

Predictors and analysis of IPOs long-term performance: evidence from the US market

Mattia Zinelli[♦]

Simone Cattaneo^{*}

Master's Thesis

Department of Finance

Stockholm School of Economics

December 2017

Abstract

This paper reassesses the long-term abnormal performance of US IPOs and seeks to detect predictors for long-run performance. We use monthly data of 600 listings over the sample period 2010-2014 to calculate performance at three different cut off points: 3, 5 and 7 years after the issue. We find that the measure of abnormal performance is extremely affected by the choice of market benchmark and asset pricing model. Thus, we cannot conclude that IPOs either over-perform or under-perform in the long-term. However, we do find that some IPO characteristics are strong predictors of long term abnormal returns, namely, institutional backing, age and overall market performance.

Keywords: Initial Public Offerings (IPOs), Abnormal Performance, Long-Term Performance

JEL Classification: G12, G14

Supervisor: Michael Halling[▲], Associate Professor, Department of Finance

[♦] 40993@student.hhs.se

^{*} 40999@student.hhs.se

[▲] We are grateful for the support and guidance throughout the course of writing this thesis.

Acknowledgments

I want to express my gratitude to my mom, sister and dad for the never-ending support and continuous encouragement over my years of study. This accomplishment would not have been possible without you. Once again, thanks.

Mattia

I would like to thank my family, who supported me unconditionally throughout my studies, and my friends, who were always there when I needed them.

Simone

Table of Contents

1	Introduction	1
2	Literature Review	3
3	Data.....	7
3.1	Sample Construction	7
3.2	Sample Characteristics	9
4	Methodology	11
4.1	Models.....	11
4.2	Benchmark	14
5	Results	15
5.1	After-Market Performance.....	15
5.2	Survivorship Bias	19
5.2.1	Data.....	19
5.2.2	Methodology	21
5.2.3	Results	22
5.3	Cross-sectional regressions.....	22
5.3.1	Industry	24
5.3.2	IPO-market cycle and Institutional Investors Involvement	25
5.3.3	Age of the Company at IPO and Value Investing Ratio	27
5.3.4	Market Characteristics	28
5.3.5	Main Drivers of IPO Long Term Performance	30
6	Robustness	31
6.1	Robustness to method.....	31
6.1.1	Institutional Involvement	31
6.1.2	Age and Value Investing Ratio.....	33
6.1.3	Market Characteristics	33
6.2	Robustness to Indices	34
6.2.1	Cycle and Institutional Involvement	34
6.2.2	Age and Value Investing Ratio.....	35
6.2.3	Market Characteristics	37

6.3	Summary	38
7	Discussion	39
8	Conclusion	41
9	References	43
10	Appendix	46

Table 1. Summary of the abbreviations used throughout this paper

Table of Abbreviations	
CAR	Reads as Cumulative Abnormal Returns
CAAR	Reads as Cumulative Average Abnormal Returns
BHAR	Reads as Buy-and-Hold Abnormal Returns
BHAAR	Reads as Buy-and-Hold Average Abnormal Returns
IPO	Reads as Initial Public Offering
SEO	Reads as Seasoned Equity Offering
CAPM	Reads as Capital Asset Pricing Model
FF3M	Reads as Fama-French 3 Factor Model
NYSE	Reads as New York Stock Exchange
NASDAQ	Refers to the NASDAQ Composite Index
Nasdaq	Refers to the Nasdaq stock market
CAPEX	Reads as Capital Expenditures
NIA	Reads as Net income over Assets
VC	Reads as Venture Capital
PE	Reads as Private Equity
M&A	Reads as Mergers & Acquisitions
SDC	Reads as Securities Data Company
CRSP	Reads as Center for Research in Security Prices
REIT	Reads as Real Estate Investment Trust
SPAC	Reads as Special Purpose Acquisition Company
API	Reads as Application Programming Interface
EMH	Reads as Efficient Market Theory

1 Introduction

The Initial Public Offering (IPO) process transforms a privately held company into a public entity, giving the opportunity to raise capital for further expansion and/or repay initial investors. The public launch comes with many benefits for the company, as it makes it easier to raise additional capital also in the form of debt, and gives the company more public exposure (Ritter and Welch, 2002). However, it entails some burdens, such as higher regulatory compliance and market pressure. Therefore, the decision of going public is one of the most important managerial decisions in a company's life. On average, in the U.S. only, there is an IPO every second day¹, which gives an indication of the sheer amount of possible opportunities investors are served with. Understanding the long-term performance of IPOs is important because of the key role of the IPO in the company's funding and development path. Our interest is to study the performance of IPOs from the investors' point of view and evaluate whether it is possible to predict which firms are going to have better long-term performance.

Despite the importance and the great attention of financial markets to IPOs, two anomalies have been documented. The most well recognized is underpricing, which is the abnormal positive return on the first trading day. Several studies have tried to characterize this issue (Reilly and Hatfield, 1969; Stickney, 1970; McDonald and Fischer, 1972), but researchers have not agreed upon a definite explanation. A second anomaly is the long-term underperformance, i.e. IPOs usually perform worse than the market over three- and five-year periods, as documented in Ritter (1991) and Ibbotson (1994). According to the Efficient Market Hypothesis (EMH) by Fama (1970), stock prices should include all public information, and should therefore react immediately to new information. Thus, we found

¹ Ritter (1991) documents 1,526 IPOs during the years 1975-84, equivalent to 0.6 listings every trading day. Our sample, counting delisted companies, 2010-14, includes 832 IPOs corresponding to 0.65 issues per trading day.

it interesting to question whether the EMH does not hold for IPOs. Possible explanations for a departure from EMH are that information asymmetry problems are extremely strong (Welch, 1989), as investors have limited access to information prior to the initial offering, or key performance drivers for IPOs are systematically misinterpreted. Our aim is to understand whether the market misjudges certain factors that influence IPO valuations, such as core value investing ratios or a firm’s characteristics, and what is the “true” relationship between these factors and the stock price returns observed in the sample.

Our analysis took inspiration from several previous studies (Ritter, 1991; Levis, 1993; Ibbotson, 1994; Loughran, 1995), but aimed to provide a more comprehensive assessment considering the most relevant findings. On average, previous literature found significant negative long-term performance of IPOs. Nevertheless, results were very sensitive to indices or methods used. Therefore, we believe that a re-analysis using a more recent, post-crisis dataset, integrated with a robust benchmark, provided an interesting opportunity for further characterizing performance and its drivers. Our sample period was also particularly noteworthy because, within the time span of a few years, it included both a cold and hot IPO market². In addition, we can also highlight how the results of underperformance were strongly dependent on benchmarks. We compared IPOs performance with three major US indices: Russell 3000, a value-weighted index that includes the 3000 largest US stocks; the NYSE Composite, and the NASDAQ Composite. Even though they were highly correlated, the three benchmarks performed differently and provided us with a perfect example of how relative performance can change a study’s conclusion. In fact, on a cumulative basis, their performance over the 2010-17 period varied from 65% for the NYSE Composite to 125% for the NASDAQ Composite. Finally, the long-term focus enabled us to more fully investigate which indicators drove performance. By doing so, we have been able to measure

² In 2010-11 only 245 firms went public, while in 2013-14 the number was 442, almost double the amount.

the effect and significance of a large variety of drivers, finding six factors that have significant impact on the performance of a company.

The paper is structured as follows: chapter 2 - Literature review; chapter 3 - Description of our dataset; chapter 4 - Description of the methodologies used and their mathematical and economic background; chapter 5 - Results of market-adjusted performance and main drivers; chapter 6 - Robustness; chapter 7 - Discussion; chapter 8 - Conclusion and areas for further research; chapter 9 - References; chapter 10 - Appendix.

2 Literature Review

In this section, we summarized what academic research has been able to explain when it comes to long-term IPO performance and present developed theories. Research has tried to explain why IPOs seemed to be unprofitable investments and to detect which variables had a significant impact on issuers performance. A very well documented pattern of IPOs is underpricing (Reilly and Hatfield, 1969; Stickney 1970; McDonald and Fischer, 1972) whereas long-term performance has never been analyzed thoroughly.

Ibbotson (1975) was one of the first to analyze the after-market performance of new issues. He used a sample spanning the years 1960 to 1969, creating a portfolio of IPOs by selecting one at random for each month. The findings were in line with previous literature regarding first day performance, which was significantly positive. The author also concluded that there was no significant departure from market efficiency in long-term performance. Later research began to cast doubts on the long-term performance of IPOs, Stern, Richard and Bornstein (1985) published an article in Forbes entitled “Why new issues are lousy investments” where they argued that IPOs represented poor long-term investments. Ritter (1991) was the first academic to characterize the issue. He analyzed the after-market performance of 1,526 IPOs using firm-adjusted returns, cumulative

average adjusted returns, and buy-and-hold average adjusted returns. By matching every newly issuing firm with an already traded company similar in industry and market capitalization, he created a control portfolio as a benchmark to calculate abnormal returns. The author found that underperformance 36 months from the IPO was both statistically and economically significant. On average, cumulative abnormal return was -29.13% with smaller firms that went public during high-volume years being the worst underperformers. On the other hand, larger and older firms with a well-established business did not show any pattern of underperformance. One explanation for these findings was that markets are subject to “Fads”³ as in Shiller (1990) and Aggarwal and Rivoli (1990) where investors are over-optimistic about new issues and thus overvalue firms. Ritter and Ibbotson (1994) reassessed long-term performance on a different sample period, from 1970 to 1990, and found that underperformance patterns were still strong and expanded to a 5-year horizon, contrary to previous belief. Moreover, they offered some insight on some of the theories that have been formulated to explain underperformance. Edward and Miller (1997) suggested that more optimistic investors will be buyers, driving up the valuation of an IPO, but as time goes by and more information about future performance becomes available, the price will drop. Another explanation was that investment bankers deliberately underprice IPOs to create an appearance of excess demand (Shiller, 1990). This hypothesis predicts that long-term performance is negatively correlated with short-term underpricing. Aggarwal *et al.* (1993) and Levis (1993) studied this phenomenon on markets different from the US. The former authors analyzed after-market performance of IPOs in South America, namely Brazil, Chile, and Mexico, and found positive first day returns, but negative long-run market-adjusted performance of -47%, -23.7%, and -19.6% respectively, thus suggesting once again a negative relationship between short and long-term performance. Levis implemented a similar study in the UK, where he evaluated the

³ Fads are referred as a wildly shared enthusiasm for new issues, that in theory would lead to a departure from intrinsic value

performance of 712 new listings. Results were again in line with what Ritter had documented, with appearance of underperformance expanding well over 36 months subsequent to the IPO. The author also suggested that the results should be interpreted with caution because of the changes in the composition of the sample due to the long-analysis period (M&As, bankruptcies, suspensions and transfers). Lastly, he found that firms earning higher first-day returns were the worst underperformers in the long-run.

