Impact of macroeconomic factors on IPO frequency

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Abstract: The purpose of this thesis is to analyze what impact different macroeconomic factors and beyond have on the frequency of IPOs in the United States. More traditionally regarded macroeconomic factors like inflation and their effect on IPOs have been previously studied quite a bit, but other variables concerning for instance uncertainty are yet to be as extensively studied. This thesis aims to both confirm and extend previous literature on the subject, by looking at if similar and different types of variables have a statistically significant impact on IPO frequency.

The data for this thesis consists of one dependent variable which is the number of IPOs through 1995-2024 on the U.S. market, as well as 12 independent variables categorized into four groups which are analyzed if and how big of an impact they have on the number of IPOs. Several data sources are used for the sampling, some of them being Jay Ritter's database, FactSet, and the Federal Reserve Bank of St. Louis. The final sample size of IPOs for the researched time period is 5485.

The variables are fitted into an OLS regression model, with a lagged model conducted as well. This is due to the fact that macroeconomic effects don't typically take place instantly. All the relevant model assumptions are checked for using diagnostics tests, and the main concerns for the underlying data are heteroskedasticity and autocorrelation. To account for this, the study uses Newey-West (1987) standard errors which are designed to deal with both issues simultaneously. Granger causality is also tested for each variable, to see if they are able to not only explain, but also if they can predict or cause a change in the number of IPOs.

The results of this thesis suggest many variables to have a statistically significant impact on IPO frequency. Some of the strongest findings were for the traditional macroeconomic variables like the unemployment rate, as well as different variables measuring uncertainty, and the credit spread. Strong statistical causal relationships were also established between the number of IPOs and interest rate, Consumer Confidence Index, and credit spread. The general conclusion of the results is that they can create both favorable and unfavorable conditions for IPOs, which either encourages companies to go public or postpone the IPO decision.

Keywords: IPO, macroeconomics, uncertainty, OLS regression, market conditions

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Sammandrag: Syftet med denna studie är att analysera vilken påverkan olika makroekonomiska faktorer och andra variabler har på frekvensen av börsintroduktioner (IPOs) i USA. Mer traditionellt betraktade makroekonomiska faktorer som inflation och deras effekt på börsintroduktioner har tidigare studerats i stor utsträckning, men andra variabler som gäller till exempel osäkerhet saknar ännu tillräckligt omfattande forskning. Denna avhandlings syfte är att både bekräfta och utveckla tidigare forskning inom området genom att undersöka om liknande och olika typer av variabler har en statistiskt signifikant påverkan på frekvensen av börsintroduktioner.

Datamaterialet i avhandlingen består av en beroende variabel, vilket är antalet börsintroduktioner under perioden 1995-2024 på den amerikanska marknaden, samt 12 oberoende variabler uppdelade i fyra grupper, vilka analyseras för att se om och i vilken grad de påverkar antalet börsintroduktioner. Flera datakällor används för insamlingen, bland annat Jay Ritter's databas, FactSet och Federal Reserve Bank of St. Louis. Det slutliga samplet av börsintroduktioner för den undersökta tidsperioden består av 5485 observationer.

Metodologin för avhandlingen är en OLS regressionsmodell, samt en fördröjd version. Detta eftersom makroekonomiska effekter inte vanlightvis sker omedelbart. Alla relevanta modellantaganden kontrolleras genom diagnostiska tester och de huvudsakliga problemen med datan gäller heteroskedasticitet och autokorrelation. För att hantera dessa används Newey-West (1987)-standardfel, som är konstruerade för att hantera dessa två problem samtidigt. Granger-kausalitet testas också för varje variabel för att se om de inte enbart har förklaringskraft, utan också i fall de kan förutsäga eller orsaka en förändring i antalet börsintroduktioner.

Resultaten i denna avhandling visar att många variabler har en statistiskt signifikant påverkan på frekvensen av börsintroduktioner. Några av de starkaste sambanden hittades bland de traditionella makroekonomiska variablerna såsom arbetslöshetsnivån, samt olika mått på osäkerhet och kreditspreaden. Starka statistiska kausalsamband kunde också fastställas mellan antalet börsintroduktioner och räntenivån, konsumentförtroendeindexet samt kreditspreaden. Den allmänna slutsatsen av resultaten är att dessa faktorer kan skapa både gynnsamma och ogynnsamma förutsättningar för börsintroduktioner, vilket antingen uppmuntrar företag att notera sig på börsen eller skjuta upp beslutet.

Nyckelord: börsintroduktion, makroekonomi, osäkerhet, OLS regressionsmodell, marknadsförutsättningar

TABLE OF CONTENTS

TABLES

FIGURES

1 INTRODUCTION

Through an Initial Public Offering (IPO), a soon-to-be-former private company transitions into a publicly traded company on the stock exchange. This is done by offering shares of the company to the public for the first time, hence the name Initial Public Offering. The decision to go public could be seen as one of the biggest milestones throughout the life of a company, as it is a pivotal moment of letting go of the full private ownership that could either make or break the company. One might ask, why companies are deciding to go through with this process as there are clear risks and disadvantages involved. The general consensus for the motive behind a company's decision to go public is to raise capital to allow for future growth of the company's operations. But as funding is something that could also be achieved while remaining as a private company without the disadvantages of public ownership, some new motives have been brought up. Possibility of future acquisitions or sell-outs, more favorable borrowing terms for capital, liquidity of the company stock, and publicity are a few motives that have been brought up to explain the IPO decision (Draho, 2004, p.1). A survey study by Brau and Fawcett (2006) suggest that the possibility for future acquisitions through the company's public stock is the main reason for companies deciding to go public.

While the benefits of becoming a public company are clearly attractive, it is still a major decision that shouldn't be made without careful consideration as it also involves a certain amount of risk and several disadvantages. There are large initial and ongoing costs related to going public, for instance fees to investment bankers and lawyers. Company financials will be under heavy scrutiny due to extensive auditing. Previous owners will have to give up parts of their controlling interest in the company. All these conditions can be planned for, but perhaps the biggest potential loss regarding IPOs is quite often disregarded as it comes in the form of an unexpected indirect cost. This indirect cost is underpricing of the IPO, or otherwise not getting the best deal possible from the initial offering. Underpricing means that the share price closes over the issue price at the end of an IPO, essentially leaving money on the table. On average, an IPO will close at 15-20% above the issue price according to Geddes (2003), which means huge amounts of foregone capital.

With all of this said, becoming publicly traded as a company grows is still desirable for many. A large part of the related risk can be mitigated through proper planning, and this planning includes timing the execution of the IPO at a certain point, when conditions are favorable to get the best deal possible and minimize costs. The timing of IPOs can historically be seen from hot and cold market trends, which have caused heavy variation in the number of IPOs throughout time. But how does one know, when it is the most favorable time to issue an IPO? Currently and historically well performing stock markets have generally been seen as indicators for companies to offer them the encouragement of issuing their IPO. The reasoning behind this is that well performing stock markets would translate to a successful IPO. These types of signals have been studied quite a bit, as to in what economic conditions companies tend to issue their IPO in. This study aims to expand on the research, by analyzing if different types of macroeconomic factors and beyond could act as a signal for when companies tend to go public.

1.1 Purpose of the study

The purpose of this study is to analyze what impact different macroeconomic factors and beyond have on the frequency of IPOs. This is done to explain the variability in the number of IPOs throughout time.

1.2 Hypothesis

To not list an overwhelming number of hypotheses, meaning one null and alternative hypothesis per variable, this thesis will set forth a general hypothesis to be tested on each variable. For each of the 12 independent variables selected for this study, the following hypothesis will be tested through a regression analysis:

H_0: The variable has no statistically significant impact on IPO frequency,

H_1: The variable has a statistically significant impact on IPO frequency.

The independent variables included in this study that the hypothesis will be tested on are the following: inflation, unemployment rate, interest rate, Consumer Confidence Index, market return, S&P 500 P/E-ratio, wealth inequality, Geopolitical Risk Index, Economic Policy Uncertainty Index, VIX Index, liquidity measure of U.S. stocks, and Moody's credit spread.

1.3 Motivation and contribution of the study

Research regarding IPOs isn't anything new to the empirical world. However, the majority of research is focused for instance on matters of IPO underpricing, survivability, and performance. The underlying reasons behind company decisions to go public in the first place, or rather the timing of going public, is on the other hand not focused on as much. While companies do have their general aspirations behind the decision of going public, for instance raising capital and public stock used for future acquisitions, these factors can't completely explain the variability in the number of IPOs throughout time. With this study I want to analyze if there are some signaling factors for when companies tend to go public, i.e., what factors would potentially indicate the best circumstances for issuing an IPO. This led to looking at macroeconomic factors like inflation or interest rates, potentially allowing for favorable economic conditions encouraging companies to issue IPOs. The research that has been done regarding this matter (for instance Foglia & Angelini, 2018; Mehmood et al., 2021) has found certain relationships between different macroeconomic factors and the number of IPOs. However, these factors tend to be quite limited to a traditional macroeconomic nature, like GDP growth rate, inflation, or interest rates. That is why I wanted to extend these factors beyond what is regarded as traditional macroeconomics and find out if for instance a relationship between uncertainty and IPO frequency could be established. Furthermore, as there hasn't been that much research done on the subject relative to other matters regarding IPOs, it also entails that the amount of new research is relatively low. By conducting a study with as fresh data as possible it could potentially uncover new trends within the IPO market or keep confirming that previous relationships still persist.

This study could contribute for companies looking to issue their IPO. Companies looking to go public, might wonder when it is the best time to do so in order to get the best deal possible, or vice versa, when it tends to not be the most favorable time to issue their IPO. Some already known favorable factors include well performing stock markets and high GDP growth rate, which essentially translate to a thriving overall economy, while high inflation and stock market volatility could be seen as unfavorable as purchasing power is low and stock prices fluctuate heavily. Through my study, I would wish to provide even more data for companies to assess whether the time for an IPO is right.

1.4 Limitations of the study

The main limitation of this study is the choice of the researched market. While IPOs do occur around the world on both developed and developing markets, the number of them is fairly limited on most markets which restricts the choice. The U.S. IPO market could be seen as one of the most active ones which is why it was chosen for this study to get more comprehensive results.

1.5 Structure of the study

This study will start by introducing the relevant concepts to IPOs and macroeconomics. Chapter 2 will begin by presenting the underlying reasons behind companies' possible choice to go public, whether it be to raise capital or the possibility of future acquisitions, as well as the advantages and disadvantages of the decision. As this study focuses on the U.S. market, the practicalities involving the whole IPO process in order to be publicly listed in the U.S. with the Securities and Exchange Commission (SEC) as the governing body is also presented. This is followed by a brief introduction to the ongoing requirements after conducting an IPO, and finally the U.S. IPO market is presented with some recent trends, statistics, and institutional background. Chapter 3 tackles the concept of macroeconomics, with brief discussions of its traditional measures. With the U.S. market in question and interest rates being a critical measure within macroeconomics, the U.S. central banking system will also be presented to offer an insight to their monetary policy.

After central concepts have been presented, the literature review section of this study will begin in chapter 4. The reviewed previous literature will include several studies conducted on the matter of the impact of external factors on the number of IPOs on both developed and developing markets. Chapter 5 will present the data, and the data sampling process of all variables used in this study, with relevant descriptive statistics. Following this, the methodology for the empirical part of this study is introduced in chapter 6. The results of the empirical study will then be presented in the chapter after that, which is followed by a discussion regarding the results in chapter 8. To end off, the study is concluded in chapter 9 with some final remarks and suggestions regarding future research.

1.6 Use of Artificial Intelligence

For referencing and transparency purposes, this subchapter is dedicated to presenting in what context Artificial Intelligence (AI) has been utilized in this thesis. As a general statement, AI has in no shape or form been used to produce, copy, or reference text in this thesis. AI has only been used in a supportive manner to provide broad guidelines and brainstorming.

Where AI has been utilized the most is the empirical part of this thesis. The empirical and statistical tests of this study have mainly been conducted in the R Studio environment. This requires generating lines of code to execute the empirical models and model diagnostics. AI is an extremely helpful tool to provide a baseline script which can then be further modified to suit the needs of your data specifically. By that said, AI has been broadly used to support the coding requirements for the empirical part of this thesis.

As will be seen in the data chapter of this thesis, the researched variables are categorized into groups to establish relevancy. For the grouping process, AI has been utilized to suggest an approximate categorization of the variables based on economic theory and similarity.

2 THE IPO MARKET

As this study focuses on the change in frequency of IPOs due to different macroeconomic factors, this chapter will introduce what IPOs actually entail. This includes the reasoning behind companies choosing to go public, advantages and disadvantages of that decision, as well as the general IPO process. As the U.S. market is the one researched in this study, a brief presentation of the U.S. IPO market is also included to shed some light on the general dynamics and recent trends which might be relevant.

2.1 Why do companies want to go public?

There are several reasons for private companies choosing to go public. The first and mainly thought of reason is the need to raise capital. The capital infusion is needed for further expansion and growth, for instance by implementing strategies, further research and development, and other operations. Another major reason is the issued stock itself, which can act as a sort of currency as it establishes a market value for the company. The stock can be used for future acquisitions or vice versa the sale of the company. Issued public stock is also commonly used to attract and compensate employees, with the company offering them public stock or stock-options as part of their compensation scheme. The stock issued through an IPO can also serve the purpose of increasing liquidity of the company's stock, which allows owners to sell their stock more easily. (Draho, 2004, p.1)

Besides the reasons of the issued stock itself and the need to raise capital, IPOs can also be a way to create publicity and brand awareness to attract customers and employees (U.S. Securities and Exchange Commission, 2024). It is also argued that there may exist a reason within the gray area for companies wanting to go public, which is insider traders executing their stock-options if/when the stock becomes overvalued due to a highly successful IPO (Draho, 2004, p.1).

These are all merely theoretical reasons behind going public, as researchers have had a hard time to establish any real empirical results as to why companies decide to go public due to data constraints. Brau and Fawcett (2006) conducted a survey study by interviewing 336 CFOs to shed some light on why companies decide to go public in practice. Through their findings, the possibility of making future acquisitions after an IPO through the company's public stock proved to be the main reason. More favorable future borrowing terms weren't for instance amongst the major reasons. The survey study also showed that tech companies specifically seek to go public as a reputation-enhancing move rather than a financial decision. After the decision to go public is made, Brau and Fawcett (2006) also came to conclusions about the timing of the IPO. The IPO market is quite cyclical with hot and cold markets due to overall market conditions, where companies try to find the perfect window for going public. Through their CFO surveys they find that the emphasis is on market and industry stock returns, both current as in bullish markets as well as historical returns as the strongest signals for a successful IPO.

2.2 Going public – advantages and disadvantages

The decision for a company to go public, in other words issue an IPO, is perhaps one of the largest decisions to be made throughout the lifetime of a company. Usually driven by the strong need for more capital to grow operations even further, it is not as straightforward as it sounds. In the process of planning to go public, a company has to carefully weigh all the different advantages and disadvantages it entails, as the decision might make or break the company. If the underlying reason for going public is for instance the need to raise capital, all alternatives have to be evaluated as it is also possible to raise capital through the private market without the downsides of going public.

By a public offering, rather than private, a company can generally achieve a higher price per share. This means that the company is essentially able to give up less equity for the same amount of capital. This can be a highly desirable aspect for the current owners, as they don't have to let go of as much controlling interest in the company. After the IPO, the company's ability to raise further capital is also increased through both borrowing and equity offerings. The IPO tends to improve the company's debt-to-equity ratio, which allows for more favorable borrowing terms. As for equity offerings, if the stock performs well, this will also allow for better terms when selling additional equity in the future. By going public the company will also establish a market value for their stock, which makes valuation and performance tracking easier. Finally, as the company stock is publicly traded after an IPO, it increases liquidity which for instance may be beneficial for the founders looking to disinvest a certain amount of their ownership. (Barden et al., 1984, p.63)

For relatively small companies, costs of an IPO might be the largest disadvantage. Companies whose purpose with going public is raising capital, should carefully evaluate if there is a possibility to do that on the private side, as it disregards most costs affiliated with IPOs. There are both direct and indirect costs related to IPOs. Commissions to investment bankers, lawyer fees, and maintaining public relations are just a few initial direct costs that need to be calculated. On top of this, costs for maintaining a quote on the stock exchange also add up over time, for instance stock exchange fees and heavy auditing. The indirect costs of an IPO may be even greater in the form of underpricing, as it is disregarded in many cases. According to Geddes (2003) an IPO will on average close at 15-20% above the issue price, which translates to large amounts of foregone capital. Public companies also fall under the rules of the SEC regarding public entities, which requires more extensive financial reporting throughout the year. For instance, annual 10-K and quarterly 10-Q forms must be filed by the company (NYSE, 2023). (Geddes, 2003, p.26-27)

2.3 How the IPO process works

Even though the principle of going public is relatively similar around the world, the road going from a private company to a public one can vary a bit depending on the market the company is to be listed on. This is mainly due to legal matters and the principles of governing bodies. As this study focuses on the U.S. market the introduction of the whole IPO process will also focus on how it's done in the U.S. where a company has to get approval from the Securities and Exchange Commission (SEC).

