market heat, models including year dummies (2 and 4) are presented in Appendix 2 and will not be the primary interest in result interpretation. The survival analysis consists of 4 AFT models, which all include the same variables. Two of the models are estimated through the generalized gamma distribution and the remaining two through the log-logistic distribution.

Table 12 Summary of variables integrated into models

	Multinomial logit models				Survival analysis
Variable	**Reduced model 1**	**Reduced model 2** (Appendix 2)	**Extended model 3**	**Extended model 4** (Appendix 2)	**AFT models 1-4**
IPO_state	x	x	x	x	x*
survival_time					x
ln_proceeds	x	x	x	x	x
return	x	x	x	x	x
sec_shares	x	x	x	x	x
UW_rank	x	x	x	x	x
ln_offerprice	x	x	x	x	x
VC_dummy	x	x	x	x	x
PE_dummy	x	x	x	x	x
ln_age	x	x	x	x	x
tech	x	x	x	x	x
leverage	x	x	x	x	x
ln_sales	x	x	x	x	x
NI_dummy	x	x	x	x	x
ln_accumdeficit			x	x	x
ln_rd			x	x	x
ln_sga			x	x	x
heat (hot/cold)	x		x		x
year		x		x	
industry	x	x	x	x	x

*IPO_state in AFT models determines non-censored and censored data

7.1 Multinomial logit models

As discussed earlier, this study aims to combine elements from traditional IPO literature and bankruptcy prediction studies which both entail unique characteristics. Therefore, two types of multinomial logit models are built, two without financial accounting information, which is typically not involved in studies examining the aftermarket performance of IPOs, and two including those, as being typically incorporated in

corporate failure prediction models. This procedure is inspired by Demers and Joos (2007) who observed whether the model's fit improves when adding accounting information to complement deal, market and company specific information.

First, reduced multinomial logit model 1 without accounting variables is presented, followed by an analysis of the relationship between independent variables and the probability of getting acquired or fail as opposed to survival. Subsequently, the extended multinomial logit model 3 including accounting information is presented. From the extended model, a likelihood ratio Chi-squared test is run to assess the power of individual independent variables to explain the variation in the probability of falling into outcome categories. Lastly, AMEs of the extended model 3 are analysed.

7.1.1 Reduced multinomial logit model

First, table 13 shows the results of reduced model 1 including deal, company, and market specific independent variables. Financial accounting variables are not incorporated into the model. The table shows collectively log-odds (estimated coefficients), and relative risk ratios (RRRs) for all outcome categories in relation to a reference category. The probability of getting acquired is compared with survival, the probability of failure with survival, and the probability of getting acquired with failure. The significance of estimated log-odds and RRRs are assigned by p-values, three stars, two stars, and one star denoting significance at 1%, 5%, and 10% levels, respectively. The same p-value is applicable to denote the significance of both log-odds and RRRs. The likelihood ratio of 560.85 with a p-value <0.01 indicates that the model including deal, company, and market specific variables provides a significantly better fit when contrasted to a null model without predictive variables. Pseudo-R^2 of 0.0959 is a measure of the explanatory power of the model.

When comparing the probability of getting acquired to survival, a one-unit increase in *ln_offerprice*, *PE_dummy, VC_dummy, hot,* and *tech* is estimated to significantly increase the probability of getting acquired when contrasted to the probability of survival. On the other hand, a slight increase in *ln_proceeds*, *return,* and *ln_age* decreases significantly the probability of acquisition as opposed to survival. RRRs reflect that the relative risk of getting acquired is 1.595 (59.5%) higher compared to survival when *ln_offerprice* increases by one unit and all other variables are held constant. Similarly, RRRs of *PE_dummy, VC_dummy, hot,* and *tech* indicate that the relative risk of getting acquired is 43.2%, 20.6%, 110.9%, and 55.0% higher, respectively, when

compared to survival if those variables increase by one unit. The relative risk ratio of 2.109 of *hot* market conditions is notably high, indicating a substantial increase in the relative risk of getting acquired when contrasted with survival if the issue is classified as *hot*. RRRs below 1 indicate that when all else being equal, the relative risk of getting acquired decreases by 14.8%, 24.0%, and 18.7% when *ln_proceeds, return,* and *ln_age*, respectively, increase by one unit.

The relative log-odds and RRRs are interpreted similarly under columns ($Log P_F/P_S$) and $Log(P_A/P_F)$. When contrasting the probability of failure with survival, an increase in *UW_rank*, *sec_shares*, *ln_age*, and presence of VC-backing (*VC_dummy*=1) decrease the probability of failure in contrast to survival. In turn, market hotness (*hot*=1) and technology industry classification (*tech*=1) increase the probability of failure as opposed to survival. Again, the estimated RRR of *hot* category is as high as 2.230, suggesting a 123.0% increase in the relative risk of failure when contrasted to survival if the indicator variable *hot* gets a value of 1. Also, the estimated RRR of *sec_shares* is 0.129, indicating that a one-unit increase in *sec_shares* reduces the probability of failure as opposed to survival by 87.1%. When comparing the probability of acquisition to the probability of failure, it seems that higher *UW_rank*, *ln_offerprice*, *sec_shares*, *ln_age*, and *VC_dummy* increase significantly the probability of acquisition. The estimated RRR of 6.183 of *sec_shares* indicates that one-unit increase in *sec_shares* increases even 518.3% of the probability of getting acquired relative to the reference category of failure.

7.1.2 Extended multinomial logit model

Reduced and extended multinomial logit models are presented in tables 13 and 14**,** respectively at the end of this subchapter to facilitate the comparison of the models' statistics. Table 14 presents the extended multinomial logit model including all independent variables. The structure of the table is similar to table 13, showing collectively the estimated log-odds and RRRs of all outcome categories in relation to their reference categories. Yet again, the statistical significance of the estimated coefficients and corresponding RRRs is assigned by a p-value. The likelihood ratio of 739.50 with a p-value <0.01 indicates that the extended model including all variables predicts the outcome of IPO significantly better than a null model. Compared to the likelihood ratio of 560.85 of the reduced model, the likelihood ratio increases when additional variables are integrated into the model. When observing pseudo-R^2s of the reduced model 1 and the extended model 3, the explanatory power of the model also seems to increase from 0.0959 to 0.1264 after introducing accounting variables into the model.

The left side of the table 14 shows the estimated log-odds and RRRs when comparing probability of getting acquired with the probability of survival. When adding accounting variables into the model, nearly all estimated log-odds and RRRs, except for *VC_dummy*, which is significant in the reduced model 1, maintain their statistical significance at least at 10% level, in the extended model. From accounting-based variables, *ln_rd*, and *accumdeficit* are significantly inversely related to the probability of getting acquired when contrasted to survival. In turn, *leverage*, and *NI_dummy* are positively associated with the probability of getting acquired when contrasted to survival. RRRs imply that one-unit increase in one of the aforementioned variables while holding all else constant, increases (decreases) the relative risk of being acquired by the factor of RRR. To illustrate this, RRR of *ln_rd* is 0.896 which implies that one-unit increase in *ln_rd* is associated with a 10.4% (1-0.896*100) decline in the relative risk of getting acquired as opposed to survival. RRR of *leverage* is 1.696 which indicates that one-unit increase in *leverage* increases the relative risk of getting acquired by 69.6%.

A similar interpretation of results can be made when comparing the probability of failure with survival. All coefficient and RRR estimates that are significant in the reduced model maintain their significance in the extended model at least at a 5% level. Also, the table shows that estimated log-odds of *leverage*, and *NI_dummy* are positively related to the probability of failure when contrasted to survival, whereas *ln_sales*, *ln_rd,* and *accumdeficit* are inversely related to the probability of failure as opposed to survival.

Finally, the column $\text{Log}(P_F/P_A)$ shows that in the extended model, *PE_dummy* becomes a statistically significant predictor of acquisition as opposed to failure at 10% level of significance. From accounting-specific metrics, *leverage* and *NI_dummy* are negatively related to the probability of getting acquired in contrast to failure, whereas a positive relationship is captured with *ln_sales, ln_rd,* and *accumdeficit*. A negative *NI_dummy* coefficient estimate implies that reporting net losses at IPO year (*NI_dummy* gets a value of 1) decreases the probability of acquisition compared to failure. Positive estimated coefficient of *accumdeficit* indicates that recurring net losses decrease the probability of acquisition as opposed to failure.

