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Impact of Macroeconomic Factors on IPO Activity

An Empirical Study on Initial Public Offering Activity in the Euro Area from 2000 to 2022

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Abstract

This thesis aims to examine the relationship between macroeconomic factors and IPO activity in the euro area from January 2000 to December 2022. By employing the Johansen test for cointegration, our analysis found evidence of two long-run equilibrium relationships between the macroeconomic factors and IPO activity. Moreover, the short- and long-run dynamics were examined using the Vector Error Correction model. Furthermore, variance decomposition and impulse response functions were applied to improve our understanding of the relative importance of shocks and the response patterns within the system. Eventually, the Granger causality test was employed to determine any potential causal relationship between the variables.

Notably, our findings confirm a significant positive relationship between the stock market and IPO activity. However, we encountered limited statistical evidence to support a relationship between the long-term interest rate, industrial production, and market volatility, and IPO activity. Although market volatility demonstrates a closer connection to IPO activity compared to the long-term interest rate and industrial production, the statistical support for this relationship remains relatively weak.

Keywords – ipo, macroeconomic factors, euro area, cointegration, vecm, empirical study

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1 Introduction

From 2000 to 2022, a total of 2,598 companies went public within the euro area, revealing substantial fluctuations across different periods.[1] This observation underscores the need for a deeper understanding of the underlying causes and mechanisms driving these fluctuations. The decision to go public is influenced by several factors, both firm specific and external, all of which are considered in a complex decision-making process. By delving into these factors, valuable insights can be gained, shedding light on the intricate dynamics behind the observed fluctuations in Initial Public Offering (IPO) activity.

Research on IPOs has revealed that clustering of IPOs tends to occur in both hot and cold markets, and the performance of companies issued during these cycles can vary (Ibbotson and Jaffe, 1975). Moreover, research evidence shows that investor sentiment and capital demand have an influence on IPO decisions (Lowry, 2003). Treating IPOs as real options, Pástor and Veronesi (2005) discovered that companies tend to delay going public in anticipation of favorable market conditions. Additionally, Benninga et al. (2005) suggest that entrepreneur considerations of diversification and reversibility impact IPO clustering.

Several studies point at positive correlation between IPO activity and the stock market index, while others emphasize the significance of investor sentiment and business cycles as key determinants (Loughran et al., 1994; Schuster, 2003b; Peterle and Berk, 2016; Meluzín et al., 2013). Additionally, factors such as financial situations of companies and investment choices may contribute to explaining IPO decisions (Baker and Wurgler, 2002; Lerner, 1994; Benninga et al., 2005). Research exploring the relationship between macroeconomic factors and IPO activity has previously been conducted in various regions (Tran and Jeon, 2011; Ameer, 2011; Angelini and Foglia, 2018; Amorim et al., 2021). However, limited attention is given to this subject within the euro area.

Emphasizing the economic integration, the euro area serves as an intriguing

[1] Source: Bloomberg. Please refer to chapter 3 for more details

market for studying the impact of macroeconomic factors on new equity issuances (ECB, nd). Consisting of 19 European Union member states, sharing a common currency, the euro area represents a diverse and interconnected market (EU, nda). This study covers data from 2000 to 2022, which encompasses various periods of economic growth, financial crises, and political interventions. The data is considered within the framework of a complex and evolving economy.

Based on our literature review, we find that the observed fluctuations in IPO activity is supported by the phenomenon of hot and cold markets (Ibbotson and Jaffe, 1975). Moreover, we identified specific macroeconomic factors that are likely to explain these fluctuations. Research evidence shows that long-term interest rates, industrial production, market volatility, and the stock market are the most relevant factors that may explain these IPO fluctuations (Tran and Jeon, 2011; Ameer, 2011; Angelini and Foglia, 2018).

Vector Autoregressive models serve as a robust tool for understanding complex dynamic systems, forecasting future behavior, and capturing the interdependencies among variables (Brooks, 2019). However, considering that some of our variables may be reliant on overall economic growth and exhibit co-movement, we assess the presence of cointegration by conducting the Johansen test and alternatively employing a Vector Error Correction model (Johansen, 1988). This adjustment accounts for such relationships.

To delve deeper into the dynamics, we analyze the impulse response functions and construct a variance decomposition, offering valuable insights into the interplay among the variables under investigation. Moreover, we employ the Granger causality test, integrating its results with our previous findings to ascertain potential causalities (Engle and Granger, 1987). These analytical methods provide a comprehensive framework to thoroughly examine the research question, enabling us to zoom in and out on the data.

This master thesis aims to contribute with knowledge on the relationship between macroeconomic factors and IPO activity in the euro area from 2000 to 2022. By analyzing this relationship, we seek to enhance the understanding of how macroeconomic conditions co-fluctuate or influence each other and how they impact new equity issuances in the euro area. In line with this objective, the central research question driving this thesis is:

What is the impact of macroeconomic factors on initial public offerings in the euro area from 2000 to 2022?

The findings of this thesis will not only contribute to the existing literature on IPOs, but may provide valuable insights for policymakers, investors, and market participants in the euro area.

2 Background

This chapter will highlight relevant findings from previous IPO research. To better understand why firms choose to go public, we present different incentives and rationales, eventually looking into the subject from a macroeconomic perspective. Building upon our problem statement, the following chapter and its theories serve as a foundation for the hypotheses.

2.1 Initial Public Offering

An Initial Public Offering refers to the process through which a privately held company offers its shares to the public for the first time (Espinasse, 2014). It is a significant milestone for a company as it allows it to access the broader public market and raise capital by selling ownership stakes in the form of shares (Espinasse, 2014).

There are two common types of offerings: primary and secondary. In a primary offering, the company issues new shares directly to the public (Espinasse, 2014). The main purpose of a primary offering is to raise fresh capital for the company's growth and expansion plans. This is the type of offering method we will focus on in our thesis. The proceeds from the sale of new shares go to the company itself to finance projects and other corporate objectives (Espinasse, 2014). In a secondary offering, existing shareholders sell their shares to the public (Espinasse, 2014). The company does not receive any proceeds from the sale of shares in a secondary offering. Instead, existing shareholders monetize their investment and realize capital gains. Secondary offerings can provide liquidity to existing shareholders or facilitate ownership transfers in the secondary market (Espinasse, 2014).

In order to facilitate the IPO process one usually involves an underwriter (Espinasse, 2014). An underwriter is an individual or financial institution, typically an investment bank, that facilitates and manages the IPO on behalf of the issuing company (Espinasse, 2014). The underwriters help determine the offering price, assess market demand, and distribute the shares to investors.

They also assist in complying with regulatory requirements and provide financial and strategic advice to the company (Espinasse, 2014).

There are several ways a company can issue its shares, but the book building process is the most common (Sherman, 2005). During this process, underwriters gather indications of interest from potential investors regarding the number of shares they wish to purchase and the price they are willing to pay (Biais and Faugeron-Crouzet, 2002). These indications are compiled into an order book, which helps to determine a price range or fixed price for the IPO shares (Espinasse, 2014). The final offering price, usually set at the higher end of the range, considers market conditions and demand (Espinasse, 2014). Alternatively, Dutch auctions can be used, where investors specify their desired amount of shares and price, where the price is eventually established to balance the supply and demand (Biais and Faugeron-Crouzet, 2002). While Dutch auctions promote transparency and fairness, they are less commonly used than the traditional book building process (Sherman, 2005).

