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Long-Term Performance of Initial Public Offerings in Norway

An empirical analysis of listings in Norway from 2000 until 2023 and their initial and long-term performance

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NORWEGIAN SCHOOL OF ECONOMICS

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Abstract

When analyzing the short- and long-term performance of Norwegian IPOs between 2000 and 2023, we find that IPOs have been underpriced with an average first-day excess return of 9.31%. The analysis also showed that the largest IPOs in the form of offer size had a lower first-day return. Furthermore, the IPOs have had poor long-term returns, and they have underperformed compared to the OSEAX. This indicates that a buy and hold strategy in Norwegian IPOs has performed poorly since 2000. On the other hand, when weighing the portfolio of IPOs based on assets, we find little signs of long-term underperformance. This means that the largest IPOs in the form of total assets performed better than smaller listings in the long run.

Our results also indicate that there are hot market effects in the Norwegian market, where issues in hot markets experience better short-term returns, but worse long-term returns compared to other listings. The long-term findings are based on an analysis where the starting price is the first-day closing price. Our analysis also shows that issues in months with few hours of daylight during the autumn and winter tend to experience higher benchmark-adjusted long-term returns compared to listings in the other months. This effect has previously received little attention in both a Norwegian and international context, and hence our analysis is hopefully able to shed light on this phenomenon and make the markets more transparent. Lastly, we found that the amount of uncertainty related to an IPO has a weak, but negative effect on long-term excess returns.

Contents

1. Introduction

This thesis analyzes IPOs in Norway in the period 2000-2023, where the goal is to explore whether there has been any initial underpricing, and how the long-term performance for IPOs has been. In recent years the IPO market has been particularly active, especially following the COVID crisis. This makes IPOs and their long-term performance a relevant topic, as it is only now that we can start to analyze the long-term returns for companies listing during the COVID crisis. Furthermore, there is limited research on the long-term IPO performance in Norway. Together, the relevance of the topic and the limited previous research on long-term IPO performance in Norway, are the motivation for writing this master thesis.

There can be multiple reasons why a firm wants to go public. One of these is better access to financing, in addition to gaining greater bargaining power with banks, which could result in the company being able to borrow at a lower cost (Pagano et al., 1998). Furthermore, going public provides liquidity and is an opportunity for owners to sell part of or all their shares. Previous studies have identified some market anomalies regarding IPOs. The most known is the initial underpricing of IPOs, which means that on average, the first-day closing price is higher than the offer price. This means that investors who invest in IPOs will gain a positive return on average as a population. There are multiple theories regarding information asymmetry, institutional explanations, ownership and control, and behavioral theories explaining why IPO underpricing might occur (Ljungqvist, 2007).

Previous studies on the topic have also highlighted the long-term IPO returns as an anomaly. Most studies such as Ritter (1991), find that IPOs perform poorly compared to the benchmark in the longer term. Although this effect has often been studied in an international context, there have been few papers analyzing the long-term performance of IPOs in the Norwegian market. Previous international papers have also highlighted the effect of listing in hot markets, as this is associated with high short-term returns but poor long-term returns. Another hypothesis that can be used to explain the poor long-term returns of IPOs, is the Miller (1977) divergence of opinion hypothesis. Ritter (1998) states this as a possible explanation for the long-term underperformance of IPOs.

This thesis aims to explore if there has been any initial underpricing for IPOs in Norway between 2000-2023. Furthermore, the thesis analyzes the long-term returns for the listings, where we want to find if the long-term underpricing effect has been apparent in Norway. In addition, our paper analyzes if there are any hot market effects, divergence of opinion effects, and seasonal darkness effects. Gori et al. (2020) found that the initial return of an IPO is positively affected by the days getting shorter in the autumn and winter months, implying that the IPOs in these months have a higher underpricing.

Throughout our analysis, we found an average first-day excess return of 9.31% for Norwegian IPOs. For the long-term analysis, we found that IPOs tend to underperform the OSEAX benchmark for all periods when using the first-day close price as the starting price, including one month, six months, one year, three years, five years, and ten years. These findings align with international results, but there have been done little studies on long-term IPO performance in Norway. Thus, our findings contribute to uncovering that long-term underperformance has also been apparent in the Norwegian market.

When analyzing our hypotheses, we find indications of hot market effects. Our data indicate that issues in a hot market experience better short-term returns, but worse long-term returns compared to IPOs in neutral and cold markets, although the long-term underperformance for hot issues is not significant at conventional levels. We also find indications of seasonal darkness effects, which is a little-researched topic for the Norwegian market. Issues in dark autumn and winter months perform better in the short- to medium-term, indicating a greater underpricing for issues in these months. Our analysis regarding divergence of opinion gives some support for the hypothesis which is that ex-ante uncertainty is negatively related to long-term excess returns, as three of the five proxies of ex-ante uncertainty had a significant impact on long-term excess returns. Relating our findings to previous studies, it is mostly in line with what has been found in other markets, but our results indicate that the effect of ex-ante uncertainty on long-term returns might be weaker in the Norwegian market.

2. Literature review

This section will cover previous papers and findings regarding the initial underpricing effect, short-term performance, and long-term performance following a listing. Furthermore, the section will also cover theories regarding initial underpricing and long-term underperformance.

2.1 Initial underpricing

There have been written several papers covering the initial underpricing effect of IPOs. For instance, Ritter (2023) finds an average first-day return of 19.0% from 1980 to 2022 for US listings[1]. This phenomenon is a result of the subscription price, often referred to as the offer price, being lower than the market price once the stock has started trading. By calculating the first-day return where one uses the offer price as the start price, one can find the initial underpricing by assuming that the first-day close price is the correct market price. This is a puzzling abnormality since this indicates that issuers are leaving money on the table because the market on average is willing to purchase shares above the offer price. One common explanation for why IPOs on average are issued with a discount is that issuers need to leave money on the table to attract sufficient demand from investors (Amihud et al, 2003).

2.1.1 Previous findings in the Norwegian market

Considering that IPOs are a popular topic, there have been previous papers analyzing the first-day effect in the Norwegian market. One of these is Emilsen et al. (1997), which analyzes IPOs from 1984 until 1996 and finds an average underpricing of 12.5%. Furthermore, Fjesme (2011) finds an average first-day return of 8% when analyzing Norwegian IPOs in the period 1993-2007. Bask and Nätter (2021) who analyzes Nordic IPOs from 2009 until 2019 finds an average first-day return of 5.19%. Lastly, Loughran et al. (2023) report an average initial return in Norway of 10.3% for the period 1984-2021. These findings indicate that the average initial underpricing in the Norwegian market has been around 10%, although there are some signs that the average underpricing has been reduced over time since the papers analyzing older IPOs seem to find a higher initial underpricing.

[1] Includes AMEX, NYSE, and NASDAQ IPOs with an offer price of at least $5.00

2.2 Theories regarding initial underpricing

There have been multiple papers exploring and trying to explain the initial underpricing and what causes it. As mentioned earlier, one theory is that issuers underprice on average to attract sufficient demand from investors. This is not the only possible explanation, and we can divide the theories regarding initial underpricing into four different categories in accordance with Ljungqvist (2007). These categories are asymmetrical information models, institutional explanations, ownership and control, and behavioral explanations. While these theories and mechanisms individually could affect underpricing, it is important to consider that the combination of these theories may better explain the historically persistent pattern of underpricing.

2.2.1 Asymmetrical information

Asymmetrical information is a concept about market participants having different information about a service or a product relative to the other participants. A classic example of this comes from the Noble Prize-winning author George A. Akerlof, who wrote “The Markets of Lemons” (Akerlof, 1970). In his paper, Akerlof illustrates how markets malfunction when sellers have more information about the product than buyers. He uses low-quality cars (lemons) and high-quality cars (peaches) in his example, and he states that these markets tend to have low-quality goods crowding out high-quality goods because buyers cannot accurately assess the quality of goods. An effect of this is that buyers might offer lower prices overall, as they fear that they are being exploited by the sellers. The result of this is that sellers would be discouraged by lower prices to sell high-quality goods, leading to a decline in the overall quality of goods available in the market.

In the case of an IPO, asymmetrical information describes the different knowledge the issuing firm, the underwriting bank, and the investors possess about the true value of shares issued. This leads to different opinions about what the correct price should be, where a typical example is that informed firms and underwriting banks (informed investors) are motivated to sell low-quality (bad IPOs) for higher prices, causing difficulties for investors to properly know how many shares they should bid on and for what price, as they cannot necessarily differentiate between good and bad IPOs. There can also be differences in information within groups of participants, for example, informed versus uninformed investors. We will introduce several concepts rooted in asymmetrical information theory and explain how they could potentially affect the outcome of who ends up with the issued shares and for what price.

Winner's Curse

One of the more known asymmetric information models is the "winner's curse" (Ljungqvist, 2007), which Rock (1986) introduced through an application of Akerlof's lemons problem on IPOs. In his paper, Rock separates between informed and uninformed investors and assumes that some investors know more about the true value of shares on offer than other investors in general, and even the underwriting bank or the issuing firm. He states that informed investors participate selectively, bidding on more attractively priced offerings while ignoring less attractive ones. This pattern leads to a situation where uninformed investors are disproportionately allocated overpriced IPOs, negatively affecting their average return. Therefore, uninformed investors possess a "winner's curse", where they receive most of the shares they have bid for in unattractive offerings, while their demand is partly crowded out by informed investors in attractive offerings. Rock expresses the importance of the continued participation of uninformed investors, as informed investors' demand is not enough to cover all shares offered even in attractive offerings. For uninformed investors to continue participating in IPOs, their conditional expected return must not be negative. Therefore, to raise conditional expected returns for uninformed investors, all IPOs must be underpriced in expectation. This itself does not remove the allocation bias towards uninformed investors, since they will still be crowded out in attractive offerings, but they will no longer expect to make losses on average. One should note that it is not the rationing itself that necessitates underpricing, but it is rather the bias in rationing, with uninformed investors' expectations of more rationing in lucrative offerings.

Information revelation theories

Information revelation theory in the context of IPOs discusses the transition of the strict pro rata allocation rules that gives rise to Rock's winner's curse to book-building methods which provide underwriters with more discretion over the allocation of shares (Benveniste & Wilhelm, 1990). There is a challenge in designing a proper mechanism to encourage investors to reveal their true information, as misrepresenting information in the form of low bids could induce the issuers to set a lower offer price, benefiting the informed investor (Ljungqvist, 2007). Benveniste and Spindt (1989) advocate that the underwriters' power of allocating shares to investors mitigates this challenge. After collecting indications of interest through a book-building process, the underwriter can allocate fewer shares to investors who bid consistently conservatively. On the other hand, investors who bid aggressively in the form of higher prices per share, thereby revealing favorable information, are rewarded with disproportionately large share allocations. At the same time, the more aggressive the investors' bids are, the more the offer price is raised, which reduces investors' returns. To ensure that investors are incentivized to place bids at the maximum price they are willing to pay, the IPO must still be underpriced. This means more money must be left on the table to encourage investors to express their indications truthfully, which is an effect often referred to as the "partial adjustment" phenomenon (Hanley, 1993).

It should be noted that if there are constraints on allocation discretion on the underwriter's behalf, it can interfere with this mechanism. An example of such restriction is the requirement of allocation of a certain fraction of shares to retail investors, which is more common in parts of Europe and Asia (Ljungqvist, 2007), which can reduce underwriters' ability to target the most aggressive bidders. Such constraints lead to issuers having to rely more on price than allocations to incentivize bidders to tell the truth. On the other hand, there can also be constraints on investors to prevent them from exploiting underwriters by giving misleading information. Norway is currently subject to the EU's market abuse regulation (MAR). This creates legal disincentives for investors to provide false indications while trading securities, which includes the bidding process of an IPO (Finanstilsynet, 2022).

Principal – agent

While book building has its benefits in creating cooperation between investors and underwriters during an IPO process, it can create conflicts of interest between underwriters (agent) and issuing firms (principal). Loughran and Ritter (2004) present two examples of how book building can create moral hazard. The first one is that the underpricing during an IPO essentially represents a transfer of wealth from the issuing firm to investors. This may result in rent-seeking activities, incentivizing investors to compete for underpriced stock allocations by offering underwriters side payments which could be in the form of trading commissions on unrelated transactions. Secondly, underwriters are incentivized to allocate underpriced stock to institutional investors, such as company executives. This practice, known as "spinning", aims to create potential future business opportunities (Ljungqvist, 2007). In both examples, underwriters stand to gain from deliberately underpricing the issuing firm's stock.

Signal of firm quality

Some authors reverse Rock's assumption regarding informed investors possessing more information than issuing firms and claim that underpricing is a result of an issuing firm's attempt to signal the company's "true" high value (Ljungqvist, 2007). Imagine a two-period model, where a firm raises equity through an IPO and once after the stock has started trading through a stock issuance. High-quality firms benefit from creditably signaling their higher quality through underpricing, especially if it is hard for investors to distinguish between high- and low-quality firms. This is because high-quality firms will be able to recoup the money lost by underpricing the IPO at a later stock issuance, while this will not be the case for low-quality firms. Therefore, low-quality firms avoid mimicking the signal (underpricing) as there is a risk of a firm's true quality being revealed before the IPO. If low-quality firms' type is revealed, it prevents them from reaping the benefits of imitating the signal of high-quality issuers. The risk of detection therefore disincentivizes low-quality firms as they may not be able to recoup the cost of underpricing at a later emission.

2.2.2 Institutional explanations

Besides asymmetrical information, there could be institutional factors that explain why initial underpricing exists and why some markets experience more underpricing than others. Ljungqvist (2007) points out three possible institutional factors. The first one is the level of legal liability, which is based on the "lawsuit avoidance hypothesis", and surrounds the topic that issuers might deliberately underprice their stock to reduce the likelihood of being sued by shareholders disappointed with the post-IPO performance of their shares. This phenomenon may be more common in markets where there are strict liability laws (Ljungqvist, 2007). Secondly, IPOs may not be deliberately underpriced, but are so as a result of underwriters supporting the stock price post-IPO, which effectively places a price floor and acts as insurance against price falls (Ruud, 1993). Ljungqvist (2007) argues that price stabilization is one of the services underwriters provide in connection with an IPO, where the goal is to reduce price drops in the after-market in the first few days or weeks. The practice of price stabilization is essentially a put-option written by underwriters and held by investors and may work as a way of counteracting the winner's curse on the most overpriced offerings.

Lastly, there may be tax incentives to underprice offered stock. If income is more heavily taxed relative to capital gains, employees and managers may benefit from getting appreciating assets instead of salary. This may be done by paying employees with appreciating assets like underpriced IPO stock (Rydqvist 1997). Another way of doing this is by paying out in stock options, where the difference between the strike price and "fair market value" of an IPO stock is taxed as income, while the difference between the sale price and the "fair market value" that the stock is attained at is taxed as capital gains (Taranto, 2003). If institutional laws consider the "fair market value" in the context of IPO stock options to be the offer price, this generates an incentive to underprice.

2.2.3 Ownership and control

An IPO can be perceived in many ways as a major step towards the eventual separation of control and ownership. Depending on the pre-IPO degree of separation of control and ownership, management may have different incentives to affect IPO pricing to maximize their own personal benefits. For example, underpricing could be seen as a mechanism for managers to create excess demand for the offered shares, giving them the ability to strategically allocate shares to limit the size of the stakes any investor can hold. This could limit the level of external scrutiny and monitoring, which might benefit managers if they partake in non-value-maximizing behavior (Ljungqvist, 2007). Diverse ownership with few large owners could make dispersed shareholders invest sub-optimally in low levels of monitoring (Shleifer & Vishny, 1986). Furthermore, a greater ownership dispersion reduces the threat to incumbent managers from hostile takeovers (Grossman & Hart, 1980).

Stoughton and Zechner (1998) offer an alternative perspective for why management has incentives to underprice and argue that it could work as a strategy to reduce agency costs. Agency costs are ultimately borne by owners in a company and manifest in the form of lower IPO proceeds and market value. If managers have shares in the company, the agency costs on their stakes due to their non-profit-maximizing behavior could outweigh the private benefits they enjoy from less monitoring from the owners, making it beneficial for them to allocate shares to large investors who can monitor the management. To encourage an investor to take a large share of the company, management might want to offer a discount in the form of underpriced IPO stocks, since the investor might require an added incentive as a large portion of shares comes with the cost of less diversification. The reason one requires large investors to obtain optimal levels of monitoring is that monitoring is a public good benefiting all shareholders. Still, each shareholder will only monitor as far as it is privately optimal, which once again is based on their ownership share. Therefore, larger shareholders have more incentives to monitor at an optimal level, reducing the agency costs.

2.2.4 Behavioral explanations

To correctly explain why IPOs historically have left large sums of money on the table in the form of underpriced IPOs, several researchers argue that asymmetrical information, institutional factors, and control incentives are not enough to explain the underpricing and that behavioral mechanisms play a role in IPO pricing (Ljungqvist, 2007). Behavioral theories advocate that the irrationality of investors or behavioral biases among issuers and underwriters create the phenomenon of underpricing. An example of this could be the development of "informational cascades", in scenarios where investors make their investment decision sequentially (Welch, 1992). Instead of investors bidding according to their expectations, they interpret former bids as signals of either favorable or disappointing to the prospect of the IPO, creating a snowball effect. This could potentially give power to early investors who can create more underpricing in return for their commitment to the IPO.