Table 13 Reduced multinomial logit model 1

Independent variables	Dependent variables								
	Log(P_A/P_S)			Log(P_F/P_S)			Log(P_A/P_F)		
	Coefficient	RRR	p-value	Coefficient	RRR	p-value	Coefficient	RRR	p-value
intercept	-1.516***	0.220	0.000	2.168***	8.743	0.000	-3.684***	0.025	0.000
ln_proceeds	-0.160**	0.852	0.020	-0.089	0.915	0.416	-0.072	0.931	0.533
UW_rank	0.038	1.039	0.277	-0.179***	0.836	0.000	0.218***	1.243	0.000
ln_offerprice	0.467***	1.595	0.003	-0.335	0.716	0.147	0.802***	2.230	0.001
sec_shares	-0.230	0.795	0.234	-2.051***	0.129	0.000	1.822***	6.183	0.000
PE_dummy	0.359***	1.432	0.003	0.032	1.033	0.879	0.326	1.386	0.138
VC_dummy	0.187*	1.206	0.066	-0.389***	0.678	0.008	0.576***	1.779	0.000
return	-0.274*	0.760	0.075	0.081	1.084	0.701	-0.355	0.701	0.106
ln_age	-0.207***	0.813	0.000	-0.562***	0.570	0.000	0.354***	1.425	0.000
hot	0.746***	2.109	0.000	0.802***	2.230	0.000	-0.056	0.946	0.719
cold	-0.238	0.788	0.166	-0.418	0.659	0.167	0.180	1.197	0.580
tech	0.438***	1.550	0.001	0.361*	1.435	0.059	0.077	1.080	0.701
Observations	3038								
Likelihood ratio	560.85								
p-value	0.000								
Pseudo-R^2 McFadden	0.0959								

***, **, * indicate coefficient estimate's (and corresponding RRR's) significance at 1%, 5%, and 10% levels respectively

Table 14 Extended multinomial logit model 3

Independent variables	Dependent variables								
	Log(P_A/P_S)			Log(P_F/P_S)			Log(P_A/P_F)		
	Coefficient	RRR	p-value	Coefficient	RRR	p-value	Coefficient	RRR	p-value
intercept	-1.917***	0.147	0.000	1.048**	2.852	0.036	-2.965***	0.052	0.000
ln_proceeds	-0.182**	0.834	0.017	-0.162	0.850	0.175	-0.019	0.122	0.876
UW_rank	0.043	1.044	0.228	-0.121***	0.886	0.007	0.164***	1.178	0.001
ln_offerprice	0.552***	1.737	0.001	-0.154	0.857	0.527	0.707***	2.027	0.005
sec_shares	-0.046	0.955	0.815	-1.123**	0.325	0.013	1.077**	2.934	0.020
PE_dummy	0.279**	1.322	0.026	-0.150	0.861	0.514	0.429*	1.536	0.067
VC_dummy	0.170	1.185	0.113	-0.452***	0.636	0.005	0.622***	1.862	0.000
return	-0.284*	0.753	0.074	0.060	1.062	0.787	-0.344	0.709	0.128
ln_age	-0.169***	0.845	0.003	-0.339***	0.713	0.000	0.170**	1.186	0.042
hot	0.747***	2.111	0.000	0.679***	1.971	0.000	0.069	1.071	0.673
cold	-0.236	0.790	0.172	-0.260	0.771	0.407	0.024	1.025	0.942
tech	0.513***	1.669	0.000	0.598***	1.818	0.005	-0.085	0.918	0.700
leverage	0.528***	1.696	0.003	1.284***	3.611	0.000	-0.756***	0.470	0.001
ln_sales	-0.059	0.943	0.101	-0.219***	0.803	0.000	0.161***	1.174	0.001
ln_rd	-0.110**	0.896	0.011	-0.505***	0.603	0.000	0.395***	1.485	0.000
accumdeficit	-0.052*	0.949	0.067	-0.138***	0.871	0.005	0.086*	1.090	0.087
ln_sga	0.007	1.007	0.833	-0.050	0.951	0.340	0.057	1.059	0.293
NI_dummy	0.235**	1.265	0.045	0.799***	2.223	0.000	-0.564***	0.569	0.002
Observations	3038								
Likelihood ratio	739.50								
p-value	0.000								
Pseudo-R^2 McFadden	0.1264								

***, **, * indicate coefficient estimate's (and corresponding RRR's) significance at 1%, 5%, and 10% levels respectively

7.1.3 Likelihood ratio Chi-Square test

To test the significance of independent variables in a multinomial logit model, a likelihood ratio Chi-Square test is performed for the variables included in the extended model 3. Table 15 shows the obtained test results, indicating that the coefficient estimates of three variables (*return, cold,* and *ln_sga*) are simultaneously equal to 0. Thus, variables *return, cold,* and *ln_sga* give no evidence to reject the null hypothesis that all coefficient estimates of given independent variables are simultaneously equal to 0. The remaining set of coefficient estimates are simultaneously indifferent from zero at 5% level of significance, and the null hypothesis of the likelihood ratio Chi-square test

can be rejected. In practice, the significance of the Chi-Square statistic implies that the specific independent variable influences on the outcome of an IPO in the extended model. Thus, it could be argued that first-day returns, cold market conditions, and SG&A expenses are not statistically significant predictors of the outcome of an IPO. In terms of cold market conditions, the number of IPOs categorised as cold issues is relatively low, so it is possible that the effect is not entirely captured by the likelihood ratio test and the regression model in general. The p-value of first-day returns (*return*) is slightly above 0.1, indicating that the factor may have some predictive capabilities, although the effect is statistically insignificant.

Table 15 Likelihood ratio Chi-square test

Independent variable	Chi-squared	p-value
ln_proceeds	6.393**	0.041
UW_rank	12.157***	0.002
ln_offerprice	14.095***	0.001
sec_shares	7.086**	0.029
PE_dummy	6.401**	0.041
VC_dummy	14.616***	0.001
return	4.079	0.130
ln_age	21.061***	0.000
hot	54.837***	0.000
cold	2.309	0.315
tech	16.980***	0.000
leverage	32.591***	0.000
ln_sales	20.380***	0.000
ln_rd	41.532***	0.000
accumdeficit	9.397***	0.009
ln_sga	1.130	0.568
NI_dummy	21.249***	0.000

***, **, * indicate significance at 1%, 5%, and 10% levels respectively

7.1.4 AMEs

Table 16 displays the estimated Average Marginal Effects (AMEs) of explanatory variables of model 3. AMEs are reported for all regressors. P-values, denoting the significance of the marginal effects, are shown in the parenthesis. When an explanatory variable increases by one unit and other variables are held constant, the probability of survival, acquisition, or failure is estimated to increase or decrease, on average, by the magnitude of the absolute AME.

The table shows that when *ln_proceeds, ln_age, ln_sales, ln_rd,* and *accumdeficit* increases by one unit, the probability of survival, on average, is estimated to increase statistically significantly. In contrast, an increase in *ln_offerprice*, *tech, hot*, *leverage* and *NI_dummy* significantly decreases the probability of survival. In this column, *hot*

and *leverage* has the highest absolute AMEs of -0.165 and -0.153, respectively. This means that one-unit increase in variables *hot* and *leverage* have the greatest estimated average effect on the probability of survival. Higher absolute AMEs are often documented among indicator variables since the measured increase from 0 to 1 often has a greater impact than the one-unit change in continuous variables.

The probability of acquisition increases, on average, along with an increase in *UW_rank, ln_offerprice*, *PE_dummy, VC_dummy*, *hot, tech,* and *leverage*. In turn, an increase in *ln_proceeds, return* and *ln_age* impact, on average, negatively on the probability of acquisition when all else is equal. *Hot* and *ln_offerprice* seem to have the largest AMEs of 0.132 and 0.119, respectively, on the probability of acquisition. It seems that besides *leverage,* the accounting metrics do not, on average, significantly affect the probability of acquisition in the long run.

Lastly, a surge in *leverage*, *NI_dummy, tech*, and *hot* indicates increasing probability of failure following an IPO. In turn, lower *UW_rank, ln_offerprice, sec_shares, ln_age, VC_dummy, ln_sales, ln_rd,* and *accumdeficit* indicate a greater probability of failure when all else is held constant. The greatest absolute AMEs of -0.101 and 0.096 are generated by a one-unit increase in *sec_shares* and *leverage*, respectively.

Table 16 Average Marginal Effects

	Dependent variable		
	Average Marginal Effect (p-value)	Average Marginal Effect (p-value)	Average Marginal Effect (p-value)
Independent variable	Survive	Get acquired	Failure
ln_proceeds	0.038**	-0.031**	-0.008
	(0.012)	(0.041)	(0.477)
UW_rank	-0.001	0.014**	-0.013***
	(0.899)	(0.046)	(0.001)
ln_offerprice	-0.083**	0.119***	-0.036*
	(0.011)	(0.000)	(0.089)
sec_shares	0.065	0.036	-0.101**
	(0.132)	(0.392)	(0.013)
PE_dummy	-0.040	0.065**	-0.024
	(0.118)	(0.014)	(0.187)
VC_dummy	-0.005	0.053**	-0.048***
	(0.812)	(0.011)	(0.001)
return	0.044	-0.061**	0.017
	(0.168)	(0.048)	(0.376)
ln_age	0.045***	-0.021*	-0.024***
	(0.000)	(0.054)	(0.001)
hot	-0.165***	0.132***	0.033**
	(0.000)	(0.000)	(0.017)
cold	0.052	-0.038	-0.014
	(0.130)	(0.263)	(0.588)
tech	-0.116***	0.082***	0.033*
	(0.000)	(0.002)	(0.063)
leverage	-0.153***	0.057*	0.096***
	(0.000)	(0.096)	(0.000)
ln_sales	0.021***	-0.003	-0.018***
	(0.003)	(0.641)	(0.000)
ln_rd	0.044***	-0.002	-0.042***
	(0.000)	(0.791)	(0.000)
accumdeficit	0.016***	-0.005	-0.010***
	(0.007)	(0.365)	(0.015)
ln_sga	0.001	0.003	-0.005
	(0.835)	(0.601)	(0.294)
NI_dummy	-0.081***	0.016	0.064***
	(0.001)	(0.478)	(0.000)

***, **, * indicate significance at 1%, 5%, and 10% levels respectively

7.2 AFT models

This section presents the results obtained from generalized gamma and log-logistic AFT models.

7.2.1 Generalized gamma AFT models

Table 17 presents two generalized gamma AFT models. Model 1 compares survival to acquisition and model 2 survival to failure. Positive (negative) coefficients are estimated to increase (decrease) the time of survival as opposed to acquisition or failure. To enhance the interpretation of the results, time ratios are presented, time ratio >1 (<1) indicating an increase (decrease) in the survival time.

