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Navn:	Erlend Strømsnes og Ambar Roy

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Master Thesis

Comparative study of short-run IPO performance in a selection of Euronext countries

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Abstract

This thesis investigates the relevance of prevalent underpricing theories on 175 IPOs occurring between 2014-2021 in the Euronext countries of Belgium, France, and the Netherlands. Across all Euronext IPOs, we observe an average underpricing of 3% adjusted for industry movements. By examining each country separately, we discover that IPOs in the Netherlands are underpriced by 5.1%, followed by 2.5% in France, and 2.3% in Belgium.

The Euronext sample provides mixed support for the winner's curse theory, as we find that using a reputable underwriter significantly reduces underpricing, while a larger offer size is associated with significantly higher underpricing. Moreover, the results contradict the hot issue market theory and investor sentiment theory, while finding no significance for either the grandstanding theory or quality/price trade-off theory. Lastly, when repeating the analysis on a country-specific basis, we find that the underpricing theories' explanatory power varies significantly among the Euronext countries.

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We would like to thank our supervisor, Siv Staubo, for helpful guidance, support and feedback throughout the process. Her contribution has been highly appreciated. Furthermore, we would like to extend our thanks to the librarians at BI Norwegian Business School for providing us access to the data and other valuable sources of information. Finally, we would like to thank our family and friends for their continuous support and encouragement.

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1. Introduction

In the first part, we provide the background and motivation of our thesis, which will be followed by formulating the research question. Subsequently, we introduce limitations which set the scope of our thesis. Lastly, the structure of the thesis is presented.

1.1 Background and Motivation

When we were in the process of selecting a topic for our thesis, we asked for a meeting with our supervisor and quickly landed on initial public offering (IPO) as the topic. Since both of us had chosen the corporate finance track, we had already been formally introduced to IPOs and the underpricing phenomenon during our finance courses. This caught our interest and provided us with the motivation to explore the underpricing topic beyond what was covered due to our studies.

Ever since the IPO underpricing phenomenon was first observed by Reilly and Hatfield (1969) in the US market, numerous finance scholars have extended Reilly and Hatfield’s research to the rest of the world, confirming that IPO underpricing is a global phenomenon. IPO underpricing is a direct violation of the efficient market hypothesis, which states that there should be no possibility of earning abnormal returns in a perfectly competitive capital market. Underpricing leads to a significant transfer of wealth from the issuing firm to the investors who are allocated IPO shares, and ultimately results in the issuing firm raising less money to invest back into the company. The fact that issuers are willing to bear this cost has puzzled researchers for decades which has led to extensive research and a vast literature on the subject.

Many of the existing theories have received empirical support and seem to explain underpricing to some extent, but the explanatory power varies significantly across countries, data sets and time periods. Most of the empirical research has been conducted on US stock exchanges on data from 1970 to early 2000s; however empirical research has been building up in other countries rather than the US over the last 15 years.

This study aims to investigate whether the most popular underpricing theories help explain underpricing on IPOs occurring in the Euronext countries of Belgium, France, and the Netherlands between 2014-2021. Initially, we were going to study the Oslo Stock Exchange as we have previous knowledge about the market. However, Euronext's acquisition of Oslo Stock Exchange in 2019 (NTB, 2019) received a lot of media attention in the Norwegian newspapers, which made us curious and eager to learn more about the other stock exchanges owned by Euronext. Additionally, the countries coordinate fiscal and economic policies, share institutional framework, and have common listing rules. After the financial crisis there have been few empirical research papers on European stock exchanges. This puts us in an interesting position to investigate the underpricing phenomenon on a unique and updated data set to analyze how the traditional IPO theories perform in modern times.

1.2 Research Question

As previously mentioned, many of the IPO underpricing theories have received empirical support in the US market. However, we want to investigate whether these theories help explain the level of underpricing in Belgium, France, and the Netherlands. As the size of their populations and economies differs, we will be able to investigate whether smaller countries share underpricing determinants with a large country. First, we will consider the total sample as the sum of all countries combined, which will be simply referred to as "Euronext" from now on. Subsequently, each country will be investigated separately to assess whether there are different explanations for underpricing among the countries. Based on the abovementioned, we form the following research questions:

1. *Do IPOs on Euronext experience a significant level of underpricing?*
2. *Can a selection of existing and popular theories help explain the level of underpricing on Euronext?*
3. *Do the selected theories provide the same explanatory power across the countries?*

The research questions will be answered through the creation of 8 different hypotheses related to theories introduced in chapter 3, while the hypotheses development process will be covered in chapter 4.

1.3 Limitations

Due to time constraints and data availability, it is necessary to set certain limitations to reduce the scope of our thesis.

Firstly, we have limited the time period to only include firms that were listed between 1.1.2014 – 31.12.2021. We believe a time frame of 8 years should be sufficient to capture different market cycles while also being a relevant time frame to provide new and updated data to test underpricing theories.

Secondly, we only included stock exchanges that were a part of Euronext during the entirety of our time frame. This led us to exclude Dublin and Oslo, as they were acquired by Euronext in 2018 and 2019, respectively. Moreover, as we intend to look at differences among the countries, we omitted Lisbon due to its small size and low IPO volume.

Thirdly, due to the large amount of available underpricing theories, it has been essential to limit theories we include in our thesis. Some have been excluded due to availability of data, and others as they have received weak empirical support among researchers. Hence, we only include theories that our data allows, while also having received strong empirical support in other developed countries.

Lastly, our thesis only considers first-day returns. Although subsequent long-run performance is another interesting and extensively researched field, it is not within the scope of our thesis.

1.4 Thesis Structure

This thesis is organized in 8 chapters (including this chapter). Chapter 2 presents information about the IPO process, empirical underpricing findings, and a short description of Euronext. Chapter 3 reviews the classical IPO underpricing literature. Chapter 4 will provide a description and theoretical reasoning for our hypotheses. In chapter 5 we will clarify our methodology, including the construction of regression variables, regression models, and explanatory variable sign prediction. Chapter 6 will describe the data gathering process. Chapter 7 starts by providing descriptive statistics. This will be followed by regression results, and a discussion of its validity considering econometrical tests. Lastly, we will discuss the results implications for the hypotheses. Chapter 8 consists of a conclusion of our thesis results, some limitations, and suggestions for future research.

2.0 Background and Literature review

In this part we will provide information about initial public offerings (IPO), including why companies go public, the players involved, the main IPO process, and the Euronext market. Lastly, we will describe the underpricing phenomenon and literature connected to the topics.

2.1 Initial Public offering

An initial public offering is the process of offering stocks to the public for the first time. This process converts a privately held company into a public company. The main reason to complete an IPO is to raise the necessary capital to finance projects, investment opportunities, or grow and expand the company. There are generally two types of stock offerings: a primary offering, where new stocks are issued and sold in the market to raise capital, or secondary offering where some existing shareholders sell some of their shares held today (Brealey et al., 2011). In any case, an IPO will involve a change in the company´s ownership structure, as the previous shareholders would have either sold or diluted by issuing additional shares.

The initial public offering makes the shares accessible to the general public through listing itself on the stock exchange, which is an organized platform where potential buyers and sellers can buy and sell stocks. According to Ritter and Welch (2002) companies only go on the stock exchange after a certain stage in their life cycle. The lifecycle theory says that a company consists of 4 phases throughout their existence. In the start-up phase, firms usually raise financing through the owner's personal funds, or by raising financing through venture capital. In the second phase, also known as the growth phase, firms companies that grow at a quick pace often choose to go public. This gives these firms the opportunity to raise capital, change strategy or expand their company. In future some IPO companies additionally get delisted from the stock exchange due to bankruptcy, buyouts or non-compliance with regulations. Maturity and decline are the two last phases of a company's life cycle.

2.2 The IPO process

The IPO process is quite comprehensive and typically takes six to nine months to complete, from the time underwriters are engaged and until the firm is listed on the stock exchange. In Jenkinson and Ljungqvist (2001) paper they describe the IPO process in five stages and are illustrated in figure 1.

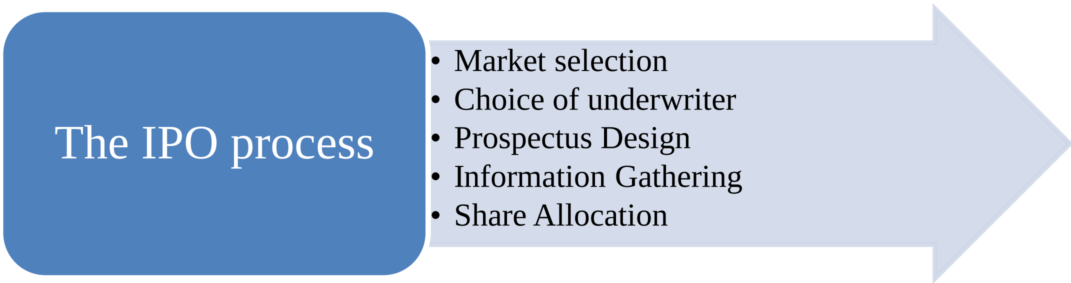


Figure 1: Five stages in the IPO process

The first stage in the IPO process is for the issuing firm to choose the market it wants to go public in. The issuing firm would need to make sure that they meet the requirements and regulations of the selected stock exchange. The issuer will also decide if the company will go public in their home country or is listed abroad on a foreign stock exchange. By listing the shares in a foreign country, it can be desirable if the selected stock exchange offers higher liquidity, more relaxed listing requirements or industry relevance. The last couple of years, the choice of stock exchange has been less limited by the governments.

In the second stage the issuing firm needs to hire one or several underwriters. For large issuers, a group of underwriters are typically hired to advise and underwrite the offering. The underwriters are usually picked based on reputation and expertise in handling offerings, or due to extensive industry knowledge. In cases where there is a group of underwriters, one is picked as the lead underwriter/book-runner and is ultimately the one in charge of making decisions regarding offering price, amount of shares issued, share allocations, pricing technique, and choosing the other underwriters forming the syndicate.

The third stage is when the prospectus is designed, and this is done after the formalities with the underwriter are in order (Jenkinson & Ljungqvist, 2001). The prospectus covers areas such as company and management descriptions, business risk and prospects, comparisons to firms operating in the same industry, and remarks regarding the valuation of the company. Companies are not only obligated to release their prospectus by the stock exchange, but the prospectus will also function as a commercial advertisement for potential future stockholders.

The fourth stage is the information gathering by the underwriter (Jenkinson & Ljungqvist, 2001). The most recognized activity is known as "road shows", where the management of the firm travels across the country to promote the offering to investors (PWC, 2022). The purpose of this is to receive non-binding bids from investors, collect demand information among investors, and gather data on how investors value the issuer, which can help the underwriter on getting a sense of what price range the IPO can end up at. This process is known as "book-building" and is the most used pricing method by issuers on Euronext. Alternatively, issuers can use "fixed price" or auction. In the case of a fixed price offer, the intention of the fourth stage is to receive bids from investors on the quantity of shares they would like to buy at the fixed offering price.

The final stage of the IPO process is share allocation (Jenkinson & Ljungqvist, 2001). Moreover, the offering price is decided, and potential investors decide to subscribe for the IPO. In case of oversubscription, the underwriter generally uses the book-building information to allocate shares to the potential investors. Investors who showed great interest or had the highest non-binding bids are often given the most shares. Another option in this situation is to allocate shares through a lottery. In a lottery, retail investors and institutional investors are allocated shares. Typically, most of the shares goes to the institutional investors. Over-allotment option also known as “greenshoe option” and is another way to deal with oversubscription. This is generally done in the underwriting agreement and grants the underwriter the right to sell more shares than initially planned, if the demand for a security is higher than expected (Smith, 2022).

2.3 Why does the company go public?

There are many reasons to go public. The main reason, as Ritter and Welch (Ritter & Welch, 2002) argue, is to raise capital and the desire to trade in a marketplace. As a result of going public, the company will attract more investors, both nationally and abroad. According to Rajan (2012), due to the informational advantage listed companies can acquire more easily capital from the banks with better terms of loan.

There are further benefits of being traded on the stock market as the stock price could reflect the performance of the firm. By having an available measure of performance, the management can be rewarded with stock options to align the management incentives with those of the owners (Brealey et al., 2011). Being listed on the stock exchange increases transparency as they are required to publish their financial reports. It also increases the protection against hostile takeovers and allows the owner(s) to use the offering as an exit strategy (Brealey et al., 2011).

There are also substantial costs involved in listing a company on the stock exchange. These include administrative costs and fees to the underwriter, which relate to the size of the IPO. The costs cover preparing the registration statement and developing the prospectus. This involves accountants, legal, advisors, and the time of the management. The issuing company is usually obligated to pay a fee when the company goes public (Brealey et al., 2011).

2.4 The players

There are three fundamental parties involved when a company goes through an IPO; the issuing firm, the underwriter and the investor. In this chapther, we will briefly cover the objectives of the parties involved in the offering process.

2.4.1 The issuer

The issuer is the company, or the management of the company, that decides if the company goes on the stock exchange. Their main task is to take decisions for the IPO and to co-operate with an underwriter who enables the sale of the stock to the public and decides the stock price. The issuing firm´s target is to get the highest price possible, without making the offering failing. That is, if the offer price decided by the firm and underwriter is set below the true market price, and the firm will not receive full potential of value of the shares. This is also known as “leaving money on the table” in IPO underpricing literature (Adams et al., 2011).

2.4.2 The underwriter

The underwriter(s) are investment banks that perform the IPO on behalf of the issuer. These are major investment or commercial banks, and their underwriter success is reliant on its financial support and experience (Brealey et al., 2011). The underwriter has one main objective or role which is to buy the shares from the issuer at a discounted price and resell it to the market. This spread will give the margin for the underwriter. The underwriter also has role of getting the issuer through IPO process by assisting them with financial advice, market research, valuation, and assisting on the offer price or price range.

Studies from Chen and Ritter (2000) shows that IPOs tend to have a gross spread of 7% of the total sum of the stocks that are bought, and this is regardless of the IPOs offer size. This implies that the underwriters make more money if the size of the IPO is bigger. In addition, the underwriter has an incentive to set lower prices which will increase the demand for the stock and make sure they will be able to sell all the shares. Contrary to the issuer, the underwriter(s) are repeat parti in this business and if they set low offer prices, they might lose future customers and business.

2.4.3 The investor

The investors play a huge role along with the issuer and underwriter when a company goes public. Several authors within IPO literature differentiate between institutional and retail investors. According to Ljungqvist (2004) institutional investors are generally classified as a financial institution, or a hedge, pension or mutual fund. Retail investors, on the other hand, are known as private investors. According to IPO underpricing literature, both institutional and retail investors share the same objective and incentive, which is to receive as large allocation as possible in underpriced IPOs. As the underwriter is ultimately the one in charge of allocating IPO shares, it is beneficial for investors to have a good relationship with the underwriter (Brealey et al., 2011).

2.5 IPO underpricing

The underpricing phenomenon of new issues was first discovered in the latter part of the 60s by Reilly and Hatfield (1969), and was subsequently confirmed by researchers such as Logue (1973) and Ibbotson (1975) to mention some. Underpricing is defined as the difference between offer price and the share price at the closing price at the day of trading, adjusting for market return between the closing of the issue and listing date (Adams et al., 2011). One of the main reasons why the underpricing phenomenon has received a lot of attention in the economic world is due to the violation or contradicting to the efficient market hypothesis. According to Fama (1970) the efficient market hypothesis is *"A market in which prices always 'fully reflect' available information is called 'efficient'".* What has made researchers perplexed is the phenomenon of why pre-IPO owners sell their stock at significantly lower rates than the true value, which results in great loss of wealth. Though it may seem illogical, many studies on IPOs have revealed a consistent pattern of underpricing on the majority of stock exchanges over several years. There are a large number of empirical evidence related to this topic. In Chambers and Dimson (2009) paper they have presented proof that in Britain, the phenomenon of underpricing has existed since 1917. Previous theories related to the phenomenon were based on asymmetric information among the parties involved in the offering, while newer studies with behavioral theories have gotten support.

2.5.1 Empirical evidence of underpricing

As mentioned above, Reilly and Hatfield (1969) were the first researchers to discover that IPO underpricing exists can be measured by short-run returns. They found an average underpricing of 20.2% on newly listed stocks between 1963 to 1966 at Dow Jones Industrial Average. Several other authors including Logue (1973) and Ibbotson (1975) found large first-day returns on IPO stocks. The results implied that offer prices in U.S. was set lower and causing a significantly price jump after the first-day of trading. Ritter and Welch (2002) provide empirical evidence that average initial IPO returns in U.S. varied from decade to decade. This ranged from 7.4% in the 1980s and peaked at 65% as an average in 1999-2000 before it came back to 14% the year after.

The presence of IPO underpricing in the European stock market has also been documented. Gajewski and Gresse (2006) found an average initial underpricing of 22% in 15 European countries between 1995 and 2004, which is also confirmed by Ljungqvist (2004) on data from 1990 to 2003 that backs similar findings with IPO underpricing in each of the 19 countries. In a paper by Loughran, Ritter and Rydqvist (1994) they sum up the results from several studies that have been conducted in different countries and time periods. The same article from 1994 is updated by Ritter almost every year with new time periods, samples, and average initial returns. In the updated article from March 2022 the results vary significantly: the highest underpricing was 270.1% in United Arab Emirates in the period 2003 to 2010, meanwhile the lowest was in Argentina which had an average IPO underpricing of 5.7% in the time streacth from 1991 to 2018. The studies also show that China and Saudi Arabia experienced extreme IPO underpricing. The figure below shows the average underpricing in a selection of countries across the world in different time periods:

Figure 2: Underpricing percentage from selected countries in the period between 1959-2021. Source: (Loughran, Ritter & Rydqvist, updated 2022)

As the figure illustrates, the degree of IPO underpricing varies a lot within Europe and other countries. In Europe, Greece is the country with the highest average IPO underpricing and if we consider countries that became part of Euronext in the early 2000s, we can see relatively similar underpricing. The results range from 9.4% in France to 12% in Netherlands. Belgium is in the middle of those countries with an IPO underpricing at 11%. Since these countries have relative few new IPOs compared to large stock exchanges like London Stock Exchange, New York Stock Exchange and even Nikkei Stock Exchange, this could affect the robustness of the research.

2.6 Euronext Stock Exchanges

Euronext is a pan-European stock exchange group formed in 2000 as a result of the merger between some of the oldest stock exchanges in the world; Amsterdam Stock Exchange founded in 1602, Paris Stock Exchange founded in 1724, and Brussels Stock Exchange founded in 1801 (Chen, 2019, 2021; Euronext 2022b; Scott, 2021). Over the years, Euronext successfully acquired multiple stock exchanges including Dublin, Lisbon, Milan, and Oslo making it the largest stock exchange group outside of China and the US (Scott, 2021). This corresponds to a total market capitalization of 6.66 trillion USD as of March 2022. In a European context, Euronext is twice the size of London Stock Exchange Group, and three times the size of Nasdaq Nordic and Baltic Exchanges in terms of market capitalization (Statista, 2022).

Euronext consists of markets with different listing requirements and regulations. Euronext Main is regulated by EU directives and is best suited for large firms that can comply with the highest standards of transparency, accountability, and financial reporting (Euronext, 2022a). Euronext Main is divided into 3 different compartments based on market capitalization: compartment A - market cap more than €1bn, compartment B - market cap from €150 to €1bn, while compartment C is for companies with less than €150m market cap. Euronext Growth targets small and medium-sized enterprises (SMEs) in need of funding to sustain high growth. In comparison to Euronext Main, the listing requirements and financial reporting is more relaxed, easing the workload and cost burden associated with being a listed company, while still gaining the capital markets advantages. Euronext Access and Access+ are designed for startups and small companies who do not meet the requirements for Euronext Growth but want to gain from the positive aspects of being listed while developing the business. Being listed on Access/Access+ also eases the process of being transferred to Euronext Growth as the business grows sufficiently large.

3. Theories of underpricing

In this part we will cover the various theories explaining IPO underpricing which forms the basis for our study. To organize the theories, we have followed Ljungqvist (2004) categorization. Hence, the theories are divided into four different explanations based on: asymmetric information, institutional explanations, ownership and control, and behavioral explanations. The last section clarifies which theories will be tested and those that are left out from our thesis.

3.1 Asymmetric Information

When an IPO transaction takes place, there are three major parties involved: the issuing company, the underwriter(s) and the investor(s). Asymmetric information refers to a situation in a transaction where one of the parties has more information than others. Among the asymmetric information theories, the winner’s curse (Rock,

1986) is the most known theory, which is an extension of Akerlof's (1970) market for "lemons" model. Rock's (1986) paper explains the relation between uniformed and informed investors through the winner's curse and free rider problem. The winner's curse occurs when an uninformed investor overpays for the IPO shares. In the scenario where the IPO returns may be unattractive, or the demand is too low, the informed investor will withdraw from the offer. Consequently, the uninformed investor will receive all the shares they initially demanded. This is opposed to the scenario where an IPO is expected to be underpriced, as the informed investor will receive a greater number of shares. This implies that the uninformed investor receives a greater proportion of less underpriced IPOs, compared to the informed investor who receives a greater proportion of highly underpriced IPOs. From this take, the uniformed investors will not be willing to buy the offerings, unless the offerings meet their expectations of a minimum return on investment or a breakeven. Rock (1986) comes up with a suggestion that the issuing firm and the underwriter(s) must underprice their IPO´s to compensate the uniformed investors for the bias and adverse selection.

