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Graduate School of Management

Master in Corporate Finance

LONG-RUN IPO PERFORMANCE OF US AND CHINESE COMPANIES: ANALYSIS OF KEY DRIVERS

Master's Thesis written by the 2nd year student
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ЗАЯВЛЕНИЕ О САМОСТОЯТЕЛЬНОМ ХАРАКТЕРЕ ВЫПОЛНЕНИЯ ВЫПУСКНОЙ КВАЛИФИКАЦИОННОЙ РАБОТЫ

Я, Буслова Александра Александровна, студентка второго курса магистратуры направления «Менеджмент», заявляю, что в моей магистерской диссертации на тему «Долгосрочная результативность первичных размещений американских и китайских компаний: анализ ключевых драйверов», представленной в службу обеспечения программ магистратуры для последующей передачи в государственную аттестационную комиссию для публичной защиты, не содержится элементов плагиата.

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Буслова

31.05.2022

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I, Buslova Aleksandra, second year master student, Master in Corporate Finance program «Management», state that my master thesis on the topic «Long-Run IPO Performance of US and Chinese Companies: Analysis of Key Drivers», which is presented to the Master Office to be submitted to the Official Defense Committee for the public defense, does not contain any elements of plagiarism.

All direct borrowings from printed and electronic sources, as well as from master theses, PhD and doctorate theses which were defended earlier, have appropriate references. I am aware that according to paragraph 9.7.1. of Guidelines for instruction in major curriculum programs of higher and secondary professional education at St. Petersburg University «A master thesis must be completed by each of the degree candidates individually under the supervision of his or her advisor», and according to paragraph 51 of Charter of the Federal State Institution of Higher Education Saint-Petersburg State University «a student can be expelled from St. Petersburg University for submitting of the course or graduation qualification work developed by other person (persons)».

31.05.2022

АННОТАЦИЯ

Автор	Буслова Александра Александровна
Название ВКР	Долгосрочная результативность первичных размещений американских и китайских компаний: анализ ключевых драйверов
Образовательная программа	Менеджмент
Направление подготовки	Корпоративные финансы
Год	2022
Научный руководитель	Смирнов Марат Владимирович
Описание цели, задач и основных результатов	Целью данной выпускной квалификационной работы является исследование долгосрочной результативности американский и китайских компаний после первичного публичного размещения акций, принадлежащих к технологическому сектору экономики, и определение ее ключевых факторов. В соответствии с поставленной целью были сформулированы исследовательские вопросы. Для достижения цели работы и проработки данных вопросов был сделан обзор существующей литературы. На основе обзора литературы были выдвинуты гипотезы и выбрана методология исследования. Результаты: американские технологические компании показывают более низкую доходность после первичного размещения акций по сравнению с рыночным бенчмарком – самые низкие показатели компании демонстрируют по прошествии двух лет после первичного размещения. Китайские технологические компании, наоборот, показывают более высокие результаты – самую высокую результативность компании показывают по прошествии двух лет после первичного размещения. Также были определены ключевые драйверы – размер компании, чистая прибыль/убыток за год до размещения, мультипликатор Debt-to-EBITDA и привлеченные в ходе первичного размещения средства.
Ключевые слова	Долгосрочная результативность, недооценка компаний при первичном размещении акций, факторы результативности первичного размещения акций, компании технологического сектора

ABSTRACT

Master Student's Name	Buslova Aleksandra
Master Thesis Title	Long-Run IPO Performance of US and Chinese Companies: Analysis of Key Drivers
Educational Program Management	Management
Main field of study	Corporate finance
Year	2022
Academic Advisor's Name	Smirnov Marat V.
Description of the goal, tasks, and main results	The goal of this Master thesis is to investigate the long-term performance of US and Chinese technology companies after the initial public offering and determine its key factors. In accordance with the goal, research questions were formulated. To achieve the goal of the work and answer these questions, a review of the existing literature was made. On the basis of literature review, several hypotheses were formulated, and the methodology of research was chosen. Results: U.S. tech companies underperformed the market benchmark in the long run, showing the worst results two years after the date of IPO. Chinese tech companies, on the other hand, overperformed, demonstrating the best results two years after the IPO date. Key drivers were also identified in this research work– these are the size of the company, net profit/loss one year prior to IPO, Debt-to-EBITDA ratio, and proceeds.
Keywords	Long-run IPO performance, underpricing, key drivers of IPO performance, technology firms

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INTRODUCTION

Nowadays there are many various ways a company can obtain capital. One of the potential sources of financing is an initial public offering (IPO). IPO is known as a phenomenon when a private company becomes public by issuing its shares and offering them to the public in an attempt to raise capital. It is a big step for every company since it has already reached a certain stage of its development and is ready to expand and grow further. Despite that this way of raising funds is considered complicated due to strict requirements and regulations from stock exchanges and such establishments as the United States Securities and Exchange Commission (SEC), it is still popular among mature companies. Only by the end of June 2021 there have been 558 IPOs on the US stock exchange[1]. This fact proves one more time that going public is a challenging yet widespread way of attracting capital.

Apart from IPO itself, the period which comes after this procedure is also of paramount importance as far as a company's overall performance is concerned. Furthermore, it is significant to analyze a firm's stock performance after going public and understand what can potentially influence it. This Master thesis is focused on the long-term IPO performance of companies that belong to the technology sector and operate in the US and China. The choice of the market sector I believe is quite obvious – it is one of the largest sectors in the market which is expected to grow significantly in the future. As for the basing countries, it goes without saying that both the US and China represent the strongest economies in the world, which makes the work on this thesis relevant and important.

This research work is focused on investigating long-run performance of IPOs of technology companies which operated in the US and China in a period from 01.01.2010 till 31.12.2019. My primary objective is to find what was going on with tech IPOs in a relatively "calm" period of time when no global macroeconomic event could influence the stock performance of a firm. To be more exact, I would like to investigate whether these IPOs underperformed or on the contrary overperformed a comparable benchmark, whether there are certain factors that can have an impact on the stock performance of a firm after going public and if yes, how these factors can explain such performance. Overall, I investigate what usually happens with tech IPOs based in the US and China when the market is stable. Based on this summary, final research objective and research questions can be defined.

The research goal of this Master thesis is *to investigate the long-run IPO performance of tech companies based in the US and China in the period of relatively stable global economy*.

[1] https://stockanalysis.com/ipos/2021-list/

The research questions are the following:

1. How do initial public offerings of US and Chinese tech firms perform in the long run?
2. What are the most significant drivers of IPO performance for US and Chinese tech firms?
3. How do these drivers affect the long-run performance of IPOs?

Although this research area is considered extensively investigated, to my knowledge there are no research works that investigate specifically US and Chinese tech IPOs from 2010 till the end of 2019.

CHAPTER 1. LITERATURE REVIEW

In the first chapter of the Master thesis a critical review on major works dedicated to the topic of IPO is done. With this goal in mind, I have gone further and outlined their main research results and formulated several research hypotheses to be tested in my work.

1.1. IPO and post-IPO performance

Initial public offering (IPO) refers to the first time a firm offers its stock to the public. Since the moment of IPO, a firm becomes public and is listed in most cases on one of the stock exchanges (however, a firm might issue, for example, American depositary shares on another stock exchange). The whole IPO process is considered complex because it involves dealing with many counterparties and providing a lot of documentation. In spite of being time- and labor-consuming, IPO is still quite popular with firms. The following chart can prove the statement above:

Source: ey.com

As we can see from the chart, 2021 witnessed unprecedented surge of IPO deals – the total number reached 2 388 IPOs. One more point worth mentioning is that the majority of the deals occurred in the US on Nasdaq stock exchange (Nasdaq.com), which implies that there are more and more tech companies emerging on the market.

For most firms the primary reason behind the decision to go public is raising capital, which they can use in many ways. However, there are academic that present other reasons for a firm to become public. Thus, Brau and Fawcett (2006) provide empirical evidence implying that the primary motivation behind an initial public offering is a possibility to facilitate future acquisitions. Lowry, Michaely and Volkova (2017) summarize the main concepts regarding IPO and highlight several more reasons the management of a firm might consider the possibility to do an IPO, among which are capital structure re-adjustment, provision of liquidity for a firm's owners, and credibility emerging as a result of numerous parties, such as analyst and institutional investors, scrutinizing a firm.

The following are the benefits from doing an IPO:

1) stimulation of management performance through implementing stock-based compensation (Holmström, Tirole. 1993),
2) a possibility to borrow at a lower cost (Pagano, Panetta and Zingales. 1998),
3) increased publicity, which can enhance company's public image and thus bring more customers (Ritter Jay, Welch Ivo. 2002)

Despite all the benefits obtained after an IPO, there are also shortcomings which deter many companies from going public. These include increased costs for marketing, underwriters and accounting, legal issues, dispersed ownership and decreased control, obligation to disclose financial and other important information, time-consuming process of IPO, etc.

However, not every firm can go public. According to conventional wisdom, the so-called life cycle theories state that every firm goes through certain stages of its development and in order to be able to issue equity a firm should be on a specific stage. Usually, it is more optimal for mature well-established firms to go public than for startups and firms with unstable profit. Pagano, Panetta and Zingales (1998), however, dispute this point of view suggesting that the going public decision is not mandatory for all firms; it is rather a choice of each company. They provide evidence that at least European companies do not tend to go public to obtain financing for some future investment opportunities and possibility of growth – they do it to rebalance their accounts following a period of extensive growth and investments.

1.2. Short-run performance

IPO underpricing, as well as IPO underperformance, is an extensively investigated topic because it is considered a rather widespread phenomenon among many IPOs. Underpricing can be defined as "the practice of listing an initial public offering (IPO) at a price below its real value in the stock market"[2]. In other words, underpricing represents a situation when investors who bought new issues at their offer price obtain high first-day returns because the first day closing price of these new issues is higher than their offer price.

Reiley and Hatfield (1969) were among the first to document underpricing. They put forward a hypothesis that those who invested in new issues would generate superior returns in the short run, which they defined as the Friday after the offering day, and in the long run, which was determined as one year period following the offering day. Furthermore, they also looked at returns four weeks after the offering, which is also considered as the short-run period. As a result, in all

[2] Investopedia. Retrieved 01.02.2022 from https://www.investopedia.com/terms/u/underpricing.asp

three periods Reiley and Hatfield discovered a significant increase in stock price, which allowed them to accept their hypothesis.

Since then, considerable attention was given to the topic of IPO underpricing. Academics have been trying to investigate reasons for superior first-day returns. Thus, in his work Ljungqvist Alexander (Ljungqvist. A, 2007) provides revision of main theories introduced to explain such a phenomenon as IPO underpricing and empirical evidence on the issue. The main result of the work is that the author structured the evidence on IPO underpricing and grouped the theories into four blocks: asymmetric information, institutional reasons, control considerations, and behavioral approaches. Ljungqvist shares the conventional view that the major cause of underpricing is information frictions, such as agency conflicts between the company going public and the investment bank. Asymmetric information approach states that there is a positive correlation between underpricing and asymmetry of information. Rock (1986) in his model suggests that there is a group of informed investors which possesses information unavailable for other investors and firms. The author documents that rationing, which happens when the demand for the offering exceeds the supply, for "good" shares is more frequent than for "bad" shares, implying that there are investors possessing inside information. Informed investors are not ready to pay for overpriced stocks, so they leave the market when the issues are overpriced, which leaves uninformed investors with a full allocation of shares. However, if the issues are not overpriced, the allocation is rationed, so uninformed investors are subject to adverse selection risk. To compensate uninformed investors for this kind of risk, companies have to deliberately set a lower value for their issues.

One more explanation of the relationship between the asymmetric information and underpricing is a signaling theory. According to this theory, high-quality issuing firms deliberately lower their offer price to give a signal that they are not low-quality firms (Ritter, Welch, 2002). Thus, Welch (1989) also sticks to asymmetry information theory behind IPO underpricing and provides another explanation which takes into account shortcomings of Rock's model. Welch is a proponent of the signaling theory and explains the determination of firms to put their issues at a lower price by setting a higher price at a seasoned offering.

Baron (1982) proposes his own explanation suggesting that principal-agency problem between the issuing firm and the investment bank causes underpricing. The bank has an advantage over the issuer - access to inside information about the capital markets. To compensate the bank for this valuable information, the issuer agrees on setting a price below the first best offer price.

Ljungqvist (2007) gives explanation for underpricing from institutional perspective. Thus, a firm on purpose underprices the new issues to try to avoid possible lawsuits from shareholders in case this firm shows bad performance of the stock after IPO. According to Ljungqvist, other academics explain underpricing by price stabilization practice, which is considered one of the services provided by underwriters, and tax benefits to IPO underpricing.

Brennan and Franks (1997) and Stoughton and Zechner (1998) are representatives of the approach explaining the impact of the separation of ownership and control every firm undergoes after going public on IPO underpricing. Brennan and Franks (1997) put forward the hypothesis that in order to minimize the risks of a possible takeover directors of the firm which went public will use underpricing as a tool resulting in oversubscription, which, in its turn, allow for a more dispersed ownership. In other words, the more shareholders the firm has, the fewer opportunities are left for large outside investors to monitor the firm's activity. Stoughton and Zechner (1998), on the other hand, view underpricing as a method to reduce agency costs by allowing large investors to monitor the firm's activity, which they believe can be beneficial in many ways.

The last approach which takes into account specific behavioral patterns are mostly represented by Welch (1992), Loughran and Ritter (2002), Ljungqvist, Nanda, and Singh (2004). Welch (1992) suggests that informational cascades, which Welch himself defines as a situation when investors who come to the market later that their predecessors do not utilize their inside information, if any, and simply imitate earlier investors' actions, can impact IPO underpricing in a way, that earlier investors can demand underpricing as a reward for them being commitment to the IPO. Loughran and Ritter (2002) take a different approach to the matter. They propose that underpricing can be beneficial not for investors, but also for issuers, that know they can compensate losses after the first trading day by subsequent gains on retained stocks which are to increase in price afterwards. Finally, Ljungqvist, Nanda, and Singh (2004) define underpricing as an instrument which allows regular investors to minimize risks of sentiment investors losing interest, which leads to decreased demand, in stocks which the former firstly buy, hold as inventory, and sell to the latter. Thus, IPO stock inventory is considered risky for regular investors, and it is a common knowledge that investors demand excess return to compensate for s given level of risk. Therefore, Welch (1992) and Ljungqvist, Nanda, and Singh (2004) share a common viewpoint that one of the possible explanations of IPO underpricing is that it can be beneficial for investors.

One more interesting finding was made by Boulton, Smart and Zutter (2010). They found a positive correlation between pre-IPO M&A activity and IPO underpricing, which can be a partial explanation of IPO first-day returns. As they say, "The results hold for various measures of corporate control and are both economically and statistically significant", which proves the findings obtained by other academics related to the positive correlation between post-IPO ownership dispersion and underpricing.

Although being a burning issue, underpricing is not covered in this Master thesis as the main object of research but is included in the list of independent variables, which will be presented in the second chapter. Thus, Ritter (1991) found that the large level of underpricing – in his sample 23.7% and more – leads to the lowest total returns in the long-run. That is why the effect of underpricing on the long-run IPO performance is going to be investigated in my work.

1.3. Long run performance of US based companies

Many academic works are dedicated to investigating the post-IPO performance of firms. One of the most significant observations in these works was a phenomenon called underperformance, which can be defined as a decline in the stock performance of a firm after its IPO. Many researchers document that companies in general underperform after going public compared to similar stocks and benchmark indices. The impetus for these research works was provided by a sentinel work of Jay Ritter "The Long-Run Performance of Initial Public Offerings" (1991), in which he documented that on average companies in the long run tend to underperform after going public. A sample of 1 526 IPOs which were held in the US from 1975 till 1984 was used to find out that in 3 years period companies in question severely underperformed companies matched by size and industry. As a result of his investigation, Jay Ritter reaches the conclusion that apart from two anomalies in the pricing of IPOs – short-run underperformance, or underpricing, and "hot issue" market phenomenon – there is also the third anomaly – underperformance in the long run. Primary reasons for such an anomaly are "industry-specific fads" and overoptimistic expectations of investors. Moreover, the author managed to state that there is certain time and industry dependence of the long-term performance of IPOs.