Another example of how irrationality could create underpricing comes from the Ljungqvist et al. (2006) paper on investor sentiment. They explain that in cases where IPO firms are young, less mature, and difficult to value, issuers benefit by maximizing the value captured from sentiment (optimistic) investors. For these firms, there can be a large discrepancy between the valuations of pessimistic and optimistic investors, and hence, the investors will have a downward-sloping demand function for the issue size. In this case, flooding the market with stocks will put downward pressure on the stock price. If regulatory constraints on price discrimination and inventory holding are not in place and short selling is prohibited, the optimal strategy for issuers will be to keep stock back to avoid prices falling (Ljungqvist, 2007). As these assumptions do not apply in the real world, the optimal strategy for issuers will be to allocate stock to regular institutional investors who then can resell it to sentiment investors. Carrying the IPO stock temporarily can be risky for regular investors, as the market can cool down and reveal the fundamental value of the stock which might be below the offer price. Therefore, the investors require the stock to be underpriced to compensate for the potential risk.

Loughran and Ritter (2002) argue that behavioral biases among issuers rather than investors could potentially explain underpricing. They advocate that issuers (decision-maker) tend to assess the success of an IPO not only in terms of the offer price but also in relation to the following performance of the stock in the after-market. Therefore, they tend to ignore the millions of dollars left on the table in the form of first-day returns, as they sum the wealth loss due to underpricing with the wealth gain on retained shares as prices increase post-IPO.

2.3 Long-term performance

Multiple studies have been analyzing the long-term performance of IPOs, and most of them, including Ritter (1991), find a long-term underperformance for IPOs. When analyzing the three-year holding period for US IPOs 1975-1984 using the closing price on the first trading day as the starting price, he found that the IPOs yielded a return of 34.47% compared to the benchmark return of 61.86%. The long-term underperformance anomaly is supported by other papers such as Firth (1997) and Loughran et al. (1994). Newer papers such as Dong et al. (2011), find similar results where the three-year buy and hold abnormal returns for IPOs are significantly negative. The underperformance of IPOs compared to non-issuing firms over the 3-5 years following the IPO date, is commonly referred to as the “New issues puzzle” (Eckbo et al., 1999). The underperformance appears to challenge the presumption of rational prices in securities markets, but Eckbo et al. (1999) argue that it reflects a failure in the matched firm technique to provide a proper control for the risk.

2.3.1 Previous findings in the Norwegian market

There have been few papers focusing on the long-term IPO performance in the Norwegian markets, which is some of the motivation for this master thesis. However, Westerholm (2006) found that Norwegian IPOs between 1991-2002 outperformed the market index slightly on a five-year basis. In an international context, this finding can be considered an anomaly since most studies find that IPOs underperform on a three-year and five-year basis compared to the benchmark.

2.4 Theories regarding long-term underperformance

Ritter (1998) states three hypotheses that can explain the long-term underperformance of IPOs. These are the divergence of opinion hypothesis, the impresario hypothesis, and the window of opportunity hypothesis.

2.4.1 Divergence of opinion

One explanation for the long-term underperformance of IPOs is the divergence of opinion hypothesis. Miller (1977) pointed out that valuations of optimistic and pessimistic investors can greatly differ, whereas the valuation of optimistic investors could be much higher. He postulated that uncertainty and the level of divergence go hand in hand. This comes from different outlooks. When an investment carries much uncertainty, there will be a greater divergence of opinion compared to an investment with little uncertainty. This leads to a surprising result; the expected market price of a security will increase with risk and uncertainty since valuations are decided by optimistic investors. This theory contrasts with most other asset pricing models, which say that investors demand higher returns if risk increases, and hence, increased risk will reduce asset value ceteris paribus. Furthermore, Miller (1977) says that as a firm matures, there will be more available information and hence, lower uncertainty. This should lower the divergence of opinion, which should result in lower share prices. Thus, the divergence of opinion hypothesis can explain the long-term underperformance of IPOs; as a firm matures, there will be more information revealed, which in turn lowers the divergence of opinion and hence the valuation.

2.4.2 Impresario

The market for IPOs is subject to fads, and the IPOs are underpriced by investment banks to create the appearance of excess demand, according to the impresario hypothesis (Ritter, 1998). This effect can be compared to a concert, where promoters attempt to make it an "event" and try to create an appearance of excess demand. Furthermore, the hypothesis predicts that the IPOs with the highest first-day returns will have the lowest subsequent returns. Ritter (1998) refers to a study of investors participating in IPOs, where only 26 percent reported that they conducted any fundamental analysis of the firm's underlying value before investing. This can support the hypothesis, as it might take some time before the IPO is correctly priced by the market, and in the short term following the IPO, it might be subject to a fad.

2.4.3 The window of opportunity

The market for listings (IPOs) varies greatly over time and can be said to open and close dramatically (Wang & Yung, 2018). In certain periods, the market is full of activity while in other periods there are barely any IPOs. In light of this, there exists a hypothesis regarding companies' timing when they decide to list. In some periods, investors might be more optimistic about the future and the growth potential of firms going public. Firms might be able to take advantage of the swings in investor sentiment by going public when the sentiment is advantageous. Lastly, Ritter (1998) argues that one should expect some natural variation in the number of listings over time due to business cycles. Still, he finds that it is difficult to explain the large volatility in volume as merely normal business cycle activity, which supports the hypothesis. The window of opportunity hypothesis predicts that firms listing in high-volume periods are more likely to be overvalued compared to other IPOs, and that they have poor long-term returns.

2.5 Hypotheses

Based on previous findings, we have developed several hypotheses to test if findings from other markets are apparent in Norway. These are related to the hot-market phenomenon, seasonal darkness, and the divergence of opinion hypothesis.

2.5.1 Market temperature

Using the variation in the number of listings, one can divide the market into hot, neutral, and cold periods. Previous overview papers such as Wang and Yung (2018) have found that market conditions affect short- and long-term performance after an IPO, and thus we want to explore if we can find the same effect in the Norwegian market. This leads us to two different hypotheses which we will analyze:

Hypothesis 1: Issues in hot markets are associated with a higher dispersion in quality leading to a higher average underpricing

Furthermore, market conditions could also have some long-term effects on returns. Baker et al. (2003) found that issuers opportunistically list their shares when markets are highly priced. This can once more lead to poor long-term performance for IPOs. To test if this effect is apparent in the Norwegian market, we develop the following hypothesis:

Hypothesis 2: Issues in hot markets have poor long-term returns, as issuers go public during periods of high market valuations

2.5.2 Seasonal darkness

One natural phenomenon which some previous studies have found can affect the excess return after an IPO, is the number of light hours per day (Gori et al., 2020). This hypothesis is not based on the efficient market hypothesis since it should not exist unless daylight has real effects. Instead, one needs to turn to behavioral economics to explain such a phenomenon. The reason excess returns after an IPO might be affected by the time of year, and thus the number of light hours per day can be linked to the mood of investors. Multiple medical and psychological studies have highlighted the impact increasing hours of darkness has on the mood of people, including economic considerations (Gori et al., 2020). Seasonal affective disorder (SAD) is a well-known psychological condition characterized by depression, hypersomnia, and augmented appetite in the autumn and winter (Zimmermann & Olcese, 2007). In our paper, we want to analyze if this effect is prevalent in the Norwegian market. This leads us to a hypothesis:

Hypothesis 3: The level of underpricing per IPO is positively correlated with the number of hours without daylight at the time of listing

2.5.3 Divergence of opinion

To analyze if ex-ante uncertainty for an IPO affects the long-term return, we included five proxies for uncertainty to test this relationship. Firstly, we have firm age as a proxy, since older companies should have more data available, reducing the uncertainty. Next, we include firm size in the form of total assets as an approximation for firm size, which again can work as a proxy for uncertainty where we expect smaller companies to have less available information. Furthermore, we also include the sector of the firm since some sectors might have greater uncertainty than other sectors. We include information regarding the financial strength of the firm since one can argue that profitable companies already have "proven" that their business model works while this is not the case for unprofitable companies, hence one can argue that unprofitable companies have a more uncertain future. We have chosen to use EBIT as a measure of profitability. Lastly, listing during a crisis might affect the uncertainty related to an IPO. Investors might have larger differences in their outlooks on how the market and firm will develop during a financial crisis. Ahmed and Mengxi (2022) found that firms listing through the COVID pandemic experienced greater information uncertainty. Therefore, we include listing during a crisis as a proxy for uncertainty. To analyze the divergence of opinion hypothesis, we have developed five hypotheses.

Hypothesis 4: The long-run performance is a positive function of firm age at the time of listing

Hypothesis 5: The long-run performance is a positive function of total assets and revenue at the time of listing

Hypothesis 6: The long-run performance of an IPO is affected by the sector of the firm

Hypothesis 7: Long run-performance is positively related to EBIT at the time of listing

Hypothesis 8: Long-run performance is worse for firms listing during a crisis

3. Data

3.1 Sample selection and data gathering

Our sample consists of 511 IPOs at Oslo Børs from January 2000 until July 2023. We have included IPOs listed at the main market and those at the junior markets. Since the junior market has changed its name over the sample period, among others called Oslo Access, Euronext Growth, and Merkur Market, we have chosen to refer to these as the junior market. Furthermore, we have excluded transfers since we are interested in analyzing the effect of listing for the first time. We have also excluded over the counter (OTC) listings as we want to analyze the effect of becoming available for trading to the public. Lastly, we wanted to perform a long-term analysis where we include the effects of listing during the dotcom bubble, the financial crisis, and the COVID crisis, and hence we chose to use a sample from 1st of January 2000 until 31st July of 2023.

The data gathering turned out to be a time-consuming task. Firstly, we found no official list covering IPOs at Oslo Børs for the entire period. Therefore, we needed to find documents at Euronext covering each of the years in our sample. We utilized "Børsrettsdagene – Vedtak og uttalelser" for each year in our sample, which covers new listings at Oslo Børs. Furthermore, this list was cross-checked against new listings based on data available at Bloomberg, LSEG Refinitiv (Datastream), and Børsprosjektet NHH. For listings in 2020 and later, we were able to extract a list of all new listings through Euronext (2023b). When extracting the offer price for each IPO, we had to use various sources. Neither Datastream, Bloomberg nor Euronext had a complete list of offer prices covering all IPOs in our sample. For each IPO, we used all three sources to check if they had the offer price available, in addition to checking the prospectus and other sources found through desktop research. Still, we were not able to uncover the offer price for all listings. Especially for the older ones, finding offer prices proved to be difficult.

When obtaining the price history for the IPOs, we have used Datastream and Børsprosjektet NHH as sources. For some of the older IPOs, Datastream did not have a price history, necessitating the use of supplementary data from Børsprosjektet NHH. At the same time, Børsprosjektet NHH lacks updated price history beyond 2018, necessitating the use of both databases as sources. For each of the IPOs, we gather the unadjusted first-day close price. This is used to analyze the first-day effect after listing. For the long-term analysis, we need to use a price history that adjusts for dividends and stock splits. This is because a buy and hold strategy will result in the investor taking part in the stock splits as well as receiving dividends which the investor can reinvest. For our long-term analysis, we downloaded adjusted daily close prices from Børsprosjektet NHH and Datastream. The price data adjusts for stock splits and dividends, resulting in an accurate representation of investor returns.

The accounting data is gathered from Datastream, Bloomberg, and annual reports, but we were not able to extract the data for all IPOs as some did not have available data the year before listing. Of the sample of 511 IPOs, we were able to extract accounting data for the year before listing for 449 IPOs.

3.2 Sample characteristics

In Table 3.1, the number of IPOs per year, the average first-day return, and the average offer size are visualized. Furthermore, we have included the number of IPOs we were able to extract offer size from for each year, as the average first-day return and offer size are based on these IPOs. One of the first notable findings is that the number of issues seems to fluctuate over time, peaking in 2021. Finding fluctuations in the number of listings is expected and in line with previous findings by for instance Santos (2017) who analyzed US IPOs. Another observation is that the average first-day return seems to have increased over time with especially strong performance in the last years. At the same time, the average first-day returns each year have large fluctuations, making it difficult to say for certain if it is a trend or just a result of natural fluctuations. Lastly, it is difficult to extract any clear trends from the development in the inflation-adjusted offer size.

Sample Characteristics

Year	Number of IPOs	Number of IPOs with Offer Size	Average First-Day Return	Average Adj. Offer Size (mNOK)
2000	29	9	5.93 %	1934.12
2001	15	5	8.67 %	2380.39
2002	6	1	4.46 %	339.39
2003	4	2	-2.26 %	198.40
2004	22	11	9.00 %	1012.20
2005	47	31	7.45 %	868.37
2006	30	19	5.03 %	1454.85
2007	57	29	7.24 %	867.81
2008	16	5	-3.26 %	248.81
2009	3	1	-7.78 %	1115.79
2010	19	11	-4.37 %	2365.90
2011	13	6	3.01 %	1448.35
2012	5	2	-3.21 %	1446.87
2013	11	11	17.53 %	1164.04
2014	19	14	3.76 %	1193.48
2015	10	9	12.44 %	1327.33
2016	13	6	13.30 %	686.02
2017	20	16	0.89 %	902.58
2018	16	8	3.47 %	1694.75
2019	15	11	1.88 %	1041.75
2020	53	44	22.49 %	683.79
2021	67	61	10.29 %	966.42
2022	17	15	16.75 %	967.48
2023	4	2	14.54 %	1611.00
Total	511	329	9.33 %	1071.98

Table 3.1: Overview of the sample of IPOs, including the average offer size and first-day return per year

3.3 Independent variables

3.3.1 Offer price

When firms are listing for the first time through an IPO, there is an opportunity for investors to invest before the stock starts trading. Shares are sold to institutional and retail investors, and the price per share is referred to as the offer price. This price can be set through book building, a fixed price offering, or an auction.

In a fixed-price public offering, the price and allocation rules are set before the underwriters have received any information regarding demand. This means that the underwriters set a fixed price at which investors can invest. An advantage of this method is that it offers flexibility in the allocation of shares. One could for example favor small orders over large orders, which is common in multiple countries (Jagannathan et al., 2010).

A book-building process results in the offer price being set once the book is full. Typically, the underwriters arrange a road show to collect indications of interest. Once the book has been filled, the issue price and issue size may be adjusted based on demand. As with the fixed price offering, this process gives the underwriters substantial discretion over allocation. Unlike the fixed price offering, where the price is set in advance, the book-building process additionally grants underwriters discretion over pricing based on demand (Jagannathan et al., 2010).

Lastly, the offer price can be set through an auction. The most common type is referred to as a "Dutch Auction". In this case, potential investors enter their bids, where they specify the number of shares they want to purchase and the price they are willing to pay (Chen, 2022). The offer price will be set as the highest price the pool of investors is willing to purchase all the allotted shares, where all investors pay the same price. This method gives the underwriters less discretion over allocation compared to a fixed-price offering and book building.

To be able to analyze the first-day effect on the stock price, we need to include the offer price. We gathered information regarding the offer price through various sources, including Bloomberg, Datastream, Euronext, and desktop research. Still, we were not able to find the offer price for all the IPOs in the sample, as there were multiple IPOs where neither Bloomberg nor Datastream had information. Out of the sample of 511 IPOs in the period, we were able to find 329 offer prices. When interpreting the analysis of the first-day effect, one needs to keep in mind that it does not include all IPOs in the period, and the results could be skewed if the case is that the IPOs we did not find offer prices for, performed worse or better than the rest.

3.3.2 Offer size

To analyze if capital raised in the IPO influences short-term performance, we need to include offer size as a variable. Furthermore, offer size can be used as weights when creating weighted portfolios. The offer size is calculated by multiplying the shares issued with the offer price. Since we did not manage to find the offer price for all IPOs, we are only able to include the offer size for the IPOs where we have found the offer price.

Furthermore, we should consider adjusting the offer sizes for inflation. Since our dataset covers over 20 years of IPOs, the offer size in nominal terms might not be the preferable version of this variable. To adjust for inflation, we have used the Norwegian consumer price index from

Statistisk sentralbyrå (2023) and adjusted the offer sizes to 2023 values based on the inflation estimates. The calculation is shown in Equations 3.1 and 3.2, where the inflation in 2023 is set to zero as we want to adjust the offer sizes to 2023 values.

$$InflationFactor_t = \prod_{q=t}^{2023} \left(Inflation_q + 1\right) \tag{3.1}$$

$$Adj.Offer_i = Offer_i * InflationFactor_t \tag{3.2}$$

Here, *t* represents the year of listing, *i* represents an individual IPO, and *q* represents a year. In Equation 3.2, *t* represents the year of listing for IPO *i*. Using the equations, we can obtain inflation-adjusted values for the offer sizes.

3.3.3 Accounting data

To analyze our divergence of opinion hypothesis, we need financial data from companies before their listing. For each of the IPOs, we have gathered the data for the year before listing[2]. For some of the listings, the accounting data is given in other currencies than NOK. In these cases, we convert to NOK using historical exchange rates from Freecurrencyrates (2023). We have chosen to extract total assets, revenue, and EBIT for each IPO. Total assets and revenue are included since they can be interpreted as an approximation of firm size. EBIT on the other hand can be interpreted as a measure of profitability. When measuring profitability, we could also have used EBITDA. The issue with EBITDA is that it is possible to manipulate, and some analysts argue that it does not truly reflect what is happening in companies (Berman & Knight, 2009). Still, the use of EBIT or EBITDA is a controversial topic since both have their advantages and disadvantages.

As with the offer size, the accounting data is inflation-adjusted using the consumer price index from Statistisk sentralbyrå (2023). The inflation factor calculation is shown in Equation 3.1, while the calculation of adjusted assets is shown in Equation 3.3. In the equations, *i* represents a specific IPO while *t* represents the year of listing for IPO *i*. When adjusting, we use the *t*-1 inflation factor since the financial data is gathered for the year before listing.

$$Adj.FinData_i = FinData_i * InflationFactor_{t-1} \tag{3.3}$$

[2] For a company listing in year t, we have gathered accounting data for year t-1

Lastly, it does not seem likely that the effect these variables might have is linear. For example, it seems likely that an increase in total assets from 1bn to 2bn has a greater effect than an increase from 11bn to 12bn. To capture relative changes in addition to removing extreme outliers, we have log-transformed the variables by taking the natural logarithm of revenue and total assets. By including these variables, we can analyze if accounting data has any effect on initial returns and long-term performance. In addition, it could be interesting to analyze revenue relative to assets, as this will provide insight into how efficiently a company is using its assets to generate revenue. Therefore, we generated the variable “RevAssets”. RevAssets is calculated by dividing the revenue by the assets for each IPO.