In Lowry et al. (2010) they found that a portion of small, medium and technology companies, also known as difficult-to-value companies, have a higher probability of receiving high levels of underpricing. The findings in Lowry et al. (2020) are in line with the theory from asymmetric information, where companies with a lot of information asymmetry should be associated with higher levels of underpricing. Another model is the signaling theory, where underpricing is used as a signal of firm quality and based on the assumption that the issuing firm has more information about real value than the investors. The main idea behind this theory is that the issuing company uses underpricing as an instrument to get a high value. If the signaling is a success, this could cost the issuing firm even more, but it may allow them to sell more stocks in the second offering (Ljungqvist, 2004). Moreover, Ibbotson (1975) argued that the issuing companies underprice IPOs to "leave a good taste in investors mouth", making the IPO investors more likely to invest in seasoned equity offerings.

Other theories connected to asymmetric information are information revelation theories, which are also known as book-building theories. This refers to the fourth stage in the IPO process, where the underwriter(s) gather interest from the potential investors during “road shows”. Another book-building theory is the quality/price trade-off theory by Ljungqvist et al. (2003) who studied the relationship between the level of underpricing and pricing techniques in U.S. The authors state that booking-building effort, which is the most expensive pricing technique, result in relatively fewer underpriced offerings than fixed price IPOs. This is attributed to the book building process being built on setting an offer price subsequent to gathering information from potential investors, making them reveal some of their information. Another implication would be that fixed pricing technique would have a higher degree of IPO underpricing than the other pricing techniques as well as higher variation in the initial returns.

There are also theories linking agency conflict and IPO underpricing known as principal-agent theories. Loughran and Ritter (2004) pointed out the “dark side” of institutional arrangements in the book-building process. The potential agency problem refers to the conflict of interest between the issuing firm and underwriter(s). The issuing firm’s interest is maximizing their proceeds from an IPO while the underwriter(s) gets higher earnings from trading, which is accomplished by creating higher demand for the IPO. This conflict of interest may lead some investors to give side-payments to the underwriter(s) in order to get underpriced IPOs. An example of this is from 2002, when Credit Suisse First Boston was fined $100 million due to receiving side-payments (Ljungqvist, 2004). Baron (1982) argues that the underwriter is offered a menu of contracts by the issuer, where the underwriter chooses the contract maximizing own benefit. To ensure that the underwriters informational advantage is optimally used, the issuer lets the underwriter set the offering price. However, although the underwriters information is optimally used, it allows them to capture positive rent in the form of underpricing due to the asymmetric information between the issuer and underwriter (Ljungqvist, 2004). Another study on agency problems in IPOs was conducted by Muscarella and Vetsuypens (1989). They investigated 38 self-underwritten investment bank IPOs during the period 1980 to 1990. According to the theory if the IPO was self-underwritten, there should not be any information asymmetry and therefore no agency conflicts. However, their findings show as high a level of underpricing of investment bank IPOs compared to other new listings. It does contradict the principal-agent explanation of IPO underpricing.

3.2 Institutional explanations

There are three institutional explanations of why IPOs are underpriced. The first theory is that lawsuit avoidance hypothesis or also known as the legal liability model. The main idea is that companies sell their shares at a discount to reduce the likelihood of future lawsuits from disappointed investors, or as a form of insurance, as stated by Logue (1973) and Ibbotson (1975).

The second theory is based on the practice of price support. This theory claims that one of tasks the underwriter(s) has is to help stabilize the stock price of the IPO to prevent large drops in the stock price. The underwriter(s) stabilize the stock price by bidding on the stock. This is done by allowing the underwriter(s) to oversell or short sell up to +/- 15%. If this is done by overselling, then the company has a short position. Hence, if the stock price falls under the offering price, the underwriter(s) will cover this by buying the share at the offer price, leading to an upwards price pressure. However, if the stock price exceeds the offer price, the underwriter(s) has a "greenshoe option" – also known as an overallotment option. This gives the underwriter(s) the right to buy the shares at the offering price. This is a mechanism for the underwriter(s) to increase the initial return on IPOs, and which keeps the stock price above the offering price. According to Ljungqvist (2004) such underwriter(s) intervention in the aftermarket tend to eliminate the left tail risk, hence limiting the underwriter(s) risk exposure.

The third theory is based on IPOs providing taxation advantages for investors involved in the IPO. Depending on the tax conditions for the issuing company and the country of listing, there could be a tax advantage for the company and its managers to prefer IPO underpricing to some extent. For instance, there could be a lower-level capital gains tax than employment income, which will give a company an incentive to pay employees in assets that can appreciate in value at a later stage. Although this theory is less studied, Rydqvist (1997) conducted a study in Sweden which showed that IPO underpricing fell from 41% between 1980-1989 to 8%

between 1990-1994. Rydqvist attributed the reduction in underpricing to the Swedish tax authorities introducing a reform on capital gains taxation, which increased capital gains tax to the level of taxable income.

3.3 Ownership and control

The retain control theory argues that underpricing gives lead underwriter(s) the opportunity to protect their private benefits by allocating shares strategically when the firm goes public. Brennan and Franks (1997) study how separation of ownership and control develops when a company goes public, and in what way the insider(s) uses IPO underpricing to retain control. Their findings show that underpricing is used as an instrument to get oversubscription for the IPO, allowing the managers to distribute the shares how they see fit. Moreover, the authors find that IPO share allocation is rationed, which takes place in oversubscribed IPOs, and tends to discriminate between applicants who want large block of shares and smaller investors. By allocating shares to a smaller investor, the manager will have the possibility to retain or have greater control over the company.

Some managers do have shares in the issuing company. This could give an incentive of reducing the agency cost if they exceed their private benefits of control. As per Ljungqvist (2004), management should seek to reduce the possibility of extracting private benefit, rather than maximizing it. Based on this, Stoughton and Zechner (1998) argued that by issuing shares to large external investors who are capable of monitoring the management can be seen as a positive value by some investors. Furthermore, they claim that monitoring is good for the public and the market, as every shareholder will benefit from it whether they directly contribute or not. Therefore, it will be most optimal to have large stakeholders, since the incentive to monitor increases with the size of stake in the firm.

3.4 Behavioral explanations

In behavioral theories, there are different parts of behavioral finance that are used to explain IPO underpricing. These theories for underpricing IPOs assume either the existence of behavioral biases or irrational investors among the issuers. There are usually two ways - either the investors bid too high such that the stock price goes above the fundamental value, or due to behavioral biases leading to a large underpricing of the IPO. The reason for this is that the investors fail to put enough pressure on the underwriter(s). It gives researchers a good setting to study the impact of irrational investors on the stock market, for IPO firms that do not have previous stock price history (Ljungqvist, 2004).

Informational cascades were introduced by Welch (1992) and occur when investors make their investment commitment or investment decision consecutively. Welch argues that investors base their valuation on bids from earlier investors rather than their own information. Thus, the initial sale functions as a signal for other investors, where a successful initial sale creates a snowball effect known as a positive cascade. In such a scenario, early investors are able to demand additional underpricing as a reward for starting the positive cascade. However, in the book-building process the bidding information is kept secret, resulting in the cascades not being present for other investors. Since the underwriter(s) keeps the information to themselves, this forces the investor to act on their own valuations based solely on their own valuations (Ljungqvist, 2004).

Ljungqvist et al. (2006) was the first to introduce the effect of irrational or sentiment investors in underpricing of IPO literature. This theory is based on investors selling and buying assets on investor sentiments instead of fundamental values of the investment. This explanation is based on optimistic investors, taking into account the assumption that some investors have sentimental beliefs about the future of a company that issues the IPO. This is consistent with the study of "hot issue" markets that was introduced by Ibbotson and Jaffe (1975). According to the theory, the issuing firm will take advantage of the high optimism in the market. From their point of view, the issuing firm´s objective is to take advantage of the investor´s behavior, and this done by maximizing the fundamental value of the share and holding back portion of shares in order to create a higher demand among sentimental investors. This is in line with Ritter's (1991) empirical study on IPOs, who argued that despite the positive short-run performance of IPOs, stock prices will converge towards the fundamental value in the long-run, leading to subsequent long-run underperformance of IPOs. However, it is harder to reflect the true value in the short-run, mainly due to the lack of maturity, data and information availability, but also due to factors not attributed to firm-specific characteristics. A problem with Ritter's (1991) empirical study is that he assumes constraints on short sales; otherwise, there could have been an opportunity for arbitrage. In markets where the investor is allowed to short sell, they would proceed to do that in order to send the stock price back to the fundamental value. This will expose risk for institutional investors. It could be risky for institutional investors to hold the share over a longer period, especially if events like a cold market appear, which will punish such investors for holding period risk.

Loughan and Ritter (2002) explain why issuers do not get upset when leaving money "on the table"; the issuers tend to sum up their wealth loss to the IPO underpricing with wealth gain on shares as the price rises in the after-market. To explain this, the authors use Kahneman and Tversky's (1979) prospect theory to argue that the investors ends up with a net gain when integrating both the positive news (increase in the net worth) and negative news (leaving money on the table). Prospect theory further assumes that losses and gains are valued differently, as shown by the expected utility function in the figure below:

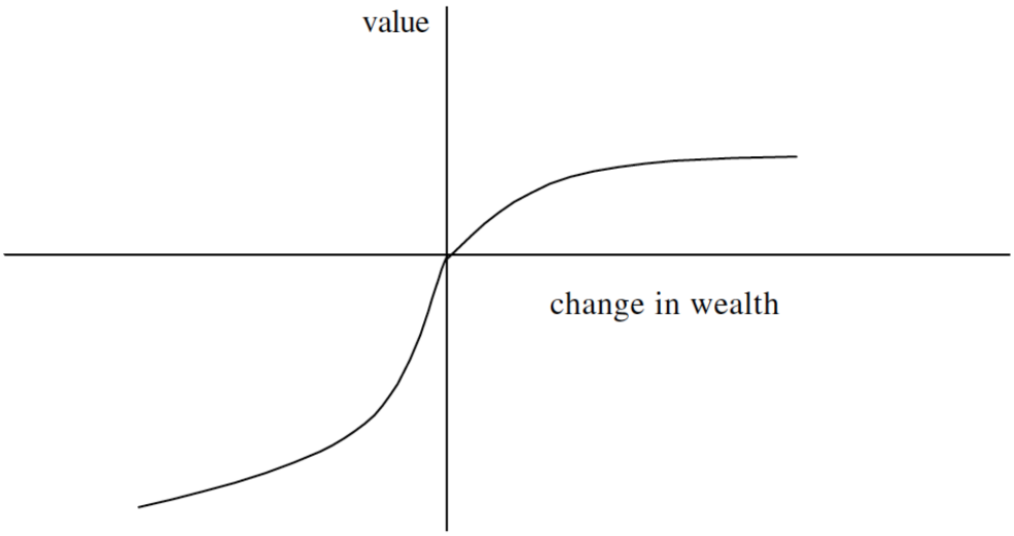


Figure 3: Prospect theory's value function is based on Kahneman and Tversky (1979). Source: (Loughran & Ritter, 2002)

The figure shows that the expected utility function is convex to losses, and concave to gains. In the case of issuing an IPO, the indicator is not the historical cost price, but instead the initial offer price. According to the prospect theory, when individuals face two outcomes, they can either treat them independently or together. The treatment usually depends on the value of the amount. Since the value function for positive value gain is concave it would be more favorable for an individual to take two gains separately rather than all in one go. On the other hand, if the value function for losses is convex then it is preferable to take all losses together. When a company has both positive (increase in net worth) and negative (leaving money on the table), the issuer could still be satisfied with the underwriter(s), if they end up with higher gains in the long run. Therefore, the underwriters can continue to underprice share to their benefits.

Further research is yet to be done on this subject, but Ljungqvist and Wilhelm (2005) tested whether CEOs of companies that recently went public make decisions with behavior determined by their subjective impression of the IPO outcome. This was done by studying if the CEOs were pleased with their underwriter. Their findings show that companies that have gone public and are pleased with their underwriter are less likely to change underwriter(s) for their seasoned equity offering (SEO).

3.5 Theories that will be tested

Due to the wide range of existing theories related to underpricing of IPOs, there are many theories to choose from, requiring us to eliminate some theories due to the scope of this thesis. The main reason for eliminating certain theories is primarily due to the lack of publically accessible data, including data containing privileged information, or because of theories receiving insufficient empirical support. An example is Da et al's (2011) paper that measured investor attention by using Google search, which was not used as only 4 IPOs were available in Google Trends, while the remaining IPOs received insufficient number of searches. Moreover, only one investment bank went public throughout our research period, which excludes the test on principal-agent theory by Muscarella and Vetsuypens (1989). The authors found that the level of underpricing is a similar between investment banks and other new listings, contrary to the implications from Baron (1982) model on information asymmetry. When it comes to testing the legal liability explanation of IPO underpricing, it will be more applicable for countries with stricter laws than the Euronext countries and for this reason it was not included. Furthermore, the cascade theory is also excluded as the majority of the firms in our sample use the book-building technique, which reduces the probability of positive cascades forming. Lastly, we are unable to test the retain control theory, as it requires detailed data on share allocation and bids which we were unable to find.

Hence, we will mostly include theories based on asymmetric information and behavioral explanations. To test asymmetric information, we will perform tests on winner's curse and the information revelation theory. In order to test the winner´s curse we will include proxies introduced in the study conducted by Beatty and Ritter (1986). The information revelation theory will be tested by using the relationship between pricing techniques and underpricing, known as the quality/price trade-off theory which was introduced by Ljungqvist et al. (2003). We also performed a test to check if the reputation of the lead managers reduces IPO underpricing. Lastly, to test behavioral theories, we decided to research investor sentiment theory which was introduced by Ljungqvist et al. (2006), and the "hot issue market" theory by Ibbotson and Jaffe (1975).

4. Hypotheses

The following hypotheses are created based on the research questions outlined in chapter 1.2. The first hypothesis seeks to answer the first research question, while hypothesis 2-7 are created to answer the second research question. Lastly, hypothesis 8 forms the basis to answer the third research question.

The vast majority of empirical studies show that IPOs experience underpricing, but the level of underpricing varies among industries, countries and time periods (Ljungqvist et al., 2006; Loughran & Ritter, 2004; Ritter, 1984). Hence, the first hypothesis tests whether the underpricing phenomenon is present on Euronext:

Hypothesis 1: *Euronext IPOs have been correctly priced from 2014-2021*

In the utopia of perfect capital markets, the efficient market hypothesis and Hypothesis 1 would hold since all information would be reflected in the offering price. We will reject Hypothesis 1 if we find proof of either significant overpricing or underpricing. In line with previous empirical studies, we expect to find significant underpricing. The next 3 hypotheses are related to asymmetric information theories. Rejecting either hypotheses 2 or 3 will provide support for Rock's (1986) winner's curse theory, while rejecting hypothesis 4 will support the information revelation theory.

Hypothesis 2: *Valuation uncertainty has no effect on the level of underpricing*
Hypothesis 3: *The level of the underwriter's reputation has no effect on the level of underpricing*

Hypothesis 2 is based on Beatty and Ritter (1986) ex-ante uncertainty theory, who argued that underpricing should increase in risk. This line of thinking is similar to pricing call options, whose value increases as the volatility of the underlying increases. Hence, if we reject hypothesis 2, we expect underpricing to be positively correlated with valuation uncertainty.

Hypothesis 3 is based on Carter & Manaster (1990) and Carter et al. (1998) who argued that hiring a reputable underwriter signal that the issuing company is of high quality. They further argued that the underwriter will not offer its services to low quality companies to preserve its reputation. This leads to less information asymmetry, and the investors will require a lower rate of return. If we reject Hypothesis 3, we expect that underpricing decreases if the issuer uses a highly reputable underwriter.

Hypothesis 4: *Pricing technique has no effect on the level of underpricing*

Hypothesis 4 is the last theory among the asymmetric information explanation umbrella. More specifically it is among the information revelation theories, which says that institutional investors reveal some of their private information during book-building roadshows. If we find support for hypothesis 4, we expect that fixed price IPOs exhibit higher underpricing than book-building IPOs. This is in line with the quality/price trade-off theory (Ljungqvist et al., 2003).

Hypothesis 5: *Investor sentiment has no effect on the level of underpricing*

Hypothesis 5 seeks to test Ljungqvist et al. (2006) Investor Sentiment theory. The essence of the theory is that institutional investors will gradually sell their allocated shares to retail investors when the sentiment among retail investors is high. Moreover, institutional investors will exploit high investor sentiment by restricting the supply of IPO shares, which in turn will increase the level of underpricing. To reject hypothesis 5, we expect a positive relationship between investor sentiment and underpricing.

Hypothesis 6: *IPO volume ("hot/cold markets") has no effect on the level of underpricing*

Hypothesis 6 is based on Ibbotson & Jaffe's (1975) "hot issue market" theory which states that the observed underpricing should be higher during times of high issue volume. This theory is based on the same logic as Ljungqvist et al. (2006) which claimed that underpricing levels is driven by investor sentiment. Ibbotson & Jaffe's (1975) theory has later been confirmed by several authors, such as Ritter (1984) and Ibbotson, Sindelar and Ritter (1988). Thus, we expect a significant positive relationship between underpricing and IPO volume.

Hypothesis 7: *VC backing has no effect on the level of underpricing*

Hypothesis 7 is based on Gompers (1996) grandstanding theory, which says that venture capital backed firms go public earlier than optimal, which suggests that underpricing level should be higher IPOs due to the added uncertainty. This is confirmed in a study by Lee & Wahal (2004). Thus, to reject Hypothesis 7, we expect that venture capital backed IPOs exhibits higher level of underpricing than non-venture capital backed IPOs.

Hypothesis 8: *Underpricing can be explained by similar theories across Euronext countries*

If we find support for hypothesis 8, we can conclude that the chosen theories provide different results across Euronext countries.

5. Methodology

This chapter starts by explaining our regression technique followed by the creation of dependent and explanatory variables. Subsequently, we define the regression models and list the expected regression outcome.

5.1 Ordinary Least Squares

We will make use of regression analysis to analyze and determine the relationship between the level of underpricing and the hypotheses from chapter 4. The most frequently used regression methods are Bootstrapping, Maximum Likelihood Estimation and Ordinary Least Squares (OLS). Due to its mathematical simplicity and prevalence among researchers, we believe OLS is the most fitting method for our research.

For the OLS to yield unbiased and efficient results, the 5 Gauss-Markov conditions must hold. The first four conditions ensure unbiasedness, while the fifth confirms whether OLS is the best linear unbiased estimator (BLUE) (Wooldridge, 2019). Lastly, normality is included as a sixth condition to finalize the assumptions of the classical regression model (CLRM):

Condition 1: Linear in parameters: $y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 \ldots + \beta_k x_k + e$
Condition 2: Random sampling: $\{x_{i1}, x_{i2}, \ldots, x_{ik}, y_i : i = 1,2, \ldots, n\}$
Condition 3: No perfect multicollinearity
Condition 4: Zero conditional mean: $E[u|x_1, x_2, \ldots, x_k] = 0$
Condition 5: Homoskedasticity: $Var[u_i|x_1, x_2, \ldots x_k] = \sigma^2$
Condition 6: Normality of residuals: $u \sim Normal(0, \sigma^2)$

Condition 1 is a simple mathematical expression that requires the dependent variable to be linearly related to the independent variables and the error term (Wooldridge, 2019). This is ensured through the way our models will be constructed. Hence, condition 1 will hold.

Condition 2 considers random sampling, which is defined by the observations being independently and identically distributed across observations (Hayashi, 2011). Our data is limited by both time and geographic locations, which is technically a violation of condition 2. However, this is of no concern due to our methodology and research questions.

Condition 3 assumes no perfect multicollinearity, which is a situation where there is an exact linear combination of one or several of the explanatory variables. This will lead to high standard errors, which in turn may lead to unreliable inference. Potential solutions are either dropping the variables causing the problem, or increasing the sample size (Wooldridge, 2019). Multicollinearity is a serious issue and will be investigated by creating correlation matrices, generating Variance Inflation Factor (VIF) for each model, and by looking at whether the R-squared is high with no significant variables. Although there are several sources of multicollinearity, there is no clear consensus among researchers as to when multicollinearity becomes a severe issue. Thus, we followed the thresholds provided by Gujarati & Porter (2009). These thresholds are > 0.8 in absolute terms for the correlation coefficients, and VIF values that exceed 10.

Condition 4 states that the explanatory variables must contain no information about the mean of the unobservable. If this property is not met, then the model is prone to endogeneity, which occurs due to either simultaneity, measurement error, sample selection or omitted variable bias (Wooldridge, 2019). Endogeneity is almost unavoidable in this line of research due to large number of underpricing theories. Additionally, it is essential to limit the included proxies to remain within the scope of our thesis. However, this leads us to potentially underfitting the model, as we may omit relevant theories. Hence, it is likely that condition 4 does not hold, however, it seems unavoidable and is something we must accept.

