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IPO Underpricing and Aftermarket Performance in the Netherlands

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ABSTRACT

In this thesis, I analyse the relationship between the degree of underpricing and aftermarket performance of Dutch Initial Public Offerings (IPO) from 2004 until 2021. I compare the degree of underpricing and the aftermarket performance of the Netherlands with Italy, and I analyse the effect policy uncertainty has on underpricing. The data used in this study has been primarily collected from Bloomberg and the respective prospectuses. I find that the degree of underpricing has a significant positive effect, which means that a higher degree of underpricing leads to better aftermarket performance. This suggests that leaving more money on the table initially leads to a higher aftermarket performance on the secondary market measured at thirty days. A clearer insight into the relationship between IPO underpricing and aftermarket performance may help a firm's board of directors to make better informed decisions.

Keywords: IPO underpricing, Aftermarket performance, Policy uncertainty

JEL Codes: G24**,** G38

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CHAPTER 1 Introduction

An Initial Public Offering (IPO) is a milestone for companies that are seeking to raise capital. When going public it often happens that the issuing company sets a lower offering price for the newly issued stock than the market value that investors are willing to pay for the shares. This is known as IPO underpricing and results in immediate gains for investors on the first day and is commonly known as 'leaving money on the table' by the issuing company (Loughran & Ritter, 2002). While IPO underpricing may benefit investors who purchase shares at a lower price, the long-term implications of IPO underpricing on long-term stock performance remain a topic of discussion. Therefore, this thesis will contribute to the ongoing debate surrounding the effectiveness of IPO underpricing as a pricing strategy and may offer valuable insights for investors, analysts and companies considering an IPO.

Dell'Acqua et al. (2015) analysed the relationship between IPO underpricing and long-term stock performance in the Italian stock market. In their paper the authors examined 129 IPOs listed on the Italian Stock Exchange from 2001 until 2012. The study suggests that companies experiencing a higher level of underpricing at the time of their IPO tend to exhibit lower long-term stock performance. The authors relate this result to temporary actions of price support by underwriters and conclude that aftermarket performance seems to be affected to some extent by the exercise of the greenshoe option, the market demand and the financial crisis period. A paper which focused on IPO underpricing and long-term stock performance during a financial crisis on Dutch IPOs, Dorsman and Gounopoulos (2013) concluded: "underwriters, when assisting issuers, have to determine lower offer prices for their newly listed stocks in order to compensate the investors for the risk in participating in the IPO process…" (p. 18). The authors of the paper found that this excessive IPO underpricing leads to long-term stock underperformance. This thesis will add to the discussion by further analysing the effects IPO underpricing has on the aftermarket performance.

In this thesis, I will replicate the study of Dell'Acqua et al. (2015). However, my analysis will focus on analysing the relationship between IPO underpricing and aftermarket performance in the Netherlands. I will also be using data of Dutch IPOs from 2004 until 2021, instead of data of Italian IPOs. The Dutch market differs from the Italian market. It has for example almost triple the market capitalization compared to the Italian stock market (The World Federation of Exchanges, n.d.). The Netherlands has also seen more IPO activity than Italy in recent years (All IPOs - Euronext Exchange Live Quotes, 2023). The effect these differences have on the relationship between IPO underpricing and aftermarket performance is unknown. In addition to using a more recent dataset, these differences will make this thesis more relevant for investors and companies in the Dutch stock market. Therefore, my research question is: "How does IPO underpricing affect aftermarket performance in the Netherlands?". To the best of my knowledge, this relationship has not been studied in the Netherlands in this timeframe.

To study the relationship of IPO underpricing and aftermarket performance I will perform a multiple regression model. The dependent variable will be the stock's aftermarket performance, and the multiple independent variables will include the degree of underpricing, the size of the offering, and control variables such as the industry sector and the year of the IPO. By doing so I will be able to estimate the coefficient of the degree of underpricing variable. If this coefficient is positive and statistically significant, it indicates that higher degrees of underpricing are associated with higher returns in the aftermarket, suggesting that underpricing may be an effective strategy for generating positive aftermarket performance and vice versa. The data regarding IPOs in the Netherlands from 2004 until 2021 can be viewed and collected directly from Autoriteit Financiële Markten (AFM), Euronext and Bloomberg. AFM will provide access to all relevant IPO prospectuses from which I can extract data regarding the company itself and relevant details regarding the IPO. Euronext Amsterdam has all data needed on the IPOs in the Dutch market: IPO dates, offering prices and first day returns. These offering prices will be measured as values in euros, while the first day returns will be measured as a percentage that indicates the difference between the initial offering price and the price at the end of the first day, by doing so I can measure the degree of underpricing. The aftermarket performance of an IPO will be measured by looking at the returns on the 30th day after the IPO. The data regarding aftermarket performance will be collected from Bloomberg. This data will be the stock's value in euros, which can be converted into a percentage representing the return at 30 days after the IPO. The aftermarket performance will be tested for robustness, Brav & Gompers (1997) achieve this by performing a benchmark comparison against broad market indexes, industry portfolios and similar book-to-market portfolios.

The Dutch market is in many ways very different than the Italian market (The World Federation of Exchanges, n.d.). However, I expect to find similar results, because I expect the phenomenon of IPO underpricing to have the same effect on the aftermarket performance of Dutch IPOs as it has on Italian IPOs. Therefore, I expect the relationship between IPO underpricing and aftermarket performance in the Dutch market to be similar to the relationship found by Dell'Acqua et al. (2015) in the Italian market. To confirm whether this expectation is true I will analyse the relationship between IPO underpricing and aftermarket performance of Dutch IPOs. This relationship should become visible after performing multivariate regression analyses and testing the aftermarket performance for robustness. It will show what statistically significant effects IPO underpricing has on aftermarket performance. The effect IPO underpricing has on aftermarket performance in the Netherlands will be a lot more relevant for Dutch investors and companies than previous papers were for them. Other papers used data from other stock exchanges and different time periods. Therefore, this thesis brings adds further value towards the discussion of IPO underpricing as a pricing strategy and its effects on aftermarket performance. However, because the data used in this thesis only concerns the Netherlands the value added to this debate will be limited and specific to the Dutch stock market.

In this thesis, I was able to compare IPO underpricing in the Netherlands with IPO underpricing in Italy. I found that the Netherlands has a slightly higher raw degree of underpricing as well as adjusted degree of underpricing. I also find that the degree of underpricing has a significant positive effect on the aftermarket performance of Dutch IPOs in all four models of my regression analysis, which means that a higher degree of underpricing leads to better aftermarket performance. Lastly, I find that the EPU index has a significant negative effect at the 10% level on the degree of underpricing, which means that higher policy uncertainty will lead to a lesser degree of underpricing in Dutch IPOs.

This paper will first discuss previous literature in Chapter 2 on the topics of IPO underpricing, aftermarket performance and policy uncertainty. I will also look further into previous literature that has already studied the relationships between IPO underpricing and aftermarket performance, as well as the relationship between policy uncertainty and the degree of underpricing. I will end this chapter by generating multiple hypotheses, which are substantiated by the literature. In Chapter 3, I will introduce the data that I use in this thesis by explaining the dataset and its variables. In Chapter 4, I will introduce my methodology and which variables are of main interest in this study. In Chapter 5, I will use this methodology to perform a regression analysis and present its results. After reporting these results and performing several robustness tests, I will discuss my findings and compare it with literature I have discussed earlier in Chapter 2. In Chapter 6, I will provide the conclusion to this thesis and mention the limitations I encountered during this thesis.

