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The Effect of Company Quality in Explaining IPO Returns

An Empirical Study on Oslo Stock Exchange from 1998 to 2018

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NORWEGIAN SCHOOL OF ECONOMICS

Abstract

The purpose of this thesis is to investigate the effect company quality has in explaining IPO returns. To conduct this analysis, we use a data set that consists of annual accounting data and monthly stock price data from publicly listed firms on the Oslo Stock Exchange from 1998 to 2018. By following the methodology of Asness, Frazzini, and Pedersen (2018), we define company quality by ranking all firms after a composite quality measure. We find that stocks with a high quality score on average have higher prices throughout the whole time period we analyze. Moreover, we find that the price of quality was higher prior to the Global Financial Crisis. When we evaluate the short-run performance of IPO companies, our analysis show that the junk companies have the best initial first day returns, while quality IPOs have the best returns for the first month. For the IPO returns over a longer time horizon, our results indicate that investors don't obtain a positive abnormal return by investing in IPO portfolios. In addition, the analysis suggests that quality IPOs explain a majority of the long-run returns of the IPO portfolios we have constructed. Finally, we find that there is a significant difference in factor loadings between quality and junk IPOs.

Keywords – Finance, IPO, Underpricing, Quality Minus Junk (QMJ)

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1 Introduction

1.1 Background

Price development after an Initial Public Offering (IPO) has been an extensively researched topic over the years. An IPO is normally the first time a company offers its shares for purchase to the general public (Ritter, 1991). While various reasons for why companies choose to go public are discussed in the literature, the general reasons centers around raising funds for balance sheet restructuring or growth and construct a liquidity event where existing shareholders can sell their shares (Pagano et al., 1998). Thus, an IPO is an important event in any firm's history.

For decades, attempts have been made to explain the variation of stock returns through empirical studies. A variety of explanatory factors have been tested and identified, but so far none of them, individually or combined, have managed to explain the entire movement of stock returns. However, they have provided insight on which characteristics that affect stock returns. Quality factors, which capture the overall quality characteristics such as profitability, safety and growth, are relatively new candidates within the financial literature to explain the variation in stock returns. Asness, Frazzini and Pedersen (2018) define a composite quality measure based on several quality characteristics. In addition, they find that investors are consistently willing to pay a higher price for quality stocks. Based on the overall quality score each company receives, they divide the stocks into portfolios. The portfolios with the lowest quality are defined as *junk*, while the portfolios with the highest quality are defined as *quality*. Finally, they construct a quality factor *quality minus junk* (QMJ), which goes long in quality stocks and short in junk stocks, following the methodology of Fama and French (1993). This factor captures the time varying premium for high quality assets and through their study Asness et al. (2018) find that it delivers a positive significant abnormal return on the international stock market.

The choice of topic for this thesis was motivated by the recent strong growth in the number of IPOs in the Norwegian stock market. Both 2020 and 2021 are record years in terms of number of IPOs, making IPOs a highly discussed topic in the media and academia lately. Over the years we have seen several investors earning large returns from investments in

IPO companies, while some investors have lost significant amount of capital. This has fed our curiosity about what characterizes a successful IPO investment. In this thesis we seek to further understand the factors that affects IPO returns. By using the quality definition of Asness et al. (2018) we will test how the quality of a company that goes public affects its returns.

Although IPO aftermarket performance and underpricing are widely researched in an international context, there are only a limited number of papers studying the Norwegian market. Moreover, there is very limited research on how quality affects IPO returns. With this thesis, we therefore aim to increase the understanding on how quality affects the returns of companies going public at the Oslo Stock Exchange (OSE). Further, we hope to complement other research on similar topics, and serve as a basis for further research.

1.2 Research Questions

The objective of this master's thesis is to investigate the effect of quality on IPO returns in the Norwegian stock market. We will replicate the methodology of Asness et al. (2018) to assign quality scores for the companies in our data sample and when creating the QMJ factor. In order to test whether the investors in the Norwegian stock market value quality stocks more than junk stocks, we need to test whether there exist a premium for quality companies traded at the Oslo Stock Exchange. Moreover, we will analyse both the short-run and long-run returns of IPO companies to obtain the best possible insight from the data we have available. Our main thesis question is therefore:

How does quality affect IPO returns at the Oslo Stock Exchange?

To investigate this, we have come up with the following research questions:

1. Is there a positive price of quality at the Oslo Stock Exchange?

2. It there a difference in the underpricing between quality and junk IPOs at the Oslo Stock Exchange?

3. How does the QMJ factor affect long-run IPO returns at the Oslo Stock Exchange?

4. Is there a difference in factor loadings between quality and junk IPOs?

1.3 Structure of the Thesis

The remainder of this thesis is structured in the following way. In the second section, we discuss literature that is relevant for the paper, and which we believe will be of benefit to the reader. Section 3 describes the data and the adjustments made. In section 4 we describe our empirical methodology, and in section 5 we discuss our findings related to our four research questions. In section 6 we discuss the limitations of our paper and bring suggestions for further research. Finally, we present our conclusion in section 7.

2 Background

The purpose of this chapter is to provide the reader with a short introduction of the literature this thesis is based upon. The first part will present relevant findings findings from empirical studies of initial public offerings (IPOs). The second part will give an overview of the findings of the quality minus junk (QMJ) paper by Asness, Frazzini, and Pedersen (2018).

2.1 Performance Studies on Initial Public Offerings

2.1.1 Short-run Performance

Numerous studies have focused on the short-run underpricing of IPOs, referred to as the underpricing phenomenon in the literature. Looking mainly at the U.S. stock market, Jay Ritter finds that over the last 31 years IPOs have averaged a 20.5% first day return (Ritter, 2022). Moreover, he estimates that the aggregate amount left on the table is $230.39 billion dollars (Ritter, 2022). Interestingly, Ritter and Welch (2002) argue that as the underpricing increases the number of companies going public increases as well. A puzzling relationship as high first day underpricing suggest that the companies going public leave substantial amounts of money for investors in the aftermarket.

Several explanations on why IPOs tend to be underpriced have been proposed in the literature without reaching consensus. However, the theories of underpricing can be organized under four broad headings: asymmetric information, control considerations, institutional reasons, and behavioral approaches (Ljunqvist, 2007). The most recognized of these are the asymmetric information based theories. The main parties of an IPO are the issuing company, the investment bank underwriting the deal, and the investors purchasing the stock. Asymmetric information models of underpricing assume that at least one of these parties has an information advantage over the others.

Possibly the best-known asymmetric information based theory is Rock's (1986) winner's curse. Rock (1986) finds that the underpricing functions as a discount to attract less-informed traders (i.e. non-professionals). The discount compensates the uninformed for the adverse selection risk they face when bidding against well-informed traders for stock allocation (Leite, 2000). This reflects the assumption that traders can be divided into informed and uninformed, and that the informed traders are better able to identify the attractive shares. In addition, Rock assumes that the informed investors know the true value of the company better than the issuing firm and its underwriting bank (Ljunqvist, 2007).

The winners curse describes the situation where the uninformed bids indiscriminately, while the informed only bid on a selection of a few solid companies (Ljunqvist, 2007). This leaves the uninformed to win all the bids on unattractive offerings, while losing the bids for attractive offerings. In total, the expected returns may be negative. The uninformed are aware of this and will restrain from bidding. The demand from the informed traders alone isn't sufficient, therefore the companies lower their offering price to attract the uninformed to participate in the bidding, and by doing so selling enough shares to prevent the listing from failing.

A differing theory, called the signalling effect, is presented by Allen and Faulhaber (1989). They argue that firms know their prospect best, and therefore wish to lower their listing price. By doing this, the good companies signal their great future prospect to the investors, because only good firms are willing to accept an initial loss as they expect to cover this loss by performing well (Allen and Faulhaber, 1989). In contrast, owners of bad companies know that they will not be able to recoup the loss as they know their true market value and performance. Therefore, they argue that underpricing is a signal for good quality and future profit.

Another well-known theory is the cascading effect. This theory, presented by Welch (1989) argues that the investors personal information is disregarded based on actions of a previous investor. The theory provides a behavioral explanation opposed to the previous models based on asymmetrical information. This implies that based on what the first investor does, others will follow, even though they might know something that the other investors do not. The pricing is therefor crucial as if one investor believes the listing price too high, they will choke out the demand as the following investors will forgo the opportunity. Analogously, if the first investors deem the price right, they create a cascade of demand (Welch, 1989). This provides an explanation of underpricing without winner's curse as the price is set in an attempt to attract early instead of late investors (Welch, 1989). Thus, a high offering price increases the probability of a listing failure. Even more so for low quality companies if the initial investment is based on information, making the marginal cost of a high price higher, which again creates a separation in the equilibrium price.

Common for the theories described above is the presence of heterogeneously informed investors and that this rationalizes underpricing. The adverse selection allows the informed investors to profit from the advantage. On the other hand, underpricing implies an initial cost for the issuing company no matter the reason. Leite (2004), provides a theory on how accessible information prior to the offering affects the underpricing, and by doing so explains the winners curse theory provided by Rock (1986).

Leite (2004) states that favorable public news reduces the differences in the pool of investors compared to the pool of investors in issues preceded by unfavorable public information. Moreover, he shows that initial returns are higher in issues preceded by favorable public information than in issues preceded by unfavorable information as the quality of the marginal investor is lower. Favorable public information is therefore a source of two effects that makes it more desirable for a company to go public; favorable public information increases the fundamental value as well as decreases adverse selection cost. Two effects that increase the expected proceeds in an IPO (Leite, 2004).

2.1.2 Long-run Performance

The long-run performance of IPOs is also an extensively research topic. As we have discussed a substantial amount of IPO studies focuses on underpricing. However, this anomaly appears to be a short-run occurrence. An early study by Ritter (1991) documents that in the long-run, IPOs appears to be overpriced. His findings suggest that the firms going public significantly underperform comparable firms matched by size and industry. Moreover, he discovers that there is substantial variation in the underperformance over the years, with firms that went public in high IPO-volume years performing the worst. He further argues that these patterns are consistent with an IPO market where investors are overoptimistic about new growth companies and the firms going public take advantage of these “windows”. These findings are further supported by Loughran and Ritter (1995) that discover that companies issuing stocks between 1970 and 1990 significantly underperform relative to nonissuing firms. These results have been dubbed the “new issues puzzle”, documenting long-run underperformance by IPO companies.

Carter et al. (2011) take contrary views, when revising the new issues puzzle. They find that the puzzle disappears in a Fama and French three-factor framework, controlling for momentum, investment, liquidity, and skewness. They conclude that IPOs do not underperform in the long-run on a risk-adjusted basis. Additionally, they find that the long-run underperformance of IPOs is concentrated to the 1980s and early 1990s, while the IPOs from 1998 to 2005 either outperform or perform the same as the rest of the market on a risk-adjusted return basis.

Several studies have also tried to explain how market cycles affect the quality of firms going public. Ritter (1984) analyses how positive shocks in the economy lead to a greater number of IPOs. He finds that waves of IPOs reveal higher underpricing and that these time-series patterns can be explained by adverse selection models, indicating that the composition of firms going public changes across time. In a more recent study, Yung et al. (2008) discover findings consistent with that of Ritter (1984). They argue that when the economy is booming the cost of capital becomes sufficiently low to offer low-quality firms NPV positive projects. Hence, adverse selection leads to increased number of low-quality companies going public.

2.2 Introduction to Quality Minus Junk

Quality minus junk builds on numerous asset pricing anomalies within the quality investing literature. Asness, Frazzini, and Pedersen (2018) seek to answer whether high quality firms command higher prices. They define quality as characteristics of a company that investors are willing to pay a higher price for, everything else being equal. From the Gordon Growth formula, they derive three quality features that should command a higher price for a stock; profitability, growth, and safety. Moreover, by exploring the quality investing anomalies Asness et al. (2018) find quality measures within these three features, and combine them into one composite quality measure. This compound quality measure is then used to show that investors pay more on average for companies with high-quality characteristics.