2.2 The Euro Area

The euro area, also known as the Eurozone, was established January 1st in 1999 (EU, ndb). It is a monetary union consisting of 19 European Union (EU) member states that have adopted the euro as their official currency (EU, nda). The establishment of the euro area aimed to promote economic integration and facilitate trade and financial transactions among participating countries (EC, ndb).

The IPO markets in the euro area have experienced significant fluctuations and developments since its origin.[2] The early 2000s marked a period of high IPO activity, with a considerable number of companies opting to go public to raise capital. However, this high level of activity was interrupted by the dot-com bubble. The bubble occurred in the late 1990s and early 2000s primarily in the United States, but had global implications (CFI, 2020). During the dot-com bubble, there was a surge in IPO activity as investors sought to capitalize on

[2] See descriptive statistics in chapter 3

"dotcom" or internet-based businesses (CFI, 2020). The market regained its positive momentum before it was interrupted by the global financial crisis in 2008, which again resulted in a severe downturn in IPO activity across the region.[3]

Furthermore, it is worth mentioning that the euro area countries known as the PIIGS (Portugal, Italy, Ireland, Greece, and Spain) experienced unique challenges during the European sovereign debt crisis, starting in 2009, having a significant impact on the economies of these nations (Tezcan, 2013). The PIIGS countries faced economic difficulties, high government debt levels, and financial instability, potentially leading to the observed decline in IPO activity.[4] Subsequently, the euro area witnessed a gradual recovery in IPO activity as the region emerged from the financial crisis.

The global COVID-19 pandemic, which started in early 2020, caused one of the most recent disturbances in economic activity. The pandemic shocked the global financial markets by disrupting the supply chain, also leading to increased uncertainty and market volatility (Remko, 2020; Albulescu, 2021). Shortly after the COVID cool-down, the IPO markets, both globally and in the euro area, experienced rapid recovery in activity. Overall, the IPO markets in the euro area from 2000 until today have exhibited a dynamic and evolving landscape, influenced by both global economic trends and regional factors.

The regulatory environment in the euro area is well known for its adherence to common rules. The euro area comprises a diverse range of financially integrated economies, each with its own regulatory frameworks and market environment. It consists of several stock exchanges that have their own specific listing rules and criteria, but follow some of the same directives (EUR-Lex, 2021). Exchanges like Euronext, Deutsche Börse, and Borsa Italiana have their own set of requirements that companies must meet to be listed on their respective exchanges. This makes it possible for companies to choose the country and exchange that offers the best match for their legal system when considering an IPO.

[3]See descriptive statistics in chapter 3

[4]See descriptive statistics in chapter 3

Financial integration is the extent to which financial services are uniformly accessible across all member countries that utilize the euro, operating under standardized regulations and conditions (ECB, nd). To build transparency and integrity within the financial activities in the region, the EU directives have established some minimum requirements, where common regulations regarding prospectus and market abuse being key pillars of the framework (EC, nda).

The benefits of financial integration in the euro area can be classified into three main categories: promoting economic growth, facilitating macroeconomic and financial stability, and enabling effective monetary policy implementation (Gnath et al., 2019). Financial integration plays an important role in ensuring the consistent transmission of the monetary policy set by the European Central Bank (ECB) across the entire euro area (ECB, nd). Additionally, financial integration in the euro area brings increased investment opportunities and the ability to diversify financial risks across borders. Moreover, it leads to consistency in retail bank interest rates across different countries, and facilitates easier access to funds for businesses seeking expansion. Eventually, this enhances the efficiency of the European economy (ECB, nd).

2.3 Literature Review

This section provides a brief overview of relevant theoretical and empirical literature that we find the most important to our thesis. To gather a comprehensive set of sources, we employed database searches on platforms such as Google Scholar and Web of Science. Additionally, we employed the snowballing technique to expand our pool of relevant studies.

2.3.1 The Rational to Go Public

There are several incentives for going public. Overall, it seems to be an agreement of the main factors why a company chooses to go public. According to Ritter and Welch (2002), the most important reasons for companies to go public are to raise capital, provide liquidity to existing shareholders, and gain access to financial markets. By going public, a company not only enhances its visibility and prestige, but also grants incentives to its management and employees through stock options (Ritter and Welch, 2002).

Pagano et al. (1998) found that the probability of an IPO is positively correlated with the market valuation of firms in the same industry. This reflects either higher investment needs in sectors with good growth opportunities or the owners' attempts to take advantage of the potential mispricing within a specific sector (Pagano et al., 1998). The study also discovered a significant relationship between a company's size and the likelihood of listing on the stock market. Furthermore, the study indicates that going public allows companies to access credit at a lower cost. Ritter and Welch (2002) emphasize that firms often go public to secure financing from sources outside the traditional banking system. Additionally, they suggest that reducing debt is a critical objective.

When a private company requires more capital than its existing shareholders can provide, and debt financing becomes prohibitively expensive, going public can be a viable strategy for sustaining growth, aligning with the pecking order theory (Myers, 1984). According to this theory, as the information asymmetry of companies increases, the cost of capital also rises. Consequently, a hierarchy of preferred financing methods emerges, with going public being a final recourse following internal capital generation and debt issuance (Myers, 1984).

Considering the pecking order perspective, choosing to raise capital through IPOs signalises that the company regards this fundraising opportunity as the most desirable option. Nevertheless, this decision may leave investors questioning why the firm did not pursue debt financing or utilize retained earnings (Hall et al., 2010). Inadequate information provision during the IPO process may result in investors demanding a discount to compensate for the uncertainties associated with the IPO, ultimately leading to a lower amount of capital raised (Ritter, 1984).

2.3.2 Hot & Cold Markets

Ibbotson and Jaffe (1975) made an intriguing observation regarding the clustering of firms going public. IPO periods can be divided into two groups: hot markets, which are characterized by a high IPO volumes, whereas cold markets are distinguished by lower IPO volumes (Ibbotson and Ritter, 1995). Additionally, the study highlights performance distinctions between companies that went public during these economic cycles and those that went public outside of such periods.

The fluctuation in IPO activity can be attributed to companies capitalizing on favorable market sentiment, or to receive high returns from emerging technologies (Bê Duc et al., 2005). A substantial portion of these IPOs can be categorized as "New Economy" offerings, as discussed by Schuster (2003a), seeking to exploit high momentum in the market (Bê Duc et al., 2005). Lerner (1994) suggests that venture capitalists tend to issue IPOs when market sentiment is positive and valuations are favorable, and private funding is not.

Research within the field has tried to explain the phenomenon of hot and cold markets. Lowry et al. (2017) presents an overview of the IPO literature since 2000, and seek to find possible explanations why these IPO waves occur. Lowry (2003) investigates why IPO volumes fluctuate, by focusing on three possible explanations; demand for capital, investor sentiment, and information asymmetry. Lowry et al. (2017) starts explaining why IPO volume fluctuate by elaborating on the investor sentiment (Lowry, 2003). According to this argument, higher investor sentiment leads to inflated stock prices compared to their intrinsic value, thereby influencing the decision to go public. Another explanation focuses on the demand for capital (Lowry, 2003). The paper draws connections between growth in the real gross domestic product (GDP) and IPO activity, implementing, among other things, GDP as a metric for private firms' capital demands. This argument stems from the notion that periods of economic expansion and more promising business conditions generate increased investment opportunities, which in turn leads to a higher demand for additional funds. Lowry (2003) finds strong support for investor sentiment and capital demands, and further claims that the effect of investor sentiment is twice as big as demand for capital.