A typical IPO process can take up to 20 weeks or more from breaking ground to execution. On top of this, companies might have done several months or even years' worth of planning before engaging in the actual IPO process. The process itself starts by reviewing the adequacy of the management team, especially the CFO, as well as preparing all financial aspects to meet the demands of an IPO. This is an important first step as the management team acts as the public face to the potential future investors. After all internal matters are in order, the company hires an underwriter (bookrunner) or usually several of them through different investment banks. One underwriter is designated as the lead bookrunner which typically befalls on the most senior investment bank involved. The underwriters play a crucial role throughout the IPO process in advising the company to construct the best deal possible. (NYSE, 2023)

Once the underwriters are chosen the management team and underwriters as well as other parties like auditors and legal counsel start drafting a registration statement for the Securities and Exchange Commission (SEC). This process has been in place in the U.S. since the 1930s due to the Securities Act of 1933 and Securities Exchange Act 1934 to guarantee a sufficient reporting standard. The registration statement contains all relevant information the SEC needs to review the company's eligibility to go public. Extensive due diligence is done at this point by the underwriters on everything from financials to business strategy as it is important that the registration statement is accurate to protect against possible liability due to omissions or misstatements. Before the statement is handed in to the SEC for review, a final valuation update is done, and the listing venue and ticker symbol is chosen. The SEC reviewal usually takes about a month, after which the company and underwriter team have to file the required amendments to the statement based on the requests of the SEC. This modifying stage of the registration statement can last several weeks, as the statement often needs to be amended at least a couple of times. With the amendments done, the final registration statement (prospectus) is filed with the SEC including a price range (also called the *red herring*) for the public offering. This marks the launch of the IPO which includes typically a week-long roadshow implementing the company's IPO marketing strategy. With the roadshow done and a book of demand with investors constructed, the underwriters set an offering price and executes and allocates the IPO to investors. For the next two business days the company is trading publicly on the chosen stock exchange after which the IPO closes, and the stock is delivered to investors against the offering price. After closing, the underwriters commonly intervene to stabilize the stock from short-term volatility or if the stock is trading a lot above the issue price, they might execute the greenshoe, i.e., sell an additional number of shares (Lago Kapital, 2024). (NYSE, 2023)

2.3.1 Requirements after an IPO

By going through an IPO, the company has to maintain a certain ongoing reporting standard set by the SEC. First and foremost, it is required for public companies to file quarterly 10-Q reports and annual 10-K reports. These reports are filed to keep both the SEC and the public informed of the company's current business and financial condition. In a way these can be seen as updated versions of the initial registration statement used in the IPO. The most important aspects of the annual 10-K report are the audited balance sheet and income statement for the year. Besides these, financials like cash flows and changes in shareholders' equity is also reported in combination with significant business events. 10-Q reports that are required to be published quarterly are more aimed towards keeping the public investors informed. This form includes the company's interim financial reports but isn't typically audited like the annual 10-K. Besides these reports that are filed at a specific time throughout the year, the company is also required to do current reporting by filing an 8-K form. The 8-K form is filed whenever a specific event occurs, for instance an out of the ordinary acquisition, and is typically done within four business days after the event. Finally, the company is required to hold an annual shareholder meeting according to stock exchange rules and state law, which typically requires drafting a proxy statement for the shareholders. (NYSE, 2023)

2.4 U.S. IPO market

This chapter will briefly introduce the general U.S. IPO market and its' history. As the U.S. market is the one to be analyzed in this study, it is important to understand the typical characteristics of this specific IPO market as well as some trends that have taken place during the time period of this study.

The U.S. IPO market can fluctuate quite heavily from year to year due to market conditions amongst other things. In 2023, IPO activity rebounded from a 32-year low in 2022 as a direct result from heightened market conditions when for instance the S&P500 grew by over 20%. During 2023 a total of 132 companies became publicly listed with 22,2 billion USD in proceeds, marking a 47% year-over-year increase in IPO frequency. Recent trends show that smaller IPOs tend to account for most activity on the U.S. IPO market, with almost 70% of all U.S. IPOs raising under 25 million USD in 2023, as the same statistic showed about 10% on average for the past decade. To further demonstrate the heavy fluctuations in the number of IPOs during recent years, the year 2021 saw a total of 416 U.S. IPOs with approximately 155 billion USD in proceeds only to drop to the previously mentioned 32-year low in 2022 with just 90 IPOs and under 9 billion USD in raised capital. (Thamodaran et al., 2024)

Nearly every sector of the economy is included in the U.S. IPO market, from healthcare to media companies both large and small. The U.S. IPO market is also not scarce of international listings, with 53% of IPOs in 2023 being non-U.S. companies. There are two main stock exchanges that companies tend to list their stock on, the New York Stock Exchange (NYSE) and the Nasdaq Stock Market. Both are under the regulation of the Securities and Exchange Commission (SEC). While the two exchanges are quite similar, some differences do exist. The NYSE has historically had stricter requirements for different quantitative measures like earnings and market capitalization, even though the difference isn't as noticeable anymore. One difference that still does prevail between the exchanges is what types of companies seek to be listed on them. Tech and biotech companies have usually preferred Nasdaq while large financial companies and the industrial sector have chosen the NYSE. Compared to the NYSE, Nasdaq does also have some requirements concerning the diversity of the board of directors. (Thamodaran et al., 2024)

While the NYSE and Nasdaq are and have technically always been the largest stock exchanges in the U.S., and specifically the NYSE regarded as the founder of the U.S. stock market, it was actually the Philadelphia Stock Exchange founded in 1790 that first introduced a market for exchanging stocks in the United States (Hwang, 2025). However, the NYSE was born shortly after that in 1792 when a group of stockbrokers signed the Buttonwood Agreement which set rules for how stocks could be traded. The agreement was signed to create public confidence in the stock market by showing that the deals were conducted by trusted parties (NYSE, 2025). Much later in 1971, the Nasdaq stock exchange was founded. This marked an important moment for the U.S. stock market, as the Nasdaq was a fully electronic stock exchange which allowed investors to trade stocks through a network of computers while the NYSE was strictly a physical stock exchange (Hwang, 2025).

Figure 1: Number of U.S. IPOs 1995-2024

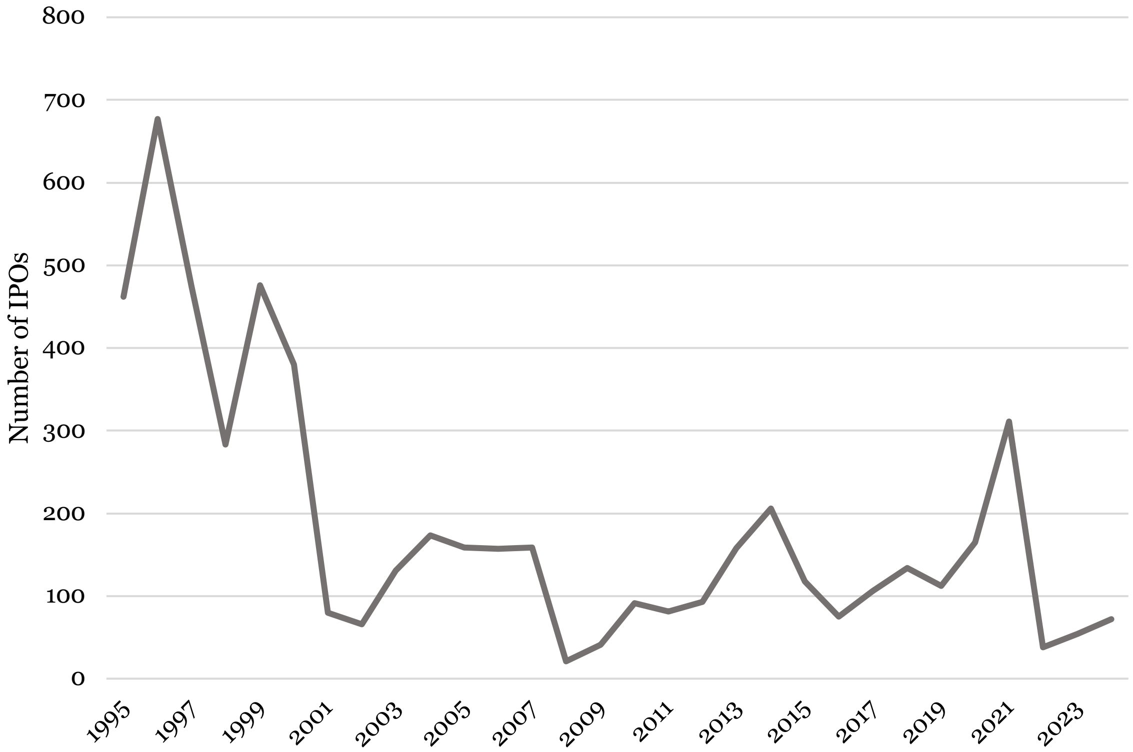

Figure 1 depicts data of the net number of IPOs on the U.S. market by year, collected from Jay Ritter's IPO database (2024). This is demonstrated solely to give a rough idea of the evolution and the frequency of IPOs on the U.S. market. The net number of IPOs means that Ritter (2024) has excluded certain IPOs for various reasons. The list is quite long but includes for instance Special Purpose Acquisition Companies (SPACs), closed-end funds, Real Estate Investment Trusts (REITs), unit offers, commercial banks, as well as IPOs with an offer price of less than 5.00 USD. SPACs are worth mentioning as they have had a surge during 2020-2021. Essentially, SPACs are companies with no operations or assets that undergo an IPO in exchange for a promise to investors that they will acquire a certain operating company usually within 2 years (Thamodaran et al., 2024).

As previously mentioned, the U.S. IPO market has fluctuated quite heavily due to market conditions that can be credited to certain trends and events throughout history. In the late 90s we can see a clear surge in the frequency of IPOs due to the dot-com bubble encouraging tech or internet-based companies to go public with a high of 677 IPOs in 1996. Conversely, we can see the burst of said bubble in 2001-2002 when the number of IPOs fell under 100. The next major event is the economic crisis of 2008, which saw the number of IPOs drop to a new low of only 21. The rest of the 2000s and 2010s remained relatively stable until a surge in 2021 with 311 IPOs which can mainly be credited to the post-Covid-19 shock in combination with favorable interest rates. Finally, from 2022 with a new 32-year low onwards we can see the effects on IPO activity of the Russian invasion of Ukraine and macroeconomic factors like rising inflation.

3 MACROECONOMICS

While this study extends beyond macroeconomics, it still focuses on the impact that changes in macroeconomic factors have on the number of IPOs, which is why this chapter will briefly introduce the subject of macroeconomics, its' typical measures of interest, and some traditional views on how macroeconomics are proposed to be utilized. Additionally, as central banks play a major role on the macroeconomic stage through their monetary policy, the United States central bank, the Federal Reserve, will be looked at as the U.S. market is the one of interest in this study. This is done to further understand the country specific monetary policy, for instance the setting of interest rates.

Macroeconomics is the study of how the overall economy works. The main areas of interest called aggregate measures are typically employment, evolution of gross domestic product (GDP), and inflation to name a few. Macroeconomic research is done to understand how the overall economy behaves due to changes in these measures. The subject in macroeconomics is generally one country, but it also extends to an international level as domestic markets are linked to foreign ones through trade and investments. When analyzing macroeconomics, the government is a major object of interest, as governments in the form of central banks are responsible for monetary policy which fights inflation and contributes to economic growth. (Rodrigo, 2025)

Before the 1930s, economic analysis mainly focused on microeconomic phenomena like individual companies and industries. Scottish economist Adam Smith's philosophies created the first macroeconomic schools of thought in the 1930s, with the theory of self-regulating markets. Smith's theories suggested that events like unemployment and recessions couldn't be avoided as they were seen as natural phenomenon. Events like these would then by time correct themselves and any government intervention would be ineffective or even destructive. This view on macroeconomics was shortly compromised by the Great Depression that started in 1929 as the repercussions of this event threatened economies worldwide. Through the re-evaluation of macroeconomic thinking, Keynesianism was born. The theoretical framework for Keynesianism was set in the 1930s by British economist John Maynard Keynes. He argued that the worst impacts of the Great Depression could have been mitigated if the government would have intervened through monetary policy to boost demand. The theories of Keynes changed the view on macroeconomics into something where the government should actively manage the economy to fight recessions. In the 1950s the Keynesian view was challenged by monetarism, a macroeconomic theory led by economist Milton Friedman. Friedman argued that the Keynesian policies applied is what created the prolonged Great Depression out of a less severe recession. The monetarist view suggests that central banks should increase the money supply in a controlled way to fight recessions, but that the economy should otherwise be left without government interference. (Bondarenko, 2025)

3.1 Macroeconomic factors

This subchapter will introduce some of the more traditional macroeconomic factors that will be used in the empirical part of this study. This includes the theoretical background, historical evolution, and measures that are taken in trying to influence these factors in a favorable manner. The macroeconomic factors to be presented are the inflation rate, unemployment rate, and finally interest rates. These are all factors that are typically controlled or influenced by central banks or governments through different mechanisms to maintain economic stability and promote growth. As this study focuses on the U.S. market, the factors will be presented from the perspective of the United States.

3.1.1 Inflation

Inflation can be seen as the one of the most influential factors within macroeconomics, and it even has a strong presence in political environments, as it is a factor which widely affects the whole society. Simply put, inflation is the rate at which prices increase over a certain time period, usually a year. It is generally used as a broad measure, the overall increase in prices, but can also be more specifically calculated, for instance the price increase of food or housing. The most common way of measuring inflation is the consumer price index (CPI), or the percentage change in the CPI called consumer price inflation. The CPI measures households' average cost of living (a household basket of goods and services) at a certain time relative to a base year, and the percentage change of this price is referred to as inflation. In the United States, housing expenses account for the largest part of the household basket. As prices of certain goods, like energy and food, can fluctuate quite heavily due to seasonal trends and government intervention, core consumer inflation is also measured in a way where these highly volatile goods are excluded. (Oner, 2025)

Inflation can also be viewed through the purchasing power of consumers. When a person's nominal income doesn't increase at the same rate as inflation, their purchasing power falls as they can afford to purchase less. This is fairly common due to some goods changing price quickly and often, while salaries are bound by contracts that take a longer time to adjust. Another way of looking at how inflation affects consumers is through fixed interest rates. A borrower with a fixed-rate mortgage benefits from higher inflation, as inflation draws down the real interest rate, the difference of the nominal rate and inflation. On the other hand, the lender of said mortgage loses in this scenario if inflation isn't properly accounted for in the nominal interest rate. Many countries have experienced high inflation at some point, or even hyperinflation which translates to an inflation rate of over 1000 percent a year. One of the most extreme cases of hyperinflation occurred in Zimbabwe in 2008, with an inflation rate of 500 billion percent. High inflation rates mean that drastic monetary policy measures have to be taken, which are often highly painful and disruptive of the economy. However, while inflation isn't economically desirable, neither is the opposite phenomenon of deflation where prices fall. With falling prices, economic activity shrinks which leads to lower economic growth. This generally happens due to consumers delaying purchases, as they are anticipating even lower future prices. While deflation or high inflation isn't desirable, the general consensus is that a low, stable, and predictable level of inflation is good for the economy. With a predictable level of inflation, it is easier to account for the future impacts it has on price changes and interest rates. Furthermore, a constant low level of inflation is seen as a positive aspect, due to incentivized consumer spending as it is known that prices will be higher in the future. (Oner, 2025) As a general rule of thumb, the desired level of inflation is approximately 2 percent (Bank of England, 2025).

Figure 2: U.S. Seasonally Adjusted Inflation 1995-2024

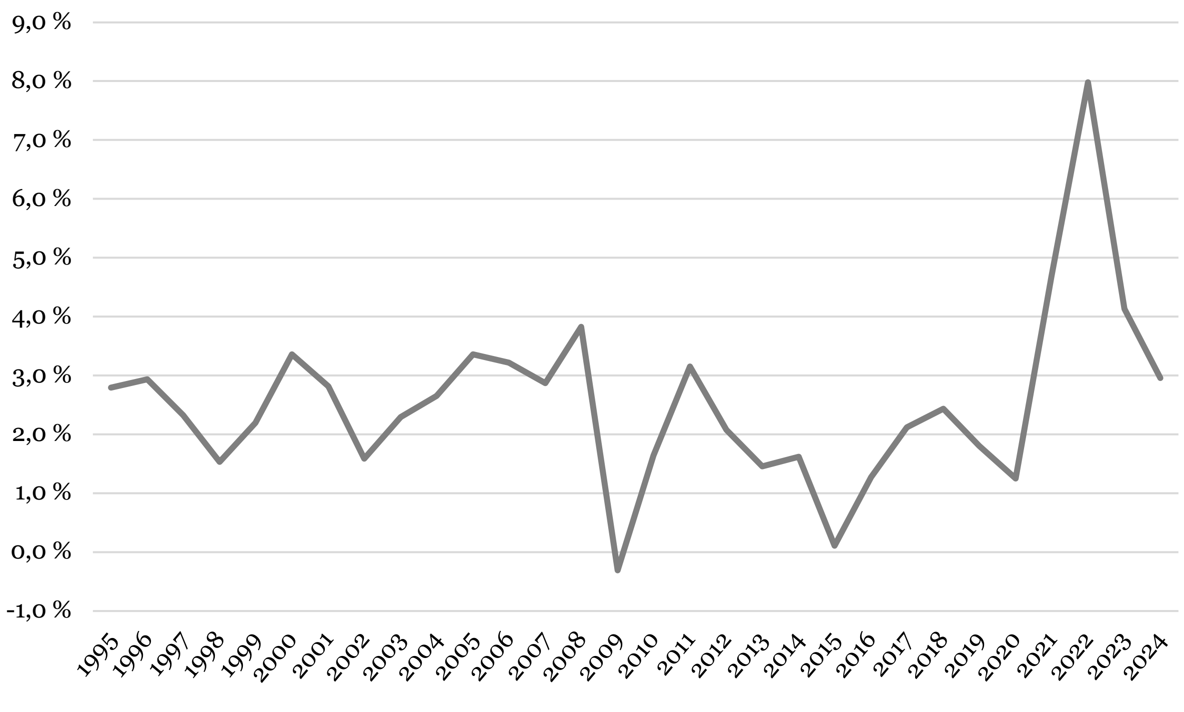

Figure 2 shows the seasonally adjusted inflation rate in the U.S. for 1995-2024 collected from the U.S. Bureau of Labor Statistics, which means that the impact of seasonal trends is accounted for. While the desired 2 percent level of inflation isn't directly comparable to the seasonally adjusted rate, Figure 2 still shows us the impact that historical events have had on the inflation rate. For instance, the financial crisis of 2008 even led to a short period of deflation in the U.S. and as for more recent events we saw inflation skyrocket from 2021 onwards, in large due to the geopolitical turmoil of the Russian invasion of Ukraine as well as Covid-19 aftershocks.