The risk-adjusted return obtained by investing in high-quality stocks, significantly outperform that of low-quality stocks, which deliver negative risk-adjusted returns. A

QMJ strategy where investors invest in portfolios consisting of high-quality stocks and sell portfolios consisting of low-quality (junk) stocks, will thus earn high abnormal risk-adjusted returns. This represents a puzzle within the field of asset pricing, as risk-reward theory states that higher prices should result in lower expected returns.

3 Data

In this section, we present the data samples and describe the adjustments made.

3.1 Accounting Data

The accounting data are retrieved from the database *Samfunns- og næringslivsforskning* (SNF) at the Norwegian School of Economics (NHH). The database contains accounts for most Norwegian companies in the period 1993 to 2018. To obtain robust results in our empirical study, it is necessary to have accounting data for a significant proportion of Norwegian listed companies. However, the SNF database lacks sufficient accounting data for a large amount of the companies listed on the Oslo Stock Exchange (OSE). The reason for this is that a substantial share of the companies only have their holding company accounts included in the database. Accounts that in several cases do not reflect the consolidated performance of a company. From the final stock data sample of 600 individual stocks (from 1998), we therefore only obtain sufficient accounting data for 394 of them using the SNF database. To improve the range of our accounting data, we collect some additional data manually from Proff Forvalt[1]. This adds additional accounting data for four companies to our stock data set.

3.1.1 Individual measures

The accounting data are used to create the individual quality measures of which the QMJ factor consists of. Following Asness et al. (2018) we create the different quality measures involved in assessing a company's profitability, growth, and safety. One major difference is the fact that we only have yearly data available, while Asness et al. (2018) uses quarterly. The growth factor also sets a natural limit for the period as it requires change over five years, making 1998 the starting year for our analysis. A detailed list of these quality measures and how they are calculated are presented in the first section of the Appendix.

[1]https://forvalt.no/

3.1.2 Negative Book Value of Equity

Some of the stocks in our sample are reported with negative book value of equity. This happens when the value of the firm's liabilities exceeds the value of the firm's total assets. Keeping these observations can lead to meaningless economical interpretations. For example, a company with negative book value of equity and negative earnings will be perceived as a profitable company by our profitability factor. Following Asness et al. (2018) we exclude all observations with negative book value of equity. We implement this restriction by removing negative price to book ratios after merging the stock and accounting data, removing 549 observations out of 8841.

3.1.3 High Price-to-book Value

In addition to the removal of negative book value of equity, a share of companies in our accounting data sample have very large price-to-book values. According to Bloomberg, the price-to-book ratio for the main index at OSE is 2.27 [2]. However, our sample average is 3.15, with a maximum value of 778,14. Such extreme observation can have negative impact on empirical analyses. We therefore choose to winsorize the sample by setting the most extreme outliers equal to the 98% percentile of the data, a winsorizing level that is considered the most used in finance (Leone et al., 2019). This brings the mean of the price-to-book values in our sample down to 2.06. A number that is much more in line with the stock exchange average.

3.1.4 Further Data Cleaning

Before we use the data to answer our research questions, we must make sure that all the values needed for the creation of the QMJ factor are present in the data set. The complete data set contains 8126 observations for 496 companies from 1993 to 2018 after the preceding adjustments. Next, we remove the observations where total income equals to zero. This is because the creation of some of the measures requires income. Furthermore, after calculating the profitability measures, we remove the observations where these are equal to zero. This is because the observations where this holds likely contain incomplete data. This restriction removes 2141 observations from the accounting data. The final raw

[2] https://www.bloomberg.com/quote/OSEBX:IND

accounting data is then 5365 observations for 461 companies. However, some of these companies will not make it into the analysis as this requires data from 1998 or after. The data beforehand is just used to create the growth measures. Filtering from 1998, we end up with 4456 observations for 452 companies. The filtering process is shown in table 3.1 below.

Table 3.1: Number of companies after filtering the accounting data

Year	Unfiltered Accounting Data	Non-zero Total Income	Non-zero Profitability Measures
1998	308	292	257
1999	310	295	263
2000	320	298	255
2001	320	299	252
2002	319	301	251
2003	330	303	167
2004	332	310	174
2005	345	321	209
2006	339	313	199
2007	367	333	206
2008	358	336	232
2009	349	314	214
2010	345	317	215
2011	355	322	214
2012	343	318	209
2013	330	304	197
2014	327	298	193
2015	322	287	189
2016	316	286	191
2017	306	274	188
2018	298	264	181
Companies in selection	487	483	452

The table gives an overview over the number of unique companies in the yearly accounting data retrieved from *SNF* and *Proff Forvalt*. Only the years used for the analysis are displayed. The third column from the left tells how many companies for each year that have a total income above zero. The right column represent the total number of companies that have both a total income above zero and non-zero profitability measure for each year. The final line gives an overview over the total unique companies throughout all the years used in the study. The final selection of accounting data consists of accounting data for 452 unique companies.

3.2 Stock Data

Stock data are retrieved from the database Børsprosjektet[3] at NHH. This database provides daily and monthly stock data on all publicly listed companies in Norway from January 1980 to present. However, the stock data sample used in this paper starts in 1998 and ends in 2018, because of the restriction of accounting data gathered from SNF. The resulting number of unique stocks in the unfiltered data sample is 611 consisting of a total of 60 597 monthly observations over a period of 21 years. Moreover, a unique identification code is assigned to each stock, corresponding to the variable CompanyID in the database. This code helps us assigning the correct accounting data for each company. Furthermore, we have used the variables Generic for share price data and ReturnAdjGeneric for monthly stock returns. Generic is always equal to the latest available last price, which is only available on days where the stock has been traded. Generic is thus a good measure to reflect the last available daily closing price for that month. To calculate the market capitalization for each stock, we need to obtain the number of shares outstanding for each company. This is retrieved through the variables SharesIssued and OffShareTurnover.

3.2.1 Penny Stocks

A common practice in the asset pricing literature when performing empirical analysis is to exclude stocks with very low value (penny stocks) from the data sample. This is specified by professor Bernt Arne Ødegaard (2021) when he writes about data filtering for empirical studies on Oslo Stock Exchange (OSE). He explains that penny stocks can misrepresent the analysis as they may have microstructure-issues related to illiquidity and inflated returns.

For Norwegian stock data, there is no practical definition of penny stocks. Ødegaard (2021), however, suggests that all stocks trading at a share price below 10 NOK and having a total market capitalization below 1 MNOK within a year be considered a penny stock. In addition, he argues that all stocks fulfilling these two requirements be removed from the stock sample. Applying the share price restriction on our stock data, would have removed 49 out of 611 stocks, having significant impact on our sample size. It is important to be careful when filtering stock data based on market capitalization and share price as

[3] https://bors.nhh.no/amadeus/index.php

these variables directly affect stock returns. Furthermore, an annual filter on our stock sample seems too strict as it can cause unwanted biases to our empirical investigations. Therefore, we only choose to follow Ødegaard's criteria regarding market capitalization. For the share price restriction, we follow the directive of the OSE. They require all stocks to trade above 1 NOK to be listed (Oslo Børs, 2021). Thus, we eliminate all observations in a year where a share has traded below 1 NOK in any month.

3.2.2 Further Stock Data Cleaning

The complete stock data retrieved originally consisted of 60 597 stock return observations for 611 companies in the time period 1998-2018. Applying the restrictions discussed in 3.2.1, as well as removing observations with missing market capitalization values, reduces the number of observations to 59 820. This effectively removes observations without share price as well. Next, we remove observations without information on return, as well as different companies with duplicated CompanyId. These add up to 3127 observations, leaving us with a total of 56 785 observations of stock data with 532 unique companies. The stock data is then merged with the accounting data, creating the final selection.

The final selection starts out with 31 349 observations and 398 unique stocks. After calculating book value of equity and price-to-book values for these, we filter out observations applying the methodologies explained in section 3.1.2 and 3.1.3. This removes 19 927 observations, out of which 1606 is due to the restriction and the rest is observations with missing values. This leaves our final selection with 29 743 stock return observations and 386 unique companies. Table 3.2 displays some summary statistics for our final stock data selection, and below that table 3.3 illustrates the filtering process.

Table 3.2: Descriptive statistics of final stock data selection

Variable	N	Mean	Std.Dev	Min	Max
Generic	29 743	77.199	172.417	1.010	3 960
MCAP	29 743	7 912 507	33 343 989	7 241	495 064 035
Return	29 743	0.005	0.161	-0.872	8.234
Price/Book	29 743	2.062	1.722	0.067	9.999

The table displays descriptive statistics for some of the key measures used for the further analysis. The monthly data is retrieved from *Børsprosjektet*. Generic is the name for the variable representing the share price. The MCAP (market capitalization) is calculated as an yearly average in order to remove extremities when calculating different measures based on yearly data throughout the analysis. Return is the variable for the monthly return of a stock. Price/Book is the price-to-book ratio for a listed company.

Table 3.3: Number of stocks after filtering

Year	Unfiltered	MCAP >1M	Shareprice >1	Return non-NA	Stocks w/ accounting data	adj. P/B (Final selection)
1998	242	242	240	239	176	168
1999	243	243	240	239	180	172
2000	243	243	240	238	176	164
2001	229	229	224	223	166	161
2002	216	216	207	206	150	145
2003	206	206	189	188	87	86
2004	201	201	195	194	92	86
2005	234	234	233	231	130	122
2006	250	250	250	249	132	122
2007	285	285	285	285	149	140
2008	280	273	273	273	158	153
2009	259	254	245	245	141	136
2010	252	244	235	235	130	120
2011	248	235	233	233	126	116
2012	237	225	220	220	119	106
2013	237	230	225	225	112	103
2014	232	227	226	226	122	114
2015	224	221	217	217	114	110
2016	214	212	208	208	114	110
2017	221	220	219	219	118	109
2018	215	215	214	214	113	105
Total Unique Companies	611	607	605	600	398	386

The table displays the filtering of the stock data, and the number of unique companies for each year. The bottom line gives the total number of unique companies for the entire period. The monthly stock data is retrieved from *Børsprosjektet*. Out of the original 611 companies we are left with 600 after removing observations with market capitalization under 1 MNOK million as well as removing observations with negative share price and missing monthly return values. These 600 are then matched with the accounting data which removes 202 companies for which we don't have accounting data (represented by second column from the right). Finally, we remove observations with negative book value of equity and winsorize the sample based on price-to book values, setting the winsorizing level to 98%. This reduces the number of companies to 386, which represents the final selection of data on which the analysis is performed.

3.3 Initial Public Offering Data

The data on initial public offerings are gathered from Oslo børs[4]. We will in this thesis focus on companies that get listed at the main market of Oslo Stock Exchange. This is because the main market is the only stock exchange that have existed the whole period

[4] https://live.euronext.com/nb/resources/statistics

we analyze. In addition, the SNF database do not cover a substantial proportion of the companies listed at Euronext Expand[5] and Euronext Growth[6], which makes it difficult to assign the correct quality measures to companies at these exchanges. Another weakness with including stocks from these smaller exchanges is that there is significantly less liquidity in these markets, which would have weakened the robustness of our analysis. As these stocks may have microstructure-issues related to illiquidity and inflated returns, in a similar way penny stocks have. In total, we therefore consider it appropriate to exclude these exchanges from our IPO data sample.

3.3.1 Data Cleaning

The IPO data we have collected includes 262 IPOs spread over 21 years. For the second research question we assign a quality score to all of the IPOs. These quality scores are calculated for the 386 unique companies of the stock sample. A quality company is defined as the top 30% and a junk company is defined as the bottom 30% of this sample ranked after the quality score each company receives. Out of the 262 IPOs, 74 of them are classified as either junk or quality at their IPO date. The low number of classifications is due to missing accounting data the year of the IPO. However, many of the companies have available data the year before and the year after the IPO. We therefore assign a quality score to the companies with missing accounting data based on the company's quality score from either the year before or the year after its IPO. Due to the quality scores being created mainly on accounting data, the quality scores for each month varies very little. We therefore assume that the quality score for one year most likely is representative for the quality score the next or previous year. Thus, we believe that this approach of assigning quality scores does not lead to any misleading results.

