THE AFTERMARKET PERFORMANCE OF PRIVATE EQUITY-BACKED ENTITIES

An empirical study of US IPO returns 2010-2015

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Master thesis

Resumé

I denne afhandling undersøger vi børsnoteringer på det amerikanske marked. Vi fokuserer på forskelle i aktiernes performance i det første år efter børsnoteringen og ser på om det har en betydning om virksomheden har været ejet af en kapitalfond op til salget. Vores sample består af 1.014 børsnoteringer i perioden 2010-2015 på henholdsvist New York Stock Exchange og NASDAQ.

Ved hjælp af anerkendte risikomodeller justerer vi afkastene og sammenligner efterfølgende abnormale afkast på tværs af grupper. Vores resultater viser, at kapitalfondsejede virksomheder i gennemsnit performer relativt bedre end andre børsnoteringer, men at børsnoteringer i gennemsnit klarer sig dårligere end sammenlignelige aktier. Forskellene i performance kan dog forklares af operationelle forhold, og efter disse er taget højde for, kan vi ikke længere bevise en sammenhæng med den kapitalfondsejede ejerskabsmodel. Vi finder også at der er stor forskel på afkast og resultater afhængig af om man som investor køber ind til børsnoteringens udbudspris eller markedets åbningskurs. Slutligt drager vi parelleler til lignende studier, forklarer afvigelser i vores resultater og diskuterer hvilke implikationer vores fund har for investorer.

Abstract

In this thesis we examine initial public offerings (IPO) in the US market. We focus on differences in stock performance one year after the IPO and investigate effects from private equity ownership prior to the offering. Our sample consists of 1,014 IPOs listed between 2010-2015 on the New York Stock Exchange and NASDAQ.

We use widely acknowledged risk-models to adjust returns and compare abnormal returns across groups. Our results show that private equity-backed IPOs outperform other IPOs, but that IPOs in general perform worse than comparable stock. The differences in performances can be explained by operational characteristics and after adjusting for these, we can ultimately not prove causation between the differences in performance and the private equity ownership model. We also find large differences in returns and results depending on if the investor buys in at the IPO offer price or at the first day market opening price. Finally, we compare our results to similar studies, explain deviations in results and discuss the implications of our findings for investors.

TABLE OF CONTENTS

1. Introduction

The stock market is a hectic and confusing place swarming with opportunities. Each year new companies lists and become available for the first time to public investors. These new listings are characterized by a relatively larger amount of uncertainty compared to regular stocks, as the transition to being a publicly owned company involves large changes in terms of transparency. This both affects the pressure on management to perform and forces the investors to interpret large amounts of new information in a relatively short time frame.

Previous studies have found that initial public offerings (IPO) underperform comparable stocks in the first few years after listing (Ritter, 1991; Brav & Gompers, 1997; Cao & Lerner, 2009). They largely disagree upon why and which groups of IPOs underperform, but all agree on the overall trend. However, when initially researching the subject, we found a gap in the literature of large-scale IPO research focusing on the post financial crisis paradigm. For this reason we ultimately decided to investigate IPO performance in the period 2010-2015.

While researching the subject further, we found an extremely interesting angle. In sharp contrast to the widespread evidence of IPO underperformance, offerings backed by a private equity funds appeared to defy the norm (Brav & Gompers, 1997; Levis, 2011; Cao, 2012). They all found that the overperformance was related to operational characteristics and the size of the private equity-backed IPOs.

Since the abovementioned research was conducted, the amount and importance of private equity-backed IPOs have increased. We found that in the period 2010-2015, 27% of all IPOs on New York Stock Exchange (NYSE) and NASDAQ was backed by a private equity fund. More importantly, these IPOs are more available to investors as they are larger and represented 42% of the total amount of capital raised.

We believe these numbers highlight the importance of potential performance differences of private equity-backed IPOs. This is also the reason why, we chose to dedicate the thesis to investigating the effects of private equity ownership on the aftermarket performance of IPOs. However, before presenting the problem statement and research questions guiding the thesis, there is one more IPO specific investment condition you need to be enlightened about.

When launching an IPO, the issuing company hires an investment bank to find investors and to price the IPO. The IPO price also known as the offer price are made available to investors that commit to buying a large amount of shares (+1%) before the company goes public. In return, they usually receive a discounted price relative to the market opening price, but commit to holding the shares for a period of typically 180 days. This phenomenon is known as underpricing and have averaged approximately 18% since 1980 (Ritter, 2017). While this thesis does not seek to find an explanation for this anomaly, it has serious implications for how we evaluate performance. In the IPO literature, the performance refers to the stock development from the market opening price and does thus not include the underpricing element.

However, we still wanted to evaluate the attractiveness of IPOs for these type of investors, as they typically end up buying 80-85% of the total amount of shares sold (Ofek and Richardson, 2000). The investors who get to buy in at the offer price are invited by the investment bank (underwriter) to participate in a bidding round, and their bid ultimately ends up deciding how many shares they get. We explain more on the process later, but the point is that these investors are typically large institutional investors. While some IPOs allow private investors to buy in at the offer price, it is the exception rather than the norm. For this reason, we differentiate between returns for institutional (offer price) investors and private investors (non-offer price investors).

The introduction laid out the most important points from the literature. In section 2, we continue to elaborate the specifics of IPO and related private equity research. While the focus is mainly on private equity backed IPOs, the study itself investigates a total of 1,014 listings. It would be foolish not to use this opportunity to say something on a broader level about IPOs. For this reason we formulated the following problem statement and research questions.

1.1 Problem statement

How does private equity ownership prior to an initial public offering affect the aftermarket performance?

Research questions

1. How does IPOs perform compared to other stocks?
2. Which pre-IPO characteristics help in explaining the aftermarket performance of an IPO?
3. Are private equity backed IPOs any different?
4. Are IPOs attractive investments for private investors?
5. Are IPOs attractive investments for institutional investors?

1.2 Delimitation

This thesis investigates differences between private equity-backed (PE) and non-private equity-backed (NPE) IPOs. As we are solely looking at differences between the two IPO groups, we ignore tax effects on returns, as these are equal for both. When we throughout the thesis refer to any kind of returns, we are always talking about pre-tax returns.

Returns are measured on a daily basis for a one-year period following the stock's IPO. Many similar research studies focus on the long-run performance i.e. performance on a 3-5 year period. We refrain from looking at periods longer than one year as it gradually becomes more and more difficult to prove casualty between pre-IPO characteristics and performance. For instance, we believe it would be nearly impossible to say with any certainty, that performance on a 3-5 year period was caused by a singular pre-IPO condition. Moreover, very few studies actually look at holding periods of less than year and it seems likely, that pre-IPO conditions could have a significant impact on performance in the short run.

We also chose to confine the research to US IPOs only. Specifically, the sample is extracted from the two largest stock exchanges i.e. New York Stock Exchange and NASDAQ. We chose the US market as a target research market due to the large availability and most importantly, reliability of data. Availability of data was important due to high volatility in IPO returns. In essence, we needed a large sample size in order to say anything statistically significant about the returns. Thanks to Copenhagen Business School, we were fortunate to gain access to the Center for Research in Security Prices (CRSP) containing reliable stock data for all American securities.

Moreover, we chose to focus on the period 2010-2015. In the pre-writing research phase, we found that almost no recognized studies on large-scale samples had been conducted on returns post the financial crisis. In short, we wanted to fill the gap in the literature and work with as contemporary data as possible. Since we measure returns up until one year after the IPO, 2015 was the most recent year, where data was available one year forward.

Finally, we do not take into account the effects of stock float rates. We found that the relatively steep float rate requirements combined with the capital requirements for listing on NYSE and NASDAQ were sufficient for it to have a negligible effect on liquidity. Instead, we evaluate liquidity through other means such as trading volume and bid-ask spreads.

1.3 Thesis structure

The thesis is divided into 7 chapters.

The following figure provides a reader-friendly overview of the thesis structure.

Figure 1.1: Thesis structure

1.4 Terminology

This thesis is written for financial practitioners and use acronyms and terminology accordingly.

IPO: Initial public offering i.e. the process of a company offering shares to public investors for the first time.

B&H: Buy-and-hold return

BHAR: Buy-and-hold-abnormal return

CTIME: Calendar-time portfolio

CTAR: Calendar-time abnormal return

NPE and PE: Non-private equity and Private Equity

Offer price investor: Investors who buy it at the typically discounted offer price and thus receive the underpricing premium. See underpricing.

Non-offer price investors: Secondary market investors

Lock-up period: An agreement the underwriter and pre-IPO investors not to sell their shares or take short positions in the company for typically 180 calendar day's equivalent to approximately 125 trading days after the IPO. Typically, 15-20% of the company is sold to private investors and the remaining 80-85% is almost always subject to a lock-up period (Ofek and Richardson, 2000). The lockup-agreement is enforced by the underwriter upon all offer price investors owning more than 1% of total shares with the exception of shareholders that held shares for more than a year before the IPO date. The minimum lock-up period allowed by Rule 144 (SEC law) is 90 days.

The period: Refers to the 01/01/2010 to 31/12/2015. Alternatively, when used in context with return data, the period refers to the first data point date 01/04/2010 and to the last 21/12/2016.

Underpricing: The premium given to early investors measured as the difference (%) between the offer price and the first-day closing price. We use the terms underpricing and first-day-return interchangeably.

Underwriter: The investment bank hired by the issuing company to undertake the process of going public. They ensure all regulatory requirements are met, provide guarantees of sale and gauge initial investment interest to determine the offer price and to allocate and sell shares to investors.

2. Literature review

2.1 Key literature

Much of the literature concerning the methodological approach of event studies revolves around a few very recognized articles published in 1980-2000. Throughout the thesis, we will be referring to these quite extensively. As a reader, you should be aware that the dividing line between of long-term and short-term event studies is blurry. Short-term event studies typically refer to a few days to a week, whereas long run is everything beyond. The articles include:

- Brown and Warner (1980): *Short-term event studies*
- Brown and Warner (1985): *Using daily stock returns – the case of event studies*
- Barber and Lyon (1997): *Detection of Long-Run Abnormal Returns*
- Barber, Lyon and Tsai (1999): *Improved methods for Tests of Long-Run Abnormal Returns*
- Fama (1998): *Market efficiency, long-run returns and behavioural finance*
- Mitchell & Stafford (2000): *Potential problems with existing long-term performance studies*
- Kothari and Warner (2004): *Econometrics of Event Studies*

These publications will however not be the focus of the literature overview, but rather the methodology section. Instead, the literature overview will be focusing on researchers that employ the abovementioned methodologies in relation to IPO research, most importantly:

- Jay Ritter (1991): *The Long-Run Performance of Initial Public Offerings*
- Brav and Gompers (1997): *The Long-Run Underperformance of Initial Public Offerings*
- Jerry Cao (2008): *What Role Does Private Equity hold when leveraged buyouts go public?*
- Mario Levis (2011): *Performance of Private Equity Backed IPO's*
- Jerry Cao (2012): *Private Equity and Public Corporations*
- Datta & Gruskin (2015): *On post-IPO stock performance*
- Dimitra Michala (2016): *Are private equity backed initial public offerings any different?*
- Jay Ritter (2010-2017): *Various articles and updates on IPO performance and underpricing*

We also refer to a wide range of articles not listed above.

However, the abovementioned articles and other publications played a key role in our understanding of the subject and in structuring the thesis. For a short review of the most relevant literature for reading and understanding the approach applied in the thesis, we recommend Fama (1998), Barber, Lyon and Tsai (1999), Kothari and Warner (2004) and Levis (2011).

2.2 General IPO literature

The majority of the research conducted on the subject falls under the category *return event studies*. This research genre focusses on the effects of an event on stock performance and typically include a large sample size, a single geographic market and relatively long investment horizons.

Numerous studies have documented historical anomalies in IPO returns. One of the well-documented anomalies is the general long-run underperformance of IPOs (Carter, Cao, Brav and Gompers, Ritter, Schultz, et al.). We mainly focus on the research conducted by Jay R. Ritter, as almost all recognized IPO event studies refer extensively to his work.

In an early study Ritter (1991) examined 1,526 IPOs in US market in 1975-1984 and discovered that IPOs exhibited underperformance of 29% over three years, benchmarked against a portfolio of matching firms listed on NYSE. More recent studies Akhigbe et al. (2006) also found evidence in the US market of underperformance using Fama French small- and big book-to-market portfolios as benchmarks. Similar evidence has been found outside the US. Levis (1993) confirmed the underperformance in the period 1980-1988 for the UK market, but found it less severe and confined to certain groups. In addition Levis noted, and we concur, that one should be careful when interpreting prior studies as result are highly sensitive to the applied methodology, the sample creation and establishment of control groups.

Since then, Ritter has conducted annual reviews of US IPO activity, performance and trends. For all years since 1990, he documents large first day returns (underpricing) followed by a stock underperformance for all periods beyond a year. However, the documentation on the long-run underperformance of IPOs has many exceptions. Carter et al (1998) and Chan et al (2008) both document a general tendency of underperformance, but identify overperformance by IPOs with prestigious underwriters. Teoh et al (1998) finds the same to be true for IPOs with conservative accruals. Other authors also confirm the general tendency of underperformance of IPOs, but instead turn to behavioral finance to understand and explain this seemingly irrational investor behavior (Loughran and Ritter, 1995; Rajan and Servaes, 1997; Schultz, 2003).

Finally, we found no large-scale publications that focused on general IPO performance post 2013. Most of the contemporary research conducted are by professional institutions or financial corporations and tend to review IPO performance for a small sample size on a quarterly or yearly basis. Luckily, the literature on PE-backed IPOs is relatively newer and has grown a lot in recent years due to the increased popularity of the ownership model.

2.3 Private equity and IPO literature

PE-backed IPOs have become increasingly popular in recent years (Michala, 2016). In the period 2010-2015, 27% of all IPOs on NYSE and NASDAQ were backed by a PE-fund and accounted for 42% of the capital raised. PE-funds have however been criticized in the media in relation to IPOs for being in business to get the highest price possible for their investment and to flatter the books to improve the appearance of the investment (Financial Times, 2014). Moreover, opponents of the PE model also argue that the PE funds are merely financial engineers who raise debt, cut costs and await the right moment to exit (KPMG C-Suite Survey, 2012).

Proponents instead argue that the PE-backed investors add value through active ownership and increases operational efficiencies. The operational efficiencies are supposedly achieved through higher levels of debt, management expertise and closer monitoring (Jensen 1986, 1989). Levis (2011) believes that these efficiencies should accumulate over time during the PE ownership period. Moreover, Levis argues, and we agree, that it is reasonable to expect that the management and financial practices put in place during the PE-ownership period will be maintained for at the least some time after the IPO.

Fortunately, we are not left pondering and contemplating the effects of PE ownership. If the arguments stated above are indeed true, we will expect to see higher returns in the PE backed entities in our sample. Historical empirical evidence does also seem to support this hypothesis with only few exceptions.

The most recent exception is Michala (2016) that conducted a study on all IPOs in the US market from 1975-2013. Using the same benchmark as other recognized studies i.e. Fama French adjustments, she found no statistically significant evidence of overperformance by PE-backed entities. Moreover, she found that IPOs listed in hot periods are more likely to default, but that PE-backed IPOs had the same default rate (risk) as NPE-backed IPOs. In other words, she argued that PE-backed are no different from NPE-backed IPOs.

However, the majority of the referred research points towards overperformance by PE-backed IPOs. Brav and Gompers (1997) found overall underperformance for the US IPO market for the period 1972-1992. They investigated 934 VC/PE-backed IPOs and 3,407 NPE-backed IPOs and concluded that the underperformance was driven by small, low book-to-market, NPE-backed IPOs.

More recently, Cao & Lerner (2009) investigated 500 US PE-backed IPOs in the period 1980-2002. They found that large PE-backed IPOs consistently outperformed other IPOs and the stock market as a whole. Furthermore, they concluded that PE-backed IPOs superior performance was not confined to a single time period, but was found in the 1980s, 1990s, and 2000s.

Mario Levis (2011) examined a sample of 1,595 IPOs listed in the UK market from 1992-2005. His research focused on the aftermarket performance of PE-backed IPOs and compared the results to equivalent samples of NPE-backed issues. Levis confirmed the overall underperformance of IPOs documented by earlier studies, and confirmed the findings of Brav and Gompers (1997). His observations suggested that UK PE-backed IPOs displayed better operational and market performance compared to their NPE counterparts. Levis also found that PE-backed IPOs were larger in terms of market capitalization, debt levels, net sales and total assets. If this holds true for the US market, we should expect to find similar properties in our sample observations.

In 2012, Cao wrote an article extending his former work (2009). The focus of the research was to shed further light upon the explanations behind the superior performance exhibited by PE-backed firms and their role in the US IPO market. In alignment with Lewis (1993, 2011), he concluded that PE-backed IPOs achieved superior performance and linked it to the PE model's active monitoring role, ultimately resulting in increased operational efficiency.

In summary, research finds that IPOs on average underperform the market. However, the underperformance seems to be driven by a small, low book-to-market, NPE backed companies. In contrast, large PE-backed IPOs seem to have outperformed other IPOs and the market in general during the 1980s, 1990s and 2000s. The general consensus between established authors is that PE-backed entities seem to outperform their NPE-backed counterparts, with only few authors finding evidence against this. In most cases, the superior performance has been linked to the increased operational efficiency the active investor role of the PE model.

Finally, no widely acknowledged research since has been conducted on the effects of PE ownership in more recent years i.e. with focus on the-post financial crisis paradigm. We hope to contribute to the literature by filling the gap in IPO research, ultimately analysing general IPO performance with focus on relative PE-backed IPO performance.

2.4 Underpricing literature

When analysing the sample returns, we noticed that results largely deviated depending on how we handled first day returns. Primary market investors who buy shares before the IPO is traded in the secondary market pay the offer price, which is determined by the investment bank. If the offer price of a new issue is lower than the first day closing price, the stock is referred to as underpriced.

From the market efficiency point of view, significant and persistent variations in the first day return of new issues contradict the basic principles of an efficient market. This has become known by financial practitioners and researchers as the underpricing puzzle.

The underpricing puzzle has attracted severe attention since Reilly and Hatfield (1969) first shed light upon the discrepancy. Riiter and Loughran (2004) documents significant underpricing with an average of 18.7% for the period 1980-2003. More recently, Ritter (2017) confirmed that the historical anomaly still is present with an average underpricing of 15.7% for 2010-2015 in the US market. Our sample includes more and smaller IPOs and averages 7.1% in the period i.e. significantly deviating from Ritter's sample.

We later show that the underpricing documented by Ritter is still to this day an important driver of returns for IPOs. However, the underpricing varies greatly across segments, years and is more prominent in larger IPOs. As the conventional risk models for stock returns cannot explain first day IPO returns, the underpricing also has a significant impact on the measurement of abnormal returns.

The literature has several theories on why IPOs are underpriced. The most prominent and empirical supported theory points towards information asymmetry between the issuer and the underwriter and most importantly the underwriter and the investor. Rock (1986) suggested that some IPO investors are better informed than others investors and therefore only bids on the underpriced IPOs and avoids the overpriced IPOs. On the other hand, uninformed investors cannot separate good IPOs from the bad IPOs and therefore bids equally on both.

Using Rocks theory, Ritter (2011) argues that the underpricing represents a form of equilibrium in the IPO market, and that the demand for non-underpriced IPOs is lower as only the uninformed investors attend in the trading and therefore receive a larger portion of shares.

The second theory is based on information revelation. Underwriters will try to access to the informed investors information before setting the offer price. However, there exists no incentive for the informed investors to reveal their true willingness to pay, as it will only make their capital gain lower. The role of the underwriter alongside a wide range of tasks, primary function is to sell shares to investors on behalf of the issuing company. The typical approach is to ask a bunch of investors how much they are willing to pay (book-building). Basically, book building is a way for the underwriter to assess demand and obtain information from potential buyers. Consequently, investors with low bids receive fewer shares relative to investors with higher bids. When the underwriters underprice the stock, the informed investors will be induced to reveal valuable information about the price. The underwriter can ultimately estimate a demand curve for each price level, at use this to deduce the investors' willingness to pay (Eckbo, 2008).

Finally, the third theory is known as signalling. The theory is not confined to IPO underpricing and is broadly used in explaining irrational behaviour in business transactions. Several studies suggest that good firms underprice their offerings to signal quality (Allen and Fauhaber, 1989). Welch (1989) emphasizes the fact that firms tend to underprice the issue deliberately to guarantee a favourable response raising funds in the future. Furthermore, the marginal cost of underpricing is lower for high-quality firms as low-quality firms would have to spend more capital on imitating high-quality firms and signalling to the market that they indeed have the same attributes as of high-quality firms. Allen and Fauhaber (1989) support this argument by suggesting that only good firms can be expected to regain the capital loss (to the initial owners) occurring because of underpricing.

In summary, there exists no singular theory that fully explains underpricing. The most recognized theories focus on information asymmetry, information revelation and signalling i.e. the behavioural finance. It is overall a subject poorly understood by financial risk models, and is one of many theories that contradict the efficient market hypothesis. Underpricing is however, a significant part of IPOs and some even suggests that underpricing is a form of equilibrium in the IPO market.

Returns are first analysed with underpricing i.e. the returns incurred by offer price investors. Since offer price investor's accounts for the majority of shares sold during an IPO, we mostly focus on these returns. However, to accommodate the underpricing issue, we also conduct a subsequent analysis for non-offer price investors i.e. the returns without underpricing. The comments for these returns are displayed throughout the main analysis, but due to the thesis size limitations, we display graphs and statistics in the appendices.

Finally, we also check for underpricing effects on stock performance using logistic regression models that include underpricing as an independent variable. This allows us to gauge the impact of the underpricing for both offer and non-offer price investors.

3. Methodology

3.1 Scientific approach

For any study conducted in economic research to be recognized, it must fulfil the requirements of testability. Testability is in essence the ability for other researchers to repeat the experiment and draw the same conclusions. This can further be broken down into two parts: reliability and validity.

For a study to have reliability means that other researches should be able to reconstruct the experiment in order to test the validity of findings. In order to accommodate this, we dedicated a large section to explain in detail how and where data was collected, how we classified observations and how we calculated the returns used to test the hypothesis. Using the methodology section as a basis, we believe that any other researcher with access to the databases and software could reconstruct the experiment, and within reasonable accuracy, reach the same results.

The second requirement is validity, which is comprised of internal and external validity. The lines are slightly blurry as both goes to verify the results and casual relations. However, internal validity is about the experimental design. The study must be conducted in compliance with the scientific research method. It is the act of using inductive thinking to state a hypothesis, then using deduction to make predictions, and finally making observations to test the predictions. There are many threats to the internal validity thoroughly discussed in the literature (Campbell & Stanley, 1963; Cook & Campbell, 1979). The most common threat to researchers is however that they at some point during the hypothesis testing make a wrongful deduction, ultimately leading to inaccurate conclusions and/or biased testing going forward. We try to accommodate the issue by explicitly stating which deductions were used to reach each conclusion. Moreover, we try our best to test the deductions before using them to state new hypothesises.

External validity is instead the examination of results and the testing for casual relationships. In relation to statistical studies, external validity is specified as the degree to which generalisation across heterogeneous populations is feasible and the applied measuring methods are valid (Pearl and Bareinboim, 2014). Luckily, there are many widely acknowledged way to measure returns, all with their flaws, but many nonetheless. In order to test the results and prove casualty we measure data using several different approaches and test a range of alternative explanations for our findings. Moreover, we use statistic tools to evaluate the degree of the correlation, apply relatively strict requirements to the significance levels and clearly state which conclusions are based on facts and which are based on speculation.

3.2 Data Collection

In order to ensure reliability we now provide a detailed description of the data collection process. The process can be broken down into three steps

1. Sample creation
2. Data collection
3. Determination of historical ownership and creation of subsamples.

3.2.1 Sample creation

In creating the sample, we start the process by identifying all IPOs in the US from primo January 2010 to ultimo December 2015. Essential IPO data such as issue date, exchange, company, amount of shares sold, offer price and identification IDs (PERMNO) is collected from CRSP, SPs Capital IQ (compustat) and NASDAQ's official record of IPOs. This initially leaves us with 18.093 IPOs.

Next, we exclude IPOs not taking place on either NYSE or NASDAQ. We focus on these two exchanges as they account for the majority of all trading in North America (and the world). This is especially true after 2008, where NYSE acquired AMEX, which at the time was the third largest stock exchange in the US (Financial Times, 2008). This heavily reduces the sample size, as most of the sample consisted of IPOs on OTC markets. We also exclude any listings where the capital raised does not exceed USD 5m in order to filter out investments not broadly available to investors. Potentially there is an argument to have an even higher cut-off limit, but similar studies have applied cut off-limits ranging as low as USD 1,5m (Michala, 2016). This lower limit also allows us to investigate the performance of smaller IPOs relative to larger IPOs.

We then remove all transfers across markets. In contrast to a number of similar research projects (Cao & Lerner, 2009; Levis, 2011; Zimmerman & Hus, 2012), we do however allow for relistings in the sample. The argument for excluding these is that the stock expectations, and thus the offer price, may be biased by historical performance of the stock. We do however believe a relisting represent the same investment opportunity as other IPOs, regardless of a potentially biased offer price.

Due to operational and ownership characteristics, we also exclude all investment funds including Real Estate Investment Trusts (REITS), other trusts, special purpose PE vehicles, acquisition companies and American Depository Receipts (ADRs). These observations distort data by for instance tracking other markets and indexes and/or are by category either PE or not PE-owned, making a comparison within the category impossible. These exclusions are also consistent with the methodology applied in similar contemporary studies (Ritter, 2017; Levis, 2011; Datta, 2015; Michala 2016; Cumming, 2012; Cao & Lerner, 2009).

After exclusions, we are left with 1.040 IPOs in the period. Some studies apply a more stringent discrimination process, which explains deviations from popular IPO researchers such as Ritter (2017) that for instance excludes banks from his research. Finally, we exclude 26 troublesome observations, where data is not available or exhibit extreme inconstancy across different sources (CRSP, S&P, ThomsonOne, Bloomberg). This leaves us with a final sample of 1.014 IPOs.

3.2.2 Company specific data

In the initial data collection, used to create the sample, we only collected information regarding the date, name, ownership and ticker/other identifiers for the IPO. Thus, in order to determine performances and trends across the sample, we collect the following information for each company.

Table 3.1: Company specific data

Data	**Frequency**
Bid, Ask and Closing price, Holding period return*	Daily
Number of shares outstanding, Trading Volume	Daily
Offer price	1
Company data	
Revenue, EBITDA, EBIT	IPO date
Capital Expenditure	IPO date
Total assets, Long term-debt, Current liabilities and assets	IPO date
Market data	
EV/Sales, EV/EBIT, EV/EBITDA	IPO date
P/E, MV/B	IPO date

*Adjusted for dividends, stock splits, and assumed dividends reinvested

The data is collected from the CRSP database, where available. If the data is not available, or if data exhibit unwarranted extremity, we instead use Capital IQ (compustat), Thomson One Banker and as a last resort Bloomberg.

3.2.3 Classifying observations

The main purpose of the study is to shed light upon differences between PE and NPE-backed IPO's. If companies are classified wrongly, the conclusions are invalid. For this reason, a large effort was done in terms of determining historical ownership of each observation.

For approximately 750 of the observations, we were able to get data on the historical ownership directly from the Thomson Reuter's SDC Platinum New Issues Database. In order to ensure the reliability of the data, we randomly selected 50 observations from the sample, for which we verified the authenticity of the data. None of the randomly selected samples exhibited signs of misclassified or false information.

The remaining 264 observations had no immediately available data on historical ownership. Therefore, in order to determine whether a company was PE-backed at the time of the IPO, we look at the original F-1 or S-1 form filed to the Securities and Exchange Commission (SEC) by each company. F-1 (foreign companies) and S-1 filings (US companies) are the initial registration forms required to register shares on an exchange (SEC, 2016) and are thus always available for inspection.

The first section of the forms includes the prospectus, which contains information on the shareholders and voting rights of the company at the time of the IPO filing. Using this information, we determined whether the majority shareholder at the time of the IPO was a PE-fund, and observations were classified as either PE or NPE-backed.

We also investigated the company structure of significant ownership stakes, that could potentially give the shareholder an indirect majority stakes in each observation. This process was essential for the scientific contribution and findings of this study and took up a significant amount of working hours.

3.3 Performance assessment

In order to asses perform we apply a two-step approach. First, we zoom in on the typical challenges also known as measurement biases in return event studies. Secondly, we address our approach in tackling these difficulties with respect to the measurement of returns, weighting of portfolios and finally in constructing unbiased benchmarks.

3.3.1 Measurement biases

Conceptually measurement biases in return event studies can be divided into two groups.

1. Failure of pricing models i.e. expected returns

Failure of pricing models leads to inference problems due to bias in the estimation of abnormal returns. The pricing models used in this thesis are the Capital Asset Pricing Model (CAPM), Fama French three-factor and the Carhart four-factor model. The models are discussed and explained in detail in section 3.3.4. A common factor is that they all assume that stock or portfolio returns are independent from each other. They do this implictly by assuming that all variation in returns can be explained by the model factors and thereby ignores cross-correlation between individual stocks. This assumption is heavily violated in our sample and the reason is surprisingly intuitive.

We chose the stocks because they all had a similar event happening within a predetermined time-period and a range of specific criteria. The sample is not random. Observations are clustered in time, industries and by the fact that they all launched an initial public offering during the period. This inevitably leads to cross-sectional dependence of the stocks, which ultimately leads to inference problems about abnormal returns.

To accommodate this, we apply a range of adjustments and different means of measuring abnormal returns. Specifically, we adjust the test-statistic for skewness and cross-correlation and also apply methods of measuring returns that fully eliminate the independence assumption.

2. Non-normality in returns i.e. wrong inference due to skewness

As returns can vary from a lower limit of -100% to an upper limit of ∞ %, return distributions are typically positively skewed. Barber and Lyon (1997a) found that the positively skewed distribution negatively bias the test-statistic, when comparing return samples. The negatively biased t-statistic leads p-values being reported as too small for lower-tailed tests and too large for upper-tailed tests.

Not correcting for this could hypothetically lead us to falsely reject an abnormal performance, i.e. falsely reject a true null hypothesis (type I error). A couple of year earlier, Sutton (1993) found that using a bootstrapped version of the t-stat reduced the tendency of incurring type I errors. This was again confirmed by Kenberry et al. (1995) and Barber and Lyon (1997a) on return data.

In order to accommodate this, a methodology was developed by Lyon, Barber & Tsai (1999) and has since then become the generally accepted methodology, when using BHAR as an estimator for abnormal returns. We apply this to our hypothesis testing using EventStudyMetrics, which accommodate the use of a bootstrapped skewness adjusted test-statistic calculated using the methodology outlined in the end of next section.

3.3.2 Return measurement

The daily company returns are measured in two steps. One, a computation of the return for the first day of trading and two, returns from the first day of trading and until year-end on an intra-day basis.

First day returns, as calculated by the CRSP database are measured from the opening price to the adjusted closing price. In other words, if the opening price differs from the offer price available to investors, the first day return as measured by CRSP data will differ from the actual gains or losses occurred by early investors. Therefore, we calculate the first day return manually for each observation as:

$$(1)\ return_{t=1} = r_{t=1} = \frac{p_1}{p_{offer}} - 1$$

Where p_1 is the last sale price or, if not available, the bid/ask average on the first day of trading, p_{offer} is the IPO offer price.

For all other periods, returns are downloaded on an adjusted level from the CRSP database, measuring returns as if dividends were reinvested in the stock and correcting for price differences due to stock splits (CRSP, 2017). We also download first-day opening prices to calculate revised first day returns for the analysis without underpricing. The returns are then analysed in the return study software *EventStudyMetrics*[1].

EventStudyMetrics allows for the three most popular ways of measuring investor returns: Cumulative Abnormal Returns (CAR), Buy-and-Hold Abnormal Returns (BHAR) and Calendar-time Abnormal Return (CTAR).

[1] Software: https://eventstudymetrics.com/

Buy-and-hold abnormal returns and cumulative abnormal returns

The difference between BHAR and CAR are in essence how the returns are measured. CAR uses an arithmetic sum of returns (dollar-weighted), whereas BHAR uses the geometric sum of returns (time-weighted). Leading authors such as all question the merit of CARs in measuring investor returns for any return study above a few days due to compounding effects (Brown, 1985; Stephen and Warner, 1985; Ritter, 1991; Barber et al, 1997 and 1999; Fama, 1998 and 2000)

Instead, BHAR has become a popular method for estimating abnormal returns in event studies of period returns. We will be using BHAR accordingly measured as the actual daily stock return minus the expected return for that day and stock:

$$BHAR_{i,t} = \prod_{t=1}^{n}(1 + r_{i,t}) - \prod_{t=1}^{n}\left(1 + E\left(r_{i,t}\middle|\sigma_{i,t}\right)\right)$$

Where $r_{i,t}$ is the daily return for an observation in the portfolio at any given time and $E\left(r_{i,t}\middle|\sigma_{i,t}\right)$ is the expected return for an observation in the portfolio given a measure of risk used in the benchmark model. For any given day portfolio BHARs are computed as the weighted average of the individual stock BHARs estimated as:

$$BHAR_t = \sum_{i=1}^{n} w_{i,t} BHAR_{i,t}$$

The returns are measured both on a cumulative level and non-cumulative level. The exact weighting methodologies (w_i) are explained in section 3.3.3, but is in short either based on the number of companies in the portfolio or their respective market cap.

BHARs do however have statistical properties that can leads to inference issues. The most crucial are skewness and cross-sectional dependence issues. First, we accommodate the skewness bias by using a procedure known as bootstrapping. The software draws 1.000 resamples at random from the original sample. For each resample, it calculates the new test-statistics as (^{b} indicates bootstrapped sample values):

$$t^{b}_{skewness\ adjusted} = \sqrt{n_b}\left(S^b + \frac{1}{3}\hat{y}^b S^{b2} + \frac{1}{6n_b}\hat{y}^b\right)$$

The parameters $\sqrt{n_b}\, S^b\ and\ \hat{y}^b$ are the conventional test statistic and the estimator for the coefficient of skewness, respectively.

These are each calculated as

$$S^b = \frac{\overline{AR}_T^b - \overline{AR}_T}{\sigma^b(AR_T)} \; and \; \hat{y}^b = \frac{\sum_{i=1}^{n_b}\left(AR_{iT}^b - \overline{AR}_T^b\right)^3}{n_b \sigma^b (AR_T)^3}$$

Where is the original sample test statistic t^b_{sa} is the bootstrapped version of the t-statistic, σ^b is the bootstrapped sample cross-sectional consistent standard deviation. AR represents the average return.

By using this test-statistic, the skewness biases have been proved nearly eliminated by Barber, Lyon and Tsai (1999). Moreover, the methodology partly accommodates cross-sectional dependency by using the bootstrapped sample standard deviation adjusted for cross-sectional dependency. The adjusted standard deviation is however an approximation as it is based on the bootstrapped sample's cross-sectional dependency rather than the original sample.

For this reason, Fama (1998) criticize the BHAR methodology and point out that since the cross-sectional dependency is not fully eliminated as thus slightly biased results.

In short, the methodology is not perfect as it does not properly account for cross-sectional dependence and is, as most statistical models, prone to human error in the construction of benchmarks. It is however still the most broadly used methodology for measuring investor returns. The reason is that it has distinct advantages in comparison to other methodologies such as calendar-time portfolios, when it comes to analysing the source of abnormal returns. Since the model measures the individual BHAR before averaging across groups, individual groups can easily be examined for trends across years, industries, operational characteristics and other relevant variables.

For the abovementioned reasons, we focus on BHARs as the main proxy for abnormal returns. While we realise that is it not a perfect measure, it is the best we got for examining and isolating drivers of abnormal returns, while maintaining a relatively high model power.

Calendar-time abnormal return

The calendar-time portfolio approach (CTIME) is an alternative method for estimating abnormal returns. The methodology is preferred by many leading authors (Fama, Brav, Gompers, Mitchell, Stafford and Karceski). For each day through the period, a portfolio is constructed and the abnormal return is measured. A total of 36 simulated portfolios are constructed in the following way:

- IPOs are included in the portfolios on the listing day and excluded after a predetermined holding period. We conduct the analysis for holding periods of 21/42/63/125/187/249 trading days corresponding to 1/2/3/6/9 and 12 calendar months after the IPO.
- The process is repeated for the period 2010-2015 for equally weighted as well as value weighted portfolios of the IPOs
- Portfolios are rebalanced on a daily basis.

This is done in two steps. First we calculate the average abnormal returns on a rolling portfolio of firms. Next, we run a time-series regression (i.e. Fama French & Carhart) and use the alpha coefficient as a measure of abnormal returns. For each day, the calendar time abnormal return (CTAR) is measured as the weighted average of daily abnormal returns of portfolio companies as

$$CTAR_{portfolio,t} = \sum_{t=1}^{n}\left(\left(1 + R_{s,t}\right) * w_i\right) - \sum_{t=1}^{n}\left(\left(1 + E\left\langle R_{s,t}\middle|\sigma_{s,t}\right\rangle\right) * w_i\right)$$

Where the $w_{i,t}$ is the weighting assigned to each return at time t and $E\left\langle R_{s,t}\middle|\sigma_{s,t}\right\rangle$ is the estimated cumulative expected return for the portfolio given a measure(s) of risk defined by the benchmark model. In essence, the abnormal return for the portfolio on any given day is measured as the weighted average return minus the expected return on the portfolio.

In contrast to normal BHARs, CTIME fully accounts for cross-sectional dependence as the returns for each day are measured on a portfolio before averaging across the sample. By pairing companies through time in a portfolio, the cross-sectional dependence is reflected in the portfolio variance, which then affects the t-statistic.

Critics of the CTIME methodology points out that the approach is a biased estimator of abnormal returns. The biggest issue is that the CTIME approach induces heteroscedasticity i.e. non-constant variance, as the number of companies in the portfolio varies over time. This issue is especially a problem due to hot/cold periods in the IPO market, which is clearly reflected in the large differences in the number of IPOs for each year (see table 4.1.1).

To accommodate this issue, we apply a methodology preferred by Fama (1998). The methodology has been proven to accommodate the issue of heteroscedasticity and hold-cold issue. Instead of using ordinary least squared regressions to estimate the alpha of CTARs, we apply a weighted least squared regression that relaxes the heteroscedasticity assumption. The weighting is based on the number of portfolios in the portfolio at the measured time. Using this methodology, periods with more IPOs are weighted accordingly in the estimation of alpha.