Other studies have focused on comparing the performance of IPOs with seasoned equity offerings (SEOs). Loughran and Ritter (1995) compared returns on IPOs and SEOs, and reported that investing in either category on a 5-year horizon would have resulted in a loss of wealth compared with market-wide indices. The average annual return was only 5% for IPOs and 7% for SEOs. Their finding was also consistent with the theory that companies decide to go public whenever the market gives them a high valuation, i.e., during periods of prolific IPO activity (Lucas and McDonalds, 1990). One of the possible explanations they gave as to why IPOs seem to be poor long-term investments is that investors “want to believe they have identified the next Microsoft”. The authors claimed that “If the true probability that a given IPO will be the next Microsoft is 3 percent, but investors have instead estimated that it is 4 percent” the resulting stock overvaluation would be 33%. Therefore, a slight change in the probability of investing in a long-shot produces a much larger overvaluation of the company. The result is that it takes a very long period for investors to revise their estimate. Finally, they argued that investors seem to systematically overestimate the potential of IPO firms, resulting in a bet much more based on hope rather than experience. Lerner (1994), by collecting information from both public and private sources added evidence about the IPO cycle window. He argued that entrepreneurs take advantage of hot markets to raise as much money as possible for their companies and in case of cold markets, many revert to additional Venture Capital (VC) financing. Brav and Gompers (1997) further investigated the performance of VC-backed IPOs. They analyzed

returns from 934 VC-backed issues and 3407 that were non-backed. Not surprisingly, the authors found that VC-backed firms did outperform the control group, but only when using an equally weighted IPO portfolio. In addition, they tested the robustness of different methods of traditional measurement of performance against different benchmarks, and found that by value weighting returns, long-term underperformance became insignificant, contrary to previous studies. Using the Fama-French three-factor model (FF3M), they showed that VC-backed firms did not underperform the benchmark and by partitioning non-backed IPOs in deciles, they revealed that underperformance resided in the smallest decile of the distribution. More recently, Krishnan *et al.* (2009) focused on IPO performance and VC reputation, and found a positive association with several measures of long-run performance. While they rightfully pointed out that more reputable VCs selected better quality companies from the beginning, the significant association still remained even after controlling for VC selectivity. Indeed, more reputable VCs exhibited much greater involvement in portfolio companies even after the IPO, which had a positive long-run impact on performance.

Another stream of research focused on improving the measurements of long-term performance, most notably Barber and Lyon (1997) analyzed the empirical power of test statistics used to detect abnormal long-run returns. They found that cumulative abnormal returns (CAR) were a biased predictor of long-run buy-and-hold abnormal returns (BHAR) and suggested the latter method as favorable when computing long-run abnormal returns.

More recently, Espenlaub *et al.* (2000) compared UK abnormal long-term returns from 1985-92, under four different benchmarks: a simple capital asset pricing model (CAPM), a CAPM-type model to account for what they called “side effects”, FF3M and the RATS

methodology proposed by Ibbotson⁴ (1975). Results were in line with previous literature, since after 24 months the under-performance was severe against all benchmarks. However, from 60 months after the IPO, the under-performance depended on the selected benchmark, and in some cases, was not statistically significantly different from zero. Lastly, Goergen *et al.* (2007) tried to relate long-term under-performance of IPOs to the pre-issue financial performance as well as to managerial decisions taken just before the listing. The authors reported that both the percentage of equity issued and the degree of multinationality of a firm were strong predictors of long-term performance. However, there were signs that smaller firms tended to behave very differently from bigger ones and to suffer worse long-run under-performance.

3 Data

3.1 Sample Construction

Our dataset was composed of three streams of data, which were:

- Firms' characteristics at the moment of the IPO
- Companies' stock prices during the years following the listing
- Data relative to the benchmarks

The first set of data included information on the total market cap at the moment of the IPO, the age of the company, the listing date and other descriptive and core value investing information for firms that went public in the period 2010-2014. We used this set mainly to detect the most important variables contributing to the performance in our timeframe. We gathered the data from four databases: Bloomberg, SDC Platinum, Wharton Research Data Service (WRDS), and IPO data from Jay R. Ritter. We used mostly Bloomberg,

⁴ Ibbotson (1975) proposed a model called RATS or "Returns Across Time and Securities" to estimate a measure of systematic risk for individual IPOs for which historical time series are not available.

from which we downloaded the descriptive information, such as market cap, bookrunner, company's ticker, lock up periods, institutional backing information, date of the IPO, and information on the industries. We first downloaded the name of the companies that went public in the years from 2010 to 2014. We excluded from our sample accelerated book building, Special Purpose Acquisition Company (SPAC), secondary offerings, seasoned offerings, and, consistent with previous literature, closed-end funds and REITs. The reason why close-end funds and REITs were usually excluded is because their performance is often anomalous due to the composition of their underlying assets. Our first set of data included 694 stocks. We reduced this to 635 because 59 companies were listed after November 2014, which was the last date available for us to meet the minimum 36-month requirement, since our study focused on long-term returns, and convention in previous literature has been to analyze performance 3 years after listing. Further, 16 companies were deleted because, even if Bloomberg registered an IPO during the four years of our sample, they started trading before 2010. Finally, 19 stocks had missing data, and consequently they were also removed from the sample. The final set included 600 stocks. SDC Platinum was used to retrieve information on firms that went public during the years in question and subsequently delisted. We dedicated Chapter 5.2 to further investigate the effects of a possible survivorship bias. From WRDS, we downloaded core value investing information, which included capital expenditures (CAPEX), revenues, assets and other financial statements information. Finally, we used the IPO data from Jay R. Ritter to include the founding date of the company. Previous literature had reported that the age was a relevant variable, and therefore we decided to introduce it into our sample and determine if the effects that have been registered are retained.

The second set of data consisted of monthly price of the companies that went public on NYSE and Nasdaq from 2010 to 2014. Prices went from each IPO date to November 2017, and they were collected from the first day closing price - measure necessary to avoid

accounting for first day underpricing as in Ritter (1991) - and adjusted for stock splits and dividends. We primarily collected the data from Yahoo Finance, through the application programming interface (API) implementation available on Python. Python provided other sources, but Yahoo was the one that gave us the highest reliability of data. We also used Thomson Data Stream to download the prices of 8 stocks that presented some errors in the original dataset.

Finally, we ran the analyses using several benchmarks, namely the Russell 3000, NYSE Composite, NASDAQ Composite, CAPM and FF3M. We used the same open-source approach that we employed in the previous point to collect the monthly return for NYSE Composite, Russell 3000 and NASDAQ Composite. For 1-month risk-free rate and monthly returns on Small-Minus-Big and High-Minus-Low portfolios, we used the French data library.

3.2 Sample Characteristics

Our final sample included a large variety of stocks that were well-diversified in different sectors. For example, Bloomberg divided stocks into 10 main industries (table 4), with each of them consisting of several subindustries.

Table 2. Distribution of Initial Public Offerings by Year, 2010-2014. The number of IPOs in the sample is based on Bloomberg's data as well as the total gross proceeds and the total market cap of the newly listed companies. The aggregate gross proceeds over yearly market cap is the ratio between the gross proceeds and the market capitalization of each year, and therefore the total percentage value is the weighted average over the period. Data source: Bloomberg

Year	600 offers in sample			Yearly percentage values		
	No. of IPOs	Aggregate gross proceeds, \$ millions	Aggregate Market capitalization, \$ million	No. Of IPOs (%)	Aggregate gross proceeds over yearly market cap (%)	Aggregate Market capitalization (%)
2010	59	27,384.1	85,994.4	9.83%	31.84%	10.08%
2011	79	28,880.7	125,094.1	13.17%	23.09%	14.67%
2012	93	33,731.7	141,539.2	15.50%	23.83%	16.60%
2013	154	45,929.7	165,820.8	25.67%	27.70%	19.45%
2014	215	73,709.6	334,261.3	35.83%	22.05%	39.20%
Total	600	209,635.9	852,709.6	100.00%	24.58%	100.00%

The largest group was the Consumer, Non-cyclical industry, whose definition is broad, as it included healthcare, pharma, biotechnology, and the food and beverages sub-industries. Other groups contained fewer sub-industries and therefore the number of total firms in their cluster was lower. Nevertheless, we considered the sample rather diversified.

Conversely, the size distribution of IPOs was far from uniform. Except for a few large cap and several medium cap IPOs, the average size was, not surprisingly, relatively small. Table 3 shows that until the 6th decile, observations had a market capitalization below 530 million \$US, and therefore it suggested to us that we needed to check and control our results for possible size-bias. Indeed, we may observe certain trends that are not related to IPOs in general, but rather to the size composition of the sample.

Table 3. Market Capitalization divided into deciles. Division of our sample by market capitalization. As we can see, there is a large number of small companies and a value-weighted approach will make our sample extremely dependent by the largest IPO we observed, Alibaba. Data source: Bloomberg

Decile	Market cap, \$ million	Ratio between decile's market cap and maximum market cap in the sample
10%	96.4	0.06%
20%	149.9	0.09%
30%	211.9	0.13%
40%	272.7	0.16%
50%	363.3	0.22%
60%	529.6	0.32%
70%	751.8	0.45%
80%	1,288.0	0.77%
90%	2,416.8	1.44%
100%	167,620.0	100%

Finally, we analyzed our sample regarding the average age at which companies went public (Table 4). Generally, we did not observe any distinctive trends for industry and age at the moment of the listing except for Financial and Energy. Tech companies tended to go public earlier than other industries, with an average age of about 14.5 years, while Cyclical Consumer companies tended to be the oldest, on average. In addition, we observed a peculiar pattern for Energy and Financials. Many of them, approximately 25% for

Energy and a 15% for Financials, went public within the first year from their founding date. In the case of Financials, many IPOs were used for fundraising purposes. In contrast, for Energy, early-public companies were often subsidiaries created by parent companies.

Table 4. Mean and Median Gross proceeds, Market capitalization and age of 600 companies by Industry. The sample includes 10 industries, as characterized from Bloomberg. On average, the higher mean than median in Gross proceeds and Total market cap shows the presence of outliers. There are few large companies and a multitude of small ones. With regard to the age, Consumer, Cyclical is the cluster with older average companies at IPOs, while Energy and Financials have a large number of early listings. Data source: Bloomberg and Ritter IPO database

Industry	No. of IPOs	Gross proceeds, \$ million		Total market cap, \$ million		Age, years	
		Mean	Median	Mean	Median	Mean	Median
Technology	54	152.5	110.1	1,150.0	499.3	14.0	10.5
Consumer, Cyclical	62	621.0	189.1	1,003.9	419.2	35.1	30.5
Consumer, Non-cyclical	190	171.1	77.0	1,978.1	329.8	15.5	10.0
Diversified	1	52.3	52.3	89.4	89.4	32.0	32.0
Financial	97	272.2	108.0	995.3	290.5	16.3	5.0
Energy	73	460.3	342.1	1,010.8	258.2	16.5	3.0
Basic Materials	16	266.5	210.0	506.6	267.8	29.1	2.5
Communications	66	881.1	132.2	2,362.7	419.5	14.2	9.0
Utilities	5	380.6	434.7	363.6	397.6	11.6	10.0
Industrial	36	167.0	139.8	434.2	310.8	22.2	11.0
Total	600	349.8	116.8	1,419.8	331.1	22.1	12.0

4 Methodology

4.1 Models

To investigate long-term returns, we followed the standard approach utilized in previous published analysis. The convention in research has been to calculate either daily or monthly abnormal returns over the analyzed period. We defined $R_{i,t}$ as the monthly return on a firm i , and $E(R_{i,t})$ as the month t expected return for firm i . Abnormal return then follows as

$$AR_{i,t} = R_{i,t} - E(R_{i,t})$$

$E(R_{i,t})$ has been a debated issue in past research. Lucas and McDonald (1990) claimed that, on an aggregate level and for simplicity, it is possible to approximate the expected return of a sample firm as the return of a well-diversified market index. However, Ritter (1991) stated that, consistent with the definition of abnormal return, it would be better to use an asset pricing model to estimate expected returns. It was well documented that, while returns can be explained by the effect of CAPM-beta, they are also influenced by book-to-market ratio and firm size (Fama and French, 1992). Dimson and Marsh (1986) took into account the size effect by creating decile portfolios and assigning each company to the respective one, based on the market capitalization at the beginning of the year. Alternatively, other studies such as Loughran and Ritter (1995) and Fama and French (1996) used a multi-factor model approach. Georgen (2007) used a portfolio of IPO firms as opposed to single firms to estimate expected returns. While this is done to minimize noise when estimating parameters, we think that, to be consistent with the definition of abnormal return, it is more correct to estimate returns for single firms rather than on an aggregate level. Indeed, we believe that in order to compare results from FF3M and CAPM with those obtained from a simple market index, computing returns for each security rather than for portfolio resulted in a more consistent measure. Furthermore, previous literature also provided the framework to compute long-term abnormal returns using two different methods: cumulative abnormal returns (CAR) and buy and hold abnormal returns (BHAR). Barber and Lyon (1996) documented that CAR is a biased predictor of BHAR and could lead to errors of statistical inference in some cases and therefore, BHAR should be the preferred method. The main advantage of BHAR was that it accounted for compounding effects, while CAR did not. Much of the related literature continued to use CAR to compute abnormal returns, thus, we decided to employ both methods to investigate the robustness of our findings.