Lowry et al. (2017) also debates whether fluctuations in IPO activity could be explained by companies trying to exploit good market conditions. This explanation is based on treating an IPO as a real option (Pástor and Veronesi, 2005). The optimal timing to exercise this option depends on market conditions. In situations where market conditions fluctuate, inventors may choose to delay their IPO in anticipation of more favorable market conditions (Pástor and Veronesi, 2005). They also find that IPO waves are typically preceded by higher market returns and followed by lower market returns.

According to Benninga et al. (2005), the decision to go public is influenced by the entrepreneur's assessment of the potential gains from diversification versus the private benefits associated with remaining a private company. Further, the paper emphasizes the importance of considering the timing and reversibility of the decision, highlighting the fact that these parameters play a role in explaining the clustering of IPO activity. They also suggest that in certain situations, when expected future cash flows are high, for instance due to a positive economic shock, the potential advantages of going public are more likely to be favorable (Lowry et al., 2017; Benninga et al., 2005). Due to presence of cross-sectional correlations in firms' cash flows, cycles in IPO volume can be observed (Lowry et al., 2017).[5]

Lastly, Lowry et al. (2017) presents an argument emphasizing the significance of information asymmetry, a concept addressed in traditional underpricing theories, which results in higher equity issuance costs (Ritter and Welch, 2002; Rock, 1986). During periods of high information asymmetry, potential investors may face uncertainties about the true value and prospects of the companies going public. This information asymmetry can lead to higher costs for companies issuing equity through IPOs, which may discourage some companies from going public during such periods. Conversely, more companies may find it favorable to go public in periods of low information asymmetry. However, Lowry (2003)

[5] Chemmanur and He (2011) propose that product market dynamics can drive IPO waves. Despite high costs and sufficient internal capital, they suggest that companies may seek external financing through an IPO, in order to enhance its competitive position and gain market shares. Eventually, this could trigger other firms in the industry to do the same in order to avoid losing market shares. As a result, IPO waves can emerge even in industries unaffected by productivity shocks (Chemmanur and He, 2011).

investigated this explanation and found minimal support for this argument.

2.3.3 The Macroeconomic Environment & IPOs

As previously elaborated, the decision to go public is a complex process that requires companies to consider various aspects. Several studies like Ibbotson and Jaffe (1975), Ibbotson et al. (1988), and Loughran et al. (1994), have confirmed significant pronounced cycles, both in the number of new issues per month and the average initial return per month. However, there is limited research on underlying causes and mechanisms of such variation from a macroeconomic perspective, especially in the euro area.

One of the first studies to examine the relationship between IPO activity and macroeconomic factors is Loughran et al. (1994), which studied how the GDP and the inflated-adjusted level of the stock market of 15 countries affected the IPO activity. The study failed to identify a relationship between the GDP and IPO activity, but found a positive correlation with the stock market index. Later, Schuster (2003b) also found a close link between the IPO activity and the general level of the stock market in six of the largest Continental European markets and Sweden. Research conducted in Central and Eastern Europe also suggests that the most relevant macro determinants for IPO volume in the 2000s are investor sentiment and business cycles (Peterle and Berk, 2016). These findings are in line with an earlier study of the polish capital market, which claims that the timing of IPOs is strongly influenced by the overall conditions of the stock market, the state of the business sector, and the level of investor interest in the sector (Meluzín et al., 2013).

Some of the same findings applies to the UK market as proposed by Rees (1997). Investigating the incentives behind going public, the results from the study suggest that both the value and the number of IPOs are positively and significantly associated with the level of the stock market, whereas the number of IPOs is positively and significantly associated with a business cycle indicator. Additionally, causal analysis indicates that the stock index serves as a predictive factor for both the value and quantity of IPOs (Rees, 1997).

The overall market and economic conditions (Baker and Wurgler, 2002; Lowry, 2003), the financial situation of the company compared to other firms (Lerner, 1994; Pagano et al., 1998), and the firm's own investment choices (Benninga et al., 2005), are all factors that are found to influence the IPO decision. Erel et al. (2012) investigated the impact of macroeconomic conditions on the ability of firms in the US market to raise capital. They found evidence that firms' capabilities to raise funds are affected by macroeconomic conditions, primarily through their influence on the supply of capital. Ritter and Welch (2002) did also find that metrics of market conditions like stock indices, GDP, and interest rate seem to be the most important factors in the decision to go public. In general, there seems to be consensus among previous studies of which direction the stock market and GDP affects the IPO activity, while the interest rate can be interpreted in different ways. Some papers argue that the interest rate positively affects a company's decision to go public, as a very low interest rate may give the company incentives to raise funds through debt financing instead of an IPO (Brau et al., 2003).

Jovanovic and Rousseau (2004) examined the impact of interest rates on IPOs and identified a non-monotonic relationship between the two variables. The findings reveal that both very high and very low interest rates can discourage investment, albeit for different reasons. At very high interest rates, investment is discouraged due to the typical reasoning that heavy discounting of future income makes it unprofitable to allocate current resources. Conversely they argue that, even at very low interest rates, investment may still be discouraged if it involves irreversible commitments. When interest rates are low, the opportunity cost of waiting for more favorable investment conditions becomes relatively low. This flexibility to delay investment until conditions are more favorable reduces the urgency to engage in IPOs or other irreversible investments.

As explained earlier, investor sentiment is found to have a significant effect on the IPO volume (Lowry, 2003). This may be related to economic uncertainty, as it creates lack of clarity and predictability in the market, which can lead to increased anxiety and hesitation among investors. Lowry and Schwert (2001) identified that changes in demand for capital and the level of investor sentiment explain a substantial portion of the variation in IPO volume, both in economic and statistical terms.

Research conducted in the US analyzed how market volatility affect corporate financing transactions between 1970 and 1998 (Schill, 2004). The study found that during periods of higher-than-average market volatility, there was a notable decrease in the occurrence of IPO transactions and a decline in the total funds raised through IPOs. Gleason et al. (2008) investigated what factors that drive IPO aftermarket risk and how risks might affect the IPO decision. Gleason et al. (2008) found evidence that firms going public during periods of high market volatility tend to have a higher level of aftermarket risk, which refers to fluctuations in the newly issued stock post their IPO process. In light of the financial crisis, Dicle and Levendis (2018) investigated whether there has been a change in IPO timing, using volatility as a proxy for investor aversion. They found that during the post-crisis period, implied volatility has a significantly greater impact on reducing IPO activity compared to the period before the crisis.

Tran and Jeon (2011) investigated the relationship between macroeconomic conditions and IPO activities in the US market between 1970 and 2005. Using time-series econometric techniques, the study reveals that IPO activities are significantly influenced by stock market performance and volatility, while the Fed funds rate and the 10-year US Treasury Bond yield are important factors in determining the amount of proceeds raised. The paper also identifies short-term dynamic adjustment mechanisms between IPOs and macroeconomic factors, which have implications for forecasting future IPO activities.