Condition 5 says that the variance of the residuals is constant and allows for simplification of other necessary formulas (Wooldridge, 2019). However, having homoscedastic variance is rare when conducting cross-sectional analysis. Heteroscedasticity occurs when the residuals are non-constant and is revealed by plotting the residuals against the independent variables, or by conducting statistical tests, such as the Breusch-Pagan test (Breusch & Pagan, 1979). If the variance of the residuals is non-constant, we will use White's heteroscedasticity robust standard errors to ensure that condition 5 holds.

The normality condition is the final condition which needs to be met for the classic linear regression model (CLRM) assumptions to hold. The normality condition says that the residuals are independent of the explanatory variables. Non-normality is mostly a small-sample problem, as the central limit theory (CLT) establishes that the distribution of the residuals will converge towards normality if the sample is sufficiently large. We will test the normality assumption by inspecting the residuals histogram, and by conducting the Jarque-Bera normality test (1980, 1987).

5.2 Creation of Regression Variables

5.2.1 Dependent Variable

The debate among researchers on how much time the market requires to efficiently price an IPO has been going on for decades. Some researchers believe that the market needs 3-7 days to reflect the fair value (Lowry et al., 2010), while Ljungqvist (2004) argues that IPOs in the modern capital market should be efficiently priced by the first-day closing time. In this thesis, we will assume that the stock price is efficient after the first-day of trading. Moreover, we will log-transform the returns to make the distribution closer to the normal distribution. The initial return is calculated by the following formula:

$$IR_i = log\left(\frac{P_{i,t}}{P_{i,t-1}}\right)$$

IR_i: First-day return of stock i

$P_{i,t}$: First-day closing price of stock i

$P_{i,t-1}$: Offer price of stock i

There are some drawbacks from using the initial return, as it does not account for movements in the stock market. This may lead to biased initial returns driven by the overall stock market rather than firm-specific characteristics. However, the opinions of researchers on this subject differ. Beatty & Ritter (1986) argue that the daily market movements tend to be small and uncorrelated with initial IPO returns and received support from Lowry & Schwert (2001), Derrien & Womack (2003), among others. On the other hand, researchers such as Logue (1973), Ibbotson & Jaffe (1975) and Ritter (1991) claim that the initial returns should be adjusted for the return in the industry benchmark the IPO company operates in. Despite some authors arguing that the difference is negligible in practice, we believe that adjusting the initial returns by an industry index makes sense. Hence, we have log-transformed Logue's (1973) formula for calculating market-adjusted returns:

$$MAR_i = IR_i - IIR_i = log\left(\frac{P_{i,t}}{P_{i,t-1}}\right) - log\left(\frac{I_{i,t}}{I_{i,t-1}}\right)$$

MAR_i = Market-Adjusted Return of stock i

IIR_i = Industry Index Return on day i

$I_{i,t}$ = Index closing value on stock i's first-day of trading

$I_{i,t-1}$ = Index value the day before stock i first trading day

We will use Bloomberg Industry Classification Standard (BICS) to identify which industry the IPOs operate in to properly adjust for index movements. An example is Belgian tech companies will be adjusted by BEL Technology Index, Dutch industry companies will be adjusted by AEX Industrials Index, while French energy companies will be adjusted by CAC Energy Index, etc.

Avoiding outlier bias is essential to circumvent a small number of observations influencing our results too much in either direction. The most common methods to treat outliers are trimming, winsorizing, or simply removing the outliers. Trimming excludes outliers in a certain range and is most appropriate if there are reasons to believe the outliers to be erroneous or irrelevant (Tukey, 1962). Winsorizing adjusts the outliers from both ends to a percentile of your choice and is most appropriate if there are reasons to limit the outliers rather than excluding them (Tukey, 1962). Adams et al. (2019) found that most finance researchers who treat outliers in cross-sectional studies use winsorizing, as it limits the impact of outliers rather than removing them completely. To maintain a somewhat unbiased sample while still limiting the impact of the largest outliers, we winsorize the market-adjusted returns at the 1% level.

5.2.2 Explanatory Variables

Explanatory variables form the foundation for the regression models and allow us to test the hypotheses. Additionally, the included control variables are based on theoretical research and proven to explain underpricing through empirical evidence.

5.2.1.1 Valuation Uncertainty

To test hypothesis 2, we include proxy variables for company age, size, and industry classification. Due to popularity among researchers, we chose company age at the time of offering, offer size, and whether the company operates in the tech industry (Ibbotson & Jaffe, 1975; A. Ljungqvist & Wilhelm, 2003; Loughran & Ritter, 2004; Megginson & Weiss, 1991; Ritter, 1984). As OLS assumes linearity, we log-transform company age and offer size in addition to winsorize at the 1% level. This limits outlier bias and ensures that the distributions are closer to the normal distribution. The company age at the time of offering is measured in the following way:

$$Company\ Age = \log\left(Year_{IPO} - Year_{Founding}\right)$$

As the IPOs are listed in different years, we need to adjust the offer size for inflation to make them comparable. Thus, the offer size will be adjusted by the individual countries' CPIs with December of 2021 as the base:

$$Inflation - Adjusted\ Offer\ Size = \log\left(OfferSize * \frac{CPI_{December\ 2021}}{CPI_{Month+Year\ of\ IPO}}\right)$$

Lastly, we use Bloomberg Industry Classification Standard to create the technology dummy, which is equal to 1 if the IPO operates in the technology sector, and 0 otherwise.

5.2.1.2 Underwriter Rank

To test hypothesis 3, we constructed a proxy for the underwriter rank. We use a slightly modified version of Megginson and Weiss (1991) framework, which in essence is based on the lead underwriters' fraction of the total amount of proceeds. In each IPO, we allocate the syndicates lead underwriter the amount of proceeds. In IPOs with more than one lead underwriter, we allocate each underwriter:

$\frac{Proceeds}{n}$, where n denotes the number of lead underwriters involved in the IPO.

Finally, each underwriter's rank is equal to their fraction of the total amount of proceeds raised in the research period. This was done for each country in the sample separately, as many of the investment banks only operate within its domestic country.

To avoid receiving uninterpretable results, we transform the ranks into a dummy variable representing the influence of each underwriter. The value is equal to 1 if the lead underwriter is among one of the two highest ranked underwriters in the respective country, 0 otherwise. This is in line with earlier studies done by Logue (1973) and Walker (2008). A full overview of all underwriters can be found in Appendix 10.1.

5.2.1.3 Pricing Technique

We created a fixed price dummy to test hypothesis 4 in order to investigate whether using fixed price as pricing technique leads to higher levels of underpricing than book-building issues. The dummy takes the value of 1 if the issuing firm used fixed price, and 0 if it used book-building. The information about which pricing technique the IPO used was collected from the SDC Platinum database.

5.2.1.4 Investor Sentiment

The investor sentiment variable is included to test hypothesis 5. As the theory is based on retail investor sentiment, we believe that the European Commission Consumer Confidence Indicator in the Eurozone (EUCCEMU) should be a good proxy. EUCCEMU is a monthly survey conducted by the Directorate-General for Economic and Financial Affairs, and the corresponding results are based on surveys conducted among a random sample of households in the Eurozone area (Bloomberg, 2022). Moreover, the survey contains questions about household expectations for unemployment rates, financial situation, and economic outlook over the coming 12 months. The downside of using EUCCEMU is that the index tracks every EU country, leading us to the assumption that the sentiment of Belgian, Dutch, and French retail investors is equal to the rest of the Eurozone retail investors, despite there being significant wealth discrepancies among the Eurozone countries.

5.2.1.5 IPO Volume (Hot/Cold)

A hot market variable is included to test hypothesis 6. The theory suggests that issuers will take advantage of hot markets, leading to higher IPO volume during periods of high returns. In line with studies by Loughran and Ritter (1995), hot and cold markets is constructed as a dummy variable measured by IPO volume, where the value of 1 denotes a hot market, and 0 for cold markets.

To recognize hot market periods, we start by measuring quarterly IPO volume, and treat each country separately. This is done to avoid potential biases arising from the countries exhibiting different periods of high IPO volume. The interval length is based on the conviction that IPO volume is cyclical, and we believe quarterly intervals are a better measurement of short-term market conditions than semi-annual or annual intervals. Finally, a quarter is defined as hot if the IPO volume is in the 90^{th} percentile of the total IPO volume in the respective country.

5.2.1.6 VC Backing

To test hypothesis 7, we created a dummy variable to study whether being backed by a venture capital firm affects the underpricing level. The variable takes the value of 1 if the issuing firm is backed by a venture capital firm, and 0 if the issuer receives no venture capital funding. Information about whether the issuing firm received venture capital backing or not was found by using Bloomberg Terminal and inspecting individual prospectuses.

5.2.1.7 Control Variables

Control variables are included to account for factors that are not among our hypotheses but are expected to have an impact on underpricing. Moreover, the control variables may provide additional exploratory power to the model, and function as a robustness check for our research variables.

The monthly stock market returns, and standard deviation has been proved to have an ex-ante effect on both IPO volume and initial returns (Butler et al., 2014; Cliff & Denis, 2004). To capture the full effect of the broader market, we used each country's All-Share indices rather than the benchmark indices, as many of the IPOs in our sample are expected to exhibit higher risk than the large cap companies benchmark indices consist of.

Lastly, in accordance with Ljungqvist et al. (2003) and Cliff & Denis (2004), we included yearly dummy variables to address potential time variation trends in the data. The dummy variable from the last year in the research period is dropped to prevent perfect multicollinearity issues.

5.3 Regression Models

From the regression variables explained above, we constructed 3 regression models. The first model is the base model, the second includes control variables for market performance, and the third includes time-specific variables:

Model 1:

$$\begin{aligned} MAR = {} & \beta_0 + \beta_1 LN\_Age + \beta_2 LN\_OfferSize + D_1 Tech + D_2 Rank \\ & + D_3 Technique + \beta_3 Sentiment + D_4 HC + D_5 VC + u \end{aligned}$$

Model 2:

$$\begin{aligned} MAR = {} & \beta_0 + \beta_1 LN\_Age + \beta_2 LN\_OfferSize + D_1 Tech + D_2 Rank \\ & + D_3 Technique + \beta_3 Sentiment + D_4 HC + D_5 VC \\ & + \beta_4 Marketreturn + \beta_5 Marketvolatility + u \end{aligned}$$

Model 3:

$$MAR = \beta_0 + \beta_1 LN\_Age + \beta_2 LN\_OfferSize + D_1 Tech + D_2 Rank + D_3 Technique + \beta_3 Sentiment + D_4 HC + D_5 VC + \beta_4 Marketreturn + \beta_5 Marketvolatility + D_6 IPO2014 + D_7 IPO2015 + D_8 IPO2016 + D_9 IPO2017 + D_{10} IPO2018 + D_{11} IPO2019 + D_{12} IPO2020 + u$$

5.4 Regression Variable Predictions

The table below summarizes all explanatory variables and control variables included in the regression models, and provides a short description of their definitions, which theory they proxy, and expected signs in the regression models.

Variable	***Description***	***Theory***	***Sign***
LN_Age	Natural logarithm of the years between foundation date and IPO date	Winner's curse	-
LN_OfferSize	Natural logarithm of the IPOs inflation-adjusted offer size	Winner's curse	-
Tech	1 if IPO company is in the tech industry, 0 otherwise	Winner's curse	+
Rank	1 if the underwriter is among the top 2 highest ranked in the country, 0 otherwise	Winner's curse/Certificat ion	-
Technique	1 if the IPO used fixed price, 0 if the IPO used book-building	Information revelation	+
Sentiment	Retail investor sentiment during the issuing month	Investor sentiment	+
HC	1 if the IPO happened during a "hot market", 0 otherwise	Investor sentiment/Hot issue market	+
VC	1 if the IPO were backed by a venture capital firm, 0 otherwise	Grandstanding	+

Marketreturn	Return in the general market over the 21 days prior to the issuing date	Control Variable	+/-
Marketvolatility	Volatility in the market index over the 21 days prior to the issuing date	Control variable	+/-
Yearly Dummy 2014-2020	7 separate dummies which takes the value of 1 if the IPO happened in the respective year, 0 otherwise	Control variable	+/-

Table 1 : Regression Variables and sign predictions

6. Data

This section explains the data gathering process, which sources were used, and data exclusion criteria.

6.1 Data Selection

This thesis uses data from all major stock exchanges in Belgium, France, and the Netherlands ranging from January 2014 throughout December 2021. As mentioned in the introduction, we exclude Portugal because of its small size and low IPO volume. To ensure that the sample size was as large as possible, the initial sample and proxy variables were gathered from a mix of financial databases such as Bloomberg Terminal, SDC Platinum, and Refinitiv. We also cross-checked Euronext's webpage which contains an extensive list of every IPO conducted on Euronext. As in Ritter (1991) we include delisted stocks to avoid survivorship bias arising from only including companies that are currently listed. A problem we faced was that the financial databases often exclude companies that are delisted. We found that the most frequent source of delisting was due to bankruptcy and M&A. To circumvent this, we manually checked all IPO prospectuses on Euronext's webpage and re-added them to our dataset.

Whenever the financial databases had conflicting information, such as underwriter(s), offer size or trading date, we relied on prospectuses and Euronext's webpage as a secondary source. For pricing technique, we solely used SDC. We used Bloomberg Terminal to collect Bloomberg Industry Classification Standard for industry classification, offering prices, and 1st day closing prices. Information about historical industry and general market indices were retrieved from Euronext's webpage, investor sentiment index from Bloomberg Terminal, and CPIs from Federal Reserve Economic Data (FRED). Founding year of each firm were collected from either Google, IPOhub, or the individual prospectuses.

6.2 Data Exclusion

Numerous companies were eliminated during the data collection process, mainly due to various difficulties in collecting all necessary variables due to missing prospectuses. Most of the eliminated companies happened during 2014-2016 before Euronext overhauled their website and made their IPO database more extensive.

We only consider companies going public on the main Euronext indices. As mentioned in 2.6, Euronext Growth targets smaller growth companies with firm characteristics associated with higher risk than the companies going public on the main index. Moreover, transferring between indices, secondary listings, dual listings, mergers, and spinoffs from listed companies have been removed from the sample. This is due to these companies' market values having already been assessed in the market and may distort our results.

Direct listings and private placements are also excluded. Direct listings strictly offer existing shares and no newly issued shares. Moreover, there are no underwriters in a direct listing. A private placement is a private offering where no shares are offered to the public, but rather to a select few institutional investors and wealthy individuals. Lastly, Special Purpose Acquisition Companies (SPACs) omitted from the sample. A SPAC is a blank check company which goes public solely to find a non-listed, non-identified company to merge with within 18-24 months after listing (Gahng et al., 2021). We found 23 SPACs in our sample, all of which went public in the Netherlands, which is fittingly crowned as the SPAC capital of Europe (Gopinath, 2021).

Initially, we counted 363 individual IPOs. However only 175 remained after all exclusion criteria were considered. The final sample consists of 23 IPOs from Belgium, 34 from the Netherlands, and 118 from France.

7. Results and Analysis

In this chapter we will introduce an overview of descriptive statistics with a focus on the general level of underpricing and different sample characteristics. Then we will comment on the results from the regression models, both for the Euronext sample as a whole and for each country. Subsequently, we will discuss econometric limitations and potential solutions in our regression models. Lastly, we will discuss the findings in a theoretical context to properly assess which hypotheses are supported in our sample. As mentioned in chapter 1.2 the total sample is referred to as “Euronext”.

7.1 Descriptive Statistics

7.1.1 General Underpricing Results

The table below summarizes the descriptive statistics of average market-adjusted returns:

	Market-Adjusted Returns			
	Euronext	*Belgium*	*France*	*Netherlands*
Mean	0.030	0.023	0.025	0.051
Median	0.012	0.027	0.008	0.025
Std dev	0.096	0.072	0.098	0.100
Standard Error	0.007	0.015	0.009	0.017
Minimum	-0.196	-0.098	-0.196	-0.078
Maximum	0.467	0.155	0.467	0.467
75th percentile	0.055	0.067	0.042	0.057
25th percentile	-0.014	-0.037	-0.016	0.000
Kurtosis	5.964	-0.904	5.493	8.457
Skewness	1.780	0.061	1.687	2.573
Observations	175	23	118	34
t-stat	4.172	1.533	2.819	2.983
p-value	4.75E-05	0.140	0.006	0.001

Table 2: Market-adjusted return statistics, t-stat and corresponding p-values from conducting two-sided t-test for the whole Euronext sample and each individual country in the period from 2014-2021.

The average market-adjusted return for the whole Euronext sample is 3%, and a two-sided t-test confirms that it is statistically significant at the 1% level. This result confirms the existence of IPO underpricing on Euronext between 2014-2021. A median of 1.2% combined with positive skewness of 1.78 implies that the Euronext sample is skewed to the right, as presented in Figure 4. This is in line with Ibbotson (1975) argument that investors who randomly selects an IPO to invest in have a higher chance of obtaining exceedingly high positive returns than suffer exceedingly negative returns.

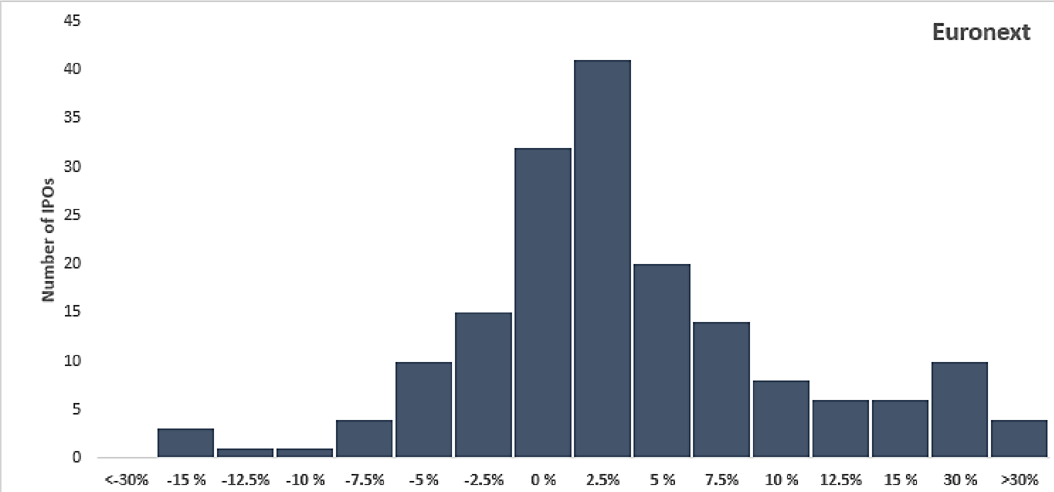


Figure 4: Distribution of market-adjusted returns for the Euronext sample in the period 2014-2021.

When we look at the country-specific results, we see that the market-adjusted returns are 2.3%, 2.5%, and 5.1% for Belgium, France, and the Netherlands, respectively. The returns are statistically significant at the 1% level in both France and the Netherlands, while being statistically insignificant at all conventional levels in Belgium. As suggested by the kurtosis and skewness in Belgium, its distribution is relatively flat and slightly skewed to the right, suggesting that the returns are positively centered, with a relatively high fraction of underpriced IPOs. On the other hand, the distributions in France and the Netherlands have a high peak combined with being skewed to the right.

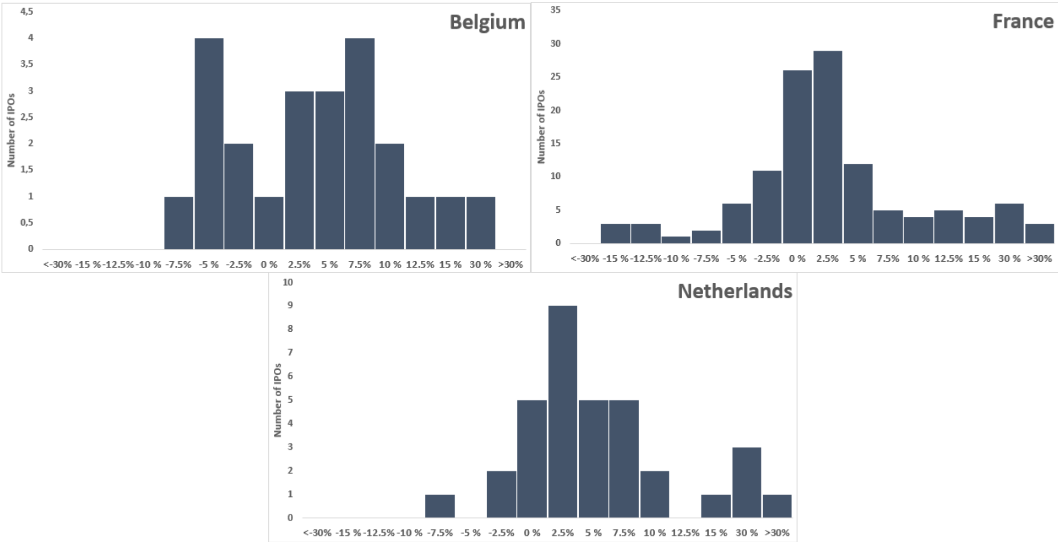


Figure 5: Distribution of market-adjusted returns for each individual country in the period 2014-2021

From the histogram in figure 4 and 5, we can see that the market-adjusted returns contain properties that violate the normal distribution. This poses a threat to the validity of the inference made from the t-test, as the test relies on the normality assumption. Thus, to formally check whether the data for Euronext and the country-specific subsamples are normally distributed, we conduct the Jarque-Bera test. P-values less than 0.05 confirms that the data is non-normal. The output in table 3 confirms that the market-adjusted returns in Belgium are normally distributed, while the remaining data is non-normal.