Model 1: Buy-and-Hold Abnormal Returns (BHAR)

Buy and hold returns for a firm i were calculated as in Ritter (1991):

$$BHAR_{i,t} = \prod_{t=1}^T (1 + R_{i,t}) - \prod_{t=1}^T (1 + R_{m,t})$$

Where $R_{i,t}$ was the return for firm i on month t and $R_{m,t}$ was the return on the market benchmark on month t . The t -statistics was adjusted for skewness as proposed by Lyon (1999) and calculated as:

$$t-stat = \sqrt{N} \left(S + \frac{1}{3} \gamma S^2 + \frac{1}{6N} \gamma \right)$$

where

$$S = \frac{\overline{BHAR_t}}{\sigma(BHAR_t)} \quad \gamma = \frac{\sum_{i=1}^n (BHAR_i - \overline{BHAR_t})^3}{n\sigma(BHAR_t)^3} \quad N = \text{number of firms}$$

This adjustment was necessary as the BHAR distribution did not behave as normal but presented a marked skewness (range 4-6). Also, we referred to BHAAR as

$$BHAAR_t = \sum_{i=1}^N \frac{1}{N} BHAR_{i,t}$$

Model 2: Cumulative Average Abnormal Return (CAAR)

Cumulative average abnormal returns were calculated as in Ritter (1991) and Levis (1993):

$$CAAR_{i,t} = \sum_{t=1}^T \frac{1}{N} \sum_i^N AR_{i,t}$$

Where $AR_{i,t} = R_{i,t} - R_{m,t}$ was the abnormal return in month t for firm i , with N firms in the sample. Given the distribution skewness adjustment was not needed.

4.2 Benchmark

We tested the two models outlined above against 3 different benchmarks: well-diversified market indices, a single factor model and a multi-factor model.

Benchmark 1: Well-Diversified Market Indices

We used three different market indices as proxies for expected returns because, as pointed out by Ritter (1991), using a single index can lead to distorted results. Buser and Chan (1987) found positive aftermarket performance by testing IPOs against the NASDAQ Composite, although during their sample period, the NASDAQ Composite substantially underperformed other indices. Consequently, we decided to use:

- NASDAQ Composite Index, which tracks the performance of all companies listed on the Nasdaq stock market; 371 firms in our sample were listed on this exchange.
- NYSE Composite Index, which covers all the companies listed on the New York Stock Exchange. The remaining 229 firms in our sample were traded on this index.
- Russell 3000 Index, which includes the 3000 largest publicly held companies in America, representing 98% of the American equity market. A drawback of using this index was that, being capitalization weighted, it was mainly driven by large cap stocks, while small and medium cap firms have a marginal impact on returns.

Benchmark 2: Single-Factor Model

We estimated abnormal returns using the standard CAPM where the abnormal return for firm i in month t was captured by $\alpha_{i,t}$:

$$\alpha_{i,t} = R_{i,t} - [r_{f,t} + \beta(R_{m,t} - r_{f,t})] .$$

where $R_{i,t}$ was the return of company i in month t , $r_{f,t}$ was the return on one-month T-bills in t and $R_{m,t}$ was the return on the market benchmark in t .

Benchmark 3: Multi-Factor Model

We followed Fama and French (1996) by estimating the abnormal return for each firm i in our sample, which was represented by $\alpha_{i,t}$:

$$\alpha_{i,t} = R_{i,t} - [r_{f,t} + \beta_i(R_{m,t} - r_{f,t}) + \gamma_i SMB + \delta_i HML]$$

where $R_{i,t}$ was the return on company i in month t , $r_{f,t}$ was the return on one-month T-bills in t , $R_{m,t}$ was the return on the market benchmark in t , and SMB and HML were respectively the returns on small firms minus returns on big firms and the return on high book-to-market firms minus returns on low book-to-market firms. We relied on the Kenneth French library for the calculation of the factors, which follows the standard approach when creating portfolios.

5 Results

5.1 After-Market Performance

In this section, we presented our findings regarding long-term abnormal returns. Table 5 reports CAAR up to 84 months after the IPO. We can see that results changed drastically according to different indices. NYSE-adjusted CAAR showed consistent over-performance of IPOs relative to the index, with significant t-stats until the 69th month of trading. In contrast, NASDAQ-adjusted CAAR showed converse behavior, with significant under-performance from the 38th month of trading. The Russell-adjusted CAAR resulted in values between the NYSE- and NASDAQ-adjusted results, with neither significant under-performance nor over-performance. A consistent finding across indices was the initial over-performance in the first few months of trading, which can be explained by the underpricing theory of IPOs (Beatty 1986, Welch 1989).

Similarly, table 6 presents average BHAR up to 84 months after the IPO. NYSE-adjusted BHAAR again appeared to be significantly positive until the 66th month of trading. NASDAQ-adjusted BHAAR resulted in significant under-performance from the 67th month of trading, while Russell-adjusted BHAR showed neither significant over-performance nor under-performance patterns. As mentioned above for cumulative returns, BHAAR were significantly positive in the first months after going public. For both methodologies, we can see that towards the end of the sample period, from month 78 onwards, the number of trading firms in the sample dropped substantially and therefore results cannot be interpreted as representative for the whole sample. In fact, the standard deviation became so large that statistical significance was lost and the portfolio of IPOs was mainly driven by a few outliers.

We plotted in figure 1 and 2 CAAR and BHAAR across the trading period. This visual representation confirmed how sensible the definition of abnormal returns can be to different benchmarks and methodologies. Brav and Gompers (1997) highlighted a similar behavior in their paper, where they found no significant underperformance between IPO firms and already traded companies of similar size and book-to-market ratio.

We also tested the two models using CAPM and FF3M to determine whether results would be in line with what our findings had shown so far. We decided to use the Russell Index as the main proxy for market return. As expected, CAPM and FF3M did alter the results we observed using a simple market index benchmark. Firms earned statistically significant abnormal returns in the first months after the IPO, steadily declining afterwards, arriving at a negative abnormal performance that ranged from -13% to -40%, albeit not being statistically significant. Table 7 reports abnormal returns for both CAAR and BHAAR.

In brief, we cannot support previous literature view of under-performance in the long term for IPOs. The measure was extremely dependent on the indices and the methods used to assess over- or under-performance. Focusing the comments only on the result of BHAAR, in the 36-month horizon, IPOs over-performed relative to both the NYSE Composite and the Russell 3000 by 22.55% and 6.91% respectively, but under-performed against the NASDAQ Composite by 7.79%. The trend continued for the 60-month horizon where significance of the results was strengthened for NYSE and NASDAQ, but not for Russell. Finally, the 84-month horizon provided the same conclusions, however, significance decreased due to the lower number of firms.

Table 5. Market-adjusted Cumulative average abnormal from month 1 to 84. We report CAAR for each month along with the number of firms trading in our sample and t-tests. For readability purposes, we do not show the full table month-by-month, which has been moved to the appendix.

Market Adjusted Cumulative Abnormal Returns							
Month	Firms	Russel Adjusted	<i>t-test</i>	NYSE Adjusted	<i>t-test</i>	NASDAQ Adjusted	<i>t-test</i>
1	600	2.17%	3.08	2.55%	3.61	1.92%	2.75
6	600	4.36%	2.36	6.56%	3.55	2.58%	1.39
12	600	4.46%	1.87	9.20%	3.85	0.59%	0.25
18	600	4.43%	1.43	11.53%	3.72	-1.19%	-0.38
24	600	2.81%	0.80	11.71%	3.36	-3.79%	-1.09
30	600	5.61%	1.39	16.41%	4.08	-2.89%	-0.72
36	600	5.83%	1.39	18.43%	4.38	-5.12%	-1.22
42	490	3.77%	0.78	18.22%	3.79	-9.22%	-1.91
48	376	5.09%	0.90	21.53%	3.79	-9.40%	-1.65
54	281	5.03%	0.80	23.72%	3.79	-10.94%	-1.74
60	227	6.43%	0.85	26.90%	3.57	-9.63%	-1.28
66	182	0.29%	0.03	22.46%	2.55	-16.56%	-1.88
72	132	-5.94%	-0.56	18.71%	1.78	-24.63%	-2.33
78	104	-8.04%	-0.63	18.14%	1.42	-29.69%	-2.30
84	47	11.01%	0.50	37.99%	1.75	-12.62%	-0.58

Table 6. Market-adjusted Buy-and-Hold average abnormal from month 1 to 84. We report BHAAR for each month along with the number of firms trading in our sample and t-tests. For readability purposes, we do not show the full table month-by-moth, which has been moved to the appendix.

Market Adjusted Buy-and-Hold Abnormal Returns							
Month	Firms	Russel Adjusted	<i>t-test</i>	NYSE Adjusted	<i>t-test</i>	NASDAQ Adjusted	<i>t-test</i>
1	600	2.60%	3.64	2.93%	4.27	2.31%	3.29
6	600	2.80%	1.55	5.13%	3.23	0.87%	0.51
12	600	3.75%	1.39	8.89%	3.78	-0.68%	-0.23
18	600	4.22%	1.00	11.89%	3.60	-1.92%	-0.39
24	600	5.74%	0.84	15.77%	3.33	-1.80%	-0.16
30	600	6.72%	0.78	19.53%	3.30	-3.79%	-0.31
36	600	6.91%	0.57	22.55%	2.88	-7.79%	-0.42
42	490	-0.57%	-0.06	18.78%	2.59	-19.59%	-1.27
48	376	4.59%	0.41	27.71%	3.26	-17.99%	-1.23
54	281	4.32%	0.29	32.14%	3.03	-22.97%	-1.08
60	227	8.67%	0.49	40.15%	3.11	-20.18%	-0.89
66	182	-6.45%	-0.37	28.63%	1.97	-37.37%	-1.61
72	132	-26.35%	-1.54	14.48%	0.97	-63.21%	-2.42
78	104	-25.97%	-1.27	19.34%	1.07	-71.70%	-2.43
84	47	5.75%	0.14	57.79%	1.68	-50.53%	-0.95

Table 7. Asset-Pricing-adjusted CAAR and BHAAR period 1-84. We report the measures for each month along with the number of firms trading in our sample and t-tests. For readability purposes, we do not show the full table month-by-moth, which has been moved to the appendix.

Asset-Pricing Adjusted Cumulative & Buy-and-Hold Abnormal Returns									
Month	Firms	CAR	<i>t-test</i>	CAR	<i>t-test</i>	BHAR	<i>t-test</i>	BHAR	<i>t-test</i>
		CAPM-Adjusted		FF3-Adjusted		CAPM-Adjusted		FF3-Adjusted	
1	600	1.91%	2.74	2.18%	3.14	1.91%	2.74	2.18%	3.14
6	600	3.17%	1.72	4.88%	2.64	1.19%	3.90	3.12%	4.37
12	600	2.72%	1.13	4.89%	2.00	0.80%	0.66	4.39%	1.74
18	600	2.31%	0.74	5.95%	1.81	0.76%	0.78	6.80%	1.92
24	600	0.44%	0.12	3.96%	1.06	2.48%	0.29	8.91%	1.61
30	600	3.03%	0.71	4.27%	0.98	2.96%	0.40	10.13%	1.60
36	600	4.11%	0.89	2.55%	0.55	2.59%	0.18	9.38%	1.58
42	490	1.71%	0.32	0.35%	0.07	-7.98%	0.62	2.21%	1.79
48	376	2.08%	0.35	-0.25%	-0.04	-6.97%	0.36	5.76%	1.30
54	281	0.51%	0.08	-1.51%	-0.23	-9.78%	0.66	3.64%	1.47
60	227	-0.01%	0.00	0.14%	0.02	-5.88%	0.34	8.61%	1.16
66	182	-7.01%	-0.76	-6.61%	-0.73	-18.99%	0.06	0.89%	0.87
72	132	-14.75%	-1.35	-16.23%	-1.51	-42.52%	0.21	-20.21%	0.78
78	104	-17.84%	-1.31	-22.45%	-1.66	-48.09%	-0.33	-28.31%	0.47
84	47	-3.23%	-0.15	-13.77%	-0.63	-33.09%	-0.80	-16.02%	0.22

Figure 1. Average Cumulative Abnormal returns month 1-84. We plot 3 different CAAR time series, NYSE composite-, Russell 3000- and NASDAQ-adjusted. All computations have been done on an equally-weighted basis.