In conjunction with WLS regressions, Fama also recommends the use of a heteroscedasticity-consistent t-statistic developed by White (1980). We will be reporting this t-stat, in conjunction with CTAR. The properties in terms of interpretation and significance levels of the white t-stat remain the same as the traditional t-stat:

- Critical value for 10% significance level: ~1.66
- Critical value for 5% significance level: ~1.96
- Critical value for 1% significance level: ~2.65

In short, the CTAR model has relatively high power (Datta, 2016) and is great at detecting abnormal returns. It does however have several shortcomings in determining the source of the abnormal returns. Since companies enter and exit the portfolio on a daily basis, the composition of the portfolio is always changing. This makes it extremely complicated to examine the effects from for instance industry and operational characteristics.

A possible solution is to run CTAR simulations on groups formed by selected variables. More portfolios however introduce a different problem in the form of high variance. As the portfolios are simulated throughout the period, each portfolio ends up having a very small amount of companies at all times and thus too high variance.

For this reason, we only use CTARs to check the robustness of the results on a more general level i.e. confirm if there exists any abnormal returns. Specifically, we use CTAR to see if each ownership group exhibits abnormal returns and use it to support the results obtained by the BHARs.

3.3.3 Return weighting

In measuring the returns, we apply two different weighting methodologies. The methodology is very similar for both the BHAR and CTIME approach and allows for valuable comparisons.

Equal weighting gives each stock's return an equal weight regardless of size, i.e. smaller stocks contribute the same to the average return as larger firms. The weighting is defined as

$$weight_{t,equal} = \frac{1}{n_t}$$

Where n represents the number of companies in the portfolio at time t. The number of companies in the portfolio differs depending on the methodology applied. For BHAR, only delistings reduces the amount of companies in the portfolio, whereas CTIME measures the returns over the period and thus have a smaller amount of companies in the portfolio at any given time.

Value weightings are slightly more complicated to implement. Each company is given weight relative to its market value, meaning that larger firms receive a more significant weighting in the calculation of the average return. The weightings are always lagged one day for logical reasons. Imagine you are an investor and you have to rebalance your portfolio. What weight will you assign to each stock? You cannot know the end of the day market capitalisations for a stock, and will thus have to rely on yesterday's closing market caps. This logic is why weightings have to be lagged one day in order to measure the returns incurred by investors accurately. We calculate the market capitalisation for all observations as

$$Market\ Cap_{i,t} = Stock\ price_{i,t-1} * Shares\ outstanding_{i,t-1}$$

If available, we use daily observations of the number of shares outstanding obtained through the CRSP database. If the number of outstanding shares is not available on a daily basis, we use the closest observation as a proxy. On the listing day for each IPO, no market cap for the previous day is available. Instead we use the offer price and the expected amount of shares sold to calculate a proxy for the market cap, which is then used to weight the IPO on the listing day. The weighting for each stock at time t is given as

$$w_{i,t} = \frac{Market\ cap_{i,t-1}}{\sum_{i=1}^{n} Market\ cap_{i\ ,t-1}}$$

In other words, the weight at any time is given as the stocks proportion of the total sample market capitalisation lagged one day.

3.3.4 Benchmark models

The construction of benchmark models is without a doubt the most important element of calculating abnormal returns. Most researchers employ one of two techniques: Risk-models or the matched-firm approach. In this thesis, we use both approaches, but focus largely on results from the risk-models. The logic we apply in construction benchmarks is remarkably simple.

The best benchmark for a stock or portfolio is the asset itself. In other words, we calculate the expected return for the asset and benchmark it against its actual performance. To do this, we apply well-known asset pricing models and compare these models by power in explain the asset's return. In total, three asset pricing models are used: CAPM, Fama French Three Factor Model and Carhart Four Factor Model. We apply the models to our data in a two ways, one for each methodology.

BHAR

Since the risk factors applied in the asset pricing models change over time, we cannot simply apply a risk model to the average return of the sample or subsample. To illustrate the problem think of the following example: You want to risk adjust the average 1-year return for a portfolio of IPOs that happened across a 5 year period. What premiums do you apply to the portfolio? Since the firms are listed over different time-periods, different risk premiums apply to each of them. In short, we need to benchmark the individual company returns before averaging across the sample.

To do this, we automate the process in Python (appendix U). We conduct 3.042 regressions, one for each benchmark model for each IPO to estimate risk factor betas. We then use the betas to calculate expected returns for each stock and use the methodology explained in 3.3.2 to estimate abnormal returns. The average beta for each model and factor is reported in appendix T for selected groups.

CTAR

The CTIME approach allows for easier risk-adjustments. In sharp contrast to the BHAR methodology, the betas are based on portfolio returns, which heavily reduce the amount of regressions. For the calendar time portfolio, we can simply apply the model to the portfolio return at any given date without the need to conduct risk-adjust individual company returns, as the CTARs are matched in time with risk premiums.

Finally, we also use a matched-firm approach in measuring returns. We apply this to the raw returns by matching PE-backed with NPE-backed IPOs based on characteristics such as industry, size, book-to-market ratio and year of the IPO.

Capital Asset Pricing Model

The model is broadly acknowledged as the most frequent used asset pricing model. For a deeper theoretical understanding, we refer to Sharp (1964) and only touch upon key elements in the following section. In essence, the model assumes that all variation in returns can be explained by the relative market premium:

$$E(R_{s,t}) = r_{f,t} + \beta_i(r_{m,t} - r_{f,t})$$

The regressions based on CAPM did not reveal themselves better at explaining the returns than any of the other risk-models. The average R^2 for the sample was 0.80 implying that the relative market risk premium can explain 80% of the variability in the IPO returns. However, as the model did not outperform any of the other applied models, the CAPM adjusted returns will thus not be reported in the thesis. The reason we include the model theory and later the coefficients of determination for the model is to show the relative improvement of using the other models.

Fama French three-factor model

The Fama French three-factor model has become one of the most recognized models among financial practitioners since its conception in 1998. When we applied the model to our sample, we found that it explained 89% of the variability (R^2 = 0.89) in IPO returns on average. The model estimates the abnormal return of a firm as:

$$E(R_{s,t} - r_{f,t}) = \alpha_i + \beta_i(r_{m,t} - r_{f,t}) + \beta_{iSMB} * SMB_t + \beta_{iHML} * HML_t$$

In essence, Eugene Fama and Kenneth French found that investors are concerned about three risk factors.

1. The equity market premium (R_m) i.e. the excess market return over the risk-free rate.
2. Small Minus Big (SMB) i.e. the return of a portfolio of small stocks in excess of the return on a portfolio of large stocks.
3. High Minus Low, (HML) i.e. the return of a portfolio of stocks with a high book-to-market ratio in excess of the return on a portfolio of stocks with a low book-to-market ratio.

The model is justified on empirical grounds rather than theoretical foundation. The equity premium is often regarded as the most important number in finance (JP Morgan 2008) and uses relative market volatility as a risk measure is widely acknowledged. While SMB and HML are not themselves obvious candidates for relevant risk factors, the argument is that they proxy for yet unknown more-fundamental variables (Bodie, Kane, Marcus, 2014). We obtain the market premium described below and the historical SMB and HML premiums from French's website (French, 2017).

You might wonder why we use the premiums calculated by French on the NASDAQ and NYSE. Why not calculate premiums for size and value premium based on our sample? That way we would measure the IPO risk premiums for our sample and thus on average eliminate the effects from these variables.

If we did that, we would essentially be saying that the risk is different for these firms because of a different ownership model. Turning towards the literature, we could not find any proof of this or specialized asset pricing models for newly listed stocks. It would also beg the very difficult question of when to stop using the sample premiums to evaluate the IPOs, and at what point to start using market premiums. In other words, when does an IPO stop being an IPO and start being a stock?

The main argument against calculating sample specific premiums is that once the stock is listed, it is in essence a stock that can be traded freely like any other stock. If we want to evaluate how good investments IPOs and specifically PE and NPE-backed IPOs are, we need to benchmark not only against itself, but also against an alternate investment i.e. other stocks. Through the thesis, we discuss the differences in risk for IPOs and stocks, but do truly believe that using NASDAQ and NYSE premiums better reflect the investment universe and provide for a better benchmark as it represents the actual comparable investment universe.

Finally, we do also apply other means that takes the sample premiums into account when analysing differences across ownership. For instance, we apply regression models that measure the abnormal premiums on these factors and only evaluate the impact of ownership in conjunction with these factors. Moreover, we use a matched firm benchmark (explained in debt later in this section) that matches similar PE and NPE-backed IPOs to accommodate the issue of abnormal premiums on IPOs.

This way we can both say something about the relative abnormal risk premiums of size and value versus growth firms, while also looking at the effects of ownership on returns.

The next pages discuss and examine the benchmark factors used in the Fama French model before finally looking towards the Carhart 4-factor model and matched/control-firm approach.

Risk free rate

Most financial risk-return analyses are based on the notion, that there exists a risk free asset and that the return on that asset is known. In selecting an appropriate security as a proxy for the risk free rate, three characteristics are especially important (Damodaran, 2015)

- The security should have no default or reinvestment risk. This definition limits the choice of securities to government bonds in AAA rated countries.
- The security should match the currency in which the analysed returns are measured (USD)
- The security should match the time horizon of investment that it is used to measure (1 year)

Based on these characteristics, we choose the 1-year US government bond as an estimator for the risk free rate. The historical daily return data is collected from the Federal Reserve Board’s website. The average benchmark risk free rate is extremely low for the entire period and displayed below:

Table 3.2: Risk free rate

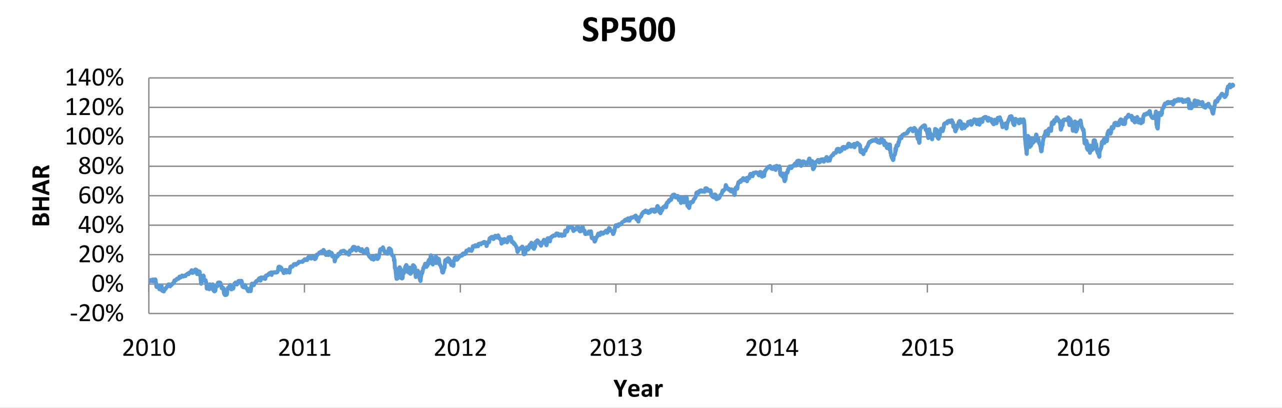
Year	Average	2010	2011	2012	2013	2014	2015	2016
Risk free rate of return (%)	0.27	0.32	0.18	0.17	0.13	0.12	0.32	0.61

The market premium

The most applied approach in choosing proxy for the market premium is using indices that come close to tracking the market movements as a whole and then subtracting the risk free rate. We use the SP500 index as an estimator for the market return. The index is a market capitalisation weighted index that is adjusted on a daily basis for share issuance, share buybacks, dividends and restructuring events (S&P Global, 2017). In other words, it is directly (with the exception of stock splits) comparable to how we plan to measure the returns of the IPOs.

The SP500 represents the largest US index with limited exposure to our sample since very few of the IPOs enter the SP500 index in their first year of public ownership. Since SP500 represents such a large part of the US market there will be some correlation, which ultimately biases our market betas towards 1. However, the problem is even larger for NASDAQ, NYSE, MSCI US or Wildshire which are the typical benchmark indexes. Moreover, we like the idea of benchmarking against SP500 as it is broadly recognized as an estimator for the market premium for developed markets. We download historical daily prices throughout the period from CRSP and use these to calculate market returns as if dividends were reinvested. The yearly benchmark market returns are displayed in the figure and table below. We include 2016 as late listings in 2015 are primarily benchmarked against the 2016 market performance.

Figure 3.1: SP500 Index returns 2010-2016



Year	**Average**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**
SP500 return (%)	15.3	15.1	1.8	16.1	32.4	13.6	15.3	13.1

With an average market return of 15.3% throughout the period, there is no denying that the analysed period is a bull market. This logically has a range of implications on the conclusions drawn and how well they can be used to generalized results. While we are fully aware of the implications, we postpone discussions of this to the conclusion and practical implication sections, as this need to be viewed in context to our results.

Small Minus Big (SMB)

The size premium is based on the notion that investors view small firms as more risky than large firms. This is the case as small stocks may be more sensitive to changes in business conditions and does not have the same opportunities in terms of economics of scale and leverage (Fama 1998). In calculating the premiums, the distinction between small and large firms are based on the median i.e. 50% quintile market capitalisation of all firms in NYSE and NASDAQ. This dividing line between small and large averages approximately USD 500m. The daily premium is then determined by taking the average return of all small firms minus the return on large stocks.

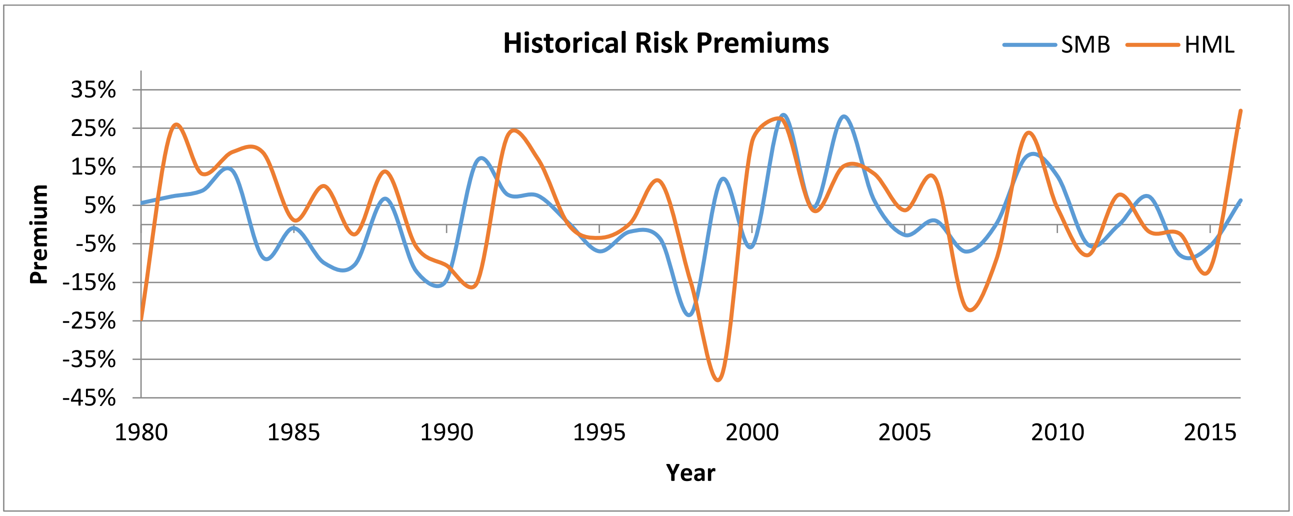
Historically this premium has been very volatile. Some years the large companies have higher returns and some years smaller companies overperform. Finally, our results later show that for IPOs the premium effect is minimal and we speculate it might be reflected in the underpricing. The figure on next page presents a graph on the historical premiums on both the SMB and HML factor.

High Minus Low (HML)

The HML factors measures the relative premium for growth and value stocks. Growth stocks are defined as companies with low book-to-market ratios and value stocks as companies with high book-to-market ratio. The traditional theory laid out by Fama (1998) argues that value stocks are more risky. He argues that value firms have lower earnings and that the market overvalues growth stocks and undervalues distressed stocks. Ultimately, when the market correct itself, value stocks end up having higher returns and growth stocks in return exhibit lower return. The theory therefore follows, that a premium should be payed when buying the value stock over the growth stock.

The actual premium is calculated by dividing the market into low, mid and high book-to-market ratios. The bottom 30% are classified as low, the middle 30-70% as mid and the top 30% are classified as high. The return for the high and low portfolio is then measured and subtracted to arrive at the premium. Looking at the premiums since 1980s, we do however see why growth stocks versus value stocks is an unfinished debate. The relative premium is highly volatile, negative and positive and there is no obvious pattern across societal growth periods and recessions.

Figure 3.2 Historical SMB and HML factor premiums



The model has been suggested expanded to five factors in 2014 by Fama and French. The new factors include profitability and an investment factor. The model has however not gained the same recognition among financial practitioners as the traditional 3-factor model. It has especially been criticized for including factors that have high correlation with the other factors. Due to the widespread criticism of the 5-factor model, we solely focus on the 3-factor model originally theorized by Fama and French (1993).

Carhart Four Factor Model

The Carhart Four Factor Model extends the Fama French Three Factor Model by adding a momentum-factor (UMD).

$$E(r_{i,t} - r_{f,t}) = \alpha_{i,t} + \beta_i(r_{m,t} - r_{f,t}) + \beta_{i,SMB} * SMB_t + \beta_{i,HML} * HML_t + \beta_{i,UMD} * UMD_t$$

Momentum in a stock is described as the tendency for the stock price to continue rising when going up and vice versa. To calculate UMD, we take the return on the highest equal-weighted average performing companies minus the lowest performing companies lagged one day. A stock is showing momentum, if its recent (varying measuring periods) returns on average returns are positive. This model has become widely used in the financial sector since its introduction, due to the factor being largely independent of the other factors (Asness, AQR Capital, 2017).

To our surprise, we found that in relation to the BHAR regressions the average momentum factor as insignificantly different from zero. We further discuss why this may be the case in 4.3.1. However, when used in relation to the CTAR regressions, the factor was significant but still only had a very small effect on the returns. Therefore, we use the Fama French model as the benchmark for BHARs and Carhart as benchmark for CTARs as it increases explanatory power for these regressions.

Matched-firm approach

The matched firm approach is often used as a robustness check by some authors (Ritter, Barber & Lyon) as it accommodates many of the issues related to pricing models. Instead of a measuring returns based on expected returns, the methodology instead applies a control firm/IPO as a benchmark. This has several advantages in terms of accommodating issues that the pricing models handles poorly, such as underpricing, 3-month IPO returns, rebalancing and relisting biases and so forth. In essence, the matched-firm approach bears many resemblances to multiple valuations, where a set of comparable companies are used to determine a company's value.

There are many ways to match companies but in essence it boils down to finding a company that is comparable by risk. To find the best matching criteria, we conducted the BHAR analysis first and then tried to determine the origin of abnormal returns. Using the conclusions drawn by the BHARs, as well as logical reasoning in terms of what characteristics constitutes the largest risk-factors. Next we assigned a control firm (NPE-backed IPO) to each PE-backed IPO and used this as a benchmark for performance. The exact matching process is analysed and described in section 5.6.

3.4 Other applied regressions techniques

After the returns have been benchmarked, we apply logistic regression to identify operational, industry and other variables that may help in explaining which IPOs incur abnormal returns.

3.4.1 Theoretical foundation

Logit analysis or logistic regression is commonly known for its applications within the healthcare industry, where it is often used to classify patients into groups such as sick or not sick. We will be using logit analysis in order to examine whether an abnormal return is more likely to occur in IPOs with certain characteristics. However, in order to understand logit analysis one needs to be familiar with multiple discriminant analysis (MDA).

MDA uses a function to classify a sample observation into a group based on one or several metric explanatory variables. In other words, a function is derived that classifies each observation based on a Z score calculated as:

$$Z = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 \dots \beta_n X_n$$

For each observation, a Z-score is calculated based on the weighting of each coefficient and their respective x-values. Next, the Z-scores are pooled together and used to calculate the mean Z-score of each group (Positive/Negative abnormal returns). Consequently, each observation is classified into one of the groups based on their Z-score and the dividing point for classifying observations is adjusted to reflect posterior probabilities based on the empirical distribution of data. For instance, say that on average $\overline{Z_{Positive}} = 1$ and $\overline{Z_{Negative}} = 2$ and the population consists of 70 observations with positive abnormal returns and 30 negative abnormal returns. It must follow that the probability of a random drawn observation belonging to the positive group ($Q_{positive}$) is 70%.

We derive the critical value, denoted C, for dividing an observation into one of the group. The dividing point is given as the simple mean of the two group Z-scores, adjusted for the empirical distribution of data:

$$C = \frac{\overline{Z_{Positive}} + \overline{Z_{Negative}}}{2} + \ln\left(\frac{q_{Positive}}{q_{Negative}}\right) = \frac{1+2}{2} + \ln\left(\frac{0.7}{0.3}\right) = 1.87$$

Thus, all observations with a Z-score of less than 1.87 are divided into the positive group and vice versa. The coefficients in MDA are chosen so that it maximizes the distance between the Z values of each group thus maximizing the models discriminating power. This intuitively simple procedure is the essence of MDA and is theoretically linked to the procedures of logistic regression.

However, one of the major issues in relation to our analysis and the application of discriminant analysis are the underlying assumptions of the MDA. Essentially the model assumes that each independent variable follows a multivariate normal distribution. Put in a different manner, using discriminant analysis limits the analysis to numerical continuous variables, and prevents us from examining the impact from categorical variables such as ownership, industry or exchange.

From multiple discriminant analysis to logistic regression

The point to disguise a discriminant analysis in the form of a regression analysis using the methodology described by Afifi, Clark and May (2013). In MDA, the (posterior) probability of belonging to a specific group, given its Z function, can be written as:

$$P_Z = \frac{1}{1 + e^{C-Z}}$$

Replacing the dividing point (C) with an intercept value (α) and Z with the discriminant function (recall $Z = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 \dots \beta_n X_n$), the following expression describes for the probability of an observation belonging to a specific group, given the discriminant function Z:

$$P_Z = \frac{1}{1 + e^{-\alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 \dots \beta_n X_n}} \; or \; \frac{e^{\alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 \dots \beta_n X_n}}{1 + e^{\alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 \dots \beta_n X_n}}$$

The probability expression is the basis for logistical regression models. However, the right side of the equation is expressed in nonlinear terms, which prevents us from using linear multiple regression analysis to solve the classification problem. A second problem is that the interpretations of the coefficients are not intuitively understandable. To solve this, one can transform the function using odds ratio (think football betting commercials):

$$P_Z = \frac{Odds}{1 + Odds} = \frac{e^{\alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 \dots \beta_n X_n}}{1 + e^{\alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 \dots \beta_n X_n}}$$

Taking the natural logarithm on both sides, you obtain a linear function given as

$$LN\left(\frac{P_Z}{1 + P_Z}\right) = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 \dots \beta_n X_n$$

This transformation of the function has two distinct advantages. First, the function is now expressed in linear form on the right side, which enables us to use a generalized linear regression model to solve the classification problem.

Secondly, the interpretations of the coefficients are now equal to those of a linear regression model i.e. the relative effects on the link function. It should however be noted, that in making the transformation, we implicitly assume that the independent variables are linearly related to the link function, which may not always be the case.

3.4.2 Estimation and interpretation

The estimation procedure is done using fishing scoring i.e. solving maximum likelihood functions numerically. It is however beyond the scope of this thesis to elaborate on the mathematics behind fisher scoring. Instead we focus on the interpretation of the coefficients.

Since the coefficients are used to calculate a Z-score, the actual coefficients for the maximum likelihood functions are not intuitively interpretable. Instead, logistic regression models use odds ratios. The smart thing about calculating odds ratios is that the interpretation is intuitively simple.

For a one unit increase in the coefficient, the probability of the event belonging to a group changes with the defined odds ratio.

In contrast to multiple regressions, odds ratios are always larger than 0. We only test one event of interest: Is the abnormal return positive? The interpretation is as follows for the logistic regressions conducted in this thesis:

- Odds ratio between 0-1: The variable decreases the probability of observing a positive abnormal return i.e. increases the probability of observing a negative return.
- Odds ratio equal to 1: The variable neither decreases or increases the probability of observing a positive abnormal return i.e. the variable is redundant.
- Odds ratio larger than 1: The variable increases the odds of observing a positive abnormal return i.e. decreases the probability of observing a negative return.

Like coefficients, odds ratios for variables are not always accurate. In the same way as traditional coefficients, we look at the odds ratio interval in a 95% confidence interval. If 1 is within the confidence interval, there is a probability that the variable has no effect. To test this, we use a p-value just like with traditional linear multiple regression.

The test is based on a Wald Chi-Squared Test, and is widely known and accepted for logistic regressions. We use this to evaluate the model as a whole (i.e. test global null hypothesis) as well as for individual variables. The test essentially takes the ratio of the square of the regression coefficient to the squared standard error of the coefficient to test if the coefficient is significantly different from 0 (Hosmer and Lemeshow, 2017).

3.4.3 Evaluating goodness of fit

Evaluating of goodness of fit in logistic regression models is slightly more difficult than traditional linear regression models as simpler measures such as R^2 do not exist for these types of models.

The most commonly used test is the Hosmer-Lemeshow Goodness of Fit test. It examines whether the observed probabilities are similar to the models predicted probabilities. The test has however been target for wide spread criticism due to its low power in models with both categorical and numerical variables.

An alternative is to use either other recognize tests such as Deviance and Pearson goodness-of-fit tests or pseudo R^2. We prefer R^2 as it widely used in empirical research, bears resemblance to many of the methodologies applied throughout our studies at CBS and is intuitively understandable by most readers with a financial background.

The pseudo R^2 are similar as they evaluate goodness-of-fit on a similar scale as R^2 i.e. from 0-1. However, as estimates of logistic regression models are based on an iterative maximum likelihood estimate and not calculated by minimizing variance the equivalent R^2 does not exist.

In the thesis we use the McFadden pseudo R^2 as it is the most accepted pseudo R^2 (along with Cox Snell R^2) for logistic regression models. It is defined as described in McFadden (1974):

$$R^2_{McFadden} = 1 - \frac{(L_c)}{\log(L_{null})}$$

Where L_C is the maximized likelihood value from the fitted model and L_{null} the maximum likelihood value from the model without coefficients. In short, it evaluates the relative change in the maximum likelihood estimator for the fitted model over the intercept only model.

McFadden states a warning in his paper from 1974. Basically, rho-squared (i.e. his pseudo R^2) tends to provide much smaller values than the R^2 known from OLS regressions. In other words, the scale upon which we value what a good model fit is, is different from linear multiple regressions.

As a rule of thumb, McFadden (1994) states that for logistic regression models, R^2 values between 0.2-0.4 can be considered a good fit. Values above 0.4 are considered exceptional models, while values below 0.2 are considered a relative bad model fit. We will be evaluating our models accordingly.

3.4.4 Model prediction power

There exists many ways of evaluating the model prediction power such as Receiver Operator Characteristic (ROC) curves, K-fold cross validation methods and classification rates. In the thesis we use ROC curves as well as c-statistics to evaluate the prediction power.

Concordance rate (C-stat)

The concordance rate measures the incremental improvement in classification rate over a model with no coefficients. Put simply, we look at the model's rate of correctly classified observations relative to the model without coefficients and use this as a proxy for model prediction power (Hosmer and Lemeshow, 2017). We use c-statistics to test for robustness of individual variables.

While the measure does not provide as much information as the ROC-curve, it is a good measure to evaluation the model fit on a more general level. Moreover, it is finally intuitively appealing and provide for a reader-friendly test.

ROC curve

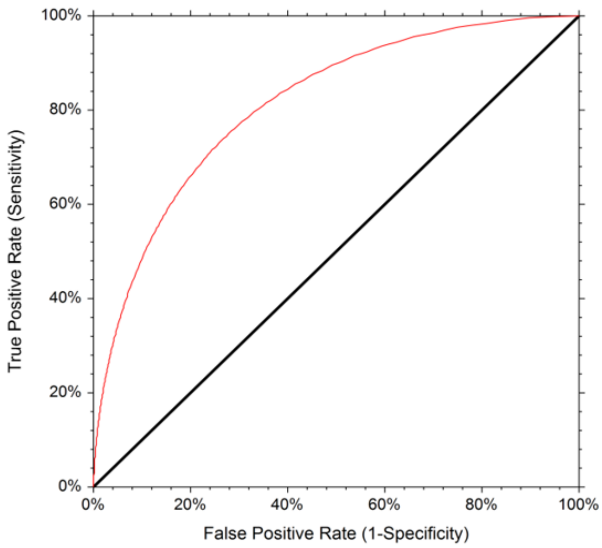
In section 5.8 we evaluate all the explanatory variables and use stepwise regression to develop the best fitting model. For this we wanted a deeper understanding about the model accuracy (i.e. c-stat), but also the model sensitivity and specificity.

Sensitivity: The proportion of correctly classified positive observations (true positive rates) i.e. how well the model predicts IPOs with positive abnormal returns

Specificity: The proportion of correctly classified negative result i.e. how well the model correctly predicts IPOs with negative abnormal returns.

The area under the curve is the concordance rate i.e. the total percentage of correctly classified IPOs.

Example of ROC curve



4. Comparative Analysis

For you as a reader, this section is important as it will reconcile expectations, educate you in IPO trends and give insight into why we later focus on certain traits when discussing the abnormal returns. In short, this section will give you a good starting point for evaluating the validity of the conclusions drawn later in the thesis.

4.1 Sample exploration

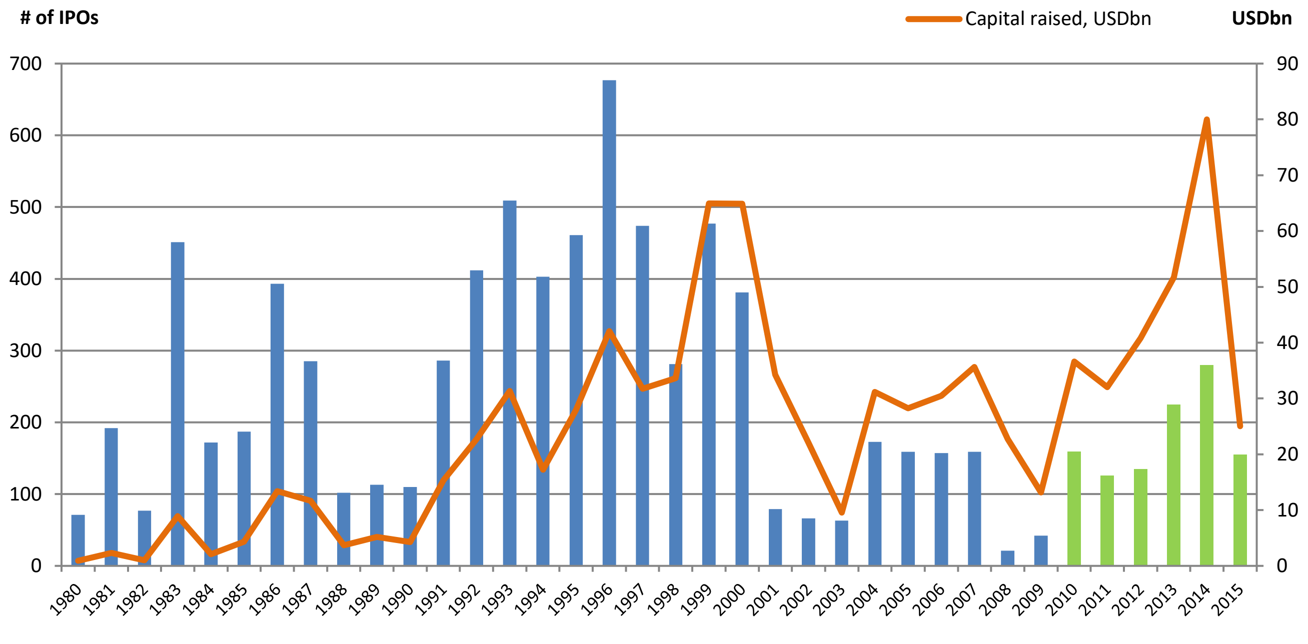
In this part of the analysis, we explore the IPO sample and look into the composition across a number of variables. When appropriate, we compare the sample to historical data and discuss how the composition based on IPO volume, capital raised, industries, operational characteristics and underpricing affects the measurement of returns.

4.1.1 IPO activity

There are two reasons why IPO activity is relevant to the problem statement examined in this thesis. First, the number of IPOs represents the availability of potential investments, which undeniably affects the relevance of the findings. Secondly, variability in the number of IPOs and capital raised introduces abnormal return measurements issues.

We start by looking at the historical trends in IPO volume. Practitioners refer to periods with low and high IPO activity as cold and hot periods/markets, respectively (Jaffe, 1975).

Figure 4.1: Number of IPOs and Capital Raised, 1980-2015



Source: 1980-2009 (Ritter), 2010-2015 (Thesis sample)

The IPO market is quite volatile in terms of volume and capital raised. The literature offers a variety of explanations for this. Most are based on the notion that hot markets are often clustered in industries and are the product of technological innovation pathing the way for new businesses (Ritter & Loughran, 2017). In short, hot markets are equivalent with good times in the IPO market.

We find the tech argument compelling as all other explanations regarding long periods of economic growth ultimately leads back to the technical advancement explanation. On a yearly basis, the IPO activity is likely to be affected of macroeconomic factors such as economic uncertainty, political circumstances, regulation and other force majeure events. Even the best macroeconomists have a hard time accurately predicting the global economic outlook for the next 2-5 years. Another recession may shock the world economy, regulation may change the competitive framework of some industries, political situations between North Korea and the US may escalate and change the political reality or maybe everything will just prosper. We simply do not know.

What we however do know, is that it is well established within macroeconomic theory that the driving force for increases in factor productivity is new technologies (OECD, 1995). With respect to the popularity of public ownership over time, it seems to follow that increased macroeconomic productivity primarily driven by new technologies will inevitably lead to an increase in new businesses opportunities, which should increase the number of IPOs. This is also exemplified historically as we can see a strong correlation in the number of IPOs with the major technological advancements in the 1980s (the PC) and 1990s (the internet). We also see a link to macroeconomic downturns such as the global recession that followed Black Monday (October 1987), the tech bubble (2001) and the financial crisis (2008). In short, and it should come as no surprise, the IPO activity is heavily linked to the overall state of the economy.

Most economists would agree that the past five years have been characterized by a healthy macroeconomic environment in terms of growth (see section 3.3.4 on SP500 5-year return). The drivers for this growth may be debatable and some economists argue that we are heading towards a new crisis. However, we do not believe it to be a farfetched statement to say that the financial markets have been healthy in recent years. Based on this trend in the financial markets, Ritter (2017) argues that it is surprising to observe a cold market period for IPOs. While we agree that the past 5 years activity levels have been low compared to the 1980s and 1990s, we still see a relatively hot market with 166% as many annual IPOs as during the 2000s. Moreover, while the numbers are low, the capital raised is not and this is a very important point.

This is the case as the market has been dominated by relatively fewer but larger IPOs. For instance, IPOs such as General Motors (2010, \$15.7bn), Facebook Inc. (2012, \$16bn) and Alibaba Group (2014, \$21.8bn) heavily influence the capital raised in their respective year. Some argue that the reason for the decrease in smaller IPOs since the tech bubble, is that is speeding products to market and economies of scope have become increasingly important (Cao, Ritter and Zhu, 2013). If this is indeed true, we would expect there to be a positive effect on the number and performance of PE-backed IPOs, as fast scaling of companies is one of the things the PE-model supposedly does well.

Looking ahead at the 10 years, we believe there are two good reasons to believe in a prosperous and active IPO market.

The first is due to the technology developing exponentially, and the fact that we are seeing promising progress within multi-purpose technology areas such as artificial intelligence. Some argue that these technologies will mostly benefit the large data companies such as Google, Amazon, IBM and Microsoft, but we cannot imagine a future where disruption of industries does not create new businesses. In relation to this, we see a large part of the cost of being a public owned company related to administrational work and financial reporting. These are the exact costs areas that are likely to be reduced by automation technologies.

The second and more down-to-earth argument is the increasing availability of IPO investments to private investors and small institutional investors. As we later discover, the majority of abnormal returns in IPOs are confined to investors that buy in before the company goes public i.e. offer price investors. In other words, there is an availability issue for private investors in relation to IPOs.

In the US, new platforms like SharesPost and SecondMarket (acquired by Nasdaq in 2015) provides access for retail investors to trade shares in private companies and implicitly early buy-ins in IPOs. This may ultimately end of reducing the actual underpricing and change the nature of IPO returns. However, given that the liquidity issues and adverse selection problems on these types of platforms are accommodated over time, we see potentially large growth base for the IPO market.

We realize that this view on the future IPO market is rather optimistic and can easily be criticized, but essentially all factors are in place for it to happen over time. We now turn towards examining the sample, which is ultimately more fact based and less speculative.

4.1.2 Size, year and ownership

The total sample consists of 1,014 IPOs in the period 2010-2015.Throughout the thesis we compare two subgroups consisting of 741 NPE and 273 PE-backed IPOs.

Table 4.1: Sample distribution by year and ownership

	# of IPO's			Capital Raised (USDbn)			PE/NPE*	PE/NPE**
	All	NPE	PE	All	NPE	PE	%	%
2010	135	95	40	36.6	27.0	9.6	42.1	35.6
2011	118	91	27	32.1	16.2	15.9	29.7	98.2
2012	130	90	40	40.8	31.5	9.3	44.4	29.5
2013	219	155	64	51.7	29.3	22.4	41.3	76.4
2014	265	194	71	80.0	33.4	46.6	36.6	139.4
2015	147	116	31	25.0	15.8	9.3	26.7	58.7
Total	1,014	741	273	266.2	153.2	113.0	34.2	73.8

**Number of PE relative to number of NPE-backed IPOs ** Amount of capital raised by PE relative to NPE-backed IPOs*

As the table shows, there have been large fluctuations in numbers of IPOs during the period. The two years with most activity, 2013 and 2014, together accounts 48% the total number of sample IPOs.