	Euronext	***Belgium***	***France***	***Netherlands***
JB-stat	332.79	0.91165	188.14	105.51
P-value	< 2.2e-16	0.6339	< 2.2e-16	< 2.2e-16

Table 3 : Test statistic and corresponding p-value from Jarque-Bera normality test on the market-adjusted returns from 2014-2021. If the p-value is higher than the threshold of 10%, then the data is normally distributed.

The fact that the whole Euronext sample is non-normal should not be concerning, as the sample size of 175 observations should be sufficient for the central limit theorem. However, it may alter the t-tests validity for the smaller subsamples. Thus, to ascertain robustness of our results, we will conduct Wilcoxon signed-rank test on the non-normal data. The Wilcoxon signed-rank test is used to assess whether the sample median is different from 0 and does not depend on the normality assumption (Gibbons & Fielden, 1993). Since the data from Belgium is normally distributed, we will omit it from the Wilcoxon test, and rely on the results from the t-test.

	Euronext	*France*	*Netherlands*
Z-value	3.72	2.17	3.25
P-value	2.03E-04	0.030	7.82E-04

Table 4: test statistic and corresponding p-value from the Wilcoxon signed-rank test from 2014-2021. A p-value of less than 10% confirms that the median is statistically different from 0.

We see from the table above that the Wilcoxon test confirms the presence of underpricing for Euronext as a whole, French and Dutch IPOs. Hence, both the t-test and Wilcoxon signed-rank test have established that underpricing is present.

7.1.2 Industry Differences

Significant differences in underpricing are expected across industries. Potential reasons for this are market cyclicality, for example the shipping industry, or industries that face inelastic demand, such as essential industries (healthcare/food/consumer). As mentioned in the data section, we use the Bloomberg Industry Classification System when sorting the industries.

	Euronext		*Belgium*		*France*		*Netherlands*	
	N	**Return**	**N**	**Return**	**N**	**Return**	**N**	**Return**
Basic Materials	4	2.19 %	1	-6.90 %	2	6.36 %	1	2.93 %
Consumer	87	2.57 %	16	1.50 %	57	1.47 %	14	8.31 %
Energy	11	3.05 %	0	N/A	10	3.34 %	1	0.15 %
Financial	17	4.15 %	4	3.51 %	6	6.05 %	7	2.90 %
Industrial	24	5.50 %	0	N/A	17	5.64 %	7	5.17 %
Technology	21	2.41 %	1	15.45 %	18	2.60 %	2	-5.85 %
Telecommunications	10	0.22 %	0	N/A	8	-1.05 %	2	5.29 %
Utilities	1	6.25 %	1	6.25 %	0	N/A	0	N/A

Table 5: Average industry returns statistics from 2014-2021.

In the whole Euronext sample, we can see that all industries support IPO underpricing. The telecommunications industry is the most correctly priced industry and would even be overpriced if the 2 Dutch IPOs did not pull the average above 0%. When omitting the sole utility IPO, it is the 24 industrial IPOs that are the most underpriced, and the underpricing distribution is also evenly spread among the French and Dutch IPOs. The most surprising finding is that the tech industry exhibits lower average underpricing than the sample mean of 3%, but also has the largest spread in performance, with the single Belgium tech IPO with 15% return, and the 2 Dutch tech IPOs with -5.85% average return. Lastly, the Consumer industry represents the largest fraction of IPOs and is also 0.5% percentage points lower underpriced than the average for the whole Euronext sample. Despite this, the Dutch Consumer IPOs consists of the highest average return among all countries, if we omit the single tech IPO in Belgium.

7.1.3 Yearly Differences

As stated above in chapter 2.5.1 numerous studies have shown that underpricing of IPOs differs across time periods. The results can be varied due to the observations and the different years where there have been few IPOs. In the table below we will present the total underpricing in the selected Euronext countries and the volatility for each IPO year.

IPO year	*Number of IPOs*	*Initial Return*	*Standard deviation*
2014	27	2.36%	9.37%
2015	36	3.87%	8.07%
2016	18	0.42%	4.56%
2017	15	1.50%	6.66%
2018	21	3.21%	11.08%
2019	7	4.65%	5.85%
2020	12	7.01%	12.91%
2021	39	2.85%	12.02%

Table 6: Number of offerings, average underpricing per year, and yearly standard deviation for Euronext IPOs in the period 2014-2021

The table illustrates that the IPO was not overpriced in total for the three Euronext countries during the period. Thus, there were positive initial returns in each IPO year. The returns are also distributed from 0.4% up to 7%, and there is a fair number of observations in the period, except for 2019. The IPO years 2019 and 2020 stand out with a high level of underpricing, which might be related to the low volume of observations. 2020 was the year with the highest level of underpricing and volatility in our sample. According to "hot issue market" theory underpricing should be higher during times of high issue volume, but our findings contradict the theory. The years 2019 and 2020 have the highest level of underpricing and lowest issued volume. This is also shown in table 7, where we can see that the returns are higher during "cold" periods. The fluctuation in the IPO underpricing from year to year could have introduced a time-varying effect in our data set, and this can be controlled in our regression analysis.

The figure below shows IPO in each of the three selected Euronext countries listed in the period 2014-2021.

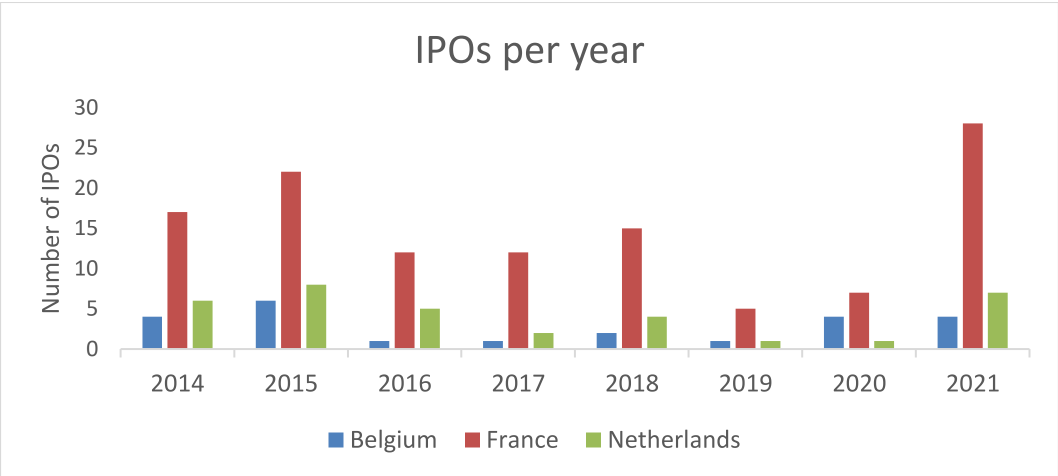


Figure 6: Overview of IPO volume per year in each country, from 2014-2021.

The above figure clearly illustrates that France has issued most IPOs in the period, followed by Netherlands and then Belgium. The reason for the high number of IPOs in France could be due to the higher market cap on the Paris Stock Exchange (France) compared to Netherlands and Belgium. A normalized view can be seen when the IPO counts are adjusted against the population or GDP as shown in figure below.

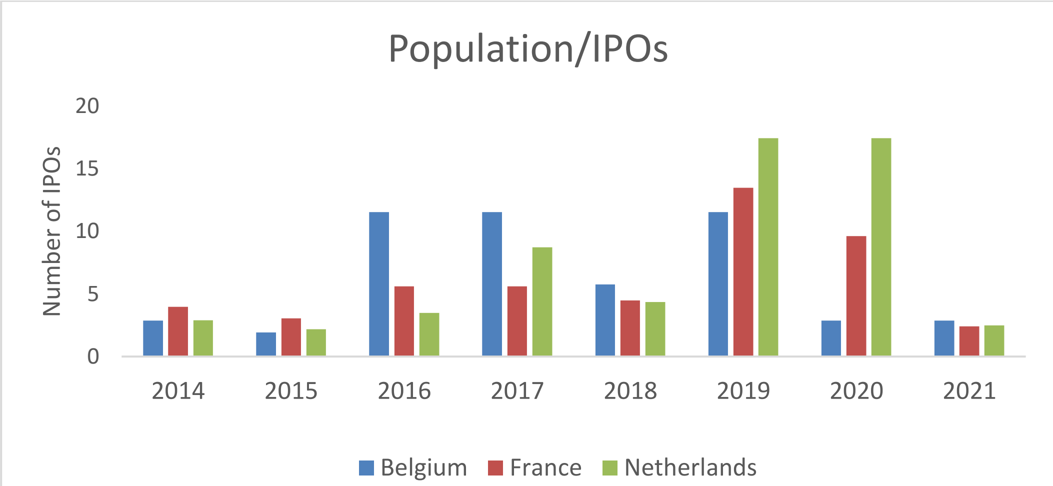


Figure 7: Population in each country divided by IPOs for the period 2014-2021. (Source for population: World Bank, 2022).

The figure shows that when you adjust for the population and IPOs, the result is substantially different. As per figure 7, France dominates only in year 2014 and 2015. On the other hand, Belgium, and Netherlands with much lower IPO count, have greater number of IPOs per citizen. In appendix 10.13, we have included the IPO adjusted for GDP, which gives a similar result as figure 7.

7.1.4 Explanatory Variable Characteristics

In this section, the results of our explanatory variables for the 175 companies listed on the main indices in Belgium, Netherlands, and France in the period from 2014 to 2021 are presented.

	Total		BE		NE		FR	
Segmented by	**Return**	**N**	**Return**	**N**	**Return**	**N**	**Return**	**N**
All	3.02 %	175	2.30 %	23	5.14 %	34	2.55 %	118
Market Condition								
Hot	1.61 %	55	4.59 %	12	2.00 %	13	0.25 %	30
Cold	3.66 %	120	-0.21 %	11	7.08 %	21	3.33 %	88
Sentiment								
High	1.34 %	82	0.90 %	12	3.23 %	14	0.97 %	58
Low	4.49 %	93	3.37 %	11	6.47 %	20	4.08 %	60
Offer Size								
High	3.24 %	87	5.31 %	11	8.25 %	17	2.56 %	59
Low	2.79 %	88	-0.47 %	12	2.02 %	17	2.53 %	59
Age								
Young (0-7 Years)	3.15 %	26	-0.57 %	3	-0.37 %	1	3.81 %	22
Old (8+ Years)	2.99 %	149	2.73 %	20	5.31 %	33	2.26 %	96
Industry								
Tech	2.41 %	21	15.45 %	1	-5.85 %	2	2.60 %	18
Non-tech	3.10 %	154	1.70 %	22	5.83 %	32	2.54 %	100
Pricing Technique								
Fixed	3.16 %	34	2.43 %	8	2.58 %	6	3.62 %	20
Book-building	2.98 %	141	2.22 %	15	5.69 %	28	2.33 %	98
Underwriter Rank								
High	2.24 %	68	2.91 %	4	4.26 %	24	0.96 %	40
Low	3.51 %	107	2.17 %	19	7.26 %	10	3.36 %	78
VC backed								
Yes	1.23 %	37	-6.68 %	2	8.99 %	6	0.18 %	29
No	3.50 %	138	3.15 %	21	4.31 %	28	3.32 %	89

Table 7: Descriptive statistics for the explanatory variables used in the regression models in the period 2014-2021. The explanatory variable Age of the firms is divided into young and old. Young firm are defined for firms between 0 to 7 years and old firms are 8 years and more. Offer Size and Sentiment is divided into high and low, where high is characterized as greater than the median, and low is less than the median. The rank of the Underwriters is divided into high (respective country top 2) and low (rest). Tech and Venture capital is also added in the table.

The results of our analysis show that during hot market conditions the average first-day return was lower than in cold conditions, except for Belgium where the theory was in line with our results. From our sample we can see that in Netherlands the average first-day return during cold market conditions was extremely high, and this has an impact on the results for the total average of the first-day return across the three countries. The results also indicate that during periods with low sentiment among the investors, the average first-day return is higher than in periods of high sentiment. So, our results in the period 2014 to 2021 for each of the three countries does not support the theory that underwriter(s) cooperate with institutional investors during periods with high sentiment and reward them with underpriced stock, as the authors Ljungqvist et al. (2006) have suggested.

We can further see that the average first-day return was slightly higher for firms with a higher offer size, and this is also the case for each individual country in our sample. The total average first-day return of the offer size is especially influenced by the high returns in Netherlands of 8.25% and these results contradict what is suggested by theories and research. Furthermore, in our total sample, the average first-day return on firms age is line with the theory - that younger companies have higher initial return. Even though there are negative first-day returns in Belgium and Netherlands for younger firms. It may be because the sample size was too small to take into consideration. For tech or non-tech firms, the average first-day return in total was higher for firms that were non-tech, which contradicts with the theory and studies. However, in Belgium and France, technology firms had higher first-day returns, but the sample of classified technology companies were too small. It also appears in France that is more common for tech firms to go public, since 22.9% of the firms when went public were classified as tech firms.

The univariate results show that issues with book-building technique had 2.98% average first-day return, while fixed prices were slightly higher with 3.15%. The results seem to be influenced by Belgium and France where the first-day returns were higher than in the Netherlands. Moreover, the results for IPOs with low-ranking underwriter(s) had higher average first-day returns compared to IPOs with high-ranking underwriter(s). This result is in line with the theory. The pattern is the same for Netherlands and France, while it is the opposite for Netherlands where high-ranking underwriter(s) have a higher average first-day return.

Lastly, in our total sample, firms that are venture capital backed had lower average first-day return than firms that were not venture capital backed. The results are specially reflected by the negative return of -6.68% on the two issues in Belgium. In the period 2014 to 2021, the pattern also shows the percentage of firms going public and being backed by venture capital was higher in France and Netherlands than in Belgium.

7.2 Regression Results

In this subsection we will identify and analyze which variables help explain underpricing measured by the market-adjusted initial returns. First, we will look at the whole Euronext sample, and then continue by examining each individual country.

7.2.1 Euronext Sample

The regression output is summarized in the table below:

	Euronext		
Variables	**(1)**	**(2)**	**(3)**
Constant	-0.043 (0.032)	-0.044 (0.036)	-0.084** (0.042)
LN_age	-0.008 (0.008)	-0.008 (0.008)	-0.006 (0.008)
LN_OfferSize	0.012** (0.005)	0.012** (0.005)	0.011** (0.005)
Tech	-0.005 (0.021)	-0.005 (0.022)	-0.006 (0.022)
Rank	-0.029* (0.017)	-0.029* (0.018)	-0.030* (0.017)
Technique	0.011 (0.018)	0.011 (0.018)	0.006 (0.019)
Sentiment	-0.009*** (0.002)	-0.009*** (0.002)	-0.018*** (0.002)
HC	-0.028* (0.016)	-0.028* (0.016)	-0.011 (0.019)
VC	-0.018 (0.018)	-0.018 (0.018)	-0.010 (0.019)
Marketreturn	No	0.039 (0.195)	-0.085 (0.206)
Marketvolatility	No	0.138 (2.116)	-1.197 (2.734)
Yearly Dummies	No	No	Yes
Observations	175	175	175

R-Squared	0.135	0.136	0.207
Adj. R-Squared	0.094	0.083	0.122
F-Statistic	3.252***	2.575***	2.417***
Prob > F	0.002	0.006	0.002

*Table 8: The table shows the OLS coefficients and the normal standard errors (in parentheses) from running the three regressions on the whole Euronext sample consisting of 175 IPOs across Belgium, France, and the Netherlands from 2014-2021. * Indicates that the coefficient is statistically significant at the 10% level, ** at the 5% level, and *** at the 1% level. For the full regression output from RStudio for the Euronext sample from 2014-2021 see Appendix 10.3*

Table 8 shows the three different OLS regression models with the market-adjusted returns as the dependent variable. In general, we see that the explanatory variables' signs and values are aligned with the descriptive statistics for the explanatory variables in table 7. The adjusted R-squared are 9.4%, 8.3%, and 12.2%, respectively. This means that the explanatory variables capture from 8.3-12.2% of the variation in the marked-adjusted returns. Although it seems low, it is similar to other empirical studies on underpricing that try to identify underpricing determinants rather than constructing predictive models. The F-statistic is significant at the 1% level in all three regression models, meaning that the explanatory variables are jointly different from 0.

Among the explanatory variables included to test asymmetric information theories, we find that *Rank* is negative and statistically significant at the 10% level throughout all regression models. Moreover, the coefficient of -0.030 indicates that issuers who use a reputable underwriter receive $e^{-0.03} - 1 = -2.95\%$ less underpricing on average. This is in corroboration with hypothesis 3. Surprisingly, *LN_OfferSize* is positive and statistically significant at the 5% level throughout all regressions. The coefficient of 0.011 translates into a 1% increase in offer size and leads to an increase of 0.011 percentage points in market-adjusted return. This goes against hypothesis 2. Moreover, neither *LN_age* nor *Tech* provide any significance, which is rather surprising, as most studies find support for higher firm age at the time of offering leads to less underpricing, and that the tech sector exhibits significantly higher underpricing due to high uncertainty and being hard to value. Lastly, *Technique* is positive and insignificant throughout all regression, but the coefficient drops from 0.011 to 0.006 when including all control variables, while the standard error remains stable.

Among the explanatory variables included to test investor sentiment theories, we find that *Sentiment* is negative and statistically significant at the 1% level throughout all regression models. This is the opposite of what was expected, as 1-point increase in the EUCCEMU, which is used to proxy retail investor sentiment, is associated with a decrease in the market-adjusted returns of -0.09%. This result receives some backing from *HC* which is negative and significant at the 10% level before controlling for time-varying components in the third regression model.

To test whether venture capital backing matters on the level of underpricing we included *VC*. However, the coefficient is insignificant at all conventional levels throughout the regression models.

Including the control variables only affects *HC's* significance level, suggesting that *HC* captures some of the initial time trend present in the regression models in the two first regression models. On the other hand, *LN_OfferSize*, *Rank*, and *Sentiment* does not lose any of its preliminary significance, proving to be robust findings.

7.2.2 Country-Specific Regressions

To be able to answer hypothesis 8 we investigated each country individually to assess whether the explanatory variables significantly differ between countries. This analysis is based on Table 9 which presents the regression output for each country.

	Belgium			France			Netherlands		
Variables	**(1)**	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
Intercept	-0.072 (0.101)	-0.140 (0.116)	-0.183 (0.115)	-0.031 (0.034)	-0.035 (0.039)	-0.077 (0.056)	-0.043 (0.108)	-0.015 (0.123)	-0.261 (0.227)
LN_age	-0.02 (0.023)	-0.008 (0.022)	-0.005 (0.030)	-0.014* (0.008)	-0.013* (0.008)	-0.008 (0.009)	-0.006 (0.017)	-0.001 (0.018)	-0.010 (0.025)
LN_OfferSize	0.022 (0.013)	0.030** (0.013)	0.028* (0.014)	0.009 (0.007)	0.009 (0.007)	0.011* (0.006)	0.015 (0.013)	0.014 (0.015)	0.029 (0.018)
Tech	0.084 (0.077)	0.121 (0.073)	0.120 (0.074)	-0.002 (0.027)	-0.001 (0.026)	-0.003 (0.025)	-0.097 (0.078)	-0.092 (0.083)	-0.016 (0.111)
Rank				-0.035 (0.022)	-0.034 (0.021)	-0.047** (0.022)	-0.014 (0.040)	-0.009 (0.042)	-0.023 (0.052)
Technique	-0.018 (0.030)	-0.002 (0.032)	-0.019 (0.038)	0.041 (0.025)	0.040 (0.025)	0.023 (0.025)	-0.021 (0.048)	-0.046 (0.063)	-0.051 (0.086)
Sentiment	-0.006 (0.005)	-0.003 (0.005)	-0.015** (0.006)	-0.011** (0.004)	-0.011** (0.004)	-0.022** (0.006)	-0.006 (0.006)	-0.009 (0.007)	-0.01 (0.011)
HC	0.019 (0.029)	0.044 (0.029)	0.056 (0.044)	-0.038** (0.017)	-0.038** (0.017)	-0.032 (0.034)	-0.045 (0.038)	-0.033 (0.042)	0.014 (0.076)
VC	-0.070 (0.053)	-0.013 (0.056)	0.012 (0.066)	-0.029 (0.022)	-0.030 (0.022)	-0.022 (0.021)	0.045 (0.052)	0.054 (0.054)	0.094 (0.068)
Marketreturn		1.050** (0.486)	1.138* (0.536)		0.127 (0.269)	-0.017 (0.284)		-0.440 (0.597)	0.369 (1.006)
Marketvolatility		-0.759 (4.945)	-9.571 (5.893)		0.598 (2.930)	-0.499 (3.372)		-5.787 (8.061)	7.527 (13.778)
Year Dummies	NO	NO	YES	NO	NO	YES	NO	NO	YES
Observations	23	23	23	118	118	118	34	34	34
R-Squared	0.465	0.609	0.824	0.171	0.174	0.290	0.278	0.307	0.442
Adj. R-Squared	0.215	0.337	0.446	0.110	0.096	0.169	0.049	0.006	-0.151
F-statistic	1.950	2.245*	2.179	2.815***	2.246**	2.403***	1.213	1.021	0.746
Prob > F	0.148	0.089	0.151	0.007	0.020	0.004	0.332	0.456	0.723

Table 9: The table shows the results from the three main regressions for each respective country from 2014-2021. The standard errors are in the parentheses. Rank is not included from the regression models in Belgium due to multicollinearity, which will be covered in 7.3.2.1.