Inflation is often caused by monetary policy itself, when central banks try to stimulate economic growth during times of lower inflation. These policies include for instance lowering interest rates and increasing the money supply to incentivize consumer spending. However, when the money supply grows too big, the value of the currency diminishes leading to decreased purchasing power. Beyond monetary policy, disruptive supply and demand shocks can also cause inflation, which can be entirely due to events out of the central bank's control, for instance natural disasters. (Oner, 2025)

When inflation is too high, central banks use monetary policy to essentially make it more expensive to purchase goods and invest, while saving is incentivized. The most common policy is raising interest rates, which can be thought of as the price of spending money while making it more lucrative to save and invest. By raising interest rates, which affects the rates offered by commercial banks, demand for products and services is usually reduced which in turn brings down inflation. Raising interest rates also impacts the currency exchange rate of the country or area where the central bank operates in. This way, central banks can make it more attractive for investors to hold domestic securities rather than foreign ones, as the raised interest rates create an exchange rate appreciation. With an exchange rate appreciation, import prices for foreign goods become relatively cheaper, slowing down demand of the domestic economy. (Central Bank of Iceland, 2025)

3.1.2 Unemployment rate

The unemployment rate is another closely followed factor within macroeconomics to understand the labor market and its' wider economic impacts. The labor market can affect and be directly affected by supply and demand within the economy, which makes it an important factor when considering monetary policy (Reserve Bank of Australia, 2025). How the unemployment rate is defined can vary a bit between countries, but it essentially stands for the share of the labor force without work. As a uniform definition which makes it internationally comparable, the labor force consists of employees, the self-employed, unpaid family workers, and the unemployed. The unemployed on the other hand are of working age without a job, that are available for work and have made certain efforts to find a job in the last month. (OECD, 2025)

Even though reasons or types of unemployment can sometimes be hard to directly measure due to overlapping, cyclical, structural, and frictional unemployment have been established as the three main types. Cyclical unemployment, arguably the most impactful one, is highly dependent on economic activity. During economic downturns, demand diminishes, and businesses will follow by layoffs or hiring less workers. This results in a cycle where more people become unemployed and those who are unemployed will have a difficult time finding work, which can even lead to a deep economic recession. In fact, during the worldwide recession of 2008, the highest global unemployment rate was recorded when 7 percent of the global labor force was looking for work (Oner, 2025). As cyclical unemployment is strongly linked to economic growth, or the lack of, a high cyclical unemployment rate could suggest that the economy is not operating at its full potential. Monetary policy that boosts demand, for instance lowering interest rates, can reduce cyclical unemployment as higher demand translates to businesses needing more employees. (Reserve Bank of Australia, 2025)

Structural unemployment exists even in positive economic conditions, meaning it doesn’t directly affect inflation, or vice versa, in contrast to cyclical unemployment. This type of unemployment happens when there is a mismatch between available jobs and people looking for work due to various reasons. It may be due to the lack of available jobs in the region or that jobseekers don’t have the necessary skill set, but the primary reason seems to be declining work industries as large advances have been made in technology and automation. The manufacturing industry is a prime example where labor intensive work previously done by people has shifted towards more effective automated solutions. Due to the nature of structural unemployment, it tends to last for a longer period of time, as it can take years for workers to learn new skills that are required or to move after jobs. (Reserve Bank of Australia, 2025)

The final major type of unemployment is frictional unemployment. This type of unemployment happens when people switch jobs and due to the transition time of into and out of the labor force. Both people and businesses usually invest some time into finding the right job or candidate, which results in a situation where all available positions aren’t filled out immediately. However, frictional unemployment can almost be seen as natural and good for the economy, because the movement of workers allows for efficient labor allocation. Some additional types of unemployment do also exist, like underemployment, hidden unemployment, and seasonal unemployment. Underemployment refers to a situation where employed people would like to work more, which is fairly common amongst part-time workers. Hidden unemployment consists of people in the labor force who don’t fit the unemployed definition, who can be long time jobseekers but have stopped looking even though they would be available for work. Finally, seasonal unemployment occurs over seasonal trends throughout the year. This can be for instance berry or fruit pickers or Christmas-time workers. Due to these recurring seasonal trends of unemployment, which cause unnecessary noise, the seasonally adjusted unemployment rate demonstrated in Figure 3 was chosen for the empirical part of this study. (Reserve Bank of Australia, 2025)

Figure 3: U.S. Seasonally Adjusted Unemployment Rate 1995-2024

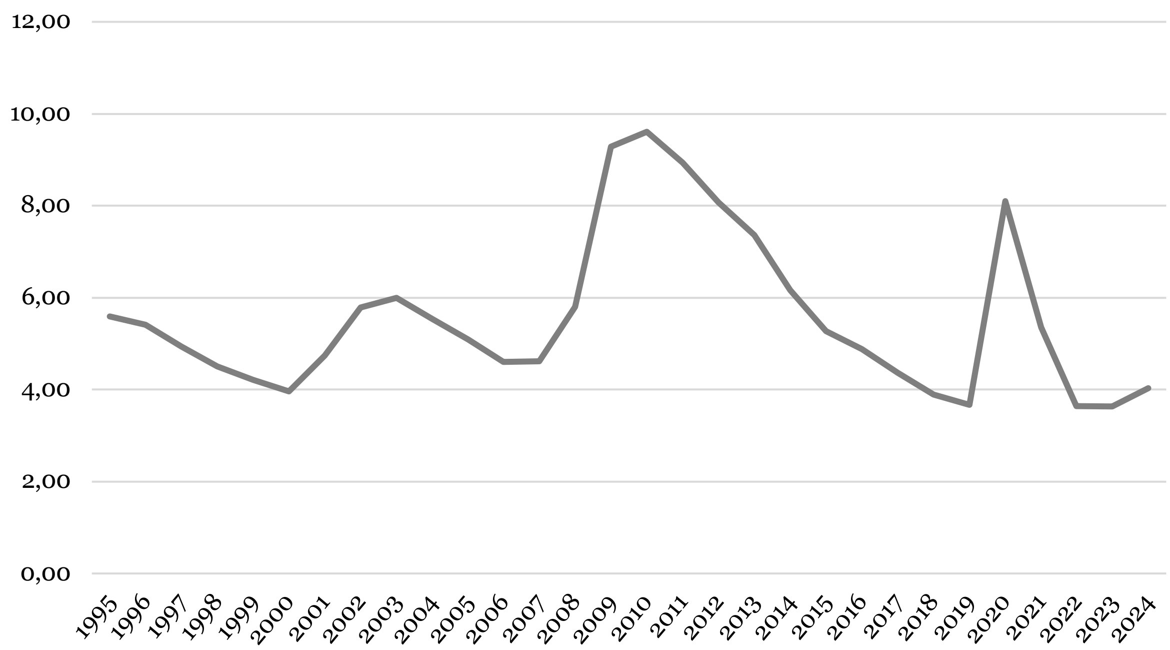

Figure 3 shows the seasonally adjusted unemployment rate in the U.S. through 1995-2024, sourced from the U.S. Bureau of Labor Statistics. Comparing Figure 3 to the historical levels of inflation in Figure 2, we can see their close relation by their similar or inverted movements during some major economic events. For instance, during the 2008 economic crisis when unemployment increased drastically and remained high for several years.

3.1.3 Interest rates

Interest rates are the main monetary policy of central banks when trying to influence consumer spending, which in turn affects prices and inflation amongst other things. An interest rate, or interest, is essentially the cost of borrowing money and the reward of saving money. By manipulating interest rates, central banks can influence household spending and characteristics of loans and mortgages. As briefly seen in chapter 3.1.1., lower interest rates tend to increase spending while higher rates discourage spending and incentivize saving. By manipulating interest rates in an appropriate manner, central banks are trying to meet their inflation target, which is usually set somewhere around 2 percent. Interest rates are seen as the main monetary policy as their effects extend beyond inflation and can affect other wider macroeconomic factors like unemployment. (Bank of England, 2025)

Everyday consumers don't directly deal with central banks, which might raise the question of how these institutions are able to influence spending across society. This happens through the so-called central bank's policy rate, which is the interest rate that is paid to commercial banks for holding funds at the central bank. The rate is set individually by each central bank, for instance, the Bank of England has the Bank Rate, the European Central Bank has Euribor, and the U.S. Federal Reserve has the Federal Funds Rate, or technically its respective target rate.

All of these policy rates are set to meet the current situation and requirements of their specific regions, mainly with the government set inflation target in mind. As the policy rate directly affects the performance of commercial banks, the financial effect will have an influence on the banks' own interest rate setting that is offered to consumers for borrowing or saving. This way, the policy rates set by central banks will indirectly affect consumer spending in a favorable way. (Bank of England, 2025)

3.2 U.S. Central Bank - the Federal Reserve

As this study will focus on the U.S. market, this subchapter will briefly present its central bank responsible for monetary policy in the region, the Federal Reserve or the Fed. The Fed was created in association with the Federal Reserve Act of 1913, with a goal of establishing an entity that could deal with the stress of the banking system. It consists of a Board of Governors in Washington D.C which acts on a federal level, twelve Reserve Banks around the U.S that operate on a regional level, as well as a group of twelve voting members from the Federal Open Market Committee that are mainly responsible for setting the U.S. monetary policy. (The Federal Reserve, 2025)

The main goal of the Fed is to keep the U.S. financial system stable as well as to promote growth. This is mainly done by being responsible for the U.S. monetary policy, but also by regulating financial institutions like commercial banks and for instance promoting consumer protection and regional development. While the Board of Governors oversees and carries the Federal guidelines to the twelve national Reserve Banks across the country, they and their 24 branches operate quite independently in their own regions as they have a better understanding of the local financial system and communities in the area. The Federal Open Market Committee (FOMC), which is responsible for setting U.S. monetary policy, holds meetings at least eight times a year. The Committee permanently consists of the Board of Governors and the New York Reserve Bank president, as well as the remaining Reserve Bank presidents who alternate between voting rights on a one-year term. The FOMC's actions are crucial to the U.S. economy, as the monetary policy set by them will influence interest rates and credit conditions across the country. (The Federal Reserve, 2025)

In practice, the Fed has two main goals set forth by the U.S. Congress, which are promoting maximum employment and stable prices. A high level of employment, or low unemployment is desirable, but there exists a maximum level of employment that the economy can sustain to maintain moderate inflation. In theory, an employment rate of close to 100 percent would overheat the economy and cause inflation to rise. These two main goals of the Fed are achieved by influencing short-term interest rates, primarily by shifting the target policy rate for the

Federal Funds Rate in a desirable manner. This rate will be used in the empirical part of this study and is demonstrated in Figure 4. (The Federal Reserve, 2025)

Figure 4: Federal Funds Effective Rate 1995-2024

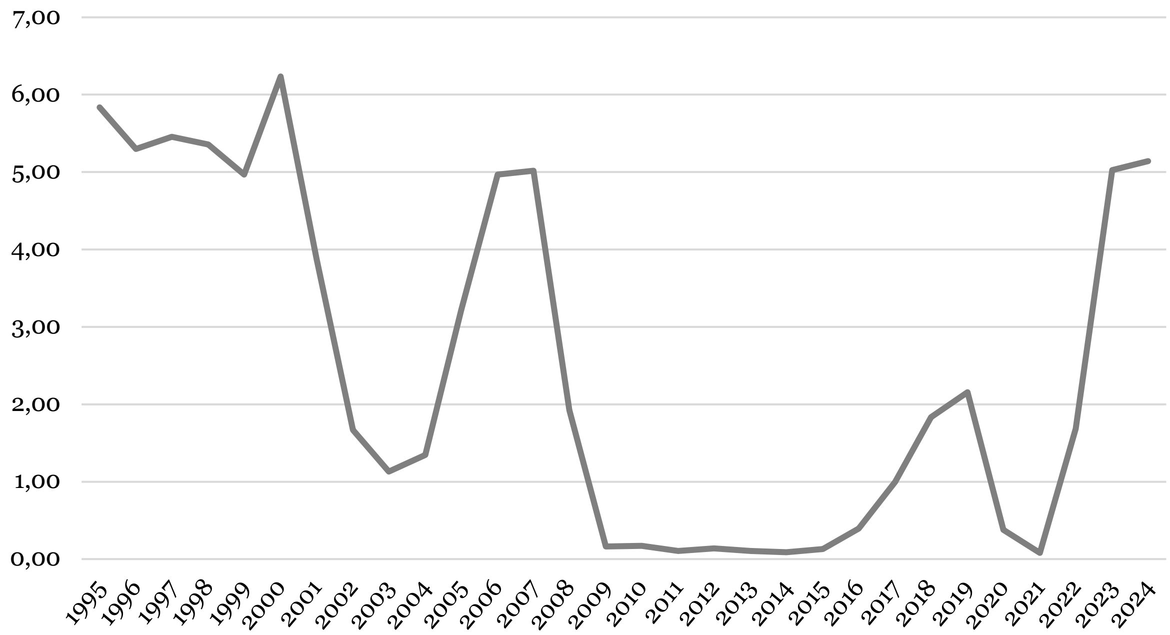

Figure 4 shows the Federal Funds Effective Rate from 1995 to 2024 sourced from the Federal Reserve Bank of St. Louis. From the figure, we can see similar trends as with inflation and the unemployment rate. For instance, during the financial crisis of 2008 when the Fed dropped its policy rate to nearly zero to try to boost economic activity when the U.S. suffered a short period of deflation. Another noticeable point is the past few years when inflation has been quite high in the U.S., and thus the Federal Funds Rate has been heavily raised to cool down the economy.

4 LITERATURE REVIEW

This chapter presents some previous literature related to this study to give an understanding of what research has been done and what kind of results could be expected. Furthermore, the previous results could help shape this study as in what variables' relationship to IPO frequency could be both interesting and relevant to research. Different methodologies have also been used, which makes it interesting to see if the results converge from one another regardless of the variables that are used. The previous literature presented includes studies made on both developed and developing markets. While this study focuses on the developed U.S. market, this still highlights some of the similarities as well as the differences between them. For instance, inflation might be a more crucial variable affecting IPO frequency on developing markets due to the high level of variance, while developed markets are able to maintain somewhat of a stable level of inflation.

4.1 Angelini & Foglia (2018)

As the frequency of IPOs doesn't remain stable throughout time, for instance during the times of the dot-com bubble and the following burst in the early 2000s, Angelini and Foglia (2018) conducted a study to analyze the short and long run equilibrium relationship between external factors (macroeconomic factors) and IPO frequency on the UK market. The aim of the study was to provide two answers. Firstly, how macroeconomic conditions influence IPO activity, and secondly how long the effects last. Four hypotheses are set forth: 1) there is a negative relationship between volatility and the number of IPOs, 2) there is a positive relationship between stock performance and IPO frequency, 3) there is a positive correlation between IP (industrial production) growth and number of IPOs, and 4) there is a negative relationship between interest rate and the number of IPOs.

4.1.1 Data & methodology

The sample data of IPOs were from the London Stock Exchange (LSE) for the time period January 1996-December 2016 on a monthly frequency which resulted in a sample of 2973 IPOs and a monthly average number of IPOs of 11,79. As per the hypotheses, four control variables were used. Growth in industrial production was designed to demonstrate growth in GDP, and as a proxy for that the Industrial production index was used. The FTSE100 index was selected as a measure of stock market performance as well as for market volatility. Volatility was estimated on an annualized basis by Angelini and Foglia (2018) themselves by a GARCH (1,1) model. As the variable for the long-term interest rate a 10-year bond yield was used. Through their descriptive statistics, it is already possible to see the cyclical nature of the IPO market relative to market volatility. In times of low volatility, there can be seen a surge in the number of IPOs and vice versa.

As the researched variable, frequency of IPOs, falls under time series data, which is usually non-stationary, Angelini and Foglia (2018) first start of by conducting an Augmented Dickey-Fuller unit root test to test for stationarity. The main methodology is then based on a cointegration test, more specifically the Johansen test. Generally, a cointegration test is used to check for long-run equilibrium causal relations between variables to see if stochastic trends are shared by the variables within the time series. If the trends show to be shared it can be said that one variable causes the other or that both are caused by a third variable (Stern 2004). For the study, two cointegration tests were used. The trace eigenvalue (1) and the maximum eigenvalue (2):

$$\lambda_{trace}(r) \ = \ -T\sum_{i=r+1}^{n}\ln(1-\lambda_i) \qquad (1)$$

$$\lambda_{max}(r, r+1) \ = \ -T\ln(1-\lambda_{r+1}) \qquad (2)$$

r represents the cointegration vector, T the sample size, and λ_i the largest canonical correlation. Appropriate lag, 2, for these tests were calculated using three criterions: Akaike Information Criteria (AIC), Schwarz Bayesian Criteria (BIC), and Hannan-Quinn Criteria (HQC). Additionally, to find out how long these possible effects last through their short and long-run dynamic relationship as well as the variables reaction to shocks, Angelini and Foglia (2018) used a Vector Error Correction model (3):

$$\Delta Y_{t,i} = \alpha_i + \gamma_i\beta_i Y_{t-i} + \sum_{z=1}^{n} T_{j,i}\Delta Y_{t-j,i} + \varepsilon_{t,i} \qquad (3)$$

Finally, the Granger causality test and a more experimental Toda-Yamamoto causality test was used to test co-movements between the number of IPOs and the macroeconomic variables, meaning finding out if the shared trends between the variables will find a long-run stable equilibrium.

4.1.2 Results & conclusions

Through their findings, the trace and maximum Johansen tests show that there exists two cointegration relationships between the selected macroeconomic variables and the number of IPOs. This means that while the individual variables might be non-stationary, there exists two stationary linear relationships between them that imply a long-run equilibrium relationship.

The dynamic relationship between the variables also shows promising results. By checking for how fast the variables are able to correct themselves after a divergence back to the long-run equilibrium path using the Vector Error Correction model, Angelini and Foglia (2018) find that the UK IPO market is highly efficient in adjusting to macroeconomic shocks. More specifically, the results show that it takes approximately 5 months for the variables to return to the equilibrium path after a divergence.

The four macroeconomic variables (IP, FTSE100, 10-year bond yield, and volatility) were able to explain 35 percent of the variation in frequency of UK IPOs. With stock market volatility being the main driver behind the decision to go public. Autocorrelation and heteroskedasticity was also tested for with the Durbin-Watson and Breusch-Pagan-Godfrey tests, respectively. The Johansen test results mainly support the implication that the variables used are a cointegrated set. These results are broadly interpreted by the fact that positive macroeconomic conditions allow for strong financial markets which encourages companies to go public and vice versa. Angelini and Foglia (2018) did however get some contradicting results to previous studies (Ress 1997) on the matter. Through the Granger causality test, they found the long-term 10-year bond yield to have a causal relationship with IPO frequency, even though Ress (1997) couldn't. This is explained by more recent data and shows how the reasons behind going public are able to change over time.

4.2 Mehmood et al. (2021)

Several studies have been conducted regarding the impact of macroeconomic factors on the number of IPOs on different markets (for instance Angelini and Foglia 2018), but the Pakistani market is yet to be researched. This is why Mehmood et al. (2021) decided to study this matter on the still developing and instable Pakistani market. The Pakistani IPO market has been through quite a lot. Between 1992 and 1997 a total of 272 IPOs were issued, in contrast, there was only one IPO in 1998 and none in 1999. This is a direct result from the various sanctions imposed by the U.S. due to Pakistan's nuclear attempt, which severely slowed down the country's development. This trend continued all the way to 2018 with only 93 IPOs during 2000-2018, with several both poor economic and political factors at blame, for instance terrorism, low GDP, inflation and political instability. The purpose of Mehmood et al. (2021) study is to investigate both the symmetric and asymmetric relationship between the variability of IPOs and the following macroeconomic factors: stock market index (KSE), treasury bill rate (TBR), inflation (INF), GDP growth rate, and foreign direct investment (FDI).