CHAPTER 2 Theoretical Framework

2.1 IPO Underpricing

IPO (Initial Public Offering) underpricing is a term used in the financial world to refer to the phenomenon where the issuing company sets a lower offering price for the newly issued stock than the market value that investors are willing to pay for the shares. According to Kagan (2020) a stock is considered underpriced when it closes its first day of trading above the set IPO price. She also mentions that IPO underpricing is a short-lived phenomenon, due to investor demand the price will quickly trade towards its market value.

This underpricing phenomenon can occur in some IPOs, when it happens it is a part of the process of going public for the issuing company. The IPO process is usually facilitated by investment banks and underwriters. They are involved in every aspect of the IPO process and most importantly determine the initial offering price in consultation with the issuing company. A higher market price on the first day than the initial offering price implies that the issuing company could have priced its shares higher and raised more capital. We measure the degree of underpricing as a percentage by calculating the percentage difference between the initial offering price and the closing price on the first trading day. The greater the percentage is, the higher the degree of underpricing is.

One of the earliest papers regarding IPO underpricing done by Logue (1973) was intrigued by the factors that affect how investment banks make their initial pricing decisions. By running multiple regressions with the relative performance of the IPO as the dependent variable and various factors including underwriter prestige and size of the offering as the independent variables. He was not completely satisfied with the reported results in his paper and kept wondering why underwriters would give up potential profits by underpricing new issues. Subsequently Ibbotson (1975) wrote a paper about new stock issues and their initial performance. Using an aggregated RATS (returns across time and securities) regression model his results showed a positive initial performance. However, he was unable to definitively pinpoint the exact reasons behind IPO underpricing. Therefore, Ibbotson labelled it a ‘mystery’. Baron (1982) argues that underpricing is due to asymmetrical information between the investment bank and the issuer. In his paper he presents a model that shows the main reason for underpricing is due to investments banks having superior information and them being able to set the issuing price. Asymmetry of information is often mentioned in subsequent papers. It is Rock (1986) who suggests a model for the underpricing of IPOs in his paper. His model is heavily based on the existence of asymmetrical information during an IPO. He argues that issuers have superior information about the value of their own firm, including informed and uninformed investors this information asymmetry leads to underpricing. Ritter (1984) focuses on ‘Hot Issue Markets” to further establish the underpricing phenomenon. These hot issue markets are defined as periods in which there is high enthusiasm and thus demand for new issues. Later

Beatty and Ritter (1986) suggest that investment banks may underprice their IPOs deliberately to build and maintain their reputation.

In addition to these periods of high demand the market can also be trending downwards or worse be in a recession. These periods prove to be equally as important to research as the hot issue markets. In recent times the COVID-19 pandemic caused a lot of uncertainty in financial markets, but in contrast the IPO market performed quite well throughout the entire pandemic. Inspired by this observation, Baig and Chen (2022) perform a thorough analysis of IPOs during the COVID-19 pandemic. After estimating multiple models with information uncertainty as the dependent variable their results suggest that the pandemic did not necessarily impact the IPO market in a positive way. In addition to information uncertainty, IPOs are also susceptible to the influence of political uncertainty. Political factors can introduce new uncertainties for companies going public. Mehmood et al. (2021) found that political uncertainty also plays a big part in developing and emerging markets. They suggest that investors have more uncertainty about their rate of return and thus a strong legal system and institutional framework lowers the cost of going public and equity financing. This affects the degree of underpricing; they conclude that the degree of underpricing is the highest in emerging markets compared to developed or developing markets. They also conclude that political factors like regulations and government interventions are amount the most significant factors that affect the degree of underpricing in developed, developing and emerging markets. Therefore, they suggest it is an interesting area in which to conduct further research. A literature review by Al-Thaqeb and Algharabali (2019) gives a comprehensive overview about political uncertainty regarding IPOs. Political uncertainty is noteworthy because it affects company’s financial decisions. In their paper they analyse a paper by Baker et al. (2016), because they are among a growing number of researchers that use the economic policy uncertainty index (EPU) to measure uncertainty. A recent paper by Boulton (2022) also uses the EPU index to research its relationship with the degree of underpricing. After performing hierarchical linear modelling with underpricing as the dependent variable, he concludes that there is a positive relationship between the EPU index and underpricing. This means that more economic policy uncertainty leads to a higher degree of underpricing.

In case of any degree of underpricing the early investors benefit from the price discrepancy instead of the issuing company, this is known as ‘leaving money on the table’ by the issuing company. A lot of questions like: “Why do companies leave money on the table? How to minimize money left on the table? Are the initial set prices mispriced or is the market mispricing the value of these companies?” arose around this subject and lead to lots of research papers regarding IPO underpricing. A seminal paper by Loughran and Ritter (2002) explored why issuers do not seem to get upset when they are leaving money on the table. By observing that most IPOs in which a lot of money was left on the table had generally higher offer and market prices than anticipated, they explain the phenomenon with a prospect theory. In their prospect theory it is assumed that issuers care more about the change of their wealth rather than their absolute wealth. Later Loughran and Ritter (2004) wrote another seminal paper, now exploring why IPO underpricing has changed over time. They explain the changing of the degree of underpricing to a shift in incentives which in turn leads to a lesser degree of underpricing. They support their hypothesis with multiple OLS regressions with the degree of underpricing as the dependent variable.

2.2 Aftermarket performance

After the IPO of a company their stocks continue to be traded on the secondary market. This variation in the company's stock price is what is commonly defined as the aftermarket performance of an IPO (Mitchell, 2021). There is no definite standard for the time frame in which aftermarket performance is measured. Therefore, the time frame should be specified when researching aftermarket performance. In this paper the aftermarket performance will be measured in a time frame of 30 days after the IPO.

Aftermarket performance is a part of the post IPO process. In the chosen time frame, there could be a lock-up period, in which major shareholders are prohibited from selling. It is also possible that there is a quiet period, in which the issuing company is prohibited from releasing new information. In general, the aftermarket performance is often considered a part of the assessment of the IPOs overall success. Aftermarket performance will be measured by calculating the buy and hold abnormal return (BHAR). The BHAR will be expressed as a percentage. A positive BHAR will indicate that the aftermarket performance outperformed relative to the benchmark, while negative BHAR indicates underperformance relative to the benchmark.

Aftermarket performance has been researched with the use of many different datasets (Aggarwal et al., 1993; Kooli and Suret, 2002; Kim et al., 1995). One of the earliest papers about aftermarket performance was done by Ibbotson & Jaffe (1975). They were interested by hot issue markets and were trying to understand the dynamics of these hot issue periods. In these hot issue periods, they observed abnormally high aftermarket performances on newly issued stock. Teoh et al. (1998) argue that firms' earning management is a factor for poor aftermarket performance as their results are robust in respect to other factors that may impact aftermarket performance. They come to this statement by performing a cross-sectional regression each fiscal year with current accruals regressed on the change in sales. Aggarwal and Rivoli (1990) present results that suggest poor long-term performance could be explained by mispricing of the newly issued stock in the early aftermarket period. They even conclude that early gains are offset by future price reductions. They are able to do so by calculating the abnormal returns of an IPO over 250 days and performing a cross-sectional analysis with the market returns to see whether they are underperforming. Schultz (2003) finds that long-run underperformance is real and suggests that pseudo market timing could be the reason for this observation. In his paper he defines pseudo market timing as a result of companies going public when they can get a higher price for their stock. Thus, resulting in more IPOs when the market values these companies higher. Another seminal paper written by Ritter and Welch

(2002) gives a comprehensive review of IPO activity, pricing and allocations. They state that models on asymmetrical information may be overemphasized in academic literature. While acknowledging that long run performance is controversial in IPO literature, the authors side more with the behavioural point of view opposed to the market efficiency point of view.