One more paper "The New Issues Puzzle" by Loughran and Ritter (1995) is focused on identifying the problem of underperformance on a sample of companies which went public from 1970 to 1990. The authors managed to prove that underperformance is typical of not only firms which did IPO, but also the ones conducting seasoned equity offering (SEO). As a result, Loughran and Ritter identified that the size of underperformance is of great economic importance since those who invested in firms conducting IPOs and SEOs did not receive enough returns (5% for IPOs and 7% for SEOs) compared to the ones who invested their money in non-issuing firms. The difference between the amount of money that needs to be invested in order to reach the same level of wealth after five years is 44%.

One point worth mentioning is that Ritter (1991) and Ritter and Loughran (1995) investigated US market only. This could have undermined the results of their research if it was not for evidence from other countries. Thus, for example, Levis (1993) took a sample of 712 IPOs traded on London Stock Exchange from 1980 till 1988 to study both long- and short-term performance after IPO. Levis proved that UK IPOs also underperformed compared to relevant benchmarks on the scale of three years after going public. The same results were obtained in a more recent study by

Jewartowski and Lizińska (2012). The authors documented significant underperformance of 195 initial public offerings listed on the Warsaw Stock Exchange from 1998 till 2008 equal to -22,6% for the buy-and-hold strategy. Aggarwal, Leal, and Hernandez (1993) investigated IPO markets of Brazil, Chile and Mexico in different time periods and found out that IPOs underperform in the long run with three-year return being - 47%, - 23,7% and – 19,6% respectively. However, the authors warn that the results of their research might not be reliable enough because of a small sample size (62 IPOs for Brazil, 36 for Chile and 44 for Mexico) and that these IPOs occurred within few years. Gohil and Vyas (2015) compare performance of private equity backed IPOs and non-private equity backed IPOs both in the long and in the short run. Their findings confirm that both PE-backed and non-PE backed IPOs underperformed in the long run with PE-backed IPOs showing a bit less underperformance.

Despite the significance of the results of these research works, some academics doubt the relevance of underperformance. They provide findings of their own research work, which contradict the results of Jay Ritter's research work. Thus, for example, Gompers and Lerner (2003) believe that the results of any study on underperformance depend on a methodology of return measurement researchers use. The authors conducted an out-of-sample study on 3 661 US IPOs from 1935 and 1972 (that is before the foundation of NASDAQ) and came up with the conclusion that using either equal-weighted buy-and-hold abnormal returns method or cumulative abnormal returns method does not show underperformance in the results of the research. At the same time, when event-time buy-and-hold abnormal returns are used in the model, the findings provide evidence of underperformance. Furthermore, such a model is statistically insignificant, which calls into question correctness of measurement based on event-time buy-and-hold abnormal returns. Brav and Gompers (1997) claim that the results obtained by Loughran and Ritter (1995) do not account for venture-backed firms which do not demonstrate significant underperformance compared to small nonventure-backed ones. Furthermore, the authors found no difference in performance of small low book-to-market IPOs and similar non-issuing companies, which suggests that underperformance is not necessarily caused by initial public offering.

Robert Schultz (2003) suggests that IPO performance be calculated using a calendar-time technique for return measurement. Many researchers use another method called event-time return measurement, which provides performance statistics of stocks after the IPOs. According to Schultz, using a calendar-time method does not show such severe underperformance compared to event-time return measurement because the latter causes the so-called "pseudo market timing", which can be defined as the following relationship: the higher the stock prices are, the more firms issue equity.

Some of the more recent evidence suggest using an upgraded version of calendar-time technique for measuring long-term IPO performance. Dutta (2015) investigates new method which is superior to buy-and-hold abnormal returns (BHAR) and calendar time approach. Standardized Calendar Time Approach (SCTA) is said to fight the problem of heteroscedasticity emerging when using calendar time approach and have a higher power than BHAR. Despite this, BHAR methodology remains the most popular in terms of estimating long-run IPO performance.

Kooli, L'He and Suret (2006), on the other hand, present interesting findings with regard to the Canadian market. In a four-year period from 1986 till 2000, a sample of 141 IPOs listed on the Toronto Stock Exchange is analyzed. The authors present the results of their work: neither event-time buy-and-hold abnormal returns, nor cumulative abnormal returns on a value-weighted basis are suitable for measuring post-IPO performance. Having used both methods, Kooli, L'He and Suret concluded that there is underperformance of IPOs with the model being statistically insignificant. Instead, they propose applying mean monthly calendar-time abnormal returns and alphas from the FF-T, which showed no underperformance in the results.

While some academics doubt the measurement used to evaluate IPO performance, others conclude that the whole IPO underperformance phenomenon is ambiguous. Perera and Kulendran (2016) state that not all researchers admit IPO underperformance exists because their findings quite often contradict each other. At the same time, the authors highlight that the short-run IPO performance is a documented phenomenon, and its evidence is quite widespread. Jakobsen and Sorensen (2001) agree on this matter adding that there are no credible theories that could possibly identify the reasons for the long-run underperformance, hence, the whole phenomenon is doubtful.

To conclude, there are plenty of works focusing on underperformance as a phenomenon typical of IPOs. However, some academics claim that the results of the research on underperformance depend on a type of measurement technique used to calculate returns after IPOs.

This leads me to formulating my first hypothesis to be tested in my Master thesis:

Hypothesis 1: *On average, US companies after going public underperform a comparable benchmark in the long run.*

1.4. Long-run IPO performance: evidence from China

The very first thing to be mentioned in connection with Chinese IPOs is that IPO markets in China are heavily regulated. The academics interested in exploring Chinese IPO markets do and did studies focused on how these strict regulatory restrictions affect Chinese IPOs, their long and short-term performance. Thus, for example, Qian, Ritter, and Shao (2021) claimed that there is a positive correlation between regulatory system in China and short-run underperformance of IPOs.

First-day returns in China are enormous – they equal 170% in the period from 1990 till 2018. Such huge returns make the offer price inefficient, which result in firms choosing foreign stock exchanges over the domestic ones. As a result, this leads to inefficient capital allocation, so that Chinese investors are left with fewer opportunities to find some good investments, whereas other companies suffer from an increased cost of capital. The authors believe that if China wants to develop a more efficient IPO market, it must diminish influence of regulators on it. Derrien, Wu, Zeng, and Zhang (2017) support Qian, Ritter, and Shao (2021), adding that the Chinese government tends to change the rules and regulations imposed on the IPO market and thereby subject firms wishing to become public to huge uncertainty. One more important thing to mention here is that if a state-owned enterprise (SOE) plans to go public, it must be restructured. Hence, to become listed, a SOE must be rearranged as a stock company by selling shares to other SEOs, legal entities and even its own employees. After receiving approval of China Securities Regulatory Commission, it is time a company sells 1/3 of their shares to the general public, thus creating a unique ownership pattern.

Due to such an instrumental role the Chinese government plays in the life of every Chinese firm, there has emerged extensive literature covering the relationship between politically connections and both long-run and short-run post-IPO performance. Fan, Wong, and Zhang (2007) investigated the relationship between firms with political connections and three-year post-IPO stock returns, as well as first-day excess returns on a sample of 790 newly partially privatized firms. Their findings suggest that firms that do not have politically connected CEOs on average outperform those with CEOs being current or former government officers. Furthermore, the evidence states that the latter present poorer performance in terms of sales and earnings growth. The authors measure political connections by applying dummy variables on CEOs and directors being a current/former officer of the central or local government, or military forces. Fan, Wong, and Zhang claim that poorer long- and short-run IPO performance and deteriorating post-IPO operating performance illustrate that politically connected CEOs carry out their duties worse than CEO with no such connections since the former lack professional background and experience which the latter, on the other hand, have.

Liu, Uchida, and Gao (2012) present the opposite findings. They also consider the impact of political connections on the long-term IPO performance of Chinese firms from 2000 till 2007. However, their choice of measurement of political connections is slightly different. They use the combination of four factors – a dummy variable with the value of 1if a firm is state-owned in the IPO year, a dummy variable with the value of 1 if a firm's chief executive officer works or used to work for the government or the military forces in the IPO year, the same variable for the chair of the board and a variable on proportion of board members with current or former political connections. The combination of all four variables is another variable which is calculated as their sum and takes values from 0 to 4. Despite a more rigorous methodology used in their analysis, the authors cannot present results confirming the previous paper's result; on the contrary, they find that political connections have a beneficial impact on a firm's performance and, as a result, cause better stock performance after IPO.

Changyun Wang (2005), on the other hand, found no evidence of the government being responsible for changing performance. The author investigated how post-issue operating performance of firms that have gone public changed over time and what potential reasons for this might be. He obtained quite interesting results. First of all, he documented a sharp decline in operating performance after IPO, then he put forward several hypotheses that should be tested to understand what really affects post-IPO performance. One of the explanations was earnings management system which was adopted by a firm before becoming public. However, the results of the research suggest that in the long run past performance of a firm cannot be a cause of these changes in operating performance. The author used return on assets, sales to assets, and operating income to assets to measure operating performance. In the end, Wang comes to the conclusion that legal entity and non-state ownership are drastically correlated with performance changes, while state ownership does not show any results in this regard. Sun and Tong (2003), on the other hand, document that state ownership exercises negative impact of firms' performance, whereas legal-person ownership, on the contrary, positively affects companies' performance.

In compliance with results obtained by other academics mentioned in the previous subsection of this chapter, some scholars investigating Chinese IPOs have also come to the same conclusion – Chinese IPOs show poor long-run performance. Kao, Wu, and Yang (2009) focused on exploring how regulatory initiatives affect post-IPO profitability, as well as first-day returns and long-term stock IPO performance. Their findings suggest that an average Chinese firm from the sample of 366 firms experiences underperformance. Chan, Wang, and Wei (2004) have set an objective to study both short and long-term performance of A- and B-share Chinese IPOs. The results of their empirical analysis seem to be quite interesting: the authors document that in the long-run A-share IPOs show slightly worse performance compared to matched portfolios, whereas B-share IPOs, on the contrary, outperform a comparable benchmark. Furthermore, they find that long-run IPO performance is positively related to certain operating characteristics of a company, such as operating return on assets, operating cash flows to total assets and sales growth rate, which proves that firm's operating performance can also be a driving force of stock performance.

Su, Bangassa and Bookfield (2011) present the opposite findings: a sample of 936 initial public offerings from 1996 to 2005 shows a significant overperformance when the equal-weighted BHAR method is utilized. However, if using cumulative abnormal returns or calendar-time abnormal returns, no significant overperformance is detected.

Consistent with the literature on Chinese IPO performance, I would like to formulate my second hypothesis:

Hypothesis 2: *On average, Chinese IPOs slightly underperform a comparable benchmark in the long run.*

An important comment here is that I would also like to test hypothesis on the degree to which political connections or certain government regulation affect the long-term IPO performance of Chinese firms. However, due to the lack of data, I cannot test this hypothesis. I did a review of literature on this issue to show that government activity is an integral part of Chinese capital markets, and that it should be accounted for when investigating Chinese IPO anomalies.

1.5. IPO performance of technology firms

Technology firms remain one of the most popular choices for investment. The demand for the stock of such firms is growing fast, because of their increased importance for the society, that is why more and more tech firms are emerging on the market. Consequently, these days academics are becoming more and more interested in investigating such firms and identifying their peculiarities. Thus, for example, Zakrzewska-Bielawska (2010) defines a high technology firm as "an innovative enterprise based on knowledge and using modern IT technology" and presents a number of characteristics describing such firms, among which are high research and development expenditures, significant number of scientific and technical professionals in the staff, constant provision of new innovative products to the market, etc. The author highlights that this sector is of paramount importance to the world economy since it determines the whole economy via huge R&D investments, which eventually result in technologically advanced products/services used to produce traditional goods. Bernstein (2015) while investigating how going public affects innovation emphasizes "the critical role of innovation in promoting economic growth … and the prevalence of technological firms in the initial public offering (IPO) market over recent years".

Undoubtedly, the influence of tech firms is enormous, which makes it such an interesting research object. However, they have gained momentum not so long ago. The turning point for tech firms occurred in 1999-2000 and is known as dot-com bubble. Dot-com bubble phenomenon is known not only for the beginning of extensive use of the Internet, but also for its direct consequence – growth in the number of IPOs of Internet-related companies. There are numerous papers which deal with IPOs during the dot-com bubble period. Thus, for example, Ljungqvist and Wilhelm, Jr. (2003) investigated the reasons for abnormal IPO initial returns during the period of

1999-2000. According to the paper, average first-day IPO returns in 1996 were equal to 17%, whereas Internet-related IPOs reached an average of 88% in the period between 1999 and 2000.

Kayne D. and Laux J. (2005) went further in their work “IPO Returns: Pre And Post Dotcom Bubble”. The authors did not only investigate first-day returns, but also the returns of tech companies that preceded and followed the dot-com bubble period. According to the empirical evidence, the returns prior to and after the emergence of dot-com bubble were within the range of 10-20%, which is considered normal, whereas first-day returns reached the abnormal levels. The latter evidence confirms the results obtained in the study conducted by Ljungqvist and Wilhelm, Jr.

One more article “Why Has IPO Underpricing Changed Over Time?” written by Tim Loughran and Jay Ritter is essential in terms of giving a description of the dot-com bubble period and the characteristics Internet-related stocks obtained during this time. The authors state that exactly in the period 1999-2000 such a widespread phenomenon as underpricing was especially noticeable and generally considered increased. As stated in the paper, three hypotheses can account for such a dramatic change in underpricing. While new risk composition and the realignment of managerial incentives have been proved to have weak relation with the dependent variable – underpricing, the changing issuer objective function is the primary reason for severe underpricing in the period of dot-com bubble.

While the literature on investigating IPO underpricing and firms’ performance in technological sector is extensive, little research is done in relation to long-run IPO performance. Research works dedicated to long-run IPO performance usually focus either on a certain time span or a certain country without accounting for a specific industry. With this in mind, I would like to investigate long-run IPO performance in relation to all these criteria – time period, country and industry.

With regard to technology industry, I believe there might be specific drivers that determine the long-run performance of IPOs. And such drivers are representative of the industry peculiarities. I assume the first thought that comes in mind to everyone concerning technology firms is that research and development investments play a crucial role, as it was stated above, because they are responsible for innovations a company brings to the market. As such, there are research works which focus on exploring the relationship between innovation and IPO performance. Heeley, Matusik, and Jain (2007) present one of such works. In particular, the authors analyze the relationship of the level of patenting and underpricing. Apart from that, one of the hypotheses they put forward is that R&D investments have a positive association with the first-day returns. They chose R&D intensity, calculated as R&D expenditure/Sales*100+1, as a measurement for research and development investment. Their findings prove that for most cases the effect of R&D intensity on first-day returns is positive with R&D coefficient in all three models being at the significant level less than 5% and 10%.

The research work by Heeley, Matusik, and Jain (2007) is in compliance with a signaling theory of underpricing which was described in the second subsection of this chapter. R&D investments and underpricing in the context of information asymmetries were investigated by several academics (Guo, Lev, and Shi, 2005; Hou and Gao, 2019). The results of their work suggest that R&D plays an important role in explaining short-term IPO performance.

Given the literature reviewed in this subsection, I would like to propose the third hypothesis I will test in my research work:

Hypothesis 3: *R&D intensity has a direct relationship with the long-run IPO performance of tech firms.*

Although academics paid attention mainly to the short-term IPO performance, I would still like to explore whether R&D investments have any explanatory power in terms of the long-run performance. Provided that R&D are crucial for every high-tech company and that underpricing and long-run performance are closely related, I believe it is quite possible that R&D is one of the key drivers of the long-term IPO performance, and this is exactly what I would like to test as a researcher.

CHAPTER 2. EMPIRICAL RESEARCH

In this chapter I will present my empirical research which is based on the research goal and research questions I formulated, as well as on hypotheses proposed on the basis of literature review done in the previous chapter. As a result, I will describe the measurement of dependent and independent variables, provide justification of the chosen methodology, build an empirical model, and present the results.

2.1. Dependent variable

Since my research work is aimed at identifying key drivers which affect the long-run IPO performance and my hypotheses are to test US and Chinese IPOs for underperformance, the dependent variable in the model should be represented by the measurement of IPO performance.