4.2.1 Data & methodology

The number of IPOs were collected on a yearly basis and includes all IPOs listed on the Pakistani stock exchange between January 2000 and December 2018. The maximum number of IPOs per year was 85 with an average of 13 yearly IPOs throughout the researched time period. The macroeconomic variables whose impact on the frequency of IPOs was studied were the following: the Pakistani Stock Exchange index KSE-100, treasury bill rate, inflation rate, GDP growth rate, and foreign direct investment. Data for these variables were collected from the International Monetary Fund's World Development Indicators.

Mehmood et al. (2021) wanted to study the symmetric and asymmetric relationship of IPOs and macroeconomic variables on a fairly restricted market, as the number of IPOs in Pakistan is relatively low. That is why they decided to use the Auto Regressive Distributive Lags (ARDL) model to measure symmetric links and the Non-Linear Auto Regressive Distributive Lag (NARDL) model for asymmetric links. The NARDL model has two main benefits, it works well with smaller sample sizes while there is no requirement for stationarity. The ARDL model is mainly used to measure short-term effects, which is why Mehmood et al. (2021) had to remodel it according to the error correction approach to also measure long-term effects:

$$\Delta NIPO_t = \theta + \sum_{k=1}^{P1} \theta_k \Delta NIPO_{t-k} + \sum_{k=1}^{P2} \theta_k \Delta KSE_{t-k} \ldots + \lambda_1 NIPO_{t-1} \ldots + \lambda_5 FDI_{t-1} \mu_t \qquad (4)$$

NIPO represents the number if IPOs, KSE the stock market index etc. The modifications to the model to be able to measure long-run effects can be seen in the latter part of the equation, where the traditional error term ε_i is replaced with a proxy which is the linear combination of the lagged level variable, denoted λ_i.

To measure the asymmetric links the ARDL model is modified even further into the NARDL model. This is done by grouping the variables in question into negative and positive components, more precisely the partial sums of the positive and negative changes in the variables and incorporating them into the equation. Finally, as the observed long-run effects are mainly based on the optimal level of lag, Mehmood et al. (2021) used the Akaike Information Criterion to establish the appropriate level.

4.2.2 Results & conclusions

The empirical results of the study support the fact that the macroeconomic factors of the stock market index, treasury bill rate, inflation, GDP growth rate, and foreign direct investment have significant long- and short-run symmetric and asymmetric effects on the number of IPOs on the Pakistani market. Due to the instable nature of the emerging Pakistani market these effects can be seen quite clearly. For instance, inflation has experienced high variance throughout the time period of the study, with a maximum value of 20,28 percent and a low of 2,5 percent.

The treasury bill rate and inflation are found to have significant negative long- and short-term effects on IPO variability. The effects that a low treasury bill rate has on the capital markets discourages companies from going public while high inflation reduces the purchasing power. On the other hand, stock market performance, GDP growth rate, and foreign direct investment are found to have significant positive long- and short-term effects on the number of IPOs.

All the results highlight the importance for companies planning to go public to consider macroeconomic factors as a signal for favorable economic conditions for conducting an IPO. The results of the study can also have implications for central banks and different policy makers as they for instance suggest that maintaining a balanced inflation rate through monetary policy is crucial for economic growth.

4.3 Dicle & Levendis (2017)

The IPO decision is based on several factors like the company's financial situation and overall market conditions, which need to be considered in current terms as well as forecasted into the future. Many papers focus on the whole IPO process, with the ideal IPO launch being when the offered shares can be sold at the highest possible price. Dicle & Levendis (2017) wanted to study companies that have already decided to go public but are waiting for the right timing. Companies usually set an IPO date later on in the whole IPO process looking for the right market timing, and this is what Dicle & Levendis (2017) wanted to research from the perspective of consumer sentiment. They argue that implied volatility works as an investor fear measure, which is why they decided to study the effect that the VIX Index has on IPO activity. It is also pointed out that the main concern affecting IPO activity isn't the realized volatility, but rather the implied or expected volatility which is exactly what the VIX Index measures.

4.3.1 Data & methodology

The sample period of Dicle & Levendis (2017) is limited to the IPO data that is obtainable from NASDAQ, meaning they had a sample period from 1997 to July 2017 with a monthly observation frequency. Their IPO data included all sorts of IPO activity including company name, symbol, marker, IPO price, number of shares, total IPO offer amount, and pricing date. For the variables tested if they have an impact on IPO activity Dicle & Levendis (2017) used two volatility measures, realized and implied volatility. As the realized volatility they used the monthly standard deviation of S&P 500 daily returns, and for the implied volatility the VIX Index which estimates the S&P 500 volatility 30 days into the future using option prices.

As for the empirical part of the study, first a GARCH(1,1) model is used to estimate the lead-lag relationship. The model is also extended to include Granger causality. Dicle & Levendis (2017) do still argue that endogeneity isn't of interest in their study, as volatility isn't a function of IPO timing due to the fact that IPO companies don't have options (which are used to estimate the VIX Index) and can't be a part of the S&P 500 index. Continuing on to the estimations for volatility and IPO activity the model of choice was an autoregressive distributed lag model (ARDL). The same model was used for both the realized and implied volatility, but for reference, the model equation estimating the effects of the implied volatility looks like the following:

$$\Delta IPO_t = \alpha_0 + \alpha_1 \Delta IPO_{t-1} + \alpha_2 \Delta IPO_{t-2} + \alpha_3 \mu_{\Delta VIX,t-1} + \alpha_4 \mu_{\Delta VIX,t-2} + \alpha_5 \mu_{\Delta SP500,t} + \varepsilon_{\alpha,t} \qquad (5)$$

Where, ΔIPO stands for the log difference change in monthly IPOs, $\mu_{\Delta VIX}$ for the monthly average of the daily changes in VIX, and $\mu_{\Delta SP500}$ for the monthly average daily returns of the S&P 500. Furthermore, as the financial crisis occurred during the researched time period, Dicle & Levendis (2017) implemented their models not only for the entire sample period, but also pre- and post-crisis. Finally, they tested for Granger causality using the Wald test.

4.3.2 Results & conclusions

To start off, it is mentioned how the financial crisis between 2007-2009 have changed IPO timing in the sense that volatility has become an increasingly important factor. Through the pre- and post-crisis estimations, the findings show that implied volatility decreased IPO activity significantly more after the financial crisis than it did before. These results support the original research statement of the study, which is that consumer sentiment can influence IPO timing.

The overall results show that it is specifically the implied volatility and not realized volatility that affects the IPO process. In other words, expected volatility will have an impact on the number of IPOs and could also technically be used to estimate the future number of IPOs. During times of low expected volatility, there tends to be more companies launching their IPOs. The final conclusion by Dicle & Levendis (2017) is that if IPOs are to be encouraged, there should be regulatory measures in place to reduce volatility. They argue that from an interventionist policy view, there could be mechanisms in place that not only force markets to take a break when there is a drastic fall, but also when markets skyrocket. However, this approach could in practice just create more uncertainty and thus also volatility.

4.4 Çolak et al. (2017)

As this thesis uses several variables focused on some sort of uncertainty, it is only reasonable to also review a paper studying the relationship between uncertainty and IPO activity. Studies regarding IPO activity are mainly based on realized factors, like inflation or interest rates, and not so much on factors like uncertainty about the future. Colak et al. (2017) bring up that research in regards of uncertainty has mainly been focused on the effects it has on corporate investment decisions, and for instance economic growth and stock market conditions. This is why they wanted to study how political uncertainty affects IPO activity in the U.S., as the effects of the increased political turmoil around the world has become ever so more interesting. The purpose of their study is to analyze IPO activity during political uncertainty when gubernatorial elections are held in the U.S.

4.4.1 Data & methodology

The sample period is from 1988 to 2011, and for this time frame all U.S. IPOs are collected from the U.S. Common Stock Data File. Similar to other IPO research, noncommon stock IPOs like closed-end funds are discarded from the sample. Then the locations in the form of state are obtained for the companies' headquarters, and all IPOs with a missing location or that are not from the 50 U.S. states are excluded. This leaves Colak et al. (2017) with a final sample size of 5727 IPOs. Different types of IPO activity data is collected, for instance issue date and offer price, as well as time series data for macroeconomic variables like the interest rate. Finally, gubernatorial election data is collected including for instance election date and winning party/candidate. IPOs are defined based on a 12-month period relative to gubernatorial elections, for instance, an IPO issued after an election but still during the same year is considered to be an IPO in year 1 (off-election year). In contrast, an issued IPO during an election year gets the definition of year 0. This classification of IPOs ranges from -1 to 2, i.e., 4 years around gubernatorial elections.

The main methodology of choice seems to be a difference-in-differences approach. This choice is motivated by the fact that the used control variables don't necessarily capture all socioeconomic conditions that could affect IPOs and uncertainty. Colak et al. (2017) construct a so-called neighboring-states method, where they use difference-in-differences to compare results of bordering states without elections to the ones with an election. The assumption is that the neighboring states are affected by similar unobserved shocks, and by calculating the difference it should render out these effects and leave the number of IPOs as the remaining difference caused by elections.

4.4.2 Results & conclusions

Colak et al. (2017) find that political uncertainty in the form of gubernatorial elections do in fact lower IPO activity from the respective election state. Instead, companies tend to delay their IPOs during these uncertain times. It is mentioned that gubernatorial elections sort of create their own IPO cycle, where IPOs decrease in the two years before an election and tend to similarly increase in the two years after. The effect is also found to be more significant for companies that are geographically concentrated, dependent on government contracts, and companies that are more difficult to valuate.

Colak et al. (2017) also conclude that IPOs issued during an election year tend to be priced lower relative to their fair value. This would indicate a higher cost of capital for the companies, which is supported by previous studies stating that political uncertainty weakens asset prices and results in a risk premium. The final conclusion is that the results of the study indicate that not only is corporate investment affected by political uncertainty, which has already been established, but so is corporate financing.

5 DATA

This chapter will present all the data used in this study to measure the impact of macroeconomic factors and beyond on IPO variability on the U.S. market. The chapter will start off with a description of the data and the data sampling process. This is followed by in-depth descriptions and motivations of the dependent variable, which is the number of IPOs, and all the independent variables used in this study. The independent variables can be categorized into four groups, macroeconomic, market performance and valuation, uncertainty and risk, and financial market conditions. Finally, descriptive statistics of all the variables are presented, and the chapter will end with a table summarizing the variables.

5.1 Description of data and sampling process

Various databases and sources will be used in this study, due to the nature of the data. Many of the researched variables could be retrieved from databases that are generally used for academic research, for instance FactSet, but as the majority of them are originally sourced from their respective governmental databases or similar, this study also opted for original sources when possible. The sample period chosen for this study is 1995 to 2024 with a monthly observation frequency, with the motivation being data restrictions for earlier periods as well as several previous studies (Angelini & Foglia, 2018; Mehmood et al., 2021) having an approximately similar time frame if not even shorter. Furthermore, as demonstrated in chapter 2.4, I see the main importance regarding the start date to have the shift to the 2000s included. This way, the results of the study are able to reflect the heavy fluctuations in IPOs during the dot-com bubble and its' respective burst. Thus, I see the chosen 25+ years as a sufficient time period.

The IPO data was retrieved directly from Jay Ritter's IPO database, where the monthly number of IPOs on the U.S. market was provided. Ritter is a professor at the University of Florida and is highly accredited due to his vast amount of research and expertise on the subject, for instance (Ritter, 1991 & 2002) (University of Florida, 2025). Besides Ritter's own publications, his IPO data is highly regarded as it is seen as reliable and easily accessible. The choice to use Ritter's database for the monthly IPO data stems from the reliability and minimization of manual work, which otherwise might have brought with it some level of human error. Retrieving the number of IPOs from a database like FactSet or similar would entail some difficulties. Mainly the restrictions on filtering, which doesn't allow for exclusion of certain non-common stock IPOs, for instance SPACs (Special Purpose Acquisition Companies). This means that the data would have to have been manually cross-referenced with Ritter's data to get the final clean sample. Ritter's database on the other hand provides the net number of IPOs, where the unwanted companies for research purposes are already excluded, which will be presented more in detail later on.

The more traditionally regarded macroeconomic variables that were chosen for this study are the unemployment rate, inflation, the Federal Funds Effective Rate, and the Consumer Confidence Index (CCI). All four variables are U.S. specific, and the three former variables were collected from their respective governmental sources, while the CCI was sourced from the Organisation for Economic Co-operation and Development (OECD). The unemployment and inflation rate, both seasonally adjusted, were gathered from the database of the U.S. Bureau of Labor Statistics, which houses all sorts of macroeconomic statistics. The Federal Funds Effective Rate was derived from the Federal Reserve Bank of St. Louis' database. Seasonal adjustment, a statistical method, for the unemployment and inflation rates were chosen as it removes the effects of recurring seasonal influences. This is done to demonstrate non-seasonal trends more clearly, by eliminating certain recurring effects that have been observed in the past. For instance, industrial production tends to slow down during the summer and holidays like Christmas typically boost the economy (Eurostat, 2025).

The category of market performance and valuation consists of the following variables: S&P 500 returns as the proxy for market return, the S&P 500 Price-to-Earnings ratio, and the Distributional Financial Accounts, i.e. wealth distribution (DFA). The market return was retrieved from FactSet in the form of S&P 500 price data, which was then transformed into monthly returns. The same price data was used for the first part of the P/E-ratio's equation, while the earnings part is in the form of Earnings Per Share (EPS) which had readily available monthly data on Robert Shiller's database. Financial ratios like the P/E-ratio aren't typically quoted on a monthly basis, in fact the majority of similar financial data is most often reported quarterly as the closest frequency. If some conversion or interpolation of data isn't wanted, it means that the values have to be manually calculated. Nevertheless, Shiller is a highly respected economist and professor at Yale University with several publications (Shiller, 2003 & 2014). He was jointly awarded the Nobel Prize in economic sciences with Eugene Fama and Lars Peter Hansen in 2013 (Yale Department of Economics, 2025). For these reasons, which are similar to Jay Ritter's IPO data, the academic world regards Shiller's data as highly reliable. Finally, the DFA was gathered from the database of the Federal Reserve Bank of St. Louis. Regarding the P/E-ratio, it would have been the most suitable for this study to have it measure the Russell 3000 index, as it measures the largest 3000 U.S. companies which represent approximately 98 percent of the U.S. equity market (LSEG, 2025). However, due to data restrictions for the index, as it is not as widely used in financial research as let's say the S&P 500, it proved to be difficult to come across appropriate data, let alone with a monthly frequency. For this reason, the S&P 500 index was chosen for this study instead to represent the overall U.S. market. I do see this as a reasonable downgrade, as the S&P 500 is widely used in financial research as a proxy for the overall U.S. economy as the index still represents approximately 80 percent of the whole U.S. market capitalization (S&P Global, 2025). The only issue regarding the S&P 500 as a representation of the U.S. market is the fact that it is dominated by large-cap companies as the index only constitutes the 500 largest U.S. firms. This means that the effects of all small- and mid-cap companies are excluded.

The third group of variables which is uncertainty and risk consists of the Geopolitical Risk Index (GPR), the Economic Policy Uncertainty Index (EPU), and the VIX index. The GPR which is measured on a global level and the U.S. specific EPU were both gathered from the research institution of Economic Policy Uncertainty that develops these types of indices for several countries, hence the name. The VIX index also known as the Chicago Board Options Exchange's Volatility Index, which is a risk measure of the expected S&P 500 volatility, was retrieved from the database of the Federal Reserve Bank of St. Louis.

Lastly, the fourth category of variables which represents financial market conditions is comprised of a liquidity measure of U.S. stocks and Moody's credit spread. The liquidity measure is a liquidity factor constructed by Pastor and Stambaugh (2003) that measures the aggregated level of liquidity of U.S. stocks and was sourced directly from Lubos Pastor's database. As for Moody's credit spread, which is the difference in yields between Seasoned BAA Corporate Bonds and Seasoned AAA Corporate Bonds, was gathered from the database of the Federal Reserve Bank of St. Louis.

5.2 Number of IPOs as dependent variable

The number of issued IPOs (*NIPO*) on the U.S. market throughout 1995-2024 will be the researched dependent variable of this study, with a final sample size of 5485 IPOs. As mentioned in the data sampling process, the IPO data was retrieved directly from Jay Ritter's IPO database with a monthly frequency. The data is in the format of the so-called net number of IPOs, in contrast to the gross amount, which would be all issued IPOs regardless of their type. What is meant by the net number of IPOs is that all non-common stock IPOs and certain other types are excluded from the sample, these include: Special Purpose Acquisition Companies (SPACs), closed-end funds, Real Estate Investment Trusts (REITs), unit offers, IPOs with offer price of under 5 USD, commercial banks, savings and loans, companies not directly listed on the NYSE, Nasdaq or Amex/NYSE MKT, master limited partnerships, small best efforts offers, and foreign companies issuing American Depositary Receipts (ADRs) (Jay Ritter, 2025). Ritter excludes these from the sample as he has a more conservative view of what defines an IPO. The main motivation behind the exclusions is data restrictions of the companies' underlying assets, but also the fact that Ritter focuses only on operating companies. It is highlighted that the most important aspect is that Ritter stays consistent with these exclusions over time, so that the overall distribution of the data isn't compromised (Jay Ritter, 2025). For this study, I opted to use the net number of IPOs as I view it as more suitable for research purposes. For instance, SPACs, which are small shell companies becoming publicly listed with a purpose of acquiring an unlisted company afterwards, don't necessarily behave or base their IPO decision in a similar way as conventional common stock companies (Nordea, 2025).