On average, there are 124 NPE-backed and 46 PE backed IPOs per year. This translates to 2.7 times as many NPE-backed IPOs during the period, but should be viewed in context to the average capital raised. Specifically, the NPE-backed entities raise USD 207m on average, whereas the PE-backed entities raise twice as much (USD 414m) per IPO. In other words, PE-backed IPOs comprise 42% of the IPO capital raised on NYSE and NASDAQ from 2010-2015. This was more than expected and just emphasizes how important is it to evaluate the relative performance of these types of IPOs.

The implications for our analysis are somewhat straight forward. We need to examine how differences in activity level and capital raised affect returns, as one year may end up driving the conclusion. To accommodate this issue, we later provide a breakdown analysis of the relative performance of PE versus NPE-backed IPOs for each year on an equal as well as value weighted basis. Moreover, we run logistic regressions to examine the predictive power of capital raised and year on returns. Ultimately, we show that the variability in the number of IPOs and capital raised only has a small and negligible effect on measurement accuracy due to the applied measurement methods. Moreover, abnormal returns turned out to be relatively consistent across years.

4.1.3 Industry

We now turn to the sample industry composition. To examine this, we divided the sample into 11 industries based on CRSP data.

Table 4.2: Sample distribution by industry and ownership

Industry name	Industry Beta*	# of IPO's All	# of IPO's NPE	# of IPO's PE	Relative percentage All	Relative percentage NPE	Relative percentage PE	χ2 P-value
Financials	1.1	160	122	38	15.8	16.5	13.9	0.37
Healthcare	1.4	251	232	19	24.8	31.3	7.0	0.00
High Technology	1.3	189	152	37	18.6	20.5	13.6	0.02
Energy & Power	1.1	101	66	35	10.0	8.9	12.8	0.08
Real Estate	0.6	43	36	7	4.2	4.9	2.6	0.12
Consumer P&S	1.2	63	37	26	6.2	5.0	9.5	0.01
Industrials	1.0	71	39	32	7.0	5.3	11.7	0.00
Retail	1.3	52	15	37	5.1	2.0	13.6	0.00
Materials	1.2	43	21	22	4.2	2.8	8.1	0.00
Media & Entertainment	1.1	25	12	13	2.5	1.6	4.8	0.00
Telecommunications	0.6	16	9	7	1.6	1.2	2.6	0.13
Total sample	1.19	1014	741	273	100.0	100.0	100.0	

*SP500 GICS sectors, *Beta: One-year regressions betas starting from IPO date and based on daily returns vs. SP500*

The relative percentage columns represent the number of IPO's specific to the industry relative to the full sample within each category. The χ2 represents the p-value for the hypothesis (Chi-square test), that the relative distribution in the PE-backed sample is the same as the NPE-backed within each industry

We use the Global Industry Classification Code (GIGS), which is also applied by the SP500 Sector Index. We refer to appendix A for industry descriptions

Looking at the table, we see that the sample is asymmetric in terms of number of IPOs per industry. Examining the sample further it becomes clear that the large industries are primarily industries that have been economically booming in recent years with the exception of Energy & Power (see appendix A for 5-year industry compounded annual growth rates (CAGRs)).

We also see a significant difference in composition for the NPE and PE-backed subsample, respectively. In 7 out of 11 industries, the composition is significantly different. Especially the largest sector (healthcare) in the sample differs significantly within NPE and PE-backed sample.

Table 4.3: Sample industry concentration by ownership

Sample concentration	All	NPE	PE
3 largest industries, % of total sample	59.2	68.3	41.0
4 largest industries, % of total sample	69.1	77.2	53.8
5 largest industries, % of total sample	76.1	82.5	65.6
7 largest industries, % of total sample	87.5	92.3	75.1

The three largest industries i.e. Financial, Healthcare and High Technology accounts for more than 600 IPOs in the period. A key takeaway from this observation is that the second and third largest industry in our sample i.e. Healthcare and High Technology also constitutes the highest-risk industries as measured by the market beta.

NPE-backed IPOs are clustered in fewer industries compared to their PE-backed counterparts. The industry differences might be due to the suitability of the PE-ownership model in each respective industry or simply due to investor preferences in the period. To be frank, we could write another thesis only focusing on this subject. The real importance of these differences in terms of our thesis is instead the statistical implications and the inference problems and differences it potentially creates.

As the differences are statistically significant, we need to control for industry effects in the analysis of abnormal returns. This is somewhat accommodated using the regression betas in the benchmark portfolios that takes into account the relative risk of the industries. As reported in appendix T, we find that PE-backed entities on average exhibit a slightly higher market beta. This may be a reflection of the sample industry composition or/and debt levels (since we measure levered betas).

However, we may still find that certain industries are driving abnormal returns and this element is crucial for the robustness of the conclusions. If we measure abnormal returns and fail to capture that it was due to a single or two industries performing well, the conclusions would most likely lose it predictive powers.

For this reason, we later measure the contribution of each industry to the abnormal returns and discuss how this affects the applicability of the conclusions in a forward-looking investment perspective. We also try to include as an independent variable in logistic regression models on a standalone basis as well as with other variables. Ultimately, we find a very small correlation between industry and abnormal returns, but not anything statically significant.

4.1.4 Operational characteristics

Previous literature such as Levis (2011) documented large differences across PE and NPE backed IPOs. We find similar properties in our sample and speculate that these significant differences may affect the aftermarket performance of the IPO groups. The table below reports the median operational characteristics in USDm and the number of IPOs that contributed to the median in parenthesis. All data is based on the closest available data point to the IPO i.e. either the IPO filing date or first day of trading.

Table 4.4: Selected operational characteristics

USDm		**All**	**NPE**	**PE**	**PE/NPE**
Revenue	Median	253	121	1,444	11.98x
	No. obs.		*(736)*	*(273)*	
EBITDA	Median	111	65	467	7.22x
	No. obs.		*(731)*	*(272)*	
EBIT	Median	138	81	294	3.64x
	No. obs.		*(736)*	*(273)*	
Operating margin (%)	Median	8.63	5.10	12.85	2.52x
	No. obs.		*(585)*	*(267)*	
Asset turnover ratio	Median	0.40	0.33	0.44	1.33x
	No. obs.		*(731)*	*(272)*	
Capital Expenditure	Median	128	112	232	2.08x
	No. obs.		*(736)*	*(272)*	
Total assets	Median	91	49	202	4.12x
	No. obs.		*(731)*	*(272)*	
Debt-to-assets*	Median	0.13	0.08	0.28	3.56x
	No. obs.		*(726)*	*(272)*	
Book value of equity	Median	279	195	1,056	5.42x
	No. obs.		*(736)*	*(272)*	
Market value of equity	Median	637	324	1,482	4.58x
	No. obs.		*(730)*	*(270)*	

**Debt = Long term debt + (Current liabilities - Current Assets)*

We find that PE backed IPOs are much larger in terms of income statement KPIs such as of revenue, EBITDA, EBIT and operating margin. The does not necessarily mean higher returns as we are quite confident an underwriter would want to reflect this in the IPO valuation.

We do however also find higher asset turnover ratios in the PE-backed entities in the year of IPO. Together, this implies that the PE-backed companies in the period have had relative higher returns on invested capital (ROIC) at the time of the IPO. Such findings are also consistent with previous studies documenting improved operating performance by PE-owned companies (Jensen 1986, 1989; Levis 2011). However, depending on how efficient the market really is, most of these effects should be reflected in the valuation of the IPOs and thus the stock price.

In terms of balance sheet items, we find the same relative size of assets (4x) as Levis (2011) did for the UK market. While assets as a size proxy have historically proved insignificant in explaining stock returns (Fama, 2000), we do find some use for it. It turns out that for a few of the predictive models in this thesis, assets in conjunction with other operational variables provide for a significant predictor of positive abnormal returns. The asset size differences may however be due to differences in industries or other correlations that we did not examine.

Levis (2011) also documents substantially higher debt levels in the PE-backed IPOs. We find the same to be true and add that higher debt-levels should be associated with higher financial risk and thus a larger premium for financial risk on PE-backed IPOs. We accommodate this issue by estimating levered market betas for each IPO and also conduct logistic regressions on a couple of debt variables to explain abnormal returns. We later find that debt negatively affects returns.

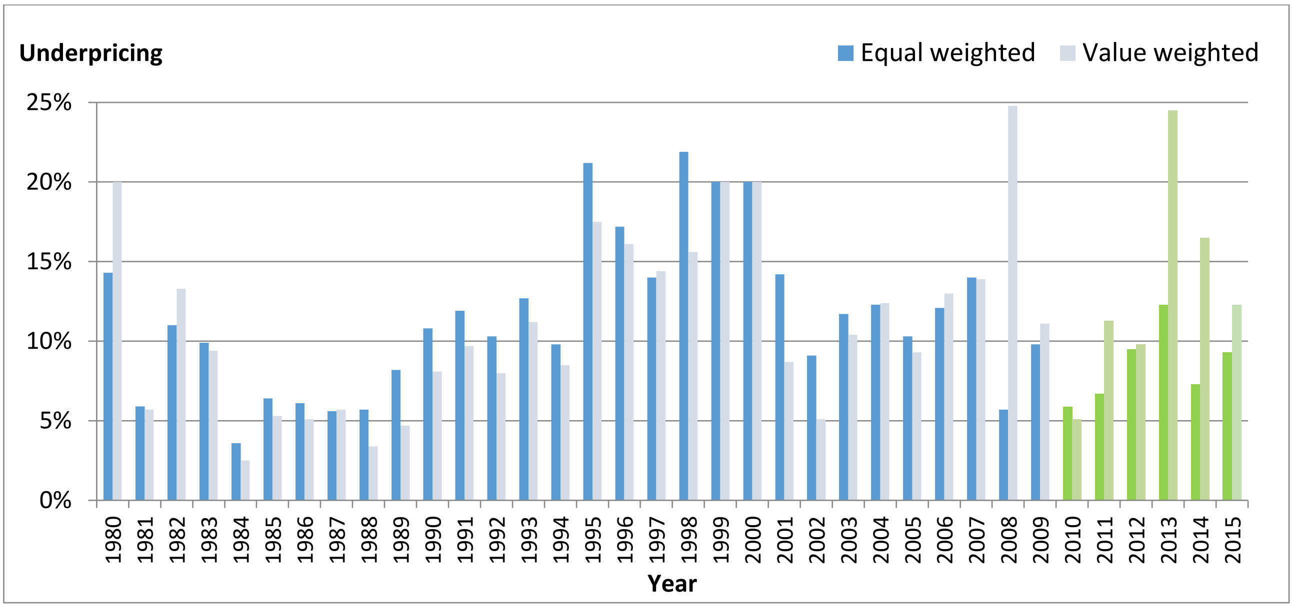
In terms of cash flow items, we find that PE-backed entities tend to invest more, but less relative to size, than their NPE backed counterparts in the year up to the IPO. This could potentially be due to PE-backed entities focusing on trimming rather than expansion just before exiting the company. As James Laing from Aberdeen Asset Management put it: "*I am not against Private Equity in general, but when it comes to IPOs they are in the business to get the highest price for their investors. This means there is a tendency to flatter the books to make the investment look a lot better than it is*." (Financial Times, 18 February 2014). We address this unresolved hypothesis after inspecting the facts.

In terms of book and market values, the PE-backed are larger in both. However, the median is somewhat misleading as the average book-to-market ratio is 0.45 and 0.34 for NPE and PE-backed entities, respectively. In short, the PE-backed IPOs are more likely to be classified as growth stocks than the NPE-backed entities. This will have a direct effect on the estimated abnormal returns, as we benchmark using risk-models that in most years include a premium on growth stocks. We discuss the issue in debt in 3.3.4. and instead move on to the best predictor of abnormal returns.

4.1.5 Underpricing

In analysing the returns, we found that our conclusions largely deviated depending on how we handled underpricing. Remember, it is the difference between the offer price and the closing first day market price and is notoriously influential on short-term IPO returns. Therefore, we dedicated a section to investigate the trends in underpricing historically as well as for our sample.

Figure 4.2: IPO Underpricing, 1980-2015



Source: 1980-2009 (Ritter), 2010-2015 (Thesis sample)

Underpricing is a well-known issue and the literature offers various explanations to this anomaly, whereas most of them are about information asymmetry, information revelation and signalling theory (see section 2.4). The historical development has been rather steady, beside the spikes around the technology bubble in 1999 and 2000, where the average underpricing hit remarkable 71.1% and 56.3%, respectively (Ritter, 2017). In these years, we normalised the graph for improved visual inspect of other years.

When observing the development in equal-weighted versus value-weighted underpricing, an interesting shift occurs in 2004. Historical equal-weighted underpricing has been superior, but this is not the case after this breaking point. There could be several explanation, whereas the most valid concern an increase in numbers of large IPOs, a decrease in numbers of small IPOs and/or the fact, that large IPOs are more likely to be heavily underpriced. We argue that it is a combination of all three factors. As shown in section 4.1.1. the capital raised has increased relatively more than the amount of IPOs since 2004, only disturbed by a dive in 2008 and 2009 (Financial Crisis).

Moreover, Ritter (2017) has documented a decrease in the total numbers small IPOs (Sales < 50USm) and also finds more underpricing in larger IPOs.

For the sample period, 2010-2015, the average underpricing is 8.5% on an equally weighted basis. We need to know how they affect returns, if there are any differences between groups and/or which IPOs are more prone to underpricing. We start by looking at underpricing by year.

Table 4.5: Sample underpricing by year

Year	Equal weighted			Value weighted		
	All	NPE	PE	All	NPE	PE
2010	5.9	5.4	6.8	5.1	4.7	5.9
2011	6.7	8.1	3.8	11.3	14.3	5.1
2012	9.5	9.9	8.5	9.8	10.6	8.3
2013	12.3	13.5	10.1	24.5	30.7	12.0
2014	7.3	8.9	3.9	16.5	11.7	26.1
2015	9.3	10.4	7.2	12.3	16.9	3.0
Average underpricing (%)	8.5	9.4	6.7	13.2	14.8	10.1

The table is based on the annual underpricing identified in our BHAR results. As documented by Ritter (1991) et al., underpricing have a massive impact on IPO returns and our examination provides no evidence that discredit earlier research on this subject.

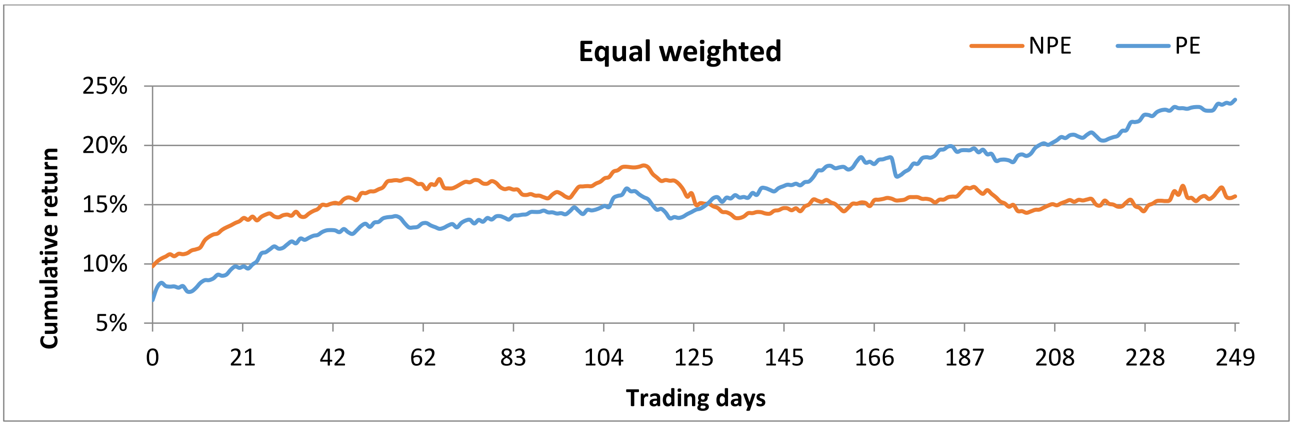
NPE-backed IPOs turn out to be approximately 1.4x more underpriced compared to their PE-backed counterparts both on an equal and value-weighted basis. There are slight deviations to this trend such as 2010 (equal-weighted) and 2014 (value-weighted) but overall it is present. Moreover, the discrepancies in results between groups in the two weighting methodologies are rather consistent, which indicates larger IPOs being underprice more heavily.

In short, the underpricing has an influence on IPO return for PE and NPE-backed IPOs. There exist discrepancy in the underpricing between the two groups, as NPE-backed IPOs are 2.7% more underpriced relative to their PE-backed counterparts measured on equal-weighted basis. Finally, large IPOs turn out to be relatively more influenced by underpricing in both the PE and NPE-backed sample. We address the underpricing throughout the thesis by analysing returns with and without underpricing.

4.2 Raw returns

In this section, we analyse raw buy-and-hold returns i.e. realised returns. We present selected graphs and refer to appendix B-C for insight into the statistical properties and further visualisations of the data i.e. visualisations of returns without underpricing. All return graphs throughout the thesis are based on weighted averages as described by section 3.3.2.

Figure 4.3: Equal-weighted B&H returns by ownership



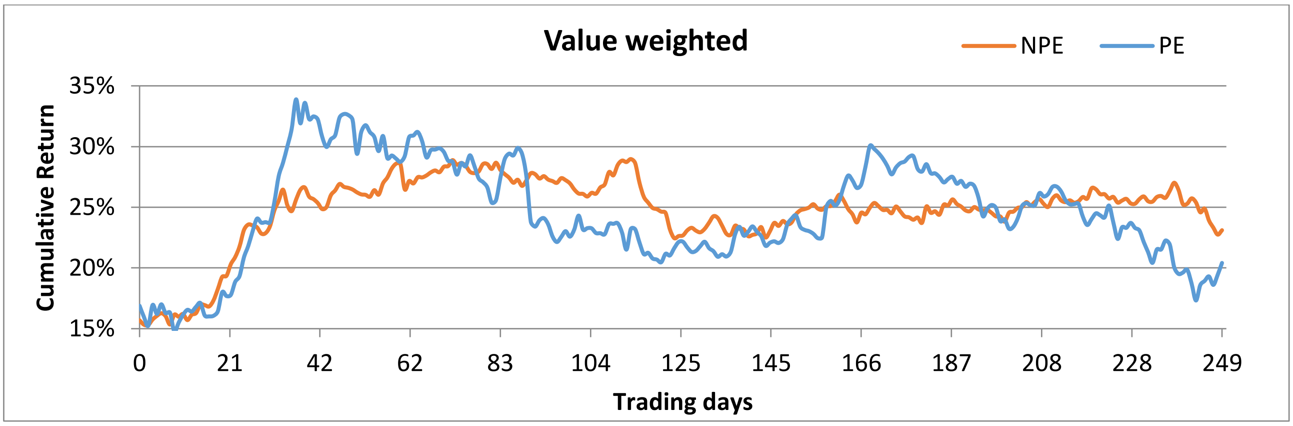
For a 1-year holding period (249 trading days), the average BHAR is 15.7% and 23.9% for NPE and PE-backed IPOs, respectively. Without underpricing these numbers drops to 5.8% and 16.1% for NPE and PE-backed IPOs (Appendix B & C). All returns are larger than zero on a 1% significance level for all holding periods (Appendix B). If this trend is to be justified on theoretical grounds, we should expect to find that PE-backed IPOs are much riskier investments.

The higher returns of PE-backed IPOs may also be linked to better timing i.e. PE-backed IPOs being more frequent in years, where stocks in general perform well. The hypothesis was however rejected by Michala (2016) for the period 1975-2013 and we later find the same to be true for our sample after risk-adjusting our returns.

Another interesting observation is that the PE-backed IPOs underperform the NPE-backed IPOs during the first 6 months. This time frame (125 trading days/180 calendar days) is exactly equal to the typical lock-period that prevents offer price investors in selling shares. After this point, NPE-backed IPOs practically flat line in the remaining part of the year and the PE-backed IPOs continues to soar.

In short, during the lock-up period the two groups of IPOs perform equally well, however NPE backed IPOs overperform their counterparts due to underpricing. This pattern becomes especially clear, when the underpricing element is left out of the analysis (see Appendix C). We speculate that this trend may be caused by investors in the NPE-backed entities, to a higher degree than PE-backed entities, sell their shares when the lockup period ends. If this is true, one could argue in favour of a relative liquidity premium on PE-backed IPOs, thus justifying at least some of the differences in returns. We later return to this by looking at trading volumes and bid-ask spreads.

Figure 4.4: Value-weighed B&H returns by ownership



For the value-weighted portfolios, the returns are significantly larger and exhibit higher volatility than the equally weighted portfolios. Both PE and NPE-backed IPO returns are extremely high in the first 3 months and then flat line for the rest of the year. The average underpricing is also significantly larger averaging 16.22%. In essence, given an average annual market return of 15.3% over the period, the offer price investors already beat the market on the first day of trading.

Without underpricing, the average IPO had returns of 6.1%. From this we can already deduct that unless the IPOs are more than ~2.5 times less risky than the market, which seems extremely unlikely, the IPOs have underperformed the market in the period for non-offer price investors.

When compared to the equal weighted returns, we can deduct that the large NPE entities on average outperform the smaller NPE-backed IPOs. The same is true for the first ~10 months for the PE-backed IPOs. One might be concerned that a few really large IPOs are driving returns, however the maximum return weight for any company in the NPE and PE sample never exceed 1% and 3%, respectively.

Finally, the 125 trading day (lock-up period) trend we found in the equal-weighted portfolios does not hold for the value-weighted portfolios. This could potentially mean that the trend is driven by smaller companies or is only found in cold periods (as these receive less weight).

4.3 Buy-and-Hold abnormal returns

The raw returns provided insight into how the IPOs performed without accounting for risk. Therefore, for each stock we now calculate the expected return using three benchmarks: CAPM, Fama French and Carhart model.

4.3.1 Model fit and risk factors

However, before analysing actual abnormal returns, we look into the model fit and underlying risk factors used to determine the BHARs. For model fit, we use R^2 as a proxy i.e. we measure the proportion of total variance in the returns that is predictable by the model factors and choose the best model to predict the sample returns.

Table 4.6: Coefficient of determination (R^2) by risk model and IPO date

Model	CAPM (R^2)		Fama French (R^2)		Carhart (R^2)	
Year	**NPE**	**PE**	**NPE**	**PE**	**NPE**	**PE**
2010	0.77	0.72	0.77	0.81	0.85	0.79
2011	0.75	0.68	0.85	0.76	0.84	0.75
2012	0.81	0.79	0.92	0.89	0.91	0.88
2013	0.82	0.79	0.92	0.89	0.91	0.87
2014	0.83	0.79	0.93	0.88	0.91	0.86
2015	0.82	0.79	0.91	0.88	0.89	0.87
All	0.81	0.77	0.90	0.86	0.89	0.85

The regressions (3 regressions for each company, total of 1014 companies) are performed using Spyder software and Python programming to automate the beta calculation process (see Appendix U for code). In doing the regressions, we found that the Fama French model was superior in terms of model fit with an average R^2 across the sample of 0.89. Moreover, the model proved better at explaining NPE returns than PE returns. This may either be due to other factors affecting PE-backed IPOs, greater sample size or simply due to differences in performance. We later explore this issue.

To our surprise, adding the momentum factor suggested by Carhart (1997) did not enhance the power of the model, which is why we will only be reporting Fama French adjusted BHARs. This means that on an individual daily level averaged across the sample and period, the IPOs does not exhibit momentum. In other words, we cannot predict whether an individual stock will go up or down daily based on the past trend, when other factors are accounted for.

We speculate that this may be due to the time period the regression was run over. Stocks may have positive momentum in the first couple of months and negative momentum in remainder of measured period. Ultimately, when measured over a year these momentum effects cancel each other out, leaving the average factor insignificantly different from zero.

While leaving out the momentum factor may not be theoretically optimal, we made the choice of using the Fama French over Carhart model for two reasons. First, almost all similar studies use the Fama French model as a benchmark and do not take into account momentum in IPO returns. Second, we tried performing regressions on shorter time periods i.e. splitting the year into two periods (0-3 months and 3-12 months) and applying the models to these. This ultimately resulted in other factors becoming insignificant and the lack of observations reduced the overall model fit. In short, we needed a full year of observations to obtain a respectable model power and even though this may not capture effects from momentum, the model showed that over the full year the average stock did not exhibit significant momentum.

We now move onto the regression coefficients. It should be emphasized, that we solely ran regressions on daily returns for a 1-year time frame. The theoretical literature on beta measurement typically recommends measuring betas over a 2-5 year period with weekly or monthly returns rather than daily. However, we feel comfortable with our market betas, as these came pretty close to the SP500 GIGS 5-year industry betas (Appendix T). As the Fama French model proved the best in explaining returns, we report average betas for the market premium, SMB and HML factors.

Table 4.7: Fama French regression betas and premiums by year

Factor	**β Market**			**β SMB**			**β HML**		
Year	β NPE	β PE	Premium	β NPE	β PE	Premium	β NPE	β PE	Premium
2010	*1.06	*1.24	15.1%	*0.48	*0.52	12.6%	*-0.10	**0.02	4.3%
2011	*1.11	*1.25	1.8%	*0.41	**0.29	-5.2%	*-0.05	*-0.25	-8.0%
2012	*1.08	*1.23	16.1%	0.45	0.55	-0.2%	-0.03	**0.04	7.7%
2013	*1.41	*1.22	32.4%	*0.72	*0.52	7.3%	*-0.73	**0.06	-1.8%
2014	*1.11	*1.18	13.6%	*0.66	*0.63	-7.9%	*-0.37	*0.20	-2.4%
2015	*1.28	*1.09	15.3%	*0.82	*0.70	-5.5%	*-0.30	**0.06	-11.5%
2016	NA	NA	13.1%	NA	NA	6.3%	NA	NA	29.6%
Average	*1.17	*1.20	15.3%	*0.59	*0.54	1.1%	*-0.26	*0.02	2.6%
Weighted average!	1.19	1.20	17.1%	0.62	0.55	-0.2%	-0.32	0.06	-2.1%

* Significant at 1% **Significant at 5% *** Significant at 10%

! Weighted average represents the beta weighted by yearly volume IPO volume excluding 2016

The first thing to notice is that all factor betas are significantly different from zero. The most important factor is logically the market equity premium, which explained 81% and 77% of the PE and NPE-backed variations in returns (CAPM), respectively. The results show that the average IPO has been approximately 20% more volatile than the market during the first year in the aftermarket for the past 5 years. This aligns very well with the fact that researchers have previously found that IPOs are much more volatile relative to the average stocks (Brav & Gompers, 1997; Michala, 2016). It also shows that PE-backed IPOs are not much different in terms of relative market volatility than their NPE counterparts. There are however small deviations within individual years. For instance, PE-backed IPOs are more volatile in 4 out of 6 years, whereas NPE-backed takes the price for the 2013 bull market (32.4%) and 2015 (15.3%). For more specific group betas divided by PE/NPE, industry and SP500 sector beta benchmark, we refer to appendix T.

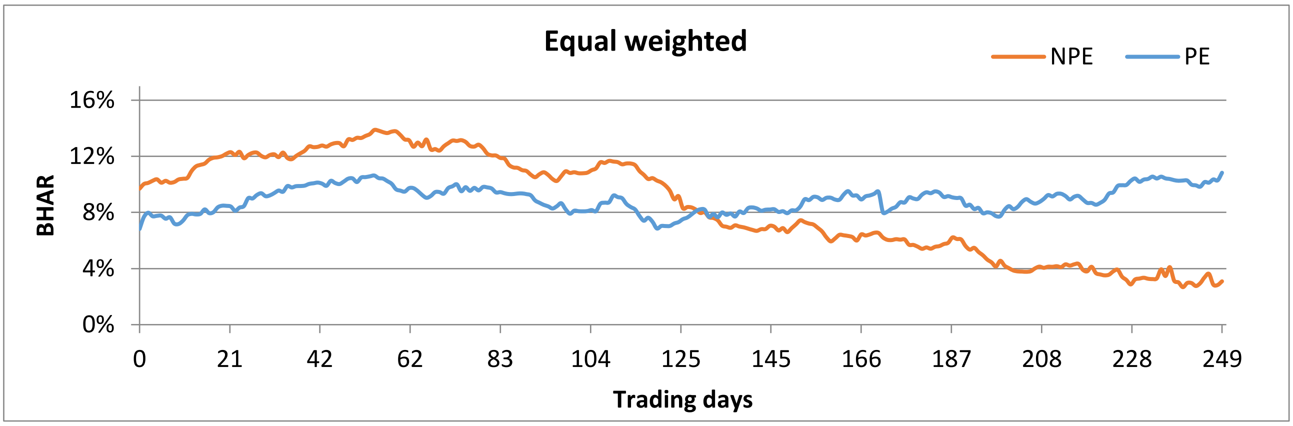
The SMB factor is more surprising in terms of results. We would have expected that PE-backed IPOs were significantly less exposed to this factor due to the sheer size in respect to the NPE-backed IPOs. This turns out not to be the case based on our regressions. The average beta is only 0.05 smaller for PE-backed IPOs, and with an average premium of 1.1% this indicates almost no difference in the expected return for the two groups. When weighted by the number of IPOs, the premium on small firms is negative, which begs the question if there really exists a consistent small-firm effect in the IPO market, that is not already reflected in the underpricing element. All coefficients are however significant on a 1% level in all years except 2012.

The HML factor i.e. the premium on value firms over growth firms is the only factor exhibiting large differences between the NPE and PE-backed IPOs. On average, we applied a negative premium of -2.1% to the IPOs in our sample implying a premium on growth stocks over value stocks. However, overall there seems to be no consistency across years and NPE/PE-backed IPOs. This is partly due to varying coefficients and partly due to the volatile premiums. In short, there seems to be only a small effect from this risk factor with annual average applied premiums (factor times premium) ranging from approximately -1% to 3.5%. The factor is nonetheless different from zero on a 1% significance level across all years and groups except for NPE-backed IPOs in 2012. Overall the premiums for all factors exhibit high volatility across years i.e. stocks are risky investments. This has also been true historically as shown in the graph detailing each of the risk premiums from 1980-2015 in section 3.2.4. Recall that Fama (1998) emphasizes that the actual premiums are not intuitively interpretable but serve as proxy for yet unknown more fundamental factors.

4.3.2 Estimated BHARs

After having established a good model fit and discussed the risk-factors, we now turn towards the BHAR results. We analyse the abnormal returns using equal and value weighting for both PE and NPE-backed IPOs accordingly.

Figure 4.5: Equal-weighted BHARs by ownership

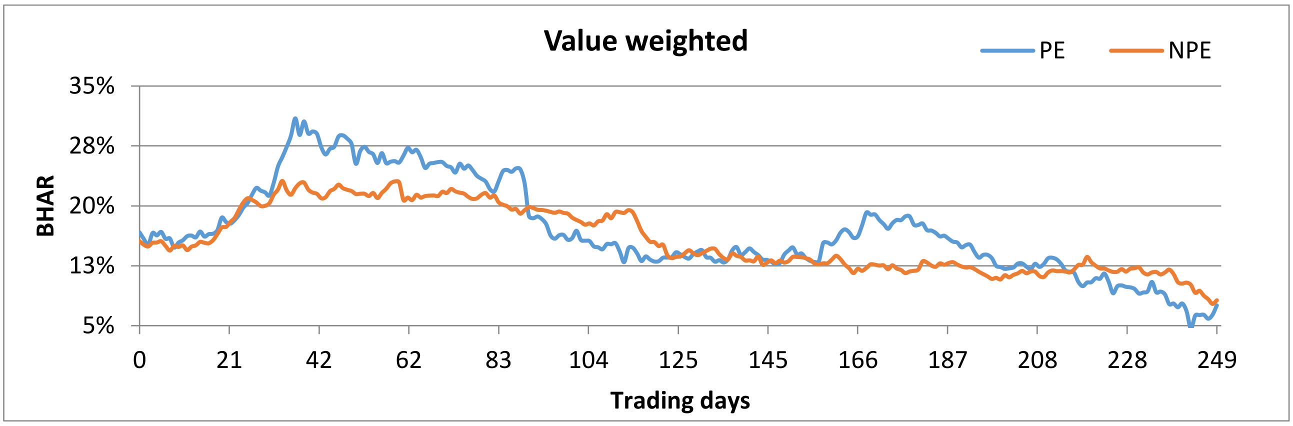


Even after adjusting the returns for risk, we observe highly positive abnormal returns of 10.8% and 3.1% annually for the PE and NPE-backed IPOs, respectively. The 125-day trend we identified in the raw returns is still valid i.e. accounting for the conventional risk factors did not capture this abnormality. Throughout the period, the returns are all significantly different from zero on a 1% significance level for both groups, with the exception of the last 3 months for NPE-backed IPOs.

The abnormal returns however are almost solely driven by the underpricing element in each IPO. This becomes especially clear when looking at the returns without underpricing (Appendix E). Both PE and NPE IPOs exhibit abnormal returns in the first 3 months of trading. Hereafter, the PE-backed returns flat line for the remainder of the year and the NPE-backed IPOs plummet. Without underpricing, we can at no point in time after three months reject that the true mean is zero for PE-backed entities. For the NPE backed, the return becomes smaller than zero for a 9 and 12 month holding period on a 10% and 1% significance level, respectively.

In short, PE-backed exhibit superior performance on an equally-weighted basis compared to their NPE-backed counterparts. However, if the underpricing element is removed from the returns, we cannot confirm that the abnormal returns for the PE-backed IPOs are larger than zero for a 1-year holding period (appendix D). Finally, the only point in time where both PE and NPE groups exhibit abnormal returns significantly larger than zero without underpricing is during the first 3 months in the aftermarket for equally weighted portfolios.

Figure 4.6: Value-weighted BHARs by ownership



For both groups, the first 3 months of trading are characterized by high abnormal returns followed by a plummet in the performance of both groups. This may be caused by model failure i.e. other risk-factors justifying the abnormal returns, lockup period effects or simply irrational investor behaviour. This trend however, does not change the fact that the PE and NPE-backed IPOs exhibit statistical significant abnormal returns of 8.2% and 7.5% for a 1-year holding period, respectively.

Another interesting observation is the effect of value-weighting the IPOs seems to affect the PE and NPE-backed IPOs differently i.e. size matters. We later confirm that the trend is more prominent in larger IPOs, hence why the trend is stronger for PE-backed entities. Moreover, both perform better in the first 3 month of trading than their smaller counterparts (value larger than equal weighted).

For a one year holding period, large PE performs relatively worse than small PE-backed IPOs. The same is not true for NPE backed IPOs, where large IPO have higher returns for all holding periods.

Again we find that the most important driver for abnormal returns is underpricing. Both groups on average underperform the market without underpricing after 5 months. Moreover, the returns become significantly negative on a 10% significance level as early as 6 months for the NPE-backed IPOs, whereas it takes 12 months for PE backed IPOs (appendix D, bottom row).

For a holding period of 6 months i.e. the end of the typical lock-up period, the average offer price investor would have incurred an average of 13.7% abnormal returns for NPE-backed IPOs and 13.9% for PE-backed IPOs. On the other hand non-offer price investors incur positive 4-month BHARS and negative returns for longer holding periods for both NPE and PE-backed IPOs, respectively. For a one year holding the abnormal return without underpricing is -8.3% (significant at 1%) and -6.58% (significant at 10%) for NPE and PE-backed IPOs, respectively.

4.3.3 Discussion of BHAR results

After analysing equal-weighted and value-weighted BHAR results it becomes clear, that PE and NPE-backed IPOs both exhibit superior performance even when all conventional risk factors are taken into account. If our risk model holds, offer price investors have incurred abnormal returns for both PE and NPE backed IPOs for most holding periods. However, we have to bear in mind that the returns could not have been realised before after the end of the lockup period. Luckily for these investors, both PE and NPE-IPOs exhibit average returns of 8-14% 6-month BHARs depending on the portfolio weighting methodology. All returns are significant at a 1% level (Appendix D).

However, without underpricing the findings change dramatically and the BHARs becomes either significantly negative or insignificantly positive. These findings are consistent with the underperformance found in most research (Ritter, 1991; Brav & Gompers 1997; Cao & Lerner, 2009; Lewis 2011). The only holding period, where abnormal returns are significantly positive for non-offer price investors is during the first 4 month in the aftermarket. In other words, abnormal returns for the average IPO is in the short to medium term primarily driven by underpricing and thus only benefit offer price investors. For non-offer price investors, the overall IPO market exhibits significant underperformance for holding periods above 4 month. They still have the possibility to incur abnormal returns as these investors are not bound by the lockup period i.e. they have the opportunity to sell their shares after 2-4 months. For this holding period, average returns are significantly positive ranging from 2-8% depending on group and weighting methodology. The returns are however consistently higher on average for value weighted portfolios.

Since the abnormal returns increase, when we weight them by market capitalisation, we can conclude that large IPOs perform better than smaller IPOs. We later explore the impact and statistical significance of size on IPO returns, as this trend may be driven by a relatively small number of really large IPOs performing exceptionally well. It may also be case, that since PE-backed IPOs are larger on average, the differences between PE and NPE in the equally weighted portfolio are a product of size effects rather than differences across ownership.

In this respect, the average return is higher for larger IPOs and this holds true for almost all holding periods and across both sample groups. The next couple of sections will provide robustness checks for our BHAR findings before finally analysing causation.

4.4 Calendar-time abnormal returns

In order to ensure the robustness of our BHAR results, we now apply a different methodology to estimating abnormal returns.

In essence, the following section runs a horse race between portfolios of IPOs for a range of holding periods. We do this by simulating a number of rolling portfolios formed on private PE-backed/NPE-backed groups and holding period for each IPO in the period 2010-2015. We refer to the methodology section 3.3.2 for further insight into how portfolios are formed and the strengths and weaknesses of this approach. A total of 36 portfolios are created for which we measure abnormal returns. Next we inspect the regression results and determine alpha values, which are then interpreted as abnormal returns.

First however, let us inspect the model fit. We also look at the effect on the model fit and applied premiums from adding the momentum factor. Secondly, we analyse the estimated CTARs together with BHARs with the purpose of comparing the results between the two methodologies. Finally, we discuss the robustness of the BHAR results in relation to results obtained from the CTARs.

4.4.1 Model fit and momentum

Before estimating abnormal returns, we first look at the model fit for the CTAR time-series regressions for the two risk models. In contrast to the BHAR returns, we did find that on a portfolio level, the effects from the momentum factor as suggested by Carhart (1997) does have a significant effect on the expected returns and did increase the explanation power of the model. We do not report the market, SMB and HML regression betas, as these were approximately the same (only slightly lower for CTAR) for both methodologies.