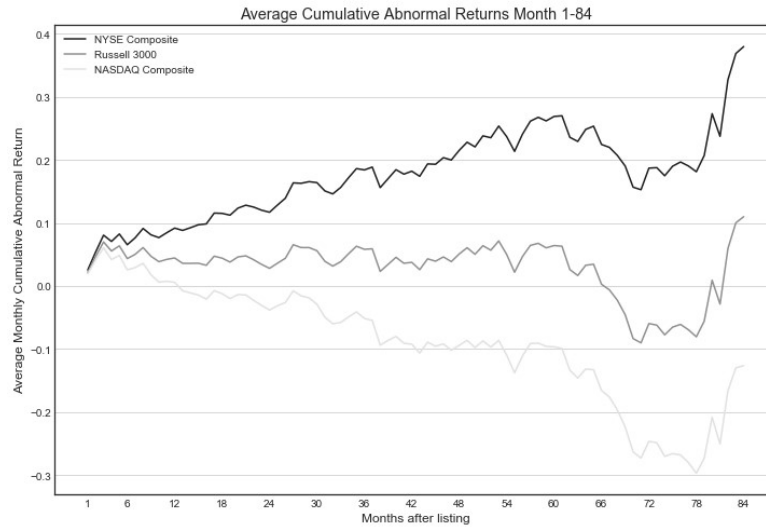


Figure 2. Average Buy-and-Hold abnormal returns month 1-84. We plot 3 different BHAAR time series, NYSE composite-Russell 3000- and NASDAQ-adjusted. All computations have been done on an equally-weighted basis



5.2 Survivorship Bias

5.2.1 Data

This section addressed the problem of survivorship bias documented in several papers that have studied post-IPO performance (Ritter, 1991; Barber and Lyon 1997; Krishnan *et al.*,

2009). Bloomberg’s IPO list was not comprehensive as it did not include information on companies that went public and were subsequently delisted for various reasons. Therefore, we downloaded from SDC Platinum additional 262 IPOs on the NYSE and Nasdaq markets that were listed between 2010 and 2014 and then delisted between 2010 and 2017. Consistent with the rest of our data sample, we avoided shell companies, REITs, and closed-end funds. Once we created the list of IPOs that were delisted, we downloaded the prices from WRDS’s Center for Research in Security Prices (CRSP) tapes, which gave prices until December 2016. Along with tickers, monthly prices and names of the companies, we downloaded delisting codes. These codes represented an extremely useful tool because they allowed us to understand the cause of the delisting. For example, a delisting code starting with “2” represented a company that delisted for Mergers and Acquisitions (M&A) activity, while a delisting code beginning with “5” represented a company that was dropped due to bankruptcy, poor performance or security inactivity. In our sample, 180 companies delisted for M&A. This meant that they could either be purchased and be incorporated into the acquirer, or merged with a company and create a new entity. In both cases, they did not appear in our initial dataset of 600 stocks. Other 72 companies delisted because of liquidation procedures or management buy-out. In these cases, trading prices simply halted. Data were available for a total of 224 stocks and among them, 10 continued to trade after December 2016. We adjusted them individually, when data were available. Overall, we considered 220 stocks.

Even though a large part of the previous literature did not discuss survivorship bias, we believed that it was important to clarify how measures of abnormal returns can change due to this bias. One of the main problems when evaluating delisted companies was the quality of data, because it was hard to find stocks’ prices and information. Barber and Lyon (1997) argued that it is not possible to have an ex-ante direction of survivorship bias, since many companies were acquired, resulting in substantial positive returns for investors,

while others failed and investors lost all their principal. Considering the high standard deviation of the returns and poor quality of the data for the regression, we decided to perform a separate analysis on the delisted companies and see if, on an aggregate level, they behaved in a manner similar to the companies that did not delist. On average, the companies in the sample were delisted after 38.5 months, with the average life of the companies that went through an M&A procedure being shorter than the ones that failed.

5.2.2 Methodology

For this part of the study, we used CAR returns benchmarked against the Russell 3000. We further assumed that if the company is acquired, the investor placed all the proceeds in the index and, if the company failed, we still assumed an investment in the index. By doing so, abnormal returns will be cumulated until the delisting date, and remain constant afterwards. We used CAR instead of BHAR for this specific case because of the problems in computing BHAR for the post-delisting period. Indeed, the compounding effect peculiar to BHAR calculations made it so that, after the delisting date, abnormal returns did not remain constant. An example can explain this better. We invest in $t = 0$ in two portfolios, each with a value of one hundred dollars and composed of one security each, namely stock A (portfolio A) and Russell 3000 (portfolio B). After one year, company A is bought and the stock returns a BHAR of 5. From this point on, if the investor invests the proceed in the Russell 3000 (new portfolio A), it will have a larger portfolio value than portfolio B. Every change in the index will have a larger dollar impact in portfolio A than in portfolio B, resulting in an increasing BHAR. Since the index performed very well over the sample period, this computation of BHAR would result in a biased measurement of the total return. Taking this into account, it would have made the comparison with the BHAR of currently listed companies nonsignificant. On the other hand, CAR did not suffer from this bias, making it a better fit for the purpose. Therefore, it was possible to compare CARs from delisted and listed companies.

5.2.3 Results

Since the sample consisted mainly of companies that delisted for M&A activity, the CAAR was often positive (68% of the monthly cross-sectional observations). The overperformance was statistically significant against all indices for the first 6 months and the sample behaved similarly to the previous dataset. However, values were more extreme, and this determined the non-significance of many monthly observation. Overall, delisted companies would have added a lot of variance to our analysis and this is why we decided to analyze them separately⁵.

In addition, we saw that delisted companies did not alter the previously found results. Considering that many firms had missing or incorrect data, and that the overall monthly performance was similar to the results found in the previous points, we decided not to include these companies in our regressions.

5.3 Cross-sectional regressions

This section presented the results obtained by cross-sectional and time series analysis to investigate potential drivers in IPO performance and understand which factors determine under- or over-performance

We conducted the analysis by grouping control variables into four thematic areas:

- Industry Group

The sample was divided into 10⁶ industries as outlined in Chapter 3. Each firm was assigned to the respective group and a regression was performed to identify whether some industries systematically outperform or under-perform others.

- IPO market Characteristics

⁵ Tables describing delisted companies' performance can be found in the appendix

⁶ In the regressions, we only use 8 different Industries groups, as Utilities and Diversified were omitted because each category counted less than 5 observations

First, we introduced a cycle dummy variable to test the “hot-market” phenomenon. Helwege and Liang (2001) suggested that hot IPO markets were inversely related to the quality of the issuer. Second, we controlled for institutional involvement to test whether Venture Capital (VC) and Private Equity (PE) are able to identify better quality companies.

- Firm Characteristics

We controlled for age of the company and a value investing ratio identified as

$$NIA = \frac{Positive\ Net\ Income}{Assets}$$

Both of these controls were proxies for how well-established a company is; therefore, a positive relationship would suggest that older companies with proven business capabilities were more likely to earn superior returns in the long-run.

- Market Characteristics

Following previous literature (Ritter, 1991; Campbell, 1992), we added controls for market performance and stock volatility. It has been documented that both variables played an important role in the long-term performance of stocks, and therefore, we wanted to test if the same results appeared in our sample.

We first studied the impact of these variables on the returns during the first three years after listing and eventually checked the effects for the five- and the seven-year horizons. The results presented in the tables that pertain to this section were computed using the BHAR method. In the robustness section, we ran the same analysis on the alternative CAR, CAPM and FF3M, as previously described in this paper, and against the indices. The idea was to analyze whether the findings were dependent on external variables or if significance persisted independently of different models and benchmarks.

5.3.1 Industry

We found that no industry was particularly relevant with regards to overall performance in the three-, five- and seven-year horizons. Table 8 summarizes the findings for the 36-month period. In the analysis, we have omitted Utilities and Diversified because the low number of observations would render coefficients and p-values misleading for these two categories.

When changing our dependent variable, i.e., using CAR and BHAR benchmarked in the CAPM and FF3M, we did not find significant divergence from the results obtained in the first set of regressions. We can therefore conclude that the industry did not have a significant effect on post-IPO performance. This finding was in line with our expectations; if any sector were proven to earn significant positive abnormal long-term returns, investors would buy IPOs from that sector only, thus driving prices upwards and returns downwards.

Table 8. Linear Regression of Industry dummies on BHAAR at month 36. Standard errors are reported in parenthesis. *, **, *** indicate significance at the 90%, 95% and 99% level, respectively. Utilities and Diversified do not appear because each of the two had less than 5 observations. No. Obs. stands for number of observations.

Dependent Variable: BHAAR36	
	36 - Mo
	<u>Coefficient</u>
Technology	0.139 (0.208)
Financial	-0.063 (0.122)
Consumer Cyclical	0.074 (0.144)
Energy	-0.042 (0.164)
Basic Materials	-0.119 (0.342)
Communications	-0.031 (0.145)
Industrial	-0.010 (0.162)
Consumer Non-Cyclical	-0.055 (-0.077)
R-squared	0.003
No. Obs.	594

5.3.2 IPO-market cycle and Institutional Investors Involvement

In this section, we tested market timing theory. Markets witness IPO-cycles, with years when only a single company per week is listed and years with more than one company per day going public. According to Lucas and McDonald (1990) this was due to asymmetric information such that entrepreneurs go public only in the presence of hot markets. A cold market would set the price of their company too low, hence, they would decide to wait for better conditions. Ritter and Welch (2002) suggested an additional semi-rational theory. They justified the cycles in issuing activity with a perspective different from entrepreneurs, who are driven by irrational private sentiment, and different from the market, which is driven by irrational public sentiment. Therefore, even if there are two different valuations, the entrepreneurs are more inclined to sell their shares when public prices increased sufficiently to provide a high valuation. Past literature also highlighted how, on average, during hot markets, lower quality firms decided to go public to take advantage of the bullishness of investors (Loughran and Ritter, 1995).

Gompers (1995) revealed that VC firms were more capable of valuating private and young companies and, by doing so, reduce asymmetric information. In addition, VCs and PEs may aid companies at developing a managerial structure that allowed them to systematically perform better than non-backed firms (Brav and Gompers, 1997). Furthermore, Berry *et al.* (1990) and Megginson (1991) reported that markets have a positive reaction to institutional involvement.

Accounting for these empirical findings, we analyzed stock performance controlling for both variables as presented above. Our test for institutional involvement was therefore robust to cycles as our sample included years of prolific issuance as well as low IPO activity.

Table 9. Linear Regression of Institutional backing and cycle on BHAAR at month 36,60 and 84. Standard errors are reported in parenthesis. *, **, *** indicate significance at the 90%, 95% and 99% level, respectively.