2.3 Relationship between: IPO Underpricing and aftermarket performance

In the literature, IPO underpricing and its aftermarket performance have been extensively studied repeatedly using different datasets. In most studies these phenomena are studied separately, a relationship is not made and thus not researched. However, Ritter (1991) wrote a seminal paper about the long-run performance of IPOs in which he linked IPO underpricing to aftermarket performance overpricing. He was intrigued by anomalies that had been documented earlier surrounding an IPO. By calculating the cumulative abnormal returns (CAR) and 3-year BHAR for both the issuing firm and their benchmark, he concludes that the immediate initial positive returns are often followed by underperformance in the long term. He suggests that the abnormal initial returns observed in IPOs can be attributed to excessively high initial aftermarket prices. This may subsequently explain underperformance of new issues in the long run. Later Loughran and Ritter (1995) agree that long-run underperformance exists mainly because of the mispricing of IPOs, which in turn leads to lower returns in the long-run. They come to this conclusion by calculating the BHAR of IPOs in a 3-year and 5-year time frame. Additionally, they examined the distribution of the BHARs to gain insights into the overall performance pattern of IPO stocks.

Overall, these studies offer evidence that there is a negative link between IPO underpricing and aftermarket performance over the long term. It is well documented that IPO underpricing is frequently followed by a period of poor performance in the secondary market. The studies suggest that underperformance seen in IPOs over the long run is a result of the mispricing during the IPO stage. Therefore, I expect to find that the aftermarket underperformance to be more severe when the degree of underpricing is higher.

Hypothesis 1: The higher the degree of underpricing, the more severe aftermarket underperformance is measured by the BHARs 30 days after the IPO.

In recent years there has been more emphasis on the use of the EPU index when researching economic policy uncertainty (Baker et al, 2016; Boulton, 2022). In this literature a positive relationship was found between higher economic policy uncertainty and the degree of IPO underpricing. Therefore, I expect to find that the degree of underpricing in Dutch IPOs will be more severe in the years that scored higher in the EPU index.

Hypothesis 2: The higher the Dutch EPU index score for the corresponding year, the more severe the degree of underpricing will be.

CHAPTER 3 Data

In this paper I examine 37 IPOs listed on the Dutch stock market during the period 2002-2022. This data was gathered from Bloomberg by filtering Initial Public Offerings. I used The Netherlands as region filter and January 1st 2002 until December 31st 2022 as time frame. After exporting this dataset, I excluded 16 IPOs that were withdrawn before they could get to the pricing or trading stage, which left 37 IPOs to be researched. These are all Dutch IPOs provided by Bloomberg, which reduced the period I have actual data of to 2004-2021. The EPU index for The Netherlands has been collected from policyuncertainty.com. By taking the average score of each year, I will be able to use this data with IPOs in their corresponding listing year.

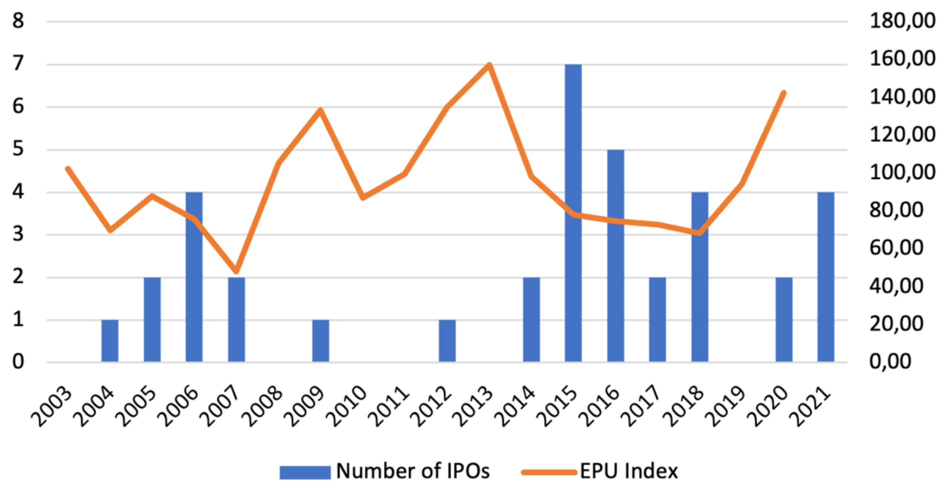


Figure 1: EPU index and IPO frequency

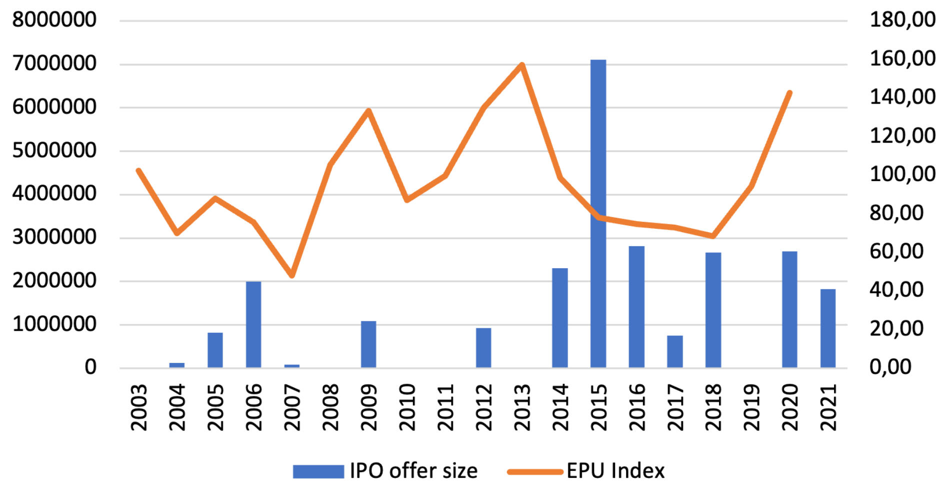


Figure 2: EPU index and Offer size

In Figure 1, both the EPU index and the IPO frequency is plotted to get a general sense of its correlation. It shows that more IPOs are issued in times when the EPU index provides a lower policy uncertainty score, less IPOs are issued in years that score relatively high. In Figure 2, the EPU index and the Offer size are plotted, which shows a similar pattern to Figure 1.

3.1 Variables

Degree of underpricing

The degree of underpricing will be calculated in two ways as proposed by Dell'Aqua et al. (2015). Firstly, I will calculate the raw initial return (RIR) as suggested by Ritter (1984) to get the degree of underpricing:

$$\mathrm{RIR}_{i,t} = \frac{\mathrm{P}_{i,1} - \mathrm{P}_{i,0}}{\mathrm{P}_{i,0}} * 100\%$$

with $P_{i,0}$ representing the offer price of firm i, while $P_{i,1}$ represents the first day closing price of firm i. The degree of underpricing represents the percentage difference between the initial offering price and the closing price on the first trading day. This is achieved by subtracting the offer price from the first trading day closing price, dividing the result by the offer price and multiple by a hundred percent. This calculation gives us the degree of underpricing expressed as a percentage, which indicates to what extent the IPO shares are initially undervalued in the market. The offer price, as well as the first day closing price, have been gathered from Bloomberg.