Financial Statistics

Year	Number of IPOs	IPOs with Financial Data	Average Adjusted Revenue (bNOK)	Average Adjusted EBIT (bNOK)	Average Adjusted Assets (bNOK)
2000	29	26	3.17	0.58	4.35
2001	15	10	37.82	9.73	36.39
2002	6	6	3.46	0.81	62.97
2003	4	2	1.46	0.00	2.98
2004	22	21	10.42	0.46	8.20
2005	47	40	0.82	0.11	1.84
2006	30	24	0.56	0.09	1.93
2007	57	49	0.44	0.06	1.57
2008	16	14	0.96	0.21	3.34
2009	3	3	0.31	-0.05	7.11
2010	19	18	6.53	0.32	10.04
2011	13	8	2.94	0.20	6.35
2012	5	5	1.93	0.75	12.08
2013	11	11	2.50	0.16	4.29
2014	19	17	4.26	0.24	6.10
2015	10	10	1.20	0.16	10.22
2016	13	11	0.59	0.18	4.10
2017	20	18	1.82	0.16	4.19
2018	16	13	3.03	0.34	7.01
2019	15	15	3.58	0.33	7.21
2020	53	49	0.48	0.02	1.31
2021	67	61	0.73	0.09	1.20
2022	17	15	4.86	1.78	16.27
2023	4	3	3.41	0.44	8.21
Total	511	449	2.97	0.46	5.72

Table 3.2: Overview of average revenue, EBIT, and assets for new listings

3.3.4 Firm age

The firm age variable is calculated by subtracting the IPO year from the year the company was established. The year of establishment is gathered from multiple sources, including company websites, annual reports, and other sources found through desktop research. To test the effect firm age might have, we have included different versions of the variable. One version is the log-transformed variable, which is used to test the relationship between excess returns and the natural logarithm of age. We decided to log-transform since our dataset includes some outliers with quite high firm age, and by log-transforming, the outliers will have less effect on the estimated coefficients. Furthermore, log-transforming can help the variable fulfill the normality assumption since the logarithm of firm age is much closer to being normally distributed compared to firm age itself. Lastly, we have also created three dummy variables. One for young companies aged 4 years or younger, one for medium-aged firms ranging from 5 to 24 years, and one for older companies aged 25 years or older. We have chosen these categories for young and old companies, as this is in accordance with the definition given in Robb (2002). This is done to test if specifically young and old companies influence excess returns since dummy variables might better represent the effect firm age has rather than the natural logarithm of firm age.

Firm Age

Statistic	Value
Average	20
P25	3
Median	8
P75	19
Firms with age 0-4	179
Firms with age 5-24	238
Firms with age 25+	94

Table 3.3: Firm age statistics

3.3.5 Crisis variable

To analyze if short- and long-term performance for companies listing during a large financial event or crisis behave differently, we have included four dummy variables. We use the Law and Smullen (2008) definition of a financial crisis: “A collapse in the price of financial obligations, which may lead to a collapse in the economy”. This definition makes us able to identify three crises for our sample. This is the dotcom bubble, the financial crisis, and the COVID crisis. Hence, we construct one dummy variable for IPOs listing during the dotcom bubble, one for IPOs listing during the financial crisis, one for IPOs listing during the COVID crisis, and one dummy variable that is equal to one if the IPO listed during either of the three crises.

The dotcom dummy variable is equal to 1 for IPOs that are listed in the period from the 10^{th} of March 2000 until the 4^{th} of October 2002, as this was the period where the NASDAQ index experienced a 78.81% fall (Hayes, 2023). The financial crisis dummy variable includes IPOs listed from the 15^{th} of September 2008 until the end of 2009. The date of September 15th was chosen as the start date of the financial crisis since this was the date Lehman Brothers went bankrupt (Hernandez, 2023). Furthermore, the COVID dummy variable has a value of 1 for IPOs listing after the 12^{th} of March 2020 until the end of 2021. We use the 12^{th} of March as the start date since this was when Norway initiated a national lockdown due to the virus (Melgård et al., 2020). For the financial crisis and the COVID crisis, defining a specific ending date is challenging. Therefore, we use the 31^{st} of December the following year as the endpoint for these crises. Lastly, the crisis dummy variable is equal to one if the listing was during one of the three crises, and zero otherwise. By including dummy variables for the individual crises in addition to one variable that covers all of the crises, we can analyze two different theories. Firstly, the three individual crisis variables can be used to analyze separately how the first-day and long-term return has been. Furthermore, the combined dummy variable is included to analyze if there have been any common developments in excess returns for listings during crises.

IPOs During Crises

Period	Number of IPOs
Dotcom	47
Financial Crisis	6
COVID	117
Non-crisis	341
Total	511

Table 3.4: Number of firms listed during each crisis

3.3.6 Industry

There are multiple industry classifications to choose from. We have chosen to base our analysis on the Industry Classification Benchmark (ICB) due to Oslo Børs using this classification (Euronext, 2023a). The benchmark divides stocks into eleven subsectors, which are Technology, Telecommunications, Health Care, Financials, Real Estate, Consumer Discretionary, Consumer Staples, Industrials, Basic Materials, Energy, and Utilities. We used Bloomberg and Datastream to find information on which stocks belong to each of the subsectors. A few IPOs were not found either on Bloomberg or Datastream, and for these companies, we classified them ourselves based on the sector description given by Oslo Børs (Euronext, 2023a).

Industry Statistics

Industry	Number of IPOs	IPOs with Offer Price	Average First-Day Return
Basic Materials	19	17	15.20 %
Consumer Discretionary	32	22	3.60 %
Consumer Staples	44	35	6.57 %
Energy	132	80	12.26 %
Financials	47	24	4.36 %
Health Care	34	27	8.22 %
Industrials	90	60	9.50 %
Real Estate	16	11	-0.14 %
Technology	71	34	5.86 %
Telecommunications	11	8	29.08 %
Utilities	15	11	17.68 %
Total	511	329	9.33 %

Table 3.5: IPOs per industry and their average first-day returns

3.3.7 Market temperature variable

To analyze if the market conditions affect the underpricing effect and long-term performance, we include a variable based on the number of listings in the period. Based on previous literature[3], the market is divided into hot, neutral, and cold periods. Furthermore, we define a period as a month. Choosing a shorter period, such as a week, would result in a poor sample size per week due to the low average number of IPOs per week. On the other hand, choosing a longer period could also create some issues. If we chose to define a market as hot or cold per year, we would not capture the differences in market conditions within a year. We also tried to analyze the effect using quarterly periods, but this definition seemed to be a worse fit for our data as it likely suffers from not being able to pick up the differences in market conditions during a quarter. Therefore, we chose to define a market as hot or cold on a monthly basis in accordance with Santos (2017).

[3] For instance Ljungqvist et al. (2006)

To divide our sample into hot, neutral, and cold periods, we first calculate the number of listings for each month of our sample. Furthermore, we define a market as high volume if the number of listings in a month is above the 75th percentile. A low-volume market was first defined as the bottom 25th percentile, leaving the IPOs between the 25th and the 75th percentile to be defined as neutral. This is in accordance with existing studies such as Santos (2017). Due to issues regarding many months without IPOs, we found it more appropriate to use a higher threshold for low-volume markets. In our analysis, we define a low-volume market as the bottom 40th percentile. Furthermore, using the high, neutral, and low volume variables, we can define "hot", "neutral" and "cold" periods. The number of IPOs in a single month might vary and can be driven by outliers. Therefore, the number of listings per month might not accurately reflect the state of the market. We have chosen to define a hot market as a market where there have been three consecutive high-volume months. The same goes for cold markets, where we have defined a month as cold if there are three consecutive low-volume months.

Market Temperature

State of Market	Number of Months	Number of IPOs
Hot	16	103
Cold	76	24
Neutral	191	384
Total	283	511

Table 3.6: Number of months and IPOs in hot, neutral, and cold markets

3.3.8 Seasonal darkness

To analyze the possible relationship between the level of underpricing and the number of hours without daylight, we include a seasonal darkness variable. This can help us analyze if it might be better to list in certain parts of the year. Inspired by previous literature (Gori et al., 2020), the variable is equal to:

$$SD = \begin{cases} H_t - 12, & H_t > 12 \\ 0, & H_t \leq 12 \end{cases} \tag{3.4}$$

Here, H_t represents the average number of hours without daylight per day for a given month. This is calculated by averaging the hours without daylight observed on the first and last day of each month. We extract the number of hours without daylight per day in 2023 in Oslo from Timeanddate (2023). Furthermore, we also include another version of the variable to test the effect of seasonal darkness on IPO pricing. We construct a dummy variable that is equal to one for the autumn and winter months with less than twelve hours of daylight.

Seasonal Darkness

Month	Hours Beyond 12 Without Daylight	Dummy Value
January	5.02	1
February	2.83	1
March	0.15	0
April	0.00	0
May	0.00	0
June	0.00	0
July	0.00	0
August	0.00	0
September	0.00	0
October	1.83	1
November	4.36	1
December	5.75	1

Table 3.7: Seasonal darkness per month, where the dummy variable is equal to one for autumn and winter months with less than twelve hours of daylight per day

3.3.9 Market choice

The companies listed on the main market might have different characteristics than the ones listed in the junior markets, even after controlling for firm size, revenue, profitability, age, and industry. Because of this, their stock price development might differ. To analyze potential differences in stock price development, we have included a dummy variable. An IPO will have a value of 1 if the IPO is listed on the main market at Oslo Børs, and 0 otherwise.

Market Choice		
Year	Main Market	Junior Markets
2000	19	10
2001	6	9
2002	4	2
2003	0	4
2004	7	15
2005	8	39
2006	5	25
2007	27	30
2008	6	10
2009	0	3
2010	12	7
2011	4	9
2012	4	1
2013	7	4
2014	12	7
2015	7	3
2016	5	8
2017	11	9
2018	6	10
2019	7	8
2020	7	46
2021	7	60
2022	4	13
2023	1	3
Total	176	335

Table 3.8: IPOs per market

3.4 Choice of benchmark

When analyzing the excess return for an IPO, one needs to compare the return with a benchmark. Ritter (1991) utilizes two types of benchmarks to examine IPO returns. These are broad market indexes or constructing a benchmark by finding comparable firms with similar risk characteristics as the IPO firms. The choice of benchmark is important since it can affect the estimated long-term underpricing effect. A previous study on German IPOs found a high benchmark sensitivity on IPO performance (Sapusek, 2000). Depending on the benchmark used, the study found neutral, over-, or underperformance of the IPOs. This highlights the importance of using a representative benchmark. Ideally, one would want to choose a benchmark replicating the risk exposure from the IPOs in the sample to get a fair comparison. Our analysis is done by utilizing a broad equity market index as the benchmark.

Since our analysis is of stocks listed in Norway, we have two relevant benchmarks. These are OSEBX and OSEAX. OSEBX is an investable index that includes the most traded and largest shares listed on Oslo Børs (Oslo Børs, 2023a). OSEAX on the other hand, is an index that consists of companies admitted to listing on Oslo Børs. Stocks are still screened to ensure that there is enough liquidity such that the index is investable, which results in some stocks being left out of the index (Oslo Børs, 2023b). Since many of the firms listed in the period are smaller firms, one could argue that OSEAX better represents the risk exposure since OSEBX only includes the largest and most traded stocks. Therefore, we will use OSEAX as the benchmark moving forward.

4. Empirical analysis

4.1 Measuring performance

When measuring performance, the result is sensitive both to the calculation method and the choice of benchmark. Thus, the robustness of our results is dependent on choosing an appropriate calculation method and benchmark. As discussed earlier, we have chosen to use OSEAX as our benchmark. Still, this index might not perfectly reflect the risk exposure of the IPO firms. If this is the case, we need to be careful when interpreting the abnormal returns since they might be a result of excess risk compared to the index.

4.1.1 Initial abnormal return

Since we did not manage to extract the offer price for all IPOs, this analysis will just be conducted for the 329 IPOs where we were able to extract the offer size. When calculating the initial abnormal return (IAR), we use Equation 4.1 in accordance with Ritter (1991). Here, *i* represents an IPO, *b* represents the benchmark and *t* is the date of listing for IPO *i*. The initial abnormal return represents the excess first-day return of an IPO compared to the benchmark return.

$$IAR_i = \frac{(ClosePrice_{i,t} - OfferPrice_i)}{OfferPrice_i} - \frac{\left(ClosePrice_{b,t} - ClosePrice_{b,t-1}\right)}{ClosePrice_{b,t-1}} \qquad (4.1)$$

4.1.2 Buy and hold returns

For our long-term analysis, we will exclude the first-day return since this is analyzed separately. Thus, our long-term analysis will represent the return for an investor who buys the stock at the end of the first trading day. The advantage of this method is that it will be an accurate representation of investor return, given that an investor invests an equal amount in each of the IPOs at the first day's close price. The offer price that we use in our short-term analysis might not be as accurate when it comes to representing investor returns. This is due to investors not knowing beforehand how many stocks one will get assigned, and one might end up getting more of the stocks in the poor-performing IPOs. At the same time, one can argue that it might be difficult to buy a large quantum of shares at the first-day close price since you might affect the price in the process. Still, the liquidity the first day after listing tends to be good which was the case for many of the IPOs in our sample. A high liquidity should result in an investor being able to buy a reasonable volume without affecting the price too much. Therefore, our analysis will use the first-day close price as the starting price.

To get robust results for the long-term analysis, we employ two different calculation methods in accordance with Ritter (1991). This includes cumulative abnormal returns (CAR) and buy and hold abnormal returns (BHAR). Both return metrics are relevant for investors since they represent the long-term excess return for different investment strategies. The CAR will represent the return for an investor who rebalances the portfolio at the end of each month, while the BHAR will represent the return of a buy and hold strategy.

The return for IPO *i* for a period *t* is calculated by Equation 4.2. As mentioned earlier, we utilize prices adjusted for stock splits and dividends to get an accurate representation of investor returns.

$$r_{i,t} = \frac{(Adj.ClosePrice_{i,t_1} - Adj.ClosePrice_{i,t_0})}{Adj.ClosePrice_{i,t_0}} \tag{4.2}$$

Furthermore, benchmark *b* returns are calculated utilizing Equation 4.3. In this case, we do not need to use adjusted prices, as the price development of the benchmark is already adjusted for stock splits and dividends for the stocks that make up the benchmark.

$$r_{b,t} = \frac{(ClosePrice_{b,t_1} - ClosePrice_{b,t_0})}{ClosePrice_{b,t_0}} \tag{4.3}$$

Lastly, we can calculate the buy and hold abnormal returns. This is given by the difference in return between the stock and the benchmark for a period *t*, where start and end dates (t_0 and t_1) are the same for the benchmark and the IPO return. This is visualized in Equation 4.4.

$$BHAR_{i,t} = r_{i,t} - r_{b,t} \tag{4.4}$$

4.1.3 Cumulative abnormal return

We also want to compute the cumulative abnormal return, since this is relevant for investors who are rebalancing their portfolio. Based on previous literature[4], we have chosen to use a period of one month, which implies monthly rebalancing. Furthermore, we have a choice between defining an event month based on calendar days or trading days. We have chosen to define an event month as 21 trading days, in accordance with Ritter (1991). We can calculate

[4] Ritter (1991)

the abnormal return for an IPO by subtracting the benchmark return from the IPO return for the same start and end dates. This will represent the benchmark-adjusted return for a given event month *t*.

$$ar_{i,t} = r_{i,t} - r_{b,t} \tag{4.5}$$

The average abnormal return for event month *t* is the arithmetic average of benchmark adjusted returns for the same period.

$$AR_t = \frac{1}{n}\sum_{i=1}^{n} ar_{i,t} \tag{4.6}$$

Lastly, we can calculate cumulative abnormal returns by adding the average benchmark adjusted returns for event month *q* to event month *s*. For our analysis, we will always use $q = 1$ since we are interested in analyzing the long-term returns an investor will obtain by investing at the first-day close price after the IPO.

$$CAR_{q,s} = \sum_{t=q}^{s} AR_t \tag{4.7}$$

4.1.4 Wealth relatives

To interpret the long-term buy and hold returns, we can compute wealth relatives. The wealth relatives tell us something about the relationship between the average IPO buy and hold return and the average benchmark buy and hold return for *t* event months. This can be interpreted as a performance measure, where a wealth relative above 1 means the IPOs have outperformed the benchmark while a wealth relative below 1 means the IPOs have underperformed. We define wealth relatives in Equation 4.8, where *t* is the number of trading days the wealth relative is computed for, *i* represents an individual IPO, *b* represents the benchmark where the starting price is the first-day closing price for the benchmark at the date of listing for the corresponding IPO, and *n* is the total number of IPOs with enough price history for *t* trading days.

$$WR_t = \frac{1 + \frac{1}{n}\sum_{i=1}^{n} r_{i,t}}{1 + \frac{1}{n}\sum_{b=1}^{n} r_{b,t}} \tag{4.8}$$

4.1.5 Value weighting

When analyzing the IPO returns, we want to employ two different metrics. These are equal-weighted returns (EW) and value-weighted returns (VW). Fama (1998) argues that value-weighted returns more accurately capture the total wealth effects experienced by investors. This is because most investors invest more in large firms than in small firms. When constructing the value-weighted portfolio, several papers[5] use offer sizes to value-weight the IPOs. When analyzing the first-day returns, we will therefore weight the portfolio based on the offer sizes. This is shown in Equation 4.9, where we utilize offer sizes adjusted for inflation. The first-day weight w_i^F per IPO *i* is dependent on the inflation-adjusted offer size of the IPO compared to the total inflation-adjusted offer sizes of all 329 IPOs in the first-day sample.

$$w_i^F = \frac{Adj.OfferSize_i}{\sum_{i=1}^{n} Adj.OfferSize_i} \tag{4.9}$$

Since we do not have the offer size for all of the IPOs in the period, we will value-weight based on inflation-adjusted total assets the year before the IPO for our long-term analysis. Total assets is an approximation, although not perfect, for firm size and market capitalization. We found the correlation between adjusted total assets and adjusted offer size to be 0.54, implying that total assets is a reasonable proxy. Furthermore, the value weights used for our long-term analysis will be calculated based on Equation 4.10.

$$w_{it}^L = \frac{Adj.Assets_i}{\sum_{i=1}^{n_t} Adj.Assets_i} \tag{4.10}$$

The weight per IPO w_{it}^L is a function of the time horizon *t* we are analyzing since the number of IPOs is dependent on the time frame. As our time frame increases, we have fewer IPOs with enough price history. One issue with weighting using assets at the time of listing is apparent in the long-term CAR. The weighted CAR calculation implies that investors rebalance their portfolio monthly based on assets at the time of listing. In reality, this is not a good assumption since most investors would rebalance their portfolio based on market capitalization. One should therefore be careful when interpreting the long-term weighted CAR, as this is not particularly representative of investor behavior.