By following this approach, we add three companies with a quality score from the year before the IPO and 35 with a quality score from the year after the IPO. In total, we have 112 IPOs assigned with a quality score. Out of these 112, 48 are classified as quality and 64 are classified as junk. This filtering process is displayed below in table 3.4

[5] Oslo Axess changed name to Euronext Expand in November 2020
[6] Merkur Markets changed name to Euronext Growth in November 2020

Table 3.4: Number of IPOs after filtering for research question two

Year	All IPOs	IPOs w/ Stock and accounting data	IPOs w/ Quality score	Quality IPOs	Junk IPOs
1998	21	15	13	5	8
1999	8	6	4	2	2
2000	19	14	12	4	8
2001	10	5	5	1	4
2002	4	3	2	1	1
2003	4	2	1	1	0
2004	17	14	12	6	6
2005	38	21	13	4	9
2006	30	18	9	4	5
2007	24	18	11	2	9
2008	5	3	2	1	1
2009	0	0	0	0	0
2010	10	4	3	2	1
2011	3	1	0	0	0
2012	6	3	2	1	1
2013	8	2	1	1	0
2014	10	7	5	2	3
2015	11	6	5	2	3
2016	6	4	3	3	0
2017	15	6	4	3	1
2018	13	5	5	3	2
Total Unique Companies	262	157	112	48	64

The table displays the number of IPOs for each year used in research question two. The bottom line is the total amount of IPOs. The filtering process is assigning a quality score created in order to create the QMJ factor in research question one. To receive a such score requires that a given IPO has both stock and accounting data. The companies are then rated either quality or junk depending on whether the company is among the 30% with highest or lowest quality score. This is done for every company, not just IPOs. Out of the 262 original IPOs, only 112 receive such a rating with 48 being labeled as quality and 64 as junk at the time of the listing.

For the last two research questions we match the 262 original IPOs with the stock data. In addition, we require that the IPO have data on returns for the next 12 months after its IPO to be included. Some of our data is incomplete with missing return data around the IPO date. Making this requirement reduces the number of companies from 157 (see table 3.4, col 3) to 133. The filtering process is shown in the table below.

Table 3.5: Number of IPOs after filtering for research question three and four

Year	All IPOs	IPOs w/ data*	Portfolio Holding Period	
			12 Months	24 month
1998	21	14	14	14
1999	8	6	6	6
2000	19	13	13	13
2001	10	5	5	5
2002	4	3	3	3
2003	4	1	1	1
2004	17	13	13	13
2005	38	19	19	19
2006	30	12	12	12
2007	24	13	13	13
2008	5	2	2	2
2009	0	0	0	0
2010	10	3	3	3
2011	3	0	0	0
2012	6	3	3	3
2013	8	1	1	1
2014	10	6	6	6
2015	11	5	5	5
2016	6	4	4	4
2017	15	5	5	5
2018	13	5	5	5
Total	262	133	133	133

The table gives an overview over the IPO data used for research question three and four. The second column from left displays the number of IPOs at the Oslo Stock Exchange for each given year. The third column from the left shows the number of IPOs in a given year that we have sufficient accounting data for. The two columns on the right show how many IPOs are included in the calendar time portfolios with respectively 12 and 24 months holding period. *IPOs with both sufficient stock return data and sufficient accounting data.

3.3.2 Risk-free Rate, Market Returns, and Consumer Price Index

We retrieve historical monthly data on the Fama and French factors and on estimates of the risk-free rate from Bernt Arne Ødegaard's website[7]. The Fama and French factors are calculated based on the Fama and French (1998) methodology, while the risk-free rate of return is the Nowegian Interbank Offered Rate (NIBOR) with one-month maturity. The NIBOR is a forward-looking estimate for borrowing at a monthly basis. In addition, we

[7] https://ba-odegaard.no/financial_data/ose_asset_pricing_data/index.html

obtain the value-weighted and equally weighted market portfolio from Ødegaard. The market portfolio is an index of all available shares listed on the Oslo Stock Exchange. Finally, we retrieve the consumer price index from 1993 to 2018 from Statistics Norway[8].

[8] https://www.ssb.no/priser-og-prisindekser/konsumpriser/statistikk/konsumprisindeksen

4 Methodology

In this section we describe the methodology we have applied to examine the effect of firm quality in explaining IPO returns of the Norwegian stock market.

4.1 Quality Minus Junk Factor Construction

4.1.1 Quality Score

In order to construct the QMJ factor we need to compute a single overall quality score for each individual stock. This overall score is derived from a composition of quality components divided into three composite quality measures: *profitability, growth, and safety.* For each firm every month, all quality measure components are ranked in ascending order, except for EVOL and BAB, which are ranked in descending order. Further, we center and scale the rank to obtain a normalized z-score (N(0,1)), in order for this ranking to be comparable across other accounting variables. Hence, the normalized z-score for variable x is given by the following formula:

$$z_x = \frac{r - \mu_r}{\sigma_r} \tag{4.1}$$

where μ_r and σ_r are the cross-sectional mean and standard deviation of all ranks for that period and r is the non-normalized stock ranking in that month.

A company is considered profitable if it has high gross profits over assets (GPOA), high return on equity (ROE), high return on assets (ROA), high cash flow over assets (CFOA), and high gross margin (GMAR), as well as, high quality of earnings (earnings adjusted for accruals, ACC). The profitability measure z-score is computed by taking the average of these z-scores.

$$\textit{Profitability} = z(z_{gpoa} + z_{roe} + z_{roa} + z_{cfoa} + z_{gmar} + z_{acc}) \tag{4.2}$$

Similarly, the growth measure z-score is constructed using the same components as the profitability measure, by taking the change over a five year period.

$$Growth = z(z_{\Delta gpoa} + z_{\Delta roe} + z_{\Delta roa} + z_{\Delta cfoa} + z_{\Delta gmar}) \tag{4.3}$$

Safe companies are associated with low beta (BAB), low leverage (LEV), low bankruptcy risk (O-Score and Z-Score), and low earnings volatility (EVOL). The safety measure z-score is calculated by taking the average of these z-scores.

$$Safety = z(z_{bab} + z_{lev} + z_o + z_z + z_{evol}) \tag{4.4}$$

Finally, we calculate the total quality score by taking the average of the z-score for *Profitability*, *Growth*, and *Safety*.

$$Quality = z(Profitability + Growth + Safety) \tag{4.5}$$

When it comes to missing data within the three quality measure components, profitability, growth, and safety, we follow the approach of Asness et al. (2018) that states that if a measure is missing due to lack of data, they average the remaining ones. However, it is unclear to what extent they follow this approach when all variables within one of the three quality measures are missing. In our dataset, there are several examples where all variables needed to compute the growth z-score are missing. The reason for this is that some of the companies have existed for less than five years. Moreover, a key issue when studying the historical performance IPOs before listing is that the quality of the accounting data varies greatly in the years before the listing of the company. Failing to give all these companies a total quality score would have a serious impact on our sample size. We therefore choose to give the companies a total quality score regardless of lacking measure component.

4.1.2 Variable Construction

Most of the variables used to construct the Quality Minus Junk (QMJ) factor are described in the appendix. However, we find it necessary to describe those that require several specific adjustment in more detail in this section. The first one of these is the betting against beta (BAB) factor which we construct following the approach of Frazzini and Pedersen (2014). The following equation describes the estimate for the monthly beta for stock i:

$$\hat{\beta}_i = \hat{\rho}_{i,m} * \frac{\hat{\sigma}_i}{\hat{\sigma}_m} \tag{4.6}$$

where $\hat{\sigma}_i$ and $\hat{\sigma}_m$ are the estimated volatilities for the share price of stock and the market. $\hat{\rho}_{i,m}$ is the correlations between the stocks share price and the value-weighted market index of all the companies at the OSE. The volatilities are estimated as the one-year daily standard deviations with a one-year rolling window. For correlations, we use three-day overlapping returns to take into account non-synchronous trading. In addition, we apply a five-year horizon because correlations are harder to estimate. To estimate volatilities and correlations, we require at least six months (120 trading days) and at least three years (750 trading days) of non-missing return data, respectively. Finally, due to noise and biases, our daily stock data sample produce several extreme beta values. To account for these extreme observations we follow the methodology of Vasicek (1973). They reduce the expected estimation errors by shrinking the stocks market beta β_i^{TS} towards the cross-sectional mean of the total stock sample β^{XS}. The new market beta for each stock, β_i is defined by this equation:

$$\beta_i = w * \beta_i^{TS} + (1 - w) * \beta^{XS}, \tag{4.7}$$

where the cross-sectional mean β^{XS} is set to 1 and the constant weight w is set to 0.6.

The measurement variable earnings volatility (EVOL) is calulated as the standard deviation of yearly return on equity (ROE). Since our accounting data sample only consists of yearly data, we follow the recommendation of Asness et al. (2018) and use yearly data instead of quarterly. Moreover, we require at least five non-missing fiscal years for a company to receive an EVOL measure for that particular year.

4.1.3 Portfolio Formation

In the following subsections, we will present how we construct quality-sorted portfolios and QMJ-sorted portfolios in order to follow the portfolio analysis of Asness et al. (2018). All deviations from the original study will be specified and justified.

To construct quality-sorted portfolios, we sort all the stocks based on their overall quality score for each month. In the original paper, Asness et al. (2018) divide the quality-sorted stock sample into ten decile portfolios. Since we perform our study on the Oslo Stock Exchange (OSE) our sample size is significant lower than the original paper. To ensure that the quality-sorted portfolios are diversified with an appropriate number of stocks we choose to reduce the number of portfolios from ten to five (quintile). We believe this deviation from the original methodology will provide a better basis for our study. The portfolios are resorted and rebalanced every month according to the original paper.

In the construction of QMJ sorted portfolios we follow Fama and French (1993) and Ansess et al. (2018). To construct the QMJ factor we first assign stocks into two size-sorted portfolios, based on market capitalization of the company. Moreover, we use 80th percentile as the breakpoint, following the recommendation of Asness et al. (2018) for OSE. Next, we create three quality-sorted portfolios within each of the two size-sorted portfolios based on their total quality score in a 30/40/30 split. The stocks in the portfolio that represent the 30 percent with the highest quality score are defined as quality stocks, while the stocks in the portfolio that represent the 30 percent with the lowest quality score are defined as junk stocks. Each of the six portfolios are value-weighted and resorted and rebalanced every calendar month. The QMJ factor is then computed as the average monthly return of buying two quality portfolios and selling two junk portfolios.

$$QMJ = \frac{1}{2}(Small\ Quality - Small\ Junk) + \frac{1}{2}(Big\ Quality - Big\ Junk) \tag{4.8}$$

4.2 IPO Performance Measures

4.2.1 Variable Construction

To measure the IPO underpricing we calculate the initial return of the issue, also refered to as the first-day return. According to Ritter and Welch (2002) and Loughran and Ritter (2004) the closing price of the first day of trading should be used as a mean of measure when calculating initial returns of IPOs. Following this, the initial return is defined by Equation 4.9.

$$IR_i = \frac{ClosingPrice_{i1} - OfferPrice_{i0}}{OfferPrice_{i0}} \tag{4.9}$$

In addition, we want to analyze the initial return for multiple IPOs at once. In order to do that, we calculate the average value-weighted and the average equally weighted initial returns. Several asset pricing anomalies are more pronounced for small firms (Schober, 2008). Hence, we want to apply both methods because small firms gets a higher weight when using an equally weighted approach and this approach therefore in general yield larger returns. The average value-weighted initial return is calculated using the following equation:

$$IR_i^{VW} = \sum_{i=1}^{n_S} w_i * IR_i \tag{4.10}$$

The average equally-weighted return are calculated using Equation 4.11. n_s is the number of listing in sample s.

$$IR_i^{EW} = \frac{1}{n_S} \sum_{i=1}^{n_S} IR_i \tag{4.11}$$

4.2.2 Factor Models

To assess the risk-adjusted long-run performance of IPOs, we will apply several factor models. In the following sub-section, we aim to explain the Fama and French three-factor model plus the QMJ factor, which is our most general model. The other factor models used in our analysis will not be explained as they will be combinations of the input variables in our general factor model.