Table 4.8: Coefficient of determination (R^2) by model and holding period

Risk model	**Fama French (R^2)**		**Carhart (R^2)**		**β momentum**		
Holding period (months)	**NPE**	**PE**	**NPE**	**PE**	**β NPE**	**β PE**	**β Premium**
1	0.05	0.07	0.06	0.08	*0.33	*0.31	1.2%
2	0.14	0.22	0.15	0.24	*0.37	*0.34	1.7%
3	0.29	0.40	0.31	0.43	*0.41	*0.40	1.4%
6	0.64	0.59	0.69	0.63	**0.20	*0.31	1.2%
9	0.73	0.66	0.78	0.71	***0.16	***0.24	0.7%
12!	0.81	0.77	0.87	0.83	***0.18	***0.21	0.9%

* Significant at 1% **Significant at 5% *** Significant at 10%

***** Same regression period length as BHARs

We start by looking at the momentum factor and find that it is significant for both groups and on all holding periods on a portfolio level. The premium showed are the average applied premiums rather than the annual premiums as displayed for the BHARs. In other words, the premiums displayed already take the momentum beta into account and should thus be viewed as the actual average premium applied to the expected return portfolio. We chose to show these, since the average annual premiums provided no additional information to you as a reader, as companies are listed throughout the year and are held for different time periods in the rolling portfolios.

We see a larger momentum during the first 3 months of trading followed by zero or negative momentum in remaining part of the year. This is in essence why the beta coefficients are relatively larger for short holding periods and the approaches zero as we increase the holding period. While the premiums may appear small and insignificant, bear in mind that the premiums are not annualized and thus are quite high in the first couple of months of trading. This is also seen reflected in the model fit as momentum on average explain 4-5% percentage points more than the Fama French model for longer holding periods.

The CTAR model confirms our suspicion in regards to the risk models failure to explain returns during the first 3 months in the aftermarket. We see that the Carhart model only explains 6-8% of the returns in this holding period and thus provide for a bad model fit. Again this may either be due to other risk factors explaining the returns during the first 3 months (i.e. before the first quarter financial reports) or simply due to investor irrationality.

Compared to the BHAR regressions, we see that the R^2s are slightly lower implying that we expect our CTAR results to be relatively more volatile. Overall, the model fit for longer holding periods is however quite similar to the BHARs as the beta values approach each other and explains a significant percentage of the return variations. Again, the differences are due to how the regressions were performed. For BHARs, each company is risk-adjusted and betas for each company are used in determining the expected return. This provides for a more accurate model for the individual firm, but fails to capture the cross-correlation i.e. portfolio effects that the CTAR approach does. On the other hand, CTAR only provides an accurate measure for investors buying all the companies that is at some point involved in the rolling portfolio.

The following page provides an overview of the estimated CTARs and compares them to BHARs.

4.4.2 Estimated CTARs

The following table provides a comparison of the two methodologies of estimating abnormal returns. The t-statistics for the CTARs are reported in conjunction with the returns in appendix F. Since we are solely focusing on validating the results of the BHARs, we make an exception to the overall theme of displaying results without underpricing in the appendix.

Table 4.9: CTAR and BHARs by holding period

CTAR and BHAR (%)	**Underpricing**	**1**	**2**	**3**	**6**	**9**	**12**
Equal weighted							
NPE, CTAR	9.7	*12.9	*14.4	*14.1	*10.2	*8.1	***5.0
NPE, BHAR		**12.3*	**12.8*	**12.7*	**8.3*	**6.2*	*3.1*
PE, CTAR	6.8	*9.0	*11.1	*11.3	*9.1	*11.9	*10.5
PE, BHAR		**8.4*	**10.0*	**9.7*	**7.5*	**9.0*	**10.8*
Value weighted							
NPE, CTAR	15.6	*19.9	*21.6	*21.8	*13.5	*12.1	*6.9
NPE, BHAR		**18.0*	**20.6*	**20.7*	**13.7*	**12.8*	**8.2*
PE, CTAR	16.7	*18.4	*28.4	*28.3	*15.5	*18.8	**7.2
PE, BHAR		**17.8*	**27.3*	**26.7*	**13.9*	**15.9*	***7.5*
CTAR and BHAR (%) without underpricing							
Equal weighted							
NPE, CTAR		*2.68	*3.96	*3.58	-0.06	***-1.97	***-4.76
NPE, BHAR		**2.07*	***2.40*	***2.15*	*-1.96*	****-3.87*	***-6.66*
PE, CTAR		**1.89	*3.82	**3.99	1.78	***3.62	2.87
PE, BHAR		****1.32*	***2.76*	****2.40*	*0.14*	*1.75*	*3.20*
Value weighted							
NPE, CTAR		*2.24	*4.08	**3.34	**-2.83	**-4.35	*-9.45
NPE, BHAR		**1.57*	**3.80*	**3.15*	****-2.73*	****-4.12*	**-8.30*
PE, CTAR		*1.71	*8.08	*9.05	***-1.86	***-1.82	**-6.87
PE, BHAR		***1.41*	**8.03*	**7.55*	*-2.26*	*-0.42*	****-6.58*

* Significant at 1% **Significant at 5% *** Significant at 10%

4.4.3 Discussion of robustness

Before commenting on the findings from the CTARs, let us quickly review the purpose of this section. We want to ensure that the results are still valid and accurate even if the assumptions behind the calculation methodology are violated. While the violations are theoretically accommodated using the Barber, Lyon and Tsai (1999) methodology, we wanted to ensure that other methods would yield approximately the same results i.e. confirm that the methodology actually did properly dealt with the issues.

First, we wanted to confirm that the overall results are valid and abnormal returns exist. The most significant remaining measure that could reduce the robustness of the BHAR results was the cross-sectional dependency issues, hence the application of CTARs. CTARs however have the issue of non-robust t-stats, which we accommodate by using a t-stat based on robust standard errors. The logic here is that if the estimators of standard deviation are robust and two methodologies with different assumptions yield the same results and accuracy measures, the results should be pretty solid and reliable.

We spent several months collecting, sorting and checking data as well as running BHAR regressions. So when the CTARs approximately confirmed our findings it was a moment of joy.

Overall we find the results are very similar. The returns vary with up to 2 percentage points for longer holding periods, but given the large volatility of IPO returns, we interpret the results as close. Not only are the trends the same, the significance levels for the returns are the same for most periods and exhibit only few outliers. The only large difference in conclusion, is that equally weighted portfolio of NPE-backed IPOs appears to have significantly positive 12-month returns on a 10% significance level using the CTAR methodology, whereas the BHAR methodology shows it is not significantly larger than zero (t-stat of 1.2).

The conclusions from the BHARs that we can confirm with the CTARs are as follows. Abnormal returns are significantly positive for almost all holding periods and across groups for offer price investors. For non-offer price investors however, returns are not significantly positive for all holdings periods above 4 month and significantly negative for all holdings periods above 6 months. Moreover, PE-backed IPOs on average have lower 1-3 month returns, almost equal 3-6 month returns and larger 9-12 month returns than their NPE counterparts.

Based on this, we view the overall conclusions drawn from the BHARs as robust.

5. Discussion and analysis of abnormal returns

After having evaluated the robustness of the overall BHAR results, we now discuss the main drivers of abnormal returns. It is not a discussion in the original sense of the word, but rather an extended analysis to prove and disprove casual relations between variables. Since we have a large data foundation, it makes more sense to find statistically significant relations rather than focusing on verbally discussing results.

The objective of this section is thus to evaluate how each variable group affects the overall results and to determine which variables can help in predicting abnormal returns. We will be addressing the following key issues for both NPE and PE backed IPOs:

- Are abnormal returns consistent across years?
- Are abnormal returns consistent across industries?
- Are abnormal returns different across book-to-market and size groups?
- Which operational characteristics can be used as predictors for abnormal returns?
- How does trading volume and bid-ask spreads explain performance differences?
- Which combination of the abovementioned factors best explain returns?
- And ultimately, does performance differ between PE and NPE-backed IPOs?

In order to answer these questions, we look at average return charts, descriptive statistics and perform statistical tests in the form of logistic regressions. One of the key issues is saying something about these variables, while properly accounting for correlations. For instance, we found it was close to impossible to determine anything statistically significant regarding industry and year on the same time and even less on the differences between ownership groups.

One of the reasons is that IPO returns are incredibly volatile and it thus requires a large number of observations to be of statistical significance on a group level. Another reason is that we already adjusted the returns for all the conventional risk factors leaving only unexplained returns i.e. alpha values. If we were to find that one factor consistently explained the abnormal returns, we could potentially have discovered the basis for a new asset pricing models for at least IPOs.

This scenario is possible, but honestly quite unlikely. Instead we focus on identifying the variables that are significant in explaining returns and see how they perform in relation to each other. Using the most influential of these variables to form groups, we apply a matched-firm approach to check for relative performance and evaluate the quality of our risk-adjustments i.e. regressions.

5.1 Variable definitions

In order to statistically examine and check the robustness of the variables, individually as well as together, we use logistic regression. Instead of listing the variables every time we conduct a regression, we instead provide you with an overview.

First, we transform all the cumulative BHARs into binomial variables. As it was almost impossible to predict actual returns with any respectable degree of certainty, we define the BHARs as either positive or negative and instead use descriptive statistics to evaluate the level of returns.

With underpricing

$Z_1 \sim b(n,p) = 21\ day\ abnormal\ return$

$Z_2 \sim b(n,p) = 42\ day\ abnormal\ return$

$Z_3 \sim b(n,p) = 63\ day\ abnormal\ return$

$Z_4 \sim b(n,p) = 125\ day\ abnormal\ return$

$Z_5 \sim b(n,p) = 187\ day\ abnormal\ return$

$Z_6 \sim b(n,p) = 249\ day\ abnormal\ return$

Without underpricing

$Z_7 \sim b(n,p) = 21\ day\ abnormal\ return$

$Z_8 \sim b(n,p) = 42\ day\ abnormal\ return$

$Z_9 \sim b(n,p) = 63\ day\ abnormal\ return$

$Z_{10} \sim b(n,p) = 125\ day\ abnormal\ return$

$Z_{11} \sim b(n,p) = 187\ day\ abnormal\ return$

$Z_{12} \sim b(n,p) = 249\ day\ abnormal\ return$

For the explanatory variables, we selected 21 variables that we had data on and that was likely to do well in explaining the abnormal returns. Some of the variables were not normally distributed at first, which is why they have been transformed logarithmically:

Categorical variables

$X_1: PE\ ownership\ (Yes/No)$

$X_2: Book - to - market\ (Low, Mid, High)$

$X_3: Size\ (Large\ /\ Small)$

$X_4: Debt\ (Yes/No)$

$X_5: IPO\ year$

$X_6: Exchange\ (NASDAQ/NYSE)$

$X_7: Industry$

$X_8: EBIT - margin\ (Low, Mid, High)$

$X_9: Lockup\ period\ (90/180\ days)$

$X_{10}: Headquarters\ (US/Foreign)$

Continuous variables

$X_{11}: Underpricing$

$X_{12}: Assets\ (LN)$

$X_{13}: Market\ value\ of equity_{t=1}$

$X_{14}: Debt - to - assets\ ratio$

$X_{15}: Debt - to - equity\ ratio$

$X_{16}: Capital\ raised\ (LN)$

$X_{17}: Revenue\ (LN)$

$X_{18-19}: EBIT\ and\ EBITDA - margin$

$X_{20}: Average\ bid - ask\ spread\ (\%)$

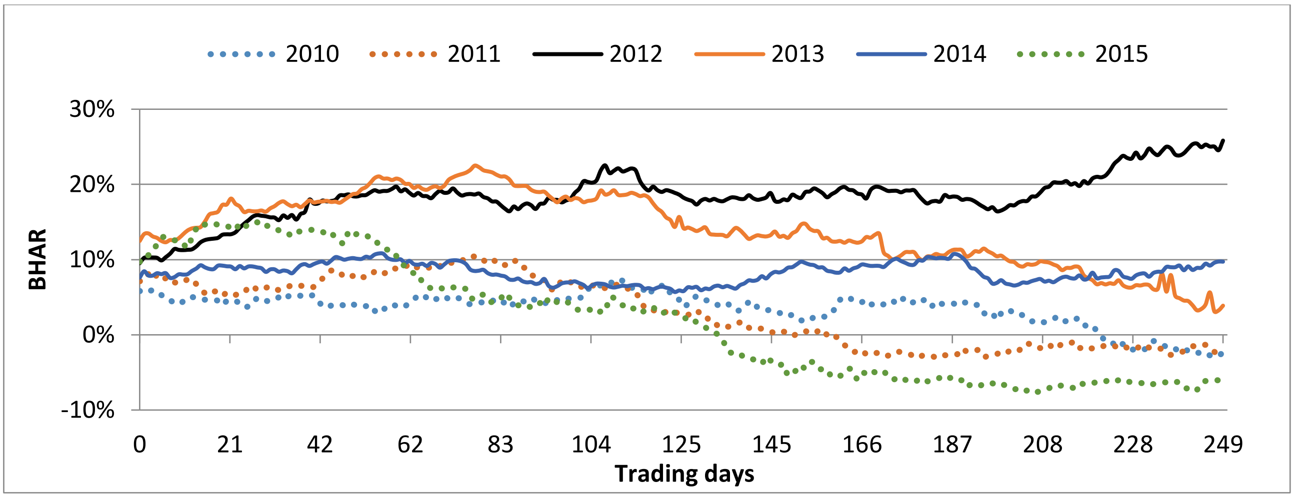
$X_{21}: Number\ of\ employees$

5.2 Abnormal returns by year

To ensure that abnormal returns are not confined or driven by a single year, we now investigate the abnormal returns on an intra-year basis. We do not examine value-weighted portfolios, as the sample size is reduced into such small groups that the relative weighting of a few companies in each years bias the results heavily. Results for the value-weighted BHARs and respective t-stats are however still attached in appendix H-J for the interested reader.

The following graph provides an overview of the BHAR distribution by year and holding period. Dotted lines represent years where the 1-year BHAR is negative.

Figure 5.1: Equal-weighted BHARs by year



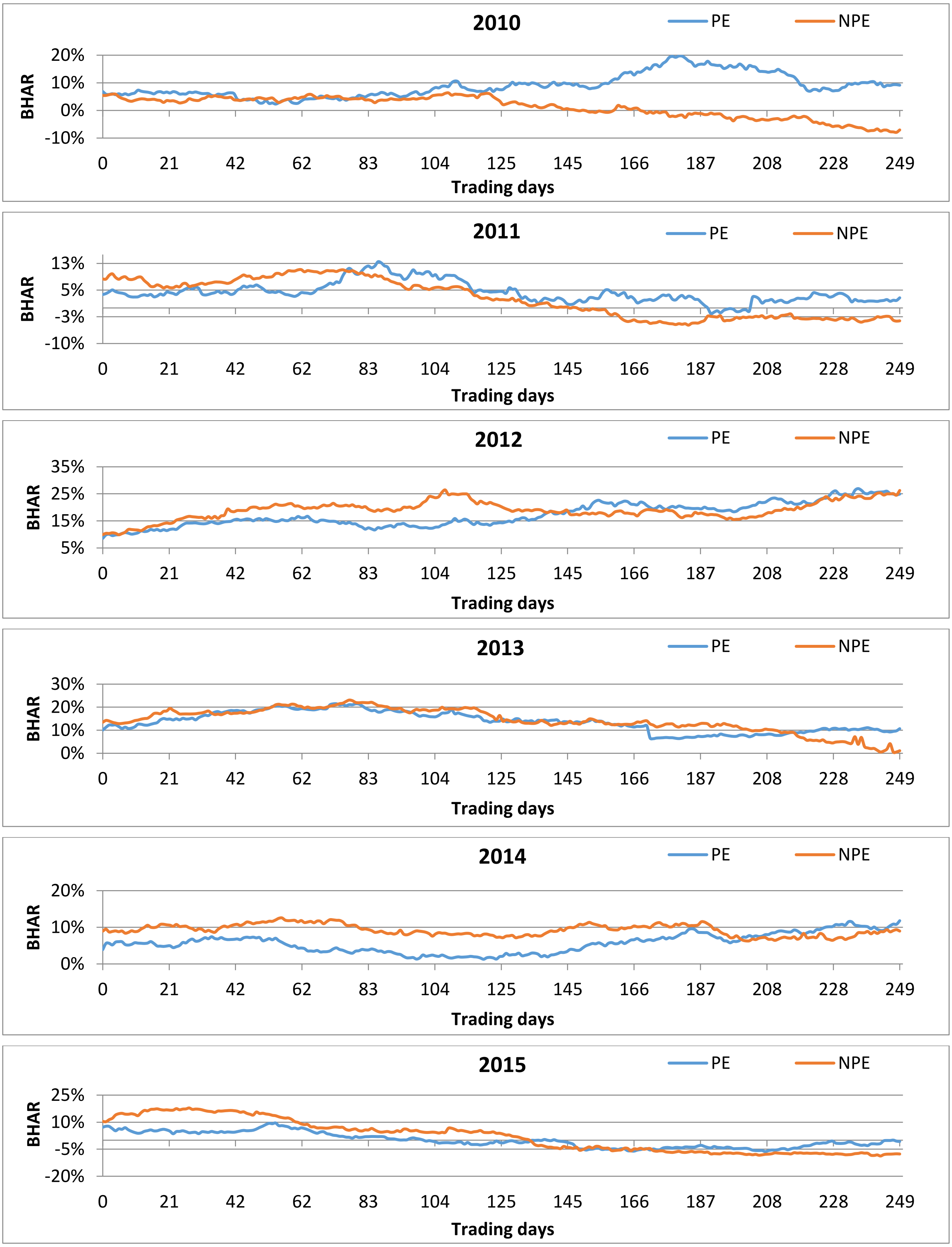
The spread between positive and negative years is well balanced. Overall we see a small correlation between the BHARs and the market (SP500) performance in four out of six years. The actual level of performance is not directly correlated, but we generally see that IPOs in years with relatively high levels of market performance also are the years with positive abnormal returns.

There is no doubt that 2012 is a driver for abnormal returns for the sample as a whole, but bear in mind that returns only comprise 130 IPOs (12.8% of total sample). More influential is 2013 (21.6%) and 2014 (26.1%), which both have positive abnormal returns.

Another interesting observation is that there are no clear correlation between performance and underpricing. In other words, years with high underpricing are not necessarily the years with high levels of abnormal returns. The same is true about SP500 performance and underpricing

To further investigate effects, we now focus on relative performance for each year. The next page provides return charts for each year for PE as well as NPE-backed IPOs.

Figure 5.2: Equal-weighted BHARs by year and ownership



The first 6 months of trading are analyzed without underpricing as offer price investors are not allowed to sell their shares until the end of the lock-up period. We refer to appendix I for statistics and appendix L for visualizations for returns without underpricing.

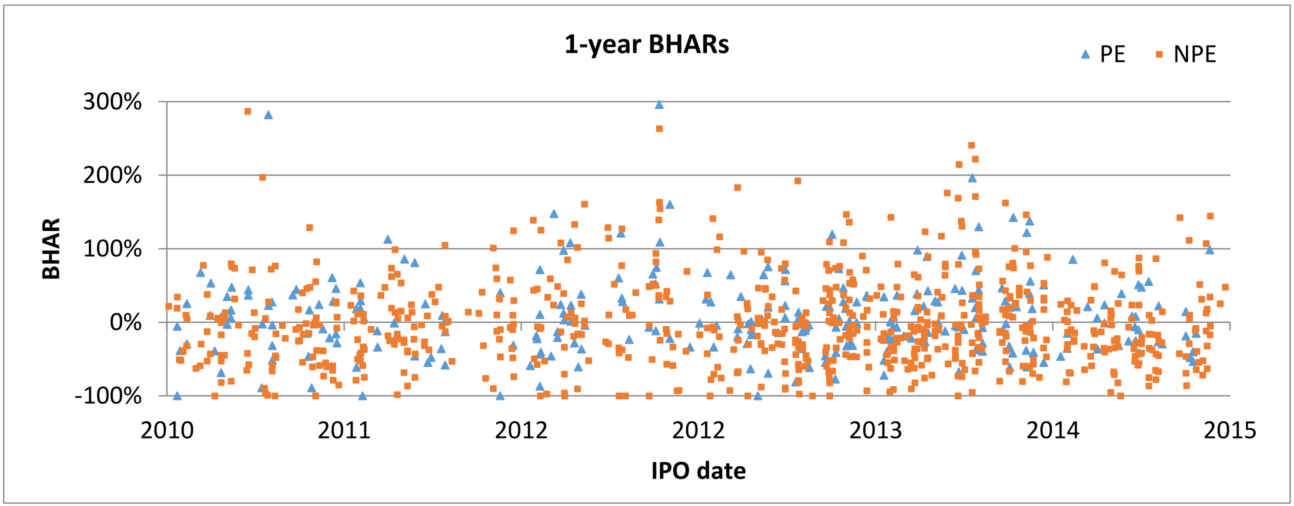
Overall, there is no significant difference across the years in the first 6 months of trading without underpricing. The only noticeable difference is that PE-backed IPOs performance slightly better in 2011, whereas NPE-backed performs slightly better in 2012. We must however conclude that there is no significant difference for non-offer price investors between the two groups the first 6 months.

Even though the average 6-month BHAR (with underpricing) on a year-by-year basis is higher for NPE-backed entities, we cannot reject that the BHARs are statistically different from each other in any other year than 2014.

Since there are no obvious differences on a 6-month or smaller basis, we now turn towards the 6-12 month aftermarket performance. With respect to the 6-month starting point (level of returns), PE-backed IPOs appears to exhibit relative superior performance. The overall trend in the 6-12 month performance is that the NPE-backed IPOs on average flat line, whereas the PE-backed IPOs have a slightly positive trend.

Before checking the statistical significance, we now look at the 1-year BHARs visualized.

Figure 5.3: Scatter plot of 1-year BHARs by IPO date



We removed 7 extreme positive outliers to smooth the graph, but the overall conclusions remain the same as year and IPO performance does not seem to correlate significantly. To be statistically certain, we now perform a final robustness check in the form of logistic regression.

The following table reports statistics for the binary dependent variables Z_1-Z_{12}. The event of interest is defined as positive abnormal returns. In essence, we evaluate the statistical properties and model fit for the logistic regression models based on year as the sole independent variable.

Table 5.1: Logistic regression model properties, X = year

Trading day holding period	**21**	**42**	**63**	**125**	**187**	**249**
With underpricing						
Goodness-of-Fit*	0.019	0.025	0.027	0.020	0.016	0.011
Wald test**	0.001	0.001	0.001	0.013	0.007	0.002
Percentage of sample correctly classified	56.71	57.50	57.87	56.69	56.81	54.77
Without underpricing						
Goodness-of-Fit*	0.029	0.018	0.034	0.024	0.026	0.012
Wald test**	0.001	0.022	0.000	0.000	0.000	0.000
Percentage of sample correctly classified	58.10	56.44	58.61	57.17	56.55	55.33

* McFadden's pseudo R^2 : Values between 0-0.2 indicates poor fit, 0.2-0.4 good fit, 0.4+ equals exceptional fit

** Wald test for global null hypothesis: Beta = 0, Low p-value indicates global p-value different from zero i.e. variable has an effect

The table indicates that year as a stand-alone explanatory variable provides for a poor predictive model. The variable itself is however significantly different from zero i.e. it does have a small effect and slightly improves the prediction rate. Knowing the empirical distribution, we would expect 50% of the classifications to be correct at random. Using the year variable, we can instead correctly predict ~55-58% of the observations. The conclusions did not change significantly when excluding underpricing from the analysis.

We inspected the models' individual parameters i.e. the coefficient and prediction rate for each year. We found that the only two years where the variable helped in categorising returns with any respectable (<10%) significance level was 2010, where returns are significantly negative, and 2012 where returns are significantly positive. The coefficients were however extremely low, and did not seem to have a large impact, which is also exemplified by the prediction rates.

Finally, we must conclude that even though a few years are significant and the model beta overall is different from zero, the BHARs are not driven by a single year in the sample. This is based on the fact, that year only increases the prediction rate incrementally and may become insignificant as soon as we take other factors into account. We find this to be true across all holding periods.

5.3 Abnormal returns by selected industries

This brings us to the question if performance varies across industries. The logical and obvious answer is that it should. The business environment is unique within each industry and subject to different regulations, valuation levels, competitive environments and performance depend on different macroeconomic factors. Moreover, business cycles differ and this problem becomes especially relevant since the sample period is only five years long.

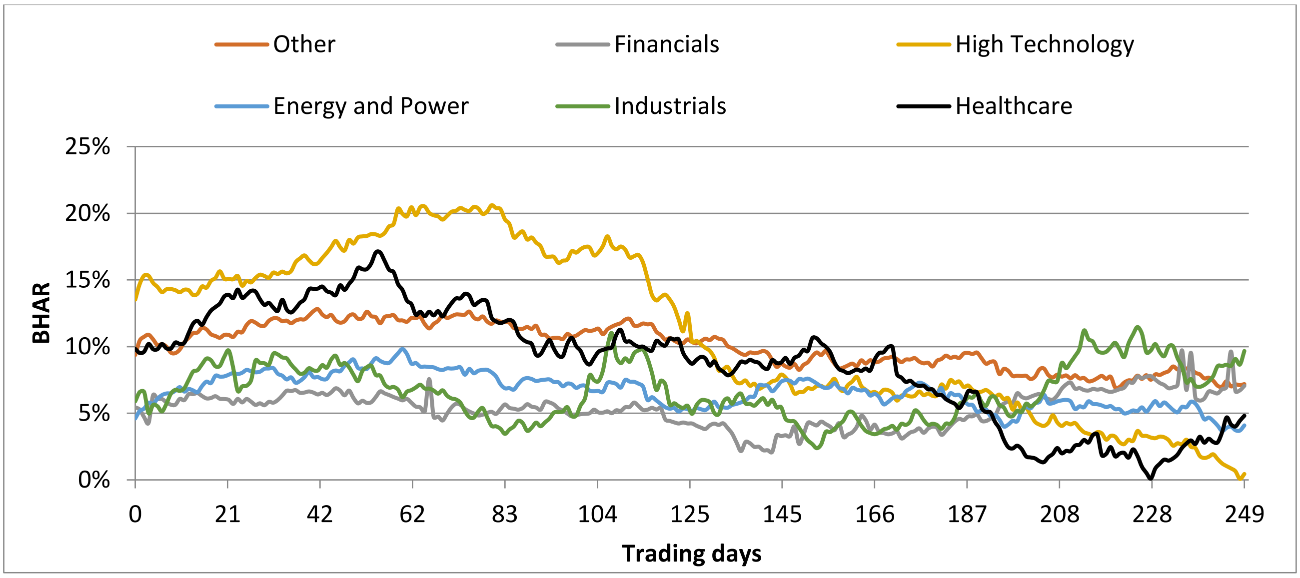
We quickly found that industry effects were small as these were mostly accommodated by the regression market betas. Moreover, we found that when dividing IPOs into samples based on both industry and ownership, the volatility became extremely high. In other words, due to the small size of the subsamples, we were not able to determine anything statistically significant and thus refrain looking at industry effects specific to pre-IPO ownership.

The reason industry effects are hard to prove is that they are complex and affect virtually every aspect of businesses. While one might have an idea or qualified guess on which industry will do well in the future, it is much more difficult to predict how valuations within that industry are going to be. For instance, the high technology will most likely perform very well in the next decade, but if valuations are too inflated due to high expectations, the returns will not properly reflect the industry performance. This suspicion was also confirmed when we looked at the sample returns.

Recall from section 4.1.3, that the five largest industries comprised 76% of the total IPO sample and that the PE sample was more diversified in terms of industries. The five industries are Healthcare (251), High Technology (189), Financials (160), Energy & Power (101) and Industrials (71). We discovered that the prediction power slightly increase defined all other industries into a new category: Other. This is partly to simplify the analysis, but mostly due to that the amount of IPOs are limited in some industries making a comparison inaccurate.

To answer these questions and concerns, we use the same two-step analysis as when looking at abnormal returns across years. First, we look at the descriptive statistics, graphs and t-tests. This gives a pretty intuitive and visual way of identifying anomalies and evaluating relative performance. Secondly, we verify the results by examining the prediction power of industry as an explanatory variable in a binomial logistic regression model.

Figure 5.4: BHARs by industry



The graph shows that no industry appears to be driving the BHARs. Almost every single industry incurs abnormal returns in the first 3 months of trading, followed by an underperformance in the remainder of the year. While High Technology and Healthcare appears to be main drivers of the 3-months BHAR trend, this is not the case. Without underpricing, we see that the trend is not confined to these industries, but simply appears to be more significant due to the underpricing. Moreover, the overall trend of underperformance seems to be valid within almost all industries i.e. they have lower 1-year BHARs than their starting point. This trend again becomes especially clear, when looking at the performance without underpricing (Appendix N).

There really is not much to say about industries as they appear to confirm the overall findings of the BHARs. There are no hard outliers other than underpricing, which seems to be higher in industries with higher market betas. Moreover, the returns appear to normalize during the one year measuring period. In short, the volatility is so high on an inter-industry basis that we cannot detect consistent i.e. significant differences even for the more extreme deviations such as industrials versus high technology.

Other authors that have analysed industry effects on IPOs are also left to contemplating and seem to largely disagree on the subject. Madura and Johnston (2006) found that firms are more likely to go public within an industry when prospects are good and valuations high. On the other hand, Michala (2016) found no evidence of industry specific overvaluation when examining IPOs for the period 1975-2013. To make sure, we now run robustness check using logistic regression.

The following table reports statistics for the binary dependent variables Z_1-Z_{12}. The event of interest is defined as positive abnormal returns. In essence, we evaluate the statistical properties and model fit for a logistic regression model based on industry as the sole independent variable.

Table 5.2: Logistic regression model properties, X = Industry

Trading day holding period	**21**	**42**	**63**	**125**	**187**	**249**
With underpricing						
Goodness-of-Fit*	0.022	0.020	0.018	0.014	0.020	0.021
Wald test**	0.108	0.148	0.190	0.408	0.270	0.113
Percentage of sample correctly classified	57.17	56.74	56.43	55.35	55.85	56.98
Without underpricing						
Goodness-of-Fit*	0.007	0.017	0.018	0.021	0.027	0.026
Wald test**	0.897	0.262	0.501	0.128	0.031	0.030
Percentage of sample correctly classified	53.73	55.82	55.13	56.83	56.65	57.85

* McFadden's pseudo R^2 : Values between 0-0.2 indicates poor fit, 0.2-0.4 good fit, 0.4+ equals exceptional fit

** Wald test for global null hypothesis: Beta = 0, Low p-value indicates global p-value different from zero i.e. variable has an effect

The table shows the industry beta coefficient is not significantly different from zero for 10/12 instances. Moreover, the model fit is poor implying that industry is not a good stand-alone predictor of abnormal returns for IPOs in the period.

The conclusion changes slightly, when underpricing is left out of the analysis. For holding periods of 9 and 12 months, the beta is significantly different from zero i.e. industry does have an effect. The model fit and prediction rates do however confirm that the effect is very small.

In inspecting the individual industry model parameters, we found that no individual industry for any holding period was significant on 10% or lower significance level. Overall we simply have to conclude, that industry is a not a good predictor of abnormal returns. Even though the previous analysis showed, that some industries on average incurred abnormal returns, the volatility among firms within the industry is too high to predict anything consistently. In conclusion, while certain industries may perform better, the overperformance is not statistically significant once returns have been adjusted with their respective market betas.

5.4 Abnormal returns by book-to-market and size

Since year and industry had no significant effect on abnormal returns, we now turn to proxies for size and value versus growth firms. These variables have been shown by Fama French to be a significant explainer of returns, but we may find that this is still the case after making risk-adjustments i.e. the premiums or betas are not accurate for our sample. We address the issue of creating our own sample benchmark premiums in section 3.3.4. i.e. eliminating the effects from our sample and also explain why this would be wrong in terms of creating a comparable benchmark.

This analysis is quite extensive as we found these two variables to be good predictors of abnormal returns. To isolate effects, we first look at book-to-market ratio, secondly size and finally the two factors combined. Within each category, we also inspect group differences for NPE and PE-backed entities.

5.4.1 Book-to-market effects

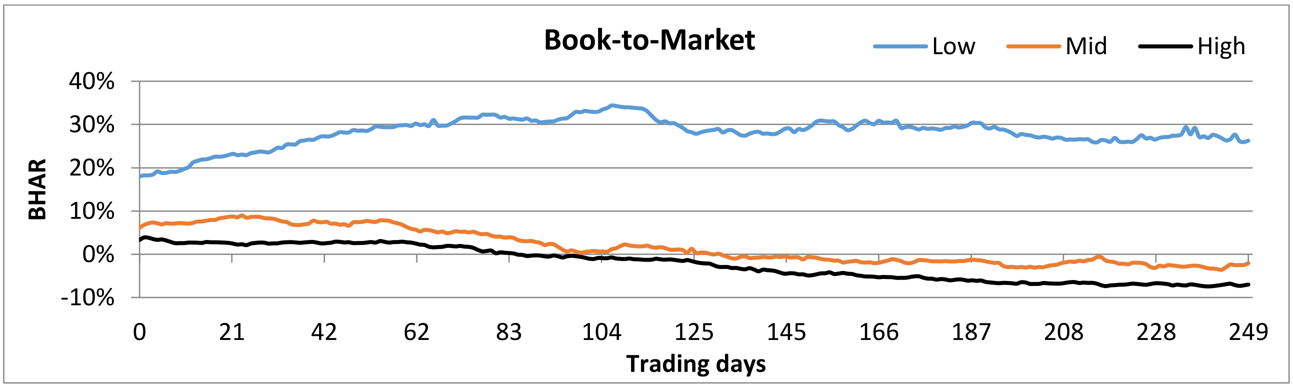
To examine book-to-market ratios, we follow the approach originally used to determine the value premiums as laid out by Eugene Fama (1998). We divide the total sample abnormal returns into three subsamples based on book-to-market ratio percentiles.

The actual calculations of the book to market ratio is based on the IPO filing book value and the first available market capitalisation i.e. the end of first day market cap.

Table 5.3: Book-to-market group descriptive statistics

Book-to-market	Percentile	Ratio interval	Average book-to-market	Standard deviation
Low (growth firms)	70 - 100	0.0 - 0.2x	0.10	0.06
Mid	30 - 70	0.2 - 0.5x	0.33	0.10
High (value firms)	0 - 30	0.5 - 5.0x	0.96	0.46

Figure 5.5: BHARs by book-to-market values



BHARs are on average much higher for low book-to-market firms i.e. growth firms. It is however worth noting, that two-thirds of the abnormal returns are due to underpricing and the remainder of abnormal returns are created in the first 3 months of trading. We also see that the mid and high book-to-market portfolios underperform throughout the year with 1-year BHARs of -2.49% and -7.19%, respectively. This is somewhat to be expected as this aligns very well with the overall previous findings of the thesis and what other researchers have found to be generally true for IPOs i.e. general underperformance.

As described earlier in the thesis, underpricing is a difficult element to justify and analyze. Therefore, we mostly focus on the 10% abnormal return created within the first three months for low book-to-market companies. To answer if this makes any rational sense, we must look towards risk. Specifically, two questions are relevant:

- How does our risk model(s) handle the first 3 months?
- If not, what risk not captured by the model can justify 3-month BHARs of 10%?

Our risk model does not perform well in the first 3 months of trading. This was showed by the CTAR model, where we found very low coefficients of determination (R^2) for any holding period less than 6 months. Moreover, the sheer fact that returns are so high in BHARs approach confirms that the risk model does not properly account all the risk unless investors are extremely irrational.

While we do concur that the stock market is not as efficient as many like to believe i.e. investors are irrational, we find it unlikely that average 3-month returns of approximately 10% are simply due to market inefficiencies. Furthermore, this trend is on average only present for the low book-to-market companies – so we ask ourselves, what risks are more prominent in growth firms relative to other firms in the time following an IPO?

It is a difficult question to answer, but we argue that the transition to being public owned company involves a higher degree of transparency and publicity for most firms. The time up to the first quarterly reporting involves a lot of uncertainty in terms of how the company handles the increased administrative workload and also the pressure on management to deliver results. But again, why is the risk more prominent in growth firms? We scoured the literature for answers, but found that all studies on major IPO trends either focused on the issue of underpricing or long run returns. We could literally not find a single piece of literature that explained this 3-month trend for growth firms. Therefore, we turn to speculation in order to answer this anomaly.

Our hypothesis is that growth firms are generally more difficult to value. This is because most of the valuation is based on profits many years after the IPO i.e. more heavily discounted cash flows. This means that a small change in the factors that affect perceived risk, affect the valuation of the stock relatively more than value firms. Consequently, changes in how the stock is perceived have the potential to influence the price to a larger degree than value firms.

As a consequence, we believe that the 3-month trend is based on momentum caused by the growth stocks being hyped among investors. We earlier saw that the trend is more common in value weighted portfolios i.e. more prominent in larger IPOs. We later get back to investigating size effects, but hypothesize that these large growth IPOs are more prone to hype leading to momentum.

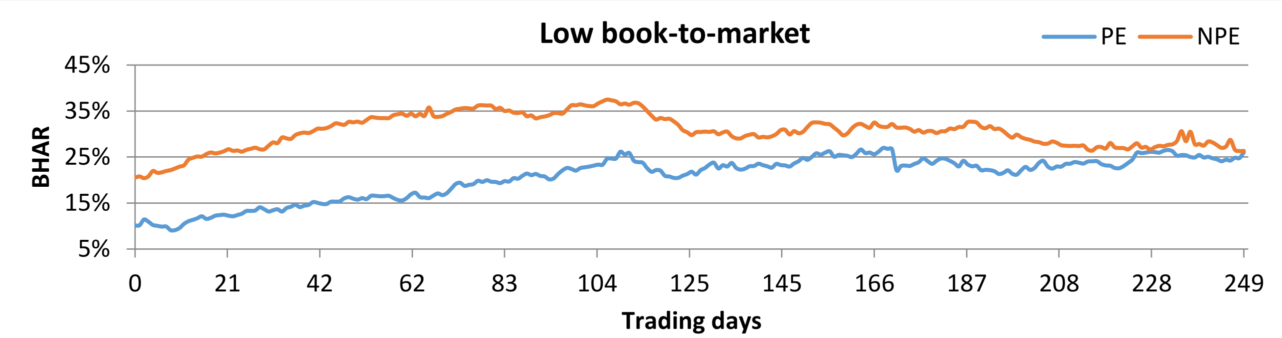
Think about it for a second. The companies are large cap firms (>USD 500m), very well known by investors, often even before they were listed. Moreover, their value is heavily dependent on how risky the investors perceive the stock to be. Basically, it is a stock receiving a lot of attention due to a large capital injection that will hopefully help it realize its growth potential. It is easy to see why this might influence investors to being overly optimistic in the beginning. We cannot properly explain why this stops after 3-month, but maybe the first quarterly reporting serves as a tangible wake-up call, or maybe the hype just wears off after 3-months. This is all speculative, but hype leading to momentum in the stock during the first 3 months somewhat aligns with the momentum measured by the CTAR model and also makes sense, as the trend is more prominent in larger and thus better-known IPOs.