[5] For instance Ritter & Welch (2002)

4.1.6 Time Horizons

The analysis is based on an event regime, in accordance with Ritter (1991). This means that we operate using event months instead of calendar months. One event month is defined as 21 trading days. When analyzing the first month's abnormal return, we are calculating the return from the first-day close price until the close price of the 21st trading day for the benchmark and the IPO. When doing statistical testing of the significance, we assume that benchmark-adjusted IPO returns are independent. This could however not be the case if the reality is that there is cross-sectional dependency (Schober, 2008). Then, one could find statistical significance due to an overstatement of the t-statistics when in reality, there is no significance (Gow et al., 2010). Since the returns are calculated for different event periods, we assume that they are independent.

For our long-term analysis, we have chosen to analyze abnormal returns for one month, six months, one year, three years, five years, and ten years. By including these time frames, we can analyze performance in a range from short to long periods, which is necessary to test our hypotheses. When comparing the results from the regressions, one needs to keep in mind that the sample size will differ between the different time horizons since the price history for the different IPOs is of varying lengths.

4.2 First-day abnormal return

The first-day abnormal return after an IPO is a well-documented phenomenon, and Ljungqvist (2007) offers a list of possible explanations for the initial IPO underpricing, which is explained in Chapter 2.2. For our first-day analysis, we will just include the IPOs which we were able to acquire offer price and offer size for. This sample consists of 329 IPOs.

First-Day Returns

Statistic	First-Day Return	Excess Return	Weighted First-Day Return	Weighted Excess Return
Average	9.33 %	9.31 %	5.56 %	5.55 %
SD	28.06 %	28.04 %	22.36 %	22.35 %
Median	1.54 %	1.88 %	1.54 %	1.88 %
P25	-2.38 %	-2.48 %	-2.38 %	-2.48 %
P75	12.29 %	11.94 %	12.29 %	11.94 %
Firms with positive return	63.83 %	61.40 %	63.83 %	61.40 %
P-value	0.0000	0.0000	0.0000	0.0000
N	329	329	329	329

Table 4.1: First-day IPO returns, excess returns are adjusted for benchmark returns. P-values are calculated using two-sided t-tests

As Table 4.1 shows, we found an average equal-weighted first-day return of 9.33%. The result is in accordance with previous studies in the Norwegian market, which find an average equally weighted first-day return of around 10%. This means that investing an equal amount in each of the IPOs in our sample and selling at the first-day close price, would yield a return of 9.33% per IPO on average. This is reduced to 9.31% when adjusting for benchmark return. We notice that adjusting for benchmark returns barely changes the first-day IPO return. This result is also in line with expectations, as the one-day benchmark return on average is close to zero. When calculating the average daily return for the OSEAX benchmark between 2000 and 2023, we found that the daily average return is 0.04%. This means that the IPOs in our first-day sample have on average listed on days where the index has had a slightly worse performance than the average daily index return since the excess equally weighted return is only 0.02% lower than the unadjusted EW first-day returns. Furthermore, the equally weighted first-day return of 9.33% is highly significant, with a p-value of less than 0.0001 which is calculated using a two-sided t-test. Finding a significant and positive first-day return is in accordance with previous studies such as Chalk and Peavy (1987). Lastly, we found that 63.83% of the IPOs yielded a positive return on the first day.

The issue with the strategy of investing at the offer price and selling at the first-day close price is that it is difficult to invest an equal amount in each IPO since you do not know ex-ante the percentage of shares you will be allocated for an IPO. You could for instance get allocated more in the poor-performing IPOs, which would result in investors experiencing a worse first-day return than 9.33% on average. This would be a typical case of the “winner’s curse”, which was mentioned in the asymmetrical information section. When weighing the portfolio based on offer size, the excess return is reduced to 5.55%. This indicates that larger offerings perform worse than smaller offerings on the first day after listing. To test further if this is a result of large outliers affecting the weighted return negatively, we create a similar table of first-day returns, where we trim the dataset by excluding the 10% largest IPOs in the form of offer size. We also tried to create a trimmed table where we removed the 5% largest IPOs, but since the weighted return still was quite a bit lower compared to the equally weighted in the trimmed table, we ended up excluding the 10% largest IPOs in the trimmed table.

First-day Returns Trimmed

Statistic	First-Day Return	Excess Return	Weighted First-Day Return	Weighted Excess Return
Average	10.24 %	10.22 %	10.52 %	10.55 %
SD	29.28 %	29.25 %	30.10 %	30.15 %
Median	1.90 %	2.19 %	1.90 %	2.19 %
P25	-2.16 %	-2.60 %	-2.16 %	-2.60 %
P75	14.07 %	14.07 %	14.07 %	14.07 %
Firms with positive return	63.51 %	61.15 %	63.51 %	61.15 %
P-value	0.0000	0.0000	0.0000	0.0000
N	296	296	296	296

Table 4.2: Overview of first-day trimmed results, where the 10% of IPOs with the largest offer sizes are removed. P-values are calculated using two-sided t-tests

When interpreting the trimmed first-day table, we observe that the weighted returns are no longer lower than the equal-weighted returns. Furthermore, the equally weighted first-day excess return has increased from 9.31% to 10.22%. This supports our initial finding when comparing the equally-weighted (EW) and value-weighted (VW) returns, which is that the largest IPOs in the form of offer price seem to perform worse than the other listings. One important factor to keep in mind is that our analysis of first-day returns does not include all IPOs in the period. This could result in skewed results. Still, the calculated first-day average return is in line with previous studies of Norwegian IPOs, which gives us confidence that the analysis and results are representative. Furthermore, we want to explore if there are any other variables impacting the first-day excess returns, and hence we perform a regression analysis.

First-Day Regression Results

	Dependent variable:					
	ExcessReturn					
	(1)	(2)	(3)	(4)	(5)	(6)
Hot	0.028	-0.029	-0.004	-0.008	0.006	0.007
	(0.037)	(0.043)	(0.043)	(0.043)	(0.040)	(0.040)
Cold	-0.005	0.027	0.003	0.002	0.039	0.030
	(0.080)	(0.083)	(0.081)	(0.081)	(0.072)	(0.072)
Dotcom		0.003				
		(0.077)				
FinCrisis		-0.174				
		(0.291)				
COVID		0.101^{**}				
		(0.040)				
CrisisDummy			0.065	0.067^{*}	0.036	0.043
			(0.040)	(0.040)	(0.038)	(0.038)
LogRevenue					0.006	
					(0.005)	
LogAssets					-0.007	-0.005
					(0.009)	(0.008)
PositiveEBIT					-0.063	
					(0.040)	
RevAssets						-0.001
						(0.002)
RealEstate			-0.146	-0.147	-0.143	-0.136
			(0.111)	(0.111)	(0.106)	(0.106)
ConsumerDiscreationary			-0.104	-0.110	-0.113	-0.113
			(0.091)	(0.092)	(0.081)	(0.081)
ConsumerStaples			-0.097	-0.093	-0.101	-0.099
			(0.083)	(0.084)	(0.074)	(0.074)
Energy			-0.019	-0.018	-0.039	-0.033
			(0.077)	(0.077)	(0.069)	(0.070)
Financials			-0.072	-0.077	-0.073	-0.082
			(0.090)	(0.091)	(0.081)	(0.081)
HealthCare			-0.054	-0.050	-0.141^{*}	-0.126
			(0.088)	(0.089)	(0.078)	(0.078)
Industrials			-0.045	-0.050	-0.085	-0.080
			(0.078)	(0.078)	(0.070)	(0.069)
Technology			-0.093	-0.091	-0.110	-0.100
			(0.083)	(0.085)	(0.074)	(0.074)
Telecommunications			0.154	0.139	0.183^{*}	0.176
			(0.122)	(0.121)	(0.110)	(0.110)
Utilities			-0.016	-0.014	-0.076	-0.056
			(0.110)	(0.111)	(0.099)	(0.098)
Junior			0.011	0.019	-0.014	-0.013
			(0.037)	(0.040)	(0.037)	(0.037)
SeasonalDarkness			-0.010			
			(0.008)			
LogFirmAge			-0.013			
			(0.013)			
SeasonalDarknessDummy				-0.033	-0.029	-0.021
				(0.032)	(0.029)	(0.029)
Age0_4				0.022	-0.023	-0.024
				(0.037)	(0.036)	(0.036)
Age25				-0.012	-0.006	-0.009
				(0.045)	(0.039)	(0.039)
LogAdjOffer				0.005	0.003	0.003
				(0.011)	(0.011)	(0.011)
Constant	0.087^{***}	0.068^{***}	0.157^{*}	0.089	0.213	0.209
	(0.018)	(0.020)	(0.084)	(0.104)	(0.130)	(0.128)
Observations	329	329	329	329	298	298
R^2	0.002	0.023	0.054	0.052	0.075	0.066
Adjusted R^2	-0.004	0.007	0.005	-0.003	0.005	-0.002
Residual Std. Error	0.281 (df = 326)	0.279 (df = 323)	0.280 (df = 312)	0.281 (df = 310)	0.238 (df = 276)	0.239 (df = 277)
F Statistic	0.301 (df = 2; 326)	1.495 (df = 5; 323)	1.111 (df = 16; 312)	0.942 (df = 18; 310)	1.065 (df = 21; 276)	0.974 (df = 20; 277)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 4.3: Regression of first-day returns

4.2.1 First-day offer size results

From the EW and VW first-day returns, we found that the 10% largest firms in terms of offer size, have a lower first-day return than the other 90% on average. Interpreting the regression results however, this effect is not apparent, and we find the logarithm of adjusted offer size to have little to no effect on excess return. The coefficient of the logarithm of adjusted offer size is even slightly positive, but far from being significant at any conventional level. This might be a result of the EW and VW analysis being based on adjusted offer size, while the regression utilizes the logarithm of adjusted offer size. By utilizing the logarithm of offer size, the regression result is less exposed to being affected by large outliers. This might explain why the negative effect of large offer sizes on excess first-day returns seems to be apparent in the EW and VW results, but the regression output in Table 4.3 shows little indication of offer size affecting first-day excess returns. In total, our analysis indicates that the IPOs with the largest offer sizes are affiliated with lower first-day excess returns.

4.2.2 First-day crisis results

Interpreting the regression results in Table 4.3, we find that listing during a crisis shows some indications of affecting the first-day return. This is especially prevalent for the COVID crisis, which has a positive and significant effect on a 5%-significance level. Our results indicate that listings during the COVID crisis experienced a 10.1% greater first-day return compared to listings not during any of the three crises. Still, one should note that the findings for the COVID crisis are not supported by the findings for the dotcom and the financial crisis. For listings during the dotcom crisis, the excess return is close to zero, while it is negative for listings during the financial crisis. Still, the sample for the financial crisis is quite small, and hence it is difficult to draw conclusions regarding the effect of listing in this period. In conclusion, our results from the first-day analysis do not support the hypothesis that listing during a crisis generally affects the first-day return. Instead, they show that listings during the COVID crisis experienced significantly better first-day returns.

4.2.3 First-day industry results

When analyzing whether first-day excess returns are dependent on the industry of an IPO, we find weak indications of dependence. IPOs belonging to the healthcare industry show indications of poor performance compared to basic materials IPOs, which is the excluded industry-dummy variable. The effect of the healthcare industry on excess returns is significant on a 10%-level in one of the regressions. Furthermore, the telecommunications industry shows an opposite and positive effect which is significant on a 10%-level in one of the regressions. Still, it is difficult to draw conclusions based on these results as there are few indications of significant effects. The significant findings could also be a result of multiple testing, as we expect to find one significant effect on a 10%-level when testing ten variables that do not affect the explanatory variable. This takes us to the conclusion, which is that industry does not seem to affect the first-day return of an IPO.

4.2.4 First-day market temperature results

When analyzing the effect of listing in hot and cold markets, our results indicate that market temperature has little effect. We find little support for our first hypothesis regarding higher underpricing for listings in hot markets on a one-day basis. Still, the underpricing effect of listing in hot markets could be apparent in the long term, which we will analyze in our long-term section. Hence, we cannot yet conclude that the hot market underpricing effect is not apparent in the Norwegian market.

4.2.5 First-day seasonal darkness results

As with the market temperature, we find little effect on first-day returns for listing during “dark” months. The hypothesis of underpricing is therefore not prevalent on a first-day basis, but as with the hot market effect, it could be apparent in the long run. Therefore, we cannot reject the hypothesis entirely based on the first-day results.

4.2.6 First-day age, accounting data, and marketplace results

Lastly, we do not find any indication that either the choice of marketplace, accounting data, or the age of the firm at the time of listing affects the first-day excess return. This result is in line with expectations, as we did not have any hypothesis regarding these variables affecting the initial excess return.

4.3 Long-term analysis

For our long-term analysis, we want to analyze how IPOs perform compared to the benchmark for different time horizons. We calculate the buy and hold abnormal returns (BHAR) and cumulative abnormal returns (CAR) from the first-day close price after an IPO. Tables 4.4 and 4.5 show BHAR and CAR for different holding periods for all IPOs which we were able to acquire information regarding total assets from. We chose to exclude IPOs where we did not find financial data the year before listing because the weighting is based on inflation-adjusted total assets the year before listing.

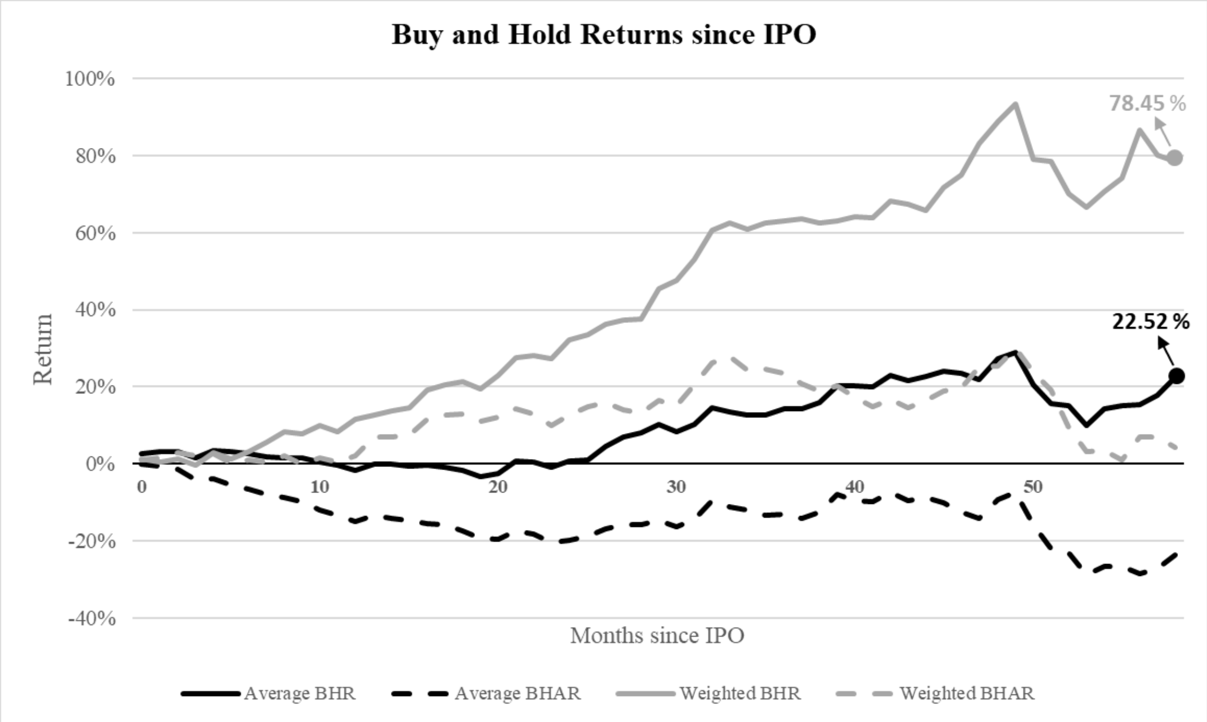

Figure 4.1: Buy and hold returns for the portfolio of IPOs, using the first-day close as the starting price. BHR - Buy and hold returns, BHAR - Buy and hold abnormal returns (adjusted for benchmark returns)