A likelihood ratio of 147.17 with a p-value <0.01 indicates that model 1 with the set of covariates provides a better fit than a null model including only the intercept. According to obtained significant time ratios in model 1 in table 17, a one-unit increase in *ln_proceeds* is estimated to extend the average survival time by 10.9% (1-1.109*100). In turn, one-unit increase in *UW_rank*, *sec_shares*, *PE_dummy, hot, tech, leverage,* and

NI_dummy is estimated to shorten the survival time, on average, by 7.2%, 25.8%, 14.0%, 27.8%, 33.5%, 17.3%, and 17.6%, respectively. Except for *NI_dummy,* financial accounting variables are estimated to have an insignificant impact on the time-to-acquisition.

Model 2 compares time of survival and time-to-failure. A likelihood ratio of 352.29 with a p-value <0.01 implies that the model with covariates provides a better fit compared to a null model. In model 2, a one-unit increase in *UW_rank*, *ln_offerprice*, *sec_shares, VC_dummy, ln_age, ln_sales*, and *ln_rd* is estimated to decelerate the time-to-failure by 8.8%, 40.6%, 125.2%, 29.4%, 43.5%, 17.5% and 47.1%, respectively. Thus, the survival time is extended accordingly. In turn, one-unit increase in *leverage* and *NI_dummy*, and classification as *hot* issue or in *tech* industry are estimated to decrease the survival time, on average, by 56.4%, 52.9%, 45.0%, and 47.6%, respectively.

Table 17 Generalized gamma AFT models 1 and 2

Independent variable	Model 1			Model 2		
	Survival vs. Acquisition			Survival vs. Failure		
	Coefficient	Time ratio	p-value	Coefficient	Time ratio	p-value
intercept	4.278***	72.129	0.000	3.147***	23.274	0.000
ln_proceeds	0.103**	1.109	0.023	0.091	1.095	0.346
UW_rank	-0.075***	0.928	0.000	0.084**	1.088	0.043
ln_offerprice	-0.153	0.858	0.126	0.341*	1.406	0.061
sec_shares	-0.299***	0.742	0.008	0.812***	2.252	0.007
PE_dummy	-0.125*	0.882	0.080	-0.004	0.996	0.978
VC_dummy	-0.053	0.948	0.400	0.257**	1.294	0.050
return	0.119	1.127	0.223	-0.005	0.995	0.979
ln_age	0.026	1.027	0.386	0.361***	1.435	0.000
hot	-0.325***	0.722	0.000	-0.597***	0.550	0.000
cold	0.077	1.080	0.430	0.062	1.064	0.764
tech	-0.407***	0.665	0.000	-0.647***	0.524	0.000
leverage	-0.190*	0.827	0.070	-0.831***	0.436	0.000
ln_sales	0.031	1.031	0.189	0.162***	1.175	0.000
ln_rd	0.018	1.018	0.460	0.344***	1.411	0.000
accumdeficit	0.025	1.026	0.128	0.054	1.056	0.179
ln_sga	0.023	1.023	0.260	0.015	1.015	0.718
NI_dummy	-0.194***	0.824	0.002	-0.753***	0.471	0.000
σ	0.145***	0.145	0.001	0.678***	0.678	0.000
κ	-3.727***	-3.727	0.000	-1.164***	-1.164	0.000
Number of observations	2637			2058		
Non-censored data	980			401		
Right-censored data	1657			1657		
Likelihood ratio	147.17			352.29		
p-value	0.000			0.000		

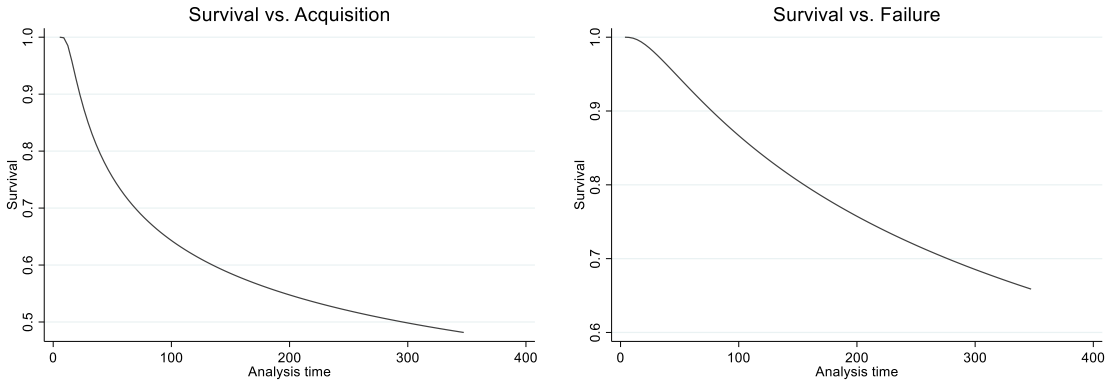
***, **, * indicate coefficient estimate's (and corresponding time ratio's) significance at 1%, 5%, and 10% levels respectively

7.2.1.1 Survival functions

The survival functions of models 1 (Survival vs. Acquisition) and 2 (Survival vs. Failure) are presented in figure 4. The y-axis denotes the probability of survival over the analysis time, which is measured in months. The starting and ending points in the analysis time are approximately 4 and 347 months, respectively, representing the shortest and longest survival time in the underlying data (*survival_time*). The survival function of model 1 is steeper compared to the one of model 2, suggesting that the probability of getting

acquired increases more rapidly over time compared to the probability of failure. Survival function of model 1 also suggests that at the end of analysis time, the probability of survival as opposed to acquisition is below 50%. In turn, the survival function of model 2 suggests that at the end of the analysis period, the probability of failure is slightly above 65%.

Figure 4 Survival functions of generalized gamma AFT models 1 and 2



7.2.1.2 Hazard and cumulative hazard functions

Figure 5 displays the hazard functions of generalized gamma AFT models 1 and 2. The analysis time on the x-axis is denoted in months similarly as in figure 4. Each point on a curve assigns a hazard rate, i.e. risk of event occurring, at a specific point in time. The hazard function of model 1 increases steeply at the early stages of the analysis time, indicating a sharply increasing risk of acquisition as opposed to survival. After the sharp surge, the hazard rate decreases steeply and remains relatively flat over the remaining analysis period. The hazard curve of model 2 shows a similar shape but is shallower, and the hazard rate is lower throughout the analysis time as opposed to model 1. The shapes of estimated hazard rates are similar to the actual frequency distributions of delistings displayed in figure 3.

Figure 5 Hazard functions of generalized gamma AFT models 1 and 2

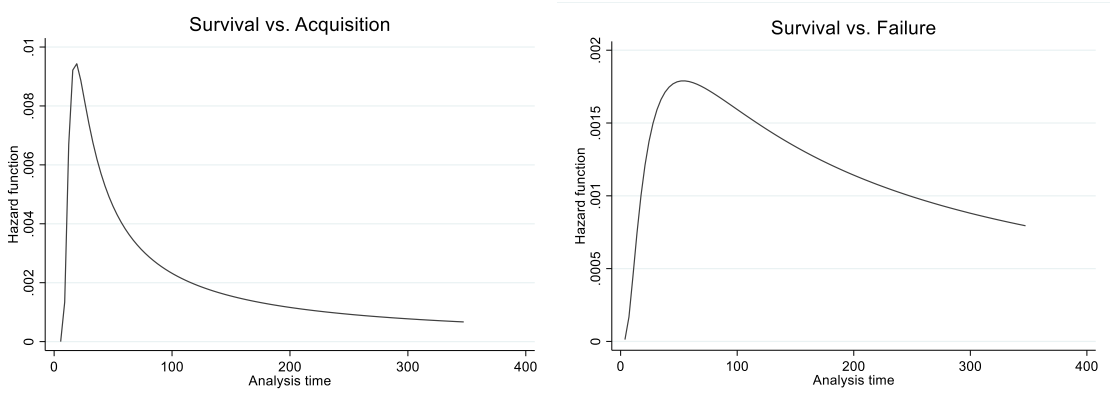
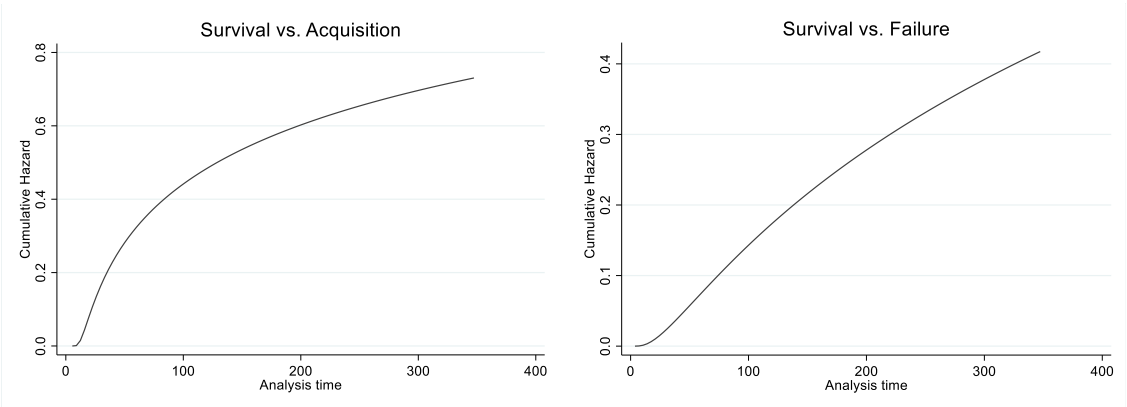


Figure 6 presents the cumulative hazard functions of generalized gamma AFT models 1 and 2. The cumulative hazard refers to accumulated risk-of-event at each point in time analysed. Cumulative hazard function of model 1 suggests a steeply increasing cumulative risk of acquisition. The accumulated risk is slightly above 70% at the end of the analysis period. The cumulative hazard curve takes a more neutral shape in model 2 compared to model 1. In model 2, at the end of the analysis period, the cumulative risk of failing is slightly above 40%.