The Fama and French three-factor model is an extension of the Capital Asset Pricing Model (CAPM) developed by Treynor (1961), Sharpe (1964), Lintner (1965), and Mossin (1966). The rationale behind the CAPM is that investors should be compensated with higher returns for taking higher systematic risk, since this risk cannot be diversified. In a scenario where the CAPM holds, the expected returns should yield an alpha of zero (Mullins, 1982). However, the CAPM model relies on assumptions that are unlikely to hold for an investor investing in the real stock market, such as lending and borrowing at the risk-free rate. We will therefore likely obtain Jensen's alpha in our factor model analysis. Jensen's alpha is the average return of an investment or a portfolio in excess of the expected return from the CAPM model (Jensen, 1969). If the investment or portfolio delivers a significant positive (negative) abnormal return, the CAPM will yield a significantly positive (negative) Jensen's alpha.

The three-factor model of Fama and French (1993) expands the CAPM and Jensen's alpha by including a size factor (SMB) and value factor (HML). SMB stands for "small minus big" and is created by taking the return of a portfolio of small market capitalization stocks minus the return of a portfolio of big market capitalization stocks. HML stands for "high minus low" and is created by taking the return of a portfolio of high book-to-market companies minus the return of a portfolio of low book-to-market companies. Fama and French (1993) concluded that by adding these two control variables to the CAPM they where better able to isolate the abnormal return of a portfolio. Thus, controlling for these factors would improve the CAPM model's ability to isolate the abnormal returns of a portfolio. To finalize our general model, we add the QMJ factor so we are able to control for the portfolio's exposure to quality and junk companies. The Fama and French three-factor model plus the QMJ factor is defined by equation 4.12:

$$\begin{aligned} R_{p,t} - R_{f,t} = \alpha_i + \beta_{mrkt} * (R_{m,t} - R_{f,t}) + \beta_{SMB} * SMB_t + \beta_{HML} * HML_t + \\ + \beta_{QMJ} * QMJ_t + \epsilon_t \end{aligned} \tag{4.12}$$

Where:

$R_{p,t} - R_{f,t}$= Return of portfolio p in excess of the risk-free rate at time t

α_i = Jensen's alpha, the intercept of the regression (i.e the abnormal return)

β_{mrkt} = Exposure to the market risk factor

$R_{m,t} - R_{f,t}$ = Return of the market portfolio in excess of the risk-free rate at time t

β_{SMB} = Exposure to the size factor

SMB_t = Size premium at time t (small minus big)

β_{HML} = Exposure to the value factor

HML_t = Value premium at time t (high minus low)

β_{QMJ} = Exposure to the quality factor

QMJ_t = Quality premium at time t (quality minus junk)

ϵ_t = Error term at time t

5 Results and Discussion

In this chapter, we conduct our empirical analysis to answer the four research questions presented in the introduction part of this thesis.

5.1 Quality Spreads at Oslo Stock Exchange

In this section, we will answer research question 1; Is there a positive price of quality at the Oslo Stock Exchange? To address this question, we first perform cross-sectional regressions to show that stocks defined as high quality command higher prices than low-quality stocks. Next, we will look at how the price of quality (quality spread) varies over our sample time period. This was previously investigated by Leira and Lerøen (2020) and Sandtveit and Seljehaug (2016). However, we base our analysis on a broader dataset. It will therefore be interesting to see how our results differ from previous investigations. Consequently, we have included several comparisons with previous studies on quality spread at the Oslo Stock Exchange in this section.

5.1.1 Price of Quality

To investigate whether quality stocks are associated with higher prices than low-quality stocks we perform Fama and Macbeth (1973) cross-sectional regressions. We run a regression on each individual stock's market-to-book (MB) ratio on their overall quality score. The regression is expressed through the following equation:

$$P_t^i = a + bQuality_t^i + controls + \epsilon_t^i \tag{5.1}$$

where $P_t^i = z(MB)_t^i$ and $Quality_t^i$ is each stocks overall quality score as explained in section 4.1. For the explanatory variable, we follow Asness et al. (2018) and use ranked z-scores. This limits the effect of extreme values, implying that the regression coefficient b has a simple interpretation; If the quality score increases by one standard deviation, then the MB ratio increases by b standard deviation. The standard errors are adjusted for autocorrelation and heteroskedasticity in line with Newey and West (1987) with a lag of twelve months. Moreover, we include control variables for firm size and return over the past year. This is motivated by the theory that large firms are more liquid and have less liquidity risk than small firms have, leading to higher prices and lower required returns (Amihud and Mendelson, 1986; Pastro and Stambaugh, 2003; Acharya and Pedersen, 2005). Last year's return is included to take into account that prices and book values are not measured at the same time. A positive coefficient on the last year's return suggests that high recent returns increase current stock prices, while book values have not been adjusted for that increase yet. For consistency we use the ranked z-scores here as well.

Table 5.1: Price of Quality (1998-2018)

	Dependent variable:					
	log(MB)					
	(1)	(2)	(3)	(4)	(5)	(6)
Quality	0.147***	0.142***				
	(0.006)	(0.007)				
Size		0.039***				0.020***
		(0.001)				(0.002)
1-Year return		0.171***				0.203***
		(0.013)				(0.014)
Profitability			0.128***			0.093***
			(0.007)			(0.009)
Growth				0.097***		0.053***
				(0.010)		(0.008)
Safety					0.135***	0.095***
					(0.007)	(0.005)
Constant	0.414***	0.441***	0.414***	0.463***	0.413***	0.474***
	(0.014)	(0.014)	(0.014)	(0.013)	(0.014)	(0.013)
Observations	29,583	28,435	29,583	21,709	29,583	21,260
R^2	0.104	0.148	0.091	0.080	0.110	0.181

Note: The table presents the average coefficients from the Fama-Macbeth regressions for the whole data sample period (1998-2018) at the Oslo stock Exchange. The dependent variable is the z-score of the market to book ratio (MB) for each stock in month t. The independent variables are the z-scores of each stocks overall quality measure, profitability measure, growth measure, and safety measure. In addition, we control for the z-score of each firms size (market capitalization) and each firms last 12 month cumulative return. The numbers in the parenthesis are heteroscedasticity-robust standard errors. ***, **, and * indicate that the associated coefficient is statistically significant at the 1%, 5%, and 10% levels, respectively.

Table 5.1 shows the results from the Fama-Macbeth regressions. From column (1) we see that quality has a significant positive impact on the price at a 1% significance level. The quality coefficient can be interpreted as an increase in quality by a standard deviation will lead to a 0.147 increase in market-to-book price. Moreover, when controlling for firm size and the previous 12 months cumulative return the coefficient for quality does not change much (column (2)). Both the firm size and last 12 month stock return loads positive on the dependent variable, indicating that firm size and last 12 months share price development have a positive impact on the market-to-book price of a firm. Next, we look at the effect the the three quality measure components, *Profitability*, *Growth*, and *Safety*, have individually. All three coefficients for the quality measures are positive and statistically significant at a 1% level. This tells us that firms that score high on these measures individually are priced higher than firms that receives a lower quality score. This results are in line with that of Asness et al. (2018).

When we compare the results illustrated in table 5.1 with those of Leira and Lerøen (2020), we see that we get very similar results. The magnitude and sign of the coefficients of the control variables are generally very similar. However, there is a significant difference between ours and their results. Their coefficient that controls for size has a negative sign, while ours has a positive sign. A positive sign can be interpreted as larger companies being priced higher for the same quality. This is in line with the size effect documented by Banz (1981), which indicates that larger companies should be priced higher than smaller companies, even for the same quality.

The results of Sandtveit and Seljehaug (2016) also have several differences from ours. When they control for profitability they obtain a negative sign on the coefficient for this variable. A result they point out cannot be explained from previous empirical evidence. Moreover, the magnitude of their coefficient that controls for safety are about 3 times the size of ours. This means that the investors in their sample size seem to be willing to pay more for safe stocks, and can therefore be seen as having higher risk aversion. For the other coefficients the results are quite similar to ours, both in terms of the magnitude and the size of the coefficients of the regression models. This means that in contrast to Leira and Lerøen (2020) they obtain a positive sign on the size coefficient. A result that strengthens the robustness of our result for this coefficient.