Secondly, to adjust the RIR for market changes I will calculate the market adjusted initial return (MAIR):

$$\mathrm{MAIR}_{i,t} = \left(\frac{\mathrm{P}_{i,1} - \mathrm{P}_{i,0}}{\mathrm{P}_{i,0}} - \frac{\mathrm{MI}_{i,1} - \mathrm{MI}_{i,0}}{\mathrm{MI}_{i,0}}\right) * 100\%$$

with $P_{i,0}$ representing the offer price of firm i, while $P_{i,1}$ represents the first day closing price of firm i. $\mathrm{MI}_{i,0}$ represents the market index at the end of the first trading day of firm i, while $\mathrm{MI}_{i,1}$ represents the market index at the end of the subscribing period of shares of firm i. MAIR represents the adjusted RIR, which is expressed as a percentage. The offer price, first day closing price, market index at the end of the first trading day, as well as the market index at the end of the subscribing period of shares, have been gathered from Bloomberg and relevant prospectuses.

Table 1: Descriptive table RIR and MAIR

	RIR	MAIR
Observations	37	37
Mean (%)	4.1445	3.9357

Standard Deviation	.0394	.17858
Median (%)	1.76	1.7082
Minimum (%)	-48.5	-48.7459
Maximum (%)	89.58	89.7467
Skewness	2.4687	2.4314
Kurtosis	17.8564	17.4391

Aftermarket performance

In this paper I measure the aftermarket performance by calculating the buy and hold abnormal return (BHAR) as proposed by Lyon et al. (1999):

$$BHARi,t = \prod_{t=1}^{T} (1+Ri,t) - \prod_{t=1}^{T} (1+Rm,t)$$

with R*i* representing the return of IPO number *i* for year *t*, and R*m* representing the return of the benchmark for year *t*. BHAR will be calculated as a percentage indicating the aftermarket performance of the IPO on the 30th day after it went public. The data regarding the return of the IPO at the 30th day after it went public, as well as the return of the benchmark, has been gathered from Bloomberg.

Table 2: Descriptive table Aftermarket performance	
Observations	37
Mean (%)	6.2884
Standard Deviation	.2769
Median (%)	5.0749
Minimum (%)	-48.4859
Maximum (%)	146.0867
Skewness	3.3334
Kurtosis	19.1155

EPU index

The EPU index for The Netherlands has been collected from policyuncertainty.com, which keeps track of the economic policy uncertainty in The Netherlands by measuring domestic uncertainty from Dutch newspaper and quantifying it in the EPU index as EBO-NL. The EPU index contains a monthly score from March 2003 until December 2020. By taking the average score of each year I will be able to use this data with IPOs in their corresponding listing year.

Table 3: Descriptive table EPU index	
Observations	33
Mean	82.8670
Standard Deviation	23.2457
Median	75.77

Minimum	47.99
Maximum	142.66
Skewness	1.5121
Kurtosis	4.7143

Offer size

The Offer size is the amount of money the IPO raised. This can be calculated by multiplying the offer price and the number of shares offered during the IPO, but the data used in this paper was gathered from Bloomberg after adding offer size to the deal overview. The offer size is measured per million euros.

Table 4: Descriptive table Offer size	
Observations	37
Mean	704,183.6
Standard Deviation	729,880.8
Median	531290
Minimum	109.144
Maximum	3.837.500
Skewness	2.6915
Kurtosis	11.2000

Table 5: IPO offer size (in million euros) by Year

Year	**Offer size (M)**	**%**
2004	128,001	0.49%
2005	820,327	3.15%
2006	1,998,490	7.67%
2007	917,290	3.52%
2009	1,088,870	4.18%
2012	925,036	3.55%
2014	2,302,290	8.84%
2015	7,101,581	27.26%
2016	2,820,010	10.82%
2017	757,451	2.91%
2018	2,670,696	10.25%
2020	2,697,515	10.35%
2021	1,827,236	7.01%
Total	**26,054,793**	**100%**

Table 6: IPO offer size (in million euros) distribution

Offer size (M)	**Number of IPOs**	**Value (M)**	**%**
100M – 250M	8	1,177,003	4.52%
250M – 500M	10	3,700,074	14.20%
500M – 750M	7	3,991,880	15.32%
750M – 1B	5	4,532,466	17.40%
1B +	7	12,653,370	48.56%
Total	**37**	**26,054,793**	**100%**

Year

The Year variable consists of the year in which the listing date was for the corresponding companies IPO. The listing date was chosen above the announcement date, because this paper does not focus on the pre-IPO period and thus the listing date will be more relevant, although only one IPO in the dataset has a different announcement year and listing year. The listing dates have been gathered from Bloomberg.

Table 7: Descriptive table Year	
Observations	37
Mean	2013.946
Standard Deviation	5.3278
Median	2015
Minimum	2004
Maximum	2021
Skewness	-.5583
Kurtosis	2.0462

Table 8: IPO frequency

Year	**Number of IPOs**	**%**
2004	1	3
2005	2	5
2006	4	11
2007	2	5
2009	1	3
2012	1	3
2014	2	5
2015	7	19
2016	5	14
2017	2	5
2018	4	11
2020	2	5
2021	4	11
Total	**37**	**100**

Greenshoe facility

The Greenshoe facility variable consists of the greenshoe option that an IPO has, which allows the issuing company to sell more shares at the offering price than they initially intended to sell. The data regarding the greenshoe facility has been collected from Bloomberg. The data provided by Bloomberg regarding the Greenshoe facility is measured in million euros.

Table 9: Descriptive table Greenshoe facility	
Observations	34
Mean	4.6794

Standard Deviation	5.2475
Median	3.325
Minimum	.14
Maximum	28.2
Skewness	2.8137
Kurtosis	12.9290

Index volatility

The Index volatility variable measures the volatility of the daily returns of the AEX over 100 days before the listing date of an IPO. This data has been gathered on Yahoo Finance and has been selected to only include data at relevant IPO listing dates.

Table 10: Descriptive table Index volatility	
Observations	37
Mean	.0005
Standard Deviation	.0005
Median	.0003
Minimum (%)	.0002
Maximum (%)	.0021
Skewness	1.7321
Kurtosis	5.7726

Age

The Age variable consists of the number of years a firm has existed when they issued an IPO. This data has been gathered from Bloomberg.

Table 11: Descriptive table Age	
Observations	37
Mean	31.5405
Standard Deviation	42.7717
Median	16
Minimum	0
Maximum	202
Skewness	2.6156
Kurtosis	9.9159

Hot issue market

The Hot issue market variable is a dummy variable that takes 1 as value when the number of IPOs in a year is higher than average. This happens in the years 2006, 2015, 2016, 2018 and 2021. This data has been gathered from Bloomberg.

Table 12: Descriptive table Hot issue market	
Observations	37
Mean	.6486
Standard Deviation	.4840
Median	1
Minimum	0
Maximum	1
Skewness	-.6228
Kurtosis	1.3878

Crisis

The Crisis variable is a dummy variable that takes 1 as value if an IPO was issued in the years 2007, 2008, 2009 and 2020. It takes 0 as value for all other years. This data has been gathered from Bloomberg.