Buy and Hold Abnormal Returns

Statistic	1 month	6 months	1 year	3 years	5 years	10 years
Average	-1.73 %	-3.87 %	-12.02 %	-12.40 %	-23.53 %	-64.05 %
Weighted average	-2.66 %	2.54 %	1.46 %	24.39 %	4.28 %	-5.28 %
SD	22.11 %	44.33 %	61.42 %	123.19 %	235.28 %	247.49 %
Weighted SD	12.04 %	22.63 %	38.53 %	104.07 %	92.88 %	119.06 %
P25	-11.52 %	-28.62 %	-47.04 %	-70.57 %	-109.79 %	-208.01 %
Median	-3.84 %	-10.21 %	-21.94 %	-34.94 %	-63.63 %	-143.79 %
P75	4.68 %	9.62 %	9.31 %	12.49 %	-9.79 %	-21.76 %
Firms with positive return	36.75 %	35.36 %	29.47 %	27.69 %	22.56 %	24.42 %
P-value	0.0971	0.0665	0.0001	0.1057	0.1642	0.0186
P-value Weighted	0.0000	0.0184	0.4313	0.0002	0.5204	0.6820
N	449	444	431	260	195	86

Table 4.4: Overview of BHAR. P-values are calculated using two-sided t-tests

Cumulative Abnormal Returns

Statistic	1 month	6 months	1 year	3 years	5 years	10 years
Average	-1.73 %	-4.48 %	-13.77 %	-14.08 %	-22.91 %	-35.80 %
Weighted average	-2.66 %	2.57 %	1.64 %	8.23 %	6.94 %	4.09 %
SD	22.11 %	42.34 %	59.33 %	112.96 %	142.35 %	186.09 %
Weighted SD	12.04 %	22.56 %	34.47 %	64.61 %	68.60 %	84.31 %
P25	-11.52 %	-25.58 %	-46.88 %	-61.68 %	-94.50 %	-181.77 %
Median	-3.84 %	-6.73 %	-14.76 %	-11.91 %	-23.83 %	3.03 %
P75	4.68 %	12.50 %	16.33 %	38.55 %	40.72 %	86.99 %
Firms with positive return	36.75 %	40.99 %	36.19 %	44.62 %	41.03 %	51.16 %
P-value	0.0971	0.0262	0.0000	0.0455	0.0257	0.0780
P-value Weighted	0.0000	0.0167	0.3238	0.0410	0.1594	0.6537
N	449	444	431	260	195	86

Table 4.5: Overview of CAR. P-values are calculated using two-sided t-tests

When interpreting the output from Table 4.4 and Table 4.5, we notice that for the equally weighted average, IPOs seem to underperform relative to the benchmark for all time horizons. This result is in accordance with previous literature such as Ritter (1991), which has found that IPOs tend to underperform in the long run. Furthermore, using a 5% significance level, we find that the negative equally weighted buy and hold abnormal returns are significant for one year and ten years. The p-values are calculated using two-sided t-tests. Interpreting the equally weighted CAR results, we find clear indications of underperformance which is significant on a 5%-level for six months, one year, three years, and five years.

However, when calculating the weighted excess returns, the results are less clear. For most horizons, the excess returns are positive. Using BHAR, only the one-month and ten-year returns yield a negative excess return while just the one-month excess return is negative for CAR. The result from the weighted analysis is somewhat surprising, as this indicates that if you weight based on total assets, IPOs will yield positive excess returns compared to the benchmark for some holding periods, although not significant for most periods. To explore the weighted returns further, we introduce a trimmed BHAR table where the 10% of firms with the largest adjusted assets are removed.

Buy and Hold Abnormal Returns Trimmed

Statistic	1 month	6 months	1 year	3 years	5 years	10 years
Average	-1.61 %	-4.16 %	-13.42 %	-17.28 %	-24.11 %	-75.38 %
Weighted average	-2.24 %	-3.34 %	-12.07 %	-17.62 %	-16.91 %	-45.07 %
SD	22.85 %	45.81 %	62.62 %	124.30 %	249.16 %	260.22 %
Weighted SD	13.80 %	29.03 %	42.84 %	119.88 %	159.62 %	246.67 %
P25	-12.13 %	-29.38 %	-49.27 %	-72.31 %	-117.88 %	-214.43 %
Median	-3.51 %	-10.89 %	-24.16 %	-42.68 %	-67.21 %	-150.17 %
P75	4.71 %	8.81 %	6.73 %	-4.01 %	-17.37 %	-94.89 %
Firms with positive return	36.88 %	34.25 %	28.02 %	24.35 %	20.35 %	20.00 %
P-value	0.1565	0.0701	0.0000	0.0361	0.2061	0.0143
P-value Weighted	0.0012	0.0219	0.0000	0.0268	0.1665	0.1178
N	404	400	389	230	172	75

Table 4.6: Overview of trimmed BHAR, where the 10% of IPOs with the largest assets are removed. P-values are calculated using two-sided t-tests

The weighted BHAR in Table 4.4 showed little indication of long-term underperformance for IPOs. After removing the 10% largest IPOs in the form of assets, the weighted portfolio of IPOs underperforms compared to the OSEAX benchmark in the long term, as the weighted average excess return is negative for all periods in Table 4.6. Comparing the result to the BHAR results in Table 4.4, it is notable that the weighted excess returns in all periods except the one-month horizon, are lower for the trimmed BHAR table. Furthermore, the weighted excess return is now significantly negative for the six-month, one-year, and three-year periods. This is in contrast to the untrimmed BHAR analysis, where the weighted excess return was significantly positive for the six-month and one-year periods. The trimmed and untrimmed BHAR results indicate that the largest firms in the form of assets have performed better than their less asset-heavy counterparties for periods of six months and longer.

When interpreting the long-term returns, one needs to keep in mind that they might suffer from survival bias. Some companies go bankrupt or get involved in an M&A transaction, which are some of the causes for companies to delist. Our analysis of long-term returns only includes companies with enough price history for each period. If a company is bought and delisted after four years, its return since IPO will not be taken into consideration when calculating the five- and ten-year excess returns. Depending on whether the delisted companies have had a more positive or negative return than the rest of the IPOs, the survival bias could be positive or negative. In addition, once the time frame increases, there will be fewer IPOs with enough price history. This is due to newer IPOs not having enough price history at the time of writing. These effects could skew our long-term results in either direction, and one should therefore tread cautiously when interpreting the long-term results where the sample is smaller. To make our analysis more robust against survival bias, we also calculate the BHAR where we include delisted companies.

The new average BHAR for 10 years is calculated by including the BHAR for all IPOs listed before the 31st of July 2013, as it is only these IPOs that are listed early enough to possibly have ten years of price history. Furthermore, the BHAR for the delisted companies is calculated by using the last available closing price, where the benchmark adjustment matches the start and end date for each IPO. The same procedure is done for the other periods, as they include the IPOs that have and could have had enough price history if they were still listed. This analysis is done to test if our previous results suffer from survival bias.

Buy and Hold Abnormal Returns Using Last Observation

Statistic	1 month	6 months	1 year	3 years	5 years	10 years
Average	-1.76 %	-3.82 %	-11.11 %	-15.07 %	-18.40 %	-44.03 %
Weighted average	-2.66 %	2.55 %	2.00 %	15.70 %	1.20 %	-7.23 %
SD	22.13 %	44.25 %	61.43 %	113.78 %	205.98 %	187.50 %
Weighted SD	12.04 %	22.62 %	38.72 %	91.69 %	81.48 %	107.74 %
P25	-11.52 %	-28.43 %	-46.70 %	-69.50 %	-96.38 %	-144.91 %
Median	-3.84 %	-10.33 %	-21.42 %	-34.95 %	-52.76 %	-73.29 %
P75	4.58 %	9.64 %	9.94 %	12.80 %	7.83 %	3.64 %
Firms with positive return	36.53 %	35.20 %	30.16 %	28.36 %	26.40 %	25.54 %
P-value	0.0926	0.0687	0.0002	0.0159	0.1210	0.0004
P-value Weighted	0.0000	0.0178	0.2782	0.0019	0.7974	0.3090
N	449	446	441	335	303	231

Table 4.7: Overview of BHAR for all IPOs, including delisted firms. P-values are calculated using two-sided t-tests

We observe that the average abnormal return per period is quite similar, but it is now slightly better for the five- and ten-year periods. When comparing the EW returns in Table 4.7 with the EW returns in Table 4.4, we find that including the delisted companies yields quite similar excess returns. Comparing the weighted returns with the ones in Table 4.4, we find that they are approximately equal for periods up to one year, a bit higher for the three-year period, and lower for the five- and ten-year periods. Seeing as our results, which include delisted firms, mostly are in line with the abnormal returns we found previously, it gives us confidence that our results do not severely suffer from survival bias. In conclusion, the results strengthen our finding regarding IPOs underperforming in the long term.

Since our dataset covers over 20 years of IPOs, and the long-term IPO performance might have changed over time, we decided to divide our dataset into three cohorts of approximately 8 years each. This is shown in Tables A9 to A14 in the appendix, which enables us to analyze how long-term performance has been for IPOs listed in the different periods. We observe that the performance has some variations, especially when comparing the one-year, three-year, and five-year results. We find that the average buy and hold abnormal return seems to be worse for the 2008-2015 and the 2016-2023 cohort compared to the 2000-2007 cohort for most long-term periods. This is not apparent in the ten-year cohort regression. However, given the poor sample size for this time frame, we do not accord significant importance to the ten-year result. When comparing the weighted abnormal returns, the results are similar as the 2000-2007 cohort seems to perform best for most periods here as well. Our results indicate that the long-term IPO excess return has decreased over time. This could be a result of newer IPOs being more subjected to hype, resulting in a first-day closing price higher than the fundamental value.

Furthermore, we perform ordinary least squares (OLS) regressions to analyze whether certain variables impact the excess return for IPOs. As one month cannot be interpreted as long term, this time frame is included to analyze short-term effects. When interpreting the regression results, it is important to keep in mind what the reference is. In tables A3 to A8, the reference is given by the excluded dummy variables. The reference for most regressions is an IPO for a company belonging to the industry “Basic Materials”, listing in a “Neutral” market, and having a firm age between 5 and 25 years at the time of listing.

4.3.1 Long-term seasonal darkness results

When analyzing the effects of seasonal darkness, we included two different variables which both capture the effects of diminishing daylight each in their separate ways. Interpreting the regression results in Tables A3 to A8 in the appendix, we find a significant and positive seasonal darkness effect for most periods. However, for the ten-year regression, we are unable to find any significant effect, but this might be due to poor sample size as there are only between 86 and 95 observations. Furthermore, the hypothesis is that listing in the dark months leads to initial underpricing, but it should not have any other long-term effects. As the period increases, the initial underpricing as a component of total return will diminish, which makes it more difficult to discover regressing long-term returns compared to short- and medium-term returns.

Regarding our hypothesis, our results indicate that there is a significant effect on the underpricing of listing in “dark” months. This is based on the fact that the seasonal darkness variables are positive and significant for most periods, indicating that listings in “dark” months overperform after listing using the first day close as the starting price. Furthermore, we can explain the overperformance as a result of the first-day closing price for firms listing in “dark” months being too low compared to listings in other months. When it comes to whether the effect is equal for all dark months or if it is a function of hours without daylight, our results are unclear. When comparing the regression outputs, we find a higher significance using the dummy variable for most periods. This indicates that the dummy variable might be more suited for the Norwegian market, indicating an equal effect for all dark months. Still, for the three-year regression, the seasonal darkness variable seemed to perform best, indicating that the effect might be stronger in the darkest months. In total, our analysis uncovered that IPOs listed in "dark" months are underpriced compared to IPOs listed in other months, but it is difficult to assess whether the underpricing effect is equal for all dark months or if it is greater for the darkest months.

4.3.2 Long-term market temperature results

Analyzing the effects of listing in hot and cold markets in the longer term, our findings depend on which period we are analyzing. For the one-month and six-month regressions in Tables A3 and A4, we find a positive and significant effect on a 1%-level for all regressions. This indicates a short-term overperformance for listing in a hot market, which could support our hypothesis regarding higher underpricing for firms listing in hot markets. The explanation for such an effect might be that if investors expect the quality of firms listing in "hot" markets to have high dispersion, they might demand a lower price to invest to compensate for the excess risk, resulting in higher underpricing. Furthermore, analyzing our long-term regressions in the appendix, we find some evidence supporting that market conditions affect long-term returns. From our five-year regression, we find a highly significant and positive effect of listing in a cold market. Still, when interpreting the three-year and ten-year regression, the effect has disappeared, making it difficult to draw any conclusions regarding long-term overperformance for firms listing in cold markets.

Furthermore, we perform a regression of buy and hold returns, not adjusted for benchmark returns, using hot and cold markets as explanatory variables. This is performed to test our hypothesis whether issuers opportunistically list when markets are priced high, resulting in poor long-term returns. To test this hypothesis, we utilize raw returns not adjusted for the benchmark. From the regression output in Table 4.8, we observe that the effect of listing in a hot market is negative for three years, five years, and ten years, although not significant at a 5%-level. Still, for the five-year regression, we observe that issues in cold markets perform significantly better than issues in neutral markets at a 1%-level. At the same time, this effect is not significant in the other regressions, indicating that the five-year results are driven by outliers. To summarize, our findings suggest that the hypothesis of poor long-term returns for firms listing in hot markets might hold for the Norwegian market. Still, we cannot reject the null hypothesis that issuing in hot markets does not affect long-term returns, as the coefficients are not significant at conventional levels.

Hot & Cold regression results

	Dependent variable:						
	FirstDayReturn	return1month	return6months	return1year	return3years	return5years	return10years
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Hot	0.029	0.104^{***}	0.245^{***}	0.096	-0.464^{*}	-0.408	-0.898
	(0.037)	(0.026)	(0.052)	(0.075)	(0.279)	(0.548)	(0.725)
Cold	-0.008	-0.037	-0.063	-0.028	0.156	2.631^{***}	0.369
	(0.080)	(0.049)	(0.106)	(0.150)	(0.331)	(0.645)	(1.025)
Constant	0.087^{***}	-0.020^{*}	-0.018	-0.011	0.126	0.076	0.586^{**}
	(0.018)	(0.012)	(0.024)	(0.035)	(0.086)	(0.171)	(0.277)
Observations	329	511	503	486	290	219	95
R^2	0.002	0.034	0.044	0.004	0.011	0.076	0.019
Adjusted R^2	-0.004	0.030	0.040	-0.001	0.004	0.068	-0.002
Residual Std. Error	0.281 (df = 326)	0.234 (df = 508)	0.472 (df = 500)	0.667 (df = 483)	1.355 (df = 287)	2.326 (df = 216)	2.417 (df = 92)
F Statistic	0.339 (df = 2; 326)	8.818^{***} (df = 2; 508)	11.554^{***} (df = 2; 500)	0.873 (df = 2; 483)	1.563 (df = 2; 287)	8.913^{***} (df = 2; 216)	0.886 (df = 2; 92)
Note:							*p<0.1; **p<0.05; ***p<0.01

Table 4.8: Effect of market temperature on raw returns (not adjusted for benchmark returns)

4.3.3 Long-term accounting data results

Interpreting the regression results in Tables A3 to A8, we find little indication that accounting data might affect long-term returns. For most of the regressions, all accounting variables are insignificant at conventional levels. Still, there are some regressions where we find some significance. In the third three-year regression, we find revenue divided by assets to be significant and positive, which might indicate that a firm that is effectively using its assets to generate revenue at the time of IPO, will have greater long-term performance. Relating this to our divergence of opinion hypothesis, one can argue that a company that is generating high revenue relative to their assets at the time of IPO, already has proven that the business model works, and hence has less uncertainty. This might lead to less divergence of opinion, resulting in better long-term performance.

Furthermore, in the second five-year regression we find the natural logarithm of assets to negatively affect long-term performance, which contradicts our divergence of opinion hypothesis. At the same time, the negative relation between assets and long-term returns is not significantly apparent in any other long-term regressions. In our BHAR analysis, we found that the largest firms in the form of assets performed better than other IPOs, but this result is not supported by the regression analysis. One explanation might be that the regression utilizes the logarithm of assets, which reduces the impact of the largest firms on the estimated coefficient. In conclusion, it seems likely that the accounting data at the time of IPO have little effect on long-term excess returns, but there are indications that the firms with the highest total assets perform better than other IPOs in the long run.

4.3.4 Long-term firm age results

When analyzing the relationship between age at the time of listing and excess returns, we find a significant correlation for multiple periods. For the short- and medium-term regressions in the appendix, there are few interesting findings. However, when looking at regressions for a one-year time horizon and longer, we find indications that young firms underperform and older firms overperform. It is unclear if the effect is best represented by dummy variables classifying companies as young, mid-aged, or old, or if the effect is continuous and therefore better represented by a continuous variable such as the logarithm of firm age. We have included both versions in our regression models, and both variables tell the same story. The logarithm of age has a positive coefficient and is significant in some of the regressions, indicating that older firms overperform compared to younger firms. When interpreting the dummy variables in the long-term regressions, we find that young firms tend to have a negative coefficient, while older firms tend to have a positive coefficient. Furthermore, both of these effects are significant in at least one of the regressions. Together with the findings using the logarithm of firm age, this supports the hypothesis regarding the long-run performance being a positive function of the age at the time of listing.