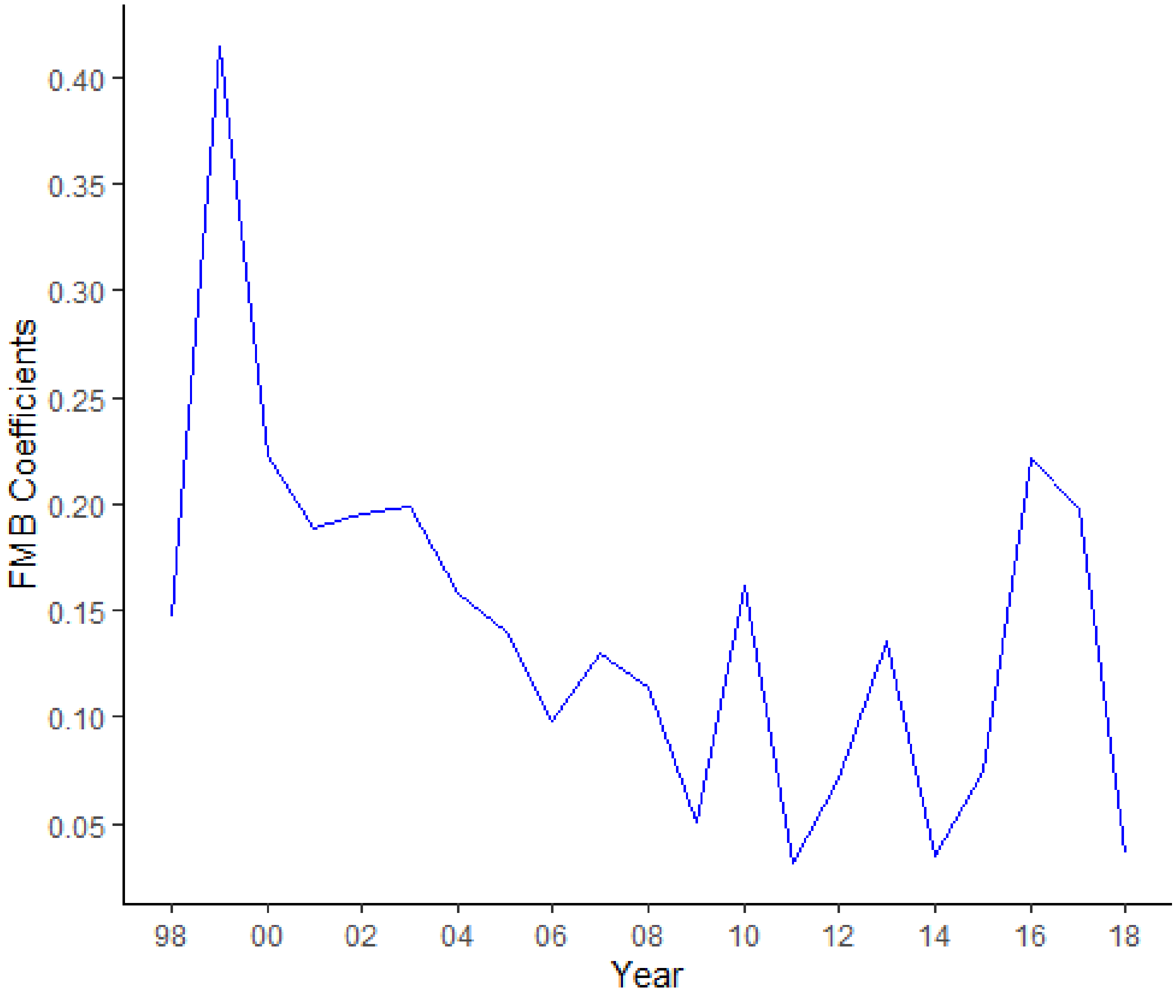
5.1.2 Price of Quality Over Time

Now that we have established that there exists a significant quality spread at the Oslo Stock Exchange, we will move forward to see how this spread varies over time. In figure 5.1, we plot how the price of quality has varied from 1998 to 2018. We see that the quality spread is positive for the whole time period, however, it has been quite volatile, varying from over 0.4 standard deviations at its highest to below 0.05 at its lowest. Moreover, the graph shows that the price of quality was larger in the beginning of our sample period, and that it was gradually declining towards the global financial crisis (GFC) in 2009. The development towards the GFC and the size of the volatility over the whole period are similar to the findings of Asness et al. (2018) for both their U.S. and Global sample. When it comes to how the price of quality correlates with the business cycles in the Norwegian economy, we see no clear tendencies. However, the price of quality increases during the GFC and during the oil crisis starting in 2014. These results could be interpreted as signs of the financial market phenomenon *flight to quality*, which often occur during strong negative imbalances in the stock market (Asness et al., 2018). The phenomenon is characterized by investors rebalancing their portfolios by selling of assets with high credit risk, and buying assets with low credit risk. The investors' preferences change from return-oriented to risk-oriented, and therefore seeking assets that provide a more stable return during economic downturns. This is also refered to as *flight to liquidity* due to the fact that liquidity costs are positively correlated with credit risk. Thereby, investors will not only require quality, but also liquidity for their investments (Beber et al., 2009).

When we compare the results illustrated in figure 5.1 with those of Leira and Lerøen (2020), we see that there are several similarities and differences. A prominent similarity is that the quality spread is largest around the time of the dotcom bubble, which happened between 1998 and 2000. Moreover, the price of quality that Leira and Lerøen (2020) illustrate also gradually falls towards the GFC. When it comes to differences between our results, their price of quality is more volatile than what we illustrate in figure 5.1. They find that that the price varies from over 0.6 standard deviations at the highest to below -0.2 at its lowest.

The results of Sandtveit and Seljehaug (2016) are more different from ours than those of Leira and Lerøen (2020). The price of quality they illustrate is at its highest around the dotcom bubble. The same result that we and Leira and Lerøen (2020) obtain. However, Sandtveit and Seljehaug (2016) get about the same price of quality around 2009 and 2011 as they get in 1999. This is a substantial deviation from ours and Leira and Lerøen (2020) results. Moreover, they find that the price of quality is negative in several instances, both prior and after GFC. Results that also deviate considerably from those of Asness et al. (2018) on price of quality over time.

Figure 5.1: Price of Quality Over Time at Oslo Stock Exchange (1998-2018)



The figure illustrates the coefficients from the Fama and Macbeth regressions over time. The dependent variable is the z-score of the market-to-book (MB) ratio of a stock. The quality score is used as the explanatory variable. We draw the graph for the time series of the cross-sectional coefficients from Table 5.1, column (1).

5.1.3 Price of Quality Robustness Test

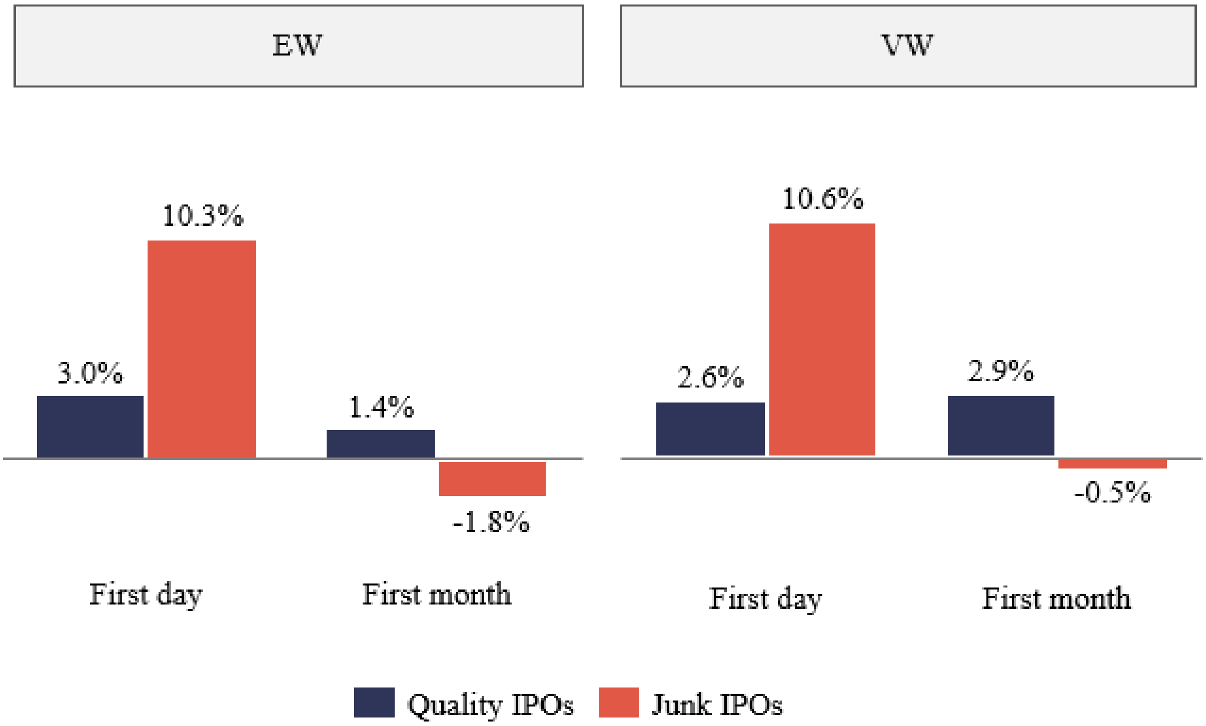
In order to test whether the results from this section are robust, we divide the sample into two time periods, 1998 to 2008 and 2009 to 2018, and repeat the Fama and Macbeth (1973) cross-sectional regressions. The goal is to check whether the results are consistent over time or move in the opposite directions. The results are presented in the appendix under section A3.1.

When we examine the regressions results from the first time period, shown in table A3.1, we observe that all coefficients load positive at a 1% significance level. The same results we get for the whole sample period. In addition, we see that the coefficients for the combined quality measure and the three quality sub-measures individually, are larger in magnitude than for the whole sample period. This is in line with the higher price of quality we observe for this period from figure 5.1. For the second time period, we also get very similar results. However, the results differ to a greater extent than for the first period. From table A3.2, column (6), we see that the growth coefficient loses its significance, when adjusting for all three quality sub-measures, firm size and previous 12 months cumulative return. Moreover, we see that the isolated effect for growth, seen in column (4), has diminished, although still significant. This could indicate that investors gave more attention to growth in the first period, while it was given lower priority in the period after the GFC. In summary, the results from the two different time periods indicate that the results in research question 1 are not very sensitive over time.

5.2 Short-run IPO Returns

In this section, we will answer research question 2; Is there a difference in the underpricing between quality and junk IPOs at the Oslo Stock Exchange? To address this question we follow the methodology of Asness et al. (2018), and assign each company a quality score on the month of its IPO. Moreover, the stocks that represent the 30 percent with the highest quality score in the whole stock data sample for that month are defined as quality IPOs, while the stocks that represent the 30 percent with the lowest quality score are defined as junk IPOs. Then we compare the average first day and first month returns of the quality and junk offerings with each other, to see if there are any considerable differences. Furthermore, we apply both equal-weighted and value-weighted returns to examine if there are a small tale of companies that drive the outcome of our analysis.

Figure 5.2: Short-run Returns of Quality Sorted IPOs (1998-2018)



The figure presents the average initial first day return and first month cumulative return (excluded for the first day initial return) for both junk and quality IPOs. The quality score for an IPO company is assigned the month of the IPO. The x-axis of the bar chart tells the cumulative returns in percentage, and the y-axis tells whether the return is for the initial first day or the first month.

From Figure 5.2 we see our results for the entire sample size. For the initial first day return we find that IPOs categorized as junk have on average a considerably larger return than IPOs categorized as quality. This holds both for equal- and value-weighted returns. The average equal-weighted first day return is 10.3% for junk IPOs and 3.0% for quality IPOs. For the value–weighted first day return, we get that the average is 10.6% for junk IPOs and 2.6% for quality IPOs. However, for the first month return, which excludes the initial first day return, we get the opposite result. The average equal-weighted first month return is -1.8% for junk IPOs and 1.4% for quality IPOs. For the value-weighted first month return, we get that the average is -0.5% for the junk IPOs and 2.9% for quality IPOs. Hence, for the first month returns, quality offerings have considerably larger returns than junk offerings.

These findings indicate that junk companies have to offer IPO investors allocations in the offering at a price that deviates more from the firm's true value than quality companies have to do. This is in line with the winner curse explanation offered by Ljungqvist (2007).

He states that the informed investors only bid on a selection of high quality companies, while the uninformed bids indiscriminately. The offering price for attractive offerings will therefore be closer to the true value of the company because all informed investors will participate in the allocation as long as the offer price don't exceed the true value of the company. This leaves the uninformed to win all the bids for allocation for unattractive offerings. However, the uninformed are aware of this and will therefore restrain from bidding. The junk offerings will therefore need to lower their offering price to raise enough capital to prevent the listing from failing. Thus, the offering price of junk IPOs will deviate more from the true value of the firm than the case is for quality IPOs.

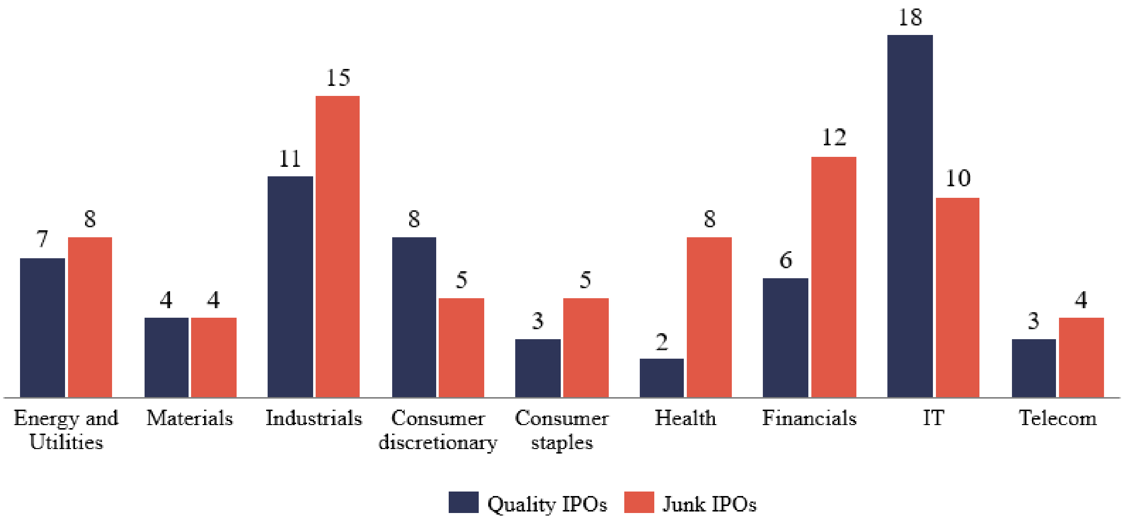
Another explanation for the larger underpricing of junk IPOs could be the timing low-quality companies choose to go public. Santos (2017) finds that companies that goes public in high-underpricing periods lack profitable projects. This suggests that when the market sentiment is good, there is a larger share of junk companies going public. Moreover, if the NPV of the available investment opportunities are sufficiently high, companies are better of going public even when they do not expect bullish retail demand to drive the IPO valuation (Santos, 2017). Thus, when the market sentiment is bad and there is a low-underpricing period, mostly quality companies choose to go public, driving the average initial return for quality companies down.