However, no matter what is causing the abnormal returns, we cannot identify any risk(s) that can justify average 3-month BHARs of 10% i.e. annualized abnormal returns of 46.5%. Therefore it must follow that investors are exhibit irrational behaviour during this period in the aftermarket. Nonetheless, non-offer price investors that invested in growth IPOs in the period incurred large 3-month abnormal returns.

While the trends are pretty clear for each book-to-market group, we speculate that these trends may vary across PE and NPE-backed IPOs.

In order to examine differences between PE and NPE, we now divide the 3 portfolios: high, mid, low book-to-market values into PE and NPE subsamples. We quickly go over the results, i.e. summarize the most important points and then after analyzing each group, we draw overall conclusions for offer and non-offer price investors.

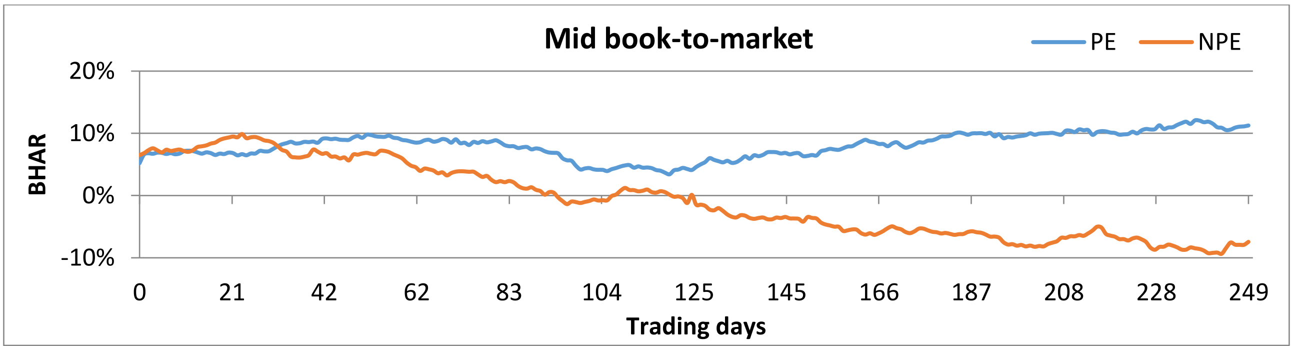
Figure 5.6: Low book-to-market BHARs by ownership



We see that growth firm within both groups have large abnormal returns. NPE-backed IPOs does however on average perform slightly better at all times. The trends are approximately the same in the first 6 months after listing, and the differences in returns are solely caused by underpricing. After 6 months, the PE-backed entities continues to sore, while the NPE-backed entities underperform.

Without underpricing, we see that the PE-backed entities outperform the NPE-backed entities with an average of 10% (Appendix P). In fact, we cannot statistically reject that the NPE-backed entities actually exhibit abnormal returns for holding periods above 10 months (Appendix O & P).

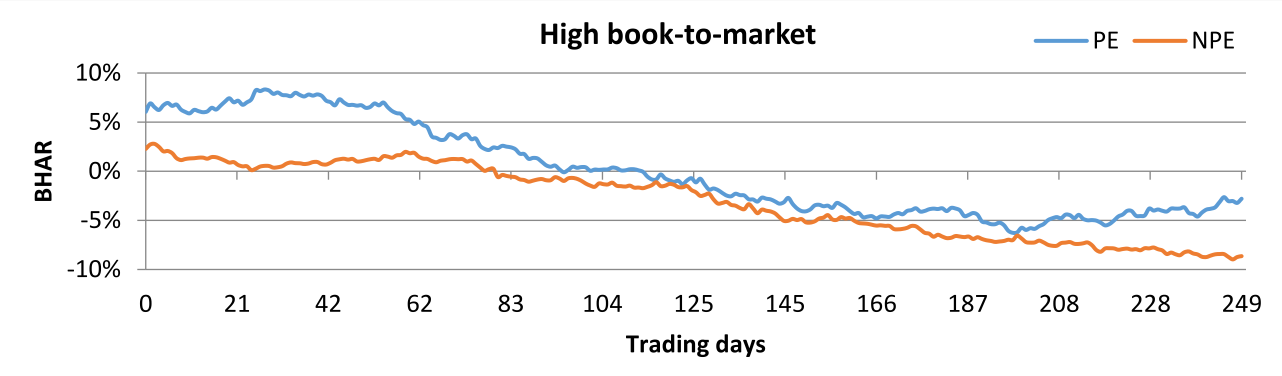
Figure 5.7: Mid book-to-market BHARs by ownership



As we saw earlier, the mid book-to-market portfolio on average underperforms. There are however difference across ownership groups. The trends are similar to the low book-to-market portfolio, but appear more significant due to equal underpricing (~6.5%). Basically, the two groups are statistically indifferent up until the 6-month point, hereafter the PE-backed IPOs overperform their counterparts significantly.

Finally, for holding periods above 7 months the PE-backed IPOs exhibit significantly larger returns (Appendix O & P).

Figure 5.8: High book-to-market BHARs by ownership



In relation to the value firms, we see a significant long-run underperformance. While the two groups may appear different, they are actually insignificantly different from each other when adjusted for underpricing. In short, both are bad investments for longer periods with average abnormal returns either insignificantly different from zero or significantly negative (Appendix O & P).

In summary, there are large differences between group performances within the three book-to-market portfolios.

For offer price investors, the overall conclusions in relation to NPE-backed IPOs have not changed by looking across ownership groups. Low book-to-market companies are the only companies that on average incur abnormal returns and this is largely due to the first three months in the aftermarket. The level of abnormal performance in the growth firms is superior in NPE-backed IPOs and this is true for all holding periods. The inspection of ownership groups did however change the conclusions for the mid book-to-market portfolio. Within the mid group, NPE exhibited significant underperformance, while PE-backed IPOs significantly overperformed the benchmark. Finally, both high book-to-market ownership groups underperformed significantly.

For non-offer price investors the conclusions for the low book-to-market portfolio changed relative to offer price investors. Without underpricing, the low book-to-market ownerships groups are now the same up until the 9-month mark. However, for holding periods above 9-months the PE-backed entities on average exhibit 10% larger BHARs (significant at 5%) than their NPE counterparts.

We can conclude that book-to-market values appears to have a significant effect on abnormal returns. In order to examine this statistically, we now turn towards logistic regression.

As a final check to confirm the effects from the overall book-to-market groups, we now perform a logistic regression for the dependent variables Z_1-Z_{12} with book-to-market group as the sole independent variable. We do not examine PE effects until later as other factors may influence results leaving the PE-factor redundant i.e. any conclusions drawn could be invalid for now.

Table 5.3: Logistic regression model properties, X = Book-to-market

Trading day holding period	**21**	**42**	**63**	**125**	**187**	**249**
With underpricing						
Goodness-of-Fit*	0.035	0.040	0.029	0.031	0.047	0.044
Wald test**	0.001	0.001	0.001	0.001	0.001	0.001
Percentage of sample correctly classified	59.0%	59.2%	57.5%	57.2%	59.1%	59.2%
Without underpricing						
Goodness-of-Fit*	0.003	0.004	0.014	0.008	0.015	0.023
Wald test**	0.339	0.251	0.005	0.045	0.003	0.002
Percentage of sample correctly classified	52.4%	52.8%	54.9%	55.1%	55.4%	56.9%

* McFadden's pseudo R^2 : Values between 0-0.2 indicates poor fit, 0.2-0.4 good fit, 0.4+ equals exceptional fit

** Wald test for global null hypothesis: Beta = 0, Low p-value indicates global p-value different from zero i.e. variable has an effect

While book-to-market alone provides for a poor predictive model, it is still a better estimator than year and industry, accordingly. Overall we can confirm that the effect is present except for a 1-2 month holding period for non-offer price investors i.e. return without underpricing.

The reason that the model does not score any higher in goodness of fit and classification rates is that the only significant model coefficient is the low book-to-market category. Since we are classifying the returns as either negative or positive, and the average for mid and high book-to-market portfolios are only slightly lower than 0, the concordance rate for these groups are low. Moreover, the differences between these two groups were insignificant i.e. odds ratio was insignificantly different from 1. In other words, if the IPO does not have a low book-to-market ratio, the model does a poor job in discriminating between positive and negative returns. However, the low book-to-market odds ratio in respect to both the mid and high book-to-market portfolios was 2.4. Basically, if the IPO has a low book-to-market value, the likelihood of abnormal returns increases with 140%. We now move onto size effects before finally looking at book-to-market and size together.

5.4.2 Size effects

In section 4.3 we found that large IPOs performed relatively better than small IPOs as measured by market capitalisation (value-weighted portfolios). For this reason we now examine the returns based on size groups and across ownership groups. To give you a clear picture on why we believe this variable is relevant even after adjusting for size premiums, take a look at the following table.

Table 5.4: BHARs by first-day market capitalisation

Abnormal returns (%)	# of IPOs	Underpricing	1	2	3	6	9	12
			NPE					
5-50m	78	1.2	-2.9	-6.0	-12.8	-17.9	-25.9	-27.5
50-200m	169	1.7	3.5	-0.5	-3.3	-8.9	-15.1	-17.1
200-500m	180	7.6	10.0	10.9	10.7	6.4	4.5	2.3
500-1500m	206	17.4	22.7	27.0	30.1	26.7	30.2	25.6
+1500m	108	17.1	21.2	23.2	26.2	22.3	20.0	15.1
			PE					
5-50m	5	28.2	27.2	20.5	11.1	4.4	-5.6	-6.8
50-200m	24	2.8	1.0	0.2	-5.4	-10.3	-13.9	-10.5
200-500m	46	3.9	2.3	2.1	1.3	-4.4	-6.9	-5.9
500-1500m	105	6.6	6.7	7.6	7.9	7.6	9.2	13.5
+1500m	93	8.3	14.3	18.7	19.8	18.1	23.6	22.3

As the table shows, the overall trend is that larger market cap typically means higher returns. We do not draw any conclusions from PE-backed IPOs (5-50m) as the portfolio only contains 5 IPOs.

For NPE-backed IPOs, offer price investors on average had positive abnormal returns for IPOs larger than USD 200m and heavily negative returns for smaller size groups (Recall, that offer price investors can only realize the returns after 6 months). Conversely, the companies with market caps above USD 500m on average had large positive returns. The majority of the returns are however caused by heavy underpricing but are nonetheless still prominent throughout the year.

The PE-backed IPOs exhibit many of the same overall trends, however slightly different and less volatile across groups. Offer price investors on average only had positive abnormal returns for companies larger than USD 500m. It is however the really large PE-backed companies that provided investors with really large returns. This is somewhat surprising, as the trend was different for the NPE-backed IPOs. The reason is that the underpricing is significantly lower for this group, ultimately causing the difference in relation to NPE-backed IPOs. Specifically, the larger PE-backed firms (USD +500m) underprice 2-3x less than their NPE counterparts. This implies that for the typical offer price investor, that exits the stock after 6 months, the large NPE-backed IPOs on average provides a relatively better investment.

But what about you, me and all the investors who usually cannot get a seat at the discounted offer price table? Without underpricing the conclusions dramatically change.

For the NPE-backed IPOs, we see large abnormal returns in the first 3 months of trading. The trend is especially prominent in IPOs with a market cap + USD 500m, but even the USD 200-500m have abnormal returns of 2-3% for short holding periods. For longer holding periods i.e. 6-12 month the average abnormal returns are negative for 4 out of 5 NPE size groups. The only NPE group that on average still provide abnormal benefits for the non-offer price investors are the companies with a market cap between USD 500-1,500. While the return is significantly different from 0 and average 8-15% throughout the year, we see that the abnormal return is created within the first three month and do not increase for 6-12 month holding periods.

For PE-backed IPOs the conclusions does not change significantly as the underpricing is less severe for this group. Bigger is still better and it is only the companies above USD 500m in market cap that have abnormal returns for longer holding periods. The trends differ from the NPE-backed IPOs as abnormal returns are more evenly spread out over the year and not confined to the first 3 month. This is especially true for the USD 500-1,500 group and to a lesser degree for the USD +1,500m PE-backed IPOs. These findings are also consistent with what Cao & Lerner found in 2009 for the 2000s.

In summary, larger companies equal higher abnormal returns for our sample. For NPE-backed IPOs the abnormal returns are largely driven by underpricing i.e. it only benefits offer price investors. In contrast, PE-backed entities are less underpriced but incur abnormal returns on a more consistent basis throughout the year.

While large companies generally perform very well and provide investors with large abnormal returns, smaller companies heavily underperform the benchmark. The consistent underperformance displayed by IPOs with a market capitalisation by less than 500m is in alignment with former research conducted (Brav and Gompers, 1997). They discussed the probability of smaller IPOs being affected by investor sentiments. Specifically, they argued that institutional investors retain from holding shares in small companies due to the fact that it potentially will make them a large block-holder within that firm. As a consequence the majority of shareholders are typically relatively less informed private investors, which in term makes the pricing of that stock less efficient and accurate i.e. more volatile.

We do to some extent agree with these findings. However, we also argue that larger IPOs are less risky investments partly due to pre-IPO ownership length and information quality. Intuitively larger companies typically have a longer track record (i.e. it takes time to grow big), which makes it easier for investors to accurately value the company.

To evaluate the statistical properties and effects from size, we turn to logistic regression and run regressions on size as the sole explanatory variable for the response variables Z_1-Z_{12}.

Table 5.5: Logistic regression model properties, X = Size

Trading day holding period	**21**	**42**	**63**	**125**	**187**	**249**
With underpricing						
Goodness-of-Fit*	0.105	0.121	0.137	0.075	0.096	0.074
Wald test**	0.001	0.001	0.001	0.001	0.001	0.001
Percentage of sample correctly classified	65.8%	66.6%	67.4%	62.9%	64.8%	62.8%
Without underpricing						
Goodness-of-Fit*	0.041	0.045	0.100	0.048	0.064	0.044
Wald test**	0.001	0.001	0.001	0.001	0.001	0.001
Percentage of sample correctly classified	59.3%	59.9%	64.6%	60.1%	61.8%	60.1%

* McFadden's pseudo R^2 : Values between 0-0.2 indicates poor fit, 0.2-0.4 good fit, 0.4+ equals exceptional fit

** Wald test for global null hypothesis: Beta = 0, Low p-value indicates global value different from zero i.e. variable has an effect

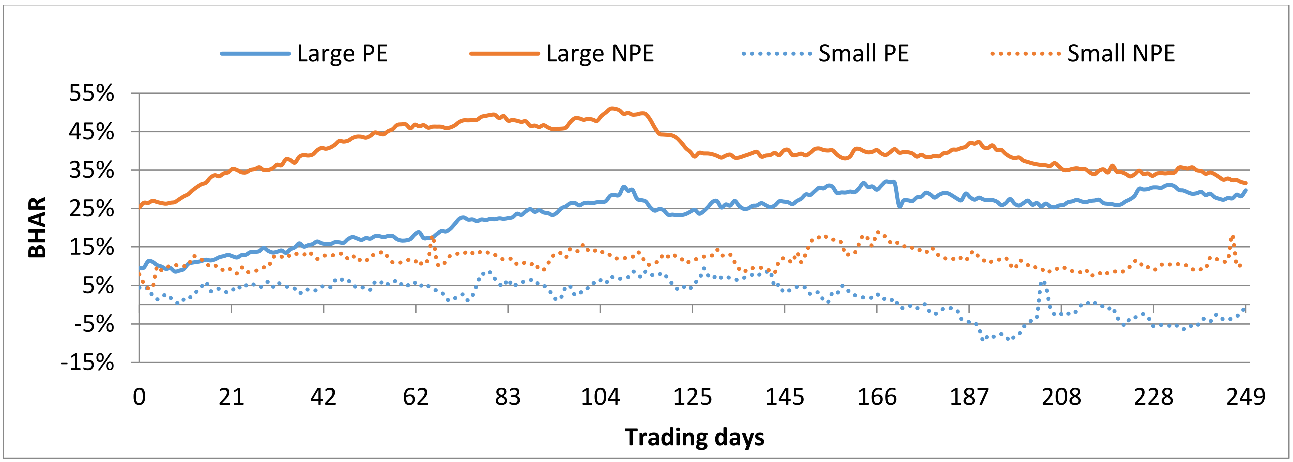
While the size variable is a bad model fit, it is far better than year, industry and book-to-market as an individual variable. Moreover, size provides for the best predictor of abnormal returns with classification rates well above 60% for the majority of the dependent variables. The variable is also significant for all holding periods with and without underpricing respectively. We later inspect the odds ratios in conjunction with other parameters, but can confirm that the larger the company, the more likely the observation is to have a positive abnormal return.

5.4.3 Combined effects

During the data exploration, we found that some of the best predictors of abnormal returns were book-to-market ratio and size in conjunction. In the previous sections we saw that individually, none of them provided for a good model, but still correctly classified approximately 60% of the IPOs correct. Size performed relatively better as an explanatory variable, but overall we find that the two parameters together provides for better predictive model.

However, when combining the two variables, we found that both the visual inspection and the predictive models became better when simplifying the size variable. In other words, since we are examining trends between PE and NPE as well as book-to-market and size, the amount of IPOs in each group became too small when using the size groups applied in last section. Instead, as the overall trend of returns being either averagely positive and negative revolves around the USD 500m mark, we design the size variable to reflect this i.e. large (+USD 500m) and small (<USD 500m).

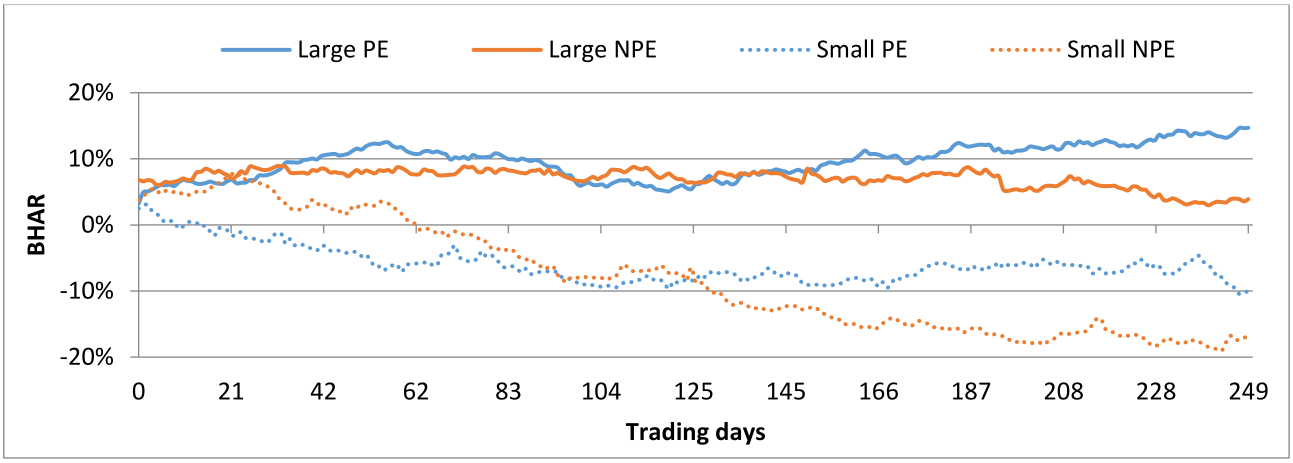
Figure 5.9: Low book-to-market BHARs by size and ownership



We see that large IPOs are the main driver of abnormal returns for the low book-to-market portfolio. Among the large IPOs, NPE-backed performs significantly better, however this is largely due to underpricing.

In contrast, the small IPOs exhibit significantly smaller BHARs. One of the more surprising discoveries is that the small PE-backed entities with low book-to-market ratios significantly underperform the other groups and becomes significantly negative after 7 months. We also see that the conclusion in regards to BHARs being created in the first 3-month is primary driven by large NPE-backed IPOs. Overall, this confirms what we found in the size and book-to-market, but illustrates that this is true on an intergroup level.

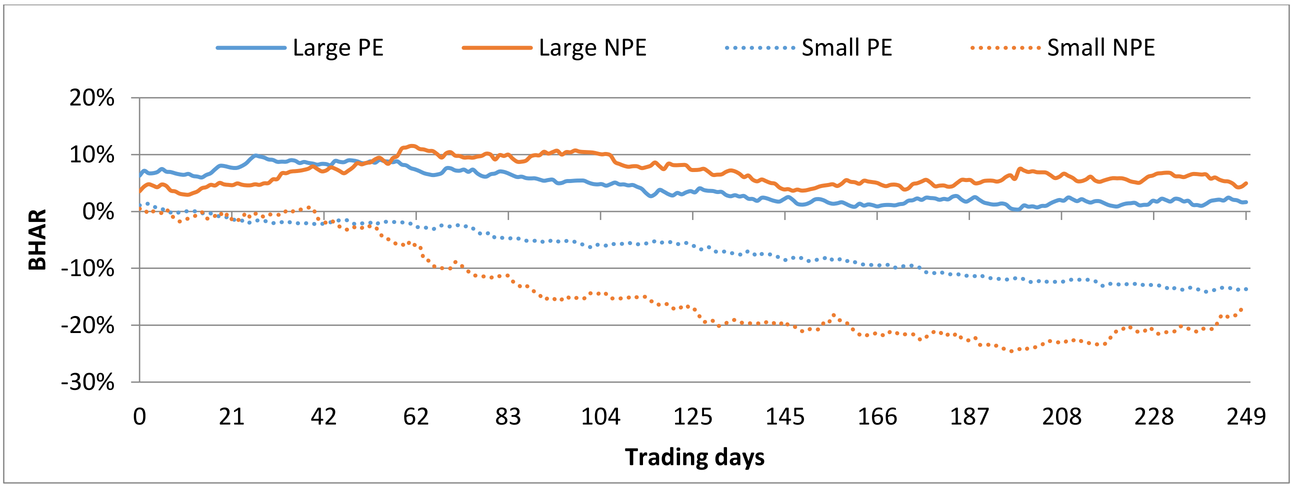
Figure 5.10: Mid book-to-market BHARs by size and ownership



The mid book-to-market portfolio provides an interesting twist in conclusions. We see that the underperformance is primarily driven by small NPE-backed IPOs. While the small PE-backed IPOs still significantly underperform their benchmark, the relatively performance is significantly better.

In contrast, the large IPOs display the opposite behavior. Large NPE-backed IPOs pretty much flat line for the entire year and actually underperforms relative to their initial underpricing. This is not true for the PE-backed entities that exhibit abnormal returns in the first 3 month and again from 6-12 months. Again, we can confirm the overall intergroup tendency of small companies driving the negative returns and large companies incurring significantly positive returns.

Figure 5.11: High book-to-market BHARs by size and ownership



In the high book-to-market portfolio we see a rather steady performance by the larger entities, while the smaller IPOs display exceptional poor performance for all holding periods. None of the large groups are significantly different from zero i.e. they approximately perform the same as the benchmark. The large underperformance by high book-to-market firms is seen to be largely driven by the small firms.

In summary, there are significant differences in performances between the three book-to-market portfolios on an intergroup level.

Many of the same conclusions from the stand-alone size and book-to-market effects are still present. Regardless of ownership groups, large IPOs outperform their smaller counterparts significantly in all three portfolios. Moreover, value firms and growth firms still exhibit opposite behaviour i.e. the low book-to-market IPOs significantly overperform and the high book-to-market underperform.

For the low book-to-market portfolios almost no new conclusions arose from combining the factors. The only large difference is that we see small NPE-backed IPOs outperforming their benchmark. This is sharp contrast to earlier studies that documented that the overall underperformance of IPOs was driven by exactly this group (Brav & Gomper, 1997).

In relation to the mid book-to-market group we earlier saw an average performance. A key insight from the combined groups is that the average underperformance is actually driven only by small companies. Both small PE and NPE-backed IPOs underperform, however the underperformance is more severe in the NPE-backed entities. It should be emphasized that the performance differences are only present after 6 months and that both size groups exhibit the same behaviour up until that point.

For the high book-to-market portfolio, we see that the same conclusions are true. The underperformance observed in section 5.4.1 is driven only by small companies, and while the large IPOs abnormal returns are not significantly from zero, they on average beat their benchmark. An interesting observation is also, that the small entities in the high book-to-portfolio is the only group that does not underprice their IPOs. Overall, it is also the worst performing group. This aligns very well with the theory laid out by Allen and Fauhaber (1989) that argued that companies that underprice signal quality. Their argument was that only good firms underprice, as these are the only companies able to regain the cost of underpricing their IPO. Thus, implicitly they are saying that if a firm does not underprice, it is likely to perform poorly and this is also what we are observing.

We later return to the overall discussion of underpricing and performance, but now turn to investigate the new and improved logistic model for predicting positive abnormal returns.

The following table reports statistics for the binary dependent variables Z_1-Z_{12}. The event of interest is defined as positive abnormal returns. In essence, we evaluate the statistical properties and model fit for the logistic regression model based on book-to-market and size groups.

Table 5.6: Logistic regression model properties, X_1 = Size and X_2 = Book-to-market

Trading day holding period	21	42	63	125	187	249
With underpricing						
Goodness-of-Fit*	0.113	0.128	0.135	0.084	0.110	0.095
Wald test**	0.000	0.000	0.000	0.000	0.000	0.000
Percentage of sample correctly classified	68.90	69.80	70.10	66.40	67.50	67.01
Without underpricing						
Goodness-of-Fit*	0.042	0.045	0.099	0.050	0.066	0.095
Wald test**	0.000	0.000	0.000	0.000	0.000	0.000
Percentage of sample correctly classified	61.60	62.10	67.00	62.40	64.30	63.30

* McFadden's pseudo R^2 : Values between 0-0.2 indicates poor fit, 0.2-0.4 good fit, 0.4+ equals exceptional fit

** Wald test for global null hypothesis: Beta = 0, Low p-value indicates global p-value different from zero i.e. variable has an effect

After combining the factor, we see that we still cannot properly explain the returns as the model fit is poor for all holding periods. We see that the goodness of fit is relatively better regressed against the returns with underpricing, ultimately implying that there is a correlation between size, book-to-market and underpricing. We will later get back to this issue and for now focus on these two factors.

Overall, there is only a marginal improvement in the prediction rate. Looking at the returns without underpricing, remember that book-to-market could predict an average of 55% and size approximately 60%. Together they now average 63%, implying a small correlation between the two factors. Still, it is a better model with the factors combined and we later find that these two factors are the superior predictors with the exception of underpricing.

Again, we refrain from looking at maximum likelihood estimates and odds ratios until later sections, as these may significantly change when other factors are included in the model. Instead, we now turn to looking at other operational characteristics.

5.5 Abnormal returns by selected operational characteristics

This section focuses on operational characteristics and in sharp contrast to the previous sections, we do not examine descriptive statistics. During the process of analysing operational characteristics, we found it did not make sense to divide the sample into groups formed on these typically continuous variables. Instead, we focus on logistic regression models for the dependent variables Z_1-Z_{12}.

Other studies have found significant evidence on abnormal returns in relation to operational characteristics (Brav & Gompers, 1997; Levis, 2011). This is interesting, as we identified large differences across operational characteristics between our two sample groups (PE/NPE). It was found that PE-backed IPOs have been larger during the period as measured by most operational characteristics (see section 4.1.4). While we do not examine the differences in prediction power on a PE/NPE group level, the conclusions drawn in this section are later used to draw inferences between the two groups.

There are many issues related to investigating the effects of operational characteristics. For instance, certain characteristics might be specific to certain industries or periods. This begs the question; is it the operational characteristics the reason for the abnormal returns or is it due to the industry? In other words, which came first: The chicken or the egg? Moreover, operational characteristics are to a higher degree reflected in many company valuations. Investment bankers typically apply the book-building, DCF and the enterprise value multiples approach when valuating companies. These fundamental valuation approaches are often based on expectations to future operational characteristics or other fundamentals. While market and industry conditions are difficult to accurately predict, persistent historical operational characteristics are often a better indicator for future performance and are relatively easier to predict. Due to this hypothesis, we had no expectations of finding significant correlations between operational characteristics and abnormal returns going into the analysis.

We also change the framework of the analysis slightly from the last couple of sections. In this section, when analysing returns we add a variable for underpricing. The reason is that earlier, the effects from underpricing were reflected in the differences between the models with and without underpricing. However, in this section we run stepwise regressions with backwards elimination on all operational variables and select the best model. Thus, correlation between variables affects the models to a much higher degree and ultimately makes it much more difficult to distinguish between the effects from underpricing and factor correlations.

The variables used in the initial model (before removing non-significant variables) is revenue, EBITDA-margin, EBIT-margin, capital expenditures, total assets, total debt, debt-to-assets ratio, debt-to-equity ratio, capital Raised, book value of equity, number of employees and underpricing.

Logically, certain variables correlated heavily with the previous size and book-to-market categories. For instance, the market cap of an IPO often correlates with value of assets and number of employees, whereas a high book/market value of equity correlates with the book-to-market values. As a consequence, the focus in this section is on the relationship between variables and their relative impact on abnormal returns.

Table 5.7: Logistic regression model properties, All significant operational variables

Trading day holding period	**21**	**42**	**63**	**125**	**187**	**249**
With underpricing						
Goodness-of-Fit*	0.434	0.310	0.275	0.182	0.162	0.136
Wald test**	0.001	0.001	0.001	0.001	0.001	0.001
Percentage of sample correctly classified	85.80	80.00	77.50	72.50	70.50	68.60
Without underpricing						
Goodness-of-Fit*	0.021	0.056	0.067	0.066	0.093	0.091
Wald test**	0.001	0.001	0.001	0.001	0.001	0.001
Percentage of sample correctly classified	57.20	62.20	62.30	63.80	64.70	65.50

* McFadden's pseudo R^2 : Values between 0-0.2 indicates poor fit, 0.2-0.4 good fit, 0.4+ equals exceptional fit

** Wald test for global null hypothesis: Beta = 0, Low p-value indicates global p-value different from zero i.e. variable has an effect

The overall model fit is much better than previous models for the returns with underpricing. The reason is that we include underpricing in the model as a variable, thus explaining large parts of the early stage returns. As the holding period increases, the overall model becomes worse in predicting abnormal returns and approaches the regression models for return without underpricing.

If not for the underpricing, we see that the models are of poor fit. While the prediction rates are slightly better than book-to-market and size regressions, we find only very small effects from variables such as debt and investment (CAPEX). The reason for the increased prediction rates is ultimately that we also include variables such as total assets, that proxy for the market size variable.

5.5.1 Models with underpricing

In the models with underpricing we only look at holding periods above 6 months, as the returns cannot be realised until the end of the lockup period. In total, we found 5 variables that were significant at a 5% level and display the odds ratio for these below.

Table 5.8: Odds ratio

Odds Ratio Estimates and Wald Confidence Intervals									
Effect	**125-day**			**187-day**			**249-day**		
	Odds	**95% limits**		**Odds**	**95% limits**		**Odds**	**95% limits**	
Underpricing	43.2	18.4	98.2	16.6	7.9	35.0	7.5	3.9	14.5
Assets (LN)	1.7	1.4	2.0	1.7	1.4	2.1	1.9	1.6	2.3
Capital raised (LN)	0.7	0.5	0.8	0.7	0.5	0.8	0.6	0.5	0.7
Debt-to-equity ratio	0.8	0.7	1.0	0.7	0.6	0.9	0.8	0.7	0.9
Capital expenditures (LN)	0.9	0.9	1.0	0.9	0.9	1.0	0.9	0.8	1.0

The odds ratio truly confirms how important underpricing is for offer price investors. While it is less significant for longer holding periods, we still see it being 4 times as important as size in prediction positive abnormal returns for a one holding period. In short, it makes every other factor seem more or less redundant. The only issue with the variable as a predictor is however that it is difficult to know the underpricing beforehand, even though industry and size may give a good indication of the level of underpricing.

The second largest predictor is assets. This is not surprising as it is a proxy for size, which was previously determined to the best predictor of abnormal returns not accounting for underpricing. We see that even when the underpricing element is taking into account, the variable is still significant and performs better in explaining returns than all other operational variables.

More surprising is the negative effect from capital raised. The larger the IPO in terms of capital raised, the smaller is the chance of incurring a positive abnormal return. Previous studies (Brav, Geczy and Gompers, 2000) have found that the reason for IPO underperformance is among other factors rooted in inefficient use of the money raised from the IPO. This could explain the negative correlation between the amount of money raised and aftermarket performance. We also speculate that other factors such as competition for the stock at offer price could have an effect. When raising a large amount of capital you ultimately need more investors. More investors cause increased competition, which ultimately results in investors bidding at a lower price than they would if the IPO was less competitive.

The final two coefficients, debt-to-equity ratio and CAPEX are extremely close to 1 implying a very small correlation. For both variables, an increase results in a decrease in the probability of incurring abnormal returns. The debt ratio makes a little sense, since increased debt levels ultimately increases the chance for a firm to come in financial distress. The investment proxy, CAPEX, does however not seem rational and we simply cannot explain this trend. The effects are however so close to zero, that we can ignore them for now and wait and see if they appear in the models that include all variables discussed in the thesis.

5.5.2 Models without underpricing

Table 5.9: Odds ratio without underpricing

Odds Ratio Estimates and Wald Confidence Intervals									
Effect	**63-day**			**125-day**			**249-day**		
	Odds	**95% limits**		**Odds**	**95% limits**		**Odds**	**95% limits**	
Assets (LN)	1.5	1.3	1.8	1.6	1.4	1.9	1.9	1.6	2.2
Underpricing	2.0	1.1	3.7	NA	NA	NA	0.5	0.3	1.0
Capital raised (LN)	0.8	0.6	0.9	0.7	0.6	0.8	0.6	0.5	0.7
Debt-to-equity ratio	0.9	0.8	1.0	0.8	0.7	0.9	0.8	0.7	0.9
Capital expenditures (LN)	NA	NA	NA	0.8	0.7	0.9	0.9	0.9	1.0

The only variable where the odds ratio changed significantly is the underpricing variable. Hence, we only comment on this. We expected it to become insignificant as it was no longer a part of the returns. This did not happen. Earlier, we saw that large and underpriced IPOs exhibited high abnormal returns during the first 3 months. This can explain why we are seeing a positive correlation with the underpricing variable for 63-trading days. Finally, the variable has the opposite effect on 249-day abnormal returns. We speculate that heavily underpriced IPO investors may sell their shares after the lockup period ends to realise their returns, which ultimately means the market is getting flooded with shares causing the price to drop causing negative 249-day correlation. We later investigate this by looking and trading patterns and find compelling evidence of this.

5.6 Predictive alpha models

Before moving onto other discussions, we wanted to come up with the best predictive model for abnormal returns based on the data available and the results from earlier regressions.

We first tried predictive linear regressions, but it quickly became clear that trying to determine the exact level of returns was close to impossible. The best models had R^2s of 0.07-0.1 and the explanatory variables were highly volatile in terms of which holding periods they were significant for. Instead, we continue our focus on determining whether or not an IPO has a positive return any at given point in time. To examine, we run logistic regressions model with all the independent variables defined in section 5.1. for the dependent variables Z_1-Z_{12}.

$$LN\left(\frac{P_{Z_n}}{1+P_{Z_n}}\right) = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 \ldots \beta_{21} X_{21}$$

Using a stepwise regression with backward elimination in SAS, we find the best model fit for each holding period for returns with and without underpricing, respectively. Variables are removed from the model at a significant level of 10% and added back if it becomes significant at any point during the selection process. Next, we analyse trends across the models and show selected models and their predictive properties on the following pages. We should issue a warning though, since the numbers have already been Fama French adjusted which explained 92% of the returns, we are down to alpha values. We are basically left with the cream of the cake and there is a lot more random to it than we would like to admit. Instead, we focus on which relative variable effects and discuss the overall model quality.

In section 5.4, we identified both size and book-to-market as significant variables. Moreover, it was found in section 5.5 that the underpricing variable, certain debt variables and capital raised also provided for good predictors of abnormal returns. So these are essentially the variables we expect to be significant. We want to emphasize, that except for the underpricing variable, we only use data from the IPO filing document or information that could easily be predicted before the IPO. For instance, we argue that it should be possible to predict the size and book-to-market group. Using the offer price and number of shares planned issued in the IPO filing document, the approximate market cap and capital raised can be estimated. On the next page you will find an overview table describing the best model for each holding period by examining the model fit, the number of variables used and the concordance rate i.e. c-stat for each model.

Table 5.11: Logistic regression model properties, X_1-X_{21} = All variables

Trading day holding period	**21**	**42**	**63**	**125**	**187**	**249**
Positive observations	633	597	429	491	531	564
Negative observations	381	417	585	523	483	450
Positive of total sample (%)	62.4	58.9	42.3	48.4	52.4	55.6
Model characteristics						
Goodness-of-Fit*	0.45	0.32	0.29	0.25	0.22	0.21
Wald test**	0.001	0.001	0.001	0.001	0.001	0.001
Number of variables used in model	3	4	4	4	5	5
Percentage of sample correctly classified	86.6	82.2	79.2	74.5	73.3	73.1
Without underpricing						
Positive observations	486	490	508	563	578	601
Negative observations	528	524	506	451	436	413
Positive of total sample (%)	47.9	48.3	50.1	55.5	57.0	59.3
Model characteristics						
Goodness-of-Fit*	0.05	0.07	0.12	0.10	0.14	0.17
Wald test**	0.001	0.001	0.001	0.001	0.001	0.001
Number of variables used in model	2	3	3	3	5	4
Percentage of sample correctly classified	63.0	66.6	70.7	68.6	71.3	72.5

* McFadden's pseudo R^2 : Values between 0-0.2 indicates poor fit, 0.2-0.4 good fit, 0.4+ equals exceptional fit

** Wald test for global null hypothesis: Beta = 0, Low p-value indicates global p-value different from zero i.e. variable has an effect

The only models that provide a good fit are models that include underpricing as an independent variable. We saw it in the section 5.5 and find that this also holds true when other variables are included.