4.3.5 Long-term crisis variable results

To examine the divergence of opinion hypothesis, we included a crisis variable. We expect that firms listed during a crisis have larger uncertainty at the time of listing, potentially leading to poor long-term performance in light of the divergence of opinion hypothesis. For multiple periods, we find that the crisis dummy variable and one or more of the individual crisis variables are significant at conventional levels and that the coefficients are negative. This is especially prevalent in the six-month, one-year, and ten-year regressions. Our results indicate that IPOs issued during crises underperform on a medium- to long-term basis compared to other IPOs. This supports the divergence of opinion hypothesis, which expects IPOs listed during crises to underperform compared to other IPOs in the long term due to higher uncertainty at the time of listing.

4.3.6 Long-term industry results

Analyzing the industry variables in the regressions, we find only telecommunication to be significant using a 5% confidence level. Our findings indicate short- and medium-term underperformance for telecommunication IPOs. In the sample there are eleven telecommunication firms, making it likely that potential outliers play a role in making the variable significant. Seven out of the eleven telecommunication IPOs were either in the dotcom bubble or the COVID crisis, but the coefficients do not lose their significance when controlling for these events. With the lack of significance in the other industry variables, it seems likely that sectors do not play a particularly large role in the long-term success of an IPO. The significant effects we found for telecommunications could also be a result of multiple testing, or they could be a result of the sample size per industry being small, which again will result in potential outliers having a large impact on the estimated coefficients. There may be certain sectors that have IPOs that perform better in certain periods, but on average, our data suggests that long-term excess returns should not be a function of industry.

4.3.7 Long-term market choice results

Our results indicate that the choice of listing on the main market or one of the junior markets has not had a significant impact on long-term excess returns. These findings are in line with expectations, especially since our regressions control for factors such as firm age, accounting data, market temperature, and industry, which might be factors explaining the difference between firms listing on the main market and junior markets.

4.3.8 Wealth relatives results

To increase the robustness of our long-term analysis, we have decided to compute wealth relatives. This is done to test if the equally weighted return for the portfolio of IPOs is unequal to benchmark returns for different holding periods. To make any conclusions regarding statistical inference, we utilize the Welch t-test for unequal variances since we cannot assume that the variance for the benchmark and the portfolio of IPOs is equal. We tested formally if the variances were equal for all periods using an F-test and ended up rejecting the null hypothesis of equal variances for all periods using a 1% significance level. As Table 4.9 shows, the wealth relatives are less than one for all time horizons. This is as expected, as we previously found that the BHAR is negative for all time horizons. One notable difference from the previous BHAR table is that wealth relatives utilize all IPOs, while the BHAR table just includes the IPOs where we were able to gather accounting data. Still, the findings are the same, which is that the benchmark seems to overperform for all time horizons. Furthermore, using a 5% significance level, we find that the benchmark overperforms for the six-month and the ten-year horizons.

Wealth Relatives

Time Horizon	Wealth Relative	P-value	N
1 month	0.99	0.1696	511
6 months	0.96	0.0698	503
1 year	0.90	0.0007	486
3 years	0.88	0.0781	290
5 years	0.83	0.1343	219
10 years	0.70	0.0110	95

Table 4.9: Wealth relatives for buy and hold IPO returns compared to OSEAX returns, using first-day close as the starting price. P-values are calculated using two-sided t-tests

4.4 Robustness

To be able to trust the results and conclusions drawn in the analysis, it is important to check whether our dataset, tests, and analysis are robust. When it comes to the dataset, the robustness depends on the time horizon. For the first-day analysis, we had some issues extracting all the offer prices, resulting in our dataset missing some listings. This could result in skewed results, as it is possible the excluded listings performed differently than the included ones. Still, our findings regarding a first-day return of 9.33% are in line with previous studies on the Norwegian market, which indicates that our first-day sample of 329 IPOs is representative of the IPOs between 2000 and 2023.

For the long-term analysis, we were able to extract the stock price development for all listings we identified in the period. At the same time, there were some listings which we were not able to extract the financial information for, resulting in the analysis including financial information suffering from some omitted listings. As with the first-day analysis, excluding some IPOs could skew our results. Still, since we were able to extract financial information for around 90% of the IPOs, this should not cause a large bias. We also perform regressions without financial data as explanatory variables where we include all IPOs to increase the robustness of our results.

Furthermore, one could also argue that the use of historical accounting data where we just adjust for inflation, has some issues. Firstly, accounting practices and regulations evolve over time, which especially impacts what one can put on the balance sheet. One example is that up until 2019, IFRS allowed leases to not be included on the balance sheet, but after IFRS 16 was implemented, leases needed to be included in the balance sheet (PWC, 2018). Furthermore, there might be a difference in which accounting practice the firms in our sample use, as it was not until 2005 that all Norwegian listed firms were required to use IFRS (Jensen, 2022). These differences could result in some inaccuracy when comparing the inflation-adjusted financial data for different IPOs.

Using a representative benchmark that replicates the risk exposure is also an important assumption that needs to hold for our results of excess returns to be valid, as previous studies such as Sapusek (2000) have found that the choice of benchmark has a high sensitivity on IPO performance. In our analysis, we have utilized the OSEAX index as the benchmark. This index might not be a perfect reflection of the systematic risk exposure one would get from investing in a portfolio of IPOs. Still, the OSEAX benchmark is the Norwegian investable index which closest replicates the risk exposure of the portfolio of IPOs, and it should be a relatively fair comparison as it also represents an alternative investment opportunity for investors. Hence, we trust our estimates of excess returns to be valid and representative.

When it comes to interpreting the regression outputs from the analysis, these assume that the ordinary least squares assumptions hold. In our analysis of these assumptions, we found indications that we might have some issues regarding heteroskedasticity. This can lead to our estimated coefficients being less precise, increasing the chance of the estimates being further from their true value (Frost, 2023). Still, since our analysis only showed indications of weak form heteroskedasticity, it should not be too much of an issue. Lastly, we also found some indications that the error terms might have heavy tails, and hence they are not perfectly normally distributed. A violation of the normality assumption can lead to the reported significance of variables being invalid. If this is the case, one should be careful when interpreting the significance from the regressions. Still, due to our sample being relatively large for most periods, the normality assumption should not cause too many issues because of the central limit theorem. We have also concluded that it seems plausible that the other Gauss-Markov assumptions hold, which makes us able to trust the OLS results with reasonable confidence.

Furthermore, we have for the most part used two-sided t-tests to estimate significance throughout the analysis. For these to be representative, the error terms should be approximately normally distributed, and the variance should be homogenous. As discussed in the appendix, there are some doubts about whether these assumptions hold, but since there are not any clear indications that they are heavily violated, the significance estimates from the t-tests should be relatively representative. Lastly, when performing the regressions, we should check for issues regarding multicollinearity. When interpreting the correlation matrix including all variables, we found that the logarithm of assets and the logarithm of revenue have a moderate correlation, as the coefficient has a value of 0.64. Furthermore, the logarithm of revenue also has a moderate correlation with the positive EBIT dummy variable, as the correlation coefficient is equal to 0.65. To reduce multicollinearity issues, we have performed multiple regressions for each period, where we include the logarithm of assets and the EBIT dummy but exclude the logarithm of revenue in at least one of the regressions for each period.

As discussed earlier, our long-term analysis might suffer from survival bias. This is because delisted firms will not be taken into account when performing the long-term regressions of excess returns. When performing the long-term EW and VW calculations where we also included the last closing price for the delisted companies, we found that the long-term excess returns are quite similar to the returns from the long-term EW and VW analysis which only includes companies with enough price history. Since the results are similar, we can be less worried about our results being biased. Still, we cannot entirely eliminate the issue of potential survival bias in our results. Hence, the possibility of survival bias should be kept in mind when interpreting the long-term regression results.

When interpreting the long-term weighted results, one could argue that it might not reflect the behavior of investors. The calculated excess returns imply initial weighing based on adjusted assets, while in reality, most investors weight and rebalance based on market capitalization. One should therefore be careful when interpreting these calculations of long-term excess returns, as they might not reflect the behavior of investors and hence, they do not provide the best estimate of long-term excess returns from investing in IPOs. Still, the weighted returns provide an estimate of excess returns which is replicable for investors, as it is possible to weight the portfolio based on assets. Lastly, we have high trust in the data used in our analysis being correct, as it is extracted from reputable and reliable sources.

4.5 Future research recommendations

As our analysis is limited to Norwegian IPOs in the period 2000-2023, it would be interesting to analyze whether the effects we found regarding market temperature, seasonal darkness, and divergence of opinion, are apparent before the year 2000 as well. Furthermore, it is also possible to do a more extensive analysis of the first-day returns by including all the listings in the period, as we were not able to obtain the offer price for all the listings. When it comes to long-term excess returns, it would also be interesting to analyze the long-term returns for IPOs before the year 2000, as we were able to find limited research on this for the Norwegian market.

To make our analysis more robust against potential survival bias issues, we performed an analysis where we included delisted companies by utilizing their last closing price observation. At the same time, the last closing price is not necessarily the correct price to represent investors' return for a specific stock that has been delisted. The correct price to use after delisting is related to the nature of the delisting. In some cases, a price of zero may be more appropriate to use if a firm was delisted due to bankruptcy. On the other hand, some firms delist under more positive circumstances, for example, due to M&A transactions. For these delisted firms it could be appropriate to use other prices than the last closing price, such as the buyout price. Therefore, one could build on our analysis by analyzing the nature behind the delistings. One could also explore whether some firm-specific characteristics make a company more or less likely to delist.

Lastly, it would also be interesting to analyze whether the hot market phenomenon, seasonal darkness, and the divergence of opinion are apparent in other Scandinavian markets. It would especially be interesting to further test the seasonal darkness phenomenon, given its limited exploration within an IPO context. If it is the case that this phenomenon is also apparent in other markets, it could make a stronger argument for the effect to be apparent, which investors once again might be able to utilize.

5. Conclusion

Through our analysis, we found that the IPOs have had an initial underpricing of around 9%, which is in accordance with previous literature on the Norwegian market. For the long-term analysis, we found that IPOs tend to underperform compared to the OSEAX benchmark. The underperformance indicates that investing in Norwegian IPOs for the long-term has not been a good investment in the period 2000-2023 compared to investing in the broad market index. This is also in accordance with previous international papers on long-term performance, but not with Westerholm (2006) who found a slight overperformance for IPOs in Norway between 1992-2001.

The weighted excess returns results differ compared to the equal-weighted average returns. Interpreting the weighted first-day returns, we noticed that firms with the largest offer sizes performed worse relative to the other IPOs. On the other hand, when we calculated the long-term weighted excess returns, the long-term underperformance seemed to disappear. This result indicates that larger firms in the form of assets perform better in the long run than their smaller counterparts. Since both offer size and total assets can work as proxies for a firm's size, a possible interpretation of the weighted results is that firm size affects short-term and long-term performance differently. Our results indicate that larger firms may perform better in the long term but worse on the first day compared to smaller IPOs.

The finding regarding larger firms performing better than their smaller peers on a long-term basis is to some degree surprising. The three-factor asset pricing model developed by Fama and French (1993), includes firm size as one of its factors. In this asset pricing model, smaller firms are considered riskier and should therefore yield higher returns, as exposure to small firms represents a form of systematic risk in the model. When performing our long-term regression of excess returns, we found no evidence of the logarithm of adjusted assets affecting returns. The reason why this might happen even though the weighted excess returns are higher than the equally weighted, is that weighted returns might be driven by a few outliers with high adjusted assets as our data includes large variations in adjusted assets. This explanation is supported by our trimmed analysis which excluded the 10% largest firms in the form of total assets, where we found the weighted long-term excess return to be negative and in the same range as the equally weighted excess return.

Relating our findings to the hypotheses, we find some support for the hot market hypotheses. From our one-month and six-month regressions, we find that issues in hot markets seem to overperform issues in neutral and cold markets. This could be a result of higher underpricing at the time of listing due to a higher dispersion in quality in hot markets. Furthermore, when interpreting the long-run returns for IPOs issued in hot markets, we find that they tend to have poor returns compared to neutral and cold issues, although the underperformance for hot issues is not significant at conventional levels. Still, the lower average long-term return for hot issues supports the finding of Baker et al. (2003), which is that issuers opportunistically list when markets are priced high, leading to poor long-term returns. In total, our analysis of market temperature indicates that issues in hot markets in Norway experience a higher short-term return but underperform in the longer term compared to issues in neutral and cold markets.

The seasonal darkness analysis regarding underpricing in months with less daylight also showed indications of being apparent in the Norwegian market. This indicates that issues in "dark" months are underpriced compared to issues in the other months. Lastly, when analyzing the divergence of opinion hypotheses, we find mixed results. Firstly, we find that long-run performance seems to be a positive function of firm age and that long-run performance is worse for firms listing during a crisis. Both findings are in line with what we expect from Miller's (1977) divergence of opinion hypothesis. When it comes to firm size, we found that the largest IPOs in the form of total assets tend to have better long-term performance, supporting the hypothesis. At the same time, we find little indication that EBIT or sector affect the long-run performance, which both are variables expected to affect long-run performance in light of the hypothesis. Hence, the conclusion of whether the divergence of opinion hypothesis is apparent in the Norwegian market is unclear. However, we found that firm age, firm size, and listing during a crisis, which are all proxies for uncertainty, seem to affect the long-term excess return. This could indicate that the divergence of opinion hypothesis has weak support, meaning that to some degree, the expected market price of a listing will increase with risk and uncertainty.

We hope that this analysis has given valuable insight into the Norwegian IPO market, especially regarding long-term performance, hot market listings, seasonal darkness, and ex-ante uncertainty.

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Appendix

When interpreting regression results, one needs to assume that certain assumptions hold for the estimates to be unbiased and consistent (Wooldridge, 2012, p. 83-86). These are the five Gauss-Markow assumptions, which are:

1. Linear in Parameters
2. Random Sampling
3. Sample Variation in x
4. Zero Conditional Mean
5. Homoscedasticity

Under the first four Gauss-Markow assumptions, the OLS estimator is unbiased. Furthermore, we also need the fifth assumption to hold for the estimator to be efficient. To make statements regarding statistical inference, we need a sixth assumption to hold. This assumption is that the error terms must be normally distributed. When interpreting our results, it is therefore important to reflect on whether the assumptions hold or not.

The first assumption, linear in parameters, is something that can be discussed but not directly tested (Frost, 2017). We have chosen to log transform the financial variables for revenue and assets in addition to firm age, as it seems more likely that performance is a function of relative changes compared to absolute changes. For some variables, we decided to utilize dummy variables. The positive EBIT variable is an example of this, which is used as a proxy for profitable firms. When looking at residual vs fitted values for the different explanatory variables, we observe that there seem to be little non-linear trends and that the average residual is usually centered around zero. This indicates that our versions of the explanatory variables are a reasonably good fit for our data, and it seems plausible that the linearity assumption holds.

The assumption of random sampling pertains to the methodology used in the specific process of collecting our sample (Wooldridge, 2012, p. 84). It is important to note that there could be common trends within the firms which we have not been able to collect all necessary data from, like financials. A possible consequence of this is that we ignore the reasons why certain companies do not have available data and the potential implications of this. Nevertheless, having successfully gathered accounting data for approximately 90% of our sample, the potential for exclusion due to data availability seems unlikely to substantially impact the validity of the random sampling assumption. We consider that our dataset is sufficiently large with few exclusions, and our results should not be significantly biased due to non-random sampling.

The third assumption is about variation in the sample, which is needed to figure out how a change in independent variable x affects the dependent variable y. This assumption holds, as there is variation in x for all variables in our dataset.

Zero conditional mean is an important assumption, as only random chance should determine the values of the error terms (Frost, 2017). It enables us to analyze results and interpret the impact of a change in x on y ceteris paribus. To explore whether this assumption is potentially violated, we extracted residuals and fitted values from several regressions and plotted them against each other. The residual plots for the BHAR regressions seem to show no strong patterns or trends in these regressions, where the mean of the residual tends to stay around 0 across all values of x. For the CAR regressions, the plots show similar results. Therefore, we conclude that it seems likely that the zero conditional mean assumption holds. Considering that assumptions 1 to 4 are likely to hold, we can with reasonable confidence state that the variable coefficients in the regression are unbiased.

For the coefficients to be not only unbiased but also efficient, the assumption of homoscedasticity must hold (Wooldridge, 2012, p. 268-269). We notice that there might be weak indications of increasing variance for larger observations of x for most of the time horizons. We can formally analyze this by doing the Breusch-Pagan test for homoscedasticity. Table A1 shows the results for this test, indicating that the 6-month and 5-year regression have issues with heteroscedasticity utilizing a 5% significance level. The implication for this is that we should tread lightly when interpreting coefficients and their significance. Even though we have limited tests of whether the variance is changing across the dataset, it seems likely that the regressions for the most part do not suffer from severe heteroskedasticity, as the residual vs fitted values plots only showed indications of weak forms of heteroskedasticity.

Breusch-Pagan Test for Homoscedasticity

Time Horizon	P-value
6 months	0.0414
1 year	0.3683
3 years	0.7590
5 years	0.0008
10 years	0.1385

Table A1: Preusch-Pagan test for homoscedasticity per time horizon

To make assumptions regarding inference, we should analyze whether the error terms are normally distributed. The QQ plots show a deviation from the normality assumption, which is heavy tails. This is a common issue, where outliers on the ends deviate from a normal distribution, disrupting potential inferences. The Shapiro-Wilk tests confirm this, as the results clearly indicate that normality is violated on a 5%-level. Hence, one could make an argument for doing inference on this dataset with robust confidence intervals, but we have proceeded to do regular two-sided t-tests. This is mainly due to the relatively large sample size we have. The central limit theorem states that for a large sample of n observations from a population with a finite mean and variance, the sampling distribution of the sum or mean of samples of size n is approximately normal (Anderson, 2010). Therefore, the central limit theorem often justifies the assumption that a distribution of a sample statistic within a large sample is normal. In light of the central limit theorem, we conclude that the normality assumption holds.