In a broader sense, IPO performance can be measured best by the use of share prices. In the narrow sense, IPO performance is usually measured by returns which stocks generate after being offered to the public. Despite the apparent simplicity, there are several available measurements which include different types of returns, and it is not quite easy to decide which approach is more suitable. As I have mentioned in the first chapter, academics suggest several methods be utilized for measuring IPO performance, and the main difficulty here is that some methods help find underperformance, whereas others do not show it at all. Thus, having acquainted with different opinions on this matter, I came up with a conclusion to follow Ritter's (1991) methodology and use event-time buy-and-hold abnormal returns (hereinafter "BHAR") for measuring IPO performance. Abnormal returns can be defined as excess returns which are generated relative to a certain benchmark.

There are several reasons for such a decision. Firstly, this approach allows to account for the benchmark, not just raw returns which are not accepted as the sufficient and reliable measure of IPO performance. What is more important, BHAR measure is widely utilized by many academics, that is why it seems to be a reliable measure, although some academics suggest using other measures to obtain more robust results.

As stated previously, BHAR is defined as abnormal returns, which are considered excess returns of a stock over a certain benchmark. The formula for abnormal returns is the following:

$$Abnormal\ return = Return\ on\ a\ stock - Return\ of\ a\ benchmark$$

The full formula is presented as follows:

$$\mathrm{BHAR_i} = \frac{1}{N}\sum_{t=1}^{N}\left[\left(\prod_{t=1}^{T}(1+R_{i,t})\right)-\left(\prod_{t=1}^{T}(1+R_{m,t})\right)\right]$$

where $R_{i,t}$ is a firm's stock return, $R_{m,t}$ is a return of a market benchmark, t – the beginning of the period and T – the end of the period.

Returns on a stock and of a benchmark are calculated as natural logarithms of daily raw returns starting from the first day of listing. The benchmark in the case of BHAR can either be a corresponding index or a set of firms matched by certain criteria. I prefer using a corresponding index as a benchmark for two reasons. Firstly, the index I am going to use as a benchmark is NASDAQ index, which I believe is an ideal match for my set of firms since all of them are traded or were traded on NASDAQ stock exchange with no exceptions. This makes the result of my research clearer and more reliable. Secondly, the sample of Chinese tech companies traded on NASDAQ in the time period I have chosen for my work is not large, which makes it difficult to find a set of matched firms.

To test my first hypotheses on IPO underperformance, I will use T-test which shows whether mean of average BHAR is different from zero. Thus, the null hypothesis for this T-test is $H0: E(ARi,t) = 0$, which says that the mean of abnormal returns is equal to 0. The test is given by the following formula:

$$tARi,t = ARi,t/SARi$$

where $SARi$ is the standard deviation of abnormal returns.

The results of this T-test can be interpreted in the following way: if the mean of BHAR is less than 0, than IPOs underperform, however, if it is more than 0, then IPOs, on the contrary, overperform. T-test is widely utilized by academics because of its simplicity. T-test will help me understand whether BHAR mean is statistically significant and different from 0.

To conclude, event-time buy-and-hold abnormal returns (BHAR) are used as measurement of IPO performance. They were chosen over other measures mainly because it is a reliable method used by many researchers. The easiest way to test the first hypothesis, which concerns BHAR, is to use the so-called T-test.

2.2. Independent variables

Independent variables in my research work are represented by factors which can possibly have influence the long-run IPO performance. I have decided to take such independent variables that can be easily found/calculated and are considered the most influential in terms of measuring the long-run performance. My next step is to present the so-called "long list" of independent variables, their measurement, and the reasons why they are chosen for the research. Moreover, as it is the long list, some of the variables are not included in the model, hence I would also like to discuss the reasons for that.

The “long list” of independent variables is divided into two groups: those which describe IPO issue characteristics and the ones which belong to company characteristics.

1. IPO issue characteristics

I believe that events which happened before, during and after IPO issue can directly affect the long-run performance of a company. For this reason, I highlight the following independent variables:

Total offer proceeds. This can be defined as the total amount of money raised in the IPO deal. Here I should make a distinction between two amounts – total proceeds amount, and total proceeds amount + overallotment. Overallotment is an option of selling additional shares that a company might issue during the IPO, which is usually given to underwriters. Sometimes these two figures are the same, sometimes they are different. In my research work I will use total proceeds amount without accounting for overallotment. Total proceeds are calculated by multiplying share volume offer and the offer price. This variable is presented in the form of natural logarithm for convenience.

Underwriter quality. Underwriters are investment banks which accompany an issuer along the whole process of IPO. They determine the initial offering price, then buy the shares and sell them to different investors[3]. Underwriters also make sure that the whole procedure is complied with all necessary requirements. To make this happen, underwriter have to have highly qualified staff and solid experience in terms of IPO deals and all consequent procedures. Thus, as we can see, underwriters play a key role in IPO, that is why it is important to find out the impact of underwriter quality on the post-IPO performance of a company. Carter, Dark and Singh (1998) share their finding that both short-run and long-run performance is less meaningful provided that more reputable underwriters are in charge of arranging IPOS. Other academics also highlighted this inverse relationship between underwriter reputation and IPO performance (e.g., Gulati and Higgins, 2003). It can be measured as a grade from various rating agencies which evaluate the quality of an investment bank based on certain criteria. However, having analyzed my data sample, I discovered that underwriters which handled IPOs in question, are almost all the same, which means that this independent variable will not have considerable influence on the model. That is why I was forced to exclude this variable from my model.

Underpricing. Underpricing is a pretty widespread phenomenon which is characterized as situation when a close price of a stock in its first trading day after IPO is above the price which was initially offered. However, in general, underpricing is a temporary phenomenon because investors’ demand moves the prices up. There are a few studies which focus on the relationship

[3] https://www.investopedia.com/terms/u/underwriter.asp

between underpricing and long-run performance, that is why for my model it would be logical to use underpricing as one of the independent variables to investigate how much in this case such a short-term situation can affect prices in the long run. The formula for underpricing is the following:

$$Underpricing = \frac{first\ day\ closing\ price - offer\ price}{offer\ price}$$

2. Company characteristics

Size. Size of a firm can be measured in many ways; however, total assets of the firm are considered one of the most popular measures used by many researchers (e.g., Heeley, Matusik, and Jain, 2007). For the model I should take the figure of total assets of the firm one year prior to IPO and also do a log transformation, thus obtaining my first control variable.

Year and industrial dummies. Two more control variables which are quite often included in the model are year and industrial dummy variables. As for year variable, I do not need to include it in the list of independent variables because I envisaged that by excluding three most distressful period in the 21st century. It is common knowledge that certain macroeconomic events have a huge impact on capital markets, and to make my research clearer, I decided to get rid of such events in the first place. Despite that all firms in my sample belong to the same industry – technology, I still prefer to include industrial dummy in the model to control for differences in business sectors. Thus, software and telecommunications areas are two different worlds, so in the model I have to control for such differences.

I assume that **profitability, liquidity, and leverage measurements** should be included in the model because these metrics are of paramount importance in terms of evaluating financial health of a firm. What is more important, these measurements are closely related to stock-based performance of any company, so they are likely to have strong explanatory power.

Profitability measurements. Profitability metrics are usually presented by net profit margin, gross margin, return on assets (ROA) and return on equity (ROE). There is one more way to account for profitability in the model – to use dummy variable on profit or loss one year prior to IPO. Despite that ROA and ROE are quite attractive ratios due to their acknowledged importance, I am not going to use them as independent variables. Return on assets can have a strong correlation with two other independent variables – firm size (which uses natural logarithm of total assets of a firm) and dummy variable on profit and loss I have just described above, and in this case the problem of multicollinearity is inevitable. My personal approach as a researcher is to try to avoid possible problems before building the model. Of course, it is not possible to envisage all difficulties, however, I can still try my best to forecast possible problems and get rid of them in the first place. As for return on equity, this metric is a little ambiguous because equity is a peculiar indicator. Thus, for example, in my sample more than half of the firms have negative equity one year prior to IPO, that is they have a shareholder's equity deficit, which makes ROE figure negative if a firm reported net profit and positive if a firm experience net loss from its operations. Hence, to avoid possible multicollinearity problem and ambiguous figures, I prefer to use net profit/loss dummy in my model as a profitability measure.

Liquidity measurements. As mentioned above, liquidity measurement can be useful in terms of having an impact on IPO performance. The most popular liquidity metrics are current and quick ratios. Although quick ratio, or acid test, seems to be more accurate measure of a firm's liquidity because it does not take into account inventory and thus measures a firm's ability to repay its short-term obligations with its most liquid assets, I would choose using more conventional and less complex measure for my analysis, so current ratio is also included in the list of independent variables. The current ratio is calculated as follows:

$$Current\ ratio = \frac{current\ assets}{current\ liabilities}$$

Leverage measurements. Possibly, the most popular leverage measurement is debt-to-equity ratio. Despite its obvious advantages, I would like to abstain from using it in the model because, as I have mentioned previously, more than half of the firms have shareholders' equity deficit. Hence, I suggest using other leverage measurement which does not account for equity in the formula. Among numerous leverage measurements, I prefer to use Debt-to-EBITDA ratio because it is easy to calculate and is widely used by banks as one of the covenants and credit agencies as an evaluation of probability of a firm's default on debt. One more ratio I was thinking about is debt-to-assets, however, there is a possibility that it will be strongly correlated with firm's size measure, which includes total assets. Thus, I decided on sticking to the debt-to-EBITDA figure. The formula is presented below:

$$\text{Debt-to-EBITDA} = \frac{Debt}{EBITDA}$$

Company's strategy concerning whether a firm is going to use proceeds from IPO on M&A. As it was mentioned in the literature review chapter, several researchers documented that among other reasons to go public there is a desire of a firm to facilitate possible acquisitions in the future. Academics have gone further and investigated the relationship between M&A activity and long-run IPO performance. Brau, Couch and Sutton (2012), for example, were among those academics who managed to prove that M&A activity can explain IPOs underperformance. I decided to include dummy variable on whether a firm has indicated in the prospectus that it plans to use a part of proceeds for M&A deal. Unfortunately, in my sample, only several firms (up to five) have indicated their intension to use proceeds for acquisition deal in progress, whereas others consider a possibility to use proceeds for an acquisition deal with no current acquisitions going on. For this reason, I am forced to exclude this M&A dummy from the independent variable because, just like underwriter quality variable, it will not have considerable influence on the model.

Research and development intensity. The last independent variable is R&D costs a firm incurred one year prior to IPO. As mentioned in the literature review, R&D investment in technology firms is of paramount importance and is usually one of the largest expenses. Thus, this measure accounts for innovation a firm supplies to the market. Following the hypothesis put forward in the first chapter, I suggest using R&D intensity variable to try to explain the long-run performance. To account for skewness in the data, this variable will undergo a log transformation. R&D intensity, as suggested by Heeley, Jain and Matusik (2009), is calculated in the following way:

$$R\&D\ intensity = \frac{R\&D\ expenditure}{Sales} * 100 + 1$$

The figure is presented in the form of natural logarithm to consider skewness in data. I included this variable in my research because I must account for innovation which is a fundamental force especially in technology firms. However, there are also ways to measure innovation other than R&D intensity. Heeley, Jain and Matusik (2009) mention that this measure has several limitations, and, as one of the alternatives, they along with other researchers suggest using patent statistics. Griliches (1990), for example, investigated patent statistics as a tool which can demonstrate the level of innovation and technical change. He concluded that patent statistics is a decent substitute for R&D intensity. Nevertheless, in my research I will stick to R&D intensity measure because the data on patents in each firm from my sample is limited, and R&D expenditure, along with sales, is usually highlighted in financial statements of a tech company.

To summarize, the following is the table containing all variables necessary for the model and their measurement:

Variable name	Measurement
BHAR – dependent variable	Abnormal return = Return on a stock-Return of a benchmark
Total offer proceeds – independent variable	Proceeds = share volume offer*the offer price
Underpricing – independent variable	Underpricing = (first day closing price-offer price)/offer price
Firm's size – independent control variable	Natural logarithm of total assets; 1 year prior to IPO

IT dummy – independent control variable	For Software&IT services firms value “1”, otherwise “0”
Profit/loss dummy – independent variable	If a firm reported profit 1 year prior to IPO, value “1”, otherwise “0”
Current ratio – independent variable	Current ratio = current assets/current liabilities; 1 year prior to IPO
Debt-to-EBITDA – independent variable	Debt-to-EBITDA = Debt/EBITDA; 1 year prior to IPO
R&D intensity – independent variable	R&D intensity = R&D expenditure/Sales*100+1; 1 year prior to IPO

As a result, I propose the following model:

$$BHAR = ai \ + \beta 1 \ Proceeds \ + \beta 2 \ Underpricing + \beta \ 3 FirmSize + \beta 4 \ IT \ + \ \beta 5 \ Profit/loss + \ \beta 6 \ CurrentRatio + \beta 7 \ DebtEBITDA + \beta 8 \ RD + \varepsilon_i$$

I should also mention that I am going to test three models for both US and Chinese IPOs, that is six models in total. The reason why I am doing this is that three time periods are to be considered – one year after IPO, one and a half and two years. Ritter (1991) and many other researchers take three-year period for their analysis, however, in my case if I take a three-year period there will be not enough IPOs to analyze, that is why the longest period I consider is two years from the moment of IPO. The models are to be run in Stata.

2.3. Data sample

For my research work data collection is crucial since I use them for identifying the key drivers affecting the long-run performance. For this purpose, I have to collect data on stock prices of each company for a certain period of time – from 01.01.2010 till 31.12.2019. This is the time range within which US and Chinese companies have gone public. I chose this period because this is the time when no cataclysm, serious macroeconomic or any other crucial event capable of affecting the world economy happened. Therefore, I avoid the dot-com bubble, the financial crisis 2007-2008 and the Coronavirus pandemic, which came as a bombshell in 2020. Without any doubts any negative global event or any black swan has a huge impact on performance of any company – in these periods stock prices are not stable, and my aim is to look at the long-run performance of companies in relatively quiet times. Thus, I minimized systematic risk, which affects the whole market.

As for idiosyncratic risk, I believe that this risk is harder to avoid. Moreover, it concerns only a company itself with no or little effect on other companies. That is why I decided to choose companies according to certain criteria notwithstanding companies' past performance or their current activity. The only thing I envisage here is that no large companies, which went public in this period, such as, for example, Facebook, are included in the final list of companies I am going to investigate. The reason for this is quite simple: due to their size and hype surrounding their IPO deal, these companies usually show abnormal returns which makes them stand out from the rest of the companies. Thus, these outliers should be eliminated to obtain clearer results.

To collect data, I used Eikon database as one of the most reliable and powerful sources. First of all, I thought of criteria to choose companies I am going to analyze. Eikon database allows users to utilize filters to narrow down the results. The first filter I applied was "Issue type". There I chose the option "IPO" and saw that all these IPO deals have different status: some of the deals were successfully finished, whereas others were either cancelled or "rumored". That is why I had to apply one more filer – "Transactions status" – and choose "Live", which means that the IPO deal went through successfully. After choosing the type of a deal it was logical to choose the countries, clicking on the filter "Issuer/Borrower Nation", and then pick United States and China (Mainland). Next step was to specify the time period by using the parameter "Dates: Issue Date". The period of the research comprises ten years from 01.01.2010 to 31.12.2019. Then an industry sector should be chosen. Here I choose "TRBC Industry" filter, which is the Refinitiv Business Classification (TRBC) industry description, as well as "TRBC Business Sector" which specifies the exact industry a company operates in – for example, semiconductors or software. Here I do not distinguish between various business areas of a company and choose the whole industry "technology". The next step was to choose the name of the exchange the companies had gone public. It is logical and obvious to choose NASDAQ stock exchange because it is a popular choice among companies that operate in the technological sector. So, I applied the filter "Issuer/Borrower Stock Exchange Name" and chose the option "NASDAQ". Furthermore, I am certain that to obtain clearer results all companies in question should be traded on one stock exchange. There are two reasons for this suggestion. Firstly, different stock exchanges have different requirements and regulations. In my research I need to bring all the companies into line so they can be on the same footing and give more or less fair results. Secondly, the Chinese stock exchange markets are heavily regulated by the government, while the US stock exchanges have more freedom in this respect. That is why if I take companies from both US and Chinese exchange markets, they will not be treated on the same basis, which might cast a shadow on the findings of my research work.

In the end, I had to do a matching procedure to finish the selection process. I decided to do a matching by industry and size. I have already applied the filter “TRBC Industry” to match companies by industry. My next step was to match them by size. I decided to match companies by the total amount of money they were able to raise during the IPO, so I applied the filter “Total Proceeds All Markets” and set a range between 10 and 1000 million dollars. As a result, I obtained 165 companies.