Dependent Variable: BHAAR			
	36 - Mo	60 - Mo	84 - Mo
	<u>Coefficient</u>	<u>Coefficient</u>	<u>Coefficient</u>
Inst. Back	0.176** (0.087)	0.124 (0.257)	0.930 (0.874)
Cycle	-0.169* (0.0937)	-0.004 (0.591)	1.327 (2.211)
R-squared	0.012	0.001	0.03
No. Obs	600	227	47

Our results pointed toward a strong significance of the market cycle and institutional involvement. The former had a p-value of 7.1%, while the latter had a p-value of 4.3%. The participation of PEs and VCs had a positive influence on stock market performance, while the cycle was contrary to the long-term performance. In the five-years horizon, coefficients maintained the same direction, but lost significance. In the longest time horizon, cycle became positive while institutional involvement held the same direction and both coefficients were not significantly different from zero. In this case, cycle lost its reliability as a variable because all the firms belong to the same listing year. Indeed, in the 7-year horizon sample there were only companies that issued in 2010, which were identified with the same cycle dummy. It would be interesting to study the effects of these variables using a larger sample, to help characterize the persistence of this phenomenon.

These results were consistent with the theories previously proposed. The three-years underperformance was consistent with Ritter and Welch (2002) in the sense that the companies went public when the market gave entrepreneurs a high valuation. Since the cycle had a negative impact, we inferred that during hot markets, companies had gone public too early, giving the entrepreneurs a possibility to raise money at favorable valuations but perhaps at a wrong stage for the company. In the years following the listing, the market realized the overpricing of the IPOs and consequently prices went down.

5.3.3 Age of the Company at IPO and Value Investing Ratio

Several papers, such as Clark (2002) and Ritter (1991), have reported the effect of the age of the company at the moment of the IPO, finding a significant positive association with long-term returns. Furthermore, as there were several studies that characterized the relationship between value investing ratios and long-term performance (Piotroski, 2000, Campbell and Shiller, 1998), we decided to evaluate whether this hypothesis held for newly listed companies as well. Since age has been documented to have a positive impact on returns, and our full sample showed the same behavior, we decided to strengthen the analysis by also focusing on companies that only had a positive net income at listing, captured by:

$$NIA = \frac{Positive\ Net\ Income}{Assets}$$

Following Ritter, the variable age was calculated as:

$$Age = \ln(1 + age)$$

Age and NIA showed significant positive impact on BHAAR. (p-values of 5.6% and 3.3% respectively). It was particularly interesting to observe the effect of NIA on BHAR. Indeed, a one percentage point change in this variable resulted in a 2.5% improvement in the dependent variable. The effect of NIA was not significant when considering the companies with a negative net income. One possible explanation pertained to the way growth companies' products are valued by the market. Companies with negative income were mostly companies with products still in development and the IPO was used to further finance the research. The market may overvalue the income generated by these products, which have not been demonstrated as successful among customers. On the other hand, firms with a stable business model and profit generation capacity seemed to be good candidates for long-term overperformance.

Table 10. Linear Regression of Age and Net Income over Assets on BHAAR at month 36,60 and 84. Standard errors are reported in parenthesis. *, **, *** indicate significance at the 90%, 95% and 99% level, respectively.

Dependent Variable: BHAAR			
	36 - Mo	60 - Mo	84 - Mo
	<u>Coefficient</u>	<u>Coefficient</u>	<u>Coefficient</u>
Age	0.119* (0.062)	0.087 (0.159)	-0.026 (0.549)
NIA	0.025** (0.012)	0.043 (0.029)	-0.059 (0.192)
R-squared	0.030	0.025	0.007
No. Obs	216	90	18

Age and NIA lost significance in the long-term. Part of the explanation resulted from the low number of observations, which were 90 over 60 months and 18 over 84 months. The constraint of using only income positive companies reduced the number of available firms and negatively affected the overall statistical power. For the five years, coefficients pointed toward the same conclusion, while the seven-year horizon coefficients indicated converse effect.

5.3.4 Market Characteristics

Our fourth regression controlled the performance of IPOs for market performance and the stock volatility. Ritter (1991) documented that overall market trend had a marked positive impact on long-term IPO returns, while Campbell (1992) studied the impact of volatility on stock returns. He found that volatility generally had little impact on performance, but it could become relevant during periods of high volatility. Hence, we ran an ex-post regression that combined the two approaches in order to determine how IPOs behave.

Table 11. Linear Regression of Market Performance and Stock Volatility on BHAAR at month 36,60 and 84. Standard errors are reported in parenthesis. *, **, *** indicate significance at the 90%, 95% and 99% level, respectively.

Dependent Variable: BHAAR			
	36 - Mo	60 - Mo	84 - Mo
	<u>Coefficient</u>	<u>Coefficient</u>	<u>Coefficient</u>
Market	0.858*** (0.334)	0.658 (0.923)	-1.558 (3.486)
Ln(vol)	-0.797 (0.549)	-0.349 (2.174)	3.327 (8.552)
R-squared	0.016	0.002	0.007
No. Obs	600	227	47

In accordance with previous literature, market performance had a statistically significant positive impact on BHAAR, while volatility had a non-significant negative relationship. A market coefficient of 0.85 means that, for every 1% increase in market return, the BHAR of a stock increases by 0.85 basis points. This result was due to the higher average beta of our sample. As explained previously, IPOs were mostly carried by small companies, which were on average more risky than larger companies. A resulting $\beta > 1$ made them overreact to market trends. In the time frame we analyzed, the markets reached all-time historical highs and our aftermarket performance benefitted from this event. In other market condition, such as recession or bearish markets in general, the IPOs should show weaker performances. In contrast, volatility did not provide us with a clear answer. Even though our results agreed with those of Campbell (1992), we cannot assert that the relationship can also hold in other samples. For instance, we observed a trend in our sample where biopharma companies, which represented almost 10% of the total IPOs, tended to have huge spikes when approaching one year of trading, followed by large plunges in the following months. This is an example of how our sample could be influenced by a single class of equity behavior.

Once again, findings were not time-proof. Five-year regression maintained coefficients in the same direction, albeit with different magnitude and significance. However, seven-year regression reported contrasting and non-significant coefficients.

5.3.5 Main Drivers of IPO Long Term Performance

Results obtained so far suggested that the main drivers of IPO abnormal performance were institutional backing, age, and market trend. If we controlled for all these variables in a single regression, we found that they all retain their significance.

Institutional backing improved abnormal returns by almost 19% on average (p-value 0.036), proving once again what Brav and Gompers (1997) and Krishnan *et al.* (2009) documented. Age was more complex to interpret. Since the variable was logged, a 1% increase in the age of the company led to a 0.06% increase in long-term BHAR. Therefore, if a company was 10 years old, listing one year later would have led to a 0.6% increase in long-term abnormal performance. It is therefore evident that this variable had a much larger impact for early years. If a company's age is 1, going public one year later represented a 100% increase of the variable, i.e. 6% higher BHAR. In conclusion, the impact of age on long-term abnormal returns was much more pronounced in earlier years, while becoming less significant afterwards. Market trend coefficients again suggested that firms in our sample had a $\beta > 1$, since a one unit increase in market BHAR led to a 0.89 increase in abnormal returns (1.89 increase in overall return).

Unfortunately, results for 60 and 84 months lost significance, yet, coefficients maintained the same positive direction (except market performance at 84 months). Much of the non-significance can be attributed to the low number of observations we had for these horizons, especially 84 months. It would be interesting to further investigate these drivers on a larger sample of observations to test the influence of the variables on abnormal performance.

Table 12. Linear Regression of main detected IPO drivers on BHAAR at month 36,60 and 84. Standard errors are reported in parenthesis. *, **, *** indicate significance at the 90%, 95% and 99% level, respectively.

Dependent Variable: BHAAR			
	36 - Mo	60 - Mo	84 - Mo
	<u>Coefficient</u>	<u>Coefficient</u>	<u>Coefficient</u>
Inst. Back	0.189** (0.089)	0.187 (0.302)	0.932 (1.104)
Age	0.069* (0.041)	0.139 (0.126)	0.237 (0.488)
Market	0.890** (0.427)	0.270 (1.064)	-0.692 (4.598)
R-squared	0.027	0.01	0.026
No. Obs	523	187	38

6 Robustness

As highlighted previously, the choice of benchmark and model may influence the results obtained. The aim of this section was to test cross-sectional results under different models (CAR, CAPM and FF3M) and different benchmarks (NYSE Composite and NADAAQ Composite). We did not include tests on industry due to the non-significance of results.

6.1 Robustness to method

In Chapter 3 – Methodology, we illustrated different approaches that can be used to calculate long-term abnormal returns. While in the after-market performance all models seemed to behave similarly, it was interesting to test them using the same controls used in Chapter 5.3. The impact of different time horizons was in line with previous findings, therefore, for a better reading structure, we did not include them in this sub-section.

6.1.1 Institutional Involvement

For a 36-month horizon, CAARs showed a similar behavior as BHAARs. Institutional backing continued to be extremely significant in explaining long-term performance with a coefficient of 0.173 (p-value 0.021), which meant that private capital increased long term abnormal returns by 17.3% on average. On the other hand, cycle lost significance although

pointing in the same negative direction. We could not provide a definite explanation as to why CAAR seemed to be less affected by cycles. One interpretation can be that this measure of abnormal returns was positively biased with respect to BHAR (Barber and Lyon, 1997), implying that negative CAR values had a lesser impact on the 36-month average. This explanation was supported by the different distribution of CARs compared with BHARs, as the latter was positively skewed (i.e., most of the observations were negative, with a few positive outliers), while the former had a more normal distribution. However, a definite conclusion cannot be drawn.

Using CAPM, institutional backing remained a strong predictor of long-term performance, while cycle became positive, but extremely non-significant. Therefore, we cannot interpret a positive cycle as a possible deviation from the standard results of previous studies. The same can be said for FF3M results, where institutional backing had a 0.164 coefficient (p-value 0.034), while cycle was non-significant.

Table 13. Linear Regression of Institutional backing and cycle on CAAR on different market-wide indices. Standard errors are reported in parenthesis. *, **, *** indicate significance at the 90%, 95% and 99% level, respectively.

Dependent Variable: CAAR			
	Market-Adjusted	CAPM-Adjusted	FF3-Adjusted
	<u>Coefficient</u>	<u>Coefficient</u>	<u>Coefficient</u>
Inst. Back	0.173** (0.075)	0.169** (0.077)	0.165** (0.078)
Cycle	-0.017 (0.076)	0.056 (0.078)	0.026 (0.078)
R-squared	0.009	0.008	0.007
No. Obs	600	600	600

This sensitivity analysis for robustness supported the strong suggestion of the positive impact of private capital on long term abnormal performance while casted some doubts on the effect of cycles.

6.1.2 Age and Value Investing Ratio

As expected, age and positive NIA had the same impact on CAAR as on BHAAR on the 36-month horizon. Age continued to be a statistically significant predictor of long-term abnormal performance. Independent of the model used, older firms performed better than younger firms. NIA, despite having a positive impact on long-term performance, did not show significance, mainly due to the high standard error relative to coefficient estimation. Considering CAPM and FF3M, the outcome did not change at all, age retained its explanatory power and NIA had a positive, yet not significant, coefficient.

Table 14. Linear Regression of Age and Net Income over Assets on CAAR on different market-wide indices. Standard errors are reported in parenthesis. *, **, *** indicate significance at the 90%, 95% and 99% level, respectively.

Dependent Variable: CAAR			
	Market-Adjusted	CAPM-Adjusted	FF3-Adjusted
	<u>Coefficient</u>	<u>Coefficient</u>	<u>Coefficient</u>
Age	0.004* (0.002)	0.004* (0.002)	0.004* (0.002)
NIA	0.011 (0.009)	0.010 (0.010)	0.014 (0.010)
R-squared	0.016	0.015	0.018
No. Obs	216	216	216

6.1.3 Market Characteristics

We found an interesting result when testing market characteristics on CAAR: volatility was positive and significant (p-value 0.000). In this case, a 1% increase in volatility, would lead to a 2.70% increase in long-term cumulative abnormal returns. This finding was in contrast with what Campbell (1992) found and what we expected. We believe that the marked discrepancy came from the difference in how abnormal returns were calculated. CARs did not account for compounding effects as explained by Barber and Lyon (1997). Therefore, it is possible to demonstrate that, if single securities are more volatile than the market, CAR is systematically greater than BHAR when the latter is less than or equal to zero. In other words, CAR was a positively biased measure, because, in our sample, the

majority of BHAR observations were indeed less than or equal to zero. We did not observe any departure in market trend coefficients or significance.