From table 9 we see that the explanatory variables explain 21.5% - 44.6% of the variation in the market-adjusted returns in Belgium, suggesting that the model fits the data well. Moreover, the second regression model is statistically significant at the 10% level, while the remaining models are significant at the 15% level. Hence, we cannot reject that all the explanatory variables are jointly equal to 0.

From the regression output we notice that only *LN_OfferSize* is statistically significant among the explanatory variables included to test asymmetric information theories. The value of the coefficient is 0.028 implying that a 1% increase in offer size increases the market-adjusted returns by 0.028 percentage points. Moreover, among the behavioral explanations we find that *Sentiment* becomes statistically significant at the 5% level when all control variables are included. The coefficient is -0.015, which suggests that a 1-point increase in the EUCCEMU is associated with a decrease of -0.015% in the market-adjusted returns.

The adjusted R-squared ranges from 11% - 16.9% in France, and the first and third model is significant at the 1% level, while the second model is significant at the 2% level. Among the information asymmetry theories, we find some support for older companies reducing underpricing, as *LN_age* is significant at the 10% level in the first two regression models. However, the coefficient drops from -0.013 to -0.008, and the corresponding p-value drops from 0.094 to 0.336 when including yearly dummies. Moreover, we find some support for *Rank* which becomes significant at the 5% level when including all control variables, suggesting that using a reputable underwriter reduces underpricing. Lastly, *LN_OfferSize* enters the regression without any significance, but turns significant at the 10% level in the third regression model. Similarly to Belgium and Euronext as a whole, the sign is positive, which suggests that larger IPOs are associated with higher underpricing.

There is a strong relationship between *Sentiment* and underpricing in all three regression models, inferring that higher retail sentiment is associated with lower underpricing. Moreover, *HC* is negative and statistically significant at the 5% level in the first two regression models. However, the standard error is doubles in size when including the time-specific component, resulting in *HC* becoming insignificant at all conventional levels.

The R-squared in the first regression model in the Netherlands is 5% but drops to 0% and -15.1% in the second and third regression. This, combined with the F-statistic being insignificant in all regression models, suggests that the chosen explanatory variables do not explain underpricing in the Netherlands at any capacity. This is further supported when looking at the regression output in table 9, as there are no significant coefficients.

7.3 Regression Validity Tests

Before we discuss the regression results it is necessary to analyze the validity of the regression models. Since the importance of the CLRM assumptions differ, we will mainly consider heteroscedasticity, multicollinearity, and normality of residuals. To identify potential violations, we will conduct statistical tests for all regression models to assess whether the inclusion of control variables affect the validity of the model. The test results will be presented in the following subchapters. The results for Euronext will be covered in detail, while the country-specific results will be kept brief.

7.3.1 Euronext

7.3.1.1 Homoscedasticity

When dealing with cross-sectional studies it is expected that the residuals suffer from non-constant variance (heteroscedasticity). This would lead to biased standard errors and potentially making inference unreliable. There are multiple tests to check for heteroscedasticity, such as White's test and the Breusch-Pagan test. White's test is an asymptotic test, which is best suited for large data sets, while the Breusch-Pagan test is better suited for smaller samples. Since our data set of 175 observations is considered somewhat small, we decided to use the Breusch-Pagan test. The null hypothesis states that the residuals are distributed with equal variance, while the alternative hypothesis states that the residuals are distributed with unequal variance. We see from Table 10 that the p-values from all three regressions are greater than 0.05, hence we have homoscedastic variance in all three regression models. An alternative approach is to visually inspect the residuals; however, we believe that a formal test provides more objective results. Nevertheless, we included plots for heteroscedasticity in Appendix 10.6.

	Euronext		
	(1)	(2)	(3)
BP-stat	12.90	13.10	19.73
DF	8	10	17
P-value	0.12	0.22	0.29

Table 10: Test-statistic, degrees of freedom, and the p-value obtained from running the Breusch-Pagan test on the regression models for the Euronext sample from 2014-2021

7.3.1.2 Multicollinearity

From the correlation matrix in Appendix 10.2 we see that the highest correlation coefficient is 0.573 between *LN_OfferSize* and *Rank*. This relationship is expected and is aligned with the theory which says that reputable underwriters will only offer their services to high quality issuers. The second largest coefficient is 0.364 between *LN_age* and *LN_OfferSize*. This makes sense, as large offerings are often mature companies with stable cashflows. We continue by looking at the VIF output in Appendix 10.5, where we can see that the highest VIF value is 2.985. This is far below the VIF cutoff value, thus there are no signs of multicollinearity. Lastly, the highest R-squared value is 0.207 and does not lead to any significant changes in any of the explanatory variables. Hence, we can conclude that there are no multicollinearity issues in any of the Euronext models, as all three methods of measurements show no violations.

7.3.1.3 Normality

Having normally distributed residuals is necessary to draw correct inference conclusions. We see from the kernel density plots overlaid by the normal distribution in Appendix 10.4 that the residuals in all three models have a higher peak and slightly fatter tails than the normal distribution. To confirm our suspicion of non-normality, we proceed by performing the Jarque-Bera normality test. The output is summarized in the table below:

	Euronext		
	(1)	(2)	(3)
JB-stat	330.01	333.56	254.65
DF	2	2	2
P-value	< 2.2e-16	< 2.2e-16	< 2.2e-16

Table 11: Output from the Jarque-Bera normality test on each regression model in the Euronext sample from 2014-2021.

As all p-values are essentially 0, the Jarque-Bera test confirms that the residuals are non-normally distributed. However, having normally distributed residuals is mainly a small sample problem. According to Wooldridge (2019) some researchers believe a sample size of 30 is sufficient for the central limit theorem to kick in, while others argue that a sample size of 100 is sufficient. Since our sample size consists of 175 observations, we believe that having non-normal residuals should be of no concern. Hence, we conclude that the t-statistics from the regression models are viable, despite having non-normal residuals.

7.3.2 Country-specific

We realize that the country-specific regressions will be prone to violations of the CLRM assumptions. Despite these shortcomings, we still believe that the regressions will show interesting results worth mentioning. Nonetheless, we will need to be cautious when drawing conclusions from the country-specific regression models.

7.3.2.1 Homoscedasticity

From the table below we see that heteroscedasticity is only present in the French regression models, as the p-value is less than the 5% threshold. This has been dealt with by applying White’s heteroscedasticity robust errors for all regression models in France.

	Belgium			France			Netherlands		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
BP-Value	8.2	8.8	19.2	16.5	19.0	30.5	6.7	8.8	19.7
DF	7	9	16	8	10	17	8	10	17
P-value	0.31	0.45	0.21	0.04	0.04	0.02	0.57	0.55	0.29

Table 12: Test-statistic, Degrees of freedom, and the p-value obtained from running the Breusch-Pagan test on the regression models for each individual country from 2014-2021.

7.3.2.2 Multicollinearity

In Belgium the correlation matrix shows that the correlation coefficient between *LN_OfferSize* and *Rank* is 0.787 which is just below the 0.80 threshold. When running the regression *Rank* had a VIF value of 40, which is a clear violation of the threshold of 10. Thus, we left *Rank* out of the regression, which seems to have solved the problem, as the highest VIF among the explanatory variables dropped to 3.92. However, the R-squared is strikingly high at 0.824 in regression model (3) with only 3 significant variables, which may suggest that the multicollinearity problem was not completely solved.

In France the values from the correlation matrix are in the interval between -0.47 and 0.598. The correlation is highest between *LN_OfferSize* and *Rank*. Further, the highest VIF value is 2.99, and the highest R-squared values are normal. Hence, there are no signs of multicollinearity in any of the French regression models.

In the Netherlands the correlation coefficients are in the interval between -0.562 and 0.595 which are within the threshold. Moreover, the highest VIF is 5 and stems from Marketvolatility, which is one of the control variables. This value is far from 10 and will not be investigated further. Lastly, the highest R-squared value is 0.442. Although this is relatively high, it is not high enough to be a problem.

7.3.2.3 Normality

	Belgium			France			Netherlands		
Model	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
JB-stat	0.56	0.96	9.91	54.51	54.65	26.61	120.10	82.91	14.03
Observations	23	23	23	118	118	118	34	34	34
DF	2	2	2	2	2	2	2	2	2
P-value	0.76	0.62	0.01	0.00	0.00	0.00	0.00	0.00	0.00

Table 13: Output from running the Jarque-Bera test for normality on each regression model for every country from 2014-2021

The perhaps most interesting finding is that the residuals in Belgium are normally distributed until the yearly dummy variables are included. For France, the impact of the normality assumption not holding should not affect the results, as the sample size should be sufficient. However, it may cause problems when drawing conclusions from hypothesis testing for the regression models in Belgium and the Netherlands.

7.4 Interpretation of results

The results from analyzing the descriptive statistics and the subsequent findings from running the regression models enables us to infer conclusions regarding the hypotheses. The discussion is structured in the following way: the first part of each subchapter will discuss the findings regarding Euronext, while the second part discusses the country-specific findings. The latter forms the basis for hypothesis 8, which will be summarized in 7.4.8.

7.4.1 Hypothesis 1 – Euronext underpricing

From the descriptive statistics in chapter 7.1.1 we find that Euronext IPOs between 2014-2021 exhibit 3% market-adjusted returns on average with a median of 1.2%. These results are statistically significant at the 1% level from conducting both a standard t-test and the non-parametric Wilcoxon signed-rank test. This leads us to rejecting hypothesis 1, as we find strong evidence that Euronext IPOs were significantly underpriced between 2014-2021.

When examining the countries separately, we discover that French and Dutch IPOs are subject to 2.5% and 5.1% underpricing on average, while the medians are 0.8% and 2.5%, respectively. These results are significant from running both the simple t-test and Wilcoxon signed-rank test. In Belgium, we find an average underpricing of 2.3%, which is statistically insignificant at all conventional levels.

In a historical perspective, Banerjee et al. (2009) found that IPOs in Belgium during the early 2000s experienced a mean underpricing of 10.3%, Dutch IPOs between 1983-1999 received 9.9% underpricing on average (Bosveld & Venneman, 2000), while French IPOs were underpriced by 13.2% on average between 1992-1998 (Derrien & Womack, 2003). These results suggest that underpricing in our selected countries has been significantly reduced over the years. In a more recent study, Silva et al. (2021) finds that IPOs in Belgium, Netherlands and France exhibit 2.16%, 2.16%, and 1.24% underpricing on average from 2009-2017, respectively. These results are more aligned with our data and confirms our suspicion that the underpricing level among the selected countries has decreased over time. A plausible explanation for this is attributable to information becoming more accessible and the financial markets becoming increasingly competitive.

7.4.2 Hypothesis 2 - Valuation Uncertainty

To test whether ex-ante uncertainty impacts the level of underpricing, we included three firm-specific proxy variables for offer size (*LN_OfferSize),* company age (*LN_age*), and industry (*Tech).* These are some of the most used proxy variables to test Beatty & Ritter (1986) ex-ante uncertainty implications for Rock's (1986) winner's curse theory.

For Euronext, we find that *LN_age* is negative even when including all control variables. This is in line with previous studies and our expectations. However, the confidence intervals are wide, suggesting that the coefficient might negative due to randomness alone.

Tech is negative and insignificant at all levels throughout the three regression models. Although this result is consistent with the descriptive statistics in section 7.1.4., it contradicts most empirical research among technology companies, as tech IPOs have exhibited drastically higher levels of underpricing compared to non-tech IPOs over the last 40 years (Ritter, 2022).

LN_OfferSize is positive and significant at the 5% level in all three regression models, hence proving to be a robust finding. This infers that larger IPOs are associated with higher underpricing, which contradicts the theoretical reasoning that larger IPOs should experience lower underpricing due to less information asymmetry. In our data set, we discover that there are in total 16 IPOs with offer size larger than €1bn, which on average receive 9.85% underpricing – strikingly higher than the average underpricing of 3% in the total sample. A possible explanation is that large IPOs attracts substantial amount of media attention leading up to the offering date resulting in high investor sentiment in the aftermarket. In conclusion, we reject hypothesis 2, as we find sufficient evidence that valuation uncertainty affects the underpricing level. More specifically, we find that higher offer size increases the underpricing level, which contradicts Beatty & Ritter (1986) ex-ante uncertainty implications for Rock's (1986) winner's curse theory.

The results for the country-speficic regressions exhibits some differences in comparison to the overall Euronext regressions. For *LN_age*, the coefficients are negative in all countries, but is only significant at the 10% level in the two first regression models in France. This suggests that there is some support for older companies receiving less underpricing in France. Similar to the Euronext regressions, we find that *LN_OfferSize* is positive and significant at the 10% level in both Belgium and France, while positive and insignificant in the Netherlands. Lastly, *Tech* is negative and insignificant in both France and the Netherlands, but positive and insignificant in Belgium. However, Belgium only had 1 tech IPO in which likely drives the result.

7.4.3 Hypothesis 3 - Underwriter Rank

In the Euronext regressions, *Rank* remains negative and statistically significant at the 10% level in all three models leading us to reject hypothesis 3. Hence, we find support for Carter & Manaster (1990) and Carter et al. (1998) who argued that using a reputable underwriter provides the issuer with a certification effect which reduces information asymmetry, and the corresponding level of underpricing. An interesting detail is that we found the syndicate size to be significantly larger when the issuer used a reputable underwriter. This may suggest that some of the reasons for the reduction in underpricing might be attributable to the fact that a larger syndicate is able to provide the lead underwriter with a more objective valuation of the issuing company.

In the country-specific regressions, we see that the coefficient is negative in all regression models in France and the Netherlands. In France, *Rank* is slightly insignificant in the first two regressions, but becomes statistically significant at the 5% level when all control variables are included. In the Netherlands, *Rank* is not significant at the conventional levels in any of the regression models

7.4.4 Hypothesis 4 - Pricing Technique

We find that the coefficient of *Technique* is positive, but insignificant at all conventional levels in the Euronext regressions. The coefficient drops from 0.011 to 0.006 when including all control variables, while the standard error remains unchanged. This leads to a wide confidence interval, implying that the coefficient may be positive due to randomness alone. The insignificance of *Technique* is in accordance with the descriptive statistics from chapter 7.1.4, where we found no significant underpricing difference between the two pricing methods. However, we did find that book-built IPOs have significantly lower standard deviation than fixed price IPOs, which is an implication of book-building being more efficient at forecasting demand.

When taking all the above-mentioned factors into account, we conclude that we do not find sufficient evidence to reasonably assume there being a quality/price trade-off between book-built and fixed price IPOs, as suggested by Ljungqvist et al. (2003).

When looking at the country-specific regressions, we find that the coefficient is negative and insignificant at all levels in both Belgium and the Netherlands, which contradicts the theory. In France, the coefficient is positive but insignificant. This is likely the driver as to why the coefficient is slightly positive in the Euronext regression.

7.4.5 Hypothesis 5 - Investor Sentiment

The Euronext regression results for *Sentiment* contradicts our expectations and the implications from the investor sentiment theory by Ljungqvist et al. (2006). The authors argued that IPO underpricing should be higher during times of high investor sentiment. However, our results show that IPO underpricing is lower during times of high investor sentiment. Moreover, *Sentiment* is significant at the 1% level in all three regression models proving to be a quite robust finding. Hence, we reject hypothesis 5 that investor sentiment impacts the level of underpricing, but not in favor of Ljungqvist et al. (2006).

There are multiple potential explanations for this. First, the EUCCEMU might be an unsuitable proxy for measuring retail sentiment among investors on Euronext. Secondly, institutional investors may simply be unable to accurately capture the changes in investor sentiment on Euronext between 2014-2021, resulting in them taking on too much risk at the wrong time. Thirdly, issuers might be aware of the high investor sentiment, leading them to exploit this fact by increasing the offering price to raise more capital.

When comparing the results from the country-specific regressions, we can see that there is a clear consensus of *Sentiment* being negative throughout all countries and models. Despite *Sentiment* being negative in all models in the Netherlands, the coefficient is not significant at any level. On the other hand, the coefficient is significant at the 5% level in all regression models in France, while significant at the 5% level when including all control variables in Belgium.

7.4.6 Hypothesis 6 - IPO volume (“hot/cold”)

Similarly to hypothesis 5, we find a negative relationship between *HC* and the level of underpricing. The coefficient is statistically significant at the 10% in the two first regressions, but the p-value drops to 0.55 when taking the yearly dummy variables into account. The descriptive statistics from section 7.1.4 shows that the average underpricing during hot market conditions were considerably lower than during cold market conditions. Based on the abovementioned findings, we believe the evidence is sufficient to partly reject hypothesis 6, as we find that IPOs going public during hot markets are significantly less underpriced than IPOs going public during cold markets. This result is in contrast with Ibbotson & Jaffe’s (1975) “hot issue markets” theory. A possible explanation for this contradicting result is that underwriters take the hot market condition into account when valuing the issuing company, thus increasing the offering price.

When looking into individual countries, we see that *HC* is positive in all regression models in Belgium. However, it is not statistically significant in any of the models. *HC* is negative and statistically significant at the 5% level in France in the first two regression models, however, it is no longer significant when the model is corrected for time trend. *HC* is negative in the Netherlands in the first two models, but the sign changes from negative to positive when time trend is captured.

7.4.7 Hypothesis 7 - Venture Capital

The *VC* coefficient is negative and highly insignificant throughout all regression models for the Euronext sample. These results seem to match up well when looking at the descriptive statistics of the explanatory variables, which reveals that venture capital backing is associated with significantly less underpricing than being non-sponsored. Hence, we fail to reject hypothesis 7, as we do not find sufficient evidence that venture capital backing impacts the level of underpricing. Although this result contradicts Gompers (1996) grandstanding theory, it is similar to studies by Brau et al. (2003) and Da Silva Rosa et al. (2003) who were unable to find any significant relationship between venture capital backing and IPO underpricing.

When analyzing the individual country regressions, we see that there are some differences, but the coefficient is insignificant at all conventional levels in all regression models.

7.4.8 Hypothesis 8 - Country-specific differences

We find that offer size and investor sentiment are determinants of underpricing in Belgium. In France, we find strong evidence that increased investor sentiment significantly reduces underpricing. Moreover, we find some support for company age, offer size, using a reputable underwriter, and that going public during hot markets are associated with less underpricing. Of these, only company age and using a reputable underwriter is aligned with the traditional asymmetric information theories, while the rest shows the opposite of what we expected. Lastly, we are unable to find any significant results among the explanatory variables in the Dutch market.

In general, we find weak evidence for our theories, as we are only able to find some support that are aligned with the asymmetric information theories in the French market. Based on this, we reject hypothesis 8, as we find evidence supporting that the theories provide different results across the Euronext countries.

8. Conclusion

This thesis examines short-term underpricing and the explanatory power of popular underpricing theories on 175 IPOs occurring between 2014-2021 in the Euronext countries of Belgium, France, and the Netherlands. We find an average underpricing, measured by the market-adjusted returns, of 3% for the whole Euronext sample. When examining each country separately, we find that IPOs issued in Belgium exhibit 2.3% underpricing, while IPOs in France and the Netherlands experience 2.5% and 5.1%, respectively. These underpricing results further confirm other empirical findings that European IPO underpricing has been trending downwards in recent decades.

The results from the multivariate regression models provide limited support for the underpricing theories in general. Among the behavioral theories, we tested

Ljungqvist et al. (2006) investor sentiment theory and Ibbotson & Jaffe's (1975) "hot market" phenomenon. Contrary to other studies, we find that IPO underpricing is significantly lower in periods of high retail sentiment in Euronext and France, and to some extent in Belgium. We offer two explanations: either that our proxy might be flawed, or that institutional investors incorrectly judge retail sentiment. Moreover, we find some evidence that issuers going public during "hot" markets receives less underpricing on average on Euronext and in France, which is the opposite of what the theory suggests. Our reasoning is that underwriters take the market condition into consideration when valuing the issuing company, hence increasing the offering price.