Next, I had to make sure that all the companies have necessary data. Thus, I had to get rid of companies that either did not have price history or missed some financial data. Furthermore, I also collected data on the deal characteristics, such as underwriter and underpricing, and company characteristics, for example, size and financials. That is, I also started collecting data on independent variables, described above. Despite Eikon being a powerful and reliable source of information, some data are still omitted, which forces me to get rid of some companies in the list. For me as a researcher it is not very good, since incompleteness of the data might undermine my findings. Nevertheless, I have to deal with data available at this time. Therefore, I managed to collect data about 34 Chinese companies and 99 US companies, which makes it 133 companies in total. The list of companies is presented in Appendix A.

2.4. Descriptive statistics

This part of my Master thesis is aimed at providing descriptive statistics for my data. I believe it to be significant for analysis because this kind of description helps to assess general properties of the data I am dealing with. I am going to start with US firms and present descriptive statistics model by model. Model 1 accounts for firms with price history available for two subsequent years after IPO, Model 2 considers one-and-a-half-year period, whereas Model 3 deals with firms with price history available for one year after going public.

1. US firms

   Model 1.

   Table 1. Summary statistics model 1 US

	N	Mean	Std. Dev.	min	max
BHAR	88	-.004	.01	-.094	.002
Underpricing	88	.325	.915	-.327	6.67
IT	88	.682	.468	0	1
Proceeds	88	4.962	.365	4.079	6
FirmSize	88	4.371	1.407	.43	8.558
Profit/loss	88	.295	.459	0	1
DebtEBITDA	88	-.813	10.518	-68.55	47.714
CurrentRatio	88	1.567	1.4	.03	10.48
RD	88	1.282	.306	.424	1.953

Here I would like to discuss the results of summary statistics. BHAR has a minimum of -0.094 and a maximum of 0.002, which means that the lowest abnormal return from the sample was -9.4%, whereas the highest one was 0.2%. The mean for underpricing is 0.325 meaning that the average underpricing in the sample is equal to almost 32.5%, which is in compliance with existing studies on this topic. IT dummy has a mean of 0.682, stating that almost 70% of firms belong to IT&Software sector, and the mean of Profit/loss dummy equal to 0.295 shows that more than 29% of the firms have net profit one year prior to IPO. Debt-to-EBITDA figure equal to -0.813 shows that on average firms in the sample have negative EBITDA, while current ratio figure of 1.567 implies that US tech firms in question have sufficient resources to cover their short-term debt. R&D intensity has a mean of 1.282, suggesting that on average 28% of firms' revenue is reinvested in R&D.

Table 2. Correlation matrix Model 1 US

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) BHAR	1.000								
(2) Underpricing	-0.697*	1.000							
	(0.000)								
(3) IT	-0.055	0.055	1.000						
	(0.614)	(0.613)							
(4) Proceeds	0.280*	-0.032	0.164	1.000					
	(0.008)	(0.770)	(0.127)						
(5) FirmSize	0.255*	-0.073	0.067	0.588*	1.000				
	(0.017)	(0.498)	(0.536)	(0.000)					
(6) Profit/loss	-0.104	0.218*	-0.039	0.130	0.050	1.000			
	(0.334)	(0.041)	(0.719)	(0.229)	(0.643)				
(7) DebtEBITDA	-0.107	-0.068	0.160	-0.118	-0.224*	-0.237*	1.000		
	(0.321)	(0.530)	(0.137)	(0.274)	(0.035)	(0.026)			
(8) CurrentRatio	0.044	0.538*	-0.081	0.054	-0.026	0.320*	0.000	1.000	
	(0.693)	(0.000)	(0.455)	(0.615)	(0.812)	(0.002)	(0.999)		
(9) RD	-0.105	0.163	0.118	-0.114	-0.028	-0.297*	0.044	-0.018	1.000
	(0.372)	(0.164)	(0.315)	(0.332)	(0.812)	(0.010)	(0.711)	(0.881)	

**** p<0.01, ** p<0.05, * p<0.1*

As we can see from the table, there are three independent variables – underpricing, proceeds and firm size - which have correlation with the dependent variable at a significant level with p<0,1 is Profit/loss dummy. This is a good sign, because it means that the variable can have an explanatory power on the long-run IPO performance. An interesting point to mention is that two independent variables – Profit/loss and current ratio - have a significant correlation (p<0,1) with underpricing, which is also IPO performance, but in the short run. Provided that researchers investigating short-run IPO performance also took these variables to trace the impact they have on underpricing, the results shown in correlation matrix should not be very surprising.

To make sure that we do not have multicollinearity problem in Model 1, I suggest using Variance Inflation Factor (VIF) test. To interpret the results of the test, I should firstly say that the problem of multicollinearity can be confirmed if VIF indicator is bigger than 10 and 1/VIF is smaller than 0,10. Judging by Table 1. VIF test Model 1 US, which is presented in Appendix B, I can conclude that there is no multicollinearity in Model 1.

Model 2.

Table 3. Summary statistics Model 2 US

	N	Mean	Std. Dev.	min	max
BHAR	93	-.001	.01	-.084	.005
Underpricing	93	.319	.891	-.327	6.67
IT	93	.699	.461	0	1
Proceeds	93	4.984	.379	4.079	6
FirmSize	93	4.412	1.415	.43	8.558
Profit/loss	93	.28	.451	0	1
DebtEBITDA	93	-.679	10.279	-68.55	47.714
CurrentRatio	93	1.548	1.368	.03	10.48
RD	93	1.296	.314	.424	2.014

BHAR has a minimum of -0.084 and a maximum of 0.005, which means that the lowest abnormal return from the sample was -8.4%, whereas the highest one was 0.5%. The mean for underpricing is almost the same as for the figure in the first model – 0.319 versus 0.325. IT dummy has a mean of 0.699, stating that again 70% of firms belong to IT&Software sector, and the mean of Profit/loss dummy equal to 0.28, which is consistent with the results obtained in the first model. R&D intensity has a mean of 1.296, so nothing really changed in this model. The same is for the mean of proceeds – in the first model it was 4.962, whereas in the second one it is 4.984.

Table 4. Correlation matrix Model 2 US

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) BHAR	1.000								
(2) Underpricing	-0.658*	1.000							
	(0.000)								
(3) IT	-0.077	0.049	1.000						
	(0.465)	(0.641)							
(4) Proceeds	0.275*	-0.027	0.190	1.000					
	(0.008)	(0.800)	(0.069)						
(5) FirmSize	0.240*	-0.066	0.083	0.615*	1.000				
	(0.021)	(0.530)	(0.430)	(0.000)					
(6) Profit/loss	-0.087	0.220*	-0.061	0.084	0.030	1.000			
	(0.406)	(0.034)	(0.560)	(0.422)	(0.777)				
(7) DebtEBITDA	-0.103	-0.068	0.166	-0.086	-0.198	-0.241*	1.000		
	(0.325)	(0.518)	(0.112)	(0.414)	(0.057)	(0.020)			
(8) CurrentRatio	-0.002	0.534*	-0.088	0.025	-0.039	0.324*	-0.006	1.000	
	(0.988)	(0.000)	(0.400)	(0.816)	(0.709)	(0.002)	(0.953)		
(9) RD	-0.096	0.166	0.137	-0.034	0.047	-0.305*	0.058	-0.027	1.000
	(0.401)	(0.144)	(0.229)	(0.769)	(0.678)	(0.006)	(0.610)	(0.812)	

**** p<0.01, ** p<0.05, * p<0.1*

This time, underpricing, proceeds, and firm size are still the only independent variables which have association with BHAR. Hence, I can expect that these variables may turn out to be able to explain the dependent variable. The rest variables remain almost unchanged compared with pairwise correlation of Model 1.

VIF test is to be done to ensure that independent variables are not correlated. All VIF coefficients are less than 10 and 1/VIF ones are larger than 0.1, which implies that we do not face a multicollinearity problem in this model (see Table 2. VIF test Model 2 US in appendix B).

Model 3

Table 5. Summary statistics Model 3 US

	N	Mean	Std. Dev.	min	max
BHAR	99	-.001	.006	-.055	.006
Underpricing	99	.497	1.958	-.327	17.799
IT	99	.687	.466	0	1
Proceeds	99	4.987	.384	4.079	6
Firmsize	99	4.417	1.462	.376	8.558
Profit/loss	99	.263	.442	0	1
DebtEBITDA	99	-.445	10.14	-68.55	47.714
Currentratio	99	1.503	1.342	.03	10.48
RD	99	1.314	.332	.424	2.519

The only thing which changed is BHAR statistics – in the third model its minimum value is -0.055, whereas the maximum one is 0.006. In general, there are insignificant changes relative to the second model. The reason for this is that only few firms were added to the third sample to complete the rest of the firms included in the first two models.

Table 6. Correlation matrix Model 3 US

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) BHAR	1.000								
(2) Underpricing	-0.349*	1.000							
	(0.000)								
(3) IT	-0.065	-0.111	1.000						
	(0.524)	(0.274)							
(4) Proceeds	0.254*	-0.225*	0.218*	1.000					
	(0.011)	(0.025)	(0.030)						
(5) Firmsize	0.238*	-0.277*	0.127	0.649*	1.000				
	(0.018)	(0.006)	(0.211)	(0.000)					
(6) Profit/loss	-0.021	0.041	-0.042	0.075	0.026	1.000			
	(0.833)	(0.685)	(0.676)	(0.462)	(0.802)				
(7) DebtEBITDA	-0.169	-0.028	0.144	-0.064	-0.154	-0.248*	1.000		
	(0.094)	(0.785)	(0.155)	(0.532)	(0.127)	(0.013)			
(8) Currentratio	0.044	0.139	-0.072	0.033	-0.022	0.336*	-0.019	1.000	
	(0.693)	(0.170)	(0.482)	(0.745)	(0.827)	(0.001)	(0.853)		
(9) RD	-0.158	0.418*	0.059	-0.141	-0.114	-0.309*	0.053	-0.093	1.000
	(0.148)	(0.000)	(0.590)	(0.197)	(0.297)	(0.004)	(0.633)	(0.399)	

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

The results presented here look the same as in the first two model – underpricing, proceeds and firm size at 10% level are significant in terms of correlation with the dependent variable.

VIF test is to be done one more time. No multicollinearity problem was revealed in the last model – all the coefficients are within normal limits (see Table 3. VIF test Model 3 US in Appendix B).

2. Chinese firms

Model 1.

Table 7. Summary statistics Model 1 China

	N	Mean	Std. Dev.	min	max
BHAR	21	0	.005	-.005	.018
Underpricing	21	2.132	5.107	-.842	20
IT	21	.714	.463	0	1
Proceeds	21	1.886	.268	1.301	2.334
Firmsize	21	1.861	.399	1.35	3.117
Profit/loss	21	.476	.512	0	1
DebtEBITDA	21	-.435	6.155	-19.592	9.646
Currentratio	21	3.194	3.591	.121	14.137
RD	21	1.085	.413	.477	1.976

BHAR has a minimum of -0.05 and a maximum of 0.018, which means that the lowest abnormal return from the sample was -5%, whereas the highest one was 1.8%. The mean for underpricing is 2.132 meaning that the average underpricing in the sample is equal to almost 213%, which is in compliance with existing studies on this topic – as it was mentioned in the literature review, underpricing figure for Chinese IPOs can reach 170%. IT dummy has a mean of 0.714, stating that 71% of firms belong to IT&Software sector, and the mean of Profit/loss dummy equal to 0.476 shows that more than 47% of the firms have net profit one year prior to IPO. Debt-to-EBITDA figure equal to -0.435 shows that on average firms in the sample have negative EBITDA, while current ratio figure of 3.194 implies that Chinese tech firms in question have sufficient resources to cover their short-term debt. R&D intensity has a mean of 1.085, suggesting that on average 8.5% of firms' revenue is reinvested in R&D.

Table 8. Correlation matrix Model 1 China

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) BHAR	1.000								
(2) Underpricing	-0.181	1.000							
	(0.432)								
(3) IT	-0.447*	0.218	1.000						
	(0.042)	(0.342)							
(4) Proceeds	0.230	-0.344	-0.005	1.000					
	(0.316)	(0.127)	(0.981)						
(5) Firmsize	0.755*	-0.364	-0.539*	0.370	1.000				
	(0.000)	(0.105)	(0.012)	(0.099)					
(6) Profit/loss	-0.325	-0.014	0.181	-0.274	-0.193	1.000			
	(0.151)	(0.953)	(0.433)	(0.229)	(0.401)				
(7) DebtEBITDA	0.091	-0.013	-0.104	-0.149	-0.136	0.570*	1.000		
	(0.695)	(0.956)	(0.653)	(0.520)	(0.556)	(0.007)			
(8) Currentratio	-0.082	-0.260	0.323	0.082	0.033	0.231	0.094	1.000	
	(0.723)	(0.255)	(0.153)	(0.725)	(0.887)	(0.314)	(0.686)		
(9) RD	0.244	-0.047	0.196	0.241	0.100	-0.182	0.011	0.395	1.000
	(0.287)	(0.840)	(0.394)	(0.292)	(0.666)	(0.429)	(0.963)	(0.076)	

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

It can be seen from the table that two independent variables – IT dummy and firm size - are correlated at a significant level with p<0,1 with the dependent one. This indicates that these variables can be potentially significant in explaining the dependent variable. Firm size is also correlated with IT dummy at the same significance level. Two more independent variables have correlation – debt-to-EBITDA figure and Profit/loss dummy. In general, correlation matrix for the first model shows consistent results implying that independent variables do not have strong correlation with each other.

To test for multicollinearity, I would again use VIF test. The results of the test, presented in Appendix B, demonstrate that all the coefficients have acceptable values meaning that there is no multicollinearity problem.

Model 2

Table 9. Summary statistics Model 2 China

	N	Mean	Std. Dev.	min	max
BHAR	27	.001	.005	-.004	.024
Underpricing	27	1.686	4.561	-.842	20
IT	27	.667	.48	0	1
Proceeds	27	1.931	.467	1.021	3.352
Firmsize	27	1.902	.526	1.252	3.492
Profit/loss	27	.444	.506	0	1
DebtEBITDA	27	-.276	5.956	-19.592	10.005
Currentratio	27	2.7	3.294	.121	14.137
RD	27	1.102	.376	.477	1.976

BHAR has a minimum of -0.004 and a maximum of 0.024, which means that the lowest abnormal return from the sample was -0.4%, whereas the highest one was 2.4%. The mean for underpricing has decreased a lot relative to the figure in the first model– 2.132 versus 1.686. The only possible explanation for this is that those firms included in the second model show no underpricing – on the contrary, their first-day returns turned out to be less than the offer price. Still, the result 168% for underpricing is consistent with the results presented by other academics. IT dummy has a mean of 0.667, stating that again almost 70% of firms belong to IT&Software sector, and the mean of Profit/loss dummy equal to 0.444, which is consistent with the results obtained in the first model. R&D intensity has a mean of 1.102, so nothing really changed in this model. The same is for the mean of proceeds – in the first model it was 1.886, whereas in the second one it is 1.931. Current ratio, on the contrary, declined from 3.194 to 2.7, which is still a high value.

Table 10. Correlation matrix Model 2 China

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) BHAR	1.000								
(2) Underpricing	-0.131	1.000							
	(0.515)								
(3) IT	-0.231	0.220	1.000						
	(0.246)	(0.270)							
(4) Proceeds	0.032	-0.215	-0.191	1.000					
	(0.876)	(0.282)	(0.339)						
(5) Firmsize	0.445*	-0.276	-0.415*	0.737*	1.000				
	(0.020)	(0.164)	(0.031)	(0.000)					
(6) Profit/loss	-0.297	0.009	0.158	-0.419*	-0.338	1.000			
	(0.132)	(0.966)	(0.431)	(0.030)	(0.084)				
(7) DebtEBITDA	0.092	-0.019	-0.024	-0.362	-0.293	0.595*	1.000		
	(0.649)	(0.926)	(0.904)	(0.063)	(0.138)	(0.001)			
(8) Currentratio	-0.130	-0.191	0.337	-0.018	-0.029	0.229	0.069	1.000	
	(0.518)	(0.339)	(0.086)	(0.928)	(0.885)	(0.251)	(0.731)		
(9) RD	0.197	-0.054	0.229	-0.002	-0.029	-0.171	0.059	0.342	1.000
	(0.325)	(0.790)	(0.250)	(0.991)	(0.885)	(0.393)	(0.771)	(0.081)	

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

In the second model only firm size variable is positively correlated with the dependent variable. Firm size is also negatively correlated with IT dummy and has positive correlation with proceeds. Debt-to-EBITDA is correlated with Profit/loss dummy, which is, in its turn, has negative association with proceeds. All in all, the correlation between variables does not seem to be significant.