CAPM and FF3M showed analogous results, with a slight loss of significance regarding market trend.

Table 15. Linear Regression of Market performance and Stock Volatility on CAAR on different market-wide indices. Standard errors are reported in parenthesis. *, **, *** indicate significance at the 90%, 95% and 99% level, respectively.

Dependent Variable: CAAR			
	Market-Adjusted	CAPM-Adjusted	FF3-Adjusted
	<u>Coefficient</u>	<u>Coefficient</u>	<u>Coefficient</u>
Market	0.838** (0.403)	0.420 (0.416)	0.423 (0.424)
Ln(vol)	2.704*** (0.624)	2.367*** (0.811)	2.349*** (0.778)
R-squared	0.05	0.04	0.04
No. Obs	600	600	600

6.2 Robustness to Indices

In this section, we described our tests for robustness of our findings regarding the different indices. Indeed, the results provided in the previous chapter related to the performance of IPOs benchmarked against Russell 3000, while in this section results are related to both the NASDAQ Composite and the NYSE Composite.

6.2.1 Cycle and Institutional Involvement

Regression results at 36, 60, and 84 months were rather robust to an index change. As shown in tables 16 and 17, Institutional involvement and cycle were statistically significant for both NASDAQ and NYSE in the 3-years horizon. Coefficients were in these cases more extreme, but maintained the same direction and statistical power.

Similar to our standard case, regressions lost significance for longer-term horizons, often changing direction of the coefficient. The institutional involvement coefficient remained

positive in all our observations, while cycle coefficients were more volatile, becoming positive for the 5-year (NYSE) and 7-year (NYSE and NASDAQ) observations. These findings were not surprising, as all observations in our sample for 5 and 7 years were companies that listed during the “cold” IPOs cycle. It would be interesting to replicate this study using a 5-year horizon with a larger set of data, in order to observe long-term performance for companies that listed during “hot” IPOs cycle.

Table 16. Linear Regression of Institutional backing and cycle on BHAAR at month 36,60, and 84. Standard errors are reported in parenthesis. *, **, *** indicate significance at the 90%, 95% and 99% level, respectively.

Dependent Variable: BHAAR NASDAQ			
	36 - Mo	60 - Mo	84 - Mo
	<u>Coefficient</u>	<u>Coefficient</u>	<u>Coefficient</u>
Inst. Back	0.398* (0.216)	0.275 (0.335)	0.928 (0.781)
Cycle	-0.452** (0.228)	-0.056 (0.554)	1.338 (0.867)
R-squared	0.010	0.003	0.030
No. Obs	600	227	47

Table 17. Linear Regression of Institutional backing and cycle on BHAAR at month 36,60, and 84. Standard errors are reported in parenthesis. *, **, *** indicate significance at the 90%, 95% and 99% level, respectively.

Dependent Variable: BHAAR NYSE			
	36 - Mo	60 - Mo	84 - Mo
	<u>Coefficient</u>	<u>Coefficient</u>	<u>Coefficient</u>
Inst. Back	0.397* (0.217)	0.266 (0.336)	0.920 (0.776)
Cycle	-0.419* (0.228)	0.082 (0.553)	1.321 (0.857)
R-squared	0.009	0.025	0.029
No. Obs	600	227	47

6.2.2 Age and Value Investing Ratio

Index changes affected this set of regressions more notably, in particular, the value investing ratio. Company’s age seemed index-proof, with significance for both the NASDAQ and NYSE. Confirming the trend indicated in the previous point, the coefficient is larger, but maintained the same direction. The coefficient for NIA also maintained the

same direction despite losing significance. The long-term effects were more difficult to interpret because of the lack of data. On a 5-year horizon, the coefficients remained positive, but with larger standard errors compared with the 36-month analysis. Overall, significance is lost, resulting in part from the fewer available data points. We observed that, in general, any regression in our sample lost significance when observations were fewer than 100. This problem was particularly evident for regressions for the 84-month horizon. In fact, only 18 out of 47 firms had a positive NIA, the coefficients changed the sign, and the statistical power decreased, making this long-term regression completely unreliable.

Table 18. Linear Regression of Age and Net Income over Assets on BHAAR at month 36,60, and 84. Standard errors are reported in parenthesis. *, **, *** indicate significance at the 90%, 95% and 99% level, respectively.

Dependent Variable: BHAAR NYSE			
	36 - Mo	60 - Mo	84 - Mo
	<u>Coefficient</u>	<u>Coefficient</u>	<u>Coefficient</u>
Age	0.214** (0.1061)	0.0989 (0.158)	-0.023 (0.549)
NIA	0.060 (0.041)	0.0690 (0.056)	-6.224 (19.199)
R-squared	0.034	0.01	0.007
No. Obs	216	90	18

Table 19. Linear Regression of Institutional Age and Net Income over Assets on BHAAR at month 36,60, and 84. Standard errors are reported in parenthesis. *, **, *** indicate significance at the 90%, 95% and 99% level, respectively.

Dependent Variable: BHAAR NASDAQ			
	36 - Mo	60 - Mo	84 - Mo
	<u>Coefficient</u>	<u>Coefficient</u>	<u>Coefficient</u>
Age	0.209** (0.106)	0.086 (0.158)	-5.647 (19.284)
NIA	0.059 (0.041)	0.069 (0.057)	-0.042 (0.552)
R-squared	0.008	0.017	0.006
No. Obs	216	90	18

6.2.3 Market Characteristics

Overall, market performance continued to have a statistically significant impact on long-term abnormal performance even when we considered different indices. In both regressions, we observed positive and significant coefficients for the 36-month horizon. In contrasts, volatility measures pointed in the opposite direction. When the Russel 3000 was used as the market index, we found a negative, non-significant, relationship. The results in the robustness section highlighted the opposite conclusion, with a positive relationship between the dependent and independent variables. It was important to notice that significance was completely lost, i.e., the statistical power was extremely low. The 60- and 84-month horizons presented the same difference, and none of the regressions resulted in statistically significant coefficients.

Table 20. Linear Regression of Institutional backing and cycle on BHAAR at month 36,60, and 84. Standard errors are reported in parenthesis. *, **, *** indicate significance at the 90%, 95% and 99% level, respectively.

Dependent Variable: BHAAR NYSE			
	36 - Mo	60 - Mo	84 - Mo
	<u>Coefficient</u>	<u>Coefficient</u>	<u>Coefficient</u>
Market	2.176*	0.676	-0.315
	(1.120)	(1.275)	(2.421)
Ln(vol)	0.087	0.051	3.043
	(1.177)	(3.002)	(7.145)
R-squared	0.009	0.001	0.003
No. Obs	600	227	47

Table 21. Linear Regression of Institutional backing and cycle on BHAAR at month 36,60, and 84. Standard errors are reported in parenthesis. *, **, *** indicate significance at the 90%, 95% and 99% level, respectively.

Dependent Variable: BHAAR NASDAQ			
	36 - Mo	60 - Mo	84 - Mo
	<u>Coefficient</u>	<u>Coefficient</u>	<u>Coefficient</u>
Market	2.184*	0.178	-0.570
	(1.120)	(1.275)	(3.043)
Ln(vol)	0.067	-0.026	3.030
	(1.171)	(3.003)	(8.584)
R-squared	0.009	0.000	0.003
No. Obs	600	227	47

6.3 Summary

As said at the beginning of the chapter, we did not report the results of the industry due to the non-significance of results that we found in both our main set of regressions and in the robustness regressions.

Robustness check with regards to method provided us with some interesting observations. Institutional involvement and age confirmed to be good predictors of performance independently of which method we used for the regression. On the contrary, alternative methods cast doubts on the significance of the cycle because, even if non-significant, the regressions robust to CAPM and FF3M resulted in a positive effect of the cycle, contrary to the conclusion obtained with the BHAAR. Effects of NIA and Market trend on long-term performance robust to method were consistent with previous findings regarding the overall direction of the phenomenon, but they did not have a high statistical power. Finally, we observed the anomalous behavior of the volatility for the long-term performance. In our standard case, we found a non-significant negative effect, which was consistent with previous studies. On the contrary, in the robustness section the variable not only was positive, but it also acquired a strong significance.

While the benchmark choice was an extremely important decision to assess whether the IPOs had over- or under-performed the market, regressions were not particularly sensitive to indices. Indeed, coefficients changed only in magnitude, but they maintained the direction for every variable except volatility. In addition, levels of significance were similar to previous findings, and only NIA had a lower significance than the one we found in the first set of regression. Volatility behaved differently also in this section and was characterized by opposite and non-significant coefficients. Over the long-term observations, we noted some differences in coefficients, but neither the main regressions nor the robust regressions showed high statistical power.

In conclusion, we can infer that the variables used in our last regression, namely Age, Institutional Involvement and Market were robust to both method and indices, and the effects detected should be solid predictors of long-term performance.

7 Discussion

As an aid to the reader, this chapter provides a brief overview of the analysis, and focuses on discussing the main challenges and limitations of the paper.

Prompted by past research on the subject, we reassessed the long-term performance of IPOs. Our main interest was to test whether after the 2007-09 financial crisis, IPOs long-term returns behaved differently from what documented previously by many researchers (Ritter, Levis and Loughran, among others), and to understand which variables influenced the performance. We also wanted to test the robustness of the methods used to detect abnormal performance to understand if results were systematically biased because of the methodologies in place. Challenges and solutions that we used can be summarized into the following three thematic areas.

First, retrieving accurate data was the single most challenging task of the study. Available databases were not comprehensive and sometimes lacked key information. For example, the list of IPOs in our sample period provided by Bloomberg did not include companies that subsequently delisted from the exchange, resulting in a survivors-biased dataset. To overcome this limitation, we cross-checked the list with data available on SDC Platinum and CRSP to assure that every company that went public in the years 2010-2014 was included in our sample. Furthermore, prices and firms' characteristics for companies that delisted were hard to retrieve, and many of them had to be adjusted manually to guarantee the quality of the analysis.

Second, we analyzed the robustness of the approach by testing several different methodologies on the same sample. We found that the measure of abnormal return is extremely sensitive to changes in market index and asset pricing model. On one hand, we were not surprised, since different indices performed differently over the analyzed period, but, on the other hand, we did not expect the magnitude of the effect that we observed. Previous literature agreed that IPOs underperformed in the long-term, and an index change only impacted the severity of the underperformance. In contrast, our paper cannot state a definite conclusion on long-term performance because IPOs significantly underperformed the NASDAQ Composite, but they over-performed the NYSE Composite as well as the Russell 3000. We are limited in this analysis because of the marked performance difference between NASDAQ Composite and NYSE Composite.

Third, cross-sectional regressions helped us understand which were the firm characteristics that drove long-term performance. In line with previous literature, we found that Institutional Backing, Age and Market Performance were strong predictors of long-term abnormal returns. However, we only detected significance at month 36 after the listing. We believe that non-significant results for longer horizons were motivated by two possible explanations. The first is that, on longer-term, IPOs abnormal returns were not influenced by firms' characteristics at the moment of the IPO and were driven by other variables. The second, and most likely, pertained to the quantity and quality of data available to us. The 60th and 84th month only had 227 and 47 observations respectively, and the variance of many of the independent variables we used was so extreme that any predictive power was lost. Although we cannot draw conclusion for these longer horizons, this limitation opened a window for future research possibilities. It would be interesting to replicate the same study with more observations for the 5- and 7-year cut off points to investigate whether firm characteristics at the moment of IPO retained their explanatory power.