Variable	Description
Hot	Dummy variable equal to one if the market is defined as hot at the time of listing
Cold	Dummy variable equal to one if the market is defined as cold at the time of listing
CrisisDummy	Dummy variable equal to one if the listing happened during one of the three crises
Dotcom	Dummy variable equal to one if the listing happened during the dotcom crisis
FinCrisis	Dummy variable equal to one if the listing happened during the financial crisis
COVID	Dummy variable equal to one if the listing happened during the COVID crisis
LogAssets	The natural logarithm of total assets the year prior to listing
LogRevenue	The natural logarithm of total revenue the year prior to listing
PositiveEBIT	Dummy variable equal to one if EBIT the year prior to listing is positive
RevAssets	Total revenue divided by total assets the year prior to listing
RealEstate	Dummy variable equal to one if the IPO is within the ICB industry classification "Real estate"
ConsumerDiscreatinoary	Dummy variable equal to one if the IPO is within the ICB industry classification "Consumer discreationary"
ConsumerStaples	Dummy variable equal to one if the IPO is within the ICB industry classification "Consumer staples"
Energy	Dummy variable equal to one if the IPO is within the ICB industry classification "Energy"
Financials	Dummy variable equal to one if the IPO is within the ICB industry classification "Financials"
HealthCare	Dummy variable equal to one if the IPO is within the ICB industry classification "Health care"
Industrials	Dummy variable equal to one if the IPO is within the ICB industry classification "Industrials"
Technology	Dummy variable equal to one if the IPO is within the ICB industry classification "Technology"
Telecommunications	Dummy variable equal to one if the IPO is within the ICB industry classification "Telecommunications"
Utilities	Dummy variable equal to one if the IPO is within the ICB industry classification "Utilities"
Junior	Dummy variable equal to one if the IPO is on one of the junior markets
SeasonalDarknessDummy	Dummy variable equal to one if the IPO is in a "dark" month
SeasonalDarkness	Average hours over twelve per day without daylight the month of listing
LogFirmAge	The natural logarithm of firm age at the time of listing
Age0_4	Dummy variable equal to one if the firm age at the time of listing is equal to or between zero and four years
Age25	Dummy variable equal to one if the firm age at the time of listing is equal to or above 25 years

Table A2: Variable description

1-Month Regression Results

	Dependent variable:					
	BHAR_1_month					
	(1)	(2)	(3)	(4)	(5)	(6)
Hot	0.098***	0.088***	0.082***	0.086***	0.110***	0.110***
	(0.025)	(0.029)	(0.028)	(0.028)	(0.029)	(0.029)
Cold	-0.038	-0.038	-0.041	-0.044	-0.027	-0.030
	(0.047)	(0.047)	(0.047)	(0.047)	(0.051)	(0.051)
Dotcom		-0.036				
		(0.035)				
FinCrisis		0.059				
		(0.092)				
COVID		0.013				
		(0.028)				
CrisisDummy			0.027	0.022	0.009	0.008
			(0.024)	(0.023)	(0.025)	(0.025)
LogRevenue					0.001	
					(0.003)	
LogAssets					-0.003	0.00004
					(0.006)	(0.005)
PositiveEBIT					0.010	
					(0.029)	
RevAssets						-0.0002
						(0.002)
RealEstate			-0.022	-0.015	-0.066	-0.064
			(0.076)	(0.076)	(0.081)	(0.081)
ConsumerDiscreationary			-0.018	-0.017	-0.033	-0.025
			(0.065)	(0.065)	(0.065)	(0.064)
ConsumerStaples			-0.046	-0.045	-0.059	-0.055
			(0.061)	(0.061)	(0.062)	(0.061)
Energy			0.015	0.016	-0.005	-0.004
			(0.055)	(0.055)	(0.056)	(0.056)
Financials			-0.029	-0.026	-0.046	-0.043
			(0.061)	(0.061)	(0.062)	(0.062)
HealthCare			0.021	0.025	0.018	0.019
			(0.064)	(0.064)	(0.064)	(0.064)
Industrials			0.007	0.010	-0.004	0.003
			(0.056)	(0.056)	(0.057)	(0.057)
Technology			-0.015	-0.010	-0.035	-0.029
			(0.058)	(0.058)	(0.059)	(0.058)
Telecommunications			-0.241***	-0.233***	-0.250***	-0.243***
			(0.085)	(0.084)	(0.086)	(0.085)
Utilities			-0.097	-0.093	-0.076	-0.074
			(0.078)	(0.078)	(0.084)	(0.083)
Junior			-0.002	0.0001	-0.011	-0.013
			(0.022)	(0.022)	(0.025)	(0.024)
SeasonalDarkness			0.012**			
			(0.005)			
LogFirmAge			0.0003			
			(0.007)			
SeasonalDarknessDummy				0.058***	0.060***	0.060***
				(0.021)	(0.022)	(0.021)
Age0_4				0.005	0.003	0.0003
				(0.023)	(0.025)	(0.025)
Age25				0.015	0.012	0.014
				(0.029)	(0.029)	(0.029)
Constant	-0.033***	-0.031**	-0.045	-0.057	-0.024	-0.038
	(0.011)	(0.013)	(0.058)	(0.055)	(0.094)	(0.092)
Observations	511	511	511	511	449	449
R^2	0.033	0.036	0.074	0.078	0.098	0.097
Adjusted R^2	0.029	0.027	0.044	0.046	0.056	0.057
Residual Std. Error	0.224 (df = 508)	0.224 (df = 505)	0.222 (df = 494)	0.222 (df = 493)	0.215 (df = 428)	0.215 (df = 429)
F Statistic	8.647*** (df = 2; 508)	3.821*** (df = 5; 505)	2.475*** (df = 16; 494)	2.461*** (df = 17; 493)	2.335*** (df = 20; 428)	2.429*** (df = 19; 429)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table A3: One-month regression results of excess returns

6-Month Regression Results

	Dependent variable:					
		BHAR_6_months			CAR_6_months	
	(1)	(2)	(3)	(4)	(5)	(6)
Hot	0.157***	0.215***	0.228***	0.157***	0.217***	0.217***
	(0.054)	(0.058)	(0.065)	(0.052)	(0.055)	(0.062)
Cold	-0.086	-0.069	-0.064	-0.070	-0.061	-0.052
	(0.098)	(0.109)	(0.110)	(0.095)	(0.104)	(0.105)
CrisisDummy	-0.088*	-0.127**		-0.086*	-0.121**	
	(0.046)	(0.050)		(0.044)	(0.048)	
LogRevenue		0.001			0.001	
		(0.007)			(0.007)	
Dotcom			-0.154**			-0.176**
			(0.078)			(0.074)
FinCrisis			-0.119			-0.094
			(0.183)			(0.174)
COVID			-0.117*			-0.092
			(0.063)			(0.060)
LogAssets		-0.004	0.004		-0.002	0.006
		(0.013)	(0.011)		(0.012)	(0.010)
PositiveEBIT		0.068			0.070	
		(0.059)			(0.056)	
RevAssets			0.003			0.003
			(0.004)			(0.004)
RealEstate	-0.112	-0.232	-0.227	-0.100	-0.228	-0.208
	(0.148)	(0.164)	(0.166)	(0.144)	(0.156)	(0.158)
ConsumerDiscreationary	-0.012	-0.064	-0.019	-0.015	-0.070	-0.012
	(0.126)	(0.131)	(0.132)	(0.122)	(0.125)	(0.126)
ConsumerStaples	-0.069	-0.112	-0.098	-0.058	-0.111	-0.088
	(0.119)	(0.125)	(0.126)	(0.116)	(0.119)	(0.120)
Energy	-0.039	-0.075	-0.058	-0.032	-0.067	-0.038
	(0.108)	(0.113)	(0.115)	(0.105)	(0.107)	(0.109)
Financials	-0.081	-0.138	-0.096	-0.102	-0.157	-0.100
	(0.119)	(0.125)	(0.126)	(0.115)	(0.119)	(0.120)
HealthCare	-0.063	-0.097	-0.105	-0.020	-0.056	-0.059
	(0.124)	(0.129)	(0.131)	(0.121)	(0.123)	(0.124)
Industrials	-0.015	-0.095	-0.073	-0.062	-0.143	-0.113
	(0.110)	(0.115)	(0.117)	(0.107)	(0.110)	(0.111)
Technology	-0.093	-0.140	-0.130	-0.050	-0.114	-0.093
	(0.112)	(0.118)	(0.119)	(0.109)	(0.112)	(0.113)
Telecommunications	-0.346**	-0.417**	-0.375**	-0.394**	-0.478***	-0.425**
	(0.164)	(0.172)	(0.175)	(0.160)	(0.164)	(0.166)
Utilities	-0.185	-0.165	-0.176	-0.119	-0.106	-0.115
	(0.151)	(0.169)	(0.169)	(0.147)	(0.160)	(0.161)
Junior	0.017	0.018	0.007	0.016	0.029	0.012
	(0.043)	(0.050)	(0.051)	(0.042)	(0.047)	(0.048)
SeasonalDarknessDummy	0.097**	0.120***		0.091**	0.109***	
	(0.041)	(0.044)		(0.039)	(0.041)	
Age0_4	0.004	0.026		0.032	0.049	
	(0.045)	(0.051)		(0.044)	(0.049)	
Age25	0.064	0.060		0.077	0.066	
	(0.056)	(0.058)		(0.055)	(0.055)	
SeasonalDarkness			0.009			0.008
			(0.011)			(0.010)
LogFirmAge			0.005			0.004
			(0.017)			(0.016)
Constant	-0.044	0.007	-0.030	-0.062	-0.045	-0.081
	(0.107)	(0.190)	(0.188)	(0.104)	(0.180)	(0.179)
Observations	503	444	444	503	444	444
R^2	0.064	0.093	0.074	0.063	0.101	0.083
Adjusted R^2	0.032	0.050	0.031	0.030	0.058	0.039
Residual Std. Error	0.431 (df = 485)	0.432 (df = 423)	0.436 (df = 423)	0.419 (df = 485)	0.411 (df = 423)	0.415 (df = 423)
F Statistic	1.963** (df = 17; 485)	2.174*** (df = 20; 423)	1.699** (df = 20; 423)	1.909** (df = 17; 485)	2.365*** (df = 20; 423)	1.905** (df = 20; 423)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table A4: Six-month regression results of excess returns

1-Year Regression Results

	Dependent variable:					
	BHAR_1_year			CAR_1_year		
	(1)	(2)	(3)	(4)	(5)	(6)
Hot	0.069	0.129	0.190**	0.068	0.140*	0.158*
	(0.076)	(0.081)	(0.090)	(0.073)	(0.077)	(0.086)
Cold	-0.112	-0.102	-0.098	-0.084	-0.096	-0.074
	(0.137)	(0.151)	(0.152)	(0.132)	(0.144)	(0.146)
CrisisDummy	-0.259***	-0.317***		-0.253***	-0.304***	
	(0.064)	(0.069)		(0.062)	(0.066)	
LogRevenue		-0.007			-0.010	
		(0.010)			(0.009)	
Dotcom			-0.209*			-0.298***
			(0.108)			(0.104)
FinCrisis			-0.332			-0.259
			(0.252)			(0.242)
COVID			-0.380***			-0.301***
			(0.088)			(0.084)
LogAssets		-0.006	-0.004		0.013	0.011
		(0.018)	(0.015)		(0.017)	(0.015)
PositiveEBIT		0.098			0.089	
		(0.083)			(0.079)	
RevAssets			0.005			0.006
			(0.005)			(0.005)
RealEstate	-0.089	-0.288	-0.324	-0.053	-0.273	-0.284
	(0.207)	(0.227)	(0.229)	(0.199)	(0.216)	(0.220)
ConsumerDiscretionary	-0.064	-0.095	-0.110	-0.077	-0.116	-0.112
	(0.176)	(0.181)	(0.182)	(0.169)	(0.173)	(0.175)
ConsumerStaples	0.005	0.004	-0.016	0.051	0.033	0.023
	(0.167)	(0.172)	(0.173)	(0.161)	(0.165)	(0.166)
Energy	-0.014	-0.040	-0.053	0.060	0.014	0.022
	(0.152)	(0.157)	(0.159)	(0.146)	(0.150)	(0.153)
Financials	-0.052	-0.086	-0.081	-0.060	-0.118	-0.090
	(0.166)	(0.174)	(0.175)	(0.160)	(0.166)	(0.168)
HealthCare	-0.034	-0.050	-0.116	0.034	0.024	-0.019
	(0.175)	(0.180)	(0.181)	(0.168)	(0.172)	(0.174)
Industrials	-0.005	-0.081	-0.093	-0.080	-0.160	-0.173
	(0.153)	(0.160)	(0.161)	(0.148)	(0.153)	(0.154)
Technology	-0.080	-0.111	-0.177	0.018	-0.029	-0.070
	(0.158)	(0.163)	(0.164)	(0.151)	(0.156)	(0.158)
Telecommunications	-0.231	-0.308	-0.315	-0.300	-0.385*	-0.383*
	(0.229)	(0.238)	(0.241)	(0.221)	(0.228)	(0.231)
Utilities	-0.003	0.113	0.082	0.083	0.170	0.127
	(0.211)	(0.233)	(0.233)	(0.203)	(0.223)	(0.224)
Junior	0.016	-0.014	0.003	0.040	0.026	0.029
	(0.062)	(0.070)	(0.072)	(0.059)	(0.067)	(0.069)
SeasonalDarknessDummy	0.110*	0.144**		0.142**	0.178***	
	(0.058)	(0.061)		(0.056)	(0.059)	
Age0_4	-0.021	-0.025		-0.023	-0.015	
	(0.064)	(0.071)		(0.062)	(0.068)	
Age25	0.157**	0.171**		0.158**	0.162**	
	(0.080)	(0.082)		(0.077)	(0.078)	
SeasonalDarkness			0.011			0.020
			(0.015)			(0.014)
LogFirmAge			0.043*			0.038
			(0.024)			(0.023)
Constant	-0.075	0.055	-0.015	-0.149	-0.233	-0.281
	(0.149)	(0.265)	(0.262)	(0.143)	(0.253)	(0.251)
Observations	486	431	431	486	431	431
R^2	0.064	0.098	0.084	0.076	0.118	0.097
Adjusted R^2	0.030	0.055	0.040	0.043	0.075	0.053
Residual Std. Error	0.602 (df = 468)	0.597 (df = 410)	0.602 (df = 410)	0.579 (df = 468)	0.571 (df = 410)	0.577 (df = 410)
F Statistic	1.881** (df = 17; 468)	2.240*** (df = 20; 410)	1.885** (df = 20; 410)	2.276*** (df = 17; 468)	2.739*** (df = 20; 410)	2.203*** (df = 20; 410)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table A5: One-year regression results of excess returns

3-Year Regression Results

	Dependent variable:					
	BHAR_3_years			CAR_3_years		
	(1)	(2)	(3)	(4)	(5)	(6)
Hot	-0.316	-0.438	-0.631^{**}	-0.286	-0.360	-0.463
	(0.274)	(0.301)	(0.315)	(0.253)	(0.269)	(0.286)
Cold	-0.090	0.139	0.091	0.002	0.112	0.123
	(0.301)	(0.348)	(0.345)	(0.278)	(0.311)	(0.314)
CrisisDummy	-0.242	-0.282		-0.118	-0.144	
	(0.217)	(0.234)		(0.200)	(0.209)	
LogRevenue		0.041			-0.029	
		(0.027)			(0.025)	
Dotcom			-0.206			-0.182
			(0.267)			(0.243)
FinCrisis			-0.251			0.333
			(0.635)			(0.577)
COVID			-0.839^{*}			-0.702^{*}
			(0.456)			(0.414)
LogAssets		-0.036	0.023		0.008	-0.015
		(0.053)	(0.044)		(0.047)	(0.040)
PositiveEBIT		0.095			0.161	
		(0.232)			(0.207)	
RevAssets			0.197^{**}			0.068
			(0.093)			(0.085)
RealEstate	-0.443	-0.393	-0.414	-0.747	-0.682	-0.657
	(0.577)	(0.611)	(0.604)	(0.533)	(0.546)	(0.549)
ConsumerDiscreationary	-0.243	-0.378	-0.402	-0.084	-0.033	-0.106
	(0.541)	(0.561)	(0.547)	(0.500)	(0.501)	(0.497)
ConsumerStaples	-0.243	-0.329	-0.317	-0.259	-0.197	-0.190
	(0.534)	(0.554)	(0.547)	(0.494)	(0.495)	(0.497)
Energy	-0.040	-0.049	-0.086	-0.270	-0.254	-0.281
	(0.487)	(0.502)	(0.498)	(0.450)	(0.448)	(0.452)
Financials	-0.239	-0.243	-0.239	-0.421	-0.308	-0.302
	(0.503)	(0.524)	(0.522)	(0.465)	(0.468)	(0.474)
HealthCare	-0.237	-0.176	-0.192	0.078	0.126	0.159
	(0.536)	(0.561)	(0.544)	(0.495)	(0.501)	(0.494)
Industrials	-0.017	-0.091	-0.113	-0.152	-0.041	-0.107
	(0.502)	(0.523)	(0.512)	(0.464)	(0.467)	(0.465)
Technology	0.003	-0.075	-0.053	-0.134	-0.236	-0.194
	(0.516)	(0.545)	(0.526)	(0.477)	(0.487)	(0.478)
Telecommunications	-0.968	-0.827	-1.017	-1.549^{**}	-1.636^{**}	-1.843^{**}
	(0.719)	(0.790)	(0.790)	(0.664)	(0.705)	(0.717)
Utilities	-0.269	-0.345	-0.142	-0.143	-0.040	0.068
	(0.847)	(0.876)	(0.865)	(0.782)	(0.782)	(0.785)
Junior	-0.101	0.038	0.017	0.116	0.078	0.114
	(0.151)	(0.180)	(0.179)	(0.140)	(0.161)	(0.162)
SeasonalDarknessDummy	0.307^{*}	0.402^{**}		0.189	0.207	
	(0.158)	(0.173)		(0.146)	(0.155)	
Age0_4	-0.217	-0.163		-0.443^{***}	-0.507^{***}	
	(0.170)	(0.192)		(0.157)	(0.171)	
Age25	0.114	0.050		-0.002	-0.031	
	(0.211)	(0.222)		(0.195)	(0.198)	
SeasonalDarkness			0.118^{***}			0.048
			(0.042)			(0.038)
LogFirmAge			0.049			0.107^{**}
			(0.059)			(0.054)
Constant	0.048	-0.040	-0.561	0.152	0.254	-0.061
	(0.483)	(0.832)	(0.806)	(0.446)	(0.743)	(0.732)
Observations	290	260	260	290	260	260
R^2	0.051	0.069	0.087	0.098	0.117	0.105
Adjusted R^2	-0.008	-0.009	0.011	0.041	0.043	0.030
Residual Std. Error	1.208 (df = 272)	1.237 (df = 239)	1.225 (df = 239)	1.116 (df = 272)	1.105 (df = 239)	1.113 (df = 239)
F Statistic	0.858 (df = 17; 272)	0.888 (df = 20; 239)	1.139 (df = 20; 239)	1.733^{**} (df = 17; 272)	1.587^{*} (df = 20; 239)	1.395 (df = 20; 239)
Note:						$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table A6: Three-year regression results of excess returns