The test results for multicollinearity are presented in Table 5. VIF test Model 2 China

Appendix B. As we see from the table, the problem of multicollinearity is not present in the model.

Model 3

Table 11. Summary statistics Model 3

	N	Mean	Std. Dev.	min	max
BHAR	34	.001	.007	-.008	.035
Underpricing	34	1.708	4.517	-.842	20
IT	34	.676	.475	0	1
Proceeds	34	1.923	.424	1.021	3.352
Firmsize	34	1.938	.497	1.252	3.492
Profit/loss	34	.412	.5	0	1
DebtEBITDA	33	-.607	5.742	-19.592	10.005
Currentratio	34	2.506	2.967	.121	14.137
RD	34	1.113	.368	.477	1.976

The mean for BHAR seems to have remained the same with the minimum value being -0.008 and the maximum one 0.035. And, again, we can see that BHAR mean value is positive, which means that Chinese IPOs actually outperform a comparable benchmark. The rest of the variables do not show significant changes compared to the second model.

Table 12. Correlation matrix Model 3

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) BHAR	1.000								
(2) Underpricing	-0.131	1.000							
	(0.476)								
(3) IT	-0.257	0.224	1.000						
	(0.155)	(0.202)							
(4) Proceeds	0.083	-0.184	-0.162	1.000					
	(0.653)	(0.297)	(0.361)						
(5) Firmsize	0.442*	-0.267	-0.258	0.639*	1.000				
	(0.011)	(0.126)	(0.140)	(0.000)					
(6) Profit/loss	-0.149	-0.040	0.068	-0.354*	-0.356*	1.000			
	(0.415)	(0.823)	(0.704)	(0.040)	(0.039)				
(7) DebtEBITDA	0.090	-0.037	-0.066	-0.313	-0.337	0.618*	1.000		
	(0.631)	(0.840)	(0.716)	(0.076)	(0.056)	(0.000)			
(8) Currentratio	-0.085	-0.177	0.248	-0.011	-0.072	0.243	0.095	1.000	
	(0.643)	(0.318)	(0.158)	(0.950)	(0.684)	(0.166)	(0.599)		
(9) RD	0.066	-0.171	0.109	-0.038	0.012	-0.159	0.056	0.315	1.000
	(0.725)	(0.342)	(0.545)	(0.834)	(0.946)	(0.378)	(0.761)	(0.074)	

**** $p<0.01$, ** $p<0.05$, * $p<0.1$*

Consistent with the second model, in the third one only firm size variable is positively correlated with the dependent variable. Firm size has positive correlation with proceeds. Debt-to-EBITDA is positively correlated with Profit/loss dummy, which is, in its turn, has negative association with proceeds and firm size.

The final VIF test is necessary to test for multicollinearity. The results of VIF test are the same for the previous models – no multicollinearity was detected (see Table 6. VIF test Model 3 China Appendix B).

To conclude this subsection, descriptive statistics show that the quality of data is sufficient for further use in regression analysis.

2.5. Results of empirical analysis

In the following subsection I present the results of empirical analysis. Firstly, the long-run IPO performance is shown, which will allow me to test the first two hypotheses put forward in the first chapter and answer the first research question. Secondly, the regression models are built, and the results of regression analysis are presented, which allows me to test my third hypothesis and answer the second and third research questions.

1. US firms

As I have mentioned in the beginning of this chapter, to understand whether IPOs underperform or overperform, a Student's one sample test will be used. Thus, I will carry out a test on all three BHARs – two year, one and a half and one year after the date of IPO.

Table 13. 2-year BHAR t-test US

One-sample t test

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
BHAR2	88	-.0037715	.0011142	.0104518	-.005986	-.001557

mean = mean(BHAR2) t = -3.3850
Ho: mean = 0 degrees of freedom = 87

Ha: mean < 0	Ha: mean != 0	Ha: mean > 0
Pr(T < t) = 0.0005	Pr(|T| > |t|) = 0.0011	Pr(T > t) = 0.9995

As we can see, the mean of two-year BHAR is -0.0037715, which means that IPOs underperformed a comparable benchmark by 3.8%. T-test confirms that BHAR mean is statistically significant – its p-value is 0.0005, which is at 1% significance value.

Table 14. 1,5-year BHAR t-test US

One-sample t test

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
BHAR15	93	-.0014747	.0009929	.0095754	-.0034467	.0004973

mean = mean(BHAR15) t = -1.4852
Ho: mean = 0 degrees of freedom = 92

Ha: mean < 0	Ha: mean != 0	Ha: mean > 0
Pr(T < t) = 0.0704	Pr(|T| > |t|) = 0.1409	Pr(T > t) = 0.9296

The mean of 1,5-year BHAR also turned out to be less than 0, to be more exact -0.0014747, which indicates that average 1,5-year BHAR underperformed the benchmark by 1.5%. P-value is 0.0704, implying that the mean is less than 0 with a significance level of 7%.

Table 15. 1-year BHAR t-test US

One-sample t test

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
BHAR1	99	-.0008507	.0006324	.0062924	-.0021057	.0004043

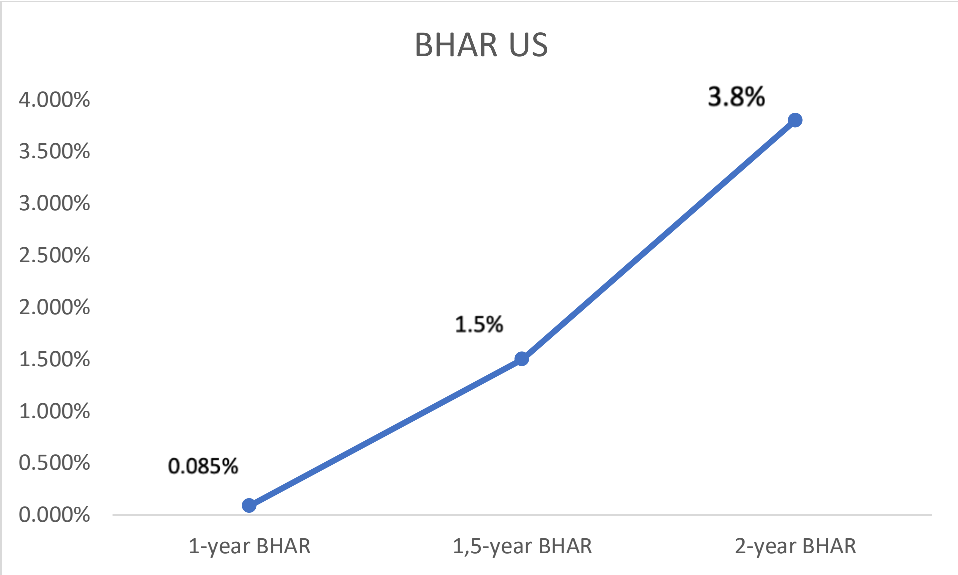
mean = mean(BHAR1) t = -1.3452
Ho: mean = 0 degrees of freedom = 98

Ha: mean < 0	Ha: mean != 0	Ha: mean > 0
Pr(T < t) = 0.0908	Pr(|T| > |t|) = 0.1817	Pr(T > t) = 0.9092

The mean of 1-year BHAR is -0.0008507, which tells us that average 1-year BHAR underperformed the NASDAQ index by 0.085%. P-value is 0.0908, which means that we can reject the null hypothesis stating that mean is equal to 0 and accept the alternative hypothesis suggesting that average mean is less than 0. We can also have a look at other alternative hypotheses which suppose that mean is 0 and mean is larger than 0 and reject both of them since the p-value is more than 1, 5 and 10%.

Hence, we can conclude that indeed on average US IPOs underperform in the long run. This allows me to accept the first hypothesis I put forward in the previous chapter. One more observation here is that for 2-year BHAR underperformance is more severe than for 1,5- and 2-

year BHAR – 3.8%, 1.5% and 0.085% respectively. Thus, I can conclude that the longer is the period after the date of IPO, the more severe is underperformance, which goes in compliance with the existing literature on this issue. The increasing trend for BHAR can be easily seen from the graph below:



Now I can go further and proceed with constructing a regression model. At the very beginning of the regression analysis, I faced a problem with one of the variables. Current ratio variable had a rather insignificant coefficient in all three models, which affected the whole model in a negative way so that the model was insignificant. That is why, for the sake of the whole model, I decided to remove this variable and make a regression analysis one more time. Furthermore, I also cleared my data from outliers to obtain better results. The results are the following:

Table 16. 2-year BHAR US regression model

```
 reg BHAR Underpricing Industry Proceeds FirmSize NetProfit DE RD

      Source |       SS           df       MS      Number of obs   =        72
-------------+----------------------------------   F(7, 64)        =      1.77
       Model |  .000011291         7  1.6130e-06   Prob > F        =    0.1094
    Residual |  .000058416        64  9.1275e-07   R-squared       =    0.1620
-------------+----------------------------------   Adj R-squared   =    0.0703
       Total |  .000069707        71  9.8179e-07   Root MSE        =    .00096

------------------------------------------------------------------------------
        BHAR |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
Underpricing |   .0002492   .0003875     0.64   0.522    -.0005249    .0010232
    Industry |   .0001403   .0002767     0.51   0.614    -.0004125    .0006931
    Proceeds |   .0005416   .0002524     2.15   0.036     .0000374    .0010458
    FirmSize |  -.0002425   .0001281    -1.89   0.063    -.0004984    .0000135
   NetProfit |   .0003077   .0002521     1.22   0.227    -.0001959    .0008113
          DE |  -.0000414   .0000227    -1.82   0.073    -.0000867    3.93e-06
          RD |  -.0000939   .0001841    -0.51   0.612    -.0004617    .0002739
       _cons |   -.005485   .0024511    -2.24   0.029    -.0103818   -.0005883
```

F-statistics indicator shows that the model is insignificant even at the 10% level. Probably, there might be heteroscedasticity problem. The next step was to test the model for heteroscedasticity. I used Breusch-Pagan test for detecting heteroscedasticity and constructed a plot showing residuals. The results of Breusch-Pagan test are depicted in Figure 1. Breusch-Pagan test US Model 1 in Appendix C. As we can see, the test rejects the null hypothesis which states that there is no heteroscedasticity present in the model. Consequently, there is a problem of heteroscedasticity which must be solved. Moreover, the plot illustrates the same results (see also Appendix C).

I also decided to look at the results of Breusch-Pagan test, updated by Cook and Weisberg to make sure that the problem of heteroscedasticity is indeed present. The results of the test are presented in Figure 3. Breusch-Pagan updated test US Model 1 Appendix C.

The problem of heteroscedasticity is serious: in this case error terms for coefficients are wrong, which distorts the coefficients. To tackle this, I decided to build a heteroscedastic model which has a random variable linked to independent variables. For this I will make the error variance dependent on variables Proceeds and Net Profit because they have the highest chi2 value obtained in the updated Breusch-Pagan test. The adjusted regression model looks like this:

```
reghv BHAR Underpricing Industry Proceeds FirmSize NetProfit DE RD, var(Proceeds
NetProfit) robust twostage
```

The results of the new regression model are the following:

Table 17. 2-year BHAR US improved regression model

```
Multiplicative heteroscedastic regression              Number of obs   =        72
Estimator: 2sls                                        Model chi2(9)   =    22.028
                                                       Prob > chi2     =     0.009
Log Likelihood              =    407.374               Pseudo R2       =   -0.0278
                                                       VWLS R2         =    0.1631
```

BHAR	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
lp_mean						
Underpricing	.0002492	.000291	0.86	0.392	-.0003212	.0008196
Industry	.0001403	.0002512	0.56	0.577	-.0003522	.0006327
Proceeds	.0005416	.00025	2.17	0.030	.0000516	.0010317
FirmSize	-.0002425	.0001136	-2.14	0.033	-.000465	-.0000199
NetProfit	.0003077	.0001822	1.69	0.091	-.0000494	.0006648
DE	-.0000414	.0000182	-2.28	0.023	-.000077	-5.82e-06
RD	-.0000939	.000177	-0.53	0.596	-.0004408	.0002531
_cons	-.005485	.0024359	-2.25	0.024	-.0102592	-.0007108
lp_lnvar						
Proceeds	-.0301096	1.049002	-0.03	0.977	-2.086116	2.025896
NetProfit	-.7567946	1.178831	-0.64	0.521	-3.067261	1.553672
_cons	-13.5781	12.45448	-1.09	0.276	-37.98843	10.83224

As it can be seen from the figure above, now the model is significant with Prob > chi2 being 0.009. In the model there are several significant coefficients – proceeds with p-value being 0.3, firm size whose p-value equals to 0.33, and debt-to-EBITDA with p-value of 0.023. All these coefficients are significant at 5% level. Profit/loss coefficient is also significant, but at the 10% significance level. Firm size and debt-to-EBITDA have a negative association with the dependent variable, whereas profit/loss and proceeds have a positive association. To obtain a clearer picture, I also need to look at the regression analysis of other models which include a 1,5- year BHAR and 1-year BHAR.

The second model with 1,5-year BHAR as the dependent variable also shows the same problem of heteroscedasticity (see Figure 4. Breusch-Pagan test US Model 2, Figure 5. Plot “Residuals vs Fitted values” US Model 2 and Figure 6. Table Breusch-Pagan updated test US Model 2 in Appendix C).

As it was the case in the second model, I will build a new heteroscedastic model which should eliminate heteroscedasticity. This time the error variance will be dependent on variables Proceeds, Underpricing and Profit/loss because they have the highest chi2 value obtained in the updated Breusch-Pagan test.

The results of the new regression model are as follows:

Table 18. 1,5-year BHAR US regression model

Multiplicative heteroscedastic regression		Number of obs	= 77
Estimator: 2sls		Model chi2(10)	= 20.285
		Prob > chi2	= 0.027
Log Likelihood	= 401.461	Pseudo R2	= -0.0259
		VWLS R2	= 0.1342

BHAR	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
lp_mean						
Underpricing	.0003239	.000305	1.06	0.288	-.000274	.0009218
Industry	.0000513	.0003781	0.14	0.892	-.0006897	.0007923
Proceeds	.0009754	.0004003	2.44	0.015	.0001908	.0017599
FirmSize	-.0002904	.0001595	-1.82	0.069	-.000603	.0000221
NetProfit	.0005633	.0002232	2.52	0.012	.0001258	.0010009
DE	-.0000433	.0000182	-2.38	0.017	-.0000789	-7.67e-06
RD	-.000316	.0002282	-1.38	0.166	-.0007632	.0001312
_cons	-.0097486	.0039607	-2.46	0.014	-.0175113	-.0019859
lp_lnvar						
Underpricing	-1.303859	1.728243	-0.75	0.451	-4.691153	2.083436
Proceeds	-.1043131	3.086759	-0.03	0.973	-6.154249	5.945623
NetProfit	-.5377585	2.175947	-0.25	0.805	-4.802537	3.72702
_cons	-12.45243	37.35609	-0.33	0.739	-85.66903	60.76417

This time I also managed to fight a heteroscedasticity problem and obtain a significant model with Prob > chi2 equal to 0.027. Proceeds and debt-to-EBITDA also have significant coefficient at 5% level with p-values being 0.015 and 0.017 respectively. This time Profit/loss coefficient is significant at 5% level, whereas firm size coefficient became significant at 10% level. As it was with the second model, firm size and debt-to-EBITDA coefficients are negatively associated with the dependent variable, and proceeds and profit/loss have positive association. All in all, the results of this regression model are similar to the ones obtained for 2-year BHAR model.

Finally, I regress the third model with 1-year BHAR as the dependent variable. The problem of heteroscedasticity is still present according to the results of the tests (see Figure 7.

Breusch-Pagan test US Model 3, Figure 8. Plot “Residuals vs Fitted values” US Model 3 and Figure 9. Breusch-Pagan updated test US Model 3 in Appendix C).