8 Conclusion

This paper focused on a post-crisis study of IPOs' long-term performance calculated over three-, five-, and seven-year time horizons. Contrary to previous literature, we did not find a unique conclusion regarding BHAR under-performance or over-performance. Results were extremely dependent on the index used as the benchmark, since we observed both significant over-performance of IPOs benchmarked against the NYSE Composite Index, and significant under-performance when considering the NASDAQ Composite. More specifically, over a 36-month horizon, BHAAR over-performed the Russell 3000 and NYSE by 6.91% and 22.55%, respectively, while under-performed the NASDAQ Composite by -7.79%.

Thus, conclusions regarding the relative performance must be drawn with extreme caution to avoid any index bias. Indeed, variations in the benchmark could lead to strikingly different outcomes, hence one should never rely on a single measure of performance. Thanks to the diverse indices employed, our study was at the same time in agreement and disagreement with previous literature and provided a tangible proof of the practicality of using a measure of abnormal performance. However, we also found that some of the drivers of performance that have been identified in previous research continued to be strong predictors of long-term abnormal returns independently of the methods or indices employed. In this regard, our findings were consistent with previous literature as we found a strong positive significance of institutional involvement, value investing ratio, age of the firm and overall market trend, as well as a significant negative impact of cycle.

In conclusion, we believe that this analysis contributed to the characterization of IPOs long-term performance, since we combined several different methodologic approaches for determining performance and drivers, and provided a comprehensive overview of the issue. In addition, we specifically used sensitivity analysis to address robustness of findings on methods and benchmarks, and to handle survivorship bias. We also discussed the

limitations of our study and indicated opportunities for potential future research. Although many institutional investors and retail investors focus on long-term performance, efforts from previous studies were focused mainly on three-year performance and less frequently on five-year. The 2008 financial crisis created a limit in our sample because the IPO activity drastically plunged during the crisis year and we were able to collect a sufficient amount of data from 2010. Therefore, it would be interesting to study the performance on seven years with more data than what was available in our sample. Indeed, regressions and aftermarket performance for the 84-month horizon were not statistically significant and much of the non-significance could be attributed to the limited number of observations. Replicating this study in three or five years could shed some light on long-term performance and performance drivers. In addition, it could also enable interesting proposals related to changes in market conditions (i.e., cycles). Our sample included a hot and a cold IPO market, but it would be extremely interesting to collect in the same sample companies that were listed during two different hot or cold periods. Finally, the three benchmarks used in this study performed better than their historical average. Future research could potentially observe the behavior of IPOs during more bearish markets, not only in extremely bullish markets as evaluated here.

9 References

- Welch, I. (1989). Seasoned Offerings, Imitation Costs, and the Underpricing of Initial Public Offerings. *The Journal of Finance*, 44(2), 421–449.
- Lucas, D. J., & McDonald, R. L. (1990). Equity Issues and Stock Price Dynamics. *The Journal of Finance*, 45(4), 1019–1043.
- Ritter, J. R. (1991). The Long-Run Performance of initial Public Offerings. *The Journal of Finance*, 46(1), 3–27.
- Megginson, W. L., & Weiss, K. A. (1991). Venture Capitalist Certification in Initial Public Offerings. *The Journal of Finance*, 46(3), 879–903.
- Lyon, J. D., Barber, B. M., & Tsai, C.-L. (1999). Improved Methods for Tests of Long-Run Abnormal Stock Returns. *The Journal of Finance*, 54(1), 165–201.
- Gompers, P. A. (1995). Optimal Investment, Monitoring, and the Staging of Venture Capital. *The Journal of Finance*, 50(5), 1461–1489.
- Fama, E. F. (1998). Market efficiency, long-term returns, and behavioural finance. *Journal of Financial Economics*, 49(3), 283–306.
- Barry, C. B., Muscarella, C. J., & Vetsuypens, M. R. (1991). Underwriter warrants, underwriter compensation, and the costs of going public. *Journal of Financial Economics*, 29(1), 113–135.
- Krishnan, C. N. V., Ivanov, V. I., Masulis, R. W., & Singh, A. K. (2011). Venture Capital Reputation, Post-IPO Performance, and Corporate Governance. *Journal of Financial and Quantitative Analysis*, 46(5), 1295–1333.
- Campbell, J. Y., & Shiller, R. J. (1998). Valuation ratios and the long run stock market outlook. *Journal of Portfolio Management*, 24(2), 11+.
- Carter, R. B., Dark, F. H., & Singh, A. K. (1998). Underwriter reputation, initial returns, and the long-run performance of IPO stocks. *Journal of Finance*, 53(1), 285–311.
- Shiller, R. J. (1990). Speculative Prices and Popular Models. *Journal of Economic Perspectives*, 4(2), 55–65.
- Beatty, R. P., & Ritter, J. R. (1986). Investment banking, reputation, and the underpricing of initial public offerings. *Journal of Financial Economics*, 15(1–2), 213–232.

- Agarwal, S., Liu, C., & Rhee, S. G. (2008). Investor demand for IPOs and aftermarket performance: Evidence from the Hong Kong stock market. *Journal of International Financial Markets, Institutions and Money*, 18(2), 176–190.
- Fama, E. F. (1970). Efficient Capital Markets-A Review of Theory and Empirical Work. *The Journal of Finance*, 25(2), 383–417.
- Barber, B. M., & Lyon, J. D. (1997). Detecting long-run abnormal stock returns: The empirical power and specification of test statistics. *Journal of Financial Economics*, 43(3), 341–372.
- Mcguinness, P. (1992). An examination of the underpricing of initial public offerings in Hong Kong: 1980–90. *Journal of Business Finance & Accounting*, 19(2), 165–186.
- Shiller, R. J. (1990). Market Volatility and Investor Behavior. *The American Economic Review*, 80(2), 58–62.
- Ibbotson, R. G. (1975). Price performance of common stock new issues. *Journal of Financial Economics*, 2(3), 235–272.
- Brav, A., Geczy, C., & Gompers, P. A. (2000). Is the abnormal return following equity issuances anomalous? *Journal of Financial Economics*, 56(2), 209–249.
- Brav, A., & Gompers, P. A. (1997). Myth or reality? The long-run underperformance of initial public offerings: Evidence from venture and nonventure capital-backed companies. *Journal of Finance*, 52(5), 1791–1821.
- Brown, S. J., & Warner, J. B. (1980). B. warner. *Journal of Financial Economics*, 8, 205–258.
- Fama, E. F., & French, K. R. (1997). Industry costs of equity. *Journal of Financial Economics*, 43(2), 153–193.
- Loughran, T. (1993). NYSE vs NASDAQ returns. Market microstructure or the poor performance of initial public offerings? *Journal of Financial Economics*, 33(2), 241–260.
- Fama, E. F., & French, K. R. (1993). Fama-French APT three-factor model. *Journal of Financial Economics*, 33, 3–56.
- Campbell, J. Y., & Hentschel, L. (1992). No news is good news. *Journal of Financial Economics*, 31(3), 281–318.
- Ritter, J. R., & Welch, I. (2002). A review of IPO activity, pricing, and allocations. *Journal of Finance*.

- T. Clark, David. (2002). A Study of the Relationship Between Firm Age-at-IPO and Aftermarket Stock Performance. *Financial Markets, Institutions & Instruments*. 11. 385 - 400.
- Loughran, T., Ritter, J. R., & Rydqvist, K. (1994). Initial public offerings: International insights. *Pacific-Basin Finance Journal*, 2(2-3), 165-199.
- Álvarez, S., & González, V. M. (2005). Signalling and the long-run performance of Spanish Initial Public Offerings (IPOs). *Journal of Business Finance and Accounting*, 32(1-2), 325-350.
- Ibbotson, R. G., & Ritter, J. R. (1995). Initial public offerings. *Handbooks in Operations Research and Management Science*.
- Levis, M. (1993). The Long-Run Performance of Initial Public Offerings: The UK Experience 1980-1988. *Financial Management*, 22(1), 28.
- Aggarwal, R., & Rivoli, P. (1990). Fads in the Initial Public Offering Market? *Financial Management*, 19(4), 45-57.
- Aggarwal, R., Leal, R., & Hernandez, L. (1993). The aftermarket performance of initial public offerings in Latin America. *Financial Management*, 22(1), 42-53.
- Goergen, M., Khurshed, A., & Mudambi, R. (2007). The long-run performance of UK IPOs: can it be predicted? *Managerial Finance*, 33(6), 401-419.
- Buser, Stephen A. and K.C. Chan. "NASDAQ/NMS Qualification Standards, Ohio Registration Experience and the Price Performance of Initial Public Offerings." *Columbus, Ohio Department of Commerce and National Association of Securities Dealer, Inc. (1987)*
- Espenlaub, S., Gregory, A., & Tonks, I. (2000). Re-assessing the long-term underperformance of UK Initial Public Offerings. *European Financial Management*, 6(3), 319-342.
- Dong, M., Michel, J. S., & Pandes, J. A. (2011). Underwriter Quality and Long-Run IPO Performance. *Financial Management*, 40(1), 219-251.
- Jaskiewicz, P., González, V. M., Menéndez, S., & Schiereck, D. (2005). Long-run IPO performance analysis of German and Spanish family-owned businesses. *Family Business Review*, 18(3), 179-202.

10 Appendix

Appendix 1. Summary and definition of the main variables used throughout the study.

Abnormal Performance Variables	
BHAR	BHAR is estimated as in section 4. The R_m is the performance of Russell 3000 in the results section, while in the robustness chapter it is substituted with the NYSE composite and the NASDAQ composite.
BHAAR	BHAAR is the cross-sectional average of single firms BHARs over a specified horizon. In this study, most often BHAAR is calculated on 36-, 60-, or 84-month.
CAR	CAR reads as cumulative abnormal return. It is the summation of actual stock returns minus expected returns over a specified period, most often 36, 60 or 84 months.
CAAR	The CAAR is estimated as in section 4. It is the cross-sectional average of single firms CARs on a specified event month. This study mainly focuses on 36-, 60- or 84-month
Independent variables	
Industries	Regression for industries are made with a dummy that registers 1 when the company belongs to a given sector and 0 otherwise.
Cycle	Cycle is defined as the ratio between the number of IPOs in a given year and the total amount of IPOs in our sample. Therefore, the values go from a minimum of 0.59 to a maximum of 1.79.
Institutional involvement	Institutional Involvement is a dummy variable that is 1 when the IPO is either VC backed or PE backed, and that is 0 otherwise.
Age	For regression, age is estimated as the logarithm of the difference between the date when the company goes public and the date of company's incorporation.
NIA	NIA is computed as indicated in section 5.3, which is the ratio between company's net income and total assets at the moment of IPO. It captures the ability of the company to generate profits before going public
Market performance	Market is a variable that captures the overall economic condition. Depending from the regression, it is the cumulative return or the buy-and-hold return of the indices Russell 3000, NYSE Composite and NASDAQ Composite.
Volatility	Volatility is estimated computing the volatility of the raw returns of each stock in the respective time horizon

Appendix 2. Summary statistics of the main variables used in the study.