Research on the emerging market of Malaysia over the period of 1990 to 2008 found evidence of a significant negative relationship between interest rates and the number of IPOs, as well as evidence of a significant positive relationship between industrial production and the number of IPOs (Ameer, 2011). Furthermore, a relationship between interest rates, industrial production, and the number of IPOs was discovered.

Angelini and Foglia (2018) used the exact same econometric approach as Tran and Jeon (2011), but for the UK market between 1996 and 2016. The study concludes that the business cycle, market volatility, and long-term interest rate have a significant impact on the number of IPOs, while the stock market return does not appear to affect IPO activity.

3 Data

The following chapter aims to establish the rationale behind the variables selected for our analysis, highlighting their relevance in potentially explaining IPO activity. Subsequently, a comprehensive investigation and descriptive statistics of the time series data employed in our analysis are presented. The variables selection is guided by the underlying theoretical framework and findings of previous research. Being fully aware that the issuance of an IPO is a complex decision, we have decided to investigate the effects of market conditions on this decision, by looking into four macroeconomic variables as predictors of IPO activity. These four variables aim to represent the market environment that firms face when initializing the IPO process.

3.1 Variables Selection

3.1.1 Long-Term Interest Rate

The interest rate affects the cost of capital, investors' yield expectations, and the market valuations, which push in different directions (Miller and Modigliani, 1958; Campbell, 1995). It is a crucial indicator of the cost of government borrowing and offers perceptions into the current market rates over a longer time horizon (Campbell, 1995). The long-term interest rate is an important component when determining the cost of capital for companies (Miller and Modigliani, 1958). When interest rates are low, borrowing costs tend to be more affordable, making it relatively cheaper for companies to access capital through debt financing, thereby positively influencing business investment in new equipment (OECD, 2023b). In such cases, companies may prefer to raise funds through debt issuance rather than going public through an IPO (Leary and Roberts, 2010).

Another way the long-term interest rate could be relevant is through the investor's yield expectations and risk appetite. In periods of low interest rates, investors may seek high-yield investment opportunities to generate returns on their investments (Lian et al., 2019). This could make IPOs more attractive, as they tend to offer higher short-term average returns compared to low-yield fixed-income investments (Ritter, 1991).

The interest rate also holds significant relevance as a key component in the valuation process, particularly in the determination of the discount factor. Mechanically speaking, lower interest rates result in softer discounting of future cash flows, which increases the value of the firm (Williams, 1938). Loughran et al. (1994) found evidence that companies successfully time their IPOs for periods when valuations are more favorable.

Based on the elaboration above, we are still uncertain about the direction it will indicate. Tran and Jeon (2011) found that the Fed funds rate and the 10-year US Treasury Bond play a significant role in determining the amount of proceeds raised in the IPO. Jovanovic and Rousseau (2004) discovered the relationship to be non-monotonic, meaning the interest rate does not follow a straightforward or consistent pattern. Their results support our intuition and underscore the importance of considering multiple variables and factors when examining the relationship between interest rate and IPO activity. Thus, we hypothesize as follows:

Hypothesis 1 (H1): There is a **negative** relationship between the long-term interest rate and the number of IPOs

3.1.2 Industrial Production Index

The industrial production index serves as a comprehensive measure of economic growth, reflecting the overall health and performance of the industrial sector (OECD, 2023a). While GDP is also a valuable indicator, its quarterly reporting frequency makes the industrial production index a more suitable choice for our analysis, given its monthly availability. Manufacturing, mining, and utility output are all measured by industrial production, which is highly related to GDP and the general activity in the economy (OECD, 2023a). During periods of robust economic growth, businesses tend to perceive more favorable conditions for expansion, innovation, and investment, which, coupled with positive market sentiment, may create an environment contributing to companies' IPO decisions (Lowry, 2003).

Economic growth can be related to periods of technological advancements or innovation breakthroughs (ECB, 2017). Incremental innovations, new technologies, and expanding markets require substantial funding (ECB, 2017). Events like the dot-com bubble in 2000 is an example of these types of expansions (CFI, 2020). In such periods, IPOs present an opportunity to access funding and enhance liquidity for the shareholders (Espinasse, 2014). This may be a part of explaining the increased IPO activity prior to the year of 2000 (Figure 3.1). Thus, industrial production will function as a proxy for capital demand, in line with (Lowry, 2003).

Previous studies have demonstrated the impact of industrial production on IPO activity, which aligns with our intuition (Ameer, 2011; Angelini and Foglia, 2018). Humpe and Macmillan (2009) found that stock prices are positively influenced by the industrial production. It is important to note that stock market performance and industrial production potentially capture similar aspects of the overall economic landscape, and provide complementary insights into IPO dynamics. We also recognize that, in contrast to stock market performance which is forward looking, industrial production reflects the value of goods and services produced within a country's borders over a specific period in the past. However, changes in industrial production over time can be an indication of the direction and pace of the economic expansion or contraction. This may influence expectations about future economic performance. Drawing upon the aforementioned rationale, we postulate the following hypothesis:

Hypothesis 2 (H2): There is a **positive** relationship between industrial production and the number of IPOs

3.1.3 Market Volatility Index

Market volatility is likely to present significant challenges concerning share valuation, investor participation, and cost of capital. The uncertainty surrounding share valuation and potential investor response may lead companies to postpone their IPOs until market conditions stabilize, also suggested by (Pástor and Veronesi, 2005). Additionally, under volatile market conditions, investors demand higher returns to compensate for the increased risk (Markowitz, 1952). Thus, higher cost of capital makes it more expensive for companies to raise funds through IPOs.

High levels of market volatility will most likely deter investors from participating in IPOs. During such periods, investors may exercise caution and be hesitant to invest in newly public companies due to its risk (Daviou and Paraschiv, 2014). The uncertainty among investors can make it more difficult for the underwriters to accurately predict the market demand for the stock. Consequently, the potential decrease in investor demand may result in reduced interest in IPO shares, leading to lower IPO prices and diminished overall success in the IPO process.

Tran and Jeon (2011) found market volatility to have a significant impact on the timing of IPOs, whereas Angelini and Foglia (2018) found that market volatility has explanatory power on the number of IPOs. We believe it is reasonable to assume that market volatility will have a negative effect on the number of IPOs issued. Hence, we hypothesize as follows:

Hypothesis 3 (H3): There is a **negative** relationship between the market volatility and the number of IPOs

3.1.4 Stock Market Index

When major stock market indices are rising, it indicates a positive market sentiment and improved investor confidence (Baker and Wurgler, 2007). As investors may exhibit greater willingness to invest in newly public companies during such periods, this may lead to an increased demand for IPOs. Additionally, in a rising stock market, companies have incentives to go public as they may receive more equity for their shares, leading to greater proceeds raised and cheaper funding for the firm. This is aligned with the pecking order theory, which suggests that firms issue equity in periods with favorable valuations (Leary and Roberts, 2010).

The stock market's performance takes into account, not only the present situation and historical trends, but also the investors' expectations and perceptions of the future. This is consistent with investor sentiment theory, which recognizes that emotional and cognitive factors play a significant role in financial decision-making and market outcomes (Baker and Wurgler, 2007). Due to its inherent connection with future expectations, stock market performance can potentially be a valuable and informative variable for predicting IPO activity. By incorporating information about the expected future state of the market, stock market performance can provide insights that contribute to explaining IPO trends.