Hence, I need to construct a new heteroscedastic model with error variance being dependent on Proceeds and Underpricing. Thus, I obtain the following results:

Table 19. 1-year BHAR US regression model

Multiplicative heteroscedastic regression
Estimator: 2sls
Log Likelihood = 431.197

Number of obs	= 82
Model chi2(9)	= 13.300
Prob > chi2	= 0.149
Pseudo R2	= -0.0157
VWLS R2	= 0.1184

BHAR	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
lp_mean						
Underpricing	.0004199	.0006993	0.60	0.548	-.0009508	.0017906
Industry	.0000294	.0003346	0.09	0.930	-.0006264	.0006851
Proceeds	.0005293	.0004423	1.20	0.231	-.0003375	.0013962
FirmSize	-.0002346	.0001465	-1.60	0.109	-.0005217	.0000525
NetProfit	.0008305	.0002831	2.93	0.003	.0002757	.0013852
DE	-.0000223	.0000168	-1.33	0.185	-.0000553	.0000107
RD	-.000142	.0002397	-0.59	0.554	-.0006118	.0003278
_cons	-.0053665	.0046636	-1.15	0.250	-.014507	.0037741
lp_lnvar						
Underpricing	-.0154627	4.953863	-0.00	0.998	-9.724856	9.69393
Proceeds	-.5557335	2.868908	-0.19	0.846	-6.17869	5.067223
_cons	-7.428737	31.79133	-0.23	0.815	-69.73859	54.88112

This time the results of the regression analysis are not satisfactory mainly because the model is not significant – p-value is 0.149, which makes it larger than 5 and even 10%. In addition, Model chi2 coefficient is less than 16.9, which also proves that the model is insignificant. The only significant independent variable is profit/loss; however, this does not bring any difference in the results of the regression since the model itself has no explanatory power.

2. Chinese firms

First of all, as it was the case with US IPOs, I would like to investigate whether Chinese IPOs underperformed or overperformed NASDAQ index. For this purpose, I will again use a simple one-sample t-test.

Table 20. 2-year BHAR t-test China

One-sample t test

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
BHAR2	21	.0003285	.0009974	.0045705	-.0017519	.002409

mean = mean(BHAR2)　　t = 0.3294
Ho: mean = 0　　degrees of freedom = 20

Ha: mean < 0	Ha: mean != 0	Ha: mean > 0
Pr(T < t) = 0.6274	Pr(|T| > |t|) = 0.7453	Pr(T > t) = 0.3726

As we can see, mean for 2-year BHAR is 0.0003285, which assumes that Chinese IPOs slightly overperform the benchmark by 0.33%. However, the p-value of alternative hypotheses indicate that we should accept the null hypothesis stating that mean is equal to 0. This is not exactly true, since 0.33% is slightly more than 0, though very close to it. Hence, despite the p-value result, we can conclude that Chinese IPOs slightly overperformed.

Table 21. 1,5-year BHAR t-test China

One-sample t test

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
BHAR15	27	.0007256	.0010109	.005253	-.0013524	.0028036

```
    mean = mean(BHAR15)                                           t =   0.7177
Ho: mean = 0                                     degrees of freedom =       26

    Ha: mean < 0                 Ha: mean != 0                 Ha: mean > 0
 Pr(T < t) = 0.7603         Pr(|T| > |t|) = 0.4793          Pr(T > t) = 0.2397

. ttest BHAR1=0
```

The result of t-test for 1,5-year BHAR is almost the same – the mean is 0.0007256, while p-values of alternative hypotheses suggest we accept the null hypotheses and say that the mean is 0. Again, I should say that Chinese IPOs slightly overperformed the benchmark by 0.73%.

Table 22. 1-year BHAR t-test China

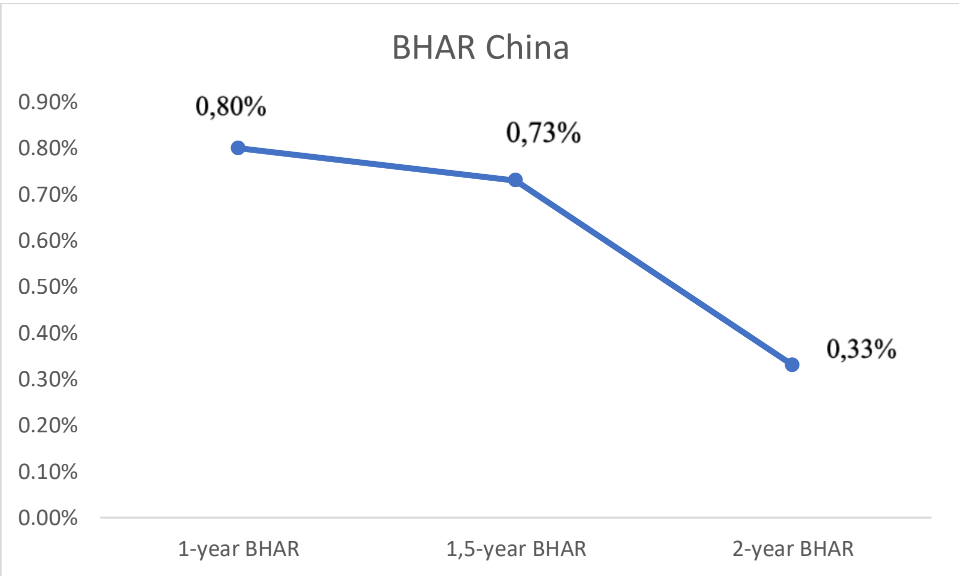
One-sample t test

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
BHAR1	34	.000798	.0011728	.0068384	-.001588	.003184

```
    mean = mean(BHAR1)                                            t =   0.6804
Ho: mean = 0                                     degrees of freedom =       33

    Ha: mean < 0                 Ha: mean != 0                 Ha: mean > 0
 Pr(T < t) = 0.7495         Pr(|T| > |t|) = 0.5010          Pr(T > t) = 0.2505
```

The result of t-test for 1-year BHAR is very close to the one obtained for 1,5-year BHAR – the mean is 0.000798, implying overperformance by 0.8%, p-values are larger than 1, 5 or 10%. All in all, I make a conclusion that Chinese IPOs slightly overperform a comparable benchmark, which leads to rejecting my second hypothesis about underperformance of Chinese tech initial public offerings. From the following graph we can clearly see a downward trend:



Now, when I am done with investigating IPO performance itself, I would like to study the drivers that might somehow influence this performance, so I continue with the regression model.

In case of Chinese IPOs, I cannot build a full eight-variable model for each time period, because the number of observations is too small – less than 30. That is why I decided to split the three models into smaller once to obtain more robust results. The splitting will be based on those variables which turned out to be the most significant in terms of explaining the dependent variable in the case of US data sample. These are profit/loss – significant in all three models, firm size – significant in two models, and debt-to-EBITDA, which is also significant in two models.

Unlike the first data sample, the data on Chinese IPOs do not contain heteroskedasticity, which allows me to construct a simple linear regression model without adjusting for heteroscedasticity. The Breusch-Pagan test results are shown below (see Figure 10. Breusch-Pagan test China Model 1 Appendix C). P-value is 0.9379, which is significantly higher than 5%, hence, we can accept the null hypothesis that the variance of residuals is homogeneous. The graphical test goes in compliance with Breusch-Pagan test (also see Appendix C).

Thus, I can certainly eliminate heteroscedasticity from the potential threats to the results of the model. Nevertheless, again I was forced to exclude current ratio from the set of independent variables because it had a negative impact on the significance of the model. The regression analysis of the first model is presented below:

Table 23. 2-year BHAR China regression model with firm size, profit/loss dummy and Debt/EBITDA as independent variables

Source	SS	df	MS			
				Number of obs	=	21
				F(3, 17)	=	15.47
Model	.000305786	3	.000101929	Prob > F	=	0.0000
Residual	.000112009	17	6.5887e-06	R-squared	=	0.7319
				Adj R-squared	=	0.6846
Total	.000417795	20	.00002089	Root MSE	=	.00257

BHAR	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Firmsize	.0083656	.0014659	5.71	0.000	.005273	.0114583
Netprofit	-.0038604	.0013787	-2.80	0.012	-.0067693	-.0009516
DebtEBITDA	.0003243	.0001135	2.86	0.011	.0000847	.0005638
_cons	-.0132591	.0029538	-4.49	0.000	-.019491	-.0070271

The model appears to be significant on the 1% level with F-statistics equal to 0.0000. R-squared coefficient is acceptable implying that 68% of the total variations in 2-year BHAR can be explained by independent variables. All the independent variables themselves show significant explanatory power – firm size and debt-to-EBITDA coefficients are significant at 1% and 5% respectively, and both of them are positively correlated with the dependent variable. As for profit/loss dummy, this variable is significant at 5% level with the coefficient being negative, which means that it has a reverse relationship with the dependent variable.

Now I will build the model with the variables which turned out to be least significant in the case of US models. These are IT dummy, R&D, and underpricing. The results of regression are presented below:

Table 24. 2-year BHAR China regression model with underpricing, IT dummy and R&D intensity as independent variables

Source	SS	df	MS			
				Number of obs	=	21
				F(3, 17)	=	2.64
Model	.000132663	3	.000044221	Prob > F	=	0.0830
Residual	.000285132	17	.000016772	R-squared	=	0.3175
				Adj R-squared	=	0.1971
Total	.000417795	20	.00002089	Root MSE	=	.0041

BHAR	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Undepricing	-.0000498	.0001846	-0.27	0.791	-.0004392	.0003396
IT	-.0049559	.0020741	-2.39	0.029	-.009332	-.0005798
RD	.003765	.0022732	1.66	0.116	-.0010309	.008561
_cons	-.0001111	.0027561	-0.04	0.968	-.0059258	.0057037

As we can see, the model is significant at 10% level, R-squared value of 0.3175 means that 31% of the total variations in 2-year BHAR can be explained by independent variables presented in this model. Only one independent variable – IT dummy – is significant and has a negative association with BHAR variable.

To involve one last independent variable – proceeds – I built two models with three most influential variables – firm size, profit/loss dummy and debt-to-EBITDA. Thus, I obtained the following models:

Table 25. 2-year BHAR China regression model with firm size, Debt/EBITDA and proceeds as independent variables

```
. regress BHAR Firmsize DebtEBITDA Proceeds
```

Source	SS	df	MS			
				Number of obs	=	21
				F(3, 17)	=	8.84
Model	.000254572	3	.000084857	Prob > F	=	0.0009
Residual	.000163223	17	9.6013e-06	R-squared	=	0.6093
				Adj R-squared	=	0.5404
Total	.000417795	20	.00002089	Root MSE	=	.0031

BHAR	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Firmsize	.0090931	.0018749	4.85	0.000	.0051373	.0130488
DebtEBITDA	.0001439	.0001143	1.26	0.225	-.0000972	.000385
Proceeds	-.0006	.0028	-0.21	0.833	-.0065074	.0053074
_cons	-.0153975	.0052245	-2.95	0.009	-.0264203	-.0043748

Table 26. 2-year BHAR China regression model with firm size, profit/loss dummy and proceeds as independent variables

```
. regress BHAR Firmsize Netprofit Proceeds

      Source |       SS           df       MS      Number of obs   =        21
-------------+----------------------------------   F(3, 17)        =      8.96
       Model |  .000255892         3  .000085297   Prob > F        =    0.0009
    Residual |  .000161903        17  9.5237e-06   R-squared       =    0.6125
-------------+----------------------------------   Adj R-squared   =    0.5441
       Total |  .000417795        20  .00002089    Root MSE        =    .00309

------------------------------------------------------------------------------
        BHAR |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    Firmsize |   .0086302     .00187     4.62   0.000     .0046849    .0125755
   Netprofit |   -.001858   .0014096    -1.32   0.205    -.004832     .0011159
    Proceeds |  -.0018091   .0028437    -0.64   0.533    -.0078088    .0041907
       _cons |  -.0114333   .0055981    -2.04   0.057    -.0232442    .0003777
------------------------------------------------------------------------------
```

In each model F-statistics and R-squared value are acceptable, however, proceeds as independent variable is not significant. Furthermore, Debt-to-EBITDA and profit/loss dummy became insignificant, though in the previous model they had explanatory power.

My next step is to do a regression analysis for the second period, where the dependent variable is a 1,5-year BHAR. Firstly, I checked for heteroscedasticity and detected no such problem in the data (see Figure 12. Breusch-Pagan test China Model 2 and Figure 13. Plot “Residuals vs Fitted values” China Model 2 Appendix C):

Next, I do a regression analysis for 1,5-year BHAR basing on the same principle as with 2-year BHAR:

Table 27. 1,5-year BHAR China regression model with firm size, profit/loss dummy and debt/EBITDA as independent variables

```
. regress BHAR Firmsize Netprofit DebtEBITDA

      Source |       SS           df       MS      Number of obs   =        27
-------------+----------------------------------   F(3, 23)        =      4.45
       Model |  .000263452         3  .000087817   Prob > F        =    0.0132
    Residual |  .000453988        23  .000019739   R-squared       =    0.3672
-------------+----------------------------------   Adj R-squared   =    0.2847
       Total |   .00071744        26  .000027594   Root MSE        =    .00444

------------------------------------------------------------------------------
        BHAR |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    Firmsize |   .0043765   .0017738     2.47   0.021     .0007071    .0080459
   Netprofit |  -.0044899   .0021911    -2.05   0.052    -.0090226    .0000428
  DebtEBITDA |   .0004211   .0001833     2.30   0.031     .0000418    .0008004
       _cons |  -.0054879   .0038059    -1.44   0.163     -.013361    .0023851
------------------------------------------------------------------------------
```

F-statistics shows that that the model is significant at 10% level, R-squared coefficient can be interpreted as that 37% of the total variations in 1,5-year BHAR can be explained by these independent variables. As for coefficients, like in the first time, all of them are significant –firm size with p-value of 0.021, profit/loss dummy showing consistent result – p-value of 0.052, as well as debt-to-EBITDA with p-value of 0.031. Furthermore, all coefficients, except profit/loss, are positively correlated with the dependent variable.

Following the logic, I regress the next model in the following way:

Table 28. 1,5-year BHAR China regression model with underpricing, IT dummy and R&D intensity as independent variables

. regress BHAR Undepricing IT RD

Source	SS	df	MS			
Model	.000087761	3	.000029254	Number of obs	=	27
Residual	.000629679	23	.000027377	F(3, 23)	=	1.07
				Prob > F	=	0.3818
				R-squared	=	0.1223
				Adj R-squared	=	0.0078
Total	.00071744	26	.000027594	Root MSE	=	.00523

BHAR	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Undepricing	-.0000644	.0002321	-0.28	0.784	-.0005445	.0004157
IT	-.0030396	.0022602	-1.34	0.192	-.0077151	.0016359
RD	.0036001	.0028217	1.28	0.215	-.002237	.0094371
_cons	-.0011065	.003282	-0.34	0.739	-.0078959	.0056829

Neither the dependent variable, nor the independent ones show any explanatory power – the model is insignificant with all the coefficients being insignificant as well.

The next step is to find out whether proceeds have relationship with BHAR. Thus, again I built two models with three most influential variables – firm size, profit/loss dummy and debt-to-EBITDA.

Table 29. 1,5-year BHAR China regression model with firm size, profit/loss dummy and proceeds as independent variables

. regress BHAR Firmsize Netprofit Proceeds

Source	SS	df	MS			
Model	.000337019	3	.00011234	Number of obs	=	27
Residual	.000380421	23	.00001654	F(3, 23)	=	6.79
				Prob > F	=	0.0019
				R-squared	=	0.4698
				Adj R-squared	=	0.4006
Total	.00071744	26	.000027594	Root MSE	=	.00407

BHAR	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Firmsize	.009013	.0022466	4.01	0.001	.0043655	.0136605
Netprofit	-.0032319	.0017365	-1.86	0.076	-.0068242	.0003603
Proceeds	-.0085828	.0026186	-3.28	0.003	-.0139999	-.0031657
_cons	.0015864	.0041624	0.38	0.707	-.0070242	.010197

Table 30. 1,5-year BHAR China regression model with firm size, Debt/EBITDA and proceeds as independent variables

```
. regress BHAR Firmsize DebtEBITDA Proceeds

      Source |       SS           df       MS      Number of obs   =        27
-------------+----------------------------------   F(3, 23)        =      5.29
       Model |  .000293083         3  .000097694   Prob > F        =    0.0064
    Residual |  .000424358        23   .00001845   R-squared       =    0.4085
-------------+----------------------------------   Adj R-squared   =    0.3314
       Total |   .00071744        26  .000027594   Root MSE        =     .0043

------------------------------------------------------------------------------
        BHAR |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    Firmsize |   .0092997   .0023721     3.92   0.001     .0043928    .0142067
  DebtEBITDA |   .0001292   .0001519     0.85   0.404    -.0001849    .0004434
    Proceeds |  -.0067588    .002737    -2.47   0.021    -.0124207   -.0010969
       _cons |  -.0038811   .0038849    -1.00   0.328    -.0119176    .0041554
------------------------------------------------------------------------------
```

Both models turned out to be significant with F-statistics being 0.0019 and 0.0064 at 1% significance level. A point to mention here is that proceeds coefficient is significant and is negatively associated with the dependent variable.