5-Year Regression Results

	Dependent variable:					
	BHAR_5_years			CAR_5_years		
	(1)	(2)	(3)	(4)	(5)	(6)
Hot	-0.269	-0.382	-0.088	-0.484	-0.354	-0.480
	(0.587)	(0.630)	(0.686)	(0.382)	(0.397)	(0.428)
Cold	1.950***	2.921***	3.072***	0.062	0.386	0.392
	(0.640)	(0.738)	(0.750)	(0.417)	(0.464)	(0.468)
CrisisDummy	0.512	0.554		0.178	0.032	
	(0.484)	(0.536)		(0.315)	(0.337)	
LogRevenue		0.106*			-0.014	
		(0.057)			(0.036)	
Dotcom			0.588			-0.146
			(0.561)			(0.350)
FinCrisis			-1.225			0.198
			(1.414)			(0.883)
LogAssets		-0.238**	-0.061		0.006	0.002
		(0.119)	(0.107)		(0.075)	(0.067)
PositiveEBIT		0.191			0.048	
		(0.483)			(0.304)	
RevAssets			0.254			0.051
			(0.267)			(0.167)
RealEstate	-0.094	0.205	0.208	-0.512	-0.371	-0.415
	(1.257)	(1.306)	(1.341)	(0.818)	(0.822)	(0.837)
ConsumerDiscreationary	0.107	-0.291	0.243	0.248	0.414	0.386
	(1.189)	(1.231)	(1.244)	(0.775)	(0.775)	(0.777)
ConsumerStaples	-0.442	-0.549	-0.288	-0.326	-0.245	-0.236
	(1.144)	(1.183)	(1.204)	(0.745)	(0.745)	(0.752)
Energy	0.369	0.435	0.545	-0.109	-0.143	-0.131
	(1.045)	(1.069)	(1.094)	(0.681)	(0.673)	(0.683)
Financials	-0.608	-0.518	-0.300	-0.014	0.014	-0.021
	(1.077)	(1.112)	(1.143)	(0.701)	(0.700)	(0.714)
HealthCare	-0.197	-0.403	-0.242	0.572	0.630	0.752
	(1.136)	(1.199)	(1.210)	(0.740)	(0.755)	(0.755)
Industrials	-0.008	-0.261	0.025	0.105	0.345	0.359
	(1.088)	(1.131)	(1.150)	(0.709)	(0.712)	(0.718)
Technology	-0.233	-0.666	-0.467	-0.107	-0.174	-0.070
	(1.115)	(1.188)	(1.197)	(0.726)	(0.748)	(0.747)
Telecommunications	-1.143	-1.780	-1.203	-0.381	-0.472	-0.448
	(1.661)	(1.950)	(2.029)	(1.082)	(1.228)	(1.267)
Utilities	-0.358	-0.630	-0.806	-0.593	-0.506	-0.481
	(2.439)	(2.488)	(2.554)	(1.589)	(1.567)	(1.594)
Junior	0.151	0.190	0.076	0.200	0.148	0.132
	(0.324)	(0.389)	(0.392)	(0.211)	(0.245)	(0.245)
SeasonalDarknessDummy	0.591*	0.797**		0.117	0.090	
	(0.350)	(0.385)		(0.228)	(0.243)	
Age0_4	-0.565	-0.609		-0.605**	-0.680***	
	(0.365)	(0.412)		(0.238)	(0.259)	
Age25	0.695	0.617		-0.057	-0.020	
	(0.438)	(0.469)		(0.285)	(0.295)	
SeasonalDarkness			0.062			0.030
			(0.095)			(0.059)
LogFirmAge			0.246*			0.114
			(0.130)			(0.081)
Constant	-0.575	1.378	-0.463	-0.108	-0.112	-0.678
	(1.022)	(1.914)	(1.917)	(0.665)	(1.205)	(1.197)
Observations	219	195	195	219	195	195
R^2	0.117	0.178	0.138	0.082	0.110	0.083
Adjusted R^2	0.042	0.083	0.045	0.004	0.007	-0.017
Residual Std. Error	2.215 (df = 201)	2.253 (df = 174)	2.300 (df = 175)	1.443 (df = 201)	1.418 (df = 174)	1.436 (df = 175)
F Statistic	1.566* (df = 17; 201)	1.882** (df = 20; 174)	1.477* (df = 19; 175)	1.050 (df = 17; 201)	1.072 (df = 20; 174)	0.828 (df = 19; 175)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table A7: Five-year regression results of excess returns

10-Year Regression Results						
	Dependent variable:					
	BHAR_10_years			CAR_10_years		
	(1)	(2)	(3)	(4)	(5)	(6)
Hot	-0.245	-0.227	0.001	0.430	0.172	0.237
	(0.804)	(0.917)	(0.953)	(0.622)	(0.686)	(0.717)
Cold	-0.358	-0.251	-0.336	-0.317	-0.301	-0.430
	(1.032)	(1.208)	(1.245)	(0.799)	(0.904)	(0.937)
CrisisDummy	-1.742***	-1.923**		-0.725	-0.855	
	(0.651)	(0.738)		(0.504)	(0.552)	
LogRevenue		-0.091			0.014	
		(0.086)			(0.064)	
Dotcom			-1.804**			-0.562
			(0.760)			(0.572)
FinCrisis			-0.120			0.023
			(1.889)			(1.422)
LogAssets		0.082	0.120		0.041	0.068
		(0.189)	(0.157)		(0.141)	(0.118)
PositiveEBIT		1.020			-0.322	
		(0.783)			(0.585)	
RevAssets			0.575			0.194
			(0.409)			(0.308)
RealEstate	-0.840	-0.775	-0.888	-0.729	-0.591	-0.731
	(1.544)	(1.703)	(1.723)	(1.195)	(1.274)	(1.297)
ConsumerDiscreationary	1.354	1.788	0.205	0.872	1.032	0.082
	(1.599)	(1.732)	(1.728)	(1.238)	(1.295)	(1.301)
ConsumerStaples	1.199	1.564	1.348	0.182	0.245	0.196
	(1.356)	(1.437)	(1.450)	(1.049)	(1.075)	(1.091)
Energy	-1.057	-1.003	-1.225	-1.627*	-1.807*	-1.918*
	(1.229)	(1.293)	(1.316)	(0.951)	(0.967)	(0.990)
Financials	-1.089	-1.081	-0.694	-1.139	-1.143	-1.089
	(1.320)	(1.416)	(1.468)	(1.021)	(1.059)	(1.105)
HealthCare	-0.637	0.314	-0.807	-0.269	-0.151	-0.454
	(1.448)	(1.637)	(1.595)	(1.121)	(1.225)	(1.201)
Industrials	-0.387	0.185	-1.029	0.251	0.606	-0.139
	(1.332)	(1.458)	(1.434)	(1.031)	(1.090)	(1.079)
Technology	0.334	1.095	-0.167	0.591	0.815	0.202
	(1.513)	(1.644)	(1.597)	(1.171)	(1.230)	(1.202)
Telecommunications	-0.730	-0.459	-0.400	-0.095	-0.169	-0.365
	(2.012)	(2.775)	(2.919)	(1.557)	(2.076)	(2.197)
Utilities						
Junior	-0.410	-0.667	-0.310	0.501	0.659	0.651
	(0.548)	(0.658)	(0.646)	(0.424)	(0.492)	(0.487)
SeasonalDarknessDummy	-0.192	-0.138		-0.265	-0.277	
	(0.578)	(0.689)		(0.447)	(0.515)	
Age0_4	-0.146	0.202		-0.063	0.220	
	(0.556)	(0.653)		(0.430)	(0.488)	
Age25	2.252***	2.294**		1.506**	1.762**	
	(0.793)	(0.907)		(0.614)	(0.678)	
SeasonalDarkness			-0.019			-0.010
			(0.145)			(0.109)
LogFirmAge			0.341			0.256
			(0.219)			(0.165)
Constant	0.053	-0.942	-2.174	-0.214	-0.998	-1.471
	(1.221)	(2.706)	(2.639)	(0.945)	(2.024)	(1.986)
Observations	95	86	86	95	86	86
R^2	0.311	0.343	0.313	0.297	0.350	0.311
Adjusted R^2	0.170	0.154	0.128	0.153	0.163	0.126
Residual Std. Error	2.181 (df = 78)	2.276 (df = 66)	2.311 (df = 67)	1.688 (df = 78)	1.703 (df = 66)	1.740 (df = 67)
F Statistic	2.205** (df = 16; 78)	1.815** (df = 19; 66)	1.693* (df = 18; 67)	2.061** (df = 16; 78)	1.870** (df = 19; 66)	1.681* (df = 18; 67)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table A8: Ten-year regression results of excess returns

1-Month Abnormal Returns per Cohort

	2000 - 2007		2008 - 2015		2016 - 2023	
Statistic	*Return*	*Excess Return*	*Return*	*Excess Return*	*Return*	*Excess Return*
Average	-1.14 %	-3.15 %	-3.56 %	-3.76 %	2.35 %	0.57 %
Weighted average	-7.87 %	-6.14 %	-0.27 %	-1.73 %	3.78 %	2.47 %
SD	16.94 %	16.27 %	16.80 %	16.32 %	30.25 %	28.34 %
Weighted SD	8.80 %	9.67 %	14.31 %	13.35 %	15.87 %	12.50 %
P25	-10.87 %	-11.67 %	-11.06 %	-12.99 %	-8.11 %	-11.26 %
Median	-2.23 %	-5.14 %	-2.03 %	-4.69 %	-0.97 %	-2.60 %
P75	7.28 %	5.93 %	3.70 %	2.24 %	6.70 %	4.95 %
Firms with positive return	43.26 %	34.83 %	45.35 %	34.88 %	47.57 %	39.46 %
P-value	0.3686	0.0105	0.0526	0.0357	0.2911	0.7841
P-value Weighted	0.0000	0.0000	0.8610	0.2316	0.1349	0.0079
N	178	178	86	86	185	185

Table A9: One-month excess returns per cohort

6-Month Abnormal Returns per Cohort

	2000 - 2007		2008 - 2015		2016 - 2013	
Statistic	*BHAR*	*CAR*	*BHAR*	*CAR*	*BHAR*	*CAR*
Average	-2.77 %	-5.04 %	-7.41 %	-8.41 %	-3.26 %	-2.09 %
Weighted average	-0.54 %	0.30 %	2.92 %	1.25 %	7.60 %	7.70 %
SD	43.01 %	41.90 %	29.52 %	32.53 %	51.03 %	46.68 %
Weighted SD	15.76 %	15.28 %	27.34 %	28.72 %	26.93 %	26.03 %
P25	-27.42 %	-24.75 %	-29.13 %	-28.40 %	-28.63 %	-24.10 %
Median	-9.14 %	-6.77 %	-10.87 %	-8.01 %	-10.25 %	-4.83 %
P75	12.76 %	13.71 %	9.47 %	10.18 %	5.54 %	11.25 %
Firms with positive return	36.93 %	40.34 %	34.88 %	38.37 %	34.07 %	42.86 %
P-value	0.3941	0.1120	0.0224	0.0187	0.3893	0.5475
P-value Weighted	0.6486	0.7972	0.3249	0.6872	0.0002	0.0001
N	176	176	86	86	182	182

Table A10: Six-month excess returns per cohort

1-Year Abnormal Returns per Cohort

	2000 - 2007		2008 - 2015		2016 - 2023	
Statistic	*BHAR*	*CAR*	*BHAR*	*CAR*	*BHAR*	*CAR*
Average	-4.27 %	-10.13 %	-17.66 %	-18.51 %	-16.86 %	-15.06 %
Weighted average	6.61 %	4.69 %	-1.58 %	-3.13 %	-5.19 %	0.11 %
SD	63.63 %	58.83 %	38.76 %	49.58 %	67.14 %	63.92 %
Weighted SD	39.17 %	29.50 %	32.89 %	39.86 %	40.34 %	37.26 %
P25	-39.25 %	-36.91 %	-48.40 %	-53.33 %	-58.01 %	-53.71 %
Median	-16.49 %	-11.44 %	-17.72 %	-13.31 %	-29.27 %	-17.06 %
P75	16.82 %	21.32 %	10.40 %	18.61 %	2.35 %	12.79 %
Firms with positive return	31.58 %	40.35 %	31.33 %	36.14 %	26.55 %	32.20 %
P-value	0.3817	0.0256	0.0001	0.0010	0.0010	0.0020
P-value Weighted	0.0287	0.0389	0.6637	0.4763	0.0884	0.9678
N	171	171	83	83	177	177

Table A11: One-year excess returns per cohort

3-Year Abnormal Returns per Cohort

	2000 - 2007		2008 - 2015		2016 - 2023	
Statistic	*BHAR*	*CAR*	*BHAR*	*CAR*	*BHAR*	*CAR*
Average	2.75 %	-14.43 %	-26.83 %	-20.23 %	-26.00 %	-6.57 %
Weighted average	54.18 %	19.28 %	5.27 %	1.97 %	-18.53 %	-9.03 %
SD	139.73 %	114.78 %	98.51 %	103.14 %	110.92 %	120.85 %
Weighted SD	118.05 %	53.89 %	65.77 %	62.42 %	94.52 %	84.18 %
P25	-60.08 %	-57.18 %	-86.96 %	-81.90 %	-95.96 %	-50.42 %
Median	-33.14 %	-8.40 %	-58.87 %	-30.59 %	-30.24 %	-9.04 %
P75	13.03 %	37.42 %	13.04 %	55.67 %	5.11 %	36.61 %
Firms with positive return	28.80 %	46.40 %	26.76 %	40.85 %	26.56 %	45.31 %
P-value	0.8262	0.1623	0.0247	0.1028	0.0654	0.6651
P-value Weighted	0.0000	0.0001	0.5018	0.7909	0.1217	0.3942
N	125	125	71	71	64	64

Table A12: Three-year excess returns per cohort

5-Year Abnormal Returns per Cohort

	2000 - 2007		2008 - 2015		2016 - 2023	
Statistic	*BHAR*	*CAR*	*BHAR*	*CAR*	*BHAR*	*CAR*
Average	-14.16 %	-30.16 %	-29.78 %	-28.36 %	-45.36 %	14.93 %
Weighted average	11.38 %	11.72 %	5.50 %	0.04 %	-34.63 %	6.03 %
SD	293.12 %	157.39 %	141.38 %	125.08 %	126.34 %	111.63 %
Weighted SD	87.58 %	64.08 %	97.87 %	78.35 %	91.90 %	51.80 %
P25	-96.50 %	-101.72 %	-123.72 %	-100.17 %	-108.97 %	-39.36 %
Median	-62.58 %	-21.27 %	-87.53 %	-31.36 %	-52.89 %	-17.33 %
P75	-2.26 %	40.45 %	2.60 %	48.39 %	-22.53 %	23.13 %
Firms with positive return	24.30 %	40.19 %	25.42 %	42.37 %	10.34 %	41.38 %
P-value	0.6184	0.0500	0.1111	0.0869	0.0633	0.4773
P-value Weighted	0.1816	0.0611	0.6674	0.9972	0.0517	0.5358
N	107	107	59	59	29	29

Table A13: Five-year excess returns per cohort

10-Year Abnormal Returns per Cohort

	2000 - 2007		2008 - 2015	
Statistic	*BHAR*	*CAR*	*BHAR*	*CAR*
Average	-81.69 %	-36.70 %	-18.47 %	-33.46 %
Weighted average	-23.69 %	-0.49 %	52.73 %	18.53 %
SD	169.73 %	185.25 %	383.34 %	192.25 %
Weighted SD	92.50 %	79.87 %	165.65 %	95.57 %
P25	-196.27 %	-173.79 %	-227.83 %	-199.19 %
Median	-141.12 %	5.43 %	-167.99 %	-17.90 %
P75	-34.76 %	85.22 %	0.32 %	103.20 %
Firms with positive return	24.19 %	51.61 %	25.00 %	50.00 %
P-value	0.0003	0.1239	0.8155	0.4026
P-value Weighted	0.0481	0.9616	0.1320	0.3515
N	62	62	24	24

Table A14: Ten-year excess returns per cohort