As earlier elaborated, the stock market index has previously proven to have positive explanatory power on IPO activity (Tran and Jeon, 2011; Rees, 1997). As our intuition further supports its direction, we hypothesize as follows:

Hypothesis 4 (H4): There is a **positive** relationship between the stock market index and the number of IPOs

3.2 Data Collection and Processing

To adequately address our hypotheses, it is crucial to collect data from reliable sources. For the purpose of our master thesis, we conducted data collection from various reputable databases, namely Bloomberg Terminal, Organisation for Economic Co-operation and Development (OECD), and Refinitive Eikon. As of December 31st, 2022, the euro area, i.e., countries which have replaced their national currencies with the euro, consists of the following 19 countries: Austria, Belgium, Cyprus, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, the Netherlands, Portugal, Slovakia, Slovenia, and Spain (EU, nda).

To maintain consistency, all currency-related data was obtained and recorded in euros. The selected timeframe for data collection extends from January 1^{st}, 2000, to December 31^{st}, 2022. This offers an sufficient amount of data, given the establishment of the euro area in 1999. All data is reported and collected on a monthly basis. As aligned above, our variables of interest are:

1. Monthly numbers of IPOs
2. Long-term interest rate, i.e., the 10-year government bond yield
3. Industrial production index
4. Market volatility
5. Stock market index

where (1) concerns our dependent variable, which we seek to explain based on the influence of the independent variables, $(2-5)$.

In the sections below, we will briefly explain the process of collecting, cleaning, and compiling of our data.

3.2.1 Number of IPOs

In the Bloomberg Terminal we employ the IPO Analytics tool in order to filter the time period of interest, the euro area, and listing date, i.e., the first trading day for IPO shares on stock exchanges. After exporting the data into excel we use the sort-function in order to gather the IPOs into their respective listing month.

3.2.2 Long-Term Interest Rate

The long-term interest rate is represented by the 10-year government bond yield for the euro area. It is expressed as a percentage on a monthly annualized basis, not seasonally adjusted. This variable represents the average yield on government bonds with a maturity of 10 years (OECD, 2023b). The long-term interest rate is collected from the OECD database.

3.2.3 Industrial Production Index

The industrial production data utilized in this study is obtained from the OECD database. The data is presented in real terms and has been subjected to seasonal adjustment. To validate the accuracy of the figures, we conducted a cross-reference with the quarterly data sourced from the FRED database. The index measures the change in production output volume relative to a reference period (OECD, 2023a).

3.2.4 Market Volatility Index

The volatility index for the euro area (VSTOXX Index) works as our volatility parameter. VSTOXX is calculated using the implied volatility derived from real-time options on the EURO STOXX 50 Index. It represents the volatility expectations and market sentiment surrounding the future price fluctuations of major European blue-chip stocks. By measuring the square root of the implied variance across all options of a given time to expiration, the index aim to reflect market expectations of volatility in the near-term and long-term. The index is sourced from Refinitive Eikon on a monthly basis with a currency conversion in euro.

3.2.5 Stock Market Index

The stock market performance is represented by the stock market index (EUR STOXX 50). The EURO STOXX 50 consists of 50 stocks sourced from 11 countries within the euro area. Notably, these 50 stocks are among the largest in terms of market capitalization and trading volume. The index data utilized in this study was sourced from Refinitive Eikon.

Table 3.1 below is an overview of the different variables, their sources and their expected effect on IPO activity.

Table 3.1: Variables

Variable	Unit	Source	Sign Exp.	Name
Number of IPOs	Frequency	Bloomberg		N_IPO
Long-Term Interest Rate	Percent	OECD	−	LT
Industrial Production	Index	OECD	+	IP
Market Volatility − V2TX	Index	Refinitiv	−	VOL
Stock Market Index − STOXX50E	Index	Refinitiv	+	INDEX

3.3 Descriptive Data

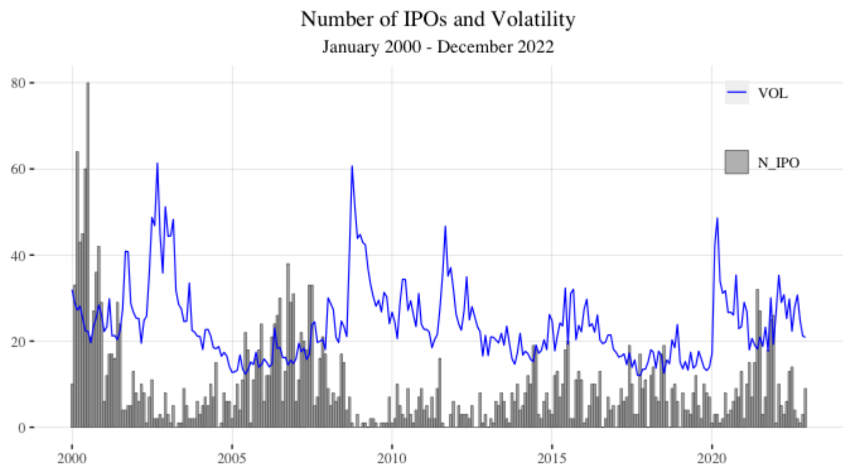
Table 3.2 presents a summary of the key statistics for all variables. Our analysis covers a total of 276 observable periods (months) from January 2000 to December 2022. Throughout this period, a total of 2,598 companies were listed on various exchanges within the euro area. On average, 9.4 IPOs were issued per month, with the highest number of listings (80) observed in July 2000.

Table 3.2: Summary Statistics

	N	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
N_IPO	276	9.413	10.600	0	80	2.759	14.047
LT	276	2.948	1.660	−0.092	5.698	−0.337	1.740
IP	276	99.849	5.201	74.894	110.091	−0.378	3.993
VOL	276	23.807	8.780	11.986	61.340	1.441	5.520
INDEX	276	3,309.522	686.258	1,993.926	5,317.080	0.635	3.240

As evidenced by the distribution, the number of IPOs is highly positively skewed. This can be attributed to several years with lower IPO activity and a few years marked by substantially higher IPO activity. Additionally, the distribution displays heavy tails and a pronounced peak, indicating a greater concentration of values around the mean and a larger number of extreme observations or outliers. Certain periods exhibit notably higher activity compared to others, as depicted in the visualisation (Figure 3.1). The years 2000 to 2001, 2006 to 2007, and 2021 have the greatest amount of IPOs issued. In Figure 3.1, the number of IPOs is plotted alongside volatility, revealing a pattern of clustering of high frequency periods with low activity in between. This observation aligns with the theory that suggests IPO activity occurs in waves, also known as “hot and cold markets" (Ibbotson and Jaffe, 1975). Market volatility is characterized by the same threats as IPO activity, i.e., positive skewness and leptokurtic properties.

Figure 3.1: IPO Frequency and Volatility



Note: Monthly number of IPOs and Volatility from 2000 to 2022.
Source: Bloomberg Terminal and Refinitiv Eikon.

In Figure 3.1, we also observe that the market volatility and the number of IPOs seem to have opposite cycles. Periods of high market volatility occur simultaneously with low IPO activity, and vice versa. This indicates a negative correlation between them. The correlation matrix shows a weak negative correlation of -0.208 between the market volatility and the number of IPOs (Table 3.3). This falls slightly below our expectations, yet it is heading in the right direction. It is important not to overinterpret the correlation in this context.