Figure 6 Cumulative hazard functions of generalized gamma AFT models 1 and 2



7.2.2 Log-logistic AFT models

Table 18 displays the log-logistic AFT models. Model 3 compares survival time and time-to-acquisition whereas model 4 compares survival time and time-to-failure. The coefficient estimates and time ratios are interpreted similarly as in generalized gamma AFT models. The likelihood ratio of 260.48 with a p-value <0.01 indicates that the model 3 with covariates provides better fit than a null model. Similarly, likelihood ratio of

608.52 with a p-value <0.01 of model 4 suggest better fit compared to a model including only an intercept.

Produced coefficient estimates and time ratios of model 3 imply that one-unit increase in *ln_proceeds, return*, *ln_age*, *ln_sales*, *ln_rd*, and *accumdeficit* is estimated to decelerate the time-to-acquisition, on average, by 19.3%, 36.7%, 19.2%, 6.5%, 13.4%, and 6.9%, respectively. Thus, an increase in these factors is estimated to extend the survival period by the corresponding percentage. In contrast, the time-to-acquisition is estimated to accelerate, on average, along with increasing *ln_offerprice*, *PE_dummy, VC_dummy, hot, tech, leverage*, and *NI_dummy* by 39.4%, 23.5%, 20.1%, 52.3%, 44.4%, 42.5%, and 25.2%, respectively.

Model 4 compares survival time with time-to-failure. Increase in *UW_rank*, *sec_shares, VC_dummy, ln_age, ln_sales, ln_rd, and accumdeficit* is estimated to significantly extend the survival time by 13.3%, 250.9%, 34.0%, 38.9%, 23.0%, 67.9%, and 13.0%, respectively. The time-to-failure is estimated to accelerate, on average, significantly when IPO is classified as *hot* issue (47.7%) or in *tech* industry (52.9%), when *leverage* increases by one unit (63.1%), and when a company experiences net losses (*NI_dummy* = 1) (56.4%).

Table 18 Log-logistic AFT models 3 and 4

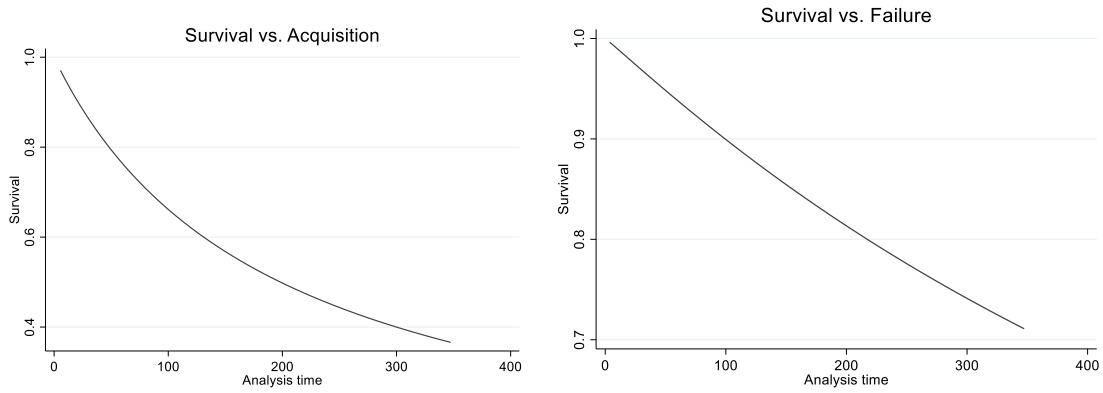
Independent variable	Model 3			Model 4		
	Survival vs. Acquisition			Survival vs. Failure		
	Coefficient	Time ratio	p-value	Coefficient	Time ratio	p-value
intercept	6.629***	756.674	0.000	3.805***	44.937	0.000
ln_proceeds	0.176**	1.193	0.018	0.095	1.099	0.411
UW_rank	-0.044	0.957	0.210	0.125***	1.133	0.004
ln_offerprice	-0.501***	0.606	0.002	0.259	1.296	0.267
sec_shares	0.134	1.143	0.502	1.255***	3.509	0.005
PE_dummy	-0.268**	0.765	0.029	0.129	1.137	0.567
VC_dummy	-0.225**	0.799	0.033	0.293*	1.340	0.055
return	0.312**	1.367	0.043	0.063	1.065	0.760
ln_age	0.176***	1.192	0.001	0.328***	1.389	0.000
hot	-0.740***	0.477	0.000	-0.648***	0.523	0.000
cold	0.282	1.326	0.108	0.219	1.245	0.473
tech	-0.588***	0.556	0.000	-0.753***	0.471	0.000
leverage	-0.553***	0.575	0.001	-0.997***	0.369	0.000
ln_sales	0.063*	1.065	0.071	0.207***	1.230	0.000
ln_rd	0.126***	1.134	0.003	0.518***	1.679	0.000
accumdeficit	0.067**	1.069	0.016	0.122***	1.130	0.008
ln_sga	-0.020	0.980	0.539	0.018	1.018	0.718
NI_dummy	-0.290***	0.748	0.010	-0.830***	0.436	0.000
γ	0.021	0.021	0.450	-0.036	-0.036	0.411
Number of observations	2637			2058		
Non-censored data	980			401		
Right-censored data	1657			1657		
Likelihood ratio	260.48			608.52		
p-value	0.000			0.000		

***, **, * indicate coefficient estimate's (and corresponding time ratio's) significance at 1%, 5%, and 10% levels respectively

7.2.2.1 Survival functions

Figure 7 displays the survival functions derived from both log-logistic AFT models. The figure displays that the survival function of model 4 (Survival vs. Failure) is shallower compared to the slightly steeper survival curve of model 3 (Survival vs. Acquisition). The survival function of model 3 suggests that the probability of survival in contrast to acquisition is less than 40% at the end of the analysis period. In turn, the probability of survival at the end of analysis time is slightly above 70% when contrasted to failure.

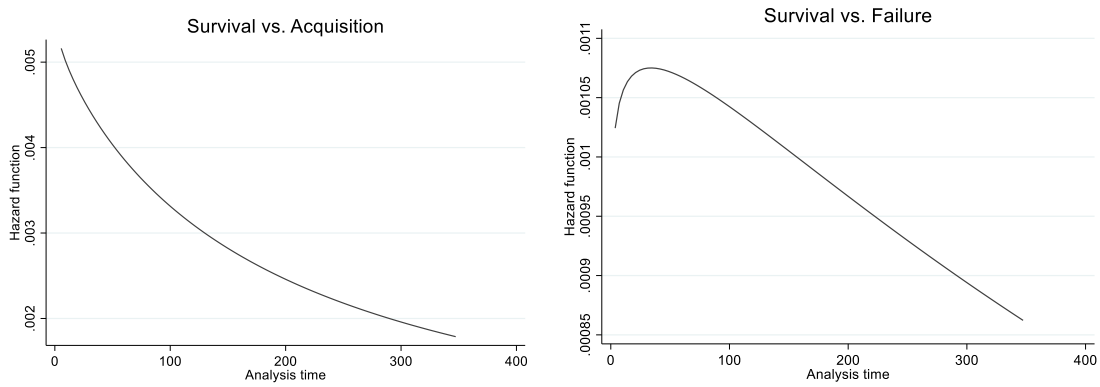
Figure 7 Survival functions of log-logistic AFT models



7.2.2.2 Hazard and cumulative hazard functions

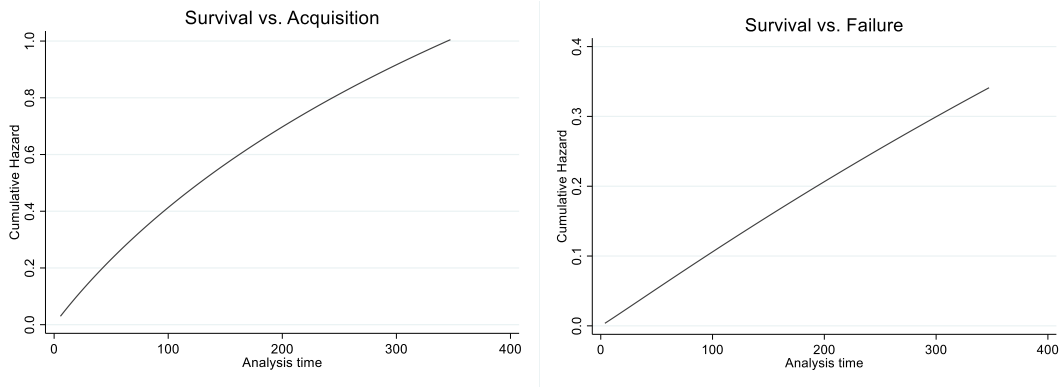
The hazard functions of log-logistic AFT models are shown in figure 8. The shapes of hazard curves between models 3 and 4 differ notably, although both demonstrate non-monotonically decreasing hazard rates over time. The hazard curve of model 3 is concave up, suggesting that the risk to acquisition decreases over time slightly more sharply at the beginning of analysis time. The hazard curve of model 4 is hump-shaped, suggesting that risk-to-failure first increases quite sharply to a maximum point at the beginning of the analysis period and decreases thereafter. The y-axis denotes hazard risk, and the acquisition risk seems to be higher compared to failure risk.