The results we get for the first month IPO returns are harder to explain using previous research. One explanation, however, may be that quality companies get more positive reviews the days following the IPO in the analyst reports and other sources of information investors use for investment decisions. This could lead to incremental returns for quality companies and negative returns for junk companies.

5.2.1 Characteristics of Quality and Junk IPOs

To better understand what drives the difference between short-run returns for quality and junk IPOs, we will evaluate some selected firm characteristics. In figure 5.3, we have illustrated the distribution of the sectors that are represented in the two groups. We observe that both quality and junk IPOs are well represented in all sectors. However, there are some sectors where the difference between the two groups is substantially large. In the health and the financials sectors we see that the junk IPOs are considerably overrepresented, compared to the quality IPOs. If we look at the IT sector, on the other hand, we observe that the quality IPOs have a larger share than the junk IPOs.

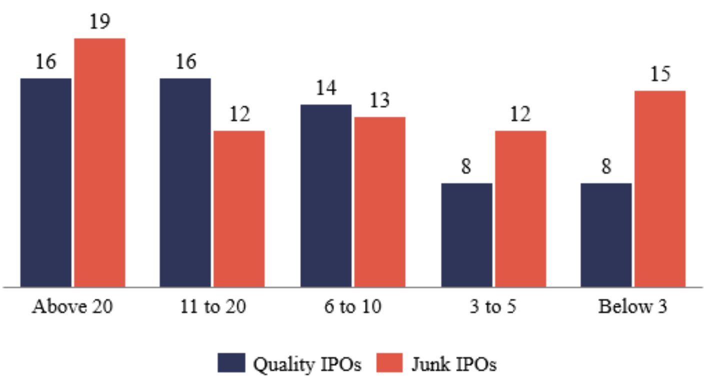
Figure 5.3: Sector Distribution of Quality Sorted IPOs



The figure presents the number of companies represented in each sector divided into quality and junk IPOs. The quality score for an IPO company is assigned the month of the IPO. The x-axis of the bar chart tells which sectors the companies belong to, and the y-axis tells the number of companies in each sector.

Next, we analyze the age distribution of the quality sorted IPOs. In figure 5.4, we present the age distribution divided into five different intervals. We define the age of an IPO company as the number of years between the company was founded and the day it was listed at Oslo Stock Exchange. Looking at the bar charts in figure 5.4, we observe that when the IPO companies are above five years old, the quality and junk IPOs are quite equally distributed. However, when the IPO companies are less than five years old, junk IPOs make up a substantially higher share than quality IPOs do. This indicate that young companies are often defined as junk the month they are listed. A reason for this could be that companies less than five years old are raising money by going public before their business model has materialized itself in terms of generating profit. Hence, the company will get a low quality score on several of the quality measures defined by Asness et al. (2018). Moreover, companies with a short history could be seen by investors as investments with higher risk than companies that have existed for a long time.

Figure 5.4: Age Distribution of Quality Sorted IPOs



The figure presents the age distribution of the quality sorted IPOs. The quality score for an IPO company is assigned the month of the IPO. The x-axis tells the number of years since the companies were founded until they were listed, and divide them into age intervals. The y-axis tells the number of companies within each age interval.

5.2.2 Robustness Test of Short-run IPO Returns

In order to test whether the results for the short term IPO returns are robust, we divide the IPO data sample into two time periods of equal length. The same method we used for research question 1. Loughran and Ritter (2004) find that the extent of underpricing changes over time for several fundamental reasons. Our results could therefore change considerably if we make changes to the time period we analyze. Thus, it is important to perform the same analysis for different time periods to validate our conclusions. The results are presented in the appendix under section A3.2.

In figure A3.1 we illustrate the results for the first period. We can see that we get the same pattern as we do for the whole period. The junk IPOs clearly outperform the quality IPOs the first day of trading. For the first month of trading, however, we get the opposite result. Moreover, all the returns are positive, except for the first month return of junk IPOs. The exact same result we get for the whole sample size. For the second time period, however, the results are not that consistent anymore. From figure A3.2, we can see that the pattern identified for the first day returns still holds, but it does not hold for the first month. The value- and equal-weighted returns yield an opposite conclusion. In addition, it is noteworthy to mention that from this robustness test we also can see that the initial underpricing for the first period is on average considerable larger than for the second period. This indicates that prior to the GFC the underpricing of IPOs was greater than for the time period that followed.

5.3 The Effect of QMJ on Long-run IPO Returns

In this section, we will answer research question 3; How does the QMJ factor affect long-run IPO returns at the Oslo Stock Exchange? By replicating the approach of Blomkvist et al. (2017) we construct calendar time portfolios that measure post-IPO performance and run regressions to obtain Jensen's Alpha. The IPO returns are measured using value-weighted and equally weighted portfolios, with holding periods of 12 and 24 months. A stock is included in the portfolio the month after its IPO, and kept in the portfolio until delisting or the maximum holding period of that portfolio. The portfolio returns are regressed in excess of the risk-free rate against the excess return of the market portfolio (MKT), Small minus big (SMB), and High minus low (HML), which are well-known for explaining stock returns. In addition, we control for the QMJ factor constructed using the whole stock data sample.

In table 5.2 we present the results for the regressions explaining the value-weighted IPO returns. For the market risk factors (MKT), we observe that all four regressions obtain a coefficient that is statistically significant at a 1% level. In addition, we see that three of the regressions get a MKT coefficient that is above 1, indicating that IPO stocks have a higher market risk than the overall market portfolio. Moreover, for regressions explaining the returns of portfolios with 12 months holding period, the SMB coefficients are significantly positive at a 5% level. For the other two regressions, the SMB coefficients are significantly positive at a 10% level. This suggests that the IPO-portfolios consists of a larger share of smaller market capitalization stocks. Furthermore, we observe that the HML coefficient loads negative for all the regressions, but only statistically significant at a 10% level for the two regressions with 24 months holding period. Next, we see that all four regressions have negative alphas, with the alpha for regression (2) being statistically significant at a 10% level. This suggests that in general investors don't obtain a positive abnormal return by investing in IPO companies. The abnormal return will most likely be around zero or negative. These findings are in line with prior research that finds alphas close to zero or negative alphas for portfolios constructed by IPOs (e.g. Carter et al. (2011)).

When evaluating the QMJ factor we see that it loads positive on IPO returns, and that the coefficient is statistically significant at a 1% level for regression (2) and at a 10% level for regression (4). These findings indicate that IPOs at Oslo Stock Exchange are of higher quality, and that quality companies accounts for a larger share of the return for the IPO-portfolios. The exact opposite result that Blomkvist et al. (2017) get when they analyze a U.S. IPO sample. Their paper suggests that IPO firms on average are perceived to be of low quality. They argue that this is because it is relatively cheaper for low quality firms to enter the market when the QMJ factor is low, leading to low quality firms representing the majority of IPO firms.

Table 5.2: Calendar time regressions for value-weighted IPO-portfolios

	Dependent variable:			
	Value-weighted IPO Returns			
	(1)	(2)	(3)	(4)
	12 months	12 months	24 months	24 months
MKT	1.039***	1.093***	0.978***	1.004***
	(0.121)	(0.120)	(0.098)	(0.099)
SMB	0.387**	0.371**	0.246*	0.238*
	(0.168)	(0.165)	(0.137)	(0.137)
HML	-0.094	-0.052	-0.194*	-0.176*
	(0.122)	(0.121)	(0.100)	(0.101)
QMJ		0.354***		0.175*
		(0.117)		(0.095)
Constant (α)	-0.008	-0.011*	-0.001	-0.003
	(0.006)	(0.006)	(0.005)	(0.005)
Observations	220	220	251	251
R^2	0.308	0.336	0.371	0.380

Note: The table presents the results from regressions explaining calendar time portfolios that measure post-IPO performance. The portfolios are constructed using monthly value-weighted IPO returns, using 133 IPOs from 1998 to 2018 at the Oslo Stock Exchange. A stock is included in the portfolio the month after its IPO, and kept in the portfolio until delisting or the maximum holding period of that portfolio. Regression (1) and (2) are regressed on portfolios with 12 months holding period, and regressions (3) and (4) are regressed on portfolios with 24 months holding period. MKT is the excess return of the market portfolio, SMB is the excess return of a portfolio of smaller market capitalization firms minus a portfolio of large market capitalization firms, HML is the excess return of a portfolio of high book-to-market firms minus a portfolio of low book-to-market firms, and QMJ is the average return of buying two portfolios of quality companies and selling two portfolios of junk companies. The alpha reported is the intercept of the regressions. The numbers in the parenthesis are heteroscedasticity-robust standard errors. ***, **, and * indicate that the associated coefficient is statistically significant at the 1%, 5%, and 10% levels, respectively.

In table 5.3 we present the results for the regressions explaining the equally weighted IPO returns. For the market risk factors (MKT), we observe that all regressions obtain a coefficient that is above 1 and statistically significant at a 1% level. This suggests that IPO stocks have a higher market risk than the overall market. To some degree a different result compared to what we obtained for the value-weighted IPO returns, where one of the MKT coefficients was below 1. Moreover, we observe that the HML factor loads negative on IPO returns and is statistically significant at a 5% level for three out of four regressions. This tells us that the return of the portfolios are mostly explained by low book-to-market stocks. Next, we see that we obtain a negative alpha for all four regressions. A similar result to what we get for the value-weighted portfolios presented in table 5.2. However, for the equally weighted portfolios the alphas for regression (1) and (2) are statistically significant at a 1% level, and substantially larger in absolute size. This means that by investing in equally weighted portfolios with a holding period of 12 months, investors would have obtained a negative abnormal return. A return that would have been substantially higher if the investors had invested in value-weighted portfolios with the same holding period.

For the QMJ factor we see that it loads negative on IPO returns in the two regression models we control for it. An opposite sign of what we get for the value-weighted IPO returns. However, the QMJ coefficients are only statistically significant at a 10% level. The reason the QMJ coefficient sign deviate from the one obtained for the value-weighted IPO returns could be because there are some high quality companies with large market cap that drives the effect for the in the value-weighted returns. This results are also more in line with the findings of Blomkvist et al. (2017) who argue that IPO companies are of lesser quality.

Table 5.3: Calendar time regressions for equally weighted IPO-portfolios

	Dependent variable:			
	Equally Weighted IPO Returns			
	(1)	(2)	(3)	(4)
	12 months	12 months	24 months	24 months
MKT	1.061***	1.053***	1.069***	1.046***
	(0.104)	(0.099)	(0.085)	(0.086)
SMB	0.012	-0.012	-0.025	-0.022
	(0.124)	(0.122)	(0.101)	(0.101)
HML	-0.244**	-0.255**	-0.149*	-0.170**
	(0.099)	(0.100)	(0.082)	(0.083)
QMJ		-0.124*		-0.142*
		(0.072)		(0.081)
Constant(α)	-0.015***	-0.016***	-0.008*	-0.006
	(0.005)	(0.006)	(0.004)	(0.004)
Observations	220	220	251	251
R^2	0.379	0.407	0.433	0.448

Note: The table presents the results from regressions explaining calendar time portfolios that measure post-IPO performance. The portfolios are constructed using monthly equally weighted IPO returns, using 133 IPOs from 1998 to 2018 at the Oslo Stock Exchange. A stock is included in the portfolio the month after its IPO, and kept in the portfolio until delisting or the maximum holding period of that portfolio. Regression (1) and (2) are regressed on portfolios with 12 months holding period, and regressions (3) and (4) are regressed on portfolios with 24 months holding period. MKT is the excess return of the market portfolio, SMB is the excess return of a portfolio of smaller market capitalization firms minus a portfolio of large market capitalization firms, HML is the excess return of a portfolio of high book-to-market firms minus a portfolio of low book-to-market firms, and QMJ is the average return of buying two portfolios of quality companies and selling two portfolios of junk companies. The alpha reported is the intercept of the regressions. The numbers in the parenthesis are heteroscedasticity-robust standard errors. ***, **, and * indicate that the associated coefficient is statistically significant at the 1%, 5%, and 10% levels, respectively.