Table 3.3: Correlation Matrix

	N_IPO	LT	IP	VOL	INDEX
N_IPO	1.000				
LT	0.213	1.000			
IP	0.126	−0.381	1.000		
VOL	−0.208	0.263	−0.377	1.000	
INDEX	0.690	0.025	0.403	−0.325	1.000

The stock market index has a moderate to strong positive correlation with the IPO activity. Its distribution is slightly positively skewed and mesokurtic, but based on their visuals they seem to co-fluctuate, both having their peaks in the same periods (Figure A1.1.3 in Appendix). The descriptive statistics reveal limited insights regarding the long-term interest rate and industrial production. Over time, both variables exhibit relative stability, apart from two significant disruptions observed during the financial crisis and the COVID-19 pandemic, specifically affecting industrial production (Figures A1.1.1 and A1.1.2 in Appendix). A trend analysis indicates a downward trajectory in the long-term interest rate, while industrial production demonstrates an upward trend (Figures A1.2.2 and A1.2.3 in Appendix).

4 Methodology

In this chapter, we provide a description and rationale for the econometric models employed to explore the relationship between IPO activity and macroeconomic factors. In our analysis, we will apply the classical cointegration model proposed by Johansen (1988). This model enables us to determine the potential presence of a long-term relationship among the variables under investigation. To capture potential dynamic relationships between the variables over time, we will apply the Vector Error Correction Model (VECM). Eventually, we will assess the presence of any potential causality by conducting the Granger causality test (Engle and Granger, 1987). The methods applied will serve as our analytical lens, allowing us to zoom in and out on the data, and facilitate a comprehensive analysis of the research question under consideration.

4.1 Testing for Unit Root

Econometric time series are usually non-stationary, i.e., have one or more unit root(s). This implies the presence of a trend and a time-varying mean (Harvey, 1990, p. 29). Consequently, they may lead to spurious regressions and incorrect estimates. If a non-stationary series y_t has to be differenced d times to become stationary, it is integrated of order d, i.e., has d unit root(s) (Harvey, 1990, p. 29).

To identify the non-stationary condition of the times series we will perform an Augmented Dickey-Fuller (ADF) test to determine whether there are unit roots in the time series (Dickey and Fuller, 1979). The Phillips-Perron test can be employed to test the null hypothesis that the variable, x, possesses a unit root (Perron, 1988). As many of the macroeconomic factors in our model feature changing statistical properties over time, we expect to encounter non-stationary time series.

The validity of the ADF test depends on the assumption that the residuals, u_t, are white noise (Brooks, 2019, p. 449). If autocorrelation exists in the residuals, u_t, the dependent variable of the regression (Δy_t) will exhibit autocorrelation as well. To address this issue, it is necessary to "augment" the test by including p lags of the dependent variable in the analysis (Brooks, 2019, p. 449).

The ADF estimation equation is given as follows, including both a drift and time trend:

$$\Delta y_t = \mu + \beta t + \delta y_{t-1} + \sum_{i=1}^{p} \alpha_i \Delta y_{t-i} + \varepsilon_t \tag{4.1}$$

where y_t represents the time series variable, Δ is the first difference operator, μ is the intercept or drift term, β is the coefficient on the time trend variable t, δ is the estimated coefficient on the lagged dependent variable y_{t-1}, p is the maximum lag length, α_i are the coefficients on the lagged first differences of y_t, and ε_t is the error term.

In addition, a confirmatory data analysis approach will be employed, comparing the ADF test and a stationary test, the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test (Brooks, 2019; Kwiatkowski et al., 1992).[6]

4.2 Testing for Cointegration

Cointegration is a statistical concept that relates to the long-term equilibrium phenomenon between time series data. More specifically, it refers to the relationship between non-stationary variables that exhibit a common stochastic trend, which means that they move together over time, despite short-term fluctuations or noise (Brooks, 2019, p. 459). Cointegration is applicable when two time series are individually integrated of order 1 (I(1)), but a linear combination of them is integrated of order 0 (I(0)) (Wooldridge, 2016, pp. 568-569). In such scenarios, conducting regression analysis between these series provides meaningful insights into their long-term relationship, thus avoiding spurious relationships (Wooldridge, 2016, pp. 568-569).

Cointegration among multiple variables is represented by a cointegrating vector. This vector represents the weights assigned to each variable in the linear

[6]See Appendix A2.1 for more details on confirmatory data analysis

combination. The coefficients within the cointegrating vector reflect the respective significance or influence of each variable in the long-term relationship (Brooks, 2019).

The Johansen test is a statistical method for determining whether or not a set of variables is cointegrated (Johansen, 1988). The Johansen test is used to test the null hypothesis of no cointegration among IPO activity and macroeconomic factors, in contrast to the alternative hypothesis of cointegration. The Johansen test is based on likelihood-ratio tests and is available in two variants: the trace (4.2) and the maximum eigenvalue (4.3) test:

$$\lambda_{\text{trace}}(r) = -T \sum_{i=r+i}^{n} ln(1 - \hat{\lambda}_i) \tag{4.2}$$

$$\lambda_{\max}(r, r+1) = -T ln(1 - \hat{\lambda}_{r+1}) \tag{4.3}$$

where r denotes the count of cointegrating vectors assumed under the null hypothesis H_0, T represents the sample size, and $\hat{\lambda}$ represents the estimated value for the i-th (ordered) eigenvalue obtained from the matrix Π. The test, denoted as λ_{trace}, tests the null hypothesis that the count of cointegrating vectors is less than or equal to r, against an unspecified alternative hypothesis that there exist more than r cointegrating vectors. $\lambda_{\text{trace}} = 0$ when all the $\lambda_{\text{i}} = 0$, meaning it is a joint test. On the other hand, the test labeled as $\lambda_{\max}$ assesses the null hypothesis that the number of cointegrating vectors is r, against the alternative hypothesis that there are $r + 1$ cointegrating vectors (Brooks, 2019, pp. 475).[7]

4.3 Vector Error Correction Model

The interdependencies and dynamic relationships between several financial time series variables are commonly examined using the Vector Autoregressive (VAR) model (Brooks, 2019). In the context of our thesis, a VAR model could be implemented to investigate any potential short-term relationships between

[7] See Appendix A2.2 for more details on the Johansen testing procedure

the number of IPOs and the macroeconomic factors. However, when dealing with econometric time series, one should be aware of the non-stationary nature of such data (Harvey, 1990, p. 29).

When working with non-stationary time series that exhibit integration of order d (I(d)), with $d > 0$, the estimation of a VAR model on the original data poses certain challenges. In such cases, differencing the variables to achieve stationarity is often suggested as a common solution to avoid spurious and misleading results. Nevertheless, for our specific analysis, this approach may have limitations and drawbacks. Differencing the variables to obtain stationarity would alter and potentially result in loss of important information and meaningful patterns inherent in the original data. Additionally, the differenced series may not adequately capture the long-term relationships among the variables, which are crucial for understanding the dynamics of the IPOs and the macroeconomic factors. Thus, our ability to fully capture the true nature of the relationships under investigation is limited.

To address these concerns, it is prudent to explore the potential existence of cointegrating relationships as elaborated in section 4.2 above. If cointegration is detected, an alternative approach involves incorporating an Error Correction Term (ECT) into the VAR model, while working directly with the original non-differenced data. The model then turns into a VECM, or a restricted VAR model (Johansen, 1988).