Figure 8 Hazard functions of log-logistic AFT models 3 and 4



The cumulative hazard functions of AFT models 3 (Survival vs. Acquisition) and 4 (Survival vs. Failure) are shown in figure 9. The estimated cumulative hazard functions suggest that the probability of acquisition and failure increases over time. According to the cumulative hazard function of model 3, the probability of getting acquired is 100% at the end of analysis time. This seems an unrealistic estimation as several companies are independently listed entities at the end of the analysis time. In contrast, the probability of failure is between 30% and 40% at the end of the analysis period.

Figure 9 Cumulative hazard functions of log-logistic AFT models 3 and 4



7.2.3 Comparison of the AFT models

Both generalized gamma and log-logistic models produce relatively similar results in terms of estimated coefficients and time ratios. However, there are some differences in the significance of covariates. When comparing models 1 and 3 that compare the survival time and time-to-acquisition, *UW_rank* and *sec_shares* are estimated to have an insignificant impact on the time-to-acquisition in the log-logistic model, whereas in the generalized gamma model, those are significant covariates. In turn, *ln_offerprice,*

VC_dummy, return, ln_age, *ln_sales, ln_rd*, and *accumdeficit* are estimated to be insignificant covariates in the generalized gamma model but significant in the log-logistic model. Moreover, the sign of *sec_shares* is positive, although not significant, (0.134) in the log-logistic model but negative (-0.299), and significant, in the generalized gamma model 1, indicating a controversy between the models. Otherwise, the signs of estimated coefficients are in harmony in both Survival vs. Acquisition models.

In models 2 and 4 comparing survival time and time-to-failure, *accumdeficit* has an insignificant impact on the survival time in the generalized gamma model, whereas in the log-logistic model it is estimated to impact the survival time at 1% level of significance. On the other hand, *ln_offerprice* is estimated to have a significant effect on the survival time in the log-logistic model 4 but it is insignificant determinant in the generalized gamma model 2. All signs of estimated coefficients in models 2 and 4 are in line, although the time ratio of *sec_shares* is 3.498, thus being much higher compared to the corresponding time ratio of 2.234 in the generalized gamma model.

The functional form of the AFT model impacts notably on the shape of the hazard function (see figures 5 and 8). This difference most likely arises from the distinct features and shapes of the distributions. In addition, log-logistic model 3 derives a cumulative hazard of 1.0 at the analysis period, suggesting that the accumulated probability of acquisition would be 100% at the end of the analysis time. In turn, the cumulative hazard of generalized gamma model 1 is slightly above 70% at the maximum time point, giving perhaps a slightly more realistic estimate of the cumulative hazard probability. The generalized gamma distribution is known to be extremely flexible and can take various shapes (Stata, 2023c, p.7), including increasing, decreasing, non-monotonic, and constant shapes, based on the parameters of the model. In turn, log-logistic distribution expects that the hazard rate increases at first and after reaching a maximum, it decreases. Due to more strict expectations, log-logistic model may not be able to capture all complexities from the underlying real-world data.

7.3 Robustness checks

To enhance the robustness of the results, three types of robustness checks are executed for multinomial logit models. First, to address the forward-looking bias caused by usage of financial accounting variables recorded at IPO year (*leverage, NI_dummy, accumdeficit, ln_sga*), the extended multinomial logit model is run by excluding 58 IPOs that delisted within the first year after initial offering (see figure 3). Secondly, in financial

literature, financial companies are often excluded from the sample since they are subject to differing regulatory environment and pose differing accounting properties. In this thesis, the final sample included 276 financial companies so as a robustness check, the extended multinomial logit model is run without those. Thirdly, instead of a 5-year tracking period, a 3-year tracking period is considered. The number of companies in the categories of acquired and failed decrease from 980 and 401 to 584 and 238, respectively, leaving 2216 companies to the survived category. Longer follow-on periods were not considered in the robustness checks since it is assumed that characteristics recorded at the time of an IPO and soon after that may not be the most reliable predictors of delisting over 5 years following an IPO.

When running first the models without 58 IPOs delisted within the first year and after that without 276 financial companies, the extended multinomial logit model yields results similar to the reported ones in terms of the signs and significance of the coefficient estimates. Pseudo-R^2 of the model increases slightly to 0.1280 when IPOs in financial industry are eliminated from the sample, but neither the significance nor the signs of individual predictors are notably affected. When applying the 3-year follow on period, few coefficient estimates pose different levels of significance compared to the reported results, especially when analysing the probability of acquisition contrasted with the probability of survival, but the signs of the coefficient estimates remain the same. However, as the number of IPOs in categories of acquired and failed decrease notably, making the division of companies in each category more unbalanced, it is expected that a shorter follow-on period has an influence on the results. To reliably examine shorter follow-on periods, longer overall time frame in the study is suggested to increase the number of companies in the categories of acquired and failed IPOs.

8 DISCUSSION

In this chapter, the salient results are linked to the theoretical framework and contrasted with findings of previous research. In addition, this chapter provides answers to the research questions that were presented in the introduction. Another subchapter is dedicated to a discussion on considerations and choices made in the empirical study.

8.1 Survival profile of IPOs

This research aims to shed light on the favorable issue, company, and market characteristics that increase the probability of survival or lengthen the survival time when contrasted to acquisition or failure. Survival is considered the most desirable outcome since it is assumed that there is a larger dispersion of quality among acquired companies. The results of this study suggest that of IPOs issued between 1995 and 2018, 55% survive, 32% get acquired, and 13% fail in the aftermarket over a tracking period of 5 years. In comparison, Lowry, Michaely and Volkova (2017) documented that among IPOs issued between 1973 and 2013, 23% got acquired and 14% delisted due to negative reasons within 5 years of issuance. Although these proportions depend on the examined period, this study finds a notably larger proportion of acquired companies, possibly due to an increase in M&A activity over the past few decades.

8.1.1 Issue specific characteristics

The offer size (*ln_proceeds*) is expected to have a positive effect on the probability of survival and a negative effect on the probability of acquisition and failure. The results imply that, on average, the probability of survival indeed increases significantly with offer size. This is in accordance with previous studies, such as Schultz (1993) and Jain and Kini (1999), who found that the probability of survival increased with offer size when contrasted with failure. Furthermore, this finding is in consensus with previous studies on the long-term performance of IPOs which found evidence that offer size is positively related to long-term returns (Stoll and Curley, 1970; Ritter, 1991; Loughran and Ritter, 1995). It is also discovered that the probability of acquisition and failure decreases, on average, with increasing offer size, although the effect on failure is not statistically significant. Additionally, when observing the results of multinomial logit models, the probability of acquisition as opposed to survival decreases significantly with increasing offer size. It is also documented that larger offer size decelerates the time-to-acquisition, indicating that companies with smaller offer sizes get acquired faster than companies with larger offer sizes. These findings indicate that companies with larger offerings could

pose a more established market position and have better prospects to survive after the initial offering.

Due to mixed evidence in previous studies on the effect of first-day returns (*return*) on the outcome of the IPO, it is challenging to determine signs of expected effects on the probability of survival and failure. The results show indications that an increase in first-day returns has a negative effect on the probability of acquisition, signaling that companies with larger first-day returns are less likely to get acquired in the aftermarket. Also, the results suggest that companies with higher first-day returns have a greater probability to survive as opposed to acquisition at 10% level of significance. The findings conflict with the impresario hypothesis proposing that IPOs experiencing the highest underpricing should perform the worst in the long run, as the abnormally high first-day returns are caused by the presence of fads in the market (Ritter, 1998). Also, due to the signaling hypothesis, it is expected that an increase in underpricing would increase the probability of acquisition. However, according to the obtained results, the effect is the opposite. The survival analysis also gives indications that when first-day return increases, time-to-acquisition is estimated to decelerate and hence, survival time is estimated to be extended. However, the results of the likelihood ratio Chi-square test implies that underpricing does not seem to have significant explanatory power in the multinomial logit model, and robust conclusions are difficult to be drawn since the reasoning behind underpricing remains an unsolved puzzle in the financial literature.

One-unit increase in offer price (*ln_offerprice*) is expected to decrease the probability of acquisition and failure and increase the probability of survival. Surprisingly, the findings reveal that, on average, the offer price is significantly negatively related to the probability of survival and failure. The negative effect on the probability of survival is stronger, implying that, on average, an increase in offer price affects more negatively on the prospects of survival than failure. These findings diverge from previous studies which suggest more favorable prospects for higher-priced offerings and stocks in general (Seguin and Smoller, 1997; Demers and Joos, 2007; Bradley et al., 2006). The probability of acquisition is estimated to increase significantly with offer price. When contrasting the probability of acquisition with survival, the probability of acquisition increases significantly with increasing offer price. This indicates that highly-priced offerings get more likely acquired in the aftermarket. Survival analysis also gives indications that time-to-acquisition is accelerated with an increase in offer price, but the models produce slightly contradicting results, so this interpretation is not conclusive. As discussed

earlier, it is difficult to intuitively explain the effect of the offer price on the outcome of an IPO, especially as the results conflict with the general wisdom of lower-priced stocks being considered riskier compared to stocks with higher prices.