We do not find any significant results supporting financial sponsorship being a determinant of IPO underpricing. Among the asymmetric information models, we found no evidence supporting that there is a quality/price trade-off between book-building and fixed price IPOs from the information revelation theory. Moreover, we find mixed results among the testable implications for the winner's curse theory. Firstly, we find strong evidence that using a reputable underwriter significantly reduces the underpricing level in Euronext as a whole, and some support in France. This is in accordance with Carter & Manaster (1990) and Carter et al. (1998). Secondly, although we find weak support for older companies being associated with less underpricing in France, the results generally contradict the proxies included to test Beatty & Ritter's (1986) ex-ante uncertainty theory. In fact, we find strong evidence for higher offer size exhibiting higher underpricing in the total Euronext sample, and weaker evidence in the sub-samples of Belgium and France.

Regarding the investigation of differences in explanatory power of the underpricing theories across the countries, we find a lot of similar initial results from the descriptive statistics in table 7, although there are some variations. However, these results are not reproduced in the multivariate regression analyses, as we find that the theories explanatory power varies among the sub-countries.

8.1 Limitations

There are several limitations in our research which could have affected our conclusions. As we have previously mentioned, the sentiment index may not accurately reflect the view of Euronext investors. We were initially going to use each country's consumer confidence, but we found some inconsistencies in the measurement which could have skewed the results. Other alternatives could be Sentix Investor Confidence or ZEW Sentiment Index. However, these indices measures equity researchers' sentiment, which in theory should be quite different retail investors.

To assess the relevance of some of the classical underpricing theories in a modern setting we chose a relatively short research period from 2014 throughout 2021. This clearly limits the total amount of observations, especially in Belgium and the Netherlands, which are relatively small exchanges in comparison to France. As we have shown, the regression models in Belgium and the Netherlands face potential large econometrical issues, which may have led to us draw the wrong conclusion in hypothesis 8.

8.2 Future Research

Our results contradict most of the classical underpricing theories, despite proving to be significant in other developed countries. For future research, it could be interesting to try different proxy variables, which might be more suitable to the data. An example would be to use a different industry classification system, or to construct a potentially more suitable sentiment index.

Although it was outside the scope of this thesis, it could be interesting to investigate whether the long-run performance of Euronext IPOs is better explained by the classical underpricing theories, and whether the difference among the countries is reduced.

9. Bibliography

Adams, J., Hayunga, D., Mansi, S., Reeb, D., & Verardi, V. (2019). Identifying and treating outliers in finance. *Financial Management*, *48*(2), 345–384. https://doi.org/10.1111/fima.12269

Adams, M., Thornton, B., & Hall, G. (2011). IPO Pricing Phenomena: Empirical Evidence Of Behavioral Biases. *Journal of Business & Economics Research (JBER)*, *6*(4). https://doi.org/10.19030/jber.v6i4.2412

Akerlof, G. A. (1970). The Market for “Lemons”: Quality Uncertainty and the Market Mechanism. *The Quarterly Journal of Economics*, *84*(3), 488–500. https://doi.org/10.2307/1879431

Banerjee, S., Dai, L., & Shrestha, K. (2009). Cross-Country IPOs: What Explain Differences in Underpricing? *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1134332

Baron, D. P. (1982). A Model of the Demand for Investment Banking Advising and Distribution Services for New Issues. *The Journal of Finance*, *37*(4), 955–976. https://doi.org/10.1111/j.1540-6261.1982.tb03591.x

Beatty, R. P., & Ritter, J. R. (1986). Investment banking, reputation, and the underpricing of initial public offerings. *Journal of Financial Economics*, *15*(1–2), 213–232. https://doi.org/10.1016/0304-405X(86)90055-3

Bloomberg. (2022). *About European Commission Consumer Confidence Indicator Eurozone*. Retrieved June 17, 2022, from: https://www.bloomberg.com/quote/EUCCEMU:IND

Bosveld, Rudolf & Merel A. Venneman. (2000). Initial Public Offerings on the Amsterdam Stock Exchange, Working Paper, NUON and Boston Consulting Group.

Brau, J. C., Francis, B., & Kohers, N. (2003). The Choice of IPO versus Takeover: Empirical Evidence. *The Journal of Business*, *76*(4), 583–612. https://doi.org/10.1086/377032

Brealey, R. A., Myers, S., & Allen, F. (2011). *Principles of Corporate Finance*. McGraw-Hill Education.

Brennan, M. J., & Franks, J. (1997). Underpricing, ownership and control in initial public offerings of equity securities in the UK. *Journal of Financial Economics*, *45*(3), 391–413.

Breusch, T. S., & Pagan, A. R. (1979). A Simple Test for Heteroscedasticity and Random Coefficient Variation. *Econometrica*, *47*(5), 1287–1294. https://doi.org/10.2307/1911963

Butler, A. W., Keefe, M. O., & Kieschnick, R. (2014). Robust determinants of IPO underpricing and their implications for IPO research. *Journal of Corporate Finance*, *27*(C), 367–383.

Carter, R. B., Dark, F. H., & Singh, A. K. (1998). Underwriter Reputation, Initial Returns, and the Long-Run Performance of IPO Stocks. *The Journal of Finance*, *53*(1), 285–311. https://doi.org/10.1111/0022-1082.104624

Carter, R., & Manaster, S. (1990). Initial Public Offerings and Underwriter Reputation. *The Journal of Finance*, *45*(4), 1045–1067. https://doi.org/10.2307/2328714

Chambers, D., & Dimson, E. (2009). IPO Underpricing over the Very Long Run. *The Journal of Finance*, *64*(3), 1407–1443. https://doi.org/10.1111/j.1540-6261.2009.01468.x

Chen, H.-C., & Ritter, J. R. (2000). The Seven Percent Solution. *The Journal of Finance*, *55*(3), 1105–1131. https://doi.org/10.1111/0022-1082.00242

Chen, J. (2019). *Amsterdam Stock Exchange (AEX) .AS Definition*. Investopedia. Retrieved June 16, 2022, from: https://www.investopedia.com/terms/a/aex.asp

Chen, J. (2021). *Paris Stock Exchange (PAR).AS Definition*. Investopedia. Retrieved June 16, 2022, from: https://www.investopedia.com/terms/p/paris-stock-exchange-par-.p.asp

Cliff, M. T., & Denis, D. J. (2004). Do Initial Public Offering Firms Purchase Analyst Coverage with Underpricing? *The Journal of Finance*, *59*(6), 2871–2901. https://doi.org/10.1111/j.1540-6261.2004.00719.x

Da Silva Rosa, R., Velayuthen, G., & Walter, T. (2003). The sharemarket performance of Australian venture capital-backed and non-venture capital-backed IPOs. *Pacific-Basin Finance Journal*, *11*(2), 197–218. https://doi.org/10.1016/S0927-538X(02)00114-2

Da, Z., Engelberg, J., & Gao, P. (2011). In Search of Attention. *The Journal of Finance*, *66*(5), 1461–1499. https://doi.org/10.1111/j.1540-6261.2011.01679.x

Derrien, F., & Womack, K. L. (2003). Auctions vs. Bookbuilding and the Control of Underpricing in Hot IPO Markets. *Review of Financial Studies*, *16*(1), 31–61. https://doi.org/10.1093/rfs/16.1.0031

Euronext. (2022a). *Choosing your Market*. Retrieved June 16, 2022, from: https://www.euronext.com/nb/raise-capital/how-go-public/choosing-market

Euronext. (2022b). *Euronext Brussels*. Retrieved June 16, 2022, from: https://www.euronext.com/en/markets/brussels

Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance*, *25*(2), 383–417. https://doi.org/10.2307/2325486

Gahng, M., Ritter, J. R., & Zhang, D. (2021). SPACs. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3775847

Gajewski, J.-F., & Gresse, C. (2006, August). *A Survey of the European IPO Market. CEPS ECMI Research Reports No. 2, 18 August 2006* (Other No. 2). The Centre for European Policy Studies. http://aei.pitt.edu/9412/

Gibbons, J. D., & Fielden, J. D. G. (1993). *Nonparametric Statistics: An Introduction*. SAGE.

Gompers, P. A. (1996). Grandstanding in the venture capital industry. *Journal of Financial Economics*, *42*(1), 133–156. https://doi.org/10.1016/0304-405X(96)00874-4

Gopinath, S. (2021, November 18). Amsterdam Hits IPO Record as Europe's SPAC Capital. *Bloomberg.Com*. https://www.bloomberg.com/news/articles/2021-11-18/amsterdam-rakes-in-record-ipo-haul-as-europe-s-spac-capital

Gujarati, D. N., & Porter, D. C. (2009). *Basic Econometrics*. McGraw-Hill Irwin.

Hayashi, F. (2011). *Econometrics*. Princeton University Press.

Ibbotson, R. G. (1975). Price performance of common stock new issues. *Journal of Financial Economics*, *2*(3), 235–272. https://doi.org/10.1016/0304-405X(75)90015-X

Ibbotson, R. G., & Jaffe, J. F. (1975). "Hot Issue" Markets. *The Journal of Finance*, *30*(4), 1027. https://doi.org/10.2307/2326721

Ibbotson, R. G., Sindelar, J. L., & Ritter, J. R. (1988). INITIAL PUBLIC OFFERINGS. *Journal of Applied Corporate Finance*, *1*(2), 37–45. https://doi.org/10.1111/j.1745-6622.1988.tb00164.x

Jarque, C. M., & Bera, A. K. (1980). Efficient tests for normality, homoscedasticity and serial independence of regression residuals. *Economics Letters*, *6*(3), 255–259. https://doi.org/10.1016/0165-1765(80)90024-5

Jarque, C. M., & Bera, A. K. (1987). A Test for Normality of Observations and Regression Residuals. *International Statistical Review / Revue Internationale de Statistique*, *55*(2), 163. https://doi.org/10.2307/1403192

Jenkinson, T., & Ljungqvist, A. (2001). *Going Public: The Theory and Evidence on How Companies Raise Equity Finance* [OUP Catalogue]. Oxford University Press. https://econpapers.repec.org/bookchap/oxpobooks/9780198295990.htm

Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica*, *47*(2), 263. https://doi.org/10.2307/1914185

Lee, P. M., & Wahal, S. (2004). Grandstanding, certification and the underpricing of venture capital backed IPOs. *Journal of Financial Economics*, *73*(2), 375–407. https://doi.org/10.1016/j.jfineco.2003.09.003

Ljungqvist, A. (2004). *IPO Underpricing: A Survey* (SSRN Scholarly Paper No. 609422). Social Science Research Network. https://papers.ssrn.com/abstract=609422

Ljungqvist, A., Nanda, V., & Singh, R. (2006). Hot Markets, Investor Sentiment, and IPO Pricing. *The Journal of Business*, *79*(4), 1667–1702. https://doi.org/10.1086/503644

Ljungqvist, A., Jenkinson, T., & Wilhelm, W. J. (2003). Global Integration in Primary Equity Markets: The Role of U.S. Banks and U.S. Investors. *The Review of Financial Studies*, *16*(1), 63–99.

Ljungqvist, A., & Wilhelm, W. J. (2003). IPO Pricing in the Dot-com Bubble. *The Journal of Finance*, *58*(2), 723–752. https://doi.org/10.1111/1540-6261.00543

Ljungqvist, A., & Wilhelm, W. J. (2005). Does Prospect Theory Explain IPO Market Behavior? *The Journal of Finance*, *60*(4), 1759–1790. https://doi.org/10.1111/j.1540-6261.2005.00779.x

Logue, D. E. (1973). On the Pricing of Unseasoned Equity Issues: 1965-1969. *The Journal of Financial and Quantitative Analysis*, *8*(1), 91. https://doi.org/10.2307/2329751

Loughran, T., & Ritter, J. (2004). Why Has IPO Underpricing Changed Over Time? *Financial Management*, 34.

Loughran, T., & Ritter, J. R. (1995). The New Issues Puzzle. *The Journal of Finance*, *50*(1), 23–51. https://doi.org/10.2307/2329238

Loughran, T., & Ritter, J. R. (2002). Why Don't Issuers Get Upset About Leaving Money on the Table in IPOs? *Review of Financial Studies*, *15*(2), 413–444. https://doi.org/10.1093/rfs/15.2.413

Loughran, T., Ritter, J., & Rydqvist, K. (1994). Initial public offerings: International insights. Pacific-Basin Finance Journal, 2(2-3), 165-199. https://doi.org/10.1016/0927-538x(94)90016-7

Loughran, T., Ritter, J., & Rydqvist, K. (Updated 2022). Initial public offerings: International insights. Pacific-Basin Finance Journal, 2(2-3), 165-199. https://site.warrington.ufl.edu/ritter/files/IPOs-International.pdf

Lowry, M. B., & Schwert, G. W. W. (2001). Biases in the IPO Pricing Process. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.260278

Lowry, M., Officer, M. S., & Schwert, G. W. (2010). The Variability of IPO Initial Returns. *The Journal of Finance*, *65*(2), 425–465. https://doi.org/10.1111/j.1540-6261.2009.01540.x

Megginson, W. L., & Weiss, K. A. (1991). Venture Capitalist Certification in Initial Public Offerings. *The Journal of Finance*, *46*(3), 879–903. https://doi.org/10.1111/j.1540-6261.1991.tb03770.x

Muscarella, C. J., & Vetsuypens, M. R. (1989). A simple test of Baron's model of IPO underpricing. *Journal of Financial Economics*, *24*(1), 125–135. https://doi.org/10.1016/0304-405X(89)90074-3

NTB. (2019). *Euronext fullfører oppkjøpet av Oslo Børs VPS*. Aftenposten. Retrieved June 16, 2022, from: https://www.aftenposten.no/okonomi/i/kJBR9Q/euronext-fullfoerer-oppkjoepet-av-oslo-boers-vps?fbclid=IwAR1xb3me2WWU5_yz-y2ZQRxm1dCgzt8b2eoBDbIKH11gXpjB4KOHDbj0OFo

PWC. (2022). *Navigating the IPO process*. Retrieved June 27, 2022, from: https://explore.pwc.com/c/navigating-the-ipo?x=nmqemH

Rajan, R. G. (2012). Presidential Address: The Corporation in Finance. *The Journal of Finance, 67*(4), 1173–1217. https://doi.org/10.1111/j.1540-6261.2012.01745.x

Reilly, F. K., & Hatfield, K. (1969). Investor Experience with New Stock Issues. *Financial Analysts Journal*, *25*(5), 73–80.

Ritter, J. R. (1984). The "Hot Issue" Market of 1980. *The Journal of Business*, *57*(2), 215–240.

Ritter, J. R. (1991). The Long-Run Performance of initial Public Offerings. *The Journal of Finance*, *46*(1), 3–27. https://doi.org/10.1111/j.1540-6261.1991.tb03743.x

Ritter, J. R., & Welch, I. (2002). *A Review of IPO Activity, Pricing and Allocations* (SSRN Scholarly Paper No. 296393). Social Science Research Network. https://doi.org/10.2139/ssrn.296393

Ritter, J.R. (2022). Initial Public Offerings: Updated Statistics. Retrieved from: https://site.warrington.ufl.edu/ritter/files/IPO-Statistics.pdf

Rock, K. (1986). Why new issues are underpriced. *Journal of Financial Economics*, *15*(1), 187–212. https://doi.org/10.1016/0304-405X(86)90054-1

Rydqvist, K. (1997). IPO underpricing as tax-efficient compensation. *Journal of Banking & Finance,* 21(3), 295–313. https://doi.org/10.1016/s0378-4266(96)00043-x

Scott, G. (2021, December 22). *Euronext*. Investopedia. Retrieved June 16, 2022, from: https://www.investopedia.com/terms/e/euronext.asp

Silva, N., Sebastião, H., & Henriques, D. (2021). Padrões dos IPOs na Euronext Após a Crise Financeira Global de 2007-2008. *Notas Económicas*, *52*, 137–155. https://doi.org/10.14195/2183-203X_52_6

Smith, T. (2022). *Underwriting Agreement*. Investopedia. Retrieved June 21, 2022, from: https://www.investopedia.com/terms/u/underwriting-agreement.asp

Statista. (2022). *Largest stock exchanges in Europe as of March 2022, by domestic market capitalization.* Retrieved June 16, 2022, from: https://www.statista.com/statistics/693587/stock-exchanges-market-capitalization-europe/

Stoughton, N. M., & Zechner, J. (1998). IPO-mechanisms, monitoring and ownership structure. *Journal of Financial Economics*, *49*(1), 45–77.

Tukey, J. W. (1962). The Future of Data Analysis. *The Annals of Mathematical Statistics*, *33*(1), 1–67. https://doi.org/10.1214/aoms/1177704711

Walker, T. (2008). Family Control, Underwriter Prestige, and IPO Underpricing: A Cross Country Analysis. *Multinational Business Review*, *16*(2), 1–42. https://doi.org/10.1108/1525383X200800006

Welch, I. (1992). Sequential Sales, Learning, and Cascades. *The Journal of Finance*, *47*(2), 695–732. https://doi.org/10.1111/j.1540-6261.1992.tb04406.x

Wooldridge, J. M. (2019). *Introductory Econometrics: A Modern Approach*. Cengage Learning.

World Bank. (2022). *Population, total - France*. Retrieved June 16, 2022, from: https://data.worldbank.org/indicator/SP.POP.TOTL?locations=FR

10. Appendix

Appendix 10.1: Underwriter Rank

Belgium

Rank	Firm	Proceeds	Market Share
1	JP Morgan	657 129 000	14,13 %
2	Goldman Sachs	475 291 667	10,22 %
3	BNP Paribas	410 275 667	8,82 %
4	HSBC	410 275 667	8,82 %
5	ING Belgium SA/NV	398 901 667	8,58 %
6	Barclays	378 285 000	8,13 %
7	Banque Degroof Petercam SA	328 427 500	7,06 %
8	KBC	285 906 667	6,15 %
9	Kempen & Co NV	279 379 833	6,01 %
10	Belfius Bank SA/NV	260 345 000	5,60 %
11	Bank of Americal Merrill Lynch	171 930 000	3,70 %
12	UBS	171 930 000	3,70 %
13	Societe Generale	120 079 000	2,58 %
14	Berenberg	109 795 000	2,36 %
15	Deutsche Bank	74 923 333	1,61 %
16	RBC	46 995 000	1,01 %
17	CM-Securities SA	19 650 000	0,42 %
18	Bryan Garnier & Company	14 250 000	0,31 %
19	Kepler Cheuvreux	14 250 000	0,31 %
20	Oppenheimer	13 622 500	0,29 %
21	Mirabaud Securities	9 776 667	0,21 %

Netherlands

Rank	Firm	Proceeds	Market Share
1	ABN Amro	2 771 504 870	9,66 %
2	JP Morgan	2 565 915 719	8,94 %
3	Morgan Stanley	2 527 814 152	8,81 %
4	Citigroup	2 242 890 667	7,81 %
5	ING Bank NV	2 032 648 819	7,08 %
6	Deutsche Bank	1 937 211 196	6,75 %
7	Barclays	1 794 901 140	6,25 %
8	Goldman Sachs	1 646 844 537	5,74 %
9	BNP Paribas	1 611 514 428	5,62 %
10	HSBC	1 550 329 466	5,40 %
11	Bank of America	1 445 612 570	5,04 %
12	Rabobank	1 283 653 839	4,47 %
13	Credit Suisse	1 001 797 594	3,49 %
14	UBS	646 999 587	2,25 %
15	Jefferies	548 088 289	1,91 %
16	Banco Santander	407 720 979	1,42 %
17	Kempen & Co NV	329 410 223	1,15 %
18	Credit Agricole	229 357 634	0,80 %
19	MUFG	229 357 634	0,80 %
20	Unicredit	229 357 634	0,80 %
21	Commerzbank	224 234 227	0,78 %
22	Nomura	224 234 227	0,78 %
23	Berenberg	216 400 666	0,75 %
24	Eerste	198 538 880	0,69 %
25	Caixabank	178 363 345	0,62 %
26	Intesa Sanpaolo	178 363 345	0,62 %
27	Societe Generale	162 963 190	0,57 %
28	KBC	60 493 664	0,21 %
29	Banque Degroof	25 291 152	0,09 %
30	RBC	25 291 152	0,09 %