5.4 Factor Loading Comparison Between Quality and Junk IPOs

In this section, we will answer research question 4; Is there a difference in factor loadings between quality and junk IPOs? To answer this question we will create several calendar time portfolios, using the same methodology as explained in research question 3. However, for this research question we will create separate portfolios for quality and junk IPOs. The IPO returns are measured using value-weighted and equally weighted portfolios, with holding periods of 12 and 24 months. We will apply the Fama and French three-factor model, regressing the portfolio returns in excess of the risk-free rate against the excess return of the market portfolio (MKT), Small minus big (SMB), and High minus low (HML).

In table 5.4 we present the results for the value-weighted IPO returns. We observe that all the market betas are above 1 and statistically significant at a 1% level. This means that the returns of the portfolios are more volatile than the overall market. When comparing the quality and junk portfolios, the market risk factor coefficients are larger for the junk portfolios than the quality portfolios. This indicate that the junk IPOs have more market risk than the quality IPOs. Moreover, we observe that the SMB coefficients for the quality portfolios are significantly positive at a 1% level, while the junk portfolios are only statistically positive at a 10% level for the portfolio with 12 months holding period. This suggests that the quality IPOs consist mostly of small market capitalization stocks. For the HML factor we also get different results for the quality and junk IPO portfolios. Both portfolios consisting of quality IPOs loads significantly negative at a 5% level, meaning that the quality IPO returns are mostly explained by low book-to-market companies. The returns of the junk portfolios also load negative on the HML factor, however not significantly. Finally, we look at the alpha's obtained from our four regressions. We observe that all the alpha's are negative, but non of them statistically significant. This means that an investor will most likely neither obtain a positive nor negative abnormal return by investing in these portfolios after controlling for the three factors in the Fama and French model we apply. Moreover, we cannot conclude that an investor achieves a different abnormal return by investing in quality IPOs, instead of in junk IPOs.

Table 5.4: Calendar time regressions for value-weighted quality and junk IPO-portfolios

	Dependent variable:			
	Value-weighted IPO Returns			
	(Quality) 12 months	(Junk) 12 months	(Quality) 24 months	(Junk) 24 months
MKT	1.130***	1.264***	1.107***	1.157***
	(0.153)	(0.242)	(0.124)	(0.175)
SMB	0.678***	0.851*	0.576***	0.127
	(0.226)	(0.465)	(0.174)	(0.243)
HML	-0.281**	-0.270	-0.249**	-0.314*
	(0.130)	(0.262)	(0.101)	(0.179)
Constant (α)	-0.011	-0.007	-0.003	-0.011
	(0.007)	(0.012)	(0.006)	(0.009)
Observations	192	165	227	218
R^2	0.292	0.196	0.321	0.198

Note: The table presents the results from regressions explaining calendar time portfolios that measure post-IPO performance. The portfolios are constructed using monthly value-weighted IPO returns. The quality portfolios are constructed by 48 quality IPOs and the junk portfolios are constructed by 64 junk IPOs from 1998 to 2018 at the Oslo Stock Exchange. A stock is included in the portfolio the month after its IPO, and kept in the portfolio until delisting or the maximum holding period of that portfolio. The two first regressions from the left explain portfolios with 12 months holding period, and the two regressions on the right explain portfolios with 24 months holding period. MKT is the excess return of the market portfolio, SMB is the excess return of a portfolio of smaller market capitalization firms minus a portfolio of large market capitalization firms, and HML is the excess return of a portfolio of high book-to-market firms minus a portfolio of low book-to-market firms. The alpha reported is the intercept of the regression. The numbers in the parenthesis are heteroscedasticity-robust standard errors. ***, **, and * indicate that the associated coefficient is statistically significant at the 1%, 5%, and 10% levels, respectively.

In table 5.5 we present the results of the equally weighed IPO returns. For the market risks coefficients we get a similar results as we did for the value-weighted returns. All the coefficients are above 1 and statistically significant at a 1% level. Moreover, when we compare the size of the coefficients, we see that the market risk factor coefficients are larger for the junk portfolios than for the quality portfolios. This confirms our finding that junk IPOs have more market risk than quality IPOs. Next, we observe that the SMB coefficients load positive and are statistically significant at a 10% and 5% level for the two regressions explaining the return of the quality portfolios. For the junk portfolios, however, this coefficient is not statistically significant. This is a similar result to what we obtained for the value-weighted returns, indicating that small market cap stocks explain most of the returns of quality IPOs. For the junk IPOs, on the other hand, the role of small and large market cap is difficult to interpret based on these analysis. The results we get for the HML factor also have several similarities with those we got from the regressions explaining value-weighted IPO returns. We observe that the HML coefficient is negative and statistically significant at a 1% level for both of the quality portfolios, while for the junk portfolios the HML coefficient is not statistically significant. This strengthens the findings for the value-weighted returns that most of the quality IPOs are low book-to-market stocks. Finally, we evaluate the alpha's we have obtained from these four regressions explaining equally weighted IPO returns. We observe that all the alpha's are negative, however, only the alpha for the junk portfolio with 24 months holding period is statistically significant at a 10% level. This indicate that an investor could obtain a lower abnormal return by investing in junk IPOs, but this tendency is statistically weak.

Table 5.5: Calendar time regressions for equally weighted quality and junk IPO-portfolios

	Dependent variable:			
	Equally Weighted IPO Returns			
	(Quality)	(Junk)	(Quality)	(Junk)
	12 months	12 months	24 months	24 months
MKT	1.117***	1.171***	1.086***	1.144***
	(0.136)	(0.217)	(0.106)	(0.159)
SMB	0.237*	0.225	0.246**	-0.259
	(0.123)	(0.276)	(0.112)	(0.188)
HML	-0.405***	-0.285	-0.386***	-0.225
	(0.133)	(0.220)	(0.105)	(0.153)
Constant (α)	-0.007	-0.010	-0.004	-0.013*
	(0.006)	(0.010)	(0.005)	(0.007)
Observations	192	165	227	218
R^2	0.338	0.190	0.321	0.239

Note: The table presents the results from regressions explaining calendar time portfolios that measure post-IPO performance. The portfolios are constructed using monthly equally weighted IPO returns. The quality portfolios are constructed by 48 quality IPOs and the junk portfolios are constructed by 64 junk IPOs from 1998 to 2018 at the Oslo Stock Exchange. A stock is included in the portfolio the month after its IPO, and kept in the portfolio until delisting or the maximum holding period of that portfolio. The two first regressions from the left explain portfolios with 12 months holding period, and the two regressions on the right explain portfolios with 24 months holding period. MKT is the excess return of the market portfolio, SMB is the excess return of a portfolio of smaller market capitalization firms minus a portfolio of large market capitalization firms, and HML is the excess return of a portfolio of high book-to-market firms minus a portfolio of low book-to-market firms. The alpha reported is the intercept of the regression. The numbers in the parenthesis are heteroscedasticity-robust standard errors. ***, **, and * indicate that the associated coefficient is statistically significant at the 1%, 5%, and 10% levels, respectively.

6 Limitations and Suggestions for Further Research

In this chapter, we will present the most prominent limitations in our paper and propose areas for further research.

6.1 Limitations of the Paper

The quality and availability of data for this research paper has varied, leading to several limitations. We will therefore in the next paragraphs present these weaknesses for all the research questions in depth.

6.1.1 Research question one

This study requires sufficient data in order to provide meaningful results. Due to time limitations we were not able to collect unlimited data. The accounting data is needed to create the quality measures which are used throughout the study. The accounting data available from *SNF* were limited to 25 years, and therefore sets a natural limitation on the time period we can conduct our study. This constraint on time period is even narrower as we need to use five years span in order to calculate the growth indicator for the stocks reducing the time period to 21 years. This leaves us with 496 companies with 8126 observations to calculate the measures needed. However, only 487 of these companies are used due to the first year in the analysis being 1998.

The accounting data sets the limit for how many companies we can include in our study. From *Børsprosjektet at NHH* we retrieve financial data as market capitalization and monthly sotck returns on 611 individual companies. Thus, the lacking accounting data makes 213 of these companies obsolete. In addition, the database contains data back to 1980 which could have expanded our selection if the accounting data was available. Another issue is the process of matching the stock data with the belonging accounting data. In order to match them, we need to match the company ID provided by the stock data with the organization number from the accounting data. We were not able to find a matching pair for all the companies in our accounting data sample. This limits the selection to the number of pairs retrieved, leaving us with 398 unique companies we can use for our analysis.

For both the accounting data and stock data, incomplete data sets have reduced the amount of data we can apply in our analysis. A more complete data set would have increased the data selection and the robustness of our results. For the accounting data, the used selection is reduced by 35 companies due to incomplete data. Similarly, the final selection is reduced from the 398 stocks with accounting data to 386 companies due to incomplete data.

Comparing our selection of 386 companies used in our study to the study done by Asness et al. (2018) consisting of 54 616 companies covering 24 countries over a span of nearly 59 years, it's clear that more data would have been beneficial. In addition, the accounting data collected for our study are yearly. Asness et. al.(2018) uses quarterly data which would have improved our results further.

6.1.2 Research question two

For research question two, we used the same data as in research question one in order to calculate the quality scores for the IPO companies. Thus, the same limitations explained above applies to this research question. In addition, we add the initial first day and the first month returns for all the IPO companies in our data sample. During the time period we analyze, there were 262 IPOs at the OSE. However, we were only able to obtain a sufficient data basis for 157 of the IPOs. This is because 105 of these IPOs where either lacking accounting data or return data. Increasing the share of IPOs in the period we analyze in our final data selection would have improved the robustness of our results.

6.1.3 Research question three and four

The data used for the two final research questions faces the same problem as the for the two other research questions. However, it's not possible to make an assumption to expand our selection as the returns are needed. Therefore, we had to limit our selection to 133 companies because we needed companies with at least 12 months continuous monthly returns in order to asses the long-run performance of the IPOs and their characteristics. Increasing the number of companies in our selection would have given our findings more validity.

6.2 Further Research

In this paper, we analyze how the quality of a firm affects its short-run and long-run IPO returns. The methodology we apply to define company quality is solely based on the quality definition used by Asness et al. (2018) in their Quality Minus Junk paper. However, the quality of a firm can be defined in many different ways. Another method for defining quality may therefore yield different results than the ones we get in this paper. It would therefore be very interesting to see whether our results hold when using another method for defining the quality of a company.

Furthermore, a limitation with the methodology used in this paper, is that it does not include qualitative quality measures. Excluding such measures could mean that we lose valuable information in terms of defining a firm as quality or as junk. For example, could the quality of the management team and board members have a substantial effect on the overall quality of a firm that files for an IPO. Moreover, several firms choose to go public in order to secure enough funds to support further growth early in their growth cycle. Such companies may be generating early stage revenue but might not be profitable yet. The quality of those companies will therefore not show on their income statements and balance sheets until several years from the offering date. Including quality measures that better capture the quality of a firm in a growth stage will therefore be a very interesting topic to look further into.