The proportion of secondary shares (*sec_shares*) is expected to have a negative effect on the probability of survival and a positive effect on the probability of acquisition and failure. However, according to the obtained results, the proportion of secondary shares is estimated to have a significant negative effect on the probability of failure, indicating that a larger proportion of secondary shares decreases the probability of failure. Logit regression analysis shows that the probability of failure as opposed to survival decreases when the proportion of secondary shares increases. When analysing the time-to-failure, an increase in the proportion of secondary shares seems to significantly extend the survival period, suggesting that IPOs with a larger proportion of secondary shares survive longer periods. These results indicate that failed companies are raising cash at IPO rather than transferring ownership. The obtained results conflict with previous literature in which the issuance of secondary shares has been associated with negative post-IPO prospects (Ritter, 1991; Loughran and Ritter, 1995; Kim and Weisbach, 2008). However, drawing definitive conclusions is challenging due to the lack of information on the proportion of shares held by insiders before and after the offering. In other words, insiders of failed companies may have held only a small share of the total number of the company's shares at the time of IPO, so a reduction in ownership is not so easy to interpret solely through the proportion of secondary shares. A positive, although insignificant effects, are captured between the proportion of secondary shares and the probability of survival and acquisition, suggesting that companies issuing larger proportion of secondary shares may be more likely to survive or get acquired. Positive effect on the probability of acquisition could indicate that insiders use IPO as a first stage to reduce their holdings and prepare for the future sell-out as Zingales (1995) proposed.

Offerings with prestigious underwriters are expected to survive or get acquired rather than fail. The documented effect of underwriter ranking (*UW_rank*) is significantly positive on the probability of acquisition and negative on the probability of failure. When assessing the results of all multinomial logit models, the probability of failure in contrast to survival decreases significantly in all models when underwriter ranking increases by one unit, suggesting that companies with more prestigious underwriters are more likely to survive than fail. Survival analysis also exhibits relatively strong evidence that survival time increases with underwriter ranking when examining time-to-failure. The significant

results are in line with previous research finding underwriter prestige and long-term performance or survival of IPOs being positively related (Michaely and Shaw, 1994; Carter, Dark and Singh, 1998; Schultz, 1993; Demers and Joos, 2007). In the theoretical part, it is discussed that the quality of IPOs impact on the underwriter's reputation. The results suggest that IPOs of highly ranked underwriters are indeed less likely to fail, although higher underwriter ranking is simultaneously suggested to increase the probability of delisting due to acquisition.

Sponsor-backing of an IPO is expected to affect positively on the probability of survival and acquisition but negatively on the probability of failure. Interestingly, PE-backing has a significantly positive effect only on the probability of acquisition, whereas VC-backing affects negatively on the probability of failure and positively on the probability of acquisition. In other words, the probability of acquisition increases, on average, with sponsor involvement and VC-backing decreases the probability of failure. The multinomial logit regression analysis shows that the probability of acquisition increases in contrast to survival if an IPO is PE-backed. Time-to-acquisition is also significantly accelerated if offering is PE-backed. In turn, VC-backed IPOs are less likely to fail when comparing the probability of failure to survival. This is supported by survival analysis, which suggests that the time-to-failure decelerates if a company is VC-backed. These findings are in line with previous research documenting that VC-backed IPOs perform better in the long run and are less likely to fail as opposed to survival (Brav and Gompers, 1997; Jain and Kini, 2000; Kooli and Meknassi, 2007). This implies that VCs aim to invest in companies with strong growth potential and solid business models. Thus, these IPOs could be speculated to deliver better quality than IPOs without VC-backing. Also, VCs can provide companies with valuable mentorship, advice and support from a wide network which may put these companies better positioned in the market compared to non-backed companies. Compared to PE-backing, VC-backing has been a much more commonly used variable to examine the effect of sponsor-backing on IPO outcome in previous literature. Thus, it is an interesting finding that the probability of acquisition increases if the offer is PE-backed. These companies may be viewed as potential targets if the PE firm has been able to create a strong market position for the company through strategic and operational guidance.

8.1.2 Company specific characteristics

In line with previous research (Ritter, 1991; Hensler, Rutherford, and Springer, 1997; Demers and Joos 2007) and the expected outcomes, company age (*ln_age*) seems to

have a positive effect on the probability of survival and a negative effect on the probability of failure and acquisition, meaning that older companies have greater prospects to survive in long run. Survival analysis indicates that time-to-acquisition and time-to-failure are decelerated with increasing company age. This enhances the assumption that older companies demonstrate an ability to tackle varying market conditions over time and possess more resilient business models. As younger companies are more likely to get acquired, they may be viewed as more attractive targets posing greater potential for growth and innovation as opposed to older companies.

On average, non-tech companies are found to be more likely to survive and tech companies are more likely to get acquired or fail in the aftermarket (*tech*). Survival analysis also shows that survival time increases if company is classified as non-tech. These results were expected as the examined period covered dot-com bubble tech IPOs that experienced high delisting rates. Also, the technology industry evolves rapidly, and innovations are prone to become obsolete in a highly competitive environment. These industry characteristics may contribute to the increased probability of acquisition and failure among tech companies.

As expected, one-unit increase in the level of leverage (*leverage*) affects significantly negatively on the probability of survival and positively on the probability of acquisition and failure. This implies that companies with greater levels of leverage are more likely to get acquired or fail in the aftermarket. The positive effect is stronger among failed companies, indicating that they possess higher leverage than acquired companies. Survival analysis produces similar results, indicating that the time-to-acquisition and -failure, significantly accelerate along with an increase in leverage. In accordance with corporate failure prediction studies, leverage is a significant determinant of failure (e.g. Altman, 1968; Zmijewski, 1984) and in this study, a determinant of delisting in general. The findings are in line with those of Demers and Joos (2007) who also documented a positive association between leverage and IPO failure. Companies with higher levels of leverage may get more easily acquired if they experience financial distress and lack bargaining power at transaction price negotiations. This sheds light into the quality of acquired companies, indicating that targets pose higher leverage than survived companies. However, the interpretation is two-fold as high leverage may also indicate growth and expansion orientation or that acquired companies operate in highly leveraged industries.

According to the results, as expected, an increase in sales (*ln_sales*) is estimated to significantly increase the probability of survival and decrease the probability of failure. This is in consensus with the findings of Demers and Joos (2007) who documented that an increase in sales improved the survival prospects as opposed to failure. A negative effect on acquisition is statistically insignificant. When analysing time-to-failure, an increase in sales is estimated to increase survival time. These results suggest that companies with higher sales survive longer and are less likely to delist due to failure. The negative effect is strong among failed companies, indicating that companies with the lowest or non-existent revenue streams are most vulnerable to delist due to negative reasons. This could be due to several reasons, but companies with higher sales often have more stable business models and they might be larger as sales can be a proxy of company size. Companies may end up failing if there is no clear strategy for generating stable revenue streams.

The expected effect of R&D expenses (*ln_rd*) on the probability of survival and acquisition is positive and negative on the probability of failure. The effect of an increase in R&D expenses is indeed positive on the probability of survival and negative on the probability of failure. Demers and Joos (2007) also documented that the probability of survival increases with R&D expenses but this effect was significant only among tech companies while the sample of this study includes all companies. The effect on acquisition turns out to be negative but is statistically insignificant. The relative risk of acquisition and failure are estimated to decrease when contrasting the outcomes with the probability of survival, indicating that an increase in R&D expenses is estimated to increase the probability of survival as opposed to two other categories. The impact is especially strong when contrasting the probability of failure with survival. These findings imply that either investing in R&D is advisable in general or that R&D intensive industries have more favourable prospects to survive post-IPO. The findings also indicate that survived companies may be implementing their product differentiation strategies more effectively through greater investments in R&D.

The data reveals that 45.2% of the companies in the sample are not able to generate positive net earnings in IPO year. This is typical for early-stage companies that invest heavily in growth (WSJ, 2018). The obtained results are in line with the expectations that companies with net losses are more likely to get acquired or fail, and are less likely to survive, although the effect on the probability of acquisition is insignificant. According to multinomial logit model analysis, recorded net losses seem to represent a risk factor

which strongly increases the probability of failure. For risk-averse investors, it is relatively easy to select investees with positive net income at the time of an IPO. However, this cautious approach may cause them to miss lucrative investment opportunities in growth-oriented companies that report net losses due to substantial investments in expansion, despite their potential for profitability.

Regarding accumulated deficit (*accumdeficit*), the expected effect on survival is positive and negative on the probability of acquisition and failure. The expected effects are realised when analysing the obtained results. Nevertheless, as with net losses, the effect is negative but insignificant on the probability of acquisition. The findings are in accordance with Demers and Joos (2007) who document that accumulated deficit impacts negatively on the probability of failure, although their results are significant only among tech companies. The history of losses may raise concerns about the company's ability to become profitable and the management of financial obligations. The time-to-event analysis provides mixed results, precluding a confident assertion that accumulated deficit affects survival time.

8.1.3 Market conditions

As discussed earlier, Ritter and Welch (2002) argued that market conditions play a role in the decision to go public and this proposition has received empirical support from academics such as Pagano, Panetta and Zingales (1998) and Kim and Weisbach (2008). Prior literature has also captured patterns of high IPO activity, volume, and first-day returns, which contribute to the presence of hot issue markets (Ibbotson and Jaffe, 1975; Ritter, 1998). In this study, 61.6% of failed companies were classified as hot issues, and only 3.5% of them as cold issues. In contrast, 31.8% of survived IPOs are categorised as hot issues and 10.0% as cold issues. This implies that a large proportion of failures are classified as hot issues whereas survivals are most frequently classified as neutral issues. This is consistent with the findings of Yung, Çolak and Wang (2008) who found that hot issues are associated with high failure rates. In consensus with previous research, this study strongly suggests that the probability of failure increases significantly if IPO is classified as a hot issue. The time-to-failure is estimated to accelerate when issue is classified hot, indicating a shorter survival time. These results imply that low-quality companies can successfully raise capital from the public in hot market periods since the demand for IPOs is higher as Loughran and Ritter (2004) argued. Moreover, the results of this study support the windows of opportunity hypothesis which suggests that the timing of IPO to periods of high valuations leads to poor long-run performance since the

valuation is corrected over time when market conditions stabilise. The results are also in accordance with previous empirical findings, such as Ritter (1991) who documented that annual IPO volume is negatively associated with the long-term performance of IPOs and Hensler, Rutherford, and Springer (1997) who documented that the market level impacts inversely the survival time of IPOs.