Figure 5: Net vs. Gross number of U.S. IPOs 1995-2024

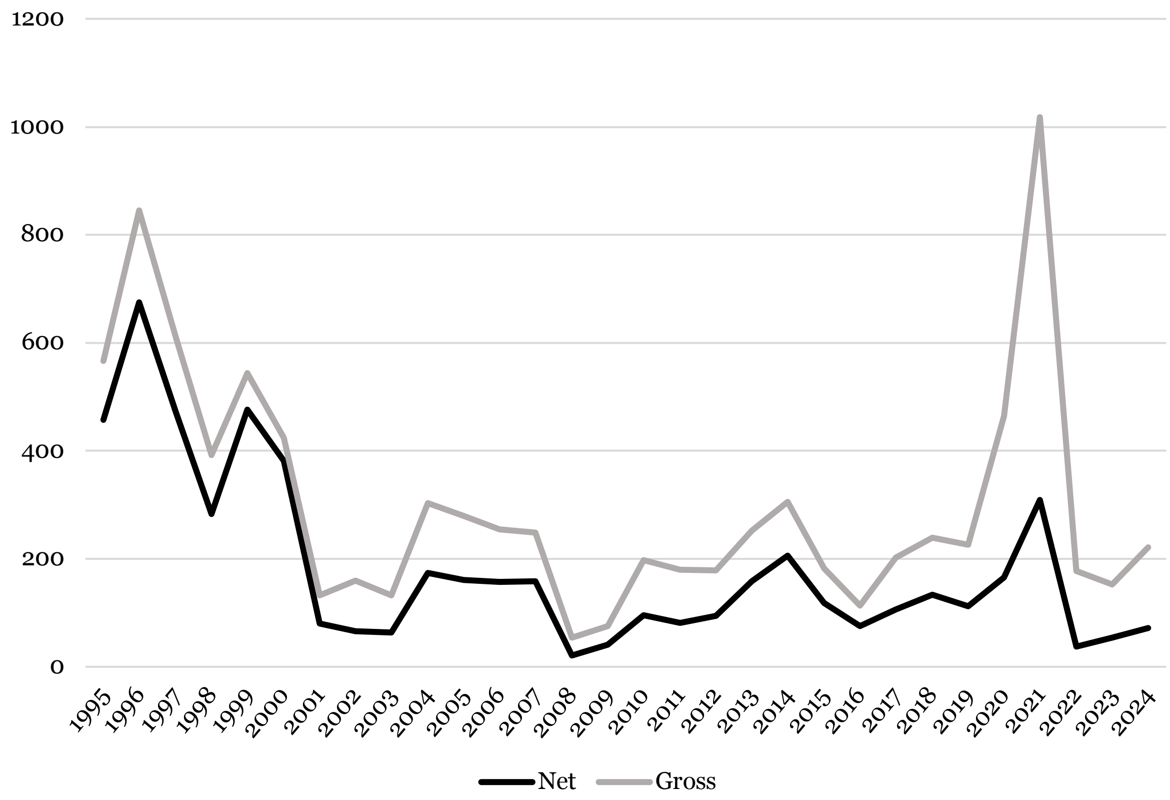

Figure 5 represents a comparison between the number of net and gross IPOs in the U.S. from Jay Ritter's database through the researched time period of 1995-2024. As we can see, both the net and gross numbers have a tendency for co-movement and similar reactions to historic trends, although the gross number evidently experienced an even stronger shock in 2021. Nevertheless, even though the number of IPOs can differ quite substantially between the two, the tendency of following a similar pattern should provide similar results. If anything, the gross amount might have even caused issues and skewed the results due to the huge IPO spike in 2021.

5.3 Independent variables

Several independent variables, mainly macroeconomic ones and similar, will be used in this study to try to explain the variation in IPOs throughout the researched time period. To establish relevancy and stay somewhat in line with previous research, the independent variables come from four different categories which are traditional macroeconomics, market performance and valuation, uncertainty and risk, and financial market conditions. The three latter categories being more exploratory. By traditional macroeconomic variables I refer to factors like interest rates, inflation, or the unemployment rate, which are generally used in research regarding the variability of IPOs. The category of market performance and valuation is comprised of variables measuring market performance and dynamics, which could be thought to influence IPO decisions. The third group, uncertainty and risk, consists of different economic measures, estimated on a large macroeconomic like scale, which includes for instance the index of Economic Policy Uncertainty. Lastly, the category of financial market conditions consists of a couple variables describing for instance credit conditions. All of the data for the independent variables that are used is on a monthly observation frequency through the researched time period of 1995-2025, resulting in 360 observations per variable. This subchapter aims to describe all the independent variables in detail.

5.3.1 Macroeconomic variables

To maintain the traditional macroeconomic aspect of this study and establish relevancy, I will use different traditional macroeconomic factors as one group of variables. Four variables will be used, and they are the seasonally adjusted unemployment rate (*UNEMP*), seasonally adjusted inflation or consumer price index (*CPI*), the Federal Funds Effective Rate (*FED*), and the Consumer Confidence Index (*CCI*). Most of these variables are frequently used in IPO research and are found to have some impact on the number of IPOs. For instance, Mehmood et al. (2021) found significant effects of inflation and the treasury bill rate on the number of IPOs, as did Angelini & Foglia (2018), who also found a relationship between interest rates and IPOs. All these macroeconomic variables can be seen as describing overall economic conditions, with a thriving economy possibly indicating increased IPO activity as companies feel confident or even encouraged to go public.

As previously mentioned, *UNEMP* and *CPI* are both seasonally adjusted, meaning the exclusion of recurring seasonal trends. By doing this, core trends are demonstrated more clearly in the coming results, as unnecessary noise from seasonal trends is excluded. The Federal Funds Effective Rate, even though it technically isn't the policy rate of the Fed, can be seen as the actual realized policy rate at which banks lend to each other overnight. It is calculated as the volume-weighted median of overnight federal funds transactions (Federal Reserve Bank of New York, 2025). The *CCI* is a standardized survey-based confidence indicator of future household consumption and saving. The survey asks households of their expected future financial situation and sentiment towards the overall economic situation amongst other things. The scaling of the index works in a way where a value of over 100 is seen as positive consumer sentiment towards the future and values under 100 represent more of a pessimistic view. Positive sentiment indicates that consumers are more likely to spend money rather than save, while pessimistic sentiment slows down consumption. (OECD, 2025)

5.3.2 Market performance and valuation

The second group of variables that will be tested for a possible relationship with IPO activity are market performance and valuation measures. This group, which describes market outcome and behavior, will include S&P 500 returns as a proxy for the U.S. market return in its natural logarithmic values (*LOG_R*), the natural logarithmic values of the S&P 500 P/E-ratio (*LOG_PE*), and a wealth inequality measure called the Distributional Financial Accounts (*WI*). Even though market return isn't technically classified as a macroeconomic variable, it has been widely used in IPO research. For instance, both Batnini & Hammami (2015) and Angelini & Foglia (2018) found market returns to have a significant relationship with the number of IPOs. Similar to the macroeconomic findings, the reasoning behind this is that a well performing economy encourages IPOs. To assure a stronger normal distribution of the monthly returns, they were transformed into log returns and calculated from historical price data as seen from equation 6:

$$LOG\_R = \ln(\frac{P_t}{P_{t-1}}) \tag{6}$$

The reasoning behind the S&P 500 P/E-ratio is strongly linked with the market return. That is, a thriving economy would encourage IPO activity. Signs of a well performing S&P 500 would also show in its P/E-ratio, which would then translate into a similar relationship to IPOs as with the market return. As the P/E-ratio for the index is only quoted on a quarterly basis like most financial ratios, this value had to be manually calculated with the use of Robert Shiller's S&P 500 earnings data to accommodate for the monthly frequency of this study:

$$PE = \frac{Price}{Earnings\ per\ Share\ (EPS)} \tag{7}$$

Furthermore, the P/E-ratio of the S&P 500 will also be measured by its log values (*LOG_PE*). This is due to the fact that quite extreme values for kurtosis and skewness were observed, indicating a heavy right-tail in the sample. By using log values, the sample becomes more normally distributed which is a wanted aspect in most empirical research.

Lastly, the wealth inequality measure (*WI*) is the Distributional Financial Accounts that measures the share of net worth held by the top 1 percent in the U.S. This variable is included to look more for the long-term relationship with IPO activity, in terms that higher wealth concentration would indicate fewer IPOs in the long run. It is closely linked to the equity market, and thus to the market return, due to high wealth inequality meaning less people having proper access to the stock market. However, it has been argued by Bilias et al. (2017) that wealth in itself isn't the restricting factor for people to participate in the stock market, but more so the behavior and education of less wealthy people. Nevertheless, the reasoning stays the same and that is, that higher wealth inequality would suggest less demand for new equity as fewer retail investors have the ability to participate in IPOs. It might even be that when wealth is concentrated with the ultra-wealthy, there is no need for companies to raise capital by going public, as private equity among other financing tends to increase with wealth concentration.

5.3.3 Uncertainty and risk

The third group of variables will consist of the Geopolitical Risk Index (*GPR*), the Economic Policy Uncertainty Index (*EPU*), and the VIX index (*VIX*). The grouping is based on the fact that all three variables measure some sort of future uncertainty, whether it's regarding market risk or unexpected events. Regarding the *GPR* and *EPU*, the final choice was based on both pure interest and the fact that the measurements of these indices are very macroeconomic like, as they estimate uncertainty on a large geographical scale. The *GPR* index is developed by Dario Caldara and Matteo Oacoviello, and it measures the evolution and economic effects of geopolitical events and tensions covered in newspapers (Economic Policy Uncertainty, 2025). The U.S. *EPU* index, which is constructed and maintained by the research institution of Economic Policy Uncertainty, consists of three components: news coverage (from 10 large U.S. newspapers) about policy-related economic uncertainty, tax code expiration data, and economic forecaster disagreement. The economic forecaster disagreement component is the dispersion of three forecasted variables influenced by government policies: CPI, purchases of goods and services by state and local governments, and purchases of goods and services by the federal government (Economic Policy Uncertainty, 2025). Both the *GPR* and *EPU* indices are interpreted in a way that a higher value indicates more uncertainty. Due to outliers in the data and quite a heavy right-tail for the *GPR* observations, which is presented later on within the descriptive statistics, log values of this variable will be used (*LOG_GPR*) to incentivize normal distribution.

The *VIX* index, or properly called the Chicago Board Options Exchange's Volatility Index, measures the expected volatility of the S&P 500. Risk measures like this have been used in previous studies regarding the impact they have on the number of IPOs. Dicle & Levendis (2017) found statistically significant signs that specifically the expected or implied volatility of the *VIX* Index rather than the realized volatility caused lower IPO activity. Similarly, Angelini & Foglia (2018) concluded that the UK market volatility was an explanatory variable behind IPO activity. The results of these previous studies seem to follow the same conclusion, future uncertainty discourages companies from going public and instead delays the IPO decision. The index itself is calculated 30 days into the future using call and put option prices of the S&P 500 index (CBOE, 2025).

5.3.4 Financial market conditions

The final category of variables in this study are measurements of financial market conditions, a liquidity measure of U.S. stocks (*LM*) and Moody's credit spread (*CS*). These variables were chosen as they are able to explain the wider condition of the U.S. financial markets, in other words, they are measurements of a larger scale similar to the other variables of this study. The liquidity measure, or rather a liquidity factor constructed by Pastor & Stambaugh (2003), looks at how changes in aggregate liquidity are reflected in stock returns. It is interpreted in a way where a higher value for the liquidity measure indicates lower liquidity (Pastor & Stambaugh, 2003). Illiquidity of the stock market can definitely be seen as a risk factor when considering IPOs. Most research regarding this has been done on IPO underpricing, but the fact that liquidity risk could entail an underpriced IPO, it could potentially also affect the IPO decision itself. For instance, Ellul & Pagano (2006) found that low expected liquidity typically increases the underpricing of IPOs. Generally speaking, high liquidity could indicate a well-functioning financial market, which could then encourage both IPOs and investor participation in the stock market.

Moody's credit spread measures the difference in yields between seasoned BAA corporate bonds and seasoned AAA corporate bonds. The motivation to include credit spread as a variable in this study is twofold, and a bit contradicting. Wider credit spreads typically mean that debt is more expensive, and in this case, could incentivize companies to rather seek financing on the equity market through IPOs. On the other hand, wider credit spreads are to some extent seen as an indicator of market risk, meaning that a wider credit spread could discourage investors to participate in IPOs.

5.4 Descriptive statistics

This chapter will present descriptive statistics for the dependent and all the independent variables used in this study. Table 1 shows the most critical and informative data points in the form of mean, median, standard deviation, kurtosis, skewness, minimum and maximum values, as well as the number of observations. For justification purposes, the table shows statistics for both the standard variables and the natural logarithmic variables in the cases where log values are used (except market return *LOG_R*). This is demonstrated to see why logarithmic values are used. Excluding *LOG_R*, the variables that will use logarithmic values are *PE*, *GPR*, and *CS*. The reasoning behind this is the same for all three variables, quite extreme values for kurtosis and skewness were observed. As can be seen from the variables' logarithmic counterparts, these values became significantly lower by using log values. Both statistics measure normal distribution and outliers in the data in a way, where kurtosis checks for the weight of the tails as well as the peak sharpness, and skewness tells us if the tail is skewed to the left or right. All three logged variables had quite similar statistics in regards of this, indicating a heavy right-skewed tail in the data.

Other statistics that are worthwhile to mention is that we have observed several months with zero IPOs, which can be seen from the min value of 0,00 for *NIPO*. The variation of *EPU* can also be seen quite clearly from its standard deviation of 43,53, with 57,20 minimum and 350,46 maximum values.

Table 1: Descriptive statistics of dependent and independent variables

Variable	Mean	Median	St Dev	Kurtosis	Skewness	Min	Max	N
NIPO	15,24	10,00	15,74	3,25	1,81	0,00	90,00	360
UNEMP	5,57	5,05	1,83	2,37	1,47	3,40	14,80	360
CPI	2,54	2,30	1,63	3,36	1,20	-2,00	9,00	360
FED	2,50	1,75	2,26	-1,55	0,34	0,05	6,54	360
CCI	100,02	100,45	1,59	-0,77	-0,35	96,27	102,86	360
LOG_R	0,01	0,01	0,04	1,37	-0,79	-0,19	0,12	360
PE	25,37	22,51	14,25	27,55	4,81	13,01	126,02	360
LOG_PE	3,16	3,11	0,34	6,97	2,06	2,57	4,84	360
WI	28,69	28,75	1,67	-1,01	-0,31	24,90	31,10	360
GPR	100,62	89,77	49,33	27,93	4,25	39,05	512,53	360
LOG_GPR	4,54	4,50	0,36	3,07	0,97	3,66	6,24	360
EPU	116,58	106,01	43,53	3,58	1,50	57,20	350,46	360
VIX	20,06	18,33	7,76	4,10	1,64	9,51	59,89	360
LM	-0,02	-0,02	0,07	2,87	-0,94	-0,31	0,20	360
CS	0,96	0,89	0,39	14,09	3,15	0,55	3,38	360
LOG_CS	-0,09	-0,12	0,31	2,60	1,16	-0,60	1,22	360

Table 1 presents all the relevant descriptive statistics for the dependent variable *NIPO* as well as for all independent variables. From left to right we have mean, median, standard deviation, kurtosis, skewness, minimum and maximum values, and finally the number of observations. Except for *LOG_R*, both the standard and natural logarithmic values are presented for the variables using log values in this study.

5.5 Summary of variables

Table 2 summarizes all the dependent and independent variables used in this study, with their respective descriptions.

Table 2: Variables and descriptions

Variable	**Description**
Dependent	
NIPO	Net number of IPOs
Independent	
UNEMP	Seasonally adjusted unemployment rate
CPI	Seasonally adjusted consumer price index
FED	Federal Funds Effective Rate
CCI	Consumer Confidence Index
LOG_R	Natural logarithm of S&P 500 returns
LOG_PE	Natural logarithm of S&P 500 P/E-ratio
WI	Distributional Financial Accounts (1 percentile)
LOG_GPR	Natural logarithm of the Geopolitical Risk Index
EPU	The Economic Policy Uncertainty Index
VIX	The VIX Index
LM	U.S. stocks liquidity factor by Pastor & Stambaugh (2003)
LOG_CS	Natural logarithm of Moody's Seasoned Corporate BAA-AAA Bond Yield

Table 2 presents a summary of all the variables used in this study. Respective descriptions are also presented to clearly show what the variable abbrevations stand for.

6 METHODOLOGY

This chapter will introduce the methodology chosen for this study. To estimate the relationship between the three categories of variables and the number of IPOs, a Multiple Ordinary Least Squares (OLS) regression model will be used. The macroeconomic factors and beyond will be the independent variables in the model, testing if a change in them will have an impact on the number of IPOs, the dependent variable.

As the impact of macroeconomic factors isn't typically instant, a model with an appropriate level of lag applied to the independent variables will also be conducted. The optimal lag will be decided with a combination of the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). Previous studies have varied a bit regarding this, with some applying the level of lag based on one criterion test while others have used three different tests to obtain the optimal lag.

6.1 Regression model

The regression model will look like the following:

$$NIPO_t = \beta_0 + \beta_1 UNEMP_t + \beta_2 CPI_t + \beta_3 FED_t + \beta_4 CCI_t + \beta_5 LOG\_R_t + \beta_6 LOG\_PE_t + \beta_7 WI_t + \beta_8 LOG\_GPR_t + \beta_8 EPU_t + \beta_8 VIX_t + \beta_8 LM_t + \beta_8 LOG\_CS_t + \varepsilon_t \quad (8)$$

where *NIPO* stands for the number of IPOs, *UNEMP* for the unemployment rate, *CPI* for inflation/consumer price index, *FED* for the Federal Funds Effective Rate, *CCI* for the Consumer Confidence Index, *LOG_R* for the natural logarithm of S&P 500 returns, *LOG_PE* for the natural logarithm of S&P 500 P/E-ratio, *WI* for wealth inequality measure, *LOG_GPR* for the natural logarithm of the Geopolitical Risk Index, *EPU* for the Economic Policy Uncertainty Index, *VIX* for the VIX Index, *LM* for the liquidity measure, *LOG_CS* for the natural logarithm of the credit spread, and finally ε_t for the error term.

6.1.1 Optimal lag

By testing for the optimal level of lag with both the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), both suggested the appropriate lag to be zero if the same lag were to be applied to the entire model or all variables. In other words, both criterions indicate that the standard model with no applied lag should be the best fit. This is at least partially due to the fact that OLS models aren't necessarily the strongest for estimating lagged variables, as models like Vector Autoregression are more suited for that purpose. The final choice of variables might also affect the proposed lag level of zero, as some variables could independently acquire a different level of lag, but when conducting an OLS regression model, it's clearer and more consistent to apply the same lag across all variables. However, due to the nature of macroeconomic factors and their tendency to have delayed effects, I have decided to also run a lagged OLS regression model with a lag level of one across all variables. In the case of this study, a lag level of one indicates a one-month delay.