For models with underpricing the predictive power decreases over time and the opposite is true for the models without underpricing. In essence, the models converge as underpricing becomes less significant as it constitutes a lower percentage of the overall return.

Moreover, we see that as time goes by the number of variables in the models increase i.e. returns gets more difficult to predict and we need more information to classify them correctly. Essentially, the effects from some variables become more pronounced over time, making them significant.

The table should give you an initial insight into the overall properties and trends of the models. We do not see the need to comment further and instead want to show you a few selected models.

5.6.1 Models with underpricing

For models with returns including underpricing, we only look at 6-12 months holding period models as returns usually cannot be realised until the end of the lock-up period. While the underpricing is not predictable, we still include it as an independent variable to accommodate the impact on other variables. Moreover, investors should have at least an approximate guess on the discount they are receiving. Basically, if you are bidding on an IPO, you can compare your own valuations to the initial offer price, size, industry and the underpricing on comparable IPOs to come up with a reasonable estimate.

We do not show the maximum likelihood estimates as these provide very little intuitively interpretable information for you as a reader, due to the nature of logistic regressions. All variables are significant at a 5% level, so instead we focus on the relative effects measured presented as odds ratios (see section 3.4.2 for interpretation help). NA implies that the variable was not significant in the model at a 10% level or lower.

Table 5.12: Odds Ratio Estimates and Wald Confidence Intervals

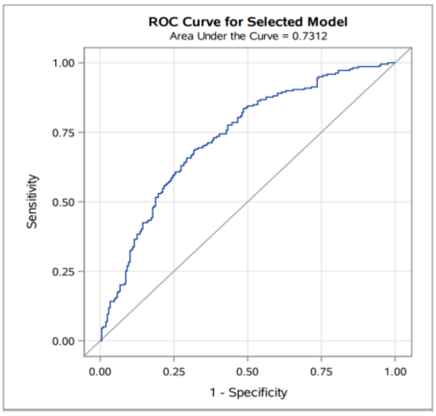
Variables	125-day			187-day			249-day		
	Odds	95% limits		Odds	95% limits		Odds	95% limits	
Underpricing	26.3	11.3	60.9	7.8	5.4	10.4	4.8	2.4	6.6
Size $5-50m vs > $1500m	0.1	0.0	0.4	0.1	0.0	0.2	0.0	0.0	0.2
Size $50-200m vs > $1500m	0.2	0.1	0.5	0.1	0.0	0.3	0.1	0.1	0.3
Size $200-500m vs > $1500m	0.3	0.1	0.8	0.3	0.1	0.5	0.3	0.2	0.6
Size $500-1500m vs > $1500m	0.6	0.3	0.9	0.5	0.2	0.8	0.5	0.3	0.8
Book-to-market ratio	0.8	0.6	0.9	NA	NA	NA	NA	NA	NA
Book-to-market: High vs Mid	NA	NA	NA	0.7	0.6	0.8	0.6	0.5	0.8
Book-to-market: Low vs Mid	NA	NA	NA	1.6	1.1	2.2	1.7	1.2	2.4
Debt: N vs Y	NA	NA	NA	NA	NA	NA	0.4	0.3	0.6
Debt-to-assets ratio	NA	NA	NA	0.4	0.2	0.9	NA	NA	NA
Capital Raised (LN)	0.6	0.5	0.7	0.6	0.5	0.8	0.6	0.5	0.7

For all examined holding periods underpricing is by far the most significant variable with the largest effects. Logically, the more underpriced the IPO is the higher the chance that BHARs after 6, 9 and 12 months are positive. After a year the effects from underpricing are heavily reduced, but still, each 1 percentage point increase in underpricing raises the odds of incurring an abnormal return by a factor of 4.8. In other words, with a low degree of underpricing the likelihood of an IPO incurring a positive abnormal return is extremely low.

Moreover, size is relevant across all examined holding periods. We also see that the asset variable discussed in section 5.5 has become insignificant as we introduced other measures of size i.e. it did proxy for size. The odds ratios are all measured in relation to the largest IPOs (+USD 1,500m) and confirm that the larger the IPO, the larger the probability of incurring positive abnormal returns. Specifically, IPOs with a market capitalisation of less than USD 200m are 5-10 times less likely to have a positive abnormal return than the largest IPOs. Conversely, IPOs with market caps between USD 200-1,500m are 2-3 times less likely to have positive abnormal returns than the largest IPOs.

The book-to-market variable is also consistent across all three models. However, we see that this abnormality is better capture by a continuous variable in the short run and postpone discussions until the next section i.e. models without underpricing. Moving on to the debt variables, we see that they are inconsistent and the spread in confidence interval is large. However, when significant the message is pretty clear, the more debt you have the less likely abnormal returns are. The capital raised variable is in contrast relevant across all periods. The larger the IPO in terms of capital raised the smaller the probability of incurring positive 6-12 month abnormal returns. We already discussed the reasons in section 5.5.1, but can confirm that even when other variables are taken into account, it does still have a significant negative impact on returns.

As a final check for model fit, we inspect the ROC curve for the 249-day BHAR with underpricing. Since we report concordance rates the interesting observation is really the slope of the curve. Overall, the model seems to be equally specific and sensitive as the curve follow as approximately round curve. This means that the classification rate is consistent across negative and positive observations.



5.6.2 Models without underpricing

For the model for returns without underpricing we examine 63, 125 and 249 day models as the odds ratio and factors were approximately the same for 0-3 month, 3-6 month and 6-12 months, respectively. The models without underpricing have significantly lower prediction rates and all models provided for a poor model fit i.e. pseudo R^2 under 0.20.

Since the model fits are bad and prediction rates low, we largely focus on relative effects for variables. Again, all variables included in the model have significance levels above 5% and it makes no sense to show you maximum likelihood estimates as these provide no intuitive interpretable information. Thus, the focus remains on relative effects measured by odds ratios.

While the returns are without underpricing, we still include underpricing as it was earlier found to be a significant predictor (see section 5.5.2).

Table 5.13: Odds Ratio Estimates and Wald Confidence Intervals without underpricing

Variables	63-day			125-day			249-day		
	Odds	95% limits		Odds	95% limits		Odds	95% limits	
Size \$5-50m vs > \$1500m	0.2	0.0	0.6	0.1	0.0	0.3	0.2	0.1	0.7
Size \$50-200m vs > \$1500m	0.2	0.1	0.4	0.1	0.0	0.2	0.2	0.1	0.5
Size \$200-500m vs > \$1500m	0.4	0.2	0.8	0.2	0.1	0.8	0.4	0.2	0.8
Size \$500-1500m vs > \$1500m	0.5	0.3	0.9	0.4	0.2	0.6	0.7	0.3	0.9
Book-to-market ratio	NA	NA	NA	0.5	0.3	0.7	NA	NA	NA
Book-to-market: High vs Mid	NA	NA	NA	NA	NA	NA	0.4	0.3	0.5
Book-to-market: Low vs Mid	NA	NA	NA	NA	NA	NA	2.0	1.7	2.5
Debt-to-equity ratio	NA	NA	NA	NA	NA	NA	0.8	0.6	0.9
Assets (LN)	1.3	1.1	1.6	NA	NA	NA	1.8	1.4	2.3
Capital Raised (LN)	0.6	0.4	0.8	0.6	0.4	0.8	0.4	0.3	0.5
Underpricing (%)	4.6	0.9	22.3	NA	NA	NA	0.5	0.3	1.0

Overall the size variable is still the most influential and consistent variable for predicting abnormal returns. Not much have changed in terms of odds ratio, so the conclusion holds, the larger the market capitalisation of the stock the higher the probability of incurring positive abnormal returns. More surprisingly is that another proxy for size, total assets, has become significant. While is it not consistent across all models, it still has a small positive impact for abnormal returns on 63-days and a fairly large impact for 249-day returns. We speculate that the market capitalisation is not always a good measure of size as small growth companies can have a relative large market capitalisation. Thus, including the asset measure for size enhances the overall model, as companies with large market cap and assets better differentiate between small and large growth companies.

It is however weird, that we find that size is such a good explainer of abnormal returns without underpricing. In section 4.3.2, we discovered that the value-weighted BHARs without underpricing exhibited significant and relative more underperformance than the equally weighted counterparts. The reason for this trend is that the largest of our IPOs underperform and these receive significant weight in the value-weighted portfolio. Basically, a few of the really large companies underperform skewing the graph downwards, but ultimately the average trend for +USD 1,500m market cap IPOs is still a positive abnormal return. This is just to emphasize how careful you have to be with value-weighted portfolios and also supports our choice to mainly focus on equally weighted returns.

In terms of growth and value companies, we earlier (section 5.4) found that both with and without underpricing, the growth companies performed better. Again, we can confirm this trend by looking at the odds ratio. The variable is not present for the 63-holding period, but has a large effect in the longer term. We find that a continuous variable is better at explaining for 125-days, but this does not change any of the conclusions. Low book-to-market companies are 2 times more likely to incur positive abnormal returns than the mid book-to-market companies and 4 times as likely relative to high book-to-market companies.

The effect from debt variables is only present for 249-day holding periods, and is so small that we cannot in good conscious draw any conclusions from this. In contrast, the capital raised is significant and seems to have a relatively large effect and small standard deviation. Earlier, we argued that this was due to effects on competitiveness of the stock and due to the discounts varying depending on how much of the company is sold off.

We can again confirm that the underpricing is affecting the returns also for non-offer price investors. The conclusions from section 5.5.2 (stock dumping after lockup period) still hold as the odds ratio did not change after including other variables. Finally, we do not show the ROC curve for this model as it had exactly the same shape as for the model with underpricing. In essence, the models do equally well in classifying negative and positive observations.

5.7 Matched firm analysis

5.7.1 Performance assessment

Having determined which pre-IPO characteristics that are causing abnormal returns, we now turn towards a final benchmark methodology. The matched firm approach is popular among many researchers due to the intuitively appealing logic. It is similar to the multiple valuation methods employed in many banks and corporate finance departments. For each PE-backed IPO, we try to find the most comparable NPE-backed IPO and use this as a benchmark for performance. It is very important to note, that this benchmark is based on raw returns, rather than abnormal returns like the past couple of sections. For this reason, we can use it to evaluate the relative performance of size and book-to-market groups to make sure that wrong measurement of relative premiums are not biasing our conclusions from the BHARs.

The idea behind the method is that two firms with similar characteristics should have the same risk and thus the same required return. Using this logic, we match firms on five variables that each represents a type of risk. The exact cut-off limits may appear random, but represents the closest fit we could find given the empirical data.

- IPO date i.e. differences in macroeconomic conditions. Maximum spread = 4 months
- Same industry classification based on GIGS
- Same book-to-market decile. Maximum spread = 2 book-to-market decile
- Same size decile. Maximum spread = 1 size deciles

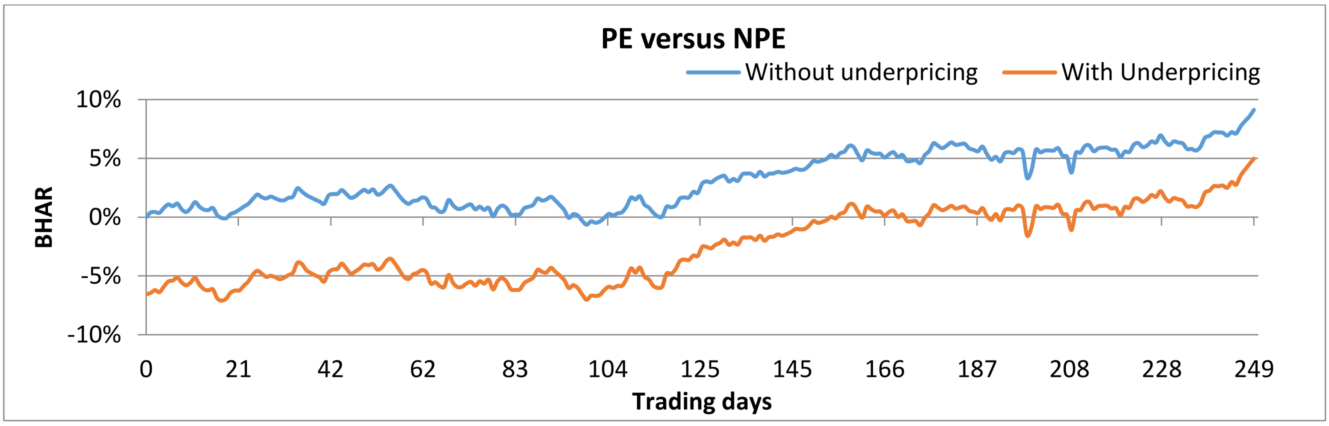
For the IPO date, the standard deviation is 26 trading days which means the matched IPOs are on average approximately 5 weeks apart. For the industry measure, it was possible to match all but two IPOs. For these two we instead chose an industry with similar beta. The standard deviation for the book-to-market decile and size deciles are 0.31 (3.1%) and 0.23 (2.3%), respectively. Overall we believe these variations to be very small which is ultimately due to the large sample size.

One of the advantages of this method is that it does not rely on beta estimates and premiums. A lot of the conclusions made with the BHAR methodology ultimately rest on the premiums and beta estimates to be accurate. While BHAR may provide for an unbiased estimate for the overall sample, individual groups may not be benchmarked correctly. For instance, if the BHAR is negatively biased for one group and positive for another they ultimately cancel each other out. However, when inspecting individual groups it may appear as one of the groups are over performing while the issue might as well be that the betas or premiums are not accurate for that particular group.

This issue is accommodated by the matching-firm approach which is why it can also be viewed a test for our results so far. The reason why this is so important is that the robustness checks made in each section i.e. the logistic regressions are also subject to measurement errors caused by the risk-adjustment. While it is very time consuming to identify matching firms and thus not suited for overall assessment of abnormal returns, it eliminates some of the IPO specific trends and allows of cleaner comparison. The model ultimately relies on the comparability in terms of risk of the matched firms.

We argue that a company matched on year, industry, book-to-market and size on average should be relatively similar in risk. One might be slightly more risky than the other and vice versa, but averaging across 274 IPOs, the benchmark should provide for a relatively unbiased biased estimator of risk. First, we let us evaluate the main problem statement, which is better PE or NPE?

Figure 5.12: Matched firms BHARs



Months after IPO	**1**	**2**	**3**	**6**	**9**	**12**
BHAR (%)	*-6.2	***-4.5	***-4.7	-2.5	0.4	***5.0
BHAR without underpricing (%)	0.6	2.0	1.6	2.9	***5.6	**9.12

* Significant at 1% **Significant at 5% *** Significant at 10%

From the BHARs we see that NPE-backed IPO are more underpriced. We cannot statistically prove a difference for the first 6 months without underpricing. In other words, for the first 6 months offer price investors are better off investing in NPE-backed IPOs. This is however irrelevant, as the incremental capital gains incurred by these investors cannot be realized until the end of the lock-up period, at which point the difference between the IPOs are statistically insignificant. After the lock-up period ends, the PE and NPE-backed IPOs are indifferent up until the 11 month mark, where after PE-backed perform better on a 10% significance level.

Basically, PE and NPE-backed IPOs are not significantly different for offer price investors with an investment horizon of less than 11 month. However, for a 12-month investment horizon the PE-backed IPOs perform better, even when accounting for the initial discount on NPE-backed IPOs in the form of underpricing.

For non-offer price investors i.e. most private investors, the return is on average slightly higher for PE-backed IPOs at all times. However, is it not until approximately 7 months in the aftermarket, where the PE-backed IPOs outperform NPE-backed on a 10% significance level or higher. In short, for these investors, there is no significant difference between the two types of IPOs unless they hold the stocks for more than 7 months. For a 7-12 month holding period however, PE-backed IPOs achieve significantly (<10%) higher returns than their matched NPE IPO counterpart.

5.7.2 Test for BHAR risk-adjustments

In order to make sure that the conclusions drawn so far are valid, we need to make sure that risk-adjustment were applied correctly. Using the logic of the matched-firm approach, i.e. the matched firms are of the same risk, the same risk should have been applied to the same groups of PE and NPE firms. Basically, we want to confirm that the same trends are present in a matched-firm analysis for PE and NPE across size and book-to-market groups.

If they are, it must follow that approximately the same risk-adjustments have been made, and we can be sure that conclusions between PE and NPE groups are not driven by differences in risk-adjustments. Since we are evaluating risk-adjustments and trying to confirm trends, we exclude underpricing from the analysis. First, we examine the small IPOs with a market capitalisation of less than USD 500m. Bear in mind that the number of IPOs may differ in some groups thus causing the difference in overall returns. The relative PE versus NPE trends we are looking to confirm is.

Table 5.10: 249-day BHAR trends without underpricing

Book-to-market group	Size group	PE versus NPE
Low	Small	PE underperformance of approximately 10%
	Large	PE overperformance of approximately 15%
Mid	Small	PE overperformance of approximately 5%
	Large	PE overperformance of approximately 10%
High	Small	PE underperformance of approximately 5%
	Large	Approximately equal performance

Figure 5.13: Small matched firms BHARs by book-to-market

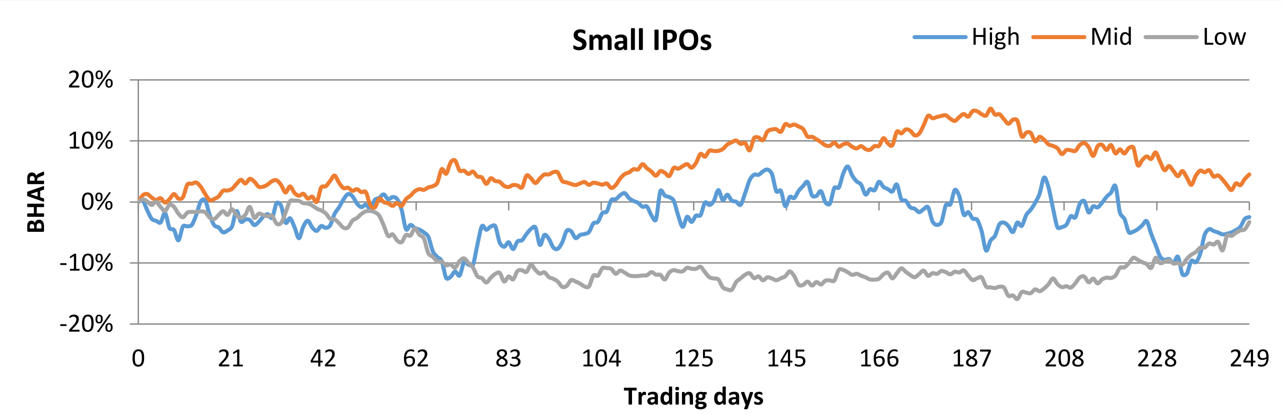
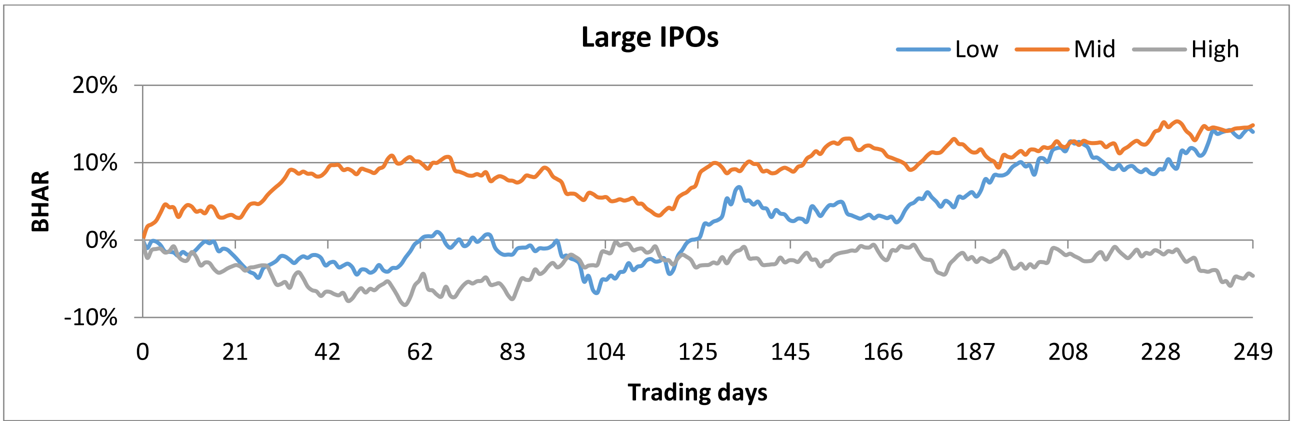


Figure 5.14: Large matched firms BHARs by book-to-market



The results confirm all of our BHAR findings surprisingly accurate. While there a minor differences of +/- 2% within some groups, overall the findings are the same for both methodologies.

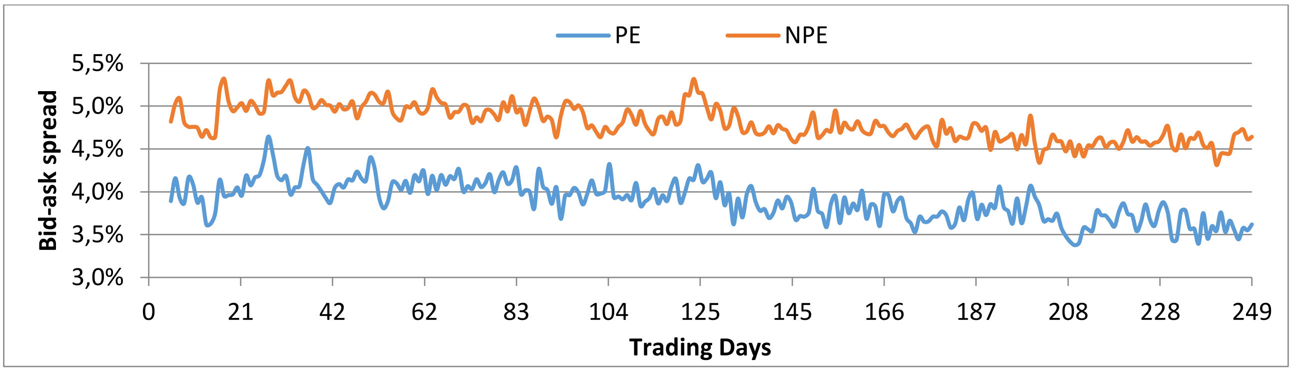
This essentially implies that the relative premiums applied do not differ between PE and NPE groups within the size and book-to-market portfolios. Ultimately, we can never be sure that the premiums and betas are 100% correct i.e. that the level of abnormal returns are 100% accurate. We can however say that based on this analysis, the betas and premiums on the NPE and PE-backed groups used to form the matched-firm analysis (year, industry, size, book-to-market) are approximately equal. This should logically be the case as firms matching on these criteria as a starting point should be of approximately the same risk.

If the logic behind the construction of benchmarks in the matched-firm approach is not flawed, and we believe it is not, it ultimately means that the relative performance measured has a strong level of robustness.

5.8 Liquidity analysis

As a final analysis we wanted to examine if liquidity had an effect on performance or at least could help explain some of the trends we have observed. We proxy liquidity using the closing daily bid-ask spread volatility and also compare the daily trading volumes for each respective group. The first days of trading are left out of the analysis as the level of trading is not normalized at this point.

Figure 5.15: Average bid-ask spread

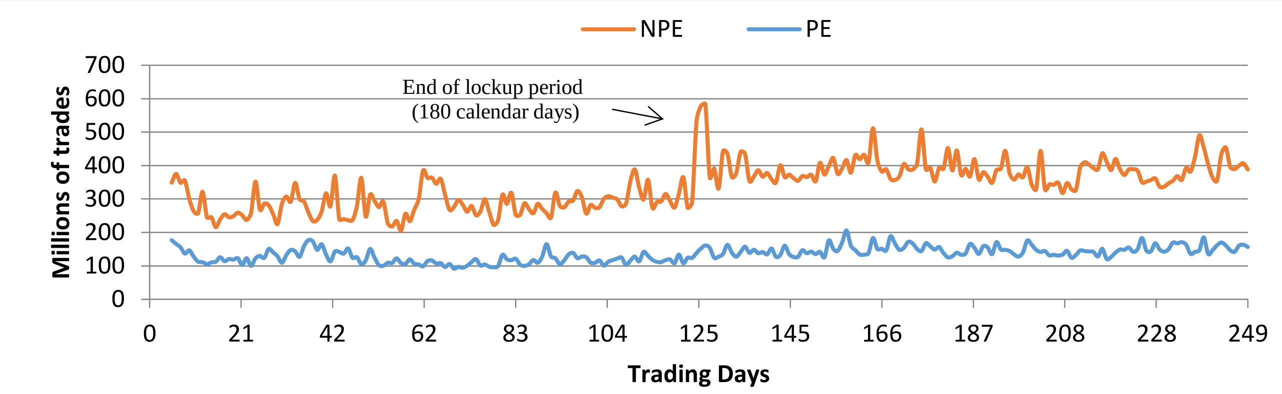


First of all, these are end-of-day bid-ask spreads and are generally higher than the spreads you would experience during the trading day (Chung, 2002). While PE and NPE may appear significantly different, a spread of 1% can easily be explained due to size differences. It is generally recognized that liquidity and size are heavily correlated (Chen, Ibbotson and Hu, 2010). Basically, investors are more aware of the stock since it takes up a bigger part of the market ultimately making the stock is more competitive. This result in a lower bid-ask spread. The median PE-backed IPO is on average 4.58x timers larger measured by market capitalisation, so seeing a 1% spread is not unexpected.

In terms of trends, the spread seems to be getting smaller and smaller after the 6 month point and continues to fall throughout the period. It therefore seems to follow that stocks become more liquid during the year following their IPO. Moreover, we see a relatively larger spike for NPE-backed IPOs at the 125 day (6 months) mark i.e. the end of the lock up period.

To explain this, we have to look at trading frequencies. The graph on top of next page provides an overview of the sum of trades for each of the respective IPO groups. While the actual number of trades is irrelevant for any conclusions due to the differences in price and number of IPOs included, the trends are much more interesting and provides for an interesting hypothesis.

Figure 5.16: Trading volume



Overall we believe this to be a very powerful graph. There are two outliers worth noticing, the 3-month (63 days) and 6 month (125 trading days) spikes in trading activity. While less than 5% of our sample IPOs had 3-month lockup periods, we still see a visible increase in the trading volume during the 3-month mark for NPE-backed entities. The trend is however way much more prominent at the 6-month mark i.e. the length of the lock-up period for the majority of the sample. While there is a small increase in trading activity for the PE-backed entities, the NPE trading activity doubles.

We speculate that this reason for the increase is that many of the offer price investors exit the NPE, but continues to stay involved in the PE-backed IPOs. This could potentially be key investors such as early founders, management or strategic investors and could have a significant effect on the stock price and operational performance. Specifically, the stock price could be affected by oversupply caused by a large amount of shares getting dumped in the market i.e. investors cashing in returns. The issue with key investors exiting is that the operational performance could also be affected negatively by key investors exiting the company.

We realize that founders and/or key management are typically bound by earn-out agreements that last longer, but it is surprising how prominent this trend is in NPE-backed IPOs. Moreover, this could explain the deviations i.e. relative overperformance of PE-backed IPOs from 6-12 months. Looking at the results (Section 5.7.1 / Appendix C and E), there seems to be a clear correlation between the 125 trading day spike and the performance of the NPE-backed IPOs.

Unfortunately, we cannot confirm this hypothesis without inspecting the order books and identifying the largest block trades on the lock-up expiration date. This would be a very demanding amount of work, and is something we would look into if we had more time. Finally, it is now time to evaluate the thesis results, draw the final conclusions and examine investor implications.

6. Conclusion

Having scrutinized returns between 2010-2015 for all IPOs on NASDAQ and NYSE from almost every possible angle, we finally reach the conclusion. Before you read on, we want to provide you with some context as our findings are divided into two sections.

This part will present the overall findings and draw parallels to what other researchers have found. Moreover, it will discuss the validity of the findings in a theoretical setting, seek to explain causation and largely focus on answering research questions 1-3. Next, section 7 will discuss the implications for investors, provide overall guidelines for IPO investing and answer research questions 4-5. To make it clear, when we refer to performance in this section, we are talking about the price development from the first day opening price i.e. returns without underpricing.

Our results show that IPOs on average overperform comparable benchmarks for the first 3 months in the aftermarket and then underperform the following 9 months. We start by addressing the underperformance. The findings are consistent with what other researchers have found for the US IPO market in the period 1970-2010 (Ritter, 1991; Lewis, 1993; Brav & Gompers, 1997; Carter et al, 1998; Akhigbe et al, 2006, Chan et al, 2008; Cao & Lerner, 2012). Researchers have tried to explain this anomaly for years and generally find two causes. IPO companies are smaller than already listed companies and tend to squander the money raised in the offering (Brav, Geczy and Gompers, 2000).

While the recent IPO market has been characterised by fewer and larger IPOs than previous decades, the average IPO is still smaller than the average US stock. Our results also confirm that smaller companies tend to underperform significantly more than larger IPOs. Specifically, companies with a first day market capitalisation of less than USD 200m are 5-10 times more likely to have negative one-year abnormal return, compared to IPOs with a market cap above USD 500m. Moreover, we also find supporting evidence of companies making inefficient use of the capital raised from the IPO. There is a strong negative correlation between the amount of capital raised and the aftermarket performance. While this does not prove causation, it does seem probable that companies are more likely to accept less profitable projects after raising a bunch of cash.

In short, we can confirm that US IPOs in recent years have continued to underperform comparable benchmarks and find supporting evidence for the explanations laid out by Brav, Geczy and Gompers (2000). While size and capital raised have significant correlations with underperformance, effects from other variables such as book-to-market ratios are also relevant. Previous studies have found that throughout the 1990s and 2000s, low book-to-market companies have been one of the main drivers for IPO underperformance (Brav & Gompers, 1997; Cao & Lerner, 2012). In sharp contrast, we find that the mid and high book-to-market companies on average underperform the market and that low book-to-market companies surprisingly overperform both other IPOs and their comparable benchmarks.

The reason for the overperformance can be linked to the state of the global economy. The period examined is a bull market with an average of 15.3% market return per year. Growth stocks have been known to perform better, when interest rates are low and company earnings are growing (Bank of America, 2017). It therefore makes perfect sense, that we find growth stocks overperforming while earlier studies find underperformance. The 1990s was characterized by relatively high interest rates and the 2000s by the tech bubble burst and the global recession in 2008 i.e. decreasing earnings. Moreover, we speculate that the overperformance exhibited by low book-to-market firms relates to the negative correlation between capital raised and performance. In other words, low book-to-market companies logically have more possibilities to make efficient use of the capital raised, as they are de facto growth companies and growth requires liquidity.

Our results also showed that the abnormal returns found in large and low book-to-market companies were created during the first 3 months in the aftermarket. None of our risk-models explained this trend, and the literature did not provide any rational explanations for this stock behaviour. The explanations we did find largely focused on the lock-up periods ending after 90 days, causing a drop in the stock due to supply shock effects. However, inspecting our data we found that more than 95% of the sample had lockup periods of 6 months, so it still did not make sense for our sample.

Ultimately, you end up in the dark corners of behavioural finance. We speculate that the trend is caused by hype ultimately causing momentum. This conclusion is based on the fact that the trend was more prominent in large IPOs, which are more exposed to the media, and growth IPOs, where the valuations can be heavily inflated by marginal changes in expectations. This was further supported by the CTAR model that showed a significant momentum premium for 2-3 month holding periods. Moreover, one could argue that since the majority of the stocks cannot be traded during the lock-up period, incremental increases in demand have a larger effect and stocks are thus more prone to momentum. Ultimately, these reasons do not explain why the trend stops after 3-months and we as other researchers cannot fully explain this anomaly. Our best guess is that the first quarterly financial report may serve as a reality check for investors putting a dampener on expectations, and that short positions in IPOs may also contribute to this trend.

While some groups may overperform the market, the reality is that the vast majority of IPOs underperform significantly. However, due to underpricing, most institutional investors still incur respectable returns.

Our models showed that underpricing had a significant effect on stock performance i.e. it also affected returns for non-offer price investors. In essence, a higher degree of underpricing affects 3-month stock performance positively and 1-year performance negatively. The reason is that there is a correlation between size and underpricing. Since large firms underprice more and have higher 3-month returns, we ultimately see a correlation between underpricing and short-term returns. Moreover, for longer holding periods, we speculate that the supply effects from the end of the lock-up period negatively affect the 1-year stock performance, ultimately causing a negative correlation. We discuss the implications for offer and non-offer price investors further in the investor recommendations section and instead turn to differences between PE and NPE-backed IPOs.

The raw returns showed that PE-backed IPOs on average display superior performance for holding periods above 6 months. Basically, in an efficient market perspective, PE-backed IPOs had to be more risky to justify the returns. However, our regressions showed that even after accounting for risk, the overperformance by PE-backed IPOs was still significant.

This ultimately answers the initial problem statement. PE-backed IPOs have displayed better performance than NPE-backed IPOs during the period. The real question is why though. One of the issues with proving the causal relation between PE-backed IPOs and overperformance is that they exhibit many of the same traits, which are ultimately driving overperformance in IPOs. We found that PE-backed IPOs were much larger in terms of assets (4x), market capitalisation (4.5x), CAPEX (2.1x) and on average had a lower book-to-market ratio. Basically, PE firms overall perform better than NPE-backed firms, but the main drivers of this performance are the operational characteristics of the companies. While this is good news for investors as you can trade on these parameters, it does not prove anything in relation to the PE-ownership model, other than size and operating characteristics are different. Other researchers have previously found significant correlations between PE-backed IPOs and overperformance (Brav & Gompers, 1997; Cao & Lerner, 2009, Cao, 2012; Levis, 2011). The overperformance was by these authors all linked to improved operating performance. So ultimately this finding does not add anything new to the literature other than confirm the trend is still valid in this decade.

To accommodate this, we created a control-firm benchmark (matched-firm) that compared the relative performance of PE and NPE-backed IPOs based on raw returns. The approach eliminated effects from year, industry, size and book-to-market effects. Our results showed that there was no significant difference between PE and NPE-backed IPOs for the first 6 months in the aftermarket. Their performance was in fact surprisingly similar and at no point varied with more than 2%. However, suddenly after 6 months, the trend changed as the NPE-backed IPOs significantly underperform from the 6 to 12 month period.

Basically, we can conclude PE-backed IPOs are different and that they perform better than NPE-backed IPOs. In contrast to other researchers, we show that the overperformance is not only driven by operational efficiencies and that the actual differences are not driven by PE overperformance, but rather NPE-backed IPOs' underperformance. This also explains why we did not find the PE variable to be a significant in our logistic regression models. Since the PE-backed IPO abnormal returns are not statistically different from zero, the PE-variable does not improve our models power significantly.

This leads us to the very last question: Why does NPE-backed in contrast to PE-backed IPOs have this abrupt decline in stock performance after 6-months?

From inspection trading patterns, we found a trend that no other researchers to our knowledge have identified. Our results showed that the trading volume on the day of the lockup-period on average increased with 99% for NPE-backed and only 22% for PE-backed IPOs. The only reasonable explanation is that NPE offer-price investors to a higher degree sell their shares immediately after the lock-up periods ends. Recall that stock prices started to drop from the 3-month point, so they are essentially abandoning a sinking ship. We argue that this is the most likely explanation for the underperformance of NPE-backed IPOs.

While we cannot confirm this, we hypothesize that insiders with operational knowhow and other offer price investors to a higher degree exit the NPE-backed IPOs. This ultimately affects the stock price in the short term due to supply shocks, and could in the longer term lead to reduced operational performance and loss of investor confidence, ultimately causing the observed decline in performance.

7. Investor recommendations

The implications of discrepancies in IPO returns are significant and highly relevant to investors. Investors can utilize inefficiencies in the IPO market in order to develop trading strategies that could potentially yield abnormal returns. Therefore, this section deals with overall recommendations for IPO investing. The recommendations are based on the findings of this thesis and while we have evaluated the validity of the findings, you should always make your own assessment of how valid the conclusions are in a forward looking investment perspective.

7.1 Recommendations for non-offer price investors

If you are a private or small institutional investor, the odds are you will not be given the opportunity to buy in at the IPO offer price. First day opening prices are typically much higher and all research points towards significant underperformance of IPOs for private investors. This is well documented throughout the 1990s and 2000s by respected researchers (Brav & Gompers, Cao, Fama, Warner and Ritter) and we find the same to be true for the period 2010-2015.

There are however large differences across IPO groups, and while we cannot recommend IPOs overall as an investment, there are certain traits that will increase the odds of earning a positive abnormal return. So in essence, stay away, but if you insist on throwing the dice anyway, here is a piece of advice.

Research points towards that large IPOs measured by market capitalisation (+USD 500m) have performed better than small IPOs in the past decades. This is essentially the only trend that is consistent from 1990-2015 for the US market. This does not mean that you should abandon common sense and invest in every large IPO, but if you deem the valuation fair and believe in the company, your odds are better for companies with a high market capitalisation.

Another important factor is the choice between value, inbetweeners or growth companies. Our observations indicate that IPOs with a book-to-market ratio lower than 0.25 (growth firms) tend to perform much better. You should however be very careful as this is the classic horse race between value and growth stocks. Basically, if you believe earnings are going to increase (i.e. bull market) and that interest rates will remain low during your investment horizon, we advice you to invest in growth IPOs. On the other hand, if you are more pessimistic and believe that earnings will decrease and/or interest rates will rise, you will probably be better off investing in value IPOs i.e. new listings with high book-to-market ratios.

In terms of holding period, we recommend no longer than 3 months for large companies. However, if your investment horizon is longer, you have historically been better of favouring IPOs of companies backed by a private-equity fund. While the private equity factor is not statistically significant on a 10% level or lower, the average raw and abnormal returns have been higher even when accounting for other variables. Finally, you should look at the amount of capital raised and try to evaluate if the company has the capability to efficiently invest that into profitable projects. A few ways to evaluate this is by looking at the prospect to see the purpose of the IPO and look into the overall industry prospects and company growth strategy.

7.2 Recommendations for offer price investors

If you instead are a large institutional investor, odds are you will have the chance to buy in at the typically discounted offer price. The discount is the only thing that gives an advantage over private investors and on the same time the only reason why the IPO market is and have historically been attractive.