	Mean	Median	Standard Deviation	Min	Max	Count
Inst. Back	0.565	1.000	0.496	0.000	1.000	600
BHAR36CAPM	-0.099	-0.278	1.112	-2.070	4.622	600
BHAR60CAPM	-0.139	-0.516	2.040	-3.660	9.569	227
BHAR84CAPM	-0.331	-1.001	3.187	-4.717	13.380	47
BHAR36FFM	-0.029	-0.244	1.117	-2.094	4.938	600
BHAR60FFM	0.009	-0.345	1.952	-3.524	9.342	227
BHAR84FFM	-0.160	-0.935	3.023	-3.790	13.226	47
BHAR36	-0.058	-0.264	1.085	-1.359	4.729	600
BHAR60	-0.002	-0.488	1.915	-1.799	9.324	227
BHAR84	0.057	-0.777	2.926	-2.344	12.923	47
CAAR36FFM	-0.002	0.025	0.944	-2.678	3.557	600
CAAR60FFM	0.001	0.126	1.128	-3.639	3.333	227
CAAR84FFM	-0.138	-0.009	1.502	-3.916	2.920	47
CAAR36CAPM	0.014	0.031	0.943	-2.772	3.693	600
CAAR60CAPM	0.001	0.140	1.150	-3.606	3.387	227
CAAR84CAPM	-0.032	0.141	1.530	-3.845	3.123	47
CAAR36	0.044	0.011	0.913	-2.364	3.379	600
CAAR60	0.067	0.044	1.106	-3.411	3.293	227
CAAR84	0.110	0.324	1.495	-3.568	2.823	47
Cycle	1.226	1.280	0.491	0.490	1.790	600
Age	2.536	2.565	1.106	0.000	5.004	523
Ln(vol)	0.138	0.120	0.081	0.025	0.881	600
MarketCAR36	0.314	0.260	0.094	0.190	0.580	600
MarketCAR60	0.570	0.585	0.081	0.400	0.750	228
MarketCAR84	0.842	0.830	0.038	0.760	0.910	48
MarketBHAR36	1.343	1.270	0.133	1.190	1.750	600
MarketBHAR60	1.711	1.750	0.139	1.430	2.030	228
MarketBHAR84	2.189	2.170	0.127	2.010	2.370	48
NIA	6.319	4.543	6.609	0.109	43.206	242

Appendix 3. Market adjusted CAAR from month 1-84. The table also reports number of trading firms and t-tests for each market index employed.

Market Adjusted Cumulative Abnormal Returns							
Month	Firms	Russel Adjusted	<i>t-test</i>	NYSE Adjusted	<i>t-test</i>	NASDAQ Adjusted	<i>t-test</i>
1	600	2.17%	3.08	2.55%	3.61	1.92%	2.75
3	600	7.00%	4.27	8.07%	4.91	6.06%	3.71
6	600	4.36%	2.36	6.56%	3.55	2.58%	1.39
9	600	4.73%	2.19	8.13%	3.77	1.79%	0.83
12	600	4.46%	1.87	9.20%	3.85	0.59%	0.25
15	600	3.63%	1.35	9.73%	3.62	-1.42%	-0.53
18	600	4.43%	1.43	11.53%	3.72	-1.19%	-0.38
21	600	4.80%	1.42	12.83%	3.81	-1.40%	-0.41
24	600	2.81%	0.80	11.71%	3.36	-3.79%	-1.09
27	600	6.56%	1.75	16.37%	4.37	-0.75%	-0.20
30	600	5.61%	1.39	16.41%	4.08	-2.89%	-0.72
33	600	3.86%	0.94	15.64%	3.79	-5.78%	-1.40
36	600	5.83%	1.39	18.43%	4.38	-5.12%	-1.22
39	542	3.44%	0.77	17.04%	3.81	-8.62%	-1.92
42	490	3.77%	0.78	18.22%	3.79	-9.22%	-1.91
45	422	3.95%	0.76	19.32%	3.70	-9.54%	-1.82
48	376	5.09%	0.90	21.53%	3.79	-9.40%	-1.65
51	319	6.41%	1.05	23.83%	3.93	-8.69%	-1.42
54	281	5.03%	0.80	23.72%	3.79	-10.94%	-1.74
57	242	6.45%	0.93	26.15%	3.79	-9.11%	-1.32
60	227	6.43%	0.85	26.90%	3.57	-9.63%	-1.28
63	199	1.67%	0.20	22.94%	2.79	-14.58%	-1.77
66	182	0.29%	0.03	22.46%	2.55	-16.56%	-1.88
69	153	-4.55%	-0.50	19.04%	2.09	-22.36%	-2.46
72	132	-5.94%	-0.56	18.71%	1.78	-24.63%	-2.33
75	120	-6.51%	-0.57	19.02%	1.68	-26.57%	-2.33
78	104	-8.04%	-0.63	18.14%	1.42	-29.69%	-2.30
81	72	-2.85%	-0.16	23.75%	1.32	-25.06%	-1.39
84	47	11.01%	0.50	37.99%	1.75	-12.62%	-0.58

Appendix 4. Market adjusted BHAAR from month 1-84. The table also reports number of trading firms and t-tests for each market index employed.

Market Adjusted Buy-and-Hold Abnormal Returns							
Month	Firms	Russel Adjusted	<i>t-test</i>	NYSE Adjusted	<i>t-test</i>	NASDAQ Adjusted	<i>t-test</i>
1	600	2.60%	3.64	2.93%	4.27	2.31%	3.29
3	600	6.76%	4.26	7.92%	6.72	5.64%	4.45
6	600	2.80%	1.55	5.13%	3.23	0.87%	0.51
9	600	4.47%	1.91	8.08%	4.08	1.29%	0.59
12	600	3.75%	1.39	8.89%	3.78	-0.68%	-0.23
15	600	4.69%	1.17	11.31%	3.75	-0.91%	-0.17
18	600	4.22%	1.00	11.89%	3.60	-1.92%	-0.39
21	490	7.12%	1.40	15.96%	4.15	0.11%	0.07
24	376	5.74%	0.84	15.77%	3.33	-1.80%	-0.16
27	281	8.71%	1.04	20.04%	3.63	-0.05%	0.09
30	227	6.72%	0.78	19.53%	3.30	-3.79%	-0.31
33	182	4.52%	0.50	18.74%	2.94	-7.74%	-0.63
36	132	6.91%	0.57	22.55%	2.88	-7.79%	-0.42
39	104	1.95%	0.18	19.49%	2.70	-14.93%	-0.87
42	47	-0.57%	-0.06	18.78%	2.59	-19.59%	-1.27
45	422	1.95%	0.18	23.08%	2.93	-18.33%	-1.20
48	376	4.59%	0.41	27.71%	3.26	-17.99%	-1.23
51	319	-1.11%	-0.10	24.45%	2.69	-25.94%	-1.61
54	281	4.32%	0.29	32.14%	3.03	-22.97%	-1.08
57	242	5.22%	0.35	34.96%	3.09	-22.00%	-1.17
60	227	8.67%	0.49	40.15%	3.11	-20.18%	-0.89
63	199	2.51%	0.14	35.40%	2.55	-26.60%	-1.20
66	182	-6.45%	-0.37	28.63%	1.97	-37.37%	-1.61
69	153	-29.09%	-2.03	8.85%	0.69	-62.62%	-2.91
72	132	-26.35%	-1.54	14.48%	0.97	-63.21%	-2.42
75	120	-32.71%	-1.88	10.77%	0.70	-73.87%	-2.68
78	104	-25.97%	-1.27	19.34%	1.07	-71.70%	-2.43
81	72	-18.53%	-0.70	30.18%	1.31	-68.44%	-1.93
84	47	5.75%	0.14	57.79%	1.68	-50.53%	-0.95

Appendix 5. Asset-pricing adjusted CAAR and BHAAR from month 1-84. The table also reports number of trading firms and t-tests for each model and employed.

Asset-Pricing Adjusted Cumulative & Buy-and-Hold Abnormal Returns									
Month	Firms	CAR CAPM- Adjusted	<i>t-test</i>	CAR FF3- Adjusted	<i>t-test</i>	BHAR CAPM- Adjusted	<i>t-test</i>	BHAR FF3- Adjusted	<i>t-test</i>
1	600	1.91%	2.74	2.18%	3.14	1.91%	2.74	2.18%	3.14
3	600	6.46%	3.97	7.12%	4.36	6.17%	3.90	6.94%	4.37
6	600	3.17%	1.72	4.88%	2.64	1.19%	0.66	3.12%	1.74
9	600	3.53%	1.62	5.11%	2.39	1.82%	0.78	4.37%	1.92
12	600	2.72%	1.13	4.89%	2.00	0.80%	0.29	4.39%	1.61
15	600	1.83%	0.68	4.86%	1.78	1.63%	0.40	6.53%	1.60
18	600	2.31%	0.74	5.95%	1.81	0.76%	0.18	6.80%	1.58
21	600	2.75%	0.79	6.02%	1.64	3.18%	0.62	9.15%	1.79
24	600	0.44%	0.12	3.96%	1.06	2.48%	0.36	8.91%	1.30
27	600	4.30%	1.08	6.87%	1.68	5.52%	0.66	12.27%	1.47
30	600	3.03%	0.71	4.27%	0.98	2.96%	0.34	10.13%	1.16
33	600	1.50%	0.34	1.42%	0.32	0.55%	0.06	7.86%	0.87
36	600	4.11%	0.89	2.55%	0.55	2.59%	0.21	9.38%	0.78
39	542	1.68%	0.34	0.34%	0.07	-3.45%	-0.33	4.95%	0.47
42	490	1.71%	0.32	0.35%	0.07	-7.98%	-0.80	2.21%	0.22
45	422	0.93%	0.17	-0.51%	-0.09	-8.34%	-0.77	4.41%	0.41
48	376	2.08%	0.35	-0.25%	-0.04	-6.97%	-0.61	5.76%	0.51
51	319	3.02%	0.45	1.63%	0.24	-13.44%	-1.12	0.54%	0.05
54	281	0.51%	0.08	-1.51%	-0.23	-9.78%	-0.64	3.64%	0.24
57	242	-0.47%	-0.06	0.17%	0.02	-9.34%	-0.61	5.24%	0.35
60	227	-0.01%	0.00	0.14%	0.02	-5.88%	-0.32	8.61%	0.49
63	199	-4.07%	-0.47	-2.31%	-0.27	-7.48%	-0.42	11.17%	0.64
66	182	-7.01%	-0.76	-6.61%	-0.73	-18.99%	-1.04	0.89%	0.05
69	153	-13.30%	-1.40	-13.45%	-1.43	-45.79%	-2.98	-23.34%	-1.60
72	132	-14.75%	-1.35	-16.23%	-1.51	-42.52%	-2.34	-20.21%	-1.19
75	120	-15.57%	-1.30	-18.04%	-1.54	-50.50%	-2.68	-27.77%	-1.62
78	104	-17.84%	-1.31	-22.45%	-1.66	-48.09%	-2.13	-28.31%	-1.35
81	72	-15.26%	-0.81	-21.51%	-1.14	-50.62%	-1.72	-26.85%	-1.00
84	47	-3.23%	-0.15	-13.77%	-0.63	-33.09%	-0.72	-16.02%	-0.37

Appendix 6. Market adjusted CAAR from month 1-72, delisted firms. The table also reports number of trading firms and t-tests. The number of trading firms is constant as assumptions to bring forward delisted companies' CARs. In addition, we stop at month 72 because no other firm was delisted later than 72 months after listing and results are therefore equal from that point on. We can see that firms earn significant positive abnormal returns in the first few months of trading, but afterward, the dispersion of CARs is so great that results are insignificant and highly volatile.

Delisted Firms Cumulative Abnormal Return, Russell-Adjusted			
Month	Firms	CAR	<i>t-test</i>
1	220	3.90%	3.00
3	220	13.09%	2.56
6	220	23.64%	1.69
9	220	28.29%	1.06
12	220	35.86%	0.88
15	220	29.82%	0.61
18	220	14.06%	0.24
21	220	-17.98%	-0.25
24	220	-29.77%	-0.36
27	220	-56.39%	-0.61
30	220	-76.73%	-0.76
33	220	-84.72%	-0.76
36	220	-81.39%	-0.68
39	220	-74.24%	-0.59
42	220	-57.70%	-0.43
45	220	-33.80%	-0.24
48	220	-15.55%	-0.11
51	220	-5.50%	-0.04
54	220	13.95%	0.09
57	220	34.09%	0.22
60	220	43.37%	0.27
63	220	56.12%	0.34
66	220	70.79%	0.42
69	220	75.28%	0.44
72	220	76.89%	0.45