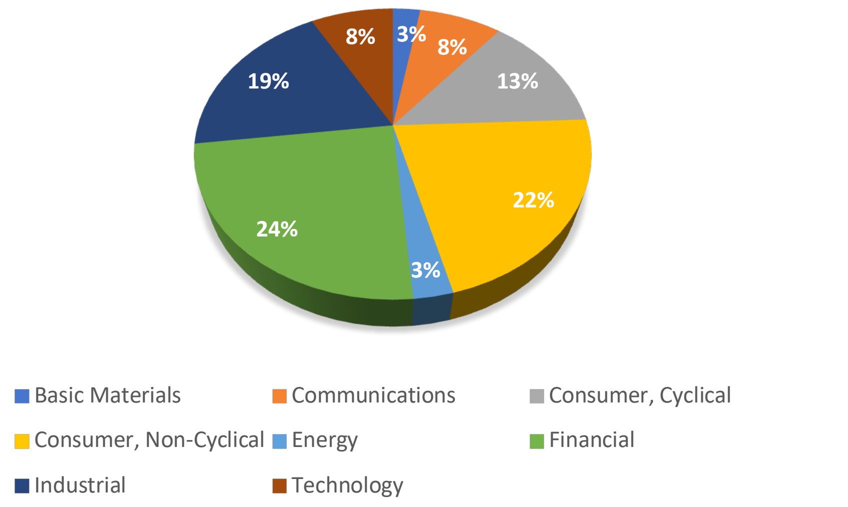
Table 13: Descriptive table Crisis	
Observations	37
Mean	.1351
Standard Deviation	.3466
Median	0
Minimum	0
Maximum	1
Skewness	2.1345
Kurtosis	5.5563

Financial Industry

All the IPOs are categorised in eight different industries: Basic Materials, Communications, Consumer cyclical, Consumer non-cyclical, Energy, Financial, Industrial and Technology. These categories and in which category a company belongs have been gathered from Bloomberg by adding industries to the deal overview.

Table 14: Industry frequency		
Industry	**Number of IPOs**	**%**
Basic Materials	1	3
Communications	3	8
Consumer, cyclical	5	14
Consumer, non-cyclical	8	22
Energy	1	3
Financial	9	24
Industrial	7	19
Technology	3	8
Total	**37**	**100**

Figure 3: Industry frequency



Dell'Aqua et al. (2015) incorporated the respective industry in their regression analysis by using a dummy variable which takes 1 as value when the issuing company belongs to the financial industry and 0 for all other industries. Therefore, I choose to replicate this dummy variable as used by Dell'Aqua et al. (2015).

3.2 Data validity

To make sure this data can be correctly used and interpreted I will perform several tests to check the data validity.

Heteroskedasticity

Firstly, to check for heteroskedasticity I performed the White test and the Breusch-Pagan test, which concluded that my data is heteroskedasticity. Therefore, I will be using robust standard errors when estimating the standard errors in the regression analysis.

Multicollinearity

By using the vif command in Stata to check for multicollinearity I will be able to control for potential multicollinearity issues, if the VIF value is greater than ten there could be a potential problem with the multicollinearity of that variable. After examining the VIF values I can conclude that there is no multicollinearity in the data.

Table 15: Highest VIF value across models

Variable	VIF
RIR	1.18
MAIR	1.21

EPU index	1.79
Offer size	5.13
Year	1.34
Greenshoe facility	6.83
Index volatility	1.25
Age	1.34
Hot issue market	2.00
Crisis	1.36
Financial industry	1.80
Mean VIF	2.29

Normality of residuals

I performed the Shapiro-Wilk test on the residuals of my regressions and found a p-value of .6309 for my first regression analysis (model 1,2,3 and 4), thus I cannot reject the null hypothesis, which means that the residuals are normally distributed. However, when performing this same test on models 5,6,7 and 8 I found a p-value of .0002, thus I can reject the null hypothesis, which means that the residuals are not normally distributed. Therefore, I will transform some variables to make the residuals more normally distributed. I transformed the variables Offer size, Age and Greenshoe facility into ln(Offer size), ln(1 + Age) and ln(Greenshoe facility) by calculating the natural logarithm of these variables. I used (1+Age) because if this variable contains a 0 as a value and this natural logarithm does not exist. I also transformed the degree of underpricing (RIR and MAIR) and the EPU index, however in my dataset these variables also consist of negative values. When confronted with this problem, Ratkowsky (1990) suggests transforming the data by taking the cubic root for all values in this variable. Therefore, I transformed the degree of underpricing and the EPU index into Cr(RIR), Cr(MAIR) and Cr(EPU index) by calculating the cubic root. After performing the Shapiro-Wilk on my regression with these transformed variables it resulted in a p-value of .8029, which means the residuals are now normally distributed.

CHAPTER 4 Method

To test hypothesis 1, "The higher the degree of underpricing, the more severe aftermarket underperformance is measured by the BHARs 30 days after the IPO", I will perform a multiple regression model based on the proposed model by Dell'Acqua et al. (2016):

$Aftermarket\ performance_i$ = β0 + β1 * $Degree\ of\ underpricing_i$ + β2 * $Offer\ size_i$ + β3 * $Year_{i_i}$ + β4 * Greenshoe facility + β5 * $Index\ volatility_i$ + β6 * Age + β7 * $Hot\ issue\ market_i$ + β8 * $Crisis_i$ + β9 * $Financial\ Industry_i$ + ε_i

with Aftermarket performance as the dependent variable, the Degree of underpricing as the independent variable and Offer size, Industry and Year as control variables. β0 represents the constant term, while β1, β2, β3 and β4 represent the coefficients belonging to the respective variables. ε represents the error term and i the different companies. By doing so I will be able to estimate the coefficient of the degree of underpricing variable. If β1 is larger than 1 and statistically significant, it indicates that higher degrees of underpricing are associated with higher returns in the aftermarket, suggesting that underpricing may be an effective strategy for generating positive aftermarket performance and vice versa**.**

To test hypothesis 2, "The higher the Dutch EPU index score for the corresponding year, the more severe the degree of underpricing will be", I will perform a hierarchical linear model based on the proposed model by Boulton (2022):

$Degree\ of\ underpricing_i$ = β0 + β1 * $EPU\ index_i$ + β2 * $Offer\ size_i$ + β3 * $Year_{i_i}$ + β4 * Greenshoe facility + β5 * $Index\ volatility_i$ + β6 * Age + β7 * $Hot\ issue\ market_i$ + β8 * $Crisis_i$ + β9 * $Financial\ Industry_i$ + ε_i

with the Degree of underpricing as the dependent variable, the EPU index as the independent variable and Offer size, Industry and Year as control variables. "β0" represents the constant term, while β1, β2, β3 and β4 represent the coefficients belonging to the respective variables. ε represents the error term and i the different companies. By doing so I will be able to estimate the coefficient of EPU index variable. If β1 is larger than 1 and statistically significant, it indicates that a higher score on the EPU index is associated with a higher degree of underpricing, suggesting that economic policy uncertainty has a positive relationship with the degree of underpricing for IPOs in the Netherlands.

CHAPTER 5 Results & Discussion

5.1 IPO underpricing analysis

The sample has a mean raw underpricing of 4.14% and a mean adjusted underpricing of 3.94%. This is lower than Dell'Acqua et al. (2015) found on the Italian stock exchange. In their paper they found that the mean raw underpricing was 5.62% and a mean adjusted underpricing of 5.75%. In their paper they noted that the results were not homogeneously distributed over time. However, the Netherlands has a broader range with a minimum for raw underpricing of -48.50% and a maximum of 89.58%, while Italy has a range of -20% to 67.57%. This also applies to the adjusted underpricing and the difference is even bigger with the adjusted underpricing of the Netherlands ranging from -48.75% to 89.75% and Italy ranging from -14.90% to 66.41%.