Just as private investors, you would want to target IPOs with a market capitalization above USD 500m. These not only tend to perform better but also underprice their IPOs more than small companies. Moreover, the same value versus growth dilemma as discussed in last section also applies institutional investors. You should evaluate the state of the economy in the investment horizon and align your portfolio balance between value and growth firms accordingly. While the growth firms have recently performed better in the aftermarket, the reasons for their overperformance for institutional investors have rather been rooted in severe underpricing. None the less, the choice of large and growth versus value firms remains the same for both type of investors.

There are however two large differences related to pre-IPO ownership form and the recommended holding period. In contrast to private investors, NPE-backed IPOs provide for a better investment as they tend to underprice significantly more. This also has the derived effect that the minimum holding period is the best holding period for institutional investors. Since NPE-backed IPOs on average underperform the market after the 3-month mark, our recommendation is to sell as soon as possible i.e. after 6 months. It is somewhat a vicious circle. Since other investors tend to sell out after 6-month, so should you. This is because the supply shock and derived effects from other investors selling out will ultimately cause the stock price to drop.

Finally, be sure to evaluate whether the company can invest the money raised from the IPO efficiently as inefficient use of the IPO capital is a catalyzer for underperformance.

8. Suggestions for further research

There is a lot of research that we wanted to do, but simply did not have the time or the resources to complete.

Starting with underpricing, there are a great lack of large scale research. Jay R. Ritter have conducted a few overall assessments of IPO underpricing and other authors have also contributed to evaluating his findings. However, there seems to be a lack of causation and predictive based research. We would recommend researchers to look into the effects from operational characteristics, size, industry and the choice of underwriter. Chan (2008) found a link between underwriters and underpricing, but failed to take other factors into account. We speculate, that some underwriters are more prone to accept for instance larger IPOs, which may be biasing his findings.

Next, we argue that someone should conduct a large-scale examination of the difference in risk-premiums between IPOs and other stocks. Even after adjusting the returns for size and value premiums, these factors are still relevant in explaining abnormal returns. This implies that the IPO market prices these premiums differently than other stocks, and there are large amounts of work to be done within this area. In other words, a research paper could focus on the relevance and applications of conventional risk factors (i.e. Fama French) in an IPO setting. The true challenge of such a study would be not only to determine cause and correct premiums, but also to answer the question of when an IPO stops being an IPO and becomes a normal stock.

Moreover, we saw that abnormal returns were mainly created within the first 3-months in the aftermarket. While we could not explain it using conventional risk-models, we speculated that the trend was caused by hype as the trend was more visible in large and growth IPOs. Thus, we would encourage any researcher with a strong quantitative skillset to examine the differences in momentum across IPOs or to find other explanations on the 3-month abnormal returns.

Finally, one of the really interesting observations of the thesis is that the trading patterns are different for PE and NPE-backed IPOs. Our hypothesis is that NPE-backed investors sell out to a higher degree causing a change in the demand-supply balance ultimately causing the price to drop. We would recommend other researchers to investigate this hypothesis and inspect the order books on the day of the lock-up period. While it may be possible to prove a link between lock-up period and performance using simple event study methodologies and regressions, the issue of proving which investors exits will be key to stating further hypothesis and to prove casualty.

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Appendices

Appendix A: Sample Industry Definitions

Sector definitions are according to Global Industry Classification Standard (GICS) as they were during the period. Be aware that a few sectors have changed name since then.

Industry	5-year β	5-year CAGR (%)	Subsectors
Consumer Products and Services*	1.1	16.3	Advertising, Apparel Retail, Auto Parts and Equipment, Automotive Manufacturing and Retail, Broadcasting, Cable & Satellite, Casinos and Gaming, Computer & Electronics Retail, Consumer Electronics, Department Stores, Footwear, Home Furnishing, Hotels & Resort lines, Household appliances, Leisure Products, Movies & Entertainment, Publishing & Printing, Restaurants, Specialty stores, Tires & Rubber
Energy & Power	1.1	0.1	Integrated Oil & Gas, Oil and Gas Drilling, Oil and Gas Equipment and services, Oil and Gas Exploration and Production, Oil and Gas refining and marketing, Oil and Gas storage and transportation
Financials	1.1	15.4	Asset management, Consumer Finance, Diversified Banks, Insurance Brokers, Investment Banking & Brokerage, Insurance and Regional Banks
Health Care**	1.3	16.0	Biotechnology, Health Care distributors, Health Care Equipment, Healthcare Facilities, Healthcare Services, Healthcare Supplies, Life Science Tools & Services, Pharmaceuticals
Industrials	1.0	14.0	Aerospace & Defence, Agricultural & Farm machinery, Air freight and Logistics, Airlines, Construction & Engineering, Environmental & Facilities services, Industrial Machinery, Railroads, Train Companies & Distributors and Trucking
High Technology	1.1	16.6	Application Software, Communications Equipment, Data processing services, Electronic components & instruments, Internet software & Services, Semiconductors, Systems Software and Technology Hardware, Storage & Peripherals
Materials	1.2	9.3	Commodity chemicals, Construction materials, Copper, Diversified Chemicals, Fertilizers & Agricultural chemicals, Gold, Industrial gases, Metal & Glass containers, Paper packaging, speciality chemicals, Steel
Real Estate	0.6	7.1	Real Estate services (All other are REITS which are excluded from the sample)
Telecommunications***	0.5	2.6	Alternative Carriers and Integrated Telecommunication Services

*We include consumer staples in this category due to lack of observations (5)

** Excluding Managed Health Care

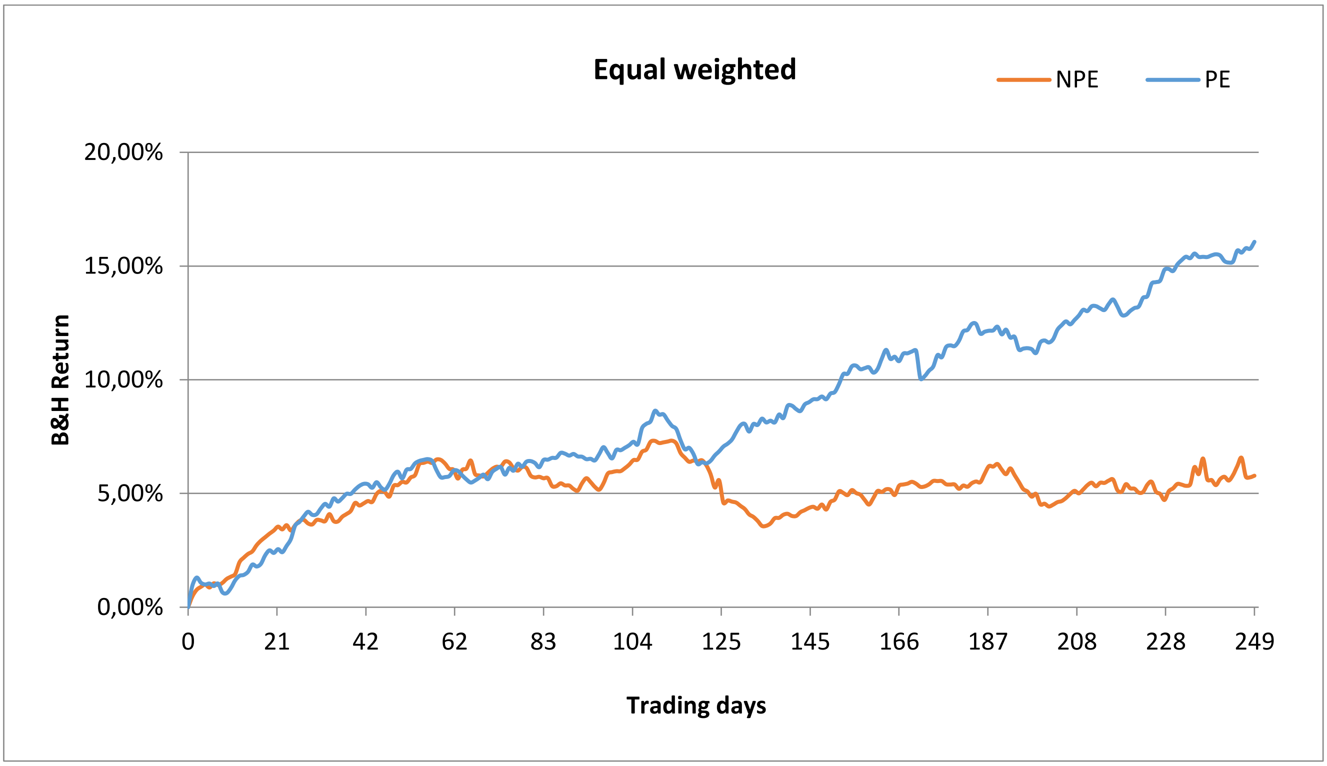
***We include utilities into this category due to lack of observations and approximately the same risk-measure (5 year beta for the sector are 0.7 and 0.8, respectively)

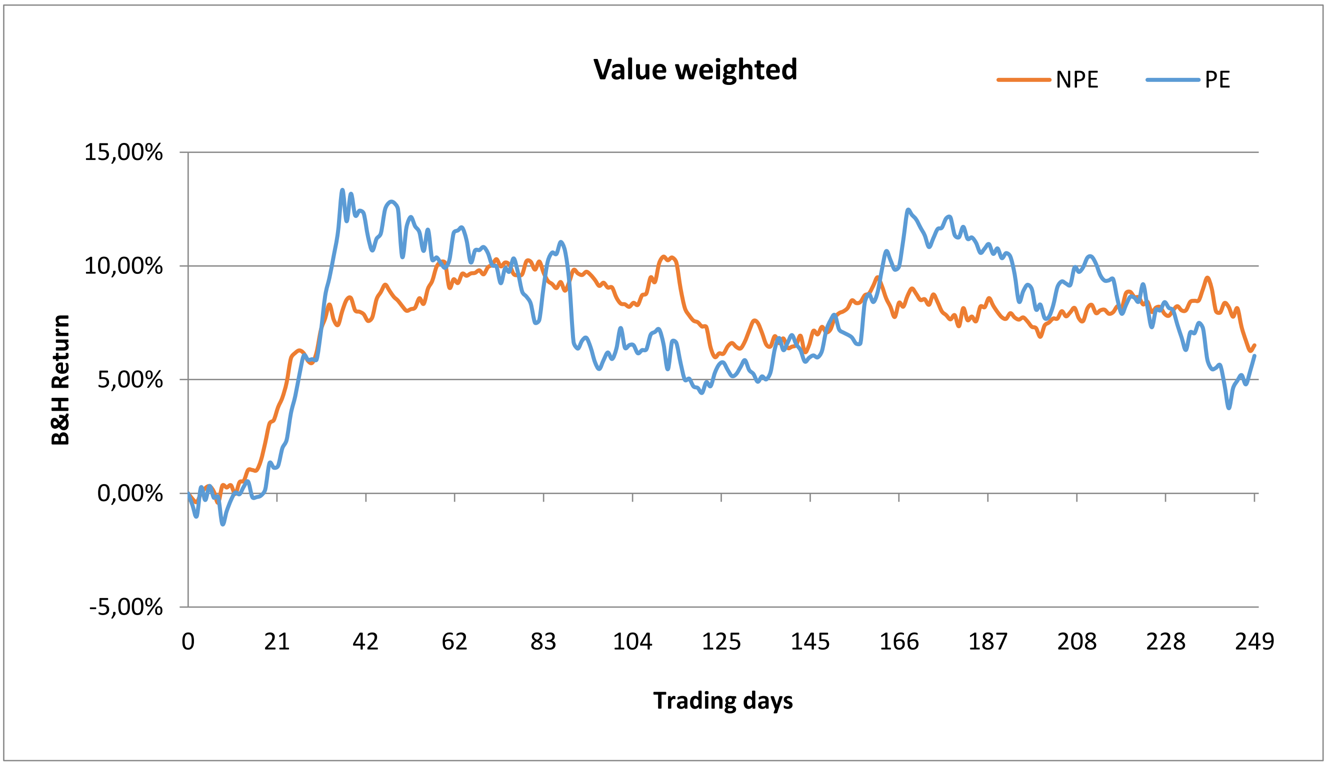
Appendix B: B&H statistics

B&H (%)	Underpricing	1	2	3	6	9	12
Equal weighted							
All	9.0	12.7	14.5	15.5	14.9	17.3	17.9
t-stat	*NA*	**16.8*	**15.3*	**13.7*	**10.5*	**10.0*	**9.6*
NPE	9.8	13.9	15.2	16.3	15.0	16.4	15.7
t-stat	*NA*	**14.1*	**12.6*	**11.3*	**8.5*	**7.6*	**6.8*
PE	6.9	9.8	12.8	13.4	14.6	19.6	23.9
t-stat	*NA*	**8.9*	**8.6*	**7.8*	**6.6*	**7.4*	**7.7*
Value weighted							
All	16.2	19.2	27.5	28.7	22.5	26.5	21.9
t-stat	*NA*	**26.0*	**25.8*	**23.3*	**16.0*	**15.6*	**12.0*
NPE	15.7	20.3	24.9	27.0	22.7	25.7	23.1
t-stat	*NA*	**21.3*	**19.9*	**18.1*	**12.9*	**12.1*	**10.4*
PE	16.9	17.8	30.8	30.9	22.2	27.5	20.4
t-stat	*NA*	**13.9*	**12.2*	**12.1*	**10.4*	**10.4*	**6.5*
B&H (%) without underpricing							
Equal weighted							
All	NA	3.3	4.9	5.8	5.3	7.8	8.6
t-stat	NA	*6.0	*6.6	*6.1	*4.1	*4.9	*4.8
NPE	NA	3.5	4.7	5.7	4.6	6.2	5.8
t-stat	*NA*	**5.0*	**5.0*	**4.7*	**3.0*	**3.1*	**2.7*
PE	NA	2.6	5.4	6.0	7.1	12.2	16.1
t-stat	*NA*	**3.4*	**4.6*	**4.4*	**3.4*	**5.0*	**5.6*
Value weighted							
All	NA	2.5	9.4	10.4	6.0	9.8	6.3
t-stat	*NA*	**4.4*	**13.2*	**11.4*	**4.7*	**6.3*	**3.5*
NPE	NA	3.8	7.6	9.3	6.1	8.6	6.5
t-stat	*NA*	**5.4*	**8.4*	**8.0*	**4.0*	**4.4*	**3.0*
PE	NA	1.2	11.3	11.6	5.8	11.0	6.1
t-stat	*NA*	*1.6*	**8.0*	**8.3*	**2.7*	**4.4*	**2.9*

** Significant at 1%   **Significant at 5%   *** Significant at 10%*

Appendix C: B&H without underpricing graphs



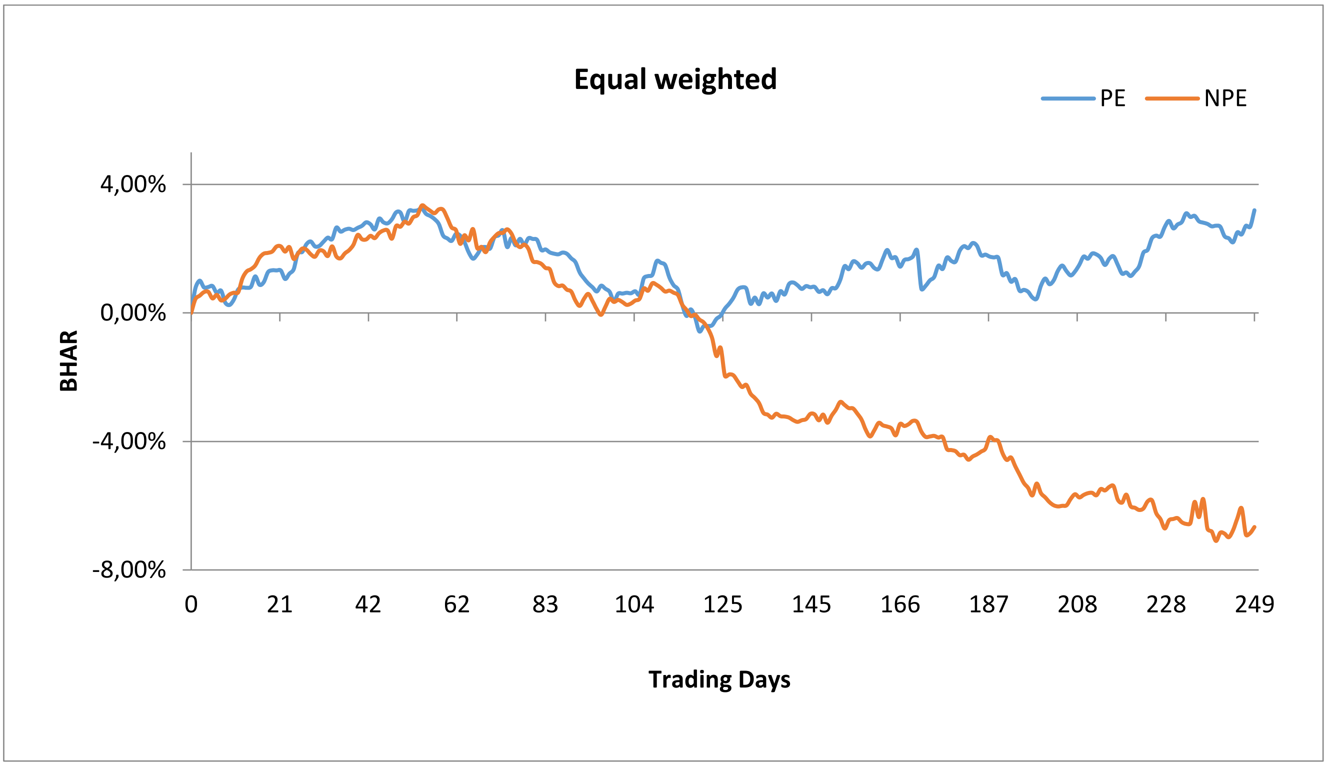


Appendix D: BHAR statistics

BHAR (%)	Underpricing	1	2	3	6	9	12
Equal weighted							
All	8.9	11.3	12.0	11.9	8.1	7.0	5.2
t-stat		**15.0*	**12.8*	**10.6*	**5.5*	**3.9*	***2.6*
NPE	9.7	12.3	12.8	12.7	8.3	6.2	3.1
t-stat		**12.6*	**12.7*	**8.9*	**4.5*	**2.8*	*1.2*
PE	6.8	8.4	10.0	9.7	7.5	9.0	10.8
t-stat		**8.0*	**7.0*	**5.8*	**3.3*	**3.4*	**3.5*
Value weighted							
All	16.1	17.9	23.8	23.4	13.8	14.2	7.9
t-stat		**24.6*	**23.4*	**20.1*	**9.6*	**8.3*	**4.0*
NPE	15.6	18.0	20.6	20.7	13.7	12.8	8.2
t-stat		**19.2*	**17.4*	**14.6*	**7.6*	**6.0*	**3.4*
PE	16.7	17.8	27.3	26.7	13.9	15.9	7.5
t-stat		**13.7*	**11.7*	**11.0*	**6.5*	**6.1*	***2.4*
BHAR (%), without underpricing							
Equal weighted							
All		1.87	2.50	2.22	-1.40	-2.35	-4.01
t-stat		**3.48*	**3.41*	***2.36*	*-1.04*	*-1.35*	*** -1.96*
NPE		2.07	2.40	2.15	-1.96	-3.87	-6.66
t-stat		**2.95*	***2.58*	***1.82*	*-1.22*	****-1.79*	***-2.60*
PE		1.32	2.76	2.40	0.14	1.75	3.20
t-stat		****1.93*	***2.48*	****1.75*	*0.09*	*0.68*	*1.04*
Value weighted							
All		1.50	5.67	5.09	-2.53	-2.49	-7.54
t-stat		**2.73*	**8.18*	**5.64*	****-1.86*	*-1.43*	**-3.45*
NPE		1.57	3.80	3.15	-2.73	-4.12	-8.30
t-stat		**2.18*	**4.22*	**2.70*	****-1.68*	****-1.90*	**-3.14*
PE		1.41	8.03	7.55	-2.26	-0.42	-6.58
t-stat		***2.05*	**6.21*	**5.45*	*-0.88*	*-0.12*	**** -1.67*

** Significant at 1%   **Significant at 5%   *** Significant at 10%*

Appendix E: BHAR without underpricing graphs



Appendix F: CTAR statistics

CTAR (%), Months after IPO	**UP**	**1**	**2**	**3**	**6**	**9**	**12**
Equal weighted							
NPE	9.7	12.9	14.4	14.1	10.2	8.1	5.0
t-stat		**14.5*	**14.6*	**10.2*	**5.2*	**3.2*	****1.8*
PE	6.8	8.97	11.1	11.3	9.1	11.9	10.5
t-stat		**9.2*	**8.1*	**6.7*	**3.8*	**3.9*	**4.0*
Value weighted							
NPE	15.6	19.9	21.6	21.8	13.5	12.1	6.9
t-stat		**22.1*	**20.0*	**16.8*	**8.7*	**6.9*	**3.9*
PE	16.7	18.4	28.4	28.3	15.5	18.8	7.2
t-stat		**15.8*	**13.5*	**12.7*	**7.5*	**7.0*	***2.5*
CTAR (%) without underpricing							
Equal weighted							
NPE		2.68	3.96	3.58	-0.06	-1.97	-4.76
t-stat		**3.4*	**3.0*	**2.9*	*-1.4*	****-1.7*	****-1.9*
PE		1.89	3.82	3.99	1.78	4.62	2.87
t-stat		***2.2*	**2.9*	***2.0*	*0.1*	****1.8*	*1.5*
Value weighted							
NPE		2.24	4.08	3.34	-2.83	-4.35	-9.45
t-stat		**2.7*	**4.9*	**3.1*	***-2.1*	***-2.2*	**-3.6*
PE		1.71	8.08	9.05	-1.86	-1.82	-6.87
t-stat		***2.4*	**7.1*	**6.3*	*-1.0*	*-0.1*	****-1.9*

** Significant at 1% **Signicant at 0.05 *** Significant at 10%*

Appendix G: BHAR by year statistics

Equally weighted BHARs (%)	Underpricing	1	2	3	6	9	12
			2010				
NPE	5.4	3.4	3.7	5.0	2.1	-1.1	-7.1
t-stat		*1.3*	*1.2*	*1.3*	*0.4*	*-0.1*	*-1.0*
PE	6.8	6.3	4.1	4.1	7.6	16.8	9.1
t-stat		***2.5*	*1.1*	*0.8*	*1.2*	****1.9*	*1.1*
			2011				
NPE	8.1	5.7	8.2	10.2	2.3	-3.9	-3.6
t-stat		**2.8*	**3.0*	**3.4*	*0.6*	*-0.9*	*-0.7*
PE	3.8	4.3	5.0	4.2	4.6	1.5	2.8
t-stat		****1.7*	*1.6*	*1.0*	*0.7*	*0.2*	*0.3*
			2012				
NPE	9.9	14.1	18.9	19.6	20.0	17.9	26.3
t-stat		**6.6*	**6.4*	**6.0*	**4.6*	**3.3*	**3.4*
PE	8.5	11.9	15.6	16.2	14.3	19.5	24.9
t-stat		**3.0*	**3.4*	**3.3*	***2.1*	***2.2*	***2.5*
			2013				
NPE	13.5	19.5	17.4	19.6	13.9	13.0	1.1
t-stat		**7.4*	**5.6*	**5.2*	**2.8*	***2.4*	*0.2*
PE	10.1	14.9	18.6	19.3	14.9	7.3	10.7
t-stat		**6.6*	**6.6*	**5.6*	**2.7*	*1.5*	****1.7*
			2014				
NPE	8.9	10.6	10.8	11.3	7.2	11.5	9.0
t-stat		**5.2*	**4.2*	**3.9*	***2.1*	***2.5*	****1.9*
PE	3.9	5.0	6.8	4.2	2.1	8.6	11.8
t-stat		***2.4*	***2.3*	*1.3*	*0.6*	****1.7*	***2.0*
			2015				
NPE	10.4	16.6	16.1	8.7	3.4	-6.4	-7.7
t-stat		**5.6*	**5.0*	***2.2*	*0.7*	*-1.0*	*-1.1*
PE	7.2	5.0	4.7	6.5	-1.5	-2.9	-0.7
t-stat		*1.6*	*1.3*	****1.8*	*-0.3*	*-0.5*	*-0.1*

** Significant at 1% **Significant at 5% *** Significant at 10%*

Appendix H: BHAR by year value-weighted statistics

Value-weighted BHARs (%)	Underpricing	1	2	3	6	9	12
			2010				
NPE	4.7	1.8	6.6	3.2	-4.5	-5.3	-14.5
t-stat		*0.7*	***2.2*	*0.8*	*-0.8*	*-0.7*	****-1.9*
PE	5.9	8.9	10.4	13.5	27.3	46.5	32.4
t-stat		**3.2*	**2.5*	**2.7*	**3.5*	**4.8*	**3.6*
			2011				
NPE	14.3	7.3	19.3	24.0	0.9	-0.8	-2.2
t-stat		**3.5*	**5.5*	**6.1*	*0.3*	*-0.2*	*-0.4*
PE	5.1	6.6	7.1	5.4	4.8	3.2	3.9
t-stat		***2.3*	***2.1*	*1.2*	*0.7*	*0.4*	*0.4*
			2012				
NPE	10.6	7.5	7.7	-1.6	0.5	-3.8	-6.4
t-stat		**3.3*	***2.3*	*-0.3*	*0.1*	*-0.5*	*-0.6*
PE	8.3	12.9	14.8	18.2	20.5	29.2	27.9
t-stat		**3.2*	**3.2*	**3.6*	**2.9*	**3.1*	**2.8*
			2013				
NPE	30.7	41.1	43.4	44.0	31.1	34.8	18.9
t-stat		**12.5*	**8.2*	**8.6*	**5.5*	**6.2*	**3.4*
PE	12.0	16.9	20.7	20.5	17.3	12.9	14.6
t-stat		**7.5*	**7.3*	**5.9*	**3.2*	**2.6*	***2.3*
			2014				
NPE	11.7	18.1	20.0	27.7	26.6	27.5	29.8
t-stat		**8.2*	**7.4*	**8.4*	**6.9*	**6.1*	**6.2*
PE	26.1	24.5	42.3	39.6	13.6	16.1	-0.2
t-stat		**4.6*	**4.6*	**4.4*	**3.1*	**3.2*	*0.0*
			2015				
NPE	16.9	20.2	20.3	15.1	6.7	.0.8	-0.7
t-stat		**7.1*	**6.6*	**4.1*	*1.4*	*-0.1*	*-0.1*
PE	3.0	6.4	5.9	12.7	-2.6	-9.4	-4.4
t-stat		***2.0*	*1.5*	***2.5*	*-0.5*	*-1.5*	*-0.6*

** Significant at 1% **Significant at 5% *** Significant at 10%*

Appendix I: BHAR by year without underpricing statistics

Equally weighted BHARs (%)	1	2	3	6	9	12
2010						
NPE	-0.3	-1.9	-1.4	1.4	10.7	3.0
t-stat	*-0.1*	*-0.5*	*-0.2*	*0.2*	*1.1*	*0.4*
PE	-2.7	-2.5	-1.4	-4.4	-7.3	-13.7
t-stat	***-1.8*	*-1.1*	*-0.4*	*-0.9*	*-0.9*	***-1.8*
2011						
NPE	0.3	1.0	0.4	0.9	-1.6	-0.6
t-stat	*0.2*	*0.4*	*0.1*	*0.1*	*-0.2*	*0.0*
PE	-2.4	-0.3	-1.6	-5.0	-11.4	-11.0
t-stat	***-1.9*	*-0.1*	*0.6*	*-1.6*	**-2.9*	***-2.5*
2012						
NPE	4.0	7.7	8.6	7.6	5.3	11.5
t-stat	**3.2*	**3.8*	**3.5*	**2.2*	****1.7*	****1.8*
PE	2.4	5.6	5.6	2.9	6.7	11.3
t-stat	*1.3*	***2.2*	***1.9*	*0.6*	****1.8*	****1.8*
2013						
NPE	4.3	2.6	3.7	-0.9	-1.1	-10.7
t-stat	**2.9*	*1.2*	*1.3*	*-0.2*	*-0.2*	*-1.4*
PE	4.0	7.0	7.2	3.2	-3.0	0.8
t-stat	**3.1*	**3.7*	**3.2*	*0.6*	*-0.6*	*0.2*
2014						
NPE	1.1	1.2	1.6	-3.0	0.8	-0.8
t-stat	*0.8*	*0.6*	*0.7*	*-1.1*	*0.2*	*-0.2*
PE	0.9	2.6	-0.1	-2.1	3.7	6.4
t-stat	*0.6*	*1.0*	*-0.0*	*-0.6*	*0.8*	*1.2*
2015						
NPE	6.6	6.2	-0.6	-4.5	-13.4	-15.4
t-stat	**2.6	**2.3	-0.1	-0.8	**-2.0	**-2.2
PE	-1.6	-1.5	0.7	-7.0	-8.0	-6.3
t-stat	*-0.9*	*-0.6*	*0.2*	*-1.7*	*-1.7*	*-0.9*

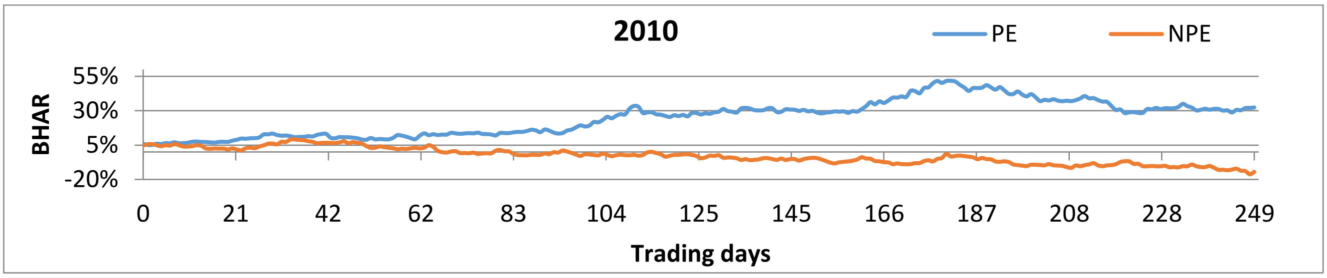
** Significant at 1% **Significant at 5% *** Significant at 10%*

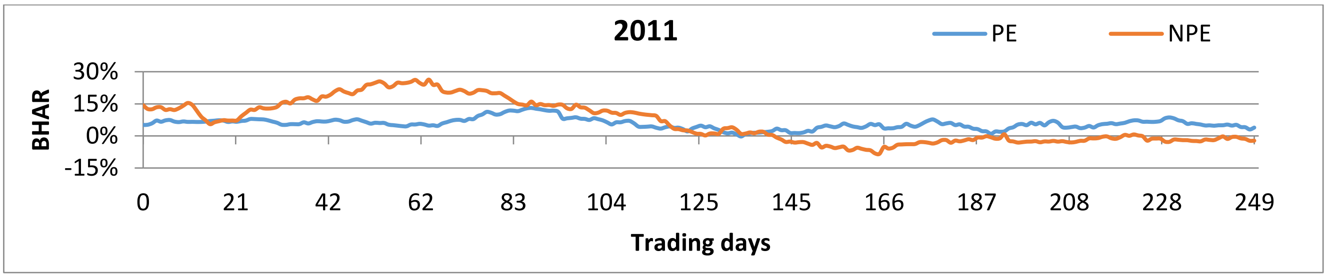
Appendix J: BHAR by year value-weighted without underpricing statistics

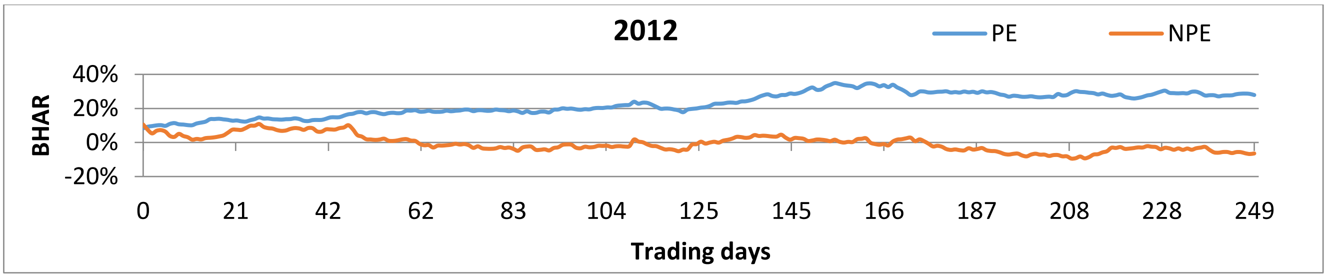
Value-weighted BHARs (%)	1	2	3	6	9	12
	2010					
NPE	-3.2	-0.8	-2.6	-10.9	-10.8	-21.2
t-stat	***-2.1*	*0.4*	*0.8*	***-1.9*	*-1.4*	***-2.2*
PE	2.9	5.0	9.0	22.4	42.5	27.5
t-stat	*1.3*	*1.2*	****1.7*	**2.9*	**4.3*	**3.1*
	2011					
NPE	-5.6	4.8	9.1	-10.2	-13.0	-13.2
t-stat	**-3.9*	**2.1*	**3.3*	**-3.0*	**-3.3*	**-2.9*
PE	1.3	1.8	0.0	-0.5	-1.7	-1.3
t-stat	*0.8*	*0.8*	*0.0*	*-0.1*	*-0.2*	*-0.1*
	2012					
NPE	-2.7	-3.4	-12.5	-12.1	-17.1	-22.1
t-stat	****-1.6*	*-1.1*	***-2.5*	***-2.2*	***-2.5*	***-2.3*
PE	3.9	5.1	7.5	9.0	15.8	14.4
t-stat	****1.9*	***2.0*	***2.4*	****1.8*	**2.1*	****1.7*
	2013					
NPE	6.7	7.5	8.9	1.0	2.8	-9.4
t-stat	**4.6*	**3.7*	**2.9*	*0.2*	*0.6*	*-1.3*
PE	3.8	7.00	6.6	3.7	0.1	1.8
t-stat	**2.9*	**3.7*	**2.9*	*0.7*	*0.0*	*0.3*
	2014					
NPE	4.9	6.6	12.8	10.4	11.5	14.4
t-stat	**3.4*	**3.4*	**5.1*	**3.6*	**3.1*	**3.4*
PE	-0.4	11.6	9.2	-10.5	-8.6	-20.0
t-stat	*-0.3*	**3.2*	***2.6*	**-2.7*	*-1.6*	***-2.4*
	2015					
NPE	4.7	5.7	1.1	-6.1	-12.6	-13.4
t-stat	****1.8*	***2.1*	*0.3*	*-1.0*	***-1.9*	***-2.0*
PE	3.4	3.0	9.5	-5.3	-11.5	-7.0
t-stat	*1.4*	*0.9*	***2.1*	*-1.3*	***-2.3*	*-1.0*

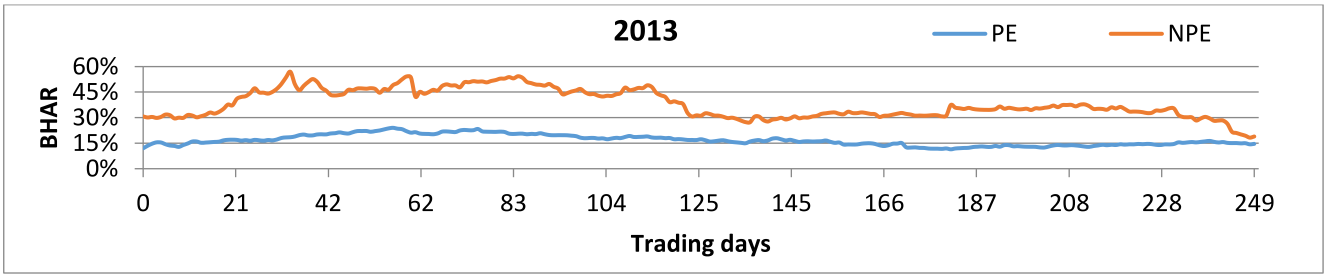
** Significant at 1% **Significant at 5% *** Significant at 10%*

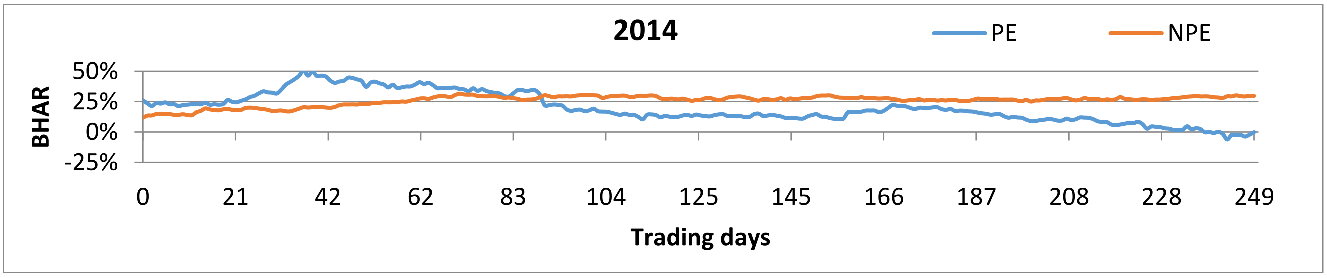
Appendix K: BHAR by year value-weighted graphs