Finally, I construct the third regression model which has 1-year BHAR as the dependent variable. This time I have enough observations to construct a full model with all eight independent variables. The tests for heteroskedasticity demonstrate that no heteroskedasticity was found in the model (see Figure 14. Breusch-Pagan test China Model 3 and Figure 15. Plot "Residuals vs Fitted values" China Model 3 in Appendix C).

The third regression model obtained the following results:

Table 30. 1-year BHAR China regression model

```
. regress BHAR Undepricing IT Proceeds Firmsize Netprofit DebtEBITDA RD

      Source |       SS           df       MS      Number of obs   =        32
-------------+----------------------------------   F(7, 24)        =      2.80
       Model |  .000651777         7  .000093111   Prob > F        =    0.0282
    Residual |  .000799475        24  .000033311   R-squared       =    0.4491
-------------+----------------------------------   Adj R-squared   =    0.2884
       Total |  .001451252        31  .000046815   Root MSE        =    .00577

------------------------------------------------------------------------------
        BHAR |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
 Undepricing |  -.0000474   .0002456    -0.19   0.848    -.0005543    .0004594
          IT |  -.0003357   .0023842    -0.14   0.889    -.0052565     .004585
    Proceeds |  -.0079703   .0034004    -2.34   0.028    -.0149883   -.0009522
    Firmsize |   .0111539   .0030744     3.63   0.001     .0048086    .0174991
   Netprofit |  -.0039446    .002837    -1.39   0.177    -.0097998    .0019106
  DebtEBITDA |   .0004799   .0002395     2.00   0.057    -.0000144    .0009742
          RD |   .0018417   .0030106     0.61   0.546    -.0043718    .0080552
       _cons |  -.0047918   .0075633    -0.63   0.532    -.0204017     .010818
------------------------------------------------------------------------------
```

F-statistics figure shows that the model is significant at 5% level with R-squared being 0.4491. Only three coefficients seem to be significant here – proceeds with a negative coefficient of -0.00797, firm size with a coefficient 0.111 and debt-to-EBITDA with a positive coefficient of 0.00047.

To sum up, I present the table which summarizes the results of hypotheses testing:

Hypothesis	Description	Result
H1: ***On average, US companies after going public underperform a comparable benchmark in the long run.***	BHAR mean is less than 0, implying that IPOs underperformed	Accepted
H2: ***On average, Chinese IPOs slightly underperform a comparable benchmark in the long run.***	BHAR mean is slightly more than 0, which means that IPOs overperformed	Rejected
H3: ***R&D intensity has a direct relationship with the long-run IPO performance of tech firms.***	R&D intensity variable shows no association with BHAR	Neither accepted, nor rejected

2.6. Discussion

In this subsection of the Master thesis, I would like to discuss the results obtained in the previous chapter.

To address the first research question "How do initial public offerings of US and Chinese tech firms perform in the long run?" the measurement of IPO performance was chosen and justified. To estimate whether the IPOs underperformed, I looked at the results of t-test and checked the mean value of BHAR for all six cases, as it was used in previous works on this topic. In the first three cases mean value is negative, which means that IPOs underperformed a comparable benchmark. This finding allows me to accept my first hypothesis H1: *On average, US companies after going public underperform a comparable benchmark in the long run.* As for Chinese IPOs, they on the contrary overperformed with BHAR mean being slightly more than 0. Hence, I reject my second hypothesis H2: *On average, Chinese IPOs slightly underperform a comparable benchmark in the long run.*

To answer the second research question "What are the most influential drivers of IPO performance for US and Chinese tech firms?" 6 regression models (with the 4th and 5th divided into smaller ones) were constructed accounting for three different time periods and two countries. According to the results of the regression analysis, I can highlight the following factors which seem to be the most significant in explaining the long-run IPO performance:

1. Debt-to-EBITDA – significant in 5 out of 6 models.

2. Firm size - significant in 5 out of 6 models.
3. Profit/loss – significant in 5 out of 6 models.
4. Proceeds – significant in 4 out of 6 models.
5. IT dummy – significant in 1 out of 6 models.

Finally, to answer the third research question "How do these drivers affect the long-tun performance of IPOs?", I again suggest using the results of regression analysis obtained in the second chapter. First of all, the significance of the first two models and insignificance of the third one in the first sample gives an idea that time period equal to one year after IPO is probably not appropriate for investigating long-run IPO performance. Although the third model which considers 1-year BHAR in the case of Chinese IPOs turned out to be significant, I still have doubts whether 1 year after the date of IPO is an appropriate tool since the small data sample of Chinese IPOs can influence the results of regression analysis The literature on this topic suggests that the long-run IPO performance is considered after all two or even three years from the moment of IPO. Probably, 1 year period is not enough for identifying key drivers affecting IPO performance.

Secondly, in the first chapter I put forward the hypothesis suggesting that R&D intensity has a direct relationship with the long-run IPO performance, and given the results of empirical analysis, I cannot neither accept nor reject my hypothesis since the coefficient for R&D in all models turned out to be insignificant. Hence, R&D intensity does not have any explanatory power in relation to 2-year, 1,5-year, and 1-year BHAR. I believe that the results of the analysis were not satisfying for this variable because the effect of R&D investments was mainly studied by academics with regard to the short-term IPO performance, not the long-term one. One more possible reason is that some researchers doubt that R&D intensity can be a sufficient measurement of firms' innovation activity, that is why they replace it with other measures. Thus, it might be the case that R&D intensity is not significant in explaining the long-run IPO performance because it is not representative enough of firms being innovative.

Lastly, I would like to discuss how exactly the most influential drivers identified above can affect IPO performance. *Debt-to-EBITDA* coefficient has a negative correlation with BHAR for US IPOS, suggesting that any negative change in the value of Debt-to-EBITDA is most likely to cause a positive change in abnormal returns – that is, if Debt-to-EBITDA ratio is decreasing, abnormal returns will increase. The result seems to be quite logical because increasing Debt-to-EBITDA ratio implies that a firm may have difficulties with paying off its debt. As the result, this influences stock performance of the firm leading to generating fewer excess returns. However, the results for Chinese IPOs are the opposite - Debt-to-EBITDA has a positive correlation with BHAR, which does not seem to be a consistent result. *Firm size* is also included in the most significant coefficients. In the first sample, firm size has a negative correlation with abnormal returns, while in the second sample the relationship between these variables is the opposite. The result obtained in the Chinese sample seems to be more consistent with the empirical results obtained by other researchers. For instance, Loughran and Ritter (1995) presented evidence that "smaller offerings…underperform by more than larger offerings". Bravo and Gompers (1997) agree with them arguing that smaller IPOs showed more severe underperformance. *Profit/loss* is positively correlated with abnormal returns in the case of US IPOs and negatively correlated in the case of Chinese IPOs. I believe that the most logical relationship that can be between net profit and abnormal returns is that net profit leads to increased stock performance, which means that their correlation should be positive. On the other hand, another explanation might be that net loss indicates that a firm is at the early stage of its development when earnings are not stable enough and the only thing a firm does is heavily investing in developing its products (R&D investments in the case of tech firms) and advertising them. Consequently, such large investments might imply that a firm is using its potential and in the long run it will be paid back in the form of larger stock returns, so in this case the correlation between net profit and stock performance should be negative. *Proceeds* has a positive relationship with IPO performance in the US sample and a negative one for Chinese sample. This finding also suggests that smaller firms which obtained fewer gross proceeds are more likely to underperform in the long run, while the larger are the proceeds, the better are the abnormal returns. *IT dummy* has a negative correlation with stock performance for Chinese IPOs. This result supports the existing opinion that technology industry is considered rather uncertain (Ritter, 1991) and thus causes worse stock performance. The last factor I would like to mention is *underpricing*. In the literature review I suggested using this figure as it was admitted significant in explaining long-run IPO performance. However, the regression analysis showed that in none of the models the coefficient has an explanatory power, which means that in my sample underpricing does not play any instrumental role for underperformance.

To conclude this subsection, I assume that the results of regression analysis for two samples are not consistent with each other for several reasons. The primary reason is that the Chinese sample is three times as little as the US one. In econometric theory it is believed that the more observations, the better and more solid research results. Thus, a small sample might potentially affect the correctness of results. Secondly, the difference in results can be explained by peculiarities attributable to different countries. Probably, it is not worth expecting that IPOs from different countries with their own specificity would behave the same way.

2.7. Limitations

The main limitation I acknowledge in my work is a small sample size. Judging by previous research works done in this area, the sufficient sample size includes several hundreds or even more than a thousand IPOs. The sample size has a great impact on the results of regression analysis, that is why the more observations, the better. Nevertheless, I still did an analysis with the existing data and obtained results, which helped me notice certain patterns and tendencies. For some IPOs there were no available data even in such huge and reliable database as Eikon, that is why not all firms which have gone public in the investigated time periods are included in the list Although I had difficulties with data collection, I believe that the results obtained in the regression analysis are representative of data available on these exact IPOs. After all, my primary objective was to investigate all IPOs which occurred as the result of US and Chinese tech firms going public in the period from 01.01.2010 till 31.12.2019, and I did it with all 133 firms I managed to find data on.

The second limitation is that I cannot fully draw a comparison between US and Chinese IPOs primarily because the sample size is too small. I collected data on 99 US firms and 34 Chinese firms, which is obviously not enough for proper comparison since Chinese sample is three times as little. Due to this gap, I obtained contradicting results. For example, while US firms showed underperformance, Chinese firms, on the contrary, overperformed. If the Chinese sample was almost at the same level, I might have received other results, for instance, that the firms also underperformed. However, I would again repeat my thought that I dealt with what was happening on the IPO market that time and with available data.

One more limitation is related to the methodology I applied in my Master thesis. To begin with, I believe that I could also have considered several more measures of IPO performance, such as, for example, cumulative abnormal returns (CAR), which is considered a popular measure along with BHAR. One more option is to compare, for example, BHAR and some other method which is viewed as the one giving opposite results, such as a calendar-time technique for return measurement. The research which accounts for several different measures of the dependent variable might look completer and more reliable. Unfortunately, I lacked time in order to carry out proper research with several dependent variables. Furthermore, I could have chosen other or simply more independent variables for the regression analysis that would have been more suitable for the model and significant in relation to the dependent variable. However, I should say that firstly, it is impossible to consider all factors which might in any way influence the IPO performance, because there is a variety of them. Secondly, in the beginning of the second chapter I tried to explain my motivation behind choosing exactly these independent variables. Mainly I wanted to comply with existing research studies, promoting at the same time my own vision of how I would like to see my research work.

2.8. Managerial implications

Investigating long-run performance of companies after going public has a practical value since it serves the interest of several counterparties. Thus, investors are interested not only in the short-term performance of stocks, but also how they perform in the long run, in one, one and a half and two years from the IPO date. Knowing price patterns, investors can apply their trading strategies to gain high returns. Next, long-run performance contributes to the understanding of the relationship between the IPO market and informational efficiency. According to Jay Ritter (1991), the most influential scholar in the area of initial public offerings studies, equities markets and IPO markets affect market prices in a way that they are prone to have fads. Ritter also states that long-run performance is of particular interest because it deals with such a phenomenon as a "window of opportunity". The phenomenon means a short period of time when an excellent profitable opportunity can be taken. In the context of IPOs this implies that issuers may time new issues because they know, for example, that high volume periods result in poor performance in the long run. So, issuers wait till the time they can take advantage of a "window of opportunity". Finally, there is a clear relationship between the cost of raising equity capital for a company and returns which investors obtain after a company has gone public.

Moreover, management of technology companies can apply the analysis of key drivers to evaluate the long-run performance of these companies after going public. Thus, they can analyze in more detail factors which affect the performance of their companies and pay more attention to them. The same results can be used by investors seeking to maximize their return on investment in a particular company, which they can do by finding out what drivers affect the long-run performance of the technology companies. According to Lowry, M., Michaely, R., Volkova, E. (2017), "one of the important puzzles regarding IPOs is that, over many time periods, evidence suggests investing in IPOs for the long term may not be a great idea". Hence, if investors are determined to invest in IPOs, they should understand all the risks and what might influence the stock performance of a company after going public. Also, one more counterparty which is interested in the long-run performance of a company is its shareholders. It is quite obvious that they would like to use information which helps them understand what can influence the price of a company one, one and a half and two years after going public.

CONCLUSION

This Master thesis is aimed at investigating the long-run IPO performance of tech companies based in the US and China in the period of stable global economy. To achieve this goal, several research questions have been formulated.

The first chapter deals with the theoretical background. I did a literature review on existing papers focusing on IPO performance in the US and China, as well as peculiarities of technology firms. The literature review allowed me to get acquainted with existing opinions of academics concerning the long-term IPO performance and drivers that affect this performance. Furthermore, as the result of providing the theoretical background, three hypotheses were formulated.

H1: *On average, US companies after going public underperform a comparable benchmark in the long run.*

H2: *On average, Chinese IPOs slightly underperform a comparable benchmark in the long run.*

H3: *R&D intensity has a direct relationship with the long-run IPO performance of tech firms.*

The next step was to choose methodology. It was decided to use t-test to investigate IPO performance and make a regression analysis to find the most influential drivers. For this purpose, buy-and-hold abnormal returns (BHAR) measure was chosen as the dependent variable because it is widely used by researchers and considered a reliable measure of IPO performance. The benchmark for calculating abnormal returns is NASDAQ index. The analysis cover three periods – two years after IPO, one and a half year and 1 year. For all these periods BHAR were calculated. As for independent variables, nine variables have been chosen for regression analysis with explanations of why exactly these variables are necessary for the research.

Then, a data sample was collected. The data on 99 US and 34 Chinese firms were collected for further analysis from Thomson Reuters. The data include share price history, financial statements, and prospectus. The chosen time range considers a period of relative calmness with no major macroeconomic distress from 01.01.2010 till 31.12.2019.

The results confirm the first hypothesis showing that US IPOs underperformed the benchmark by 3.8%, 1,5% and 0.085% for two-year, one and a half-year and one-year BHAR respectively. As for Chinese sample, the results, on the contrary, suppose rejecting the second hypothesis because IPOs slightly overperformed the benchmark – by 0.33%, 0.73% and 0,8% for two-year, one and a half-year and one-year BHAR respectively. The third hypothesis cannot be neither accepted nor rejected because the coefficient of R&D intensity turned out to be statistically insignificant in each model. Apart from that, the most influential drivers have been identified –

these are debt-to-EBITDA, firm size, Profit/loss dummy, proceeds and IT dummy – as well as the description of their relationship with the dependent variable BHAR.

Finally, the results were discussed, limitations were identified, and managerial implications were provided.

This research work seems to close the research gap – as to my best knowledge, there are no prior research works which are focused on investigating the long-run IPO performance of US and Chinese technology firms in the period of stable global economy. In my opinion, it is vital to investigate the market not only in the times of financial crisis, but also in its ordinary days because it gives insights on what is usually going on with a firm stock performance after listing and what factors can possibly affect this performance.