Table 16: IPOs mean initial return by listing year

Year	Number of IPOs	RIR			MAIR		
		Mean(%)	Positive	Negative	Mean(%)	Positive	Negative
2004	1	-1.81	0	1	-1.23	0	1
2005	2	4.35	2	0	4.29	2	0
2006	4	1.26	3	1	1.40	2	2
2007	2	11.46	2	0	11.50	2	0
2009	1	-3.19	0	1	-4.09	0	1
2012	1	14.86	1	0	14.48	1	0
2014	2	6.41	2	0	6.46	2	0
2015	7	2.78	4	3	3.12	5	2
2016	5	3.15	4	1	1.85	2	3
2017	2	3.10	2	0	3.17	2	0
2018	4	9.55	2	2	8.47	1	3
2020	2	8.09	2	0	7.11	2	0
2021	4	-.43	3	1	.21	2	2
Total	37	4.14	27	10	3.94	23	14

Although the paper by Dell'Aqua et al. (2015) has a time frame up until 2012, the Netherlands has less IPOs in every listing year compared to Italy. With 2007 as exception, Italy has a higher degree of underpricing in every listing year. It also has a notably more positive ratio than the Netherlands.

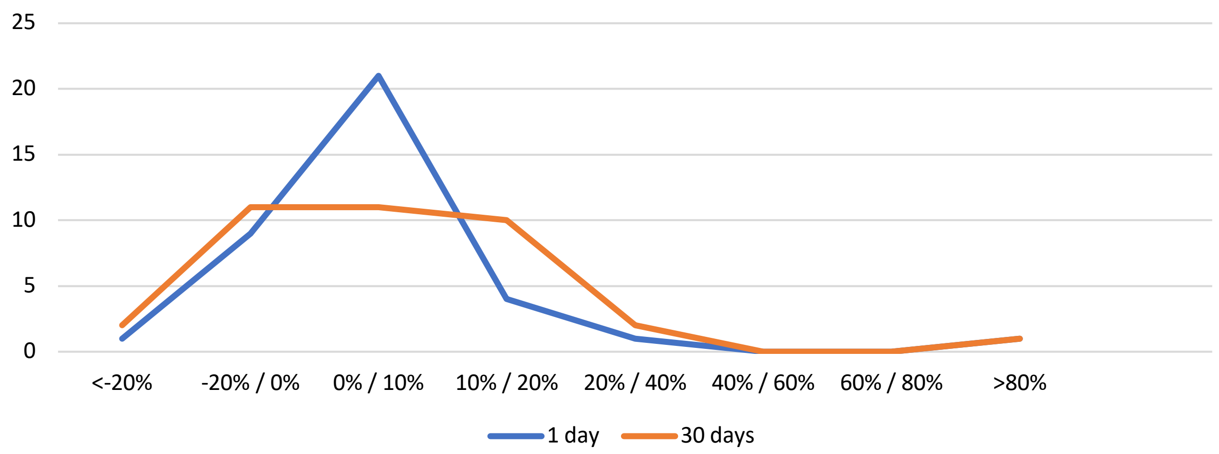
Table 17: Distribution and statistics of raw and adjusted underpricing

Distribution	RIR		MAIR	
	Number of IPOs	%	Number of IPOs	%
Less than 0	10	27.03	14	37.84
0 – 4.99	17	45.95	13	35.14
5 – 9.99	4	10.81	4	10.81
10 – 19.99	4	10.81	4	10.81

20 – 29.99	1	2.70	1	2.70
30 – 49.99	0	0	0	0
Over 50	1	2.70	1	2.70
Total	37	100	37	100

It is notable that by calculating the raw degree of underpricing most IPOs fall in the 0-4.99 range, while calculating the adjusted degree of underpricing most IPOs fall in the less than zero range. In the paper by Dell'Aqcua et al. (2015) most IPOs fall in the less than zero range when calculating the raw as well as the adjusted degree of underpricing.

Figure 4: Performance of IPOs on the listing day and on the 30th day after listing



The figure above shows a very similar performance of IPOs on the listing day and on the 30th day after listing when comparing it to the performance of the Italian IPOs. However, it is interesting to note that in my dataset 5 IPOs (13.51%) have a positive first day return, but a negative 30th day return. This is very close to Italy where this occurred in 19.37% of the IPOs.

5.2 IPO underpricing and aftermarket performance regression

The following model was estimated using Ordinary Least Squares, with the aftermarket performance as the dependent variable and the degree of underpricing as the main variable of interest.

Table 18: Regression results with aftermarket performance as dependent variable

Explanatory variables	Aftermarket performance as dependent variable			
	Model 1	**Model 2**	**Model 3**	**Model 4**
Degree of underpricing				
RIR	1.4497*** (.0950)		1.5631*** (.1000)	
MAIR		1.4364*** (.0936)		1.5593*** (.0125)

Offer size			.0000 (.0000)	.0000 (.0000)
Year			-.0009 (.0032)	-.0007 (.0033)
Greenshoe facility			-.0012 (.0063)	.0002 (.0065)
Index volatility			-70.7387*** (29.9448)	-51.8415* (31.0068)
Age			.0008** (.0004)	.0009** (.0004)
Hot issue market			.0956* (.0418)	.0954* (.0428)
Crisis			.0182 (.0523)	.0265 (.05357)
Financial Industry			-.0369 (.0440)	-.0436 (.0451)
Constant	.0049 (.0170)	.0084 (.1689)	1.7570 (6.5084)	1.2500 (6.6636)
Observations	37	37	37	37
F value	232.99	235.49	34.59	32.83
R-squared	.8694	.8706	.9284	.9249
Adjusted R-squared	.8657	.8669	.9016	.8967

Note: *OLS regression with Robust standard errors. Standard deviations are in parenthesis. Asterisks ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level respectively.*

With the results of these models, I do not accept my first hypotheses that the higher the degree of underpricing, the more severe aftermarket underperformance is measured by the BHARs 30 days after the IPO. My results indicate a significant positive effect, which means a higher degree of underpricing leads to better aftermarket performance.

In model 1 our main variable of interest, the degree of underpricing (RIR), has a p-value smaller than .01, thus it is statistically significant at the 1% level. It has a positive effect of 1.4497, which means that if the degree of underpricing increases by 1, the aftermarket performance (BHAR) increases by 1.4497. In model 2 the degree of underpricing (MAIR) is also statistically significant at the 1% level and has a positive effect of 1.4363, which means that if the degree of underpricing increases by 1, the aftermarket performance (BHAR) increases by 1.4363. The constant in both models 1 and 2 have a p-value over 0.1, thus we cannot conclude anything meaningful over the constants in these models.

In model 3 the variables Offer size, Year, Greenshoe facility, Crisis and Financial industry have a p-value over 0.1, thus we cannot conclude anything meaningful over these variables. The degree of underpricing (RIR) has a p-value smaller than .01, thus it is statistically significant at the 1% level. It has a positive effect of 1.5631, which means that if the degree of underpricing increases by 1, the aftermarket performance (BHAR) increases by 1.5631. The Index volatility, Age and Hot issue market variables have a p-value smaller than .05, thus they are statistically significant at the 5% level. Index volatility has a negative effect of 70.7387, which means that if the Index volatility increases by 1, the aftermarket performance decreases by 70.7387. Age has a positive effect of .0008, which means that if Age increases by 1, the aftermarket performance increases by .0008. Hot issue market has a positive effect of .0956, which means that if the dummy variable takes 1 as value the aftermarket performance increases by .0956. In model 4 the variables Offer size, Year, Greenshoe facility, Index volatility, Crisis and Financial industry have a p-value over 0.1, thus we cannot conclude anything meaningful over these variables. The degree of underpricing (MAIR) has a p-value smaller than .01, thus it is statistically significant at the 1% level. It has a positive effect of 1.5593, which means that if the degree of underpricing increases by 1, the aftermarket performance (BHAR) increases by 1.5593. Variables Age and Hot issue market have a p-value smaller than .05, thus they are statistically significant at the 5% level. Age has a positive effect of .0009, which means that if Age increases by 1, the aftermarket performance increases by .0009. Hot issue market has a positive effect of .0954, which means that if the dummy variable takes 1 as value the aftermarket performance increases by .0954. The constant in both models 3 and 4 have a p-value over 0.1, thus we cannot conclude anything meaningful over the constants in these models.