Considering the potential non-stationary nature of the time series variables and the limitations of differencing, we proceed with the VECM approach, in order to account for cointegrating relationships. Several prior studies have adopted the same modeling approach (Angelini and Foglia, 2018; Ameer, 2011; Tran and Jeon, 2011). This method provides a more comprehensive and accurate analysis, preserving the integrity of the original time series and enhancing our understanding of the interaction between IPOs and the macroeconomic factors. The VECM is used to effectively capture both the short-term dynamics and long-term equilibrium relationships between cointegrated time series. The model incorporates an ECT, which measures the speed of adjustment towards the long-run equilibrium relationship in the model (Brooks, 2019, p. 461). The VECM can be expressed as follows:

$$\Delta Y_{t,i} = \alpha_i + \gamma_i \beta_i Y_{t-1,i} + \sum_{j=1}^{k} \Gamma_{j,i} \Delta Y_{t-j,i} + \varepsilon_{t,i} \tag{4.4}$$

where α denotes a constant vector that captures a linear trend, while the matrix Γ reflects the short-term dynamics among the variables in the $Y_{t,i}$ vector. The cointegrating vector is denoted by β, and the error correction coefficient is represented by γ, which provide details regarding the rate at which the system adjusts towards the long-term equilibrium state (Tran and Jeon, 2011). From previous research within the field, it is expected that the error correction coefficient will exhibit a negative sign within the range of $-1 < \gamma < 0$ (Angelini and Foglia, 2018; Ameer, 2011; Tran and Jeon, 2011), but generally < 0 (Wooldridge, 2016, p. 585).

4.4 Variance Decomposition & Impulse Response Function

Forecast Error Variance Decompositions (FEVDs) are used to examine the dynamics of a VAR system. Utilizing this technique helps revealing the proportion of movements in the dependent variable that can be attributed to shocks in themselves compared to shocks from other variables in the system. A shock in one of the variable in the system, will not only directly affect itself, but also influence the other variables in the system through the VAR's dynamic structure. Further, this can help us determine the extent to which innovations in each explanatory variable explain the forecast error variance of a specific variable for different time horizons ($s = 1, 2, \ldots$). One would expect that own series shocks will explain the majority of the forecast error variance in a VAR (Brooks, 2019, pp. 424-425).

On the other hand, Impulse Response Functions (IRFs) illustrate how the dependent variables in the VAR system react to shocks in individual variables. To analyze the impact on the VAR system, a unit shock is introduced to the error term for each variable in every equation, and the resulting effects are observed over time. In essence, the impulse responses represent the partial derivatives of the variables ($y_{jt}, j = 1, \ldots, g$) with respect to each error term ($u_{kt}, k = 1, \ldots, g$) : $\frac{\partial y_{jt}}{\partial u_{kt}}$ (Brooks, 2019, p. 423). In practical applications, it is common to use one standard deviation shocks rather than one unit shocks. This approach is favored because a one unit shock may be empirically implausible in some cases, whereas a one standard deviation shock remains relevant and meaningful in almost all situations (Brooks, 2019, p. 423).

4.5 Granger Causality Test

Our objective is to ascertain whether there are causal relationships between IPO activity and the macroeconomic factors. A key advantage of VAR models is that they treat all variables as endogenous. In the presence of cointegration, there must be a causal ordering in at least one direction (Engle and Granger, 1987; Brooks, 2019). Hence, we aim to determine the direction of causality. Because of its simplicity and robustness, we examine the causality by employing the Granger causality framework (Engle and Granger, 1987). The Granger causality test enables us to find potential lagged dependencies between variables and gain understanding of how they interact dynamically.

The test will be performed on a VAR model in first difference. It is not inherently troublesome to estimate a VAR model for a cointegrated VAR in levels, but doing so can produce spurious results in the Granger causality test (Brooks, 2019, p. 438). When analyzing causality in a cointegrated VAR, where the variables have a long-run equilibrium relationship, it is essential to consider the cointegration relationship.

Granger causality results may be deceiving when a VAR is estimated in levels without explicitly considering the cointegration relationships. Due to the existence of a common stochastic trend, the levels of cointegrated variables may show spurious correlations. If cointegration rather than actual causal links, is the driving force behind a relationship, the Granger causality test may indicate significant causality between variables. By eliminating the long-run equilibrium component, the differencing process concentrates on the short-run dynamics but still provide insights into the short-run causal links between the variables.

The F−test framework can be used to test joint hypotheses, with each set of restrictions involving parameters from a single equation (Brooks, 2019, p. 421). By employing this method, we can seek answers to questions such as: "Does the variation in the macroeconomic factors lead to changes in the number of IPOs?"[8]

[8] See Appendix A2.3 for more detailed description on the joint hypothesis testing

5 Analysis

In this chapter, we will present the findings from our empirical analysis. By following the methodology outlined in the previous chapter, we have conducted a series of tests on the time series data related to IPO activity and the macroeconomic factors.

5.1 Unit Root Test Results

Prior to incorporating the variables into the analysis, it is essential to assess their stationarity. The ADF test was conducted on the natural logarithm of the variables in order to stabilize variance. Considering the monthly nature of our data, we have opted to incorporate 12 lags in our analysis to account for potential autocorrelation in the error terms. Further, we imposed no restrictions, thereby allowing the regression equation for the test to include both drift and a time trend. This version of the test exhibits the most restrictive critical value, and we can be fairly confident of stationarity if we can reject the null hypothesis. The results show that all the variables contain a unit root at level, meaning they are non-stationary (Table 5.1). First differencing imposes stationarity in all variables. The results obtained from both the ADF test and the KPSS test (Table A3.1 in Appendix) provide conclusive evidence. Hence, they are integrated of order 1 (I(1)), and they may exhibit a long-run relationship.

Table 5.1: Augmented Dickey-Fuller Test

Variable	Log Level	Log Difference
N_IPO	-3.306	-10.214^{*}
LT	-2.106	-5.523^{*}
IP	-3.151	-6.966^{*}
VOL	-2.993	-7.884^{*}
INDEX	-3.201	-5.516^{*}

Notes: T-statistics are reported.
* $p < .05$, ** $p < .01$, *** $p < .001$

To investigate the potential existence of a long-run relationship among the variables, we proceeded by conducting the cointegration test.

5.2 Cointegration Results

We implented the Johansen cointegration test, to evaluate the potential of cointegration between our variables. First, we specified the optimal lag length for our model. Every VECM is built upon an underlying VAR model, and selecting the appropriate lag length is essential. Specifying an incorrect number of lags can introduce specification errors and cause autocorrelation within our model.

We utilized the *VARselect* function from the *vars* package in R. This function provides the information criteria and final prediction error for sequentially increasing the lag order up to a VAR(p) process. Importantly, all these computations are based on a consistent sample size. According to the test, the number of lags that minimized the Akaike Information Criterion (AIC) was *three* (Table A3.2 in Appendix) (Akaike, 1974).[9] In the structure of a VECM, the count of lags consistently trails that of its foundational VAR model by one. This distinctive characteristic is attributed to the fact that the underlying VAR model is defined using original variables, whereas the VECM includes the variables in their first-differenced form. However, this correction is automatically considered when estimating the VECM using the *cajorls* function from the *urca* package.