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APPENDIX A

US tech firms

Meru Networks Inc
Convio Inc
TeleNav Inc
BroadSoft Inc
Qlik Technologies Inc
RealPage Inc
SciQuest Inc
Cornerstone OnDemand Inc
ServiceSource International LLC
Responsys Inc
Boingo Wireless Inc
FriendFinder Networks Inc
HomeAway Inc
Skullcandy Inc
Tangoe Inc
Carbonite Inc
Ubiquiti Networks Inc
Intermolecular Inc
Jive Software Inc
Zynga Inc
Synacor Inc
Brightcove Inc
M/A-COM Technology Solutions Hldg Inc
CafePress Inc
Proofpoint Inc
Envivio Inc
Audience Inc
Exa Corp
E2open Inc
Peregrine Semiconductor Corp
Qualys Inc
Ambarella Inc
Professional Diversity Network Inc
Marketo Inc
Liquid Holdings Group Inc
Control4 Corp
Benefitfocus Inc
FireEye Inc
Applied Optoelectronics Inc
Covisint Corp

CommScope Holding Co Inc
Endurance International Group Holdings Inc
Varonis Systems Inc
Paylocity Holding Corp
Five9 Inc
Sabre Corp
TrueCar Inc
SunEdison Semiconductor Ltd
Resonant Inc
MobileIron Inc
GoPro Inc
Medical Transcription Billing Corp
VWR Corp
Hortonworks Inc
Connecture Inc
Inovalon Holdings Inc
MINDBODY Inc
AppFolio Inc
Alarm.com Holdings Inc
Rapid7 Inc
CPI Card Group Inc
Adesto Technologies Corp
Xtera Communications Inc
Atlassian Corp PLC
SecureWorks Corp
Acacia Communications Inc
Impinj Inc
Talend Sa
Atomera Inc
Airgain Inc
Everbridge Inc
Apptio Inc
Nutanix Inc
Coupa Software Inc
Blackline Inc
Quantenna Communications Inc
Ichor Holdings Ltd
Presidio Inc
Okta Inc
Veritone Inc
Appian Corp
Tintri Inc
Cargurus Inc
MongoDB Inc

Bandwidth Inc
One Stop Systems Inc
Cardlytics Inc
Zscaler Inc
Dropbox Inc
DocuSign Inc
Everquote Inc
Domo Inc
Apigee Corp
Tenable Holdings Inc
Sonos Inc
Upwork Inc
Yodlee
Summit Semiconductor
SVMK

Chinese tech firms

AutoNavi Holdings ADR
ChinaCache International Holdings Ltd
RDA Microelectronics Inc
SGOCO Group Ltd
BCD Semiconductor Manufacturing Ltd
Trunkbow International Holdings Ltd
21Vianet Group Inc
Jiayuan.com International Ltd
China Mobile Games & Entertainment Group Ltd
YY Inc
Qunar Cayman Islands Ltd
Sungy Mobile Ltd
Tarena International Inc
Tuniu Corp
Xunlei Ltd
iDreamSky Technology Ltd
Momo Inc
Gridsum Holding Inc
Lexinfintech Holdings Ltd
Wowo
AHG(Hexinday)
Golden Bull Ltd
Bilibili Inc
iQIYI Inc

AGM Group Holdings Inc
CLPS Inc
Uxin Ltd
Aurora Mobile Ltd
Qutoutiao Inc
Viomi Technology Co Ltd
Pintec Technology Holdings Ltd
360 Finance Inc
Tudou Holdings Ltd
Montage Technology Group Ltd

APPENDIX B

Table 1. VIF test Model 1 US

Variable	VIF	1/VIF
Proceeds	2.39	0.418992
RD	2.07	0.483833
CurrentRatio	1.50	0.664801
FirmSize	1.41	0.708650
IT	1.39	0.717627
DebtEBITDA	1.36	0.734554
Underpricing	1.24	0.808005
Profit/loss	1.13	0.888683
Mean VIF	1.56	

Table 2. VIF test Model 2 US

Variable	VIF	1/VIF
Proceeds	2.82	0.355081
RD	2.34	0.426816
FirmSize	1.52	0.658804
IT	1.38	0.726434
CurrentRatio	1.37	0.731057
DebtEBITDA	1.33	0.753885
Underpricing	1.23	0.816135
Profit/loss	1.13	0.888413
Mean VIF	1.64	

Table 3. VIF test Model 3 US

Variable	VIF	1/VIF
Proceeds	2.81	0.355555
RD	2.44	0.409886
FirmSize	1.52	0.659652
IT	1.37	0.732201
CurrentRatio	1.29	0.772981
DebtEBITDA	1.25	0.801782
Underpricing	1.25	0.803157
Profit/loss	1.14	0.878470
Mean VIF	1.63	

Table 4. VIF test Model 1 China

Variable	VIF	1/VIF
Proceeds	1.49	0.670799
RD	1.47	0.679155
FirmSize	2.04	0.491140
IT	2.24	0.445790
CurrentRatio	1.63	0.612691
DebtEBITDA	1.81	0.553850
Underpricing	1.41	0.707109
Profit/loss	2.05	0.486632
Mean VIF	1.77	

Table 5. VIF test Model 2 China

Variable	VIF	1/VIF
Proceeds	2.49	0.401880
RD	1.37	0.727282
FirmSize	2.75	0.364152
IT	1.62	0.617964
CurrentRatio	1.48	0.674511
DebtEBITDA	1.79	0.558287
Underpricing	1.20	0.835613
Profit/loss	2.13	0.469983
Mean VIF	1.85	

Table 6. VIF test Model 3 China

Variable	VIF	1/VIF
Proceeds	2.00	0.498955
RD	1.29	0.773828
FirmSize	2.20	0.364152
IT	1.33	0.753621
CurrentRatio	1.40	0.716456
DebtEBITDA	1.82	0.550197
Underpricing	1.24	0.804358
Profit/loss	2.05	0.487425
Mean VIF	1.85	

APPENDIX C

Figure 1. Breusch-Pagan test US Model 1

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of BHAR

         chi2(1)      =    25.93
         Prob > chi2  =   0.0000
```

Figure 2. Plot "Residuals vs Fitted values" US Model 1

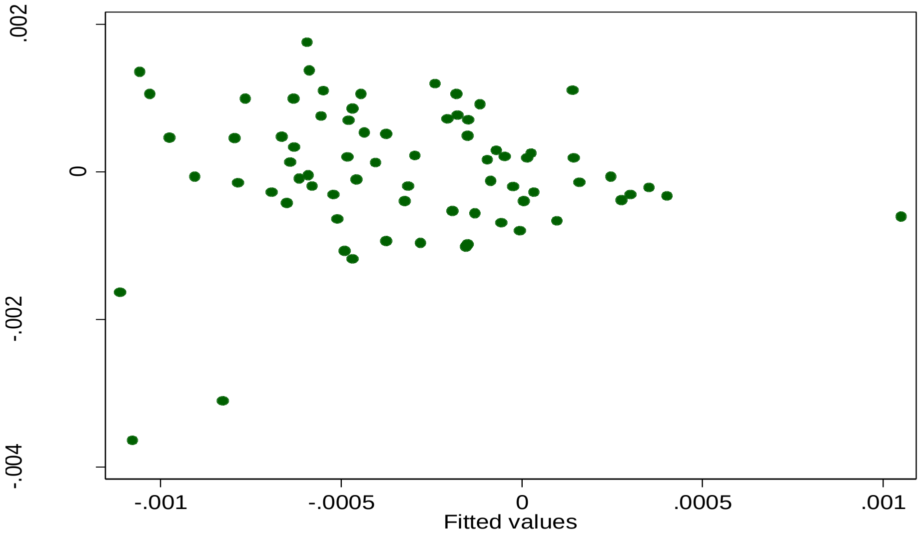

Figure 3. Breusch-Pagan updated test US Model 1

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
---------------------------------------
    Variable |      chi2   df        p
-------------+-------------------------
Underpricing |      5.27    1   0.1523 #
    Industry |      2.18    1   0.9785 #
    Proceeds |      9.86    1   0.0118 #
    FirmSize |      1.84    1   1.0000 #
 Profit/loss |      6.85    1   0.0622 #
  DebtEBITDA |      0.78    1   1.0000 #
          RD |      0.91    1   1.0000 #
-------------+-------------------------
simultaneous |     37.01    7   0.0000
```

Figure 4. Breusch-Pagan test US Model 2

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of BHAR

         chi2(1)      =    52.47
         Prob > chi2  =   0.0000
```

Figure 5. Plot "Residuals vs Fitted values" US Model 2

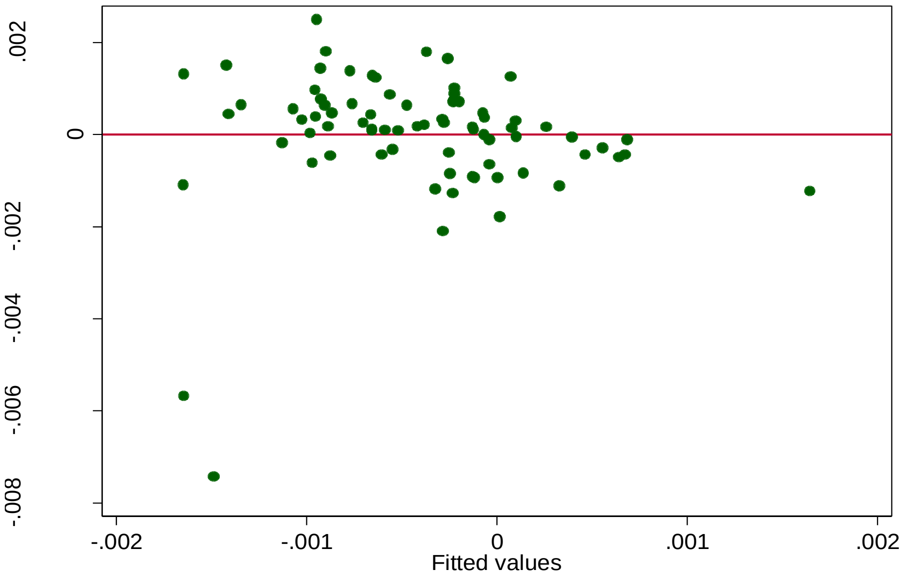

Figure 6. Breusch-Pagan updated test US Model 2

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance

---------------------------------------
    Variable |      chi2   df       p
-------------+-------------------------
Underpricing |      9.37    1   0.0155 #
    Industry |      0.63    1   1.0000 #
    Proceeds |     27.89    1   0.0000 #
    FirmSize |      0.08    1   1.0000 #
 Profit/loss |      6.85    1   0.0621 #
  DebtEBITDA |      2.39    1   0.8529 #
          RD |      0.00    1   1.0000 #
-------------+-------------------------
simultaneous |     65.64    7   0.0000
---------------------------------------
         # Bonferroni-adjusted p-values
```

Figure 7. Breusch-Pagan test US Model 3

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of BHAR

         chi2(1)      =    21.60
         Prob > chi2  =   0.0000
```

Figure 8. Plot “Residuals vs Fitted values” US Model 3

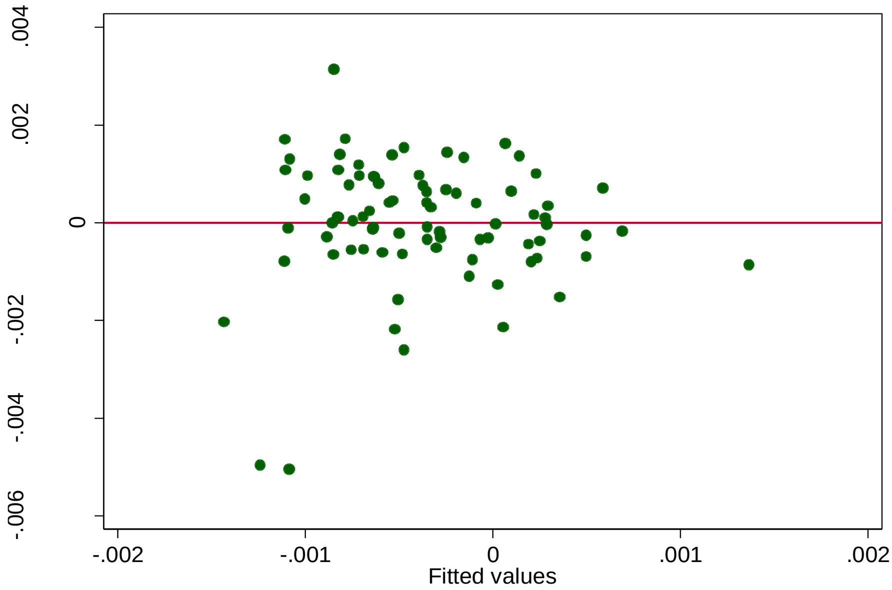

Figure 9. Breusch-Pagan updated test US Model 3

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance

---------------------------------------
    Variable |       chi2   df        p
-------------+-------------------------
Underpricing |       8.03    1   0.0323 #
    Industry |       1.28    1   1.0000 #
    Proceeds |      12.19    1   0.0034 #
    FirmSize |       0.40    1   1.0000 #
 Profit/loss |       3.12    1   0.5398 #
  DebtEBITDA |       1.51    1   1.0000 #
          RD |       0.01    1   1.0000 #
-------------+-------------------------
simultaneous |      32.76    7   0.0000
---------------------------------------
         # Bonferroni-adjusted p-values
```

Figure 10. Breusch-Pagan test China Model 1

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of BHAR

         chi2(1)      =     0.01
         Prob > chi2  =   0.9379
```

Figure 11. Plot "Residuals vs Fitted values" China Model 1

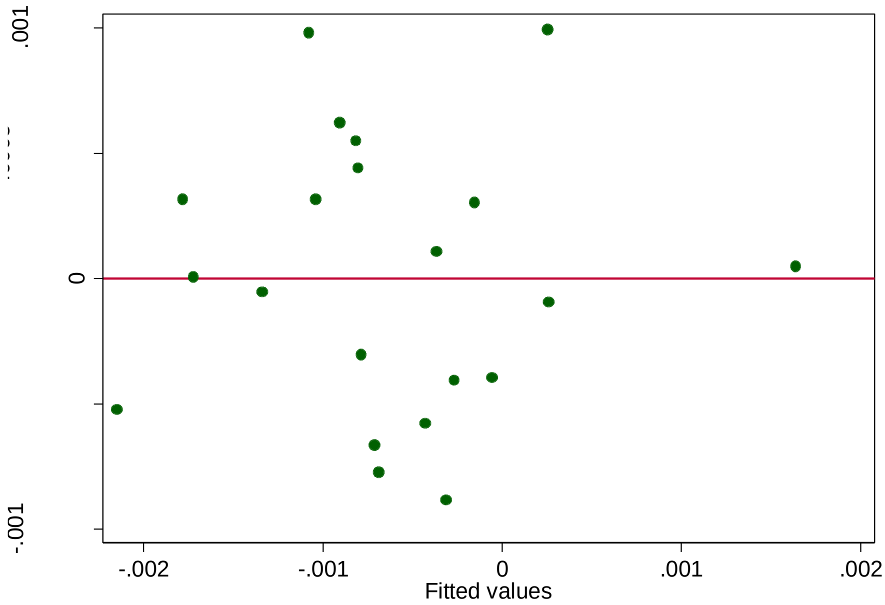

Figure 12. Breusch-Pagan test China Model 2

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of BHAR

         chi2(1)      =     0.02
         Prob > chi2  =   0.8961
```

Figure 13. Plot “Residuals vs Fitted values” China Model 2

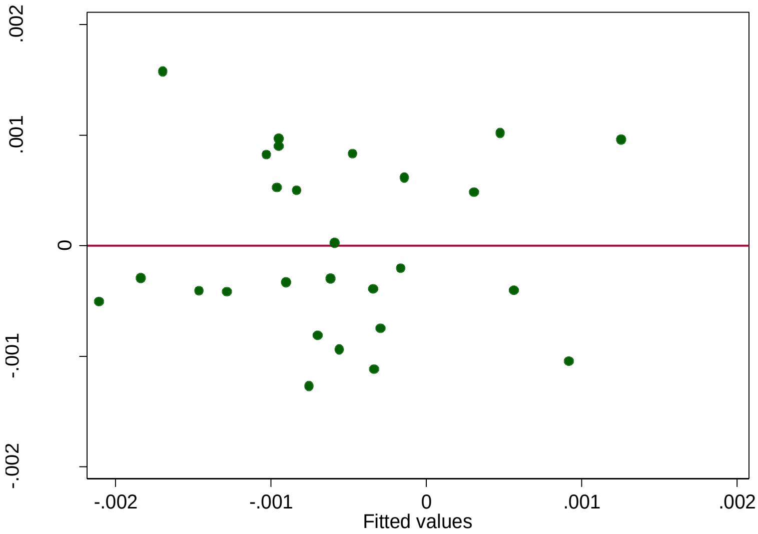

Figure 14. Breusch-Pagan test China Model 3

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
   Ho: Constant variance
   Variables: fitted values of BHAR

   chi2(1)       =     2.04
   Prob > chi2   =   0.1528
```

Figure 15. Plot “Residuals vs Fitted values” China Model 3