7 Conclusion

The objective of this paper has been to contribute to better understanding of the effect company quality has in explaining IPO returns. We have used a well-known methodology for defining firm quality and used it to analyze the performance of companies going public at the Oslo Stock Exchange from 1998 to 2018. First, we document that there exists a significant positive price of quality over the whole period we analyze. This means that investors at the Oslo Stock Exchange are willing to pay a higher price for quality companies than companies that get a lower quality score. In addition, we find that the price of quality was higher in the period prior to the Global Financial Crisis than in the period that followed. A result that may have an impact on the performance of quality and junk companies going public during this period.

In the second research question, we study the short-run performance of IPO companies. We find that during the first day of trading the junk IPOs clearly outperform the quality IPOs. This result also holds when we divide our time series into two different periods. Investors should therefore be careful when investing in high quality companies that are going public as these stocks have a great chance of being overpriced. For the first month of trading, however, the results are opposite. The quality IPOs clearly outperform the junk IPOs, when we look at the first month returns, excluding the returns of the initial first day. For investors considering to invest in quality companies it is therefore better to wait until after the day of the listing. In addition, we compare some characteristics of the quality and junk IPOs to see if this can give us a better understanding of what drives the difference in returns. We find that quality companies are overrepresented within the IT sector, while the junk IPOs are overrepresented within the health and financials sectors. Moreover, we find that companies with short history before going public are more often defined as junk IPOs compared to quality IPOs.

In the third research question, we evaluate the effect of the QMJ factor on long-run IPO returns. Our analysis indicate that the portfolios consisting of only IPOs have more market risk than the overall market portfolio. Moreover, we find that in general investors don't obtain a positive abnormal return by investing in IPO companies when holding them for a longer period. Findings that are in line with prior research on other stock exchanges. In addition, we find that the QMJ factor loads significantly positive on value-weighted IPO returns. This finding indicates that it is the quality IPOs that explain the majority of the long-run returns of the companies that went public during our sample period. However, when we analyze equally weighted IPO returns the QMJ factor obtain a negative sign on its coefficient. A result that indicate that there are some high quality companies with large market cap that drive the results of the regressions explaining the value-weighted returns.

In the last research question, we compare factor loadings between quality and junk IPOs. We find that both quality and junk IPOs have more market risk than the overall market, and that the market risk is highest for the junk IPOs. Moreover, our analysis suggests that small market cap stocks and low book-to-market stocks explain most of the returns of quality IPOs. For the junk IPOs, however, we do not find any meaningful effects on the role of market cap size and book-to-market ratio on IPO returns. This allows us to conclude that there is a difference in factor loadings between quality and junk IPOs at the Oslo Stock Exchange.

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Appendix

amssymb

A1 Variables

Sales Income = SI

Total Income = TI

Cost of materials = CM = Consumption of goods + Inventory Change

Total assets = Assets

Equity = Equity

Net result for the year = RES

Depreciation = DEPR

Current Assets = CA

Current Debt = CD

Cash = CASH

Δ Working capital = $(CA - CD)_t - (CA - CD)_{t-1}$

Liabilities = Liabilities

Investments = Invest = $Fixedassets_t - Fixedassets_{t-1} + DEPR_t$

Consumer Price Index = CPI

Long term Liabilities = LL

Market value = MCAP = $(Generic * Sharesissued)/1000$

Aggregated MCAP = $\frac{1}{12}(\Sigma MCAP_{i,t})$ for t=1,...,12, i= company i

Beta = Beta

Ordinary result before taxes = RESBT

Cashflow = (RES + DEPR - ΔWorking capital - Invest)

A2 Calculations of the Factors Used to Construct the QMJ Factor

Profitability factor

GPOA = (SI - CM)/ Assets

ROE = RES / Equity

ROA = RES / Assets

CFOA = Cashflow / Assets

GMAR = (SI - CM) / TI

ACC = (DEPR - ΔWorking capital) / Assets

Growth factor

Δ defines the growth in the profitability measures over a span of five years.

Δ GPOA = $((SI - CM)_t - (SI - CM)_{t-5})/Assets_{t-5}$

Δ ROE = $(RES_t - RES_{t-5})/Equity_{t-5}$

Δ ROA = $(RES_t - RES_{t-5})/Assets_{t-5}$

Δ CFOA = $(Cashflow_t - Cashflow_{t-5})/Equity_{t-5}$

Δ GMAR = $((SI - CM)_t - (SI - CM)_{t-5})/TI_{t-5}$

Safety factor

BAB = - Beta = $-\beta$

$\beta_i = (\sigma_i/\sigma_m) * \rho$

Where σ_i and σ_m is the standard deviation for a given stock and the whole market respectively, and ρ is the correlation between the two.

LEV = - (LL-CD)/Equity

Ohlson's O score = $-(-1.32 - 0.407 * log(ADJASSET/CPI) + 6.03 * TLTA - 1.43 * WCTA + 0.076 * CLCA - 1.72 * OENEG - 2.37 * NITA - 1.83 * FUTL + 0.285 *$

$INTWO - 0.521 * CHIN)$

Where: ADJASSET = Assets * 0.1(MCAP-Equity)

TLTA = Liabilities / ADJASSET

WCTA = (CA - CD) / ADJASSET

CLCA = CD / CA

OENEG = Dummy variable = 1 if current commitments is larger than total assets

NITA = RES / ASSETS

FUTL = RESBT / Liabilities

INTWO = Dummy variable = 1 if current and last years results both are negative

CHIN = $(RES_t - RES_{t-1})/(|RES_t| + |RES_{t-1}|)$

EVOL = The standard deviation for ROE over the last five years

A3 Robustness Tests

A3.1 For research question 1

Table A3.1: Price of Quality (1998-2008)

	Dependent variable:					
	log(MB)					
	(1)	(2)	(3)	(4)	(5)	(6)
Quality	0.189***	0.206***				
	(0.007)	(0.008)				
Size		0.041***				0.027***
		(0.002)				(0.002)
1-Year return		0.093***				0.110***
		(0.008)				(0.009)
Profitability			0.161***			0.114***
			(0.011)			(0.008)
Growth				0.116***		0.055***
				(0.014)		(0.011)
Safety					0.169***	0.101***
					(0.010)	(0.004)
Constant	0.509***	0.483***	0.505***	0.577***	0.509***	0.547***
	(0.021)	(0.021)	(0.021)	(0.018)	(0.021)	(0.016)
Observations	16,994	16,151	16,994	12,063	16,994	11,736
R^2	0.141	0.176	0.120	0.100	0.145	0.186

Note: The table presents the average coefficients from the Fama-Macbeth regressions for the first half of the data sample period (1998-2008) at the Oslo stock Exchange. The dependent variable is the z-score of the market to book ratio (MB) for each stock in month t. The independent variables are the z-scores of each stocks overall quality measure, profitability measure, growth measure, and safety measure. In addition, we control for the z-score of each firms size (market capitalization) and each firms last 12 month cumulative return. The numbers in the parenthesis are heteroscedasticity-robust standard errors. ***, **, and * indicate that the associated coefficient is statistically significant at the 1%, 5%, and 10% levels, respectively.

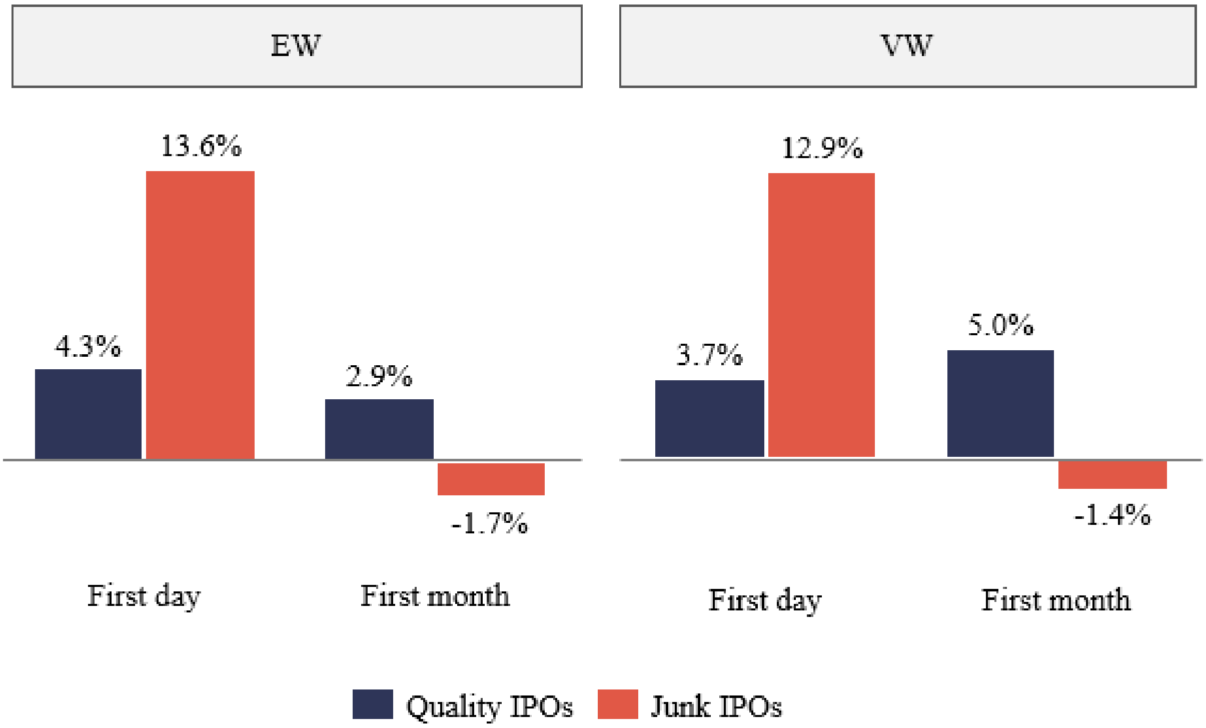
Table A3.2: Price of Quality (2009-2018)

	Dependent variable:					
	log(MB)					
	(1)	(2)	(3)	(4)	(5)	(6)
Quality	0.127***	0.095***				
	(0.009)	(0.009)				
Size		0.034***				0.010***
		(0.002)				(0.003)
1-Year return		0.269***				0.303***
		(0.023)				(0.025)
Profitability			0.128***			0.163***
			(0.013)			(0.019)
Growth				0.064***		0.018
				(0.009)		(0.011)
Safety					0.125***	0.098***
					(0.012)	(0.009)
Constant	0.331***	0.408***	0.332***	0.355***	0.327***	0.398***
	(0.011)	(0.018)	(0.012)	(0.011)	(0.012)	(0.019)
Observations	12,749	12,435	12,749	9,762	12,749	9,637
R^2	0.045	0.107	0.047	0.023	0.051	0.162

Note: The table presents the average coefficients from the Fama-Macbeth regressions for the second half of the data sample period (2009-2018) at the Oslo stock Exchange. The dependent variable is the z-score of the market to book ratio (MB) for each stock in month t. The independent variables are the z-scores of each stocks overall quality measure, profitability measure, growth measure, and safety measure. In addition, we control for the z-score of each firms size (market capitalization) and each firms last 12 month cumulative return. The numbers in the parenthesis are heteroscedasticity-robust standard errors. ***, **, and * indicate that the associated coefficient is statistically significant at the 1%, 5%, and 10% levels, respectively.

A3.2 For research question 2

Figure A3.1: Short-run Returns of Quality Sorted IPOs (1998-2008)



The figure presents the average initial first day return and first month cumulative return (excluded for the first day initial return) for both junk and quality IPOs. The quality score for an IPO company is assigned the month of the IPO. The x-axis of the bar chart tells the cumulative returns in percentage, and the y-axis tells whether the return is for the initial first day or the first month.

Figure A3.2: Short-run Returns of Quality Sorted IPOs (2009-2018)

The figure presents the average initial first day return and first month cumulative return (excluded for the first day initial return) for both junk and quality IPOs. The quality score for an IPO company is assigned the month of the IPO. The x-axis of the bar chart tells the cumulative returns in percentage, and the y-axis tells whether the return is for the initial first day or the first month.