6.2 Assumptions and model diagnostics

When conducting an OLS regression model, certain assumptions have to hold for the underlying data to provide credible results. For statistical accuracy, the model assumes no perfect multicollinearity between the independent variables, no heteroskedasticity, normal distribution of the data, no autocorrelation, no endogeneity, and finally, linearity between the variables. This section of the thesis aims to provide diagnostics regarding these assumptions to see if they hold, or otherwise what remedies have to be taken.

6.2.1 Multicollinearity

When conducting a regression analysis, the desired aspect is to find a level of correlation between the dependent and independent variables. However, correlation amongst the different independent variables of the model is undesired. When two or more of the independent variables in the model are highly correlated, multicollinearity is present. The issue that multicollinearity brings is that the standard errors will increase, possibly making some variables statistically insignificant when they actually aren't. Two methods that are widely used to detect possible multicollinearity are the simple correlation matrix and the Variance Inflation Factors test (VIF), which are the ones that I will be implementing in this thesis. (Daoud, 2017)

Regarding a correlation matrix, the values range from +1 to -1, with +1 indicating perfect positive correlation and -1 perfect negative correlation. It is generally interpreted in a way, that a value of either above 0,80 or below -0,80 indicates that multicollinearity is present. All the independent variables were fitted into a correlation matrix, which can be seen from Table 3. No extreme values of correlation between the variables are observed, suggesting no strong multicollinearity. The strongest correlation can be observed between the unemployment rate and the Federal Funds Effective Rate, with a negative correlation of -0,56.

Table 3: Correlation matrix

Variable	UNEMP	CPI	FED	CCI	LOG_R	LOG_PE	WI	LOG_GPR	EPU	VIX	LM	LOG_CS
UNEMP	1,00											
CPI	-0,40	1,00										
FED	-0,56	0,24	1,00									
CCI	-0,41	-0,32	0,40	1,00								
LOG_R	0,10	-0,13	0,03	0,07	1,00							
LOG_PE	0,04	-0,31	-0,06	-0,04	0,04	1,00						
WI	-0,08	0,03	-0,36	-0,24	0,10	-0,20	1,00					
LOG_GPR	-0,11	0,15	-0,24	-0,26	-0,08	0,05	-0,04	1,00				
EPU	0,48	0,00	-0,53	-0,54	-0,05	0,12	0,31	0,07	1,00			
VIX	0,24	-0,04	-0,11	-0,25	-0,43	0,43	-0,29	-0,09	0,44	1,00		
LM	0,04	-0,06	-0,06	0,05	0,22	-0,14	0,19	0,00	-0,06	-0,33	1,00	
LOG_CS	0,40	-0,22	-0,42	-0,52	-0,12	0,39	-0,06	0,15	0,44	0,49	-0,17	1,00

Table 3 presents a correlation matrix of all the independent variables. The correlation values are not suggesting the presence of any significant multicollinearity between the variables.

The second method to test for multicollinearity is the VIF test. When correlation is present, standard errors will increase and thus the variance will increase as well. The VIF test measures how much the variance has increased (Daoud, 2017). How VIF values are interpreted is a bit case sensitive, but as a general rule of thumb VIF > 5 suggests potential multicollinearity that should be investigated while VIF > 10 indicates serious multicollinearity that has to be addressed. When VIF = 1 no correlation is present whatsoever (The Pennsylvania State University, 2025). When running the VIF test on my data sample, no severe signs of multicollinearity was observed according to the VIF values. In line with the correlation matrix, the unemployment rate was assigned the highest VIF value of 4,96, which is still under the threshold of VIF > 5 that would potentially require further investigation.

6.2.2 Heteroskedasticity

The OLS regression model assumes that the variance of the error term is constant, i.e., homoscedastic. If the variance isn't constant, heteroskedasticity is present. What the presence of heteroskedasticity means is that the standard errors can be biased, which translates to possibly misleading significance values. However, if heteroskedasticity is observed, the coefficients in the OLS model still remain unbiased. The most common way to detect heteroskedasticity in the underlying data is through the Breusch-Pagan (1979) test (Williams, 2020). The BP test returns a p-value that is interpreted in a way that if $p > 0{,}05$ homoskedasticity is present, and if $p < 0{,}05$ heteroskedasticity is observed.

By running the BP test on the underlying data, it's clear that some extreme heteroskedasticity is present, as the returned p-value is far below 0,05. The general remedy for this issue is to use robust standard errors, but as will soon be presented the data also has some issues regarding autocorrelation, which also has to be dealt with. For this reason, I have opted to use Newey-

West (1987) standard errors which are designed to deal with both heteroskedasticity and autocorrelation. In fact, when dealing with time series heteroskedasticity and autocorrelation, Newey-West standard errors are most commonly used (Kolokotrones et al., 2024).

6.2.3 Normality

Linear regression models like the one used in this study, the OLS model, assumes normal distribution of the residuals of the underlying data. Perhaps the most general way to see if this assumption holds is to first plot the residuals of the data, to understand where the possible issue lies. Afterwards, a suitable statistical test can be chosen to confirm the results. In my case, the largest issue was regarding outliers and heavy right-skewed tails in the residuals. This was partially dealt with as previously mentioned by using the natural logarithms of the *PE*, *GPR*, and *CS* variables, which had some outliers. Also, by using Newey-West (1987) standard errors, this issue is to some extent dealt with as they do not require normally distributed residuals. Nevertheless, to further test for the normality of the residuals, the Jarque-Bera (1980) test was the most suitable for my purpose as it specifically focuses on skewness and kurtosis. The test returned a p-value of far below 0,05, indicating non-normally distributed residuals. However, due to the natural logarithms and the Newey-West standard errors, as well as the Central Limit Theorem (CLM), the issue with non-normality doesn't appear to be that severe. Even though my sample size is relatively small, with N = 360, the CLM still regards it large enough for the theorem to hold. The general view for the CLM to hold is that N > 30 (Kwak & Kim, 2017), but some other views have also been brought forward, for instance Schmidt & Finan (2018) argued that observations divided by the number of parameters (n/p) > 10 for the CLM to hold. In my case, both of these requirements are met.

6.2.4 Autocorrelation

The fourth assumption of the OLS regression model is that no autocorrelation should be present. This is especially tricky when dealing with time series data, as there is a tendency for some form of autocorrelation. Essentially, autocorrelation refers to the measurement of the degree of similarity of a time series with itself (Dondurur, 2018). If individual values of the data are dependent on past values, autocorrelation is said to be present. This is an issue with OLS models as the assumption is that the standard errors are independent and identically distributed (IID), i.e. uncorrelated. If this assumption doesn't hold, the standard errors become biased which can lead to misleading significance values.

There are several ways to test for autocorrelation in the residuals, but the most common way is the Durbin-Watson (1950) test. The test returns a value ranging from 0 to 4, with a value of 2 indicating no autocorrelation. Regarding the residuals of this study, the test returned a value of 0,90, indicating strong positive autocorrelation. To further confirm the presence of autocorrelation, I also ran the Ljung-Box (1978) test which provided similar results. Due to autocorrelation being present, I have used Newey-West (1987) standard errors to mitigate the issue.

6.2.5 Stationarity

As this study is dealing with time series data, stationarity of the variables is required. Some variables exhibited non-stationarity, for instance the unemployment rate, which had to be further inspected. This led to running the Augmented Dickey-Fuller (1979) test on the residuals of the model, which provided some promising results. The test returned a p-value of 0,01, indicating that the residuals are stationary/cointegrated, i.e., they move together in the long run, even though the variables themselves might be non-stationary.

6.2.6 Endogeneity

Another OLS regression model assumption that will be tested on the data is endogeneity. In other words, OLS assumes no endogeneity in the data, or rather that the variables should be exogenous. This means that the regressors (independent variables) should be uncorrelated with the error term. If this assumption doesn't hold, it can lead to biased and inconclusive results. Endogeneity usually comes from the fact that the dependent and independent variable in question both affect each other but can also occur when a third variable that is not included in the model affects them. (Ao, 2009)

Many variables could by theoretical means be motivated to be exogenous, but this way there isn't any statistical proof. The most common way of testing if a variable is endogenous is the Durbin-Wu-Hausman (DWH) test. To conduct this test, instrumental variables (IVs) are needed to perform an IV regression which controls for endogeneity. This is then compared to the regular OLS regression to show if any of the variables are endogenous. IVs are essentially variables that account for the part of the variable that is not correlated with the error term. Many variables can be used as IVs, but one common method is using the suspected endogenous variable's lagged counterpart. It is also argued that if some variable was to be found endogenous, its IV, or in this case its lagged counterpart could be used in the model instead to deal with the issue. (Wang & Bellemare, 2020)

For this study, I opted to use the variables lagged counterparts as IVs and perform the DWH test on all independent variables. The test showed no strong evidence of endogeneity for the majority of variables, but the unemployment rate (*UNEMP*) and liquidity measure (*LM*) showed signs of endogeneity. However, as will be presented in the results chapter of this study, *UNEMP* shows strong statistical significance in both the regular and lagged OLS regression model, and as suggested by Wang & Bellemare (2020), variables' lagged counterparts could be used if a variable is found endogenous. For this reason, I have decided to keep *UNEMP* in the model in its current form, but when interpreting the results of the standard regression it should be kept in mind that the results for *UNEMP* might be biased to some extent. As for *LM*, it will not show any statistical significance in either of the models, nor is it theoretically important for this specific study due to it being more of an exploratory variable, which is why I have decided to exclude it from the model and final results. The variable could be kept in the model by simply disregarding its results, but due to concerns of it affecting the results of other variables, I think exclusion is the safer choice.

6.2.7 *Linearity*

Finally, linearity of the data will be tested, as it is also an assumption of the OLS regression model. Linearity essentially stands for the straight-line relationship between the dependent and independent variables. There are several methods to check for data linearity, and one common method is through visual plotting which is what I have decided to do in this study (Larsen & McCleary, 1972). Using residuals versus fitted plots, a scatter around zero is what would suggest linearity. I fitted all the variables in the plot and the majority of observations are scattered around zero. However, some outliers definitely exist, but I don't see the curvature or number of outliers to be that severe of an issue. This is nevertheless something that should be kept in mind when interpreting the results of this study.

6.3 Summary of model diagnostics

Table 4 summarizes the test statistics of all relevant diagnostics tests that were implemented on the data to see if the model assumptions hold. Table 5 on the other hand shows solely the results of the Durbin-Wu-Hausman test for endogeneity for all variables.

Table 4: Model diagnostics tests

Test	Statistic	p-value	Null hypothesis
VIF	All VIF < 5		No severe multicollinearity
Breusch-Pagan	BP = 61,875, df = 11	< 4,1e-09	Homoskedasticity
Jarque-Bera	X-squared = 315,52, df = 2	< 2,2e-16	Residuals normally distributed
			Skewness = 0, kurtosis = 3
Durbin-Watson	DW = 0,88145	< 2,2e-16	No autocorrelation
Augmented Dickey-Fuller	ADF = -4,6915, lag order = 7	0,01	Unit root, non-stationary

Table 4 shows the relevant diagnostics tests performed on the underlying data to check for multicollinearity, heteroskedasticity, normality, autocorrelation, and stationarity. The test statistics and respective p-values show signs of heteroskedasticity, non-normally distributed residuals, and autocorrelation in the data.

Table 5: Durbin-Wu-Hausman test

Durbin-Wu-Hausman	p-value	Result
UNEMP	0,0108	Endogenous
CPI	0,9238	Exogenous
FED	0,1879	Exogenous
CCI	0,0718	Exogenous
LOG_R	0,3614	Exogenous
LOG_PE	0,1265	Exogenous
WI	0,6869	Exogenous
LOG_GPR	0,9261	Exogenous
EPU	0,4648	Exogenous
VIX	0,2193	Exogenous
LM	0,0213	Endogenous
LOG_CS	0,4339	Exogenous

Table 5 presents the test results of the Durbin-Wu-Hausman test, used to check if the independent variables are endogenous or not. Variables *UNEMP* and *LM* are suggested to show signs of endogeneity as their p-values < 0,05.

7 RESULTS

This chapter will present the results of the empirical part of this thesis. Two separate OLS regression models were employed, a standard and a lagged model. The choice to include a lagged model comes from the fact that macroeconomic factors, for instance inflation, generally don't showcase their effects instantly. A lag length of 1 was incorporated into all the independent variables, as AIC and BIC didn't suggest any universal lag to be applied at all. As the utilized data is on a monthly frequency, the lag length of 1 represents a one-month delay. Both the standard and lagged model use Newey-West (1987) standard errors to account for heteroskedasticity and autocorrelation, which were both present. By using these robust standard errors, the following results which will be presented can be perceived as more reliable but at the same time make it more difficult to end up with statistically significant results. A couple of other aspects that should be kept in mind is the possibly biased results due to small non-linearity issues. However, the effect should be fairly weak and thus shouldn't warrant anything more than to stay critical when interpreting the results. The variable *UNEMP* did show some signs of endogeneity, but as this can be sorted by including the variables lagged counterpart instead, it shouldn't be an issue as the variable is highly statistically significant in the lagged model (Wang & Bellemare, 2020). The liquidity measure (*LM*) is on the other hand excluded due to its endogenous nature.

As for the interpretation of the results, estimate coefficients and their respective t-values will be presented, combined with a p-value assigning the level of statistical significance. The statistical significance will be assigned on 0,1%, 1%, 5%, and 10% levels. Finally, to see how well the combined independent variables of this study are able to explain the variation in the number of IPOs, i.e. model fit, an Adjusted R^2 statistic will be presented for both models.

7.1 Standard OLS model with Newey-West (1987) standard errors

Table 6 presents the test statistics for the standard OLS model using Newey-West (1987) standard errors. To start off, the group of more traditional macroeconomic variables containing the unemployment rate (*UNEMP*), inflation (*CPI*), interest rate (*FED*), and Consumer Confidence Index (*CCI*) are all suggested to have high statistical significance in the variation of IPOs. For instance, *UNEMP* and *CCI* acquiring significance levels of under 0,1 percent ($p < 0{,}001$), and in practical terms a unit increase in the *CCI* would indicate an increase of 3,85 in the number of IPOs by looking at the estimate column of Table 6.

The second group of variables that included performance and valuation metrics did not yield as interesting results as the previous group. Here, only the wealth inequality measure (*WI*) showed slight statistical significance, but only on a 10 percent level ($p = 0{,}099$). The natural logarithmic values of S&P 500 returns (*LOG_R*) and P/E-ratio (*LOG_PE*) were both far from measuring statistical significance, with *LOG_R* receiving the highest p-value of this model (p = 0,217).

Uncertainty and risk measures are coming in at group three with the natural logarithmic values for the Geopolitical Risk Index (*LOG_GPR*), the Economic Policy Uncertainty Index (*EPU*), and the *VIX* Index. All three variables showed statistical significance in this study, even though *VIX* only on a weak level with a p-value staying barely below the 10 percent threshold. *LOG_GPR* and *EPU*, which are both slightly less studied variables within IPO research, showed quite high explanatory power for the variation in the number of IPOs. *LOG_GPR* with a p-value of 0,04 and *EPU* showing statistical significance even on a 1 percent level with p = 0,002 indicating that a one unit increase in *EPU* would decrease the number of IPOs by 0,09.

The final group, which now only consists of the logarithmic values for Moody's credit spread (*LOG_CS*) since the liquidity measure (*LM*) got dropped out due to endogeneity, measured financial market conditions. *LOG_CS* got assigned one of the strongest levels of statistical significance in this study (p < 0,001) with an estimate indicating a decrease of almost 15 IPOs if Moody's credit spread increased by one unit. All the variables in this model using Newey-West (1987) standard errors were in total able to explain around 51 percent of the variation in the number of IPOs, indicated by the Adjusted R-squared statistic. A reasonable and quite typical number, considering that the primary focus of this study is to analyze the explanatory power of individual variables, rather than the overall model.

Table 6: Standard OLS regression model test statistics

Variable	Estimate	Std. Error	t-value	p-value
Intercept	-422,57	135,02	-3,13	0,002 **
UNEMP	3,88	1,04	3,71	0,000 ***
CPI	2,39	0,81	2,96	0,003 **
FED	1,89	0,59	3,19	0,002 **
CCI	3,85	0,99	3,90	0,000 ***
LOG_R	26,07	21,09	1,24	0,217
LOG_PE	3,78	2,61	1,44	0,150
WI	1,46	0,88	1,65	0,099 °
LOG_GPR	-6,89	3,34	-2,06	0,040 *
EPU	-0,09	0,03	-3,18	0,002 **
VIX	0,35	0,21	1,65	0,099 °
LOG_CS	-14,96	3,50	-4,27	0,000 ***
Adj. R^2	0,51			

*** < 0,001, ** < 0,01, * < 0,05, ° < 0,10 indicating statistical significance

Table 6 presents the test results of the standard OLS regression model using Newey-West (1987) standard errors. From left to right we have the variables, coefficient estimate, standard error, t-value, and p-value indicating the level of statistical significance. The most statistically significant variables are assigned ***. The final row of the table shows the Adjusted R-squared value for the model, indicating model fit.

7.2 Lagged OLS model with Newey-West (1987) standard errors

The test statistics for the lagged OLS model using Newey-West (1987) standard errors is presented in Table 7. All the independent variables were assigned a lag level of 1, in the case of this study indicating a one-month delay. The results with the lagged independent variables follow quite closely the standard model with several coefficients being highly statistically significant, but the overall model nor the significance levels didn't improve as expected. On the contrary, some variables' statistical significance even diminished a bit in the latter groups. The traditional macroeconomic factors, *UNEMP*, *CPI*, *FED*, and *CCI* remained highly significant, with *FED* even improving its significance level to a 0,1 percent level while the significance of *CPI* decreased a bit (p = 0,028), with everything else staying the same.

In the second group with performance and valuation metrics *LOG_R* and *LOG_PE* retained their high levels of non-statistical significance, even though *LOG_R* was assigned a higher t-value and lower p-value compared to the standard model, possibly indicating that an even further lagged effect could have been beneficial. *WI* lost its previous weak level of statistical significance with a p-value of 0,155 for the lagged variable, leaving the overall results of the second group non-statistically significant in regards of IPO variability.

The variables measuring uncertainty and risk were all assigned weaker levels of statistical significance for their lagged counterparts. In fact, *EPU* was the only variable in this category that was able to retain some statistical significance (p = 0,034) on a 5 percent level. It is interesting to note however, that the p-value of *VIX* increased all the way to 0,332 from being previously statistically significant on a 10 percent level, which is the highest p-value assigned to any variable in this study.