All four models have high adjusted R-squared values ranging from .8657 (model 1) to .9016 (model 3), which indicates on average 90% of the output is explained by the input variables of these models. When removing the variable of interest and relevant control variables in models 3 and 4 the R-squared value drops to around .1000.

5.3 Policy uncertainty and IPO underpricing regression

The following model was estimated using Ordinary Least Squares, with the transformed degree of underpricing as the dependent variable and the transformed EPU index as the main variable of interest.

Table 19: Regression results with the degree of underpricing as dependent variable				
Explanatory variables	Cr(RIR) as dependent variable		Cr(MAIR) as dependent variable	
	Model 4	**Model 6**	**Model 6**	**Model 7**
Cr(EPU index)	.1953 (.2643)	-.2098* (.1201)	.1850 (.2724)	-.2614* (.1328)
Ln(Offer size)		.3135*** (.0500)		.3316*** (.0558)
Year		.0001 (.0110)		-.0033 (.0126)
Ln(Greenshoe facility)		.0993* (.0503)		.1040* (.0499)
Index volatility		-170.876 (115.0075)		-235.6078** (88.8139)
Ln(1 + Age)		-.0681* (.0331)		-.1907* (.0409)
Hot issue market		-.0784 (.1215)		-.1147 (.1236)

Crisis		-.1980** (.0843)		-.1907* (.0942)
Financial industry		-.1273 (.1424)		-.1016 (.1580)
Constant	-.6931 (1.1764)	.2315 (21.8405)	-.6704 (1.2147)	7.4372 (24.9208)
Observations	33	29	33	29
F value	.55	16.61	.46	13.04
R-squared	.0181	.6794	.0143	.6847
Adjusted R-squared	-.0136	.5276	-.0175	.5353

Note: *OLS regression with robust standard errors. Standard deviations are in parenthesis. Asterisks ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level respectively.*

With the results of these models, I do not accept my second hypotheses that the higher the Dutch EPU index score for the corresponding year, the more severe the degree of underpricing will be. In models 5 and 7 the policy uncertainty index is statistically significant at the 10% level and has a negative effect, which suggests that a higher score in the Dutch EPU index leads to a lesser degree of underpricing.

In model 4 our main variable of interest, the policy uncertainty index (Cr(PU index), has a p-value bigger than .10, thus we cannot conclude anything meaningful over this variable. However, it can be worth noting that it is not statistically significant against my expectations. In model 5 the policy uncertainty index does have a p-value smaller than 0.1, thus it is statistically significant at the 10% level. It has a negative effect of .2098, which means that when Cr(EPU index) increases with 1%, the degree of underpricing (Cr(RIR)) increases by .2098%. The variables year, index volatility, hot issue market and financial industry have a p-value over 0.1, thus we cannot conclude anything meaningful over these variables. Ln(Offer size) is significant at the 1% level and has a positive effect of .3135. Thus, when Ln(Offer size) increases with 1%, the degree of underpricing (Cr(RIR) increases by .3135%. Ln(Greenshoe facility) is significant at the 10% level and has a positive effect of .0993. Thus, when Ln(Greenshoe facility) increases with 1%, the degree of underpricing (Cr(RIR) increases by .0993%. Ln(Age) is significant at the 10% level and has a negative effect of .0681. Thus, when Ln(Age) increases with 1%, the degree of underpricing (Cr(RIR) increases by .0681%. The crisis dummy variable is significant at the 5% level and has a negative effect of .1980. Thus, when the dummy variable takes 1 as value it decreases Cr(RIR) by exp(-.1980) or .8204%. The constant in both models 4 and 5 have a p-value over 0.1, thus we cannot conclude anything meaningful over the constants in these models.

In model 6 our main variable of interest, the policy uncertainty index (Cr(PU index), has a p-value bigger than .10, thus we cannot conclude anything meaningful over this variable. However, it can be worth noting that it is not statistically significant against my expectations. In model 7 the policy uncertainty index does have a p-value smaller than 0.1, thus it is statistically significant at the 10% level. It has a negative effect of .2614, which means that when Cr(EPU index) increases with 1%, the degree of underpricing (Cr(MAIR)) increases by 0.2614%. The variables year, hot issue market and financial industry have a p-value over 0.1, thus we cannot conclude anything meaningful over these variables. Ln(Offer size) is significant at the 1% level and has a positive effect of .3316. Thus, when Ln(Offer size) increases with 1%, the degree of underpricing (Cr(MAIR) increases by .3316%. Ln(Greenshoe facility) is significant at the 10% level and has a positive effect of .1040. Thus, when Ln(Greenshoe facility) increases with 1%, the degree of underpricing (Cr(MAIR) increases by .1040%. Ln(Age) is significant at the 10% level and has a negative effect of .1907. Thus, when Ln(Age) increases with 1%, the degree of underpricing (Cr(MAIR) increases by .1907%. The index volatility variable is significant at the 5% level and has a positive effect of -235.6078. Thus, when the Index volatility variable increases with 1 the degree of underpricing (CR(MAIR) decreases by exp(-235.6078) or .0000%. The crisis dummy variable is significant at the 10% level and has a negative effect of .1907. Thus, when the dummy variable takes 1 as value it decreases Cr(MAIR) by exp(-.1907) or .8264%. The constant in both models 6 and 7 have a p-value over 0.1, thus we cannot conclude anything meaningful over the constants in these models.

Models 4 and 6 have very low adjusted R-squared values, indicating that the output is not very well explained by the input variables in these models. However, after adding more variables the adjusted R-squared values of models 5 and 7 increase significantly (.5276) and (.5353).

5.4 Robustness check

To check the robustness of my results I performed the Ramsey Reset test to find if my regression analysis is suffering from omitted variables and thus if I should use a linear or non-linear test. The test has a p-value of .2104, thus we cannot reject the Ramsey Reset null hypothesis. This means that the model used does not suffer from misspecification.

To check the robustness of my results I will perform an adjusted regression analysis with transformed variables of the significant variables. I have winsorized the Degree of underpricing, Aftermarket performance, Index volatility and EPU index variables at 1% and transformed them into Win(RIR), Win(MAIR), Win(Aftermarket performance), Win(Index volatility) and Win(EPU index). I have also enlarged all ages by 1 and then taken the natural logarithm of the age variable to transform it into Ln(1 + Age).

In the robustness check for models 1,2,3 and 4 the degree of underpricing (RIR and MAIR) remains significant at the 1% level and has a positive coefficient of 1.0750 in model 3 and 1.1060 in model 4. I have done the same robustness check for models 5,6,7 and 8. The policy uncertainty variable (Win(EPU index)) remains significant at the 1% level and has a negative coefficient of .0006 in model 5 and .0007 in model 7. These regression analyses can be found in Appendix A and indicate that my results remain robust.