France

Rank	Firm	Proceeds	Market Share
1	Societe Generale	2 288 076 393	10,83 %
2	BNP Paribas	2 076 035 828	9,82 %
3	JP Morgan	1 677 917 474	7,94 %
4	Deutsche Bank	1 504 738 655	7,12 %
5	Morgan Stanley	1 378 928 899	6,52 %
6	HSBC	1 339 337 836	6,34 %
7	Credit Agricole	1 322 526 415	6,26 %
8	Goldman Sachs	1 240 390 597	5,87 %
9	Citigroup	1 214 722 852	5,75 %
10	Lazard	1 006 863 483	4,76 %
11	Barclays	904 510 515	4,28 %
12	Bank of America	871 031 987	4,12 %
13	Credit Suisse	849 185 454	4,02 %
14	Gilbert Dupont	481 985 627	2,28 %
15	UBS	406 545 865	1,92 %
16	Portzamparc	400 508 587	1,89 %
17	bryan Garnier	243 566 171	1,15 %
18	Oddo & Cie	208 855 319	0,99 %
19	CM-CIC	185 921 302	0,88 %
20	KKR	171 572 411	0,81 %
21	Berenberg	166 032 746	0,79 %
22	ABN Amro	151 489 319	0,72 %
23	ING Bank	151 489 319	0,72 %
24	Midcap Partners	125 505 367	0,59 %
25	Banco Santander	124 119 744	0,59 %
26	Swisslife	113 136 806	0,54 %
27	Jefferies	102 244 123	0,48 %
28	Invest Securities	97 608 947	0,46 %
29	RBC	53 554 348	0,25 %
30	Stifel	44 852 177	0,21 %
31	Louis Capital Marke	42 023 814	0,20 %
32	KBC	34 966 511	0,17 %
33	Aurel	32 515 323	0,15 %
34	Mainfirst Bank AG	22 422 999	0,11 %
35	Kempen	18 105 793	0,09 %
36	Banque Delubac	15 920 866	0,08 %
37	Petercam SA	14 560 715	0,07 %
38	NIBC	14 250 347	0,07 %
39	TP ICAP	12 709 149	0,06 %
40	Sponsor Finance	10 974 415	0,05 %
41	GFI Securities	9 036 706	0,04 %
42	Arkeon Finance	4 604 715	0,02 %

Appendix 10.2: Correlation Matrix – Euronext Sample

	LN_age	LN_Offe	Tech	Rank	Techniq	Sentime	HC	VC	Mret	Mvol	D2014	D2015	D2016	D2017	D2018	D2019	D2020
LN_age	1																
LN_Offer	0,364	1															
Tech	0,005	-0,070	1														
Rank	0,179	0,573	-0,078	1													
Techniqu	0,010	-0,041	-0,004	-0,036	1												
Sentimen	-0,080	-0,039	0,024	0,045	-0,003	1											
HC	0,054	0,110	-0,098	0,117	0,290	-0,030	1										
VC	-0,233	-0,124	0,110	-0,040	-0,077	0,116	-0,140	1									
Mret	-0,012	0,058	-0,025	0,037	0,035	-0,092	0,082	0,059	1								
Mvol	-0,034	-0,107	-0,110	-0,120	-0,086	-0,323	-0,115	-0,029	-0,137	1							
D2014	0,025	0,036	-0,012	0,017	0,030	-0,424	0,290	-0,027	-0,084	-0,270	1						
D2015	-0,008	0,041	-0,144	-0,029	-0,107	0,004	-0,010	-0,021	0,100	0,341	-0,217	1					
D2016	0,049	-0,037	-0,067	0,000	-0,119	-0,056	-0,067	0,055	-0,081	0,257	-0,145	-0,172	1				
D2017	-0,027	0,029	0,075	0,049	0,056	0,217	-0,207	0,291	0,009	-0,302	-0,131	-0,156	-0,104	1			
D2018	-0,038	-0,050	0,080	-0,078	-0,048	0,365	-0,250	0,024	-0,195	-0,163	-0,158	-0,188	-0,125	-0,113	1		
D2019	0,044	0,071	-0,075	0,136	-0,027	0,034	-0,138	-0,106	0,015	-0,032	-0,087	-0,104	-0,069	-0,062	-0,075	1	
D2020	0,073	-0,065	0,109	-0,124	0,095	-0,496	-0,086	-0,085	0,068	0,284	-0,116	-0,138	-0,092	-0,083	-0,100	-0,055	1

Appendix 10.3 Regression output for Euronext Sample:

Model (1):

```
Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.042717   0.032167  -1.328 0.186014
LN_age      -0.008441   0.008420  -1.002 0.317576
LN_OfferSize 0.012491   0.005377   2.323 0.021379 *
Tech        -0.005237   0.021477  -0.244 0.807656
Rank        -0.029350   0.017382  -1.689 0.093191 .
Technique    0.010570   0.018272   0.578 0.563726
Sentiment   -0.008500   0.002230  -3.812 0.000194 ***
HC          -0.027703   0.015816  -1.752 0.081687 .
VC          -0.017632   0.017699  -0.996 0.320606
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.09107 on 166 degrees of freedom
Multiple R-squared:  0.1355,    Adjusted R-squared:  0.09383
F-statistic: 3.252 on 8 and 166 DF,  p-value: 0.001818
```

Model (2):

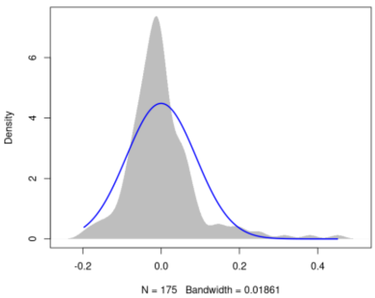
```
Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)      -0.043536   0.036023  -1.209   0.2286
LN_age           -0.008387   0.008475  -0.990   0.3238
LN_OfferSize      0.012461   0.005426   2.296   0.0229 *
Tech             -0.004963   0.021806  -0.228   0.8202
Rank             -0.029305   0.017506  -1.674   0.0960 .
Technique         0.010570   0.018423   0.574   0.5669
Sentiment        -0.008403   0.002401  -3.500   0.0006 ***
HC               -0.027828   0.016022  -1.737   0.0843 .
VC               -0.017917   0.017866  -1.003   0.3174
Marketreturn      0.039217   0.194944   0.201   0.8408
Marketvolatility  0.138214   2.116066   0.065   0.9480
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.09161 on 164 degrees of freedom
Multiple R-squared:  0.1357,    Adjusted R-squared:  0.08301
F-statistic: 2.575 on 10 and 164 DF,  p-value: 0.006398
```

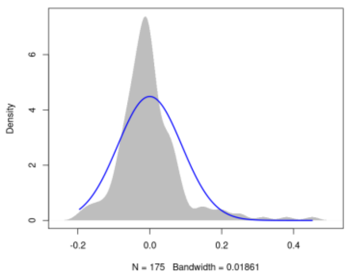
Model (3)

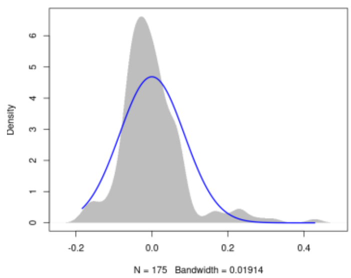
```
Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)      -0.084112   0.041953  -2.005  0.04669 *
LN_age           -0.005806   0.008377  -0.693  0.48928
LN_OfferSize      0.010761   0.005359   2.008  0.04635 *
Tech             -0.006162   0.021777  -0.283  0.77758
Rank             -0.030276   0.017382  -1.742  0.08351 .
Technique         0.005956   0.018521   0.322  0.74821
Sentiment        -0.018370   0.003749  -4.900 2.37e-06 ***
HC               -0.010813   0.018344  -0.589  0.55640
VC               -0.010440   0.018527  -0.564  0.57389
Marketreturn     -0.084581   0.205951  -0.411  0.68186
Marketvolatility -1.196938   2.733874  -0.438  0.66212
Dummy2014        -0.093245   0.030610  -3.046  0.00272 **
Dummy2015        -0.018908   0.022848  -0.828  0.40916
Dummy2016        -0.058648   0.028134  -2.085  0.03873 *
Dummy2017        -0.006324   0.031512  -0.201  0.84120
Dummy2018         0.022783   0.027515   0.828  0.40892
Dummy2019        -0.004612   0.038608  -0.119  0.90506
Dummy2020        -0.092415   0.039376  -2.347  0.02018 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.08966 on 157 degrees of freedom
Multiple R-squared:  0.2074,	Adjusted R-squared:  0.1216
F-statistic: 2.417 on 17 and 157 DF,  p-value: 0.002316
```

Appendix 10.4 Normality of Residual Plots for Euronext Sample

Model (1) **Model (2)** **Model (3)**







Appendix 10.5 VIF output for Euronext Sample

Model (1)

Variables	Tolerance	VIF
LN_age	0.8261668	1.210409
LN_OfferSize	0.5949145	1.680914
Tech	0.9729079	1.027847
Rank	0.6601647	1.514773
Technique	0.9067247	1.102871
Sentiment	0.9771633	1.023370
HC	0.8791107	1.137513
VC	0.9073228	1.102144

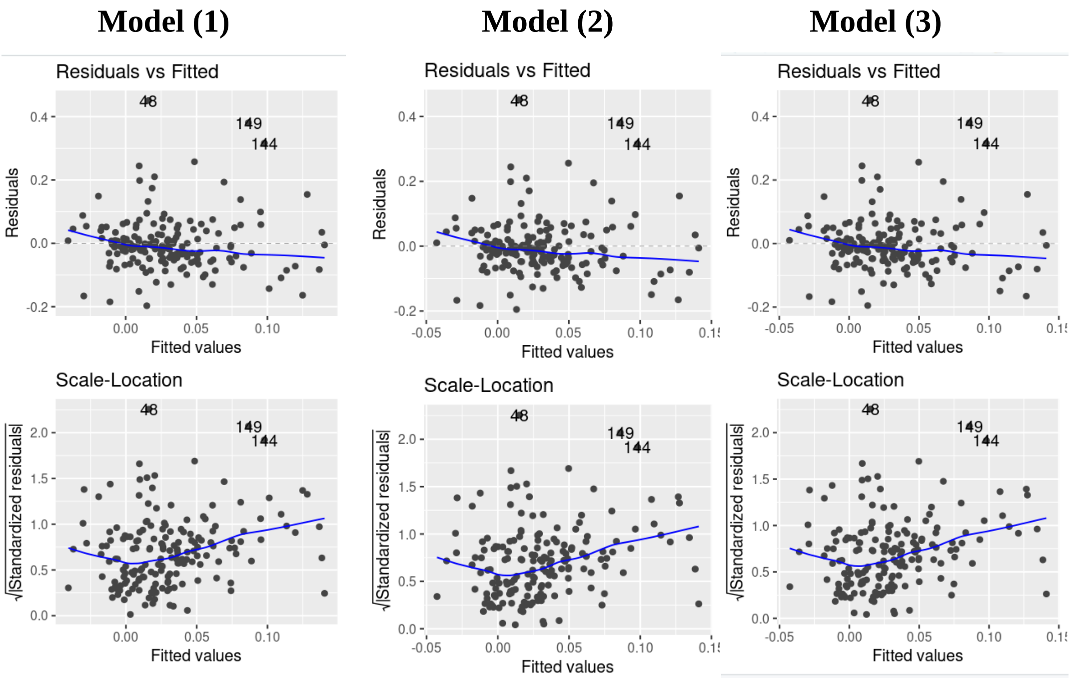
Model (2)

Variables	Tolerance	VIF
LN_age	0.8252731	1.211720
LN_OfferSize	0.5910844	1.691806
Tech	0.9550713	1.047042
Rank	0.6586139	1.518340
Technique	0.9026506	1.107848
Sentiment	0.8526486	1.172816
HC	0.8668501	1.153602
VC	0.9010899	1.109767
Marketreturn	0.9471755	1.055771
Marketvolatility	0.8247133	1.212543

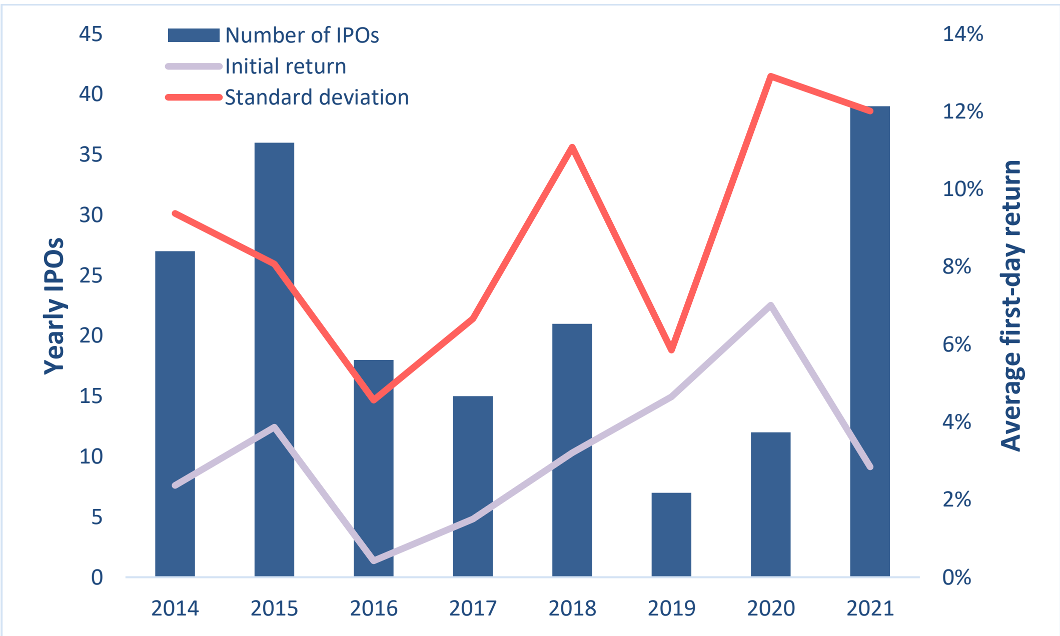
Model (3)

Variables	Tolerance	VIF
LN_age	0.8091848	1.235812
LN_OfferSize	0.5804808	1.722710
Tech	0.9173188	1.090134
Rank	0.6399583	1.562602
Technique	0.8555027	1.168903
Sentiment	0.3350532	2.984600
HC	0.6334298	1.578707
VC	0.8026964	1.245801
Marketreturn	0.8129340	1.230112
Marketvolatility	0.4733008	2.112821
Dummy2014	0.3757544	2.661313
Dummy2015	0.5385819	1.856728
Dummy2016	0.6289370	1.589984
Dummy2017	0.5903334	1.693958
Dummy2018	0.5746005	1.740340
Dummy2019	0.8025739	1.245991
Dummy2020	0.4638905	2.155681

Appendix 10.6: Heteroscedasticity Plots



Appendix 10.7: Number of IPOs, standard deviation and return



Appendix 10.8: Correlation Matrix – Country-Specific

Belgium

	LN_age	LN_Offe	Tech	Rank	Techniq	Sentime	HC	VC	Mret	Mvol	D2014	D2015	D2016	D2017	D2018	D2019	D2020
LN_age	1																
LN_Offer	0,287	1															
Tech	0,097	0,210	1														
Rank	0,590	0,787	-0,098	1													
Techniqu	-0,178	0,087	0,292	-0,094	1												
Sentimen	0,170	0,247	-0,328	0,331	-0,126	1											
HC	0,093	0,213	0,204	-0,020	-0,032	-0,013	1										
VC	-0,265	-0,166	-0,066	-0,142	0,099	0,115	-0,322	1									
Mret	-0,228	-0,419	-0,281	-0,309	-0,213	-0,283	-0,293	-0,259	1								
Mvol	-0,333	-0,259	0,192	-0,474	0,472	-0,430	-0,037	-0,035	0,101	1							
D2014	0,094	-0,177	-0,098	0,092	-0,335	-0,298	0,210	0,265	0,010	-0,304	1						
D2015	-0,182	-0,040	-0,127	-0,273	0,190	0,237	0,371	-0,183	-0,039	0,295	-0,273	1					
D2016	0,317	-0,216	-0,045	-0,098	-0,156	-0,007	-0,223	-0,066	0,074	0,042	-0,098	-0,127	1				
D2017	0,436	0,178	-0,045	0,465	0,292	0,205	-0,223	-0,066	-0,294	-0,280	-0,098	-0,127	-0,045	1			
D2018	0,066	0,155	-0,066	0,265	0,099	0,362	-0,322	0,452	-0,285	-0,003	-0,142	-0,183	-0,066	-0,066	1		
D2019	-0,054	-0,196	-0,045	-0,098	-0,156	0,109	-0,223	-0,066	0,206	-0,100	-0,098	-0,127	-0,045	-0,045	-0,066	1	
D2020	-0,278	0,020	0,465	-0,211	0,387	-0,748	-0,020	-0,142	0,109	0,547	-0,211	-0,273	-0,098	-0,098	-0,142	-0,098	1

France

	LN_age	LN_Offe	Tech	Rank	Techniq	Sentime	HC	VC	Mret	Mvol	D2014	D2015	D2016	D2017	D2018	D2019	D2020
LN_age	1																
LN_Offer	0,281	1															
Tech	0,006	-0,019	1														
Rank	0,067	0,598	-0,105	1													
Techniqu	0,125	-0,036	-0,003	0,011	1												
Sentimen	-0,095	0,034	0,003	-0,031	0,111	1											
HC	0,009	0,089	-0,085	0,199	0,359	0,028	1										
VC	-0,206	-0,062	0,141	0,007	-0,100	0,061	-0,062	1									
Mret	-0,061	0,095	-0,025	0,073	0,098	-0,081	0,124	0,118	1								
Mvol	-0,087	-0,190	-0,124	-0,126	-0,142	-0,297	-0,202	-0,007	-0,174	1							
D2014	0,079	0,140	0,027	0,063	-0,057	-0,457	0,370	-0,010	-0,069	-0,275	1						
D2015	-0,023	0,038	-0,143	0,025	-0,216	-0,056	-0,280	-0,021	0,075	0,329	-0,196	1					
D2016	0,000	-0,108	-0,065	-0,063	-0,077	-0,088	-0,196	0,068	-0,065	0,361	-0,138	-0,161	1				
D2017	-0,109	0,082	0,091	0,055	-0,003	0,216	-0,196	0,329	0,026	-0,303	-0,138	-0,161	-0,113	1			
D2018	-0,072	-0,083	0,121	-0,220	-0,037	0,346	-0,223	-0,041	-0,159	-0,182	-0,157	-0,183	-0,128	-0,128	1		
D2019	0,069	0,163	-0,089	0,205	0,017	0,008	-0,123	-0,120	-0,001	-0,025	-0,086	-0,101	-0,071	-0,071	-0,080	1	
D2020	0,141	-0,135	0,093	-0,104	-0,018	-0,417	-0,147	-0,060	0,080	0,186	-0,103	-0,120	-0,084	-0,084	-0,096	-0,053	1

Netherlands

	LN_age	LN_Offe	Tech	Rank	Techniq	Sentime	HC	VC	Mret	Mvol	D2014	D2015	D2016	D2017	D2018	D2019	D2020
LN_age	1																
LN_Offer	0,280	1															
Tech	0,106	-0,090	1														
Rank	0,007	0,160	0,161	1													
Techniqu	-0,149	-0,232	-0,116	-0,040	1												
Sentimen	-0,092	-0,182	0,208	0,201	-0,170	1											
HC	0,100	-0,113	-0,197	-0,023	0,271	-0,078	1										
VC	-0,337	-0,244	-0,116	-0,209	-0,012	0,234	-0,205	1									
Mret	0,151	0,089	0,143	-0,031	0,074	0,004	0,262	-0,050	1								
Mvol	0,217	0,025	-0,114	0,050	-0,466	-0,309	0,017	-0,050	-0,145	1							
D2014	-0,164	-0,268	-0,116	-0,209	0,595	-0,411	0,112	-0,214	-0,224	-0,271	1						
D2015	0,065	-0,012	-0,139	-0,098	-0,075	0,057	0,420	0,107	0,317	0,415	-0,257	1					
D2016	0,024	0,077	-0,104	0,086	-0,192	-0,004	0,357	0,026	-0,250	0,013	-0,192	-0,230	1				
D2017	0,141	-0,043	-0,063	-0,113	0,212	0,204	-0,197	0,212	0,120	-0,275	-0,116	-0,139	-0,104	1			
D2018	0,012	-0,023	-0,091	0,236	-0,169	0,430	-0,287	0,070	-0,303	-0,167	-0,169	-0,203	-0,152	-0,091	1		
D2019	0,062	0,006	-0,044	0,112	-0,081	0,061	-0,137	-0,081	-0,073	-0,002	-0,081	-0,097	-0,072	-0,044	-0,064	1	
D2020	0,361	0,240	-0,044	0,112	-0,081	-0,562	-0,137	-0,081	0,050	0,466	-0,081	-0,097	-0,072	-0,044	-0,064	-0,030	1

Appendix 10.9: Regression output – Country-Specific

Belgium – Model (1)

```
Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  -0.072170   0.100851  -0.716    0.485
LN_age       -0.019852   0.022909  -0.867    0.400
LN_OfferSize  0.022453   0.013085   1.716    0.107
Tech          0.083979   0.077132   1.089    0.293
Technique    -0.018042   0.030160  -0.598    0.559
Sentiment    -0.005531   0.004649  -1.190    0.253
HC            0.018640   0.029029   0.642    0.530
VC           -0.069791   0.052667  -1.325    0.205

Residual standard error: 0.06362 on 15 degrees of freedom
Multiple R-squared:  0.4646,	Adjusted R-squared:  0.2147
F-statistic: 1.859 on 7 and 15 DF,  p-value: 0.1484
```