Finally, the lagged variable of *LOG_CS* remained as one of the most statistically significant explanatory variables of this study, with a significance level of 0,1 percent. However, we can see some decreasing of its explanatory power compared to the standard model, as the assigned t-value has shrunk to -3,64 from the previous -4,27. The final model fit, or Adjusted R-squared, remained quite similar to the standard model, with the lagged model receiving a value of 0,47. This would indicate that the lagged model as a whole, wasn't able to explain the variation in the number of IPOs better than the standard model.

Table 7: Lagged OLS regression model test statistics

Variable	Estimate	Std. Error	t-value	p-value
Intercept	-434,90	145,49	-2,99	0,003 **
UNEMP_lag	4,09	1,08	3,79	0,000 ***
CPI_lag	2,01	0,91	2,20	0,028 *
FED_lag	2,31	0,62	3,71	0,000 ***
CCI_lag	3,89	1,10	3,55	0,000 ***
LOG_R_lag	28,51	18,58	1,53	0,126
LOG_PE_lag	3,89	2,82	1,38	0,168
WI_lag	1,28	0,90	1,43	0,155
LOG_GPR_lag	-4,58	3,18	-1,44	0,151
EPU_lag	-0,06	0,03	-2,12	0,034 *
VIX_lag	0,21	0,22	0,97	0,332
LOG_CS_lag	-14,77	4,05	-3,64	0,000 ***
Adj. R^2	0,47			

*** < 0,001, ** < 0,01, * < 0,05, ° < 0,10 indicating statistical significance

Table 7 shows the test results for the lagged OLS regression model using Newey-West (1987) standard errors. The variables are lagged by one unit, indicating a one month delay. Coefficient estimates, standard errors, t-values, and p-values assigning the level of statistical significance are presented. The variables suggested to be the most statistically significant are assigned ***. Finally, the Adjusted R-squared statistic is presented to show the model fit.

7.3 Causality

As this thesis researches what impact changes in different macroeconomic factors and beyond have on IPO frequency, causality is important to establish and present, even though the variables themselves can show statistical significance through regressing. Generally speaking, causality establishes if a change in X leads to a change in Y, not just if they are correlated in some way. In the case of this thesis, it would mean if a change in the chosen macroeconomic variables and beyond directly affects a change in the number of IPOs. One of the more popular ways of establishing causality and the method chosen for this study is through Granger (1969) causality. It is essentially a measure within time series which tests how well past values can predict future values of another series (Shojaie & Fox, 2022). The results of the Granger (1969) causality test are typically interpreted in a similar way to other statistical tests, where a p-value < 0,05 indicates Granger causality, i.e., the respective independent variable Granger causes the dependent variable.

Through the test findings, which can be seen from Table 8, changes in the variables *FED*, *CCI*, and *LOG_CS* seem to strongly cause changes in the number of IPOs with p-values far below 0,05. Additionally, *LOG_R* got assigned a borderline p-value of 0,05 and *LOG_GPR*, *EPU*, and *VIX* are also indicated to have e causal relationship, even though a weak one, with the number of IPOs. The rest of the variables aren't able to show any meaningful causal relationships to the variability in IPOs.

Table 8: Granger causality of independent variables

Variable	F-stat	p-value	Granger-causes *NIPO*
UNEMP	0,00	0,95	No
CPI	0,65	0,42	No
FED	9,39	0,00	Yes
CCI	11,12	0,00	Yes
LOG_R	3,84	0,05	Yes/No
LOG_PE	0,51	0,48	No
WI	1,59	0,21	No
LOG_GPR	2,75	0,10	Weak
EPU	3,27	0,07	Weak
VIX	3,24	0,07	Weak
LOG_CS	13,48	0,00	Yes

Table 8 shows the test results for Granger (1969) causality between the dependent variable *NIPO* and the independent variables. The F-statistic and p-value for each variable is presented, with a p-value of under 0,05 indicating a strong causal relationship to the number of IPOs. Variables with $p < 0{,}10$ could be suggested to have a weak causal relationship.

8 DISCUSSION

This chapter will further discuss and analyze the previously presented results as to what they mean and provide potential explanations for the findings. For this, economic theory and previous literature will be utilized. Additionally, answers for the hypotheses set forth in the beginning of this thesis will be given.

8.1 Impact of macroeconomics on IPOs

As recalled from the results of this study, all of the more traditional macroeconomic variables from the first group showed strong statistical significance in regards of being able to explain the variation in the number of IPOs. This is merely confirming the results of previous studies (Angelini & Foglia, 2018; Mehmood et al., 2021), where for instance interest rates and inflation have been found to explain parts of the variation in IPOs. These results were conclusive for both the standard and lagged model, even though the levels of statistical significance varied a bit. One important difference is in regard of the variable *UNEMP*, as it was found to be potentially endogenous. The test results for this variable might be slightly biased in the standard OLS model, however as Wang & Bellemare (2020) suggested, replacing the endogenous variable with its lagged counterpart could to a large extent fix the issue. As the unemployment rate still showed strong statistical significance in the lagged model, in fact even stronger than in the standard one, I see this as an adequate justification to interpret the results as quite reliable. Thus, the null hypothesis is rejected for all the macroeconomic variables, and the alternative hypothesis is accepted, meaning that the unemployment rate, inflation, interest rate, and Consumer Confidence Index all have a statistically significant impact on IPO frequency.

For the unemployment rate, no causal relation to the number of IPOs were found indicating that it necessarily isn't a variable that is able to predict the number of IPOs. However, its high statistical significance still confirms its importance in being a variable that is able to explain the observed variation to some extent. The explanation behind the explanatory power of *UNEMP* is quite simple and extends to many macroeconomic factors. It is the fact that unemployment goes hand in hand with wider economic conditions (Reserve Bank of Australia, 2025), which is also the case for IPOs indicating that they are all highly correlated. This can be seen for instance during the financial crisis of 2008, when unemployment in the U.S. skyrocketed while the number of IPOs drastically sunk. Generally speaking, when economic conditions aren't great, companies aren't encouraged to go public.

The rest of the macroeconomic variables' results, inflation, interest rate, and Consumer Confidence Index can be explained in a similar manner as the unemployment rate. Periods of high inflation or deflation can be seen as signals that the economy is either overheating or not living to its full potential. Indicating poorer economic conditions for companies to go through with their IPOs. The results can be further backed up by economic theory due to the fact that Granger causality wasn't detected for inflation, but a causal relationship with the interest rate and number of IPOs was established. This is due to the fact that inflation doesn't directly cause variation in IPOs, but interest rates do as they are the main monetary policy used by central banks to influence inflation levels (The Federal Reserve, 2025). So even though inflation and the number of IPOs can be highly correlated, it is in fact interest rates that are set by central banks in accordance with the inflation target that cause the shift in IPOs throughout time. The statistically significant results and causality of the *CCI* can on the other hand be explained by that the index measures consumers' attitudes towards future financial conditions, whether they are bullish or bearish (OECD, 2025). It's a large-scale estimator, which could potentially be seen as an indicator of the expected economic conditions that would similarly to other macro factors either encourage or discourage IPOs depending on the economic situation. The people in charge of launching IPOs, like CFOs and others, could be a part of the index themselves, and if they have a pessimistic view of the future economy, they presumably wouldn't launch their company's IPO either. Essentially, high consumer confidence signals a positive future outlook for market conditions, which can possibly cause an increase in the number of IPOs.

8.2 Impact of market performance and valuation on IPOs

The group of market performance and valuation measures with S&P 500 returns (*LOG_R*), S&P 500 P/E-ratio (*LOG_PE*), and the wealth inequality measure (*WI*) didn't really show any statistical significance in either of the regression models, except *WI* being statistically significant on a weak 10 percent level in the standard model. For this reason, we can't reject the null hypothesis for any of the three variables, concluding that they don't have any statistically significant impact on IPO frequency, at least with the current model specification. The results of this group were a bit unexpected, as several previous studies (Mehmood et al., 2021; Angelini & Foglia, 2018) have looked at how market returns affect the number of IPOs. Specifically, Mehmood et al. (2021) found a statistically significant relationship between market returns and IPO frequency on the Pakistani market. Due to results like by Mehmood et al. (2021) is why market return and consequently the P/E-ratio was chosen for this thesis. Remembering that the P/E-ratio was justified by the fact that if market return was an explanatory variable of IPO frequency, so could the P/E-ratio, as a healthy market could mirror its effects on the ratio. Nevertheless, as *LOG_PE* did not show any statistical significance nor causal relations to the number of IPOs, I see the results as quite conclusive.

The results for *LOG_R,* however, do need some further analyzing. Even though the results of this specific study didn't show any statistical significance, there are still some interesting aspects about the results. Mainly the fact that the p-value of *LOG_R* decreased quite drastically (or increased t-value) from the standard model to the lagged model. This could indicate that the variable was more suited to be applied within a lagged model, only that the level of lag used in this study wasn't enough to show results. Due to the nature of the OLS model, applying more lag wasn't really justifiable, so another model like the Vector Autoregressive model could have been able to show stronger results. These speculations are further justified by the fact that as Mehmood et al. (2021) found market return to have some explanatory power, they used a modified model accounting for long-term effects as well. Going even further, the fact that *LOG_R* was found to have a moderate causal relationship with the number of IPOs, shows the variable's importance, but also suggests that more statistically significant results could be reached by delaying the effects of market returns even further. Causality measures the predictive power of *LOG_R* on *NIPO*, meaning if past values of *LOG_R* could predict changes in the number of IPOs. Thus, these past values could technically also be seen as lagged values. The general motivation for why market returns could have statistically significant explanatory power fits quite well with macroeconomic variables. A well performing market suggests favorable IPO conditions, encouraging IPO issuance.

WI was the only variable in this group to show any kind of statistical significance, even though on a weak level, this significance disappeared going into the lagged model. However, as previously mentioned, the reason for including this variable in the study was more so to observe the long-term trend of wealth distribution relative to IPO issuance. As can be seen from Figure 6, the overall trend throughout the researched time period of 1995-2024 is increasing wealth inequality and decreasing IPO activity. *WI* doesn't look like it's increasing by that much, but this is typical for wealth inequality measures, and the important aspect is the long-term increase. The values for *WI* in the figure are multiplied by 10 for clearer visualization, but the actual values range from about 27 in 1995 to 31 in 2024. This indicates growing wealth inequality in the U.S., as *WI* measures the share of wealth held by the top one percent of wealthiest individuals (Federal Reserve Bank of St. Louis, 2025). The long-term decreasing IPO activity is often referred to as the listing gap. This essentially stands for the phenomenon where less firms are going public, creating a situation where the number of de-listings is surpassing new listings, which has become the nature of the U.S. market. Previous literature is suggesting the reason behind the listing gap to be increased M&A activity as well as industry changes, such as increased costs and other factors driving companies to the growing private equity market instead. In this manner, regular retail investors aren't able to participate in the wealthy markets of private equity, thus the phenomenon is ever so more increasing wealth inequality or at least restricting access to accumulate wealth through investing. By that said, it seems that wealth inequality doesn't dictate the number of IPOs, but the listing gap and the decreasing number of IPOs over the long run could very well be contributing to the increasing wealth inequality in the U.S. (Doidge et al., 2017)

Figure 6: Long-term trend, *NIPO* vs *WI*

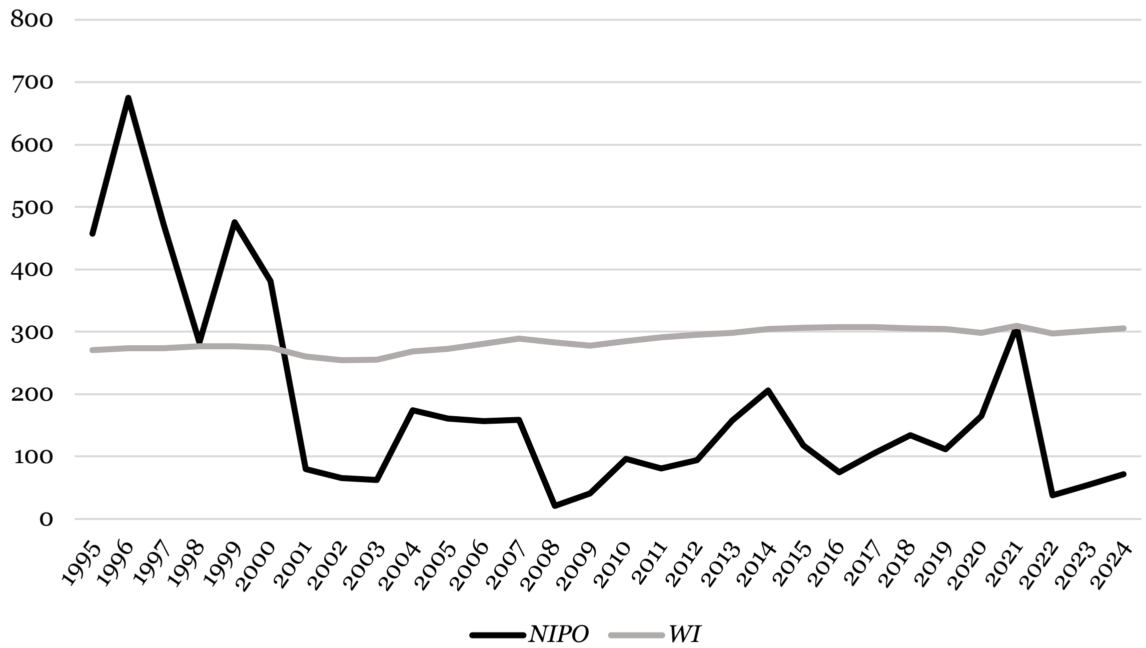

Figure 6 compares the long-term trends of the number of IPOs and wealth distribution in the U.S. Values for *WI* in the figure are multiplied by 10 for visualization purposes, the actual values range approximately between 27 and 31. The figure shows an overall decreasing number of IPOs from 1995 to 2024, while wealth inequality has simultaneously been increasing.

8.3 Impact of uncertainty and risk on IPOs

This group of variables is quite macroeconomic like, as they mainly measure uncertainty in different ways on a large macroeconomic scale. The specific variables in the group were the Geopolitical Risk Index (*LOG_GPR*), the Economic Policy Uncertainty Index (*EPU*), and the *VIX* Index. A common factor between these variables is that they are all forward looking, with the two former measuring already established uncertainty about the future, and *VIX* indicating the expected 30-day volatility of the S&P 500 index. I think the results are able to reflect this quite well, as all the variables except for *EPU* lost all their statistical significance moving from the standard model to the lagged one. By merely speculating, I see this happening due to the variables already accounting for the future, so by lagging them, this expected future doesn't hold any longer. For instance, if the *VIX* was to be lagged, which already estimates the one-month future expected volatility, the measured volatility would in this case be today's volatility as the lag level used was one month. Nevertheless, all three variables acquired statistically significant results in the standard model, with *EPU* being the most statistically significant one. Weak Granger causality was also found for all three variables, meaning that past values are to some extent able to predict or estimate the future number of IPOs. What the results of *LOG_GPR* and *EPU* indicate is that an increase in their value (higher uncertainty), can to some extent both explain and cause a decrease in the number of IPOs. Thus, I think it's fair to say that we can reject the null hypothesis for these two variables and accept the alternative hypothesis by stating that *LOG_GPR* and *EPU* have a statistically significant impact on IPO frequency. As for *VIX*, the results are somewhat contradicting which will be explained later on. Due to this, and the fact that its statistical significance was weak by barely staying under the 10 percent threshold, I have decided to not reject the null hypothesis for *VIX*.

The acquired results weren't so surprising, as for instance the Geopolitical Risk Index falls quite closely under previous research regarding the subject. Colak et al. (2017) found that specifically political uncertainty on a state level in the U.S. decreased IPO activity, and while the measure of uncertainty isn't the same, it is regardless some type of uncertainty, which creates a discouraging environment for companies to go public. Economic Policy Uncertainty can also be linked quite close to this and is even perhaps a more similar measure of uncertainty to the one used by Colak et al., (2017). The *EPU* uses for instance tax code expiration data as one component of the index, which in the U.S. can either be on a federal or state level. This could also be one possible explanation as to why the *EPU* showed stronger statistical significance compared to *LOG_GPR*. Not only is the *EPU* measuring U.S. specific uncertainty, but it can also include fairly local or regional components, while the *LOG_GPR* used in this study was measured on a global level. The Geopolitical Risk Index is also available on a country specific basis, and in hindsight it could have been better to use the U.S. specific index for stronger results.

The *VIX* Index has also been used in similar IPO research (Dicle & Levendis, 2017) and have been found to have an impact on IPO variability. The crucial difference, stated by Dicle & Levendis (2017), is that it's specifically the implied or expected volatility that is for instance estimated by the *VIX* and not the realized one that has the strongest effect on IPOs. Dependent on individual risk aversion, risk is something that is seen as unfavorable in financial theory, and the same could apply for IPOs. This uncertainty of the future, whether it be an unsuccessful IPO issuance due to underpricing or something else, discourages companies from going public as there are unknown factors that can potentially be avoided. In a scenario where there is too much expected risk, companies can decide to postpone their IPO instead. The issue with this theory and the results is that *VIX* got assigned a positive estimate coefficient (0,35 in the standard model). This would indicate that an increase in expected volatility would increase the number of IPOs, which seems counterintuitive. However, this is most likely due to the model specification, where other variables might already be accounting for the implied volatility of *VIX*, leaving it to only measure other effects. Another doubtful but possible explanation for this could be that certain companies actually issue their IPOs during times of higher expected volatility, which is driving up the regression estimate. This could include companies with publicity as one of their main motives behind the IPO decision.

8.4 Impact of financial market conditions on IPOs

The final group's results that will be discussed are measurements of financial market conditions, which in the end only consisted of Moody's credit spread (*LOG_CS*) as the liquidity measure got dropped out due to endogeneity. The goal with these variables, or in the end just with the credit spread, was similarly to other groups to try and measure large scale economic effects. *LOG_CS* was assigned one of the most statistically significant results of this study, both in the standard and lagged model. The significance was greater in the standard model with a t-value of -4,27 indicating that the current credit spread has a stronger impact on IPOs. Not only were the regression results highly statistically significant, but the variable was also suggested to have a strong causal relationship to the number of IPOs. These combined results propose that Moody's BAA-AAA seasoned corporate bond yields are able to explain some variation and can cause the number of IPOs to either decrease or increase. I think the results for this variable are quite clear, and hence, we can reject the null hypothesis and accept the alternative hypothesis. This means that *LOG_CS* has a statistically significant impact on IPO frequency.