5.5 Discussion

My results show that the degree of underpricing (RIR and MAIR) does have a significant impact on the aftermarket performance (30 days BHAR). However, the impact it has is positive, which means that a higher degree of underpricing will lead to better aftermarket performance. This is in contrary to a previous paper by Ritter (1991) who concludes high IPO underpricing would lead to underperformance in the long term. Later Loughran and Ritter (1995) suggest that underperformance seen in IPOs over the long run is a result of the mispricing during the IPO stage. These studies offer evidence that there is a negative link between IPO underpricing and aftermarket performance over the long term. This led to my first hypothesis in which I expected the aftermarket underperformance to be more severe when the degree of underpricing is higher. However, I do not accept this hypothesis, because my results do not support this.

In his paper Ritter (1991) stated that Hot issue markets are windows of opportunity that firms tend to take advantage of. Dell'Aqua et al. (2015) performed a regression analysis with aftermarket performance as the dependent variable and found a Hot issue market as a dummy variable to have a significant positive effect. I found similar results in my regression analysis that concludes that issuing in a hot issue market has a significant positive effect on the aftermarket performance. In my results I also found that the index volatility had a significant impact on the aftermarket performance when the degree of underpricing was calculated using the raw initial return (RIR), this is congruent with the results Dell'Acqua et al. (2015) found, however my results indicate a negative impact while the regression analysis in their paper indicates a positive impact.

In this same regression analysis Dell'Aqua et al. (2015) also found age to have significant impact on the aftermarket performance, although 2 of their models gave conflicting results whether this impact is positive or negative. In my results I also found that age has a significant positive result, however the effect it has is very small.

My results show that the policy uncertainty index (Cr(EPU index) has a significant effect at the 10% level. The impact it has is negative, which means that a higher score on the Dutch EPU index will lead to a lesser degree of underpricing. This is in contrary to what was found in literature about policy uncertainty and its relationship with the degree of underpricing (Baker et al, 2016; Boulton, 2022). However, in his paper Boulton (2002) posits that the relationship between the EPU index and the degree of underpricing is sensitive to the characteristics of the respective country. I have used the same policy uncertainty index for the Netherlands by Kroese et al. (2015) as was used in the paper by Boulton. The Netherlands has a lot of the characteristics that affect the relationship between these two, for example Boulton suggests that countries with accounting disclosures of higher quality reduces the effect policy uncertainty has as well as good governance by the respective country. These characteristics apply to the Netherlands, and its results on the relationship between policy uncertainty and the degree of underpricing is shown in my regression analysis.

CHAPTER 6 Conclusion

In this thesis I have looked at the relationship between IPO underpricing and aftermarket performance. By firstly comparing the IPO underpricing phenomenon with the results of a paper by Dell'Aqua et al. (2015) I was able to compare IPO underpricing in the Netherlands with IPO underpricing in Italy. I concluded that the Netherlands has a slightly higher raw degree of underpricing as well as adjusted degree of underpricing.

Previous studies (Ritter, 1991; Loughran and Ritter, 1995) have offered evidence that there is a negative link between IPO underpricing and aftermarket performance over the long term. To my knowledge this relationship had not been studied earlier in the Netherlands over a 20-year period from 2002 until 2022. Therefore, my research question was: "How does IPO underpricing affect aftermarket performance in the Netherlands?". To answer this question, I gathered data on IPOs from AFM, Euronext, Bloomberg and the respective prospectuses. After conducting a regression analysis, I found that the degree of underpricing has a significant positive effect on the aftermarket performance. This suggests that a higher degree of underpricing will improve the aftermarket performance on the secondary market. Therefore, I reject my first hypothesis in which I expected the higher the degree of underpricing, the more severe aftermarket underperformance would be measured by the BHARs 30 days after the IPO.

This has implications for firms that want to go public in the Netherlands and their respective underwriters. Leaving more money on the table initially leads to a higher aftermarket performance on the secondary market measured at 30 days. The setting of the initial price are decisions a firm and underwriter are confronted with when going public and a clearer insight into the relationship between IPO underpricing and aftermarket performance may help them make a more informed decision.

In this thesis I also looked at the relationship between policy uncertainty and the degree of underpricing. Previous literature suggests that there is a positive link between higher policy uncertainty and the degree of underpricing (Baker et al, 2016; Boulton, 2022). To answer this, I used the EPU index for the Netherlands by Kroese et al. (2015). I found that the EPU index has a significant negative effect on the degree of underpricing in the Netherlands. Therefore, I reject my second hypothesis in which I expected the higher the Dutch EPU index score for the corresponding year, the more severe the degree of underpricing would be.

Earlier Boulton (2022) already posits that the characteristics of a country can impact the relationship between policy uncertainty and the degree of underpricing. The Netherlands possesses characteristics such as accounting disclosures of higher quality and good governance which has reduces the impact of policy uncertainty on the degree of underpricing. It would be interesting to further research these topics and compare countries individually with each other to get a better understanding of the relationship between policy uncertainty and the degree of underpricing.

The main research question of this thesis is: “How does IPO underpricing affect aftermarket performance in the Netherlands?”. To provide an answer to this question, I can look at my results and conclude that IPO underpricing has a significant positive effect on the aftermarket performance of an IPO in the Netherlands. This means that a higher degree of underpricing leads to a better aftermarket performance.

6.1 Limitations

In this paper I studied IPOs in the Netherlands in a time frame of 2004 until 2021. After cleaning up the dataset and removing unusable IPOs, that for example never went to the trading stage, I was left with 37 usable IPOs. I would have liked to use more observations, but due to the scope of my paper these do not exist. Nonetheless, I found it very interesting to study the IPO dynamics in a specific country and would encourage others to do so as well.

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APPENDIX A Robustness check regression analyses

Table 20: Robustness check with aftermarket performance as dependent variable				
Explanatory variables	**Win(Aftermarket performance) as dependent variable**			
	Model 1	**Model 2**	**Model 3**	**Model 4**
Degree of underpricing				
Win(RIR)	.9578*** (.1638)		1.1046*** (.2358)	
Win(MAIR)		.9251*** (.1591)		1.0962*** (.2529)
Win(Index volatility)			-51.2201 (38.9178)	-43.8454 (34.4481)
Ln(1+Age)			.01838 (.0117)	.0213* (.0118)
Hot issue market			.01972 (.0237)	.0177 (.0261)
Constant	.0096 (.0153)	.0116 (.0149)	-.03921 (.04852)	-.0479 (.0478)
Observations	37	37	37	37
F value	34.21	33.81	12.79	6.62
R-squared	.3218	.3463	.4242	.4526
Adjusted R-squared	.3024	.3276	.3522	.3842

Note: *OLS regression with robust standard errors. Standard deviations are in parenthesis. Asterisks ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level respectively.*

Table 21: Robustness check with the degree of underpricing as dependent variable				
Explanatory variables	**Win(RIR) as dependent variable**		**Win(MAIR) as dependent variable**	
	Model 4	**Model 6**	**Model 6**	**Model 7**
Win(EPU index)	.0007 (.0006)	-.0006* (.0003)	.0007 (.0007)	-.0007* (.0004)
Ln(Offer size)		.0457*** (.0071)		.0477*** (.0081)
Win(Greenshoe facility)		.0003 (.0017)		.0000 (.0020)
Ln(1 + Age)		-.0188*** (.0056)		-.0209*** (.0060)
Crisis		-.0011 (.0227)		-.0042* (.0245)
Constant	-.0240 (.0513)	-.0965** (.0449)	-.0212 (.0552)	-.0954* (.0486)
Observations	33	33	33	33
F value	1.29	18.17	.96	16.17
R-squared	.0703	.6096	.0501	.5654
Adjusted R-squared	.0403	.5373	.0194	.4849

Note: *OLS regression with robust standard errors. Standard deviations are in parenthesis. Asterisks ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level respectively.*