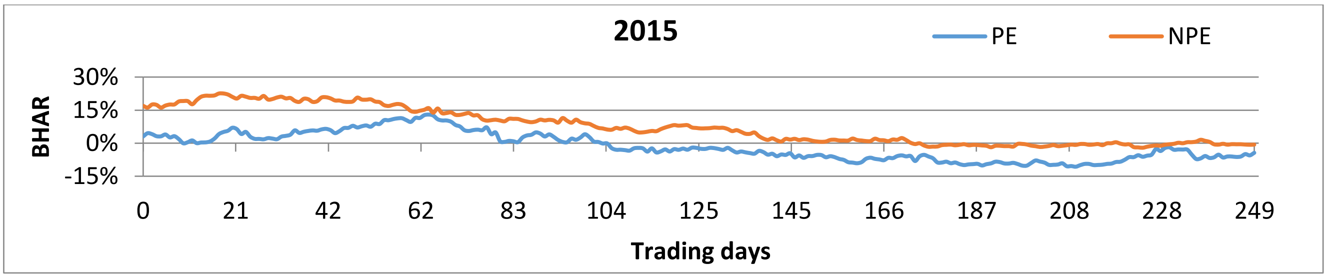




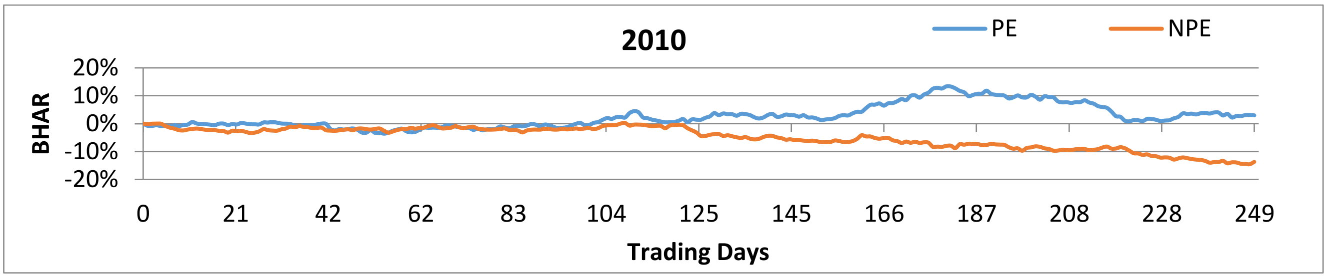


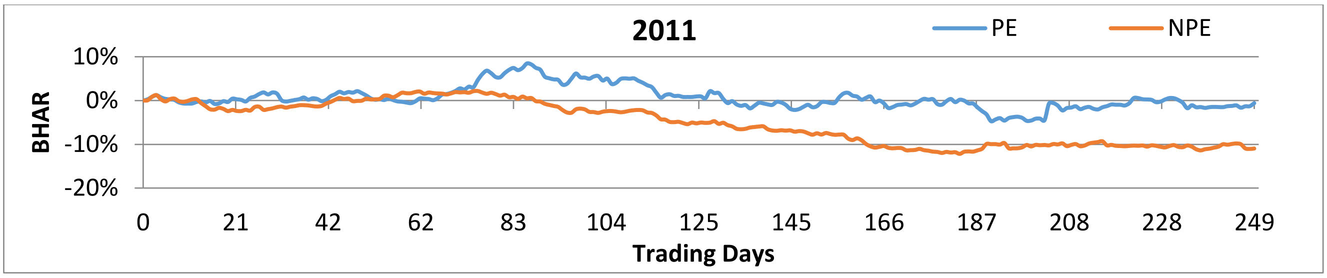


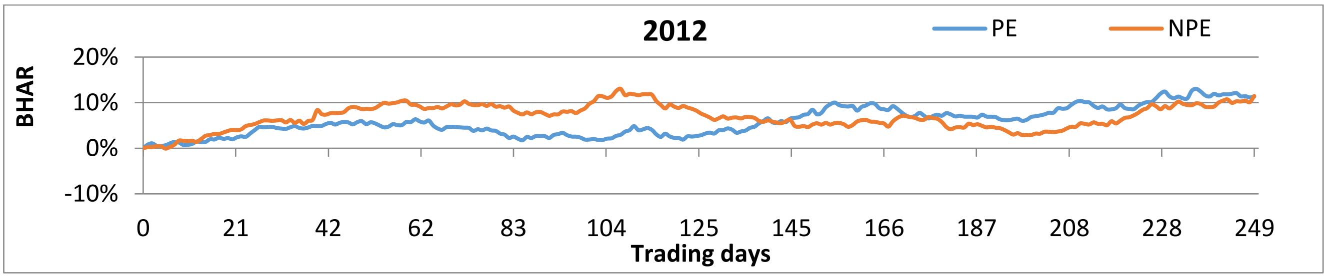


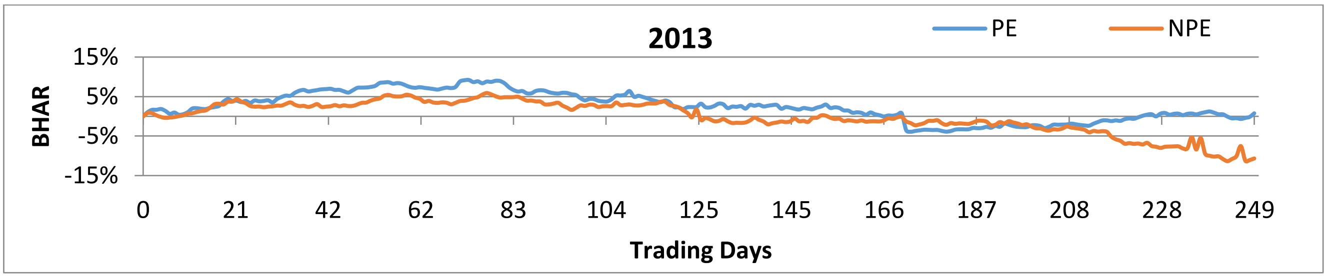


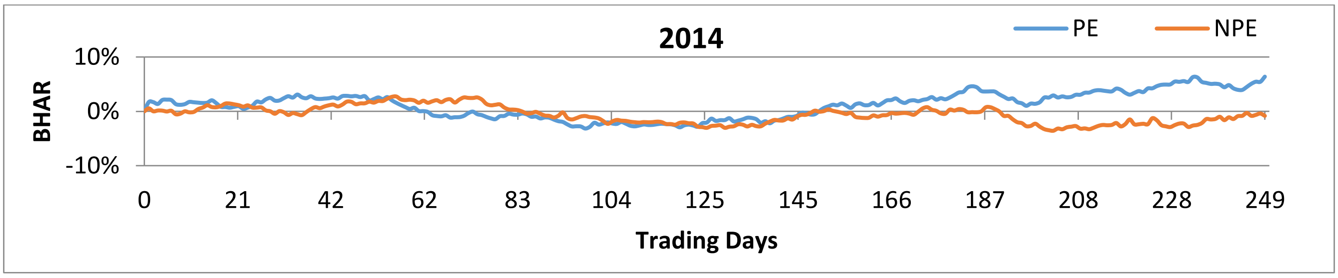
Appendix L: BHAR by year equal-weighted without underpricing graphs

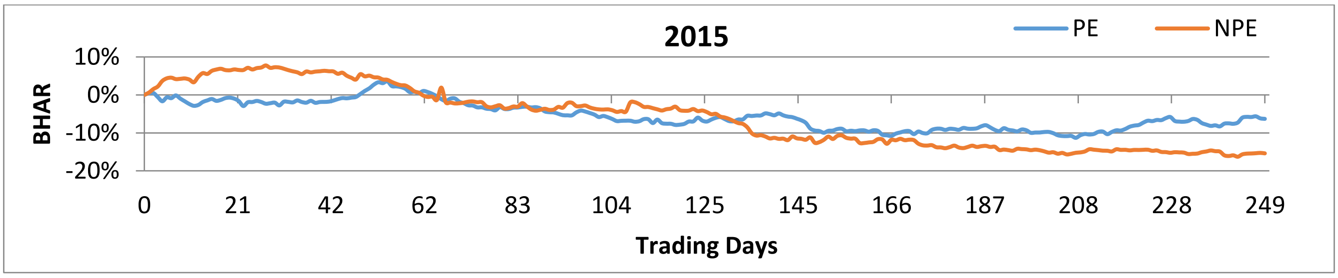












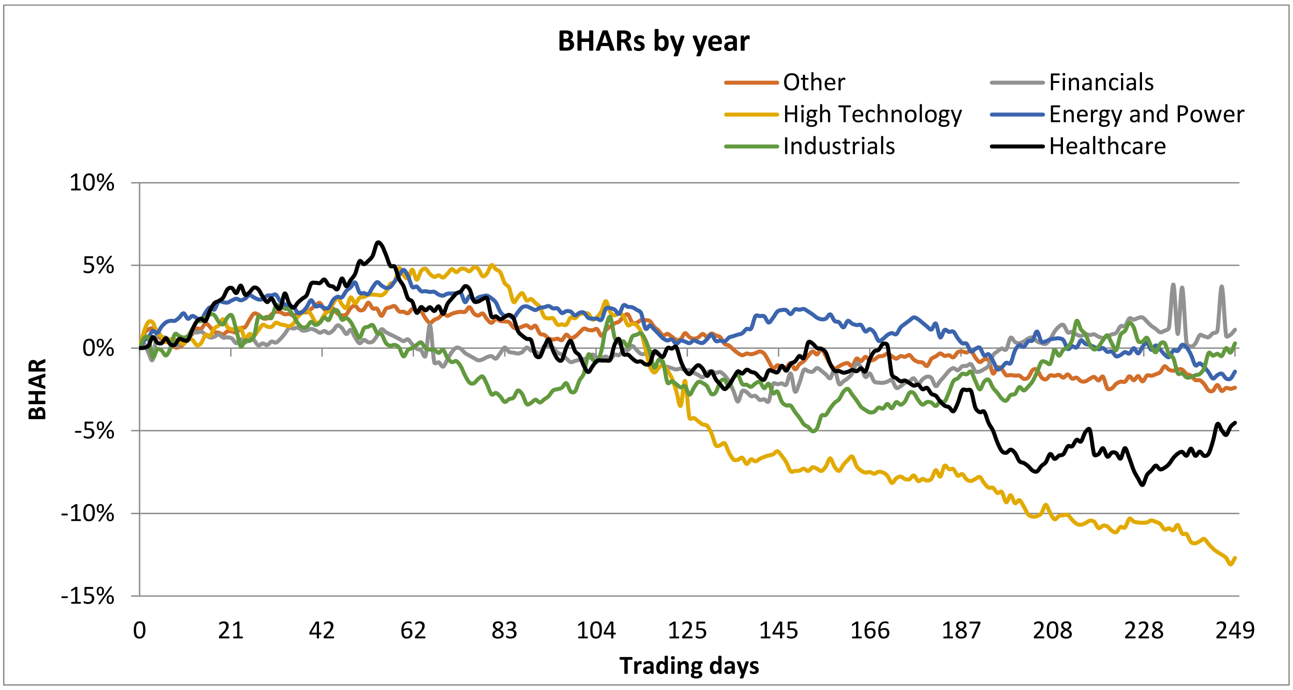
Appendix M: BHAR by selected industries statistics

BHAR (%)	**Underpricing**	**1**	**2**	**3**	**6**	**9**	**12**
Industry							
Financials	5.4	6.0	6.5	5.5	4.2	4.8	7.1
t-stat		**3.3*	**3.4*	**2.3*	*1.2*	*1.3*	****1.7*
High Technology	13.5	15.1	16.7	19.9	10.4	7.1	0.4
t-stat		**7.1*	**6.3*	**6.4*	**2.7*	*1.5*	*0.1*
Healthcare	9.8	13.9	14.5	12.4	8.7	6.7	4.8
t-stat		**6.8*	**5.8*	**4.3*	***2.4*	*1.5*	*0.9*
Energy and Power	4.6	7.9	7.6	8.8	5.2	5.6	4.1
t-stat		**5.0*	**3.6*	**3.5*	****1.7*	*1.4*	*0.7*
Industrials	5.9	9.7	8.6	6.9	5.0	6.2	9.7
t-stat		**2.7*	**2.9*	***2.1*	*1.0*	*1.2*	*1.4*
Other	9.4	10.9	12.4	12.1	10.3	9.5	7.2
t-stat		**7.3*	**6.8*	**6.1*	**4.1*	***3.1*	***2.2*

BHAR (%) without underpricing	**1**	**2**	**3**	**6**	**9**	**12**
Industry						
Financials	0.6	1.0	-0.0	-1.3	-1.1	1.1
t-stat	*0.4*	*0.6*	*0.1*	*-0.4*	*-0.3*	*0.3*
High Technology	1.1	2.0	4.1	-4.2	-7.6	-12.7
t-stat	*1.0*	*1.1*	****1.8*	*-1.2*	*-1.6*	** *-2.6*
Healthcare	3.6	4.2	2.1	-1.6	-2.6	-4.5
t-stat	***2.5*	**2.1*	*0.9*	*-0.5*	*-0.6*	*-0.8*
Energy and Power	2.9	2.4	3.7	0.3	0.3	-1.4
t-stat	**2.8*	*1.5*	****1.8*	*0.1*	*0.1*	*-0.2*
Industrials	2.0	1.9	0.2	-2.8	-1.6	0.3
t-stat	*1.1*	*1.0*	*0.1*	*-0.6*	*-0.3*	*0.1*
Other	1.0	2.3	2.3	0.7	-0.2	-2.4
t-stat	*1.2*	**1.8*	*1.5*	*0.3*	*-0.0*	*-0.7*

** Significant at 1% **Significant at 5% *** Significant at 10%*

Appendix N: BHAR by selected industries without underpricing graph



Appendix O: BHAR by book-to-market statistics

BHAR (%)	Underpricing	1	2	3	6	9	12
Group							
Low - All	18.01	23.2	27.2	30.0	27.9	30.4	26.3
t-stat		**14.4*	**13.9*	**12.8*	**9.7*	**8.9*	**6.6*
Low - NPE	20.52	26.7	31.2	33.9	29.8	32.6	26.3
t-stat		**13.4*	**13.3*	**12.1*	**8.5*	**7.9*	**5.5*
Low - PE	10.12	12.3	14.8	17.2	21.8	23.4	26.0
t-stat		**4.8*	**4.4*	**4.3*	**4.4*	**4.2*	**3.7*
Mid - All	6.14	8.7	7.5	5.3	0.3	-1.3	-2.1
t-stat		**7.1*	**5.1*	**3.1*	*0.1*	*-0.4*	*-0.6*
Mid - NPE	6.51	9.5	6.8	4.0	-1.5	-5.7	-7.4
t-stat		**5.8*	**3.6*	****1.8*	*-0.5*	*-1.4*	*-1.4*
Mid - PE	5.21	6.8	9.2	8.6	4.6	10.0	11.3
t-stat		**4.5*	**4.3*	**3.7*	*1.4*	***2.5*	***2.6*
High - All	3.32	2.5	2.6	2.2	-1.9	-6.0	-7.0
t-stat		***2.2*	****1.95*	*1.4*	*-0.9*	***-2.4*	***-2.6*
High - NPE	2.27	0.6	0.9	1.3	-2.1	-6.7	-8.7
t-stat		*0.5*	*0.6*	*0.7*	*-0.8*	***-2.2*	**-2.7*
High - PE	6.05	7.2	7.0	4.7	-1.1	-4.5	-2.8
t-stat		**3.8*	**2.9*	****1.7*	*-0.3*	*-1.1*	*-0.5*

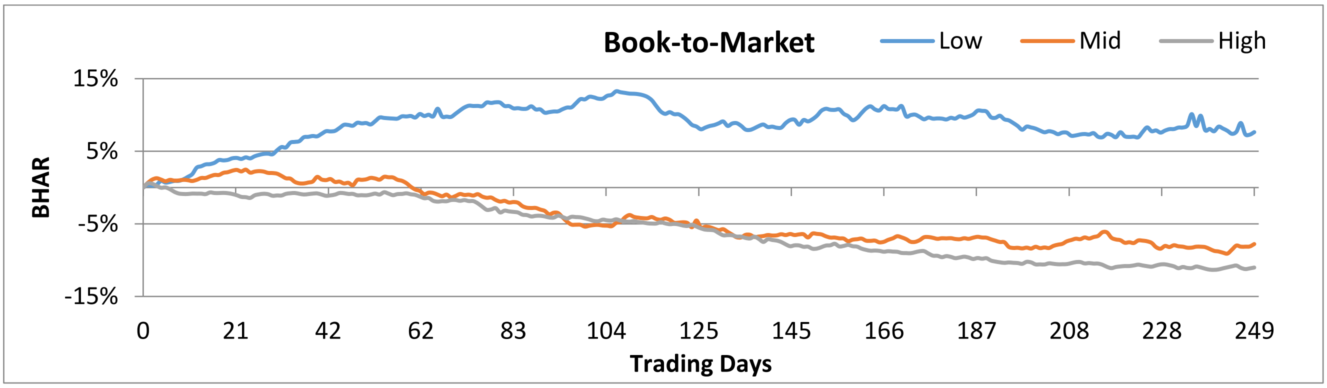
** Significant at 1% **Significant at 5% *** Significant at 10%*

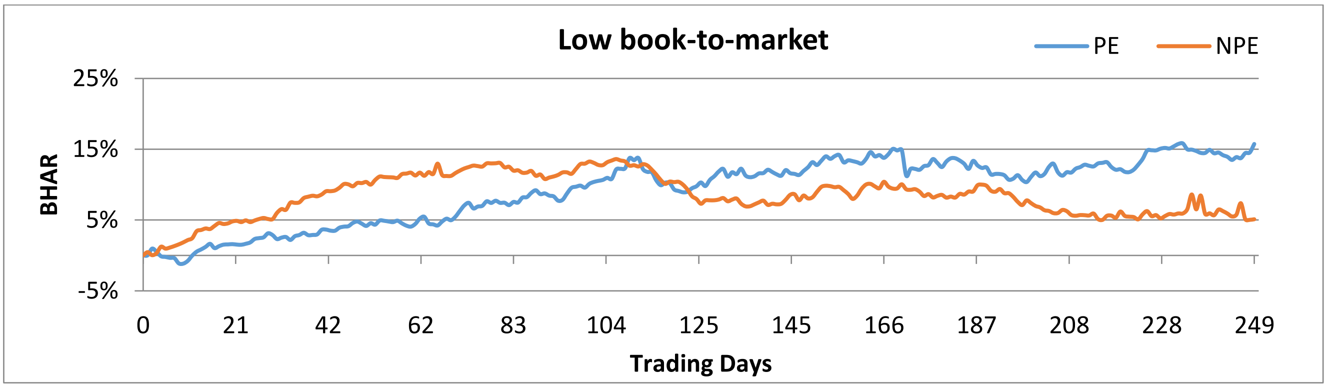
Appendix P: BHAR by book-to-market statistics without underpricing statistics

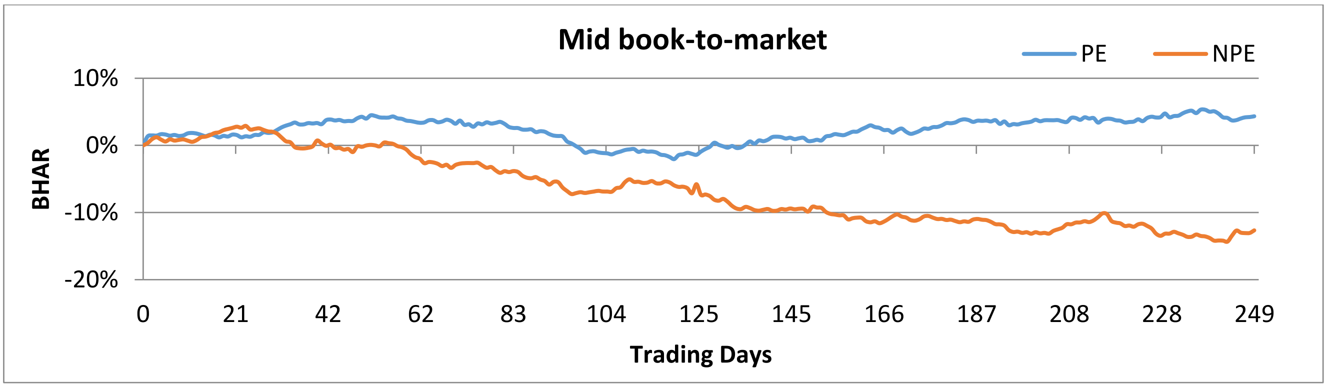
BHAR (%)	Underpricing	1	2	3	6	9	12
Group							
Low - All		4.1	7.7	9.9	8.0	10.6	7.6
t-stat		**3.6*	**5.1*	**5.0*	**3.1*	**3.3*	***2.0*
Low - NPE		4.9	9.1	11.3	7.3	9.9	5.1
t-stat		**3.3*	**4.8*	**4.7*	***2.5*	***2.6*	*1.2*
Low - PE		1.5	3.5	5.5	10.3	12.7	15.6
t-stat		*1.2*	*1.5*	****1.7*	***2.0*	***2.2*	***2.1*
Mid - All		2.4	1.2	-0.1	-0.6	-0.7	-0.8
t-stat		**2.9*	*1.0*	*-0.6*	***-2.6*	***-2.4*	***-2.1*
Mid - NPE		2.8	0.1	-2.7	-7.4	-11.0	-12.7
t-stat		***2.5*	*0.1*	*-1.4*	***-2.6*	**-2.8*	***-2.3*
Mid - PE		1.5	3.7	3.4	-0.9	3.7	4.3
t-stat		*1.4*	***2.3*	****1.7*	*-0.3*	****1.7*	****1.9*
High - All		-1.1	-1.5	-5.6	-9.7	-11.0	-11.0
t-stat		*-1.0*	*-1.2*	**-3.1*	**-4.6*	**-4.6*	**-4.6*
High - NPE		-1.8	-1.8	-1.4	-5.0	-9.5	-11.2
t-stat		***-2.1*	*-1.5*	*-1.0*	***-2.3*	**-3.9*	**-4.2*
High - PE		0.9	0.7	-1.6	-7.4	-10.1	-9.1
t-stat		*0.7*	*0.4*	*-0.8*	***-2.6*	**-2.8*	***-2.0*

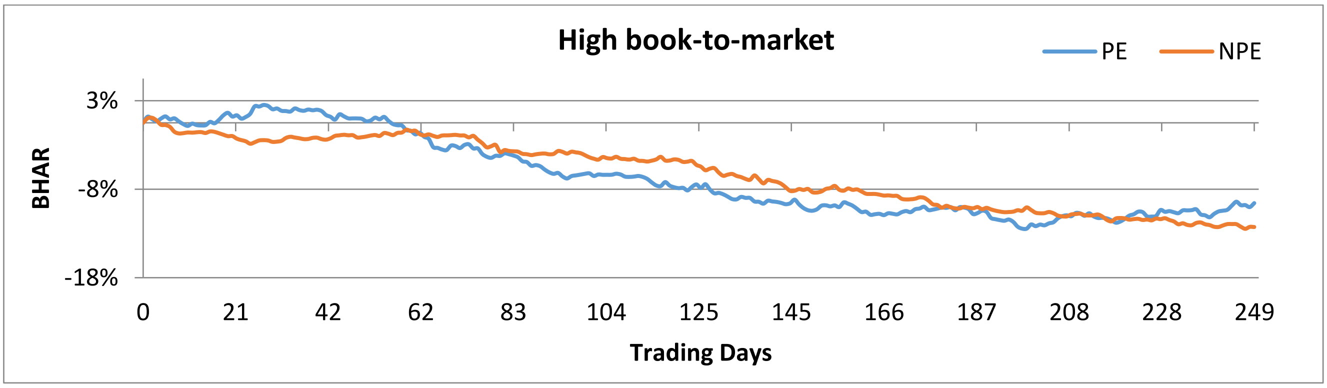
** Significant at 1% **Significant at 5% *** Significant at 10%*

Appendix Q: BHAR by book-to-market without underpricing graphs

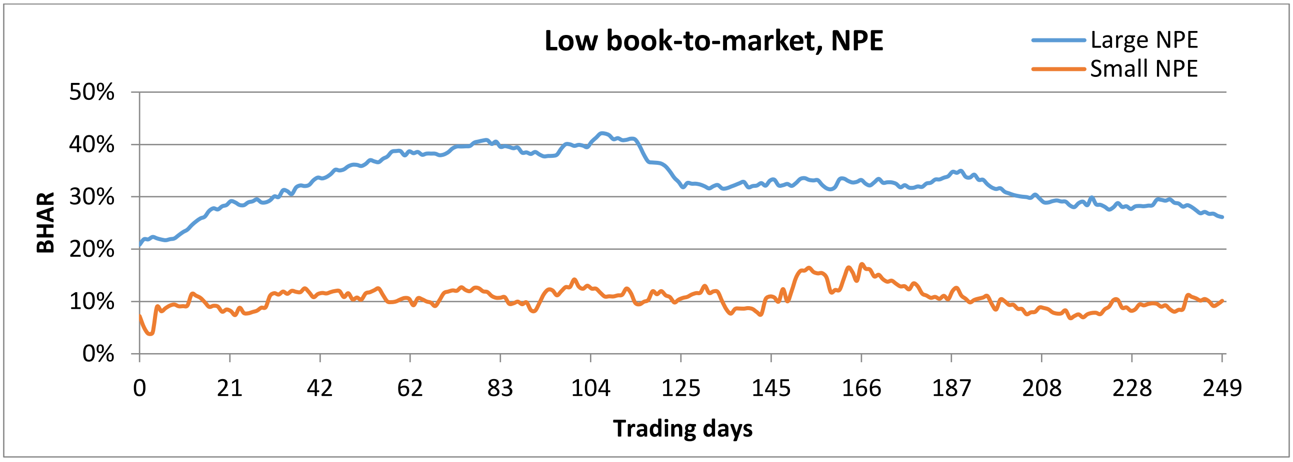


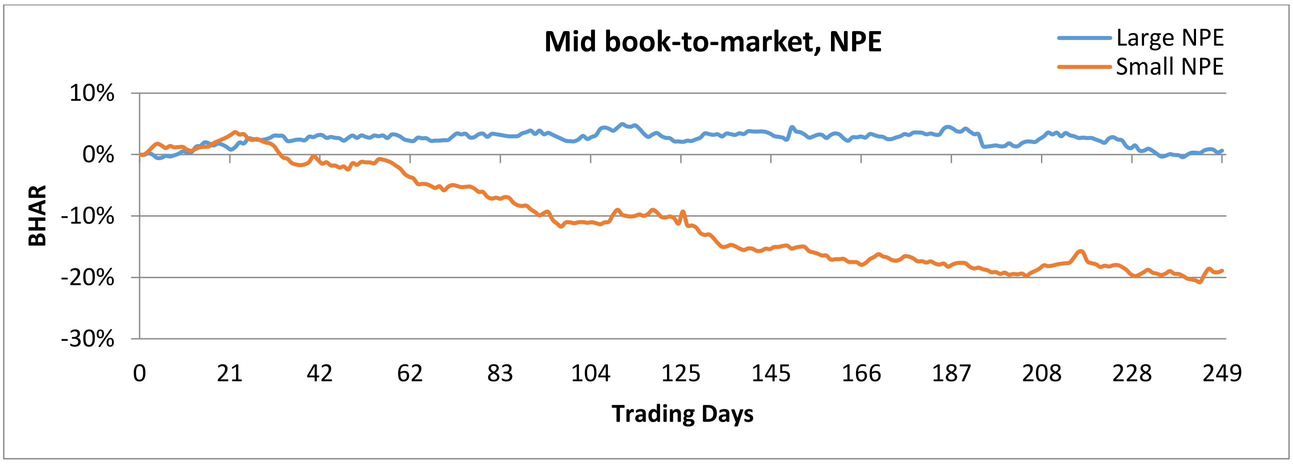


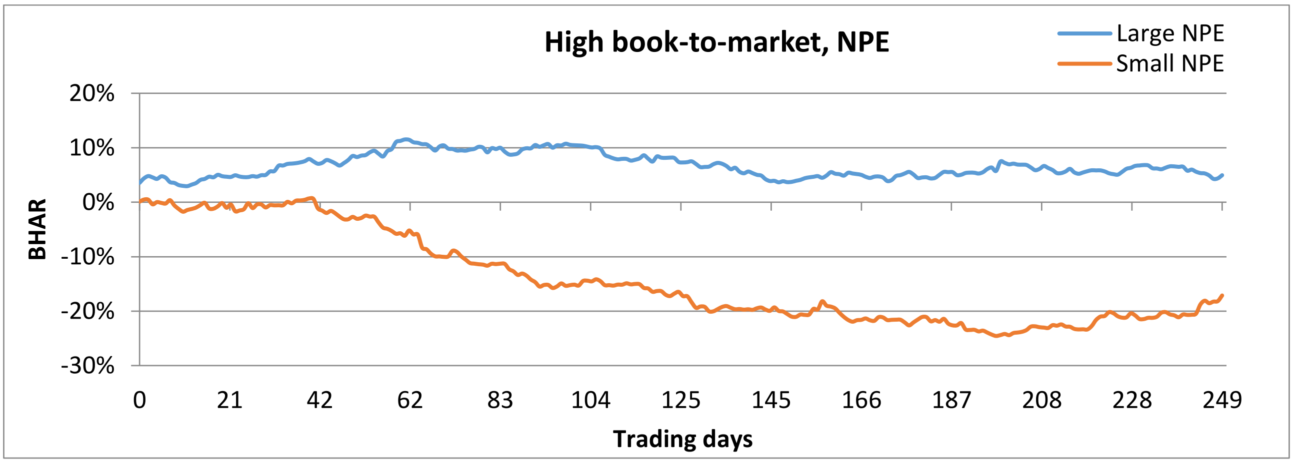




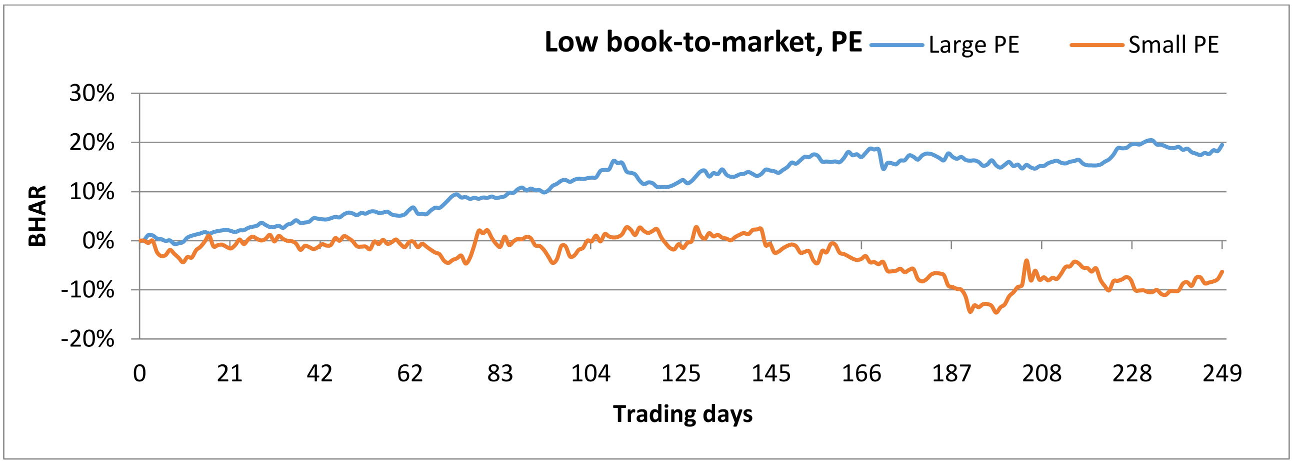
Appendix R: BHAR (NPE) by book-to-market and size without underpricing graphs

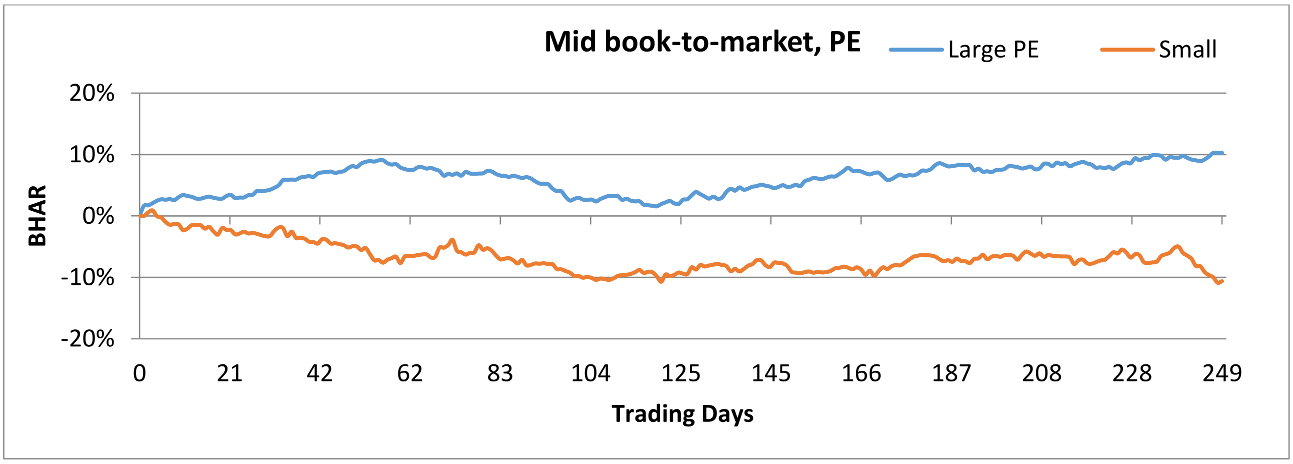


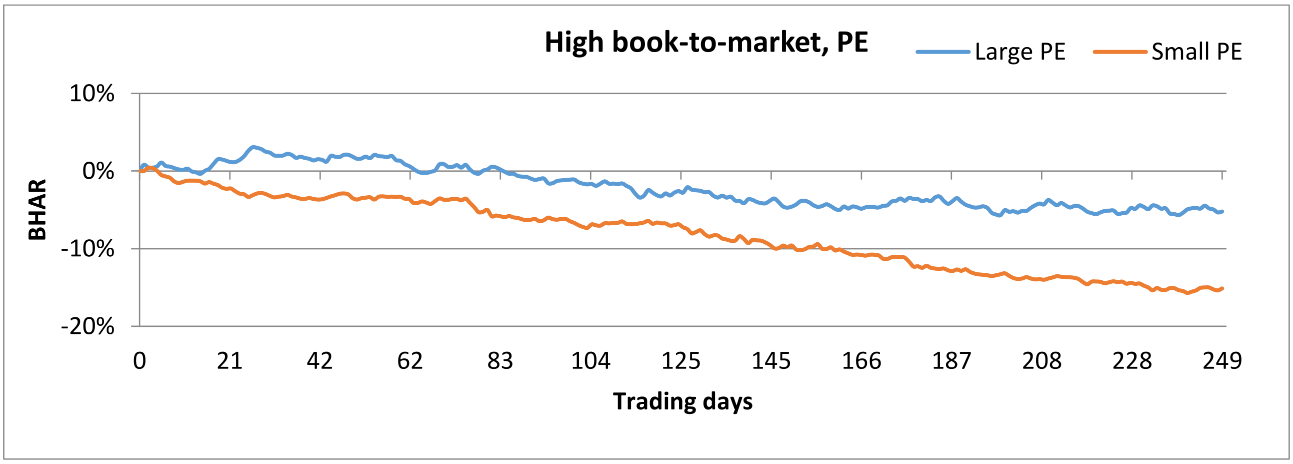




Appendix S: BHAR (PE) by book-to-market and size without underpricing graphs







Appendix T: Selected regression betas

Industry	Beta SP500	Beta sample	Beta PE	Beta NPE
High Technology	1.1	1.3	1.15	1.29
Retail	1.2	1.3	1.18	1.44
Real Estate	0.6	0.6	0.85	0.57
Energy and Power	1.1	1.1	1.35	0.98
Financials	1.1	1.1	1.45	0.97
Consumer Products and Services	1.1	1.2	1.12	1.18
Industrials	1.0	1.0	0.98	1.11
Healthcare	1.3	1.4	1.16	1.45
Media and Entertainment	1.2	1.1	1.27	0.96
Telecommunications	0.5	0.6	0.48	0.65
Materials	1.2	1.2	1.44	0.95
Average	**1.02**	**1.08**	**1.13**	**1.05**
Weighted average	**1.04**	**1.19**	**1.19**	**1.20**

Appendix U, Automated regression code

```
Import pandas as pd,
import numpy as np, import statsmodels.api as sm,
path = "C:\\Users\\Rasmus\\Desktop \\"
dataset = pd.read_csv(path + "Dataset-daily.csv", delimiter=",", header=0), dataset.set_index('Date', inplace=True)
carhartt = pd.read_csv(path + "Returnset_Carhartt.csv", delimiter=";", header=0), carhartt.set_index('Dato', inplace=True)

def reg_m(y, x):  ones = np.ones(len(x[0]))
    X = sm.add_constant(np.column_stack((x[0], ones)))
    for elem in x[1:]:
        X = sm.add_constant(np.column_stack((elem, X)))
    results = sm.OLS(y, X).fit()
    return results

def lin_reg(type, column_name):
    a = dataset[column_name]
    a = a.dropna()
    local_vars = carhartt[carhartt.index.isin(a.index)]
    rm_rf = []
    for x in local_vars['rm-rf']:
        try:
            rm_rf.append(float(x))
        except:
            rm_rf.append(0)
    x1 = rm_rf    x2 = local_vars['SMB'].values.squeeze()    x3 = local_vars['HML'].values.squeeze()    x4 = local_vars['Momentum'].values.squeeze()
    if type=='carhartt': x = [list(x1), list(x2), list(x3), list(x4)]
    if type=='famafrench': x = [list(x1), list(x2), list(x3)]
    if type=='capm':  x = [list(x1)]
    y =  a - local_vars['RF']
    return reg_m(y, x)
param_dict = {}
for col in dataset.columns:
    lr = lin_reg('capm', col)
    lr = lr.params.append(pd.DataFrame([[1-lr.rsquared]], index=['rsquared']))
    param_dict[col] = list(lr[0])
df = pd.DataFrame(param_dict).T
df.columns = ['const', 'x1', 'rsquared']
df.to_csv(path + 'capm_results.csv', sep=',')
param_dict = {}
for col in dataset.columns:
    lr = lin_reg('famafrench', col),  lr = lr.params.append(pd.DataFrame([[1-lr.rsquared]], index=['rsquared'])),  param_dict[col] = list(lr[0])
df = pd.DataFrame(param_dict).T
df.columns = ['const', 'x1', 'x2', 'x3', 'rsquared']
df.to_csv(path + 'famafrench_results.csv', sep=','), param_dict = {}
for col in dataset.columns:
    lr = lin_reg('carhartt', col)
    lr = lr.params.append(pd.DataFrame([[1-lr.rsquared]], index=['rsquared'])),  param_dict[col] = list(lr[0])
df = pd.DataFrame(param_dict).T, df.columns = ['const', 'x1', 'x2', 'x3', 'x4', 'rsquared'], df.to_csv(path + 'carhartt_results.csv', sep=',')
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