The majority if not all research related to credit spreads and IPOs are focused on matters such as how credit ratings of the IPO firms themselves affect the pricing of the IPO (An & Chan, 2008), and not if credit spreads affect the IPO decision itself. But as credit ratings can be seen as a sort of risk measure, so can credit spreads. An & Chan (2008) found that IPO companies with a credit rating are underpriced far less than those without. This can be interpreted in a way, where a credit rating reduces information asymmetry and thus reduces risk and allows the IPO to be more fairly priced (An & Chan, 2008). Credit spreads can similarly be thought of as risk measures, with a wider credit spread suggesting more risk. In the case of *LOG_CS,* this could for instance mean that the lower rated BAA corporate bonds have an increased yield to compensate for the risk they carry, and as the credit spread measures the difference in BAA and AAA yields, this would lead to a wider spread. This risk that is portrayed by the credit spread, could technically also be seen as broader market risk (Tang & Yan, 2010). Thus, investors can become more risk averse which ends up reducing the demand for IPOs. From an IPO company perspective, this ultimately indicates that raising capital is more expensive during a wider credit spread, through both debt and equity. The results of this study support these theories, with *LOG_CS* being assigned an estimate coefficient of -14,96 suggesting that one unit increase in the credit spread would decrease the number of IPOs by approximately 15.

9 CONCLUSION

This thesis studied Initial Public Offerings and what impact different macroeconomic factors and beyond have on the change in the number of IPOs through 1995-2024 in the United States. The aim was to confirm and extend already established relationships from previous literature, by including more traditional macroeconomic variables and some more exploratory ones which still lack research. The alternative hypothesis set forth in this thesis states that variable X has a statistically significant impact on IPO frequency.

The data consists of all common stock IPOs in the U.S. between 1995 and 2024, with a final sample size of 5485 IPOs. Besides that, twelve independent variables grouped into four categories were chosen for this study to try to explain the variation in the number of IPOs. The data was fitted into an OLS regression model contrary to previous studies (Angelini & Foglia, 2018; Dicle & Levendis, 2017), with a lagged regression model also included as macroeconomic effects are generally delayed. As the study focused more on the individual effects of the variables on IPO frequency, Granger causality was also measured to see if the variables not only are explanatory but also predictive.

The results showed the standard regression model to be better at explaining the variation in the number of IPOs, compared to the lagged model where several variables lost their statistical significance due to their nature. This thesis' main findings were in many ways in line with previous literature both directly and indirectly. All of the more traditionally regarded macroeconomic factors (unemployment, inflation, interest rate, Consumer Confidence Index) showed strong statistical significance in accordance with both economic theory and previous studies (Angelini & Foglia, 2018; Mehmood et al., 2021), suggesting that the variables are able to explain the variability of IPOs to some extent. The interest rate and Consumer Confidence Index was also suggested to have a causal relationship to the number of IPOs. Variables regarding different types of uncertainty and risk (mainly Geopolitical Risk Index and Economic Policy Uncertainty Index,) also showed statistically significant results. Uncertainty and IPO activity has been previously studied (Colak et al., 2017; Dicle & Levendis, 2017) and relationships have been established between them two which is in line with the results of this thesis. These uncertainty and risk measures were also found to have causal relationships to the number of IPOs, however only weak ones. Moody's credit spread showed one of the strongest results of this thesis with highly statistically significant results in the regression model as well as a strong causal relationship. A wealth inequality measure calculating the distribution of wealth in the U.S. was also included to look at the long-term relationship to IPOs for the researched time period. The results are inconclusive and speculative, but it does seem like the listing gap and decreasing number of IPOs could in some way be contributing to higher wealth inequality in the U.S.

In light of the results, many variables accepted the alternative hypothesis of having a statistically significant impact on IPO frequency. The general view of the results is that variables like the ones included in this thesis, can cause large scale unfavorable conditions for IPOs, or vice versa. Many of the variables go hand in hand like inflation and interest rates, and they can create an environment where IPO issuances are postponed instead for more favorable conditions. Uncertainty and risk also create an unknown for IPO companies, where the risk is simply too large for IPO issuance. These kinds of large-scale economic effects was the purpose behind the chosen variables in this thesis. However, it is still important to keep in mind that the variables of this thesis aren't the sole explanation for the number of IPOs, they are merely suggested to be contributing on some level. This thesis contributes by confirming several results from previous literature, as well as by providing possible new insights on some less studied variables in relation to IPOs. Both the confirmations and new insights can be further used in the academic world and by companies planning their IPOs.

This thesis was partially limited to the choice of market. To get a large enough sample, an active and large IPO market had to be chosen. Hence, the United States market was chosen as it is one of the few large and active ones enough to get somewhat conclusive results. Further research could extend on the same subject, by looking at for instance the European market and incorporating even additional variables that have been less studied. Another interesting suggestion for further research would be to look more closely at the relationship between wealth inequality and the number of IPOs.

REFERENCES

An, H. & Chan, K. (2008). Credit ratings and IPO pricing. *Journal of Corporate Finance*. 14(5). 584-595. Available at: https://doi.org/10.1016/j.jcorpfin.2008.09.010.

Angelini, E. & Foglia, M. (2018). The Relationship Between IPO and Macroeconomic Factors: An Empirical Analysis from UK Market. *Annals of Economics and Finance*. 19(1), 319-336.

Ao, X. (2009). Introduction to Endogeneity-related Methods. Harvard Business School. Available at: https://www.hbs.edu/research-computing-services/Shared%20Documents/Training/intro_endogeneity.pdf. Accessed: 17.6.2025.

Bank of England. (2025). Inflation and the 2% target. Available at: https://www.bankofengland.co.uk/monetary-policy/inflation. Accessed: 5.6.2025.

Bank of England. (2025). Interest rates and Bank Rate. Available at: https://www.bankofengland.co.uk/monetary-policy/the-interest-rate-bank-rate. Accessed: 15.6.2025.

Barden, R., Copeland, J., Hermanson, R. & Wat, L. (1984). Going public-what it involves: A framework for providing advice to management. *Journal of Accountancy*. 157(3), 63.

Batnini, F. & Hammami, M. (2015). IPO Waves: How Market Performances Influence The Market Timing Of IPO?. *The Journal of Applied Business Research*. 31(5). 1679-1692. Available at: http://dx.doi.org/10.19030/jabr.v31i5.9382.

Bilias, Y., Georgarakos, D. & Haliassos, M. (2017). Has Greater Stock Market Participation Increased Wealth Inequality in the US?. *Review of Income and Wealth*. 63(1). 169-188. Available at: http://dx.doi.org/10.1111/roiw.12225.

Bondarenko, P. (2025). Macroeconomics. Available at: https://www.britannica.com/money/macroeconomics/Later-developments. Accessed: 2.3.2025.

Brau, J. & Fawcett, S. (2006). Initial public offerings: An analysis of theory and practice. *The Journal of Finance*. 61(1). 399-436. Available at: https://doi.org/10.1111/j.1540-6261.2006.00840.x.

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

CBOE. (2025). Making Sense of the VIX Index. Available at: https://www.cboe.com/tradable_products/vix/. Accessed: 15.6.2025.

Colak, G., Durnev, A. & Qian, Y. (2017). Political Uncertainty and IPO Activity: Evidence from U.S. Gubernatorial Elections. *Journal of Financial and Quantitative Analysis*. 52(6). 2523-2564. Available at: https://doi.org/10.1017/S0022109017000862.

Daoud, J. (2017). Multicollinearity and Regression Analysis. *Journal of Physics*. 949. 8-9. Available at: https://doi.org/10.1088/1742-6596/949/1/012009.

Dickey, D. & Fuller, W. (1979). Distribution of the Estimators for Autoregressive Time Series With a Unit Root. *Journal of the American Statistical Association*. 74(366). 427-431. Available at: https://doi.org/10.2307/2286348.

Dicle, M. & Levendis, J. (2018). IPO activity and market volatility. *Journal of Entrepreneurship and Public Policy*. 7(1). 2-13. Available at: https://doi.org/10.1108/JEPP-D-17-00017.

Doidge, C., Karolyi, A. & Stulz, R. (2017) The U.S. listing gap. *Journal of Financial Economics*. 123(3). 464-487. Available at: https://doi.org/10.1016/j.jfineco.2016.12.002.

Dondurur, D. (2018). Acquisition and Processing of Marine Seismic Data. Available at: https://doi.org/10.1016/C2016-0-01591-7.

Draho, J. (2004). The IPO Decision: Why and how Companies Go Public. 1-2. Accessed: 21.2.2025.

Durbin, J. & Watson, G. S. (1950). Testing for Serial Correlation in Least Squares Regression: I. *Biometrika*. 37(3). 409-428. Available at: https://doi.org/10.2307/2332391.

Ellul, A. & Pagano, M. (2006). IPO Underpricing and After-Market Liquidity. *The Review of Financial Studies*. 19(2). 381-421. Available at: https://doi.org/10.1093/rfs/hhj018.

Eurostat. (2025). Glossary: Seasonal adjustment. Available at: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Seasonal_adjustment. Accessed: 3.4.2025.

Federal Reserve Bank of New York. (2025). Effective Federal Funds Rate. Available at: https://www.newyorkfed.org/markets/reference-rates/effr. Accessed: 15.6.2025.

Federal Reserve Bank of St. Louis. (2025). CBOE Volatility Index: VIX. Available at: https://fred.stlouisfed.org/series/VIXCLS#. Accessed: 1.6.2025.

Federal Reserve Bank of St. Louis. (2025). Federal Funds Effective Rate. Available at: https://fred.stlouisfed.org/series/FEDFUNDS. Accessed: 2.4.2025.

Federal Reserve Bank of St. Louis. (2025). Moody’s Seasoned Baa Corporate Bond Yield-Moody’s Seasoned Aaa Corporate Bond Yield. Available at: https://fred.stlouisfed.org/graph/?g=f09. Accessed: 1.6.2025.

Federal Reserve Bank of St. Louis. (2025). Share of Net Worth Held by the Top 1% (99^{th} to 100^{th} Wealth Percentiles). Available at: https://fred.stlouisfed.org/series/WFRBST01134. Accessed: 1.6.2025.

Geddes, R. (2003). IPOs and Equity Offerings. 26-27.

Granger, C. (1969). Investigating Causal Relations by Econometric Models and Cross-spectral Methods. *Econometrica*. 37(3). 424-438. Available at: https://doi.org/10.2307/1912791.

Hwang, I. (2025). A Brief History of the Stock Market and Stock Exchanges. Available at: https://www.sofi.com/learn/content/history-of-the-stock-market/. Accessed: 28.2.2025.

Jarque, C. & Bera, A. (1987). A Test for Normality of Observations and Regression Residuals. *International Statistical Review*. 55(2). 163-172. Available at: https://doi.org/10.2307/1403192.

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

Kolokotrones, T., Stock, J. & Walker, C. (2024). Is Newey-West optimal among first-order kernels?. *Journal of Econometrics*. 240(2). Available at: https://doi.org/10.1016/j.jeconom.2022.12.013.

Kwak, S. & Kim, J. (2017). Central limit theorem: the cornerstone of modern statistics. *Korean Journal of Anesthesiology*. 70(2). 144-156. Available at: https://doi.org/10.4097/kjae.2017.70.2.144.

Lago Kapital. (2025). Price stabilization and Greenshoe option. Available at: https://www.lagokapital.com/greenshoe. Accessed: 20.2.2025.

Larsen, W. & McCleary, S. (1972). The Use of Partial Residual Plots in Regression Analysis. *Technometrics*. 14(3). 781-790. Available at: https://doi.org/10.1080/00401706.1972.10488966.

Ljung, G. M. & Box, G. E. P. (1978). On a Measure of Lack of Fit in Time Series Models. *Biometrika*. 65(2). 297-303. Available at: https://doi.org/10.2307/2335207.

London Stock Exchange Group. (2025). FTSE Russell. Available at: https://www.lseg.com/en/ftse-russell. Accessed: 3.4.2025.

Mehmood, W., Mohd-Rashid, R., Ong, C.Z. and Abbas, Y.A. (2021). Factors driving IPO variability: evidence from Pakistan stock exchange. *Journal of Economics, Finance and Administrative Science*. 26(52). 300-316. Available at: https://doi.org/10.1108/JEFAS-04-2021-0036.

Newey, W. & West, K. (1987). A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica*. 55(3). 703-708. Available at: https://doi.org/10.2307/1913610.

Nordea. (2025). What is a SPAC?. Available at: https://www.nordea.fi/en/personal/our-services/savings-investments/investments/spac.html. Accessed: 15.4.2025.

NYSE. (2023). NYSE IPO Guide. Third Edition. Available at: https://www.nyse.com/publicdocs/nyse/listing/nyse_ipo_guide.pdf#process-timeline. Accessed: 20.2.2025.

NYSE. (2025). The History of NYSE. Available at: https://www.nyse.com/history-of-nyse. Accessed: 28.2.2025.

Oner, C. (2025). Inflation: Prices on the Rise. International Monetary Fund. Finance & Development Magazine. Available at: https://www.imf.org/en/Publications/fandd/issues/Series/Back-to-Basics/Inflation#:~:text=Inflation%20is%20the%20rate%20of,of%20living%20in%20a%20country. Accessed: 6.6.2025.

Oner, C. (2025). Unemployment: The Curse of Joblessness. International Monetary Fund. Finance & Development Magazine. Available at: https://www.imf.org/external/pubs/ft/fandd/basics/unemploy.htm. Accessed: 6.6.2025.

Organisation for Economic Co-operation and Development. (2025). Unemployment rate. Available at: https://www.oecd.org/en/data/indicators/unemployment-rate.html. Accessed: 6.6.2025.

Pastor, L. & Stambaugh, R. (2003). Liquidity Risk and Expected Stock Returns. *Journal of Political Economy*. 111(3). 642-685. Available at: https://doi.org/10.1086/374184.

Reserve Bank of Australia. (2025). Unemployment: Its Measurement and Types. Available at: https://www.rba.gov.au/education/resources/explainers/unemployment-its-measurement-and-types.html#:~:text=The%20unemployment%20rate%20is%20the%20percentage%20of%20people%20in%20the,are%20either%20employed%20or%20unemployed. Accessed: 6.6.2025.

Ritter, R. & Welch, I. (2002). A Review of IPO Activity, Pricing and Allocations. *Yale ICF Working Paper*. 2(1). Available at: https://dx.doi.org/10.2139/ssrn.296393.

Ritter, R. (2025). Initial Public Offerings: Updated Statistics. *Eugene F. Brigham Department of Finance, Insurance, and Real Estate. Warrington College of Business, University of Florida*. Available at: https://site.warrington.ufl.edu/ritter/files/IPO-Statistics.pdf. Accessed: 23.2.2025.

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

Rodrigo, G. (2025). Micro and Macro: The Economic Divide. Available at: https://www.imf.org/en/Publications/fandd/issues/Series/Back-to-Basics/Micro-and-Macro. Accessed: 1.3.2025.

Schmidt, A. & Finan, C. (2018). Linear regression and the normality assumption. *Journal of Clinical Epidemiology*. 98. 146-151. Available at: https://doi.org/10.1016/j.jclinepi.2017.12.006.

Shiller, R. (2003). From Efficient Markets Theory to Behavioral Finance. *Journal of Economic Perspectives*. 17(1). 83-104. Available at: https://doi.org/10.1257/089533003321164967.

Shiller, R. (2014). Speculative Asset Prices. *American Economic Review*. 104(6). 1486-1517. Available at: https://doi.org/10.1257/aer.104.6.1486.

Shojaie, A. & Fox, E. (2022) Granger Causality: A Review and Recent Advances. *Annual Review of Statistics and Its Application*. 9. 289-319. Available at: https://doi.org/10.1146/annurev-statistics-040120-010930.

Stern, D. (2004). Economic Growth and Energy. *Encyclopedia of Energy*. 35-51. Available at: https://doi.org/10.1016/B0-12-176480-X/00147-9. Accessed: 24.2.2025.

S&P Global. (2025). S&P 500. Available at: https://www.spglobal.com/spdji/en/indices/equity/sp-500/#overview. Accessed: 4.4.2025.

Tang, D. & Yan, H. (2010). Market conditions, default risk and credit spreads. *Journal of Banking & Finance*. 34(4). 743-753. Available at: https://doi.org/10.1016/j.jbankfin.2009.05.018.

Thamodaran, A., Bonnie, J., Thompson, K. & Golden III, W. (2024). In brief: the IPO market and regulatory framework in USA. Available at: https://www.lexology.com/library/detail.aspx?g=c1cda015-2d7a-48f1-b1c5-091e03dad227. Accessed: 20.2.2025.

The Federal Reserve. (2025). How We Conduct Monetary Policy. Available at: https://www.federalreserve.gov/aboutthefed/fedexplained/monetary-policy.htm. Accessed: 15.6.2025.

The Federal Reserve. (2025). Who We Are. Available at: https://www.federalreserve.gov/aboutthefed/fedexplained/who-we-are.htm. Accessed: 15.6.2025.

The Pennsylvania State University. (2025). Detecting Multicollinearity Using Variance Inflation Factors. Available at: https://online.stat.psu.edu/stat462/node/180/. Accessed: 16.4.2025.

The University of Chicago. (2025). Lubos Pastor Database. Available at: https://faculty.chicagobooth.edu/lubos-pastor/data. Accessed: 1.6.2025.

U.S. Bureau of Labor Statistics. (2025). Database. Available at: https://www.bls.gov. Accessed: 2.4.2025.

U.S. Securities and Exchange Commission. (2024). Should My Company “Go Public”?. Available at: https://www.sec.gov/resources-small-businesses/going-public/should-my-company-go-public. Accessed: 20.2.2025.

Wang, Y. & Bellemare, M. (2020). Lagged Variables as Instruments. Available at: https://marcfbellemare.com/wordpress/wp-content/uploads/2020/09/WangBellemareLagIVsJuly2020.pdf. Accessed: 17.6.2025.

Williams, R. (2020). Heteroskedasticity. *University of Notre Dame*. Available at: https://www3.nd.edu/~rwilliam/stats2/l25.pdf. Accessed: 16.4.2025.

Yale Department of Economics. (2025). Home Page of Robert J. Shiller. Available at: http://www.econ.yale.edu/~shiller/. Accessed: 10.4.2025.