Belgium – Model (2)

```
Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)      -0.140157   0.115844  -1.210   0.2479
LN_age           -0.008055   0.022463  -0.359   0.7257
LN_OfferSize      0.030167   0.012973   2.325   0.0369 *
Tech              0.120619   0.072803   1.657   0.1215
Technique        -0.002335   0.031683  -0.074   0.9424
Sentiment        -0.003161   0.004652  -0.679   0.5088
HC                0.043520   0.029079   1.497   0.1584
VC               -0.012605   0.056229  -0.224   0.8261
Marketreturn      1.050189   0.485798   2.162   0.0499 *
Marketvolatility -0.759112   4.944766  -0.154   0.8803
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.05843 on 13 degrees of freedom
Multiple R-squared:  0.6085,	Adjusted R-squared:  0.3375
F-statistic: 2.245 on 9 and 13 DF,  p-value: 0.08998
```

Belgium – Model (3)

```
Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)      -0.182689   0.115453  -1.582   0.1576
LN_age           -0.005492   0.030054  -0.183   0.8602
LN_OfferSize      0.028032   0.013750   2.039   0.0809 .
Tech              0.120482   0.074290   1.622   0.1489
Technique        -0.019035   0.038454  -0.495   0.6358
Sentiment        -0.015338   0.006227  -2.463   0.0433 *
HC                0.055567   0.044169   1.258   0.2487
VC                0.012186   0.065978   0.185   0.8587
Marketreturn      1.137600   0.535736   2.123   0.0714 .
Marketvolatility -9.570847   5.893080  -1.624   0.1484
Dummy2014        -0.059653   0.048982  -1.218   0.2627
Dummy2015         0.080368   0.037445   2.146   0.0690 .
Dummy2016         0.022315   0.078642   0.284   0.7848
Dummy2017         0.023914   0.115421   0.207   0.8418
Dummy2018         0.106595   0.068493   1.556   0.1636
Dummy2019         0.019479   0.064794   0.301   0.7724
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.05345 on 7 degrees of freedom
Multiple R-squared:  0.8236,	Adjusted R-squared:  0.4456
F-statistic: 2.179 on 15 and 7 DF,  p-value: 0.151
```

France – Model (1)

```
               Estimate Std. Error t value Pr(>|t|)
(Intercept)  -0.0310638  0.0343478 -0.9044  0.36778
LN_age       -0.0136406  0.0075236 -1.8131  0.07258 .
LN_OfferSize  0.0088532  0.0066741  1.3265  0.18745
Tech         -0.0019673  0.0268793 -0.0732  0.94179
Rank         -0.0345484  0.0216534 -1.5955  0.11349
Technique     0.0407577  0.0254075  1.6042  0.11157
Sentiment    -0.0110532  0.0042842 -2.5800  0.01121 *
HC           -0.0381263  0.0174368 -2.1865  0.03091 *
VC           -0.0286186  0.0222312 -1.2873  0.20071
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

France – Model (2)

```
                    Estimate  Std. Error t value Pr(>|t|)  
(Intercept)      -0.03505164  0.03905689 -0.8975  0.37149  
LN_age           -0.01287602  0.00761606 -1.6906  0.09382 .
LN_OfferSize      0.00855334  0.00659970  1.2960  0.19776  
Tech             -0.00058528  0.02640570 -0.0222  0.98236  
Rank             -0.03398471  0.02131512 -1.5944  0.11380  
Technique         0.03959801  0.02547533  1.5544  0.12305  
Sentiment        -0.01063979  0.00449763 -2.3656  0.01980 *
HC               -0.03819730  0.01731408 -2.2061  0.02951 *
VC               -0.03010269  0.02174413 -1.3844  0.16911  
Marketreturn      0.12689459  0.26786895  0.4737  0.63667  
Marketvolatility  0.59797731  2.92966946  0.2041  0.83865  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

France – Model (3)

```
                   Estimate Std. Error t value  Pr(>|t|)    
(Intercept)      -0.0774940  0.0562048 -1.3788 0.1710394    
LN_age           -0.0082712  0.0085520 -0.9672 0.3357938    
LN_OfferSize      0.0105191  0.0062240  1.6901 0.0941254 .  
Tech             -0.0027516  0.0247640 -0.1111 0.9117490    
Rank             -0.0472412  0.0216543 -2.1816 0.0314816 *  
Technique         0.0229949  0.0247809  0.9279 0.3556795    
Sentiment        -0.0221592  0.0060652 -3.6535 0.0004141 ***
HC               -0.0320313  0.0343836 -0.9316 0.3537927    
VC               -0.0217234  0.0213535 -1.0173 0.3114549    
Marketreturn     -0.0171213  0.2839894 -0.0603 0.9520462    
Marketvolatility -0.4986366  3.3724145 -0.1479 0.8827530    
Dummy2014        -0.1243142  0.0456053 -2.7259 0.0075731 ** 
Dummy2015        -0.0418672  0.0423428 -0.9888 0.3251637    
Dummy2016        -0.0990148  0.0421358 -2.3499 0.0207430 *  
Dummy2017        -0.0144157  0.0410119 -0.3515 0.7259522    
Dummy2018        -0.0195530  0.0362356 -0.5396 0.5906673    
Dummy2019        -0.0148094  0.0438201 -0.3380 0.7361020    
Dummy2020        -0.1300864  0.0629567 -2.0663 0.0413864 *  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Netherlands – Model (1)

```
Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  -0.042943   0.107933  -0.398    0.694
LN_age       -0.005712   0.017449  -0.327    0.746
LN_OfferSize  0.015483   0.013406   1.155    0.259
Tech         -0.096568   0.077956  -1.239    0.227
Rank         -0.014494   0.040079  -0.362    0.721
Technique    -0.020505   0.048401  -0.424    0.675
Sentiment    -0.006176   0.005693  -1.085    0.288
HC           -0.045434   0.038319  -1.186    0.247
VC            0.045477   0.051892   0.876    0.389

Residual standard error: 0.09796 on 25 degrees of freedom
Multiple R-squared:  0.2797,	Adjusted R-squared:  0.04914 
F-statistic: 1.213 on 8 and 25 DF,  p-value: 0.3316
```

Netherlands – Model (2)

```
Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)      -0.015231   0.122684  -0.124    0.902
LN_age           -0.001398   0.018494  -0.076    0.940
LN_OfferSize      0.013978   0.014507   0.964    0.345
Tech             -0.092356   0.082633  -1.118    0.275
Rank             -0.008816   0.042415  -0.208    0.837
Technique        -0.045794   0.062692  -0.730    0.472
Sentiment        -0.008555   0.006759  -1.266    0.218
HC               -0.032852   0.041581  -0.790    0.438
VC                0.053656   0.053740   0.998    0.328
Marketreturn     -0.440336   0.597112  -0.737    0.468
Marketvolatility -5.787343   8.061008  -0.718    0.480

Residual standard error: 0.1001 on 23 degrees of freedom
Multiple R-squared:  0.3074,	Adjusted R-squared:  0.006335 
F-statistic: 1.021 on 10 and 23 DF,  p-value: 0.4565
```

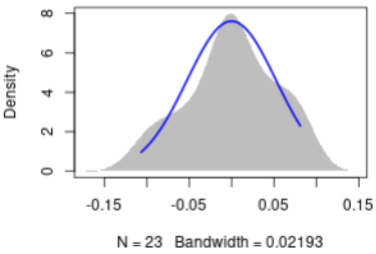
Netherlands – Model (3)

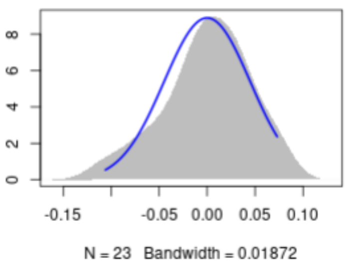
```
Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)     -0.260584   0.226623  -1.150    0.267
LN_age          -0.009623   0.024802  -0.388    0.703
LN_OfferSize     0.028634   0.018226   1.571    0.136
Tech            -0.016301   0.110713  -0.147    0.885
Rank            -0.023224   0.052056  -0.446    0.661
Technique       -0.051284   0.086366  -0.594    0.561
Sentiment       -0.009864   0.010953  -0.901    0.381
HC               0.012969   0.075575   0.172    0.866
VC               0.093798   0.067683   1.386    0.185
Marketreturn     0.368712   1.006312   0.366    0.719
Marketvolatility 7.526976  13.778419   0.546    0.592
Dummy2014        0.094038   0.107064   0.878    0.393
Dummy2015       -0.043417   0.089219  -0.487    0.633
Dummy2016       -0.004901   0.109568  -0.045    0.965
Dummy2017        0.046628   0.116576   0.400    0.694
Dummy2018        0.148925   0.108799   1.369    0.190
Dummy2019        0.049452   0.131736   0.375    0.712
Dummy2020       -0.077766   0.198789  -0.391    0.701

Residual standard error: 0.1078 on 16 degrees of freedom
Multiple R-squared:  0.4421,    Adjusted R-squared:  -0.1506
F-statistic: 0.7459 on 17 and 16 DF,  p-value: 0.7227
```

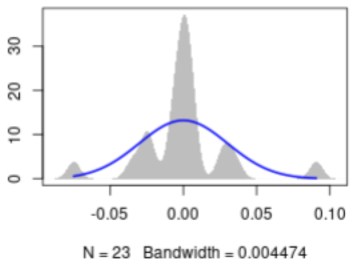
Appendix 10.10: Normality of Residual Plots – Country-Specific

Belgium

Model (1) **Model (2)** **Model (3)**

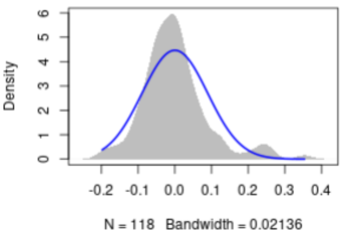


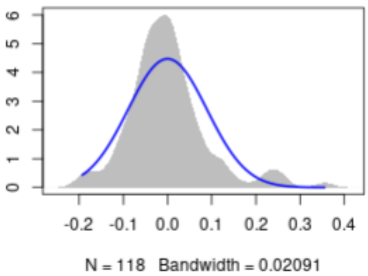


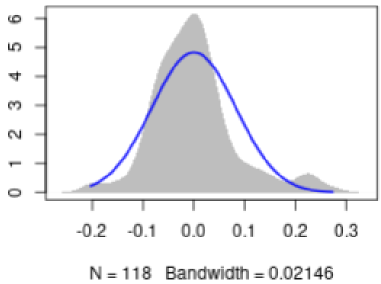


France

Model (1) **Model (2)** **Model (3)**

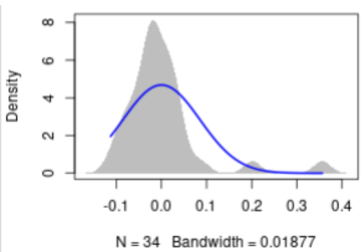


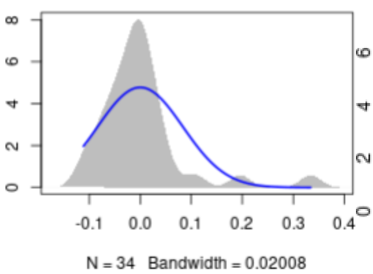


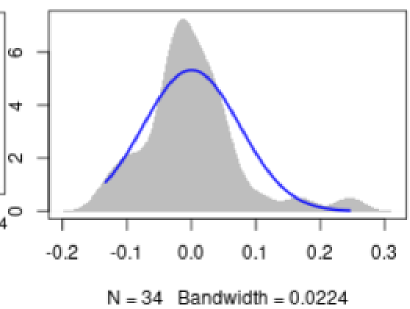


Netherlands

Model (1) **Model (2)** **Model (3)**







Appendix 10.11: VIF output – Country-Specific

Belgium

Model (1)

Variables	Tolerance	VIF
LN_age	0.8025892	1.245967
LN_OfferSize	0.7647422	1.307630
Tech	0.7111738	1.406126
Technique	0.8527585	1.172665
Sentiment	0.7388220	1.353506
HC	0.8368064	1.195020
VC	0.7989974	1.251568

Model (2)

Variables	Tolerance	VIF
LN_age	0.7042833	1.419883
LN_OfferSize	0.6562820	1.523735
Tech	0.6734732	1.484840
Technique	0.6519290	1.533909
Sentiment	0.6224381	1.606585
HC	0.7035693	1.421324
VC	0.5913819	1.690955
Marketreturn	0.4810467	2.078800
Marketvolatility	0.5538648	1.805495

Model (3)

Variables	Tolerance	VIF
LN_age	0.3292165	3.037515
LN_OfferSize	0.4888681	2.045541
Tech	0.5412341	1.847629
Technique	0.3703445	2.700189
Sentiment	0.2907515	3.439364
HC	0.2551813	3.918783
VC	0.3594358	2.782138
Marketreturn	0.3309995	3.021152
Marketvolatility	0.3263181	3.064494
Dummy2014	0.3603907	2.774766
Dummy2015	0.4594982	2.176287
Dummy2016	0.4829814	2.070473
Dummy2017	0.2242209	4.459888
Dummy2018	0.3335248	2.998278
Dummy2019	0.7114904	1.405500

France

Model (1)

Variables	Tolerance	VIF
LN_age	0.8401312	1.190290
LN_OfferSize	0.5685206	1.758951
Tech	0.9595804	1.042122
Rank	0.5971266	1.674687
Technique	0.8258591	1.210860
Sentiment	0.9594436	1.042271
HC	0.8259158	1.210777
VC	0.9251134	1.080949

Model (2)

Variables	Tolerance	VIF
LN_age	0.8261918	1.210373
LN_OfferSize	0.5558924	1.798909
Tech	0.9332756	1.071495
Rank	0.5958242	1.678347
Technique	0.8162208	1.225159
Sentiment	0.8478450	1.179461
HC	0.8001723	1.249731
VC	0.9080530	1.101257
Marketreturn	0.9007936	1.110132
Marketvolatility	0.7918379	1.262885

Model (3)

Variables	Tolerance	VIF
LN_age	0.7764276	1.287950
LN_OfferSize	0.5156052	1.939469
Tech	0.8961922	1.115832
Rank	0.5380376	1.858606
Technique	0.7632946	1.310110
Sentiment	0.3465976	2.885190
HC	0.3623296	2.759918
VC	0.7799738	1.282094
Marketreturn	0.7488642	1.335356
Marketvolatility	0.4217072	2.371314
Dummy2014	0.3335048	2.998458
Dummy2015	0.3805231	2.627961
Dummy2016	0.4843005	2.064834
Dummy2017	0.4572695	2.186894
Dummy2018	0.4734628	2.112098
Dummy2019	0.6832175	1.463663
Dummy2020	0.4932073	2.027545

Netherlands

Model (1)

Variables	Tolerance	VIF
LN_age	0.8033542	1.244781
LN_OfferSize	0.7629029	1.310783
Tech	0.8388964	1.192042
Rank	0.8463132	1.181596
Technique	0.8290364	1.206220
Sentiment	0.7889789	1.267461
HC	0.8139337	1.228601
VC	0.7212448	1.386492

Model (2)

Variables	Tolerance	VIF
LN_age	0.7473669	1.338031
LN_OfferSize	0.6807690	1.468927
Tech	0.7802284	1.281676
Rank	0.7897065	1.266293
Technique	0.5163961	1.936498
Sentiment	0.5849319	1.709601
HC	0.7223560	1.384359
VC	0.7027634	1.422954
Marketreturn	0.8312118	1.203063
Marketvolatility	0.5009108	1.996364

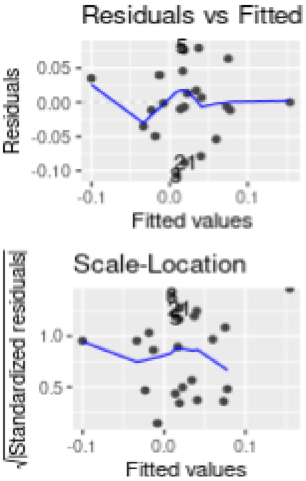
Model (3)

Variables	Tolerance	VIF
LN_age	0.4811773	2.078236
LN_OfferSize	0.4993968	2.002416
Tech	0.5032893	1.986929
Rank	0.6070780	1.647235
Technique	0.3150645	3.173953
Sentiment	0.2578965	3.877525
HC	0.2532064	3.949348
VC	0.5130155	1.949259
Marketreturn	0.3388763	2.950930
Marketvolatility	0.1985284	5.037064
Dummy2014	0.2050187	4.877605
Dummy2015	0.2384610	4.193557
Dummy2016	0.2268081	4.409013
Dummy2017	0.4539348	2.202959
Dummy2018	0.2779447	3.597838
Dummy2019	0.6894026	1.450531
Dummy2020	0.3027563	3.302987

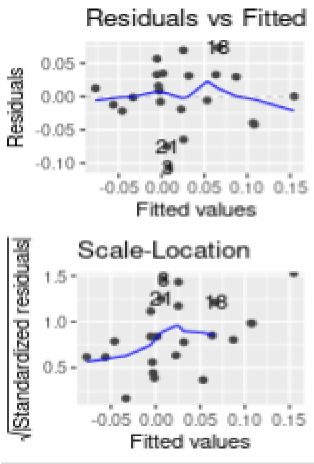
Appendix 10.12: Heteroscedasticity Plots – Country-Specific

Belgium

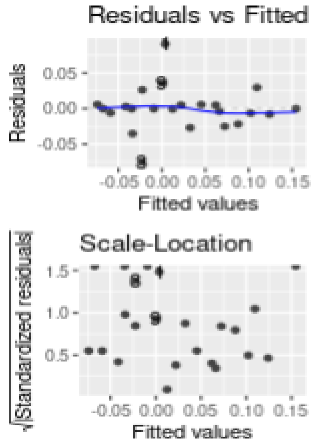
Model (1)



Model (2)

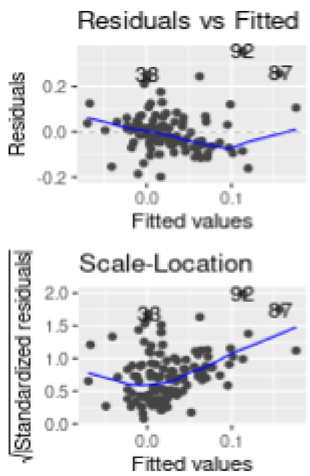


Model (3)

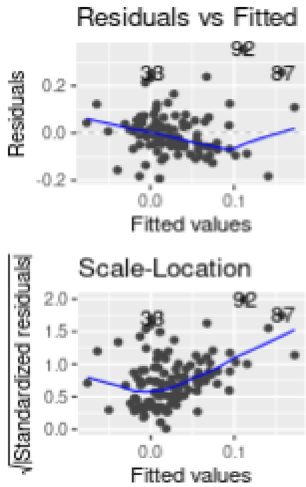


France

Model (1)



Model (2)



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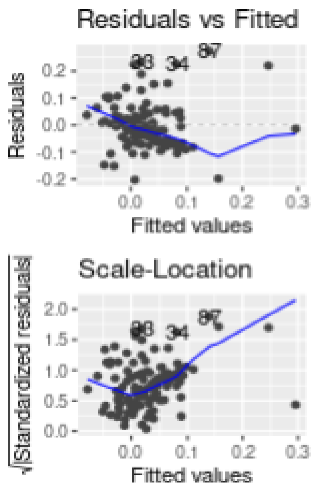
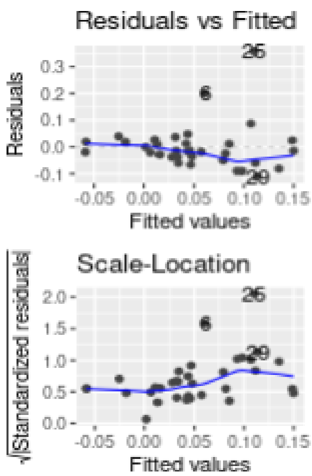


Netherlands

Model (1)



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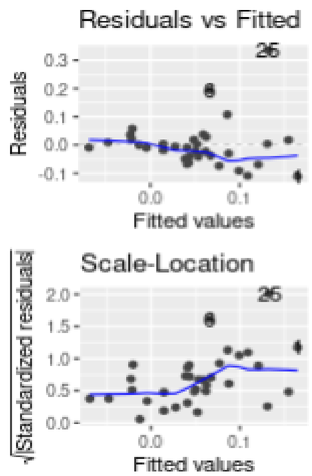
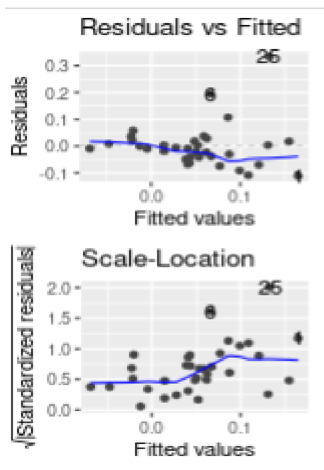


Model (3)



Appendix 10.13: GDP in each country divided by IPOs