A large proportion (53.5%) of acquired companies are classified as hot issues. Also, the probability of acquisition increases, on average, even more (0.132) than the probability of failure (0.033) if the IPO is classified as a hot issue. Survival analysis indicates a shorter survival time for hot issues when analysing the time-to-acquisition. These results may be affected by a larger number of IPOs in the acquired category as opposed to failure. However, it can be observed that market conditions have similar effects on the probability of acquisition and failure as contrasted with survival.

8.2 Differences between acquired and failed companies

This study provides interesting insights into the similarities and differences between acquired and failed companies. Certain factors have the same directional effect on acquisition and failure, but the effect is of different magnitude. To illustrate this, an increase in leverage and net losses in the IPO year accelerate both, time-to-acquisition and -failure but the effect is much stronger on failure. Similarly, the effect on the probability of failure seems to be higher than the probability of acquisition when leverage increases or net losses are reported in the IPO year. This reveals that both acquired and failed companies are predicted to be, on average, more levered than survived companies and failed companies are predicted to be the most levered. Net losses also exhibit a greater negative impact on the probability of failure than on the probability of acquisition. Furthermore, an increase in company age, accumulated deficit, sales, and R&D expenses decelerate the time-to-acquisition and -failure as well as the probability of getting acquired or failure when contrasted with survival. However, the effects are stronger among failed companies, indicating that acquired companies are predicted to be more mature, have less accumulated deficit and have higher sales and R&D expenses as opposed to failed companies. The relationships between financial accounting variables and IPO outcomes indicate that failed companies pose, on average, more financial distress and report worse financial numbers as opposed to acquired companies.

This study also reveals differences in the predictors of failure and acquisition. PE-backing is estimated to increase the probability of acquisition and accelerate the time-

to-acquisition when compared to survival but it does not have a significant impact neither on the probability of failure nor the time-to-failure. Thus, PE-backing does not decrease the probability of delisting on all occasions and hence, is not considered a favourable characteristic when the ultimate goal is to survive. VC-backing is estimated to decrease the probability of failure as opposed to survival and decelerate the time-to-failure, but also accelerate the time-to-acquisition. This implies that if the issue is VC-backed, the company is more likely to get acquired when contrasted to survival but the least likely outcome is failure. Similarly, underwriter ranking has a positive effect on the probability of acquisition whereas the effect is negative on failure, indicating that an increase in underwriter ranking increases the probability of acquisition and decreases the probability of failure. Survival analysis also indicates that an increase in underwriter ranking accelerates the time-to-acquisition whereas it decelerates the time-to-failure. These findings signal that failed companies have a tendency to be lower quality, on average, than acquired ones and that IPOs with highly ranked underwriters seem to be most likely to get acquired, thus increasing the probability of delisting, although the probability of failure is the most unlikely outcome in such case.

To summarise, acquired companies pose similar characteristics to failed companies. However, the results endorse the pre-assumption that the group of acquired companies entails companies of varying quality. Based on the differences in the magnitude of effects and some controversial findings, it could be argued that the average quality of acquired companies falls in between the categories of survivors and failures. Surprisingly, sponsor-backing of IPOs, and increase in underwriter ranking signals that acquisition is the most likely outcome and thus, these characteristics are not considered being favourable in terms of survival as they may increase the probability of delisting, although not necessarily due to negative reasons.

8.3 Answers to research questions

In the introduction, two research questions were proposed. The first research question is "*Which issue-, company-, and market-specific characteristics impact the survival of IPOs in the aftermarket?*". This research question is answered primarily through interpreting the AMEs. For a factor to be considered as a significant determinant of survival, a one-unit increase in the independent variable should affect similarly on the probability of acquisition and failure and have an opposite effect on the probability of survival, thereby reducing the probability of delisting in general. According to the obtained results, the probability of survival most confidently increases with offer size,

company age, sales, and R&D expenses. In turn, the probability of survival decreases with an increase in leverage, and the amount of accumulated deficit, as well as with hot market conditions, technology industry classification, and if a company reports net losses at IPO year.

The second research question "*Which issue-, company-, and market-specific characteristics impact the survival time of IPOs in the aftermarket?*" is answered through the obtained results from AFT models. Survival time decreases collectively in all models with an increase in leverage, hot market conditions, technology industry classification and reported net losses. Thus, lower leverage, non-hot market conditions, non-tech industry classification, and positive net income are estimated to increase the survival time. Although other significant relationships are captured in AFT models, the results slightly contradict depending on the determined functional form of the model, so the answer to the second research question is conservative.

8.4 Considerations

Other variables that were tested in the regressions included gross spread, the number of managers, and gross margin. Gross spread and the number of managers correlated highly with offer size. In addition, these variables did not increase the explanatory power of the models and produced distorted outputs so those were omitted from all models. Gross margin was a highly skewed variable so it was excluded from the analysis as severe modifications would have been required to address its statistical deficiencies. In addition, several variables, including the proportion of shares held by directors after the offering and variables related to filing price ranges were left out from the models due to a reduction in sample size. Overall, creativity regarding the variable selection was limited due to restricted data availability and exhausting data processing.

It was a conscious choice to include accounting variables reported at IPO year (*leverage, NI_dummy, accumdeficit, ln_sga*), although Wysocki (2007) criticised Demers and Joos (2007) about look-ahead bias when using such variables. The usage of ex-post variables also slightly violates the assumption of the AFT model which assumes that covariates obtain the value at $t = 0$ which represents the IPO date. However, only 58 IPOs delisted during the first year after initial offering (see figure 3) and robustness checks did not reveal crucial differences in the results when these 58 IPOs were excluded from multinomial logit and AFT models.

9 CONCLUSION

This thesis analyses comprehensively the determinants of post-IPO outcomes and factors impacting the length of survival time in the aftermarket. From the total sample of 3038 IPOs that occurred between 1995 and 2018, 55% survive, whereas 32% get acquired and 13% fail in the aftermarket over a tracking period of 5 years. It is documented that several issue, company, and market characteristics provide valuable information regarding the quality of IPOs and their delisting prospects.

This research builds upon prior research by employing previously applied methodologies (e.g. Demers and Joos, 2007; Hensler, Rutherford, and Springer, 1997; Jain and Kini, 1999; Jain and Kini, 2000) and extends the statistical techniques associated with them. This study also combines two distinct methodologies which is rarely done in previous research. First, multinomial logit models and corresponding post-estimation techniques, including Average Marginal Effects and a likelihood ratio Chi-square test, are applied. The multinomial logit models enable to estimate the probability of IPOs transitioning to each post-issuance state. Secondly, AFT models are developed to estimate which factors accelerate or decelerate the time-to-acquisition and -failure in relation to survival. These methods complement each other effectively and enhance the robustness of results. This study also advances the appropriate use of statistical techniques, addressing gaps in the analysis and post-estimation techniques of previous research involving multinomial logit and AFT models. Additionally, to the author's knowledge, this study is the first one to include financial accounting metrics in the AFT models. Overall, this study demonstrates a high level of model complexity as the set of variables comprehensively describe issue, company and market characteristics associated with IPOs.

The first research question "*Which issue-, company-, and market-specific characteristics impact the survival of IPOs in the aftermarket?*" is answered by analysing the effects of selected factors on the probability of survival in the aftermarket as opposed to the probability of delisting due to acquisition and failure. According to the obtained results, the probability of survival as opposed to delisting either due to acquisition or failure is significantly positively affected, on average, by an increase in offer size, company age, sales, and R&D expenses. In contrast, the probability of survival is estimated to significantly decrease, on average, with an increase in leverage, and accumulated deficit, as well as with the presence of hot market conditions, technology industry classification, and net losses.

The second research question *"Which issue-, company-, and market-specific characteristics impact the survival time of IPOs in the aftermarket?"* is answered through survival analysis which accounts for the duration that an IPO remains listed on a stock exchange. Specifically, the AFT model identifies factors that increase the survival time as opposed to delisting due to acquisition or failure. The survival time is estimated to increase significantly if a company has low leverage, is classified as non-tech, is issued at non-hot market conditions, and reports positive net income in IPO year. These characteristics are estimated to significantly increase the survival time in all AFT models when considering both, time-to-acquisition and -failure.

In several previous studies, the category of acquired companies is neglected from the analysis and these companies are either included in the category of failed or survived companies, or omitted from the analysis. This research provides evidence that acquired and failed companies pose similar characteristics when contrasted individually with survivors but the effects on the probability of failure are often estimated to be more extreme. To illustrate, failed companies seem to be, on average, more financially distressed and report higher leverage and accumulated deficit, and lower sales, R&D expenses, and net income. In turn, both acquired and failed companies are associated with technology industry classification and with the presence of hot market conditions, but the effects are stronger among acquired companies, suggesting that acquired IPOs are more concentrated in the technology industry and are more strongly associated with hot market conditions. Surprisingly, sponsor-backing of IPOs, and an increase in underwriter ranking signals that acquisition is the most likely outcome and thus, these characteristics are not considered the most favorable as they decrease the probability of survival. These findings add valuable perspective to the current understanding of the nature of acquired companies and the results endorse the pre-assumption that the group of acquired companies entails companies of varying quality. Based on the differences in the magnitude of effects and some controversial findings between acquired and failed IPOs, it could be argued that the average quality of acquired companies falls in between the categories of top-performing survivors and worst-performing failures.

9.1 Suggestions for further research

The survival of IPOs provides several avenues for further research. First, the phenomenon has been mostly studied in the U.S. market and according to the author's investigation, peer-reviewed studies in other geographical areas have not been conducted. This creates an excellent opportunity to examine the survival of IPOs in other

geographical areas, such as Europe, and the characteristics of survived and delisted companies.

Demers and Joos (2007) introduced a detailed industry analysis to the topic by separating technology and non-tech IPOs in their analysis. In addition, Hensler, Rutherford, and Springer (1997) and Kooli and Meknassi (2007) analysed industry differences on a high level. However, more industry-focused analysis could be conducted as done previously in IPO long-run performance studies (e.g. Ritter, 1991). Industry plays a crucial role, particularly in the analysis of accounting information, suggesting a need for further exploration in future research. The findings of this study also suggest industry-specific differences as companies in the technology industry are more likely to get acquired or fail in the aftermarket and that the survival time is estimated to be shorter if a company is classified in the technology industry.

This study shows that failure and acquisition rates have been relatively low over the past two decades. This likely explains the lack of recent literature on the topic. In the spirit of Fama and French (2004), it would be interesting to examine the altering characteristics of IPOs more thoroughly over time in the 21st century. Moreover, the characteristics of companies in different outcome categories would be interesting to analyse in more detail and compare the results with long-term returns. In addition, the dispersion of quality among companies under same category, would be interesting to examine through a performance analysis. To enhance the economic significance of the results, portfolios could be constructed based on the characteristics of a predicted ideal, neutral, and poor survival profiles of IPOs and examine the long-run performance of the portfolios.

The findings of this study suggest that hot market conditions affect positively on the probability of failure and acquisition. Given the record high IPO volume in 2021, studying the long-term survival of the companies that gone public over that period, would be interesting when feasible. Additionally, a notably large proportion of issues were classified as hot issues over the study period from 1995 to 2018. Therefore, it would be interesting to use alternative measures of market heat which could be linked to the level of underpricing, IPO volume, or market returns around the event of issuance. Moreover, in studies on bankruptcy prediction, a wide set of financial ratios have been applied. Hence, it would be intriguing to witness a greater emphasis on the utilisation of financial accounting determinants in IPO studies in general.

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APPENDIX 1 CORRELATION MATRIX AND VIFS

Table 19 Correlation matrix

Independent variable	ln_proceeds	UW_rank	ln_offerprice	sec_shares	PE_dummy	VC_dummy	return	ln_age	hot	neutral	cold	tech	leverage	ln_sales	ln_rd	accumdeficit	ln_sga	NI_dummy
ln_proceeds	1.000																	
UW_rank	0.643	1.000																
ln_offerprice	0.647	0.519	1.000															
sec_shares	0.292	0.146	0.192	1.000														
PE_dummy	0.332	0.192	0.125	0.155	1.000													
VC_dummy	-0.079	0.211	-0.044	-0.134	-0.251	1.000												
return	0.062	0.111	0.239	-0.082	-0.139	0.233	1.000											
ln_age	0.289	0.139	0.150	0.240	0.314	-0.286	-0.179	1.000										
hot	-0.325	-0.199	0.089	-0.062	-0.256	-0.047	0.086	-0.147	1.000									
neutral	0.279	0.165	-0.061	0.045	0.226	0.031	-0.062	0.113	-0.857	1.000								
cold	0.081	0.059	-0.052	0.031	0.052	0.029	-0.043	0.052	-0.248	-0.285	1.000							
tech	-0.017	0.119	0.042	-0.031	-0.158	0.279	0.282	-0.162	0.084	-0.065	-0.035	1.000						
leverage	0.233	0.047	0.065	0.148	0.302	-0.305	-0.223	0.310	-0.142	0.100	0.078	-0.178	1.000					
ln_sales	0.565	0.318	0.306	0.304	0.416	-0.290	-0.151	0.548	-0.278	0.218	0.109	-0.105	0.441	1.000				
ln_rd	0.115	0.248	-0.031	-0.043	-0.106	0.384	0.119	-0.019	-0.227	0.183	0.079	0.305	-0.161	-0.025	1.000			
accumdeficit	-0.219	-0.260	0.025	0.145	-0.088	-0.317	-0.098	0.040	0.294	-0.245	-0.087	-0.136	-0.087	0.022	-0.440	1.000		
ln_sga	0.422	0.316	0.238	0.144	0.276	-0.013	0.090	0.279	-0.224	0.182	0.075	0.219	0.204	0.535	0.191	-0.218	1.000	
NI_dummy	-0.096	-0.004	-0.160	-0.295	-0.126	0.310	0.146	-0.283	-0.058	0.065	-0.014	0.093	-0.137	-0.385	0.247	-0.554	-0.072	1.000

Table 20 VIFs

Variable	VIF
ln_sales	2.72
accumdeficit	2.09
NI_dummy	1.87
UW_rank	1.83
ln_sga	1.73
ln_offerprice	1.72
VC_dummy	1.57
ln_rd	1.56
ln_age	1.53
leverage	1.44
hot	1.40
PE_dummy	1.38
tech	1.34
return	1.28
sec_shares	1.18
cold	1.08

APPENDIX 2 MULTINOMIAL LOGIT MODELS 2 AND 4

Reduced models 2 and 4 include year dummies as control variables instead of heat dummies.

Table 21 Reduced multinomial logit model 2

	Dependent variables								
Independent variables	$Log(P_A/P_S)$			$Log(P_F/P_S)$			$Log(P_A/P_F)$		
	Coefficient	RRR	p-value	Coefficient	RRR	p-value	Coefficient	RRR	p-value
intercept	-0.629	0.533	0.111	3.026***	20.623	0.000	-3.655***	0.026	0.000
ln_proceeds	-0.091	0.913	0.212	0.040	1.041	0.729	-0.131	0.877	0.280
UW_rank	0.040	1.041	0.256	-0.187***	0.830	0.000	0.227***	1.255	0.000
ln_offerprice	0.286*	1.331	0.093	-0.741***	0.476	0.003	1.028***	2.794	0.000
sec_shares	-0.259	0.772	0.192	-1.845***	0.158	0.000	1.587***	4.888	0.001
PE_dummy	0.365***	1.441	0.003	0.189	1.208	0.388	0.177	1.193	0.431
VC_dummy	0.259**	1.295	0.013	-0.288*	0.750	0.056	0.546***	1.727	0.000
return	-0.262	0.770	0.105	-0.113	0.893	0.604	-0.149	0.862	0.513
ln_age	-0.203***	0.816	0.000	-0.517***	0.596	0.000	0.314***	1.368	0.000
tech	0.429***	1.536	0.001	0.143	1.154	0.467	0.286	1.331	0.164
Observations	3038								
Likelihood ratio	662.63								
p-value	0.000								
Pseudo-R^2 McFadden	0.1133								

***, **, * indicate coefficient estimate's (and corresponding RRR's) significance at 1%, 5%, and 10% levels respectively

Table 22 Extended multinomial logit model 4

	Dependent variables								
Independent variables	$Log(P_A/P_S)$			$Log(P_F/P_S)$			$Log(P_A/P_F)$		
	Coefficient	RRR	p-value	Coefficient	RRR	p-value	Coefficient	RRR	p-value
intercept	-1.042**	0.353	0.011	1.726***	5.621	0.002	-2.768***	0.063	0.000
ln_proceeds	-0.131*	0.877	0.097	-0.076	0.927	0.545	-0.055	0.947	0.674
UW_rank	0.040	1.041	0.264	-0.135***	0.874	0.003	0.175***	1.191	0.000
ln_offerprice	0.394**	1.483	0.023	-0.468*	0.626	0.071	0.863***	2.369	0.001
sec_shares	-0.082	0.921	0.684	-1.090**	0.336	0.017	1.007**	2.738	0.030
PE_dummy	0.266**	1.305	0.037	-0.001	0.999	0.998	0.267	1.306	0.264
VC_dummy	0.233**	1.263	0.033	-0.373**	0.689	0.023	0.606***	1.833	0.000
return	-0.235	0.791	0.155	-0.032	0.968	0.888	-0.203	0.817	0.385
ln_age	-0.176***	0.838	0.002	-0.328***	0.721	0.000	0.151*	1.163	0.075
tech	0.499***	1.646	0.000	0.374*	1.454	0.088	0.124	1.132	0.582
leverage	0.576***	1.779	0.001	1.479***	4.390	0.000	-0.903***	0.405	0.000
ln_sales	-0.048	0.953	0.193	-0.205***	0.815	0.000	0.157***	1.170	0.003
ln_rd	-0.096**	0.908	0.029	-0.431***	0.650	0.000	0.335***	1.397	0.000
accumdeficit	-0.062**	0.940	0.030	-0.150***	0.860	0.003	0.088*	1.092	0.088
ln_sga	0.019	1.019	0.581	-0.052	0.949	0.338	0.071	1.073	0.207
NI_dummy	0.287**	1.332	0.016	0.749***	2.114	0.000	-0.462**	0.630	0.013
Observations	3038								
Likelihood ratio	830.13								
p-value	0.000								
Pseudo-R^2 McFadden	0.1419								

***, **, * indicate coefficient estimate's (and corresponding RRR's) significance at 1%, 5%, and 10% levels respectively