Subsequently, we conducted the Johansen test using the *ca.jo* function from the *urca* package. The results presented in Table 5.2 provide compelling evidence to reject the null hypotheses of no cointegration and, at most, one cointegrating relationship. This conclusion held for both the trace and maximum test. However, our analysis did not provide sufficient evidence to reject the null hypothesis for $r <= 2$ in either of the tests. This indicates the potential existence of two cointegrating relationships among the variables under consideration. The test is statistically significant at a 1% significance level. This finding holds substantial significance, considering the VECM's sensitivity to lag order, whether it is employed by the Johansen (1988) or the Engle

[9]
$$AIC = log(\hat{\sigma}^2) + \frac{2k}{T}$$

and Granger (1987) approach. The result implies that the individually non-stationary variables have a linear combination which is integrated of order zero (I(0)), and therefore stationary. This suggests the existence of a long-run equilibrium relationship among the variables.

Table 5.2: Johansen's Cointegration Results

Hypothesized	Trace	Max-Eigen	Critical Value (5%)	
No. of CE(s)	Statistic	Statistic	Trace	Max
$r = 0$	203.31	113.51	87.31**	37.52**
$r <= 1$	89.80	51.82	62.99**	31.46**
$r <= 2$	37.98	17.03	42.44	25.54
$r <= 3$	20.95	14.61	25.32	18.96
$r <= 4$	6.34	6.34	12.25	12.25

Note: * $p < .05$, ** $p < .01$, *** $p < .001$

Nevertheless, the Johansen test is not without its flaws. Gonzalo and Lee (1998) discovered that, in general, the Engle-Granger test was more robust than Johansen's likelihood ratio test. For the purpose of avoiding any potential hazards or pitfalls, the authors advise using both the Engle-Granger and Johansen tests. Keeping this in mind, to validate our findings regarding cointegration, we opted to apply the initial step of the Engle-Granger two-step procedure. This methodology, which adopts a single equation approach, is implemented in the following manner:

- Make sure that all the individual variables are I(1).
- Estimate the cointegrating regression using OLS (Table A3.3 in Appendix).
- Save the residuals of the cointegrating regression, $\hat{u}$.
- Test these residuals to ensure that they are I(0), using the Engle-Granger-ADF (EG-ADF) test.

Should the residuals demonstrate stationarity, that is, they follow an I(0) process, it may be indicative of the variables within the regression being cointegrated.

The EG-ADF test conducted on the estimated residuals showed no presence of a unit root (Table A3.4 in Appendix).[10] A visual inspection of the plot provides evidence of a stationary time series (Figure A3.1 in Appendix). The stable fluctuation around a constant mean, as well as a consistent variance over time, further corroborate the results of the EG-ADF test.

5.3 Dynamic Relationships

5.3.1 Vector Error Correction Model

After confirming the existence of a long-term equilibrium through the Johansen test, we proceeded to estimate the Vector Error Correction Model to analyze the dynamic relationship in our system. By utilizing this approach, we were able to quantify the corrective mechanism that come into effect when the number of IPOs deviates from its long-term equilibrium path.

In a VECM, the Error Correction Term represents the speed at which a variable returns to equilibrium after a shock or disturbance. The coefficient of the ECT is typically expected to be negative. A negative ECT suggests that any deviation from the long-run equilibrium will be corrected over time, indicating the system is stable and converges back to equilibrium. The estimated equation from the VECM is presented in Table 5.3 below.[11]

The results of our VECM estimation demonstrate that all ECT coefficients have the expected negative sign, and they are also statistically significant at a 0.1% significance level. The speed of adjustment to equilibrium for these variables is 121.1% and 15.9%, respectively. The coefficient of -1.121 implies that 121.1% of the disequilibrium from the previous period (month $t-1$) is corrected in the current period (month t). In contrast, an ECT of -0.159 implies a slower speed of adjustment. This suggests that the system represented by this ECT would require more time to return to the equilibrium following a shock or disturbance. A relatively high coefficient in the first ECT may imply

[10] As the EG-ADF test is applied to the residuals, critical values from MacKinnon (2010) were used

[11] See Table A3.5 in Appendix for comprehensive coefficient estimates of the VECM

that the market in the euro area is efficient in terms of responding to shocks in the variables investigated.

Table 5.3: VECM Results

	Estimate	Std. Error	t value	Pr(> $\|t\|$)
ECT_1	-1.121	0.110	-10.162	$< 2e-16^{***}$
ECT_2	-0.159	0.023	-6.975	$2.53e-11^{***}$
Constant	-25.737	4.717	-5.456	$1.13e-07^{***}$
ΔlnN_IPO_{t-1}	-0.883	0.064	-13.923	$< 2e-16^{***}$
$\Delta lnLT_{t-1}$	0.952	0.676	1.409	0.160
$\Delta lnIP_{t-1}$	2.572	2.175	1.183	0.238
$\Delta lnVOL_{t-1}$	-0.669	0.263	-2.542	0.011^{*}
$\Delta lnINDEX_{t-1}$	3.256	1.193	2.729	0.006^{**}
ΔlnN_IPO_{t-2}	-1.080	0.085	-12.773	$< 2e-16^{***}$
$\Delta lnLT_{t-2}$	-0.484	0.674	-0.717	0.473
$\Delta lnIP_{t-2}$	0.767	2.074	0.370	0.711
$\Delta lnVOL_{t-2}$	-0.417	0.309	-1.349	0.178
$\Delta lnINDEX_{t-2}$	2.092	1.110	1.886	0.060.

Residual Std. Error: 0.6753 on 260 degrees of freedom
R^2: 0.489, Adjusted R^2: 0.4634
F-statistic: 19.14 on 13 and 260 DF, p-value: $< 2.2e-16$

Note: * $p < .05$, ** $p < .01$, *** $p < .001$

However, an ECT greater than -1 (in absolute terms) might be considered unusual, as it implies an "over-correction" back to equilibrium within one period. This could potentially result in oscillations around the long-run equilibrium, meaning that we have a situation where the variables overshoot their equilibrium values, then undershoot, and so on, in a cyclical pattern (Narayan and Smyth, 2006). We acknowledge that this oscillating behavior may be problematic for several reasons. It may indicate instability in the system being modeled, suggesting that the model's assumptions are not being met or that the model is not correctly specified for the data.

Looking into the short-run dynamics and the contemporaneous relationships between the variables, we observe that the lagged first differences of N_IPO, VOL, and INDEX are all statistically significant at 5% (Table 5.3). Nevertheless, our model has a highly negative and statistically significant constant term. This could imply that there are other omitted variables or macroeconomic factors that are exerting downward pressure on the number of IPOs, or that our model does not perform well for extreme values.

As we identified weaknesses in our model, diagnostic tests are highly important to strengthen the validity and reliability of our findings. In Table 5.4, we have presented results from the Breusch-Godfrey test for serially correlated errors, Engle's test for residual heteroscedasticity, and Jarque-Bera normality test of the residuals (Breusch, 1978; Engle, 1982; Jarque and Bera, 1987). The non-normality test suggests that the residuals are not normally distributed. While this does not invalidate the model, it might be problematic for forecasting. Furthermore, it suggests that the model's error terms have skewness, outliers, or heavy-tailed distributions, all of which could contribute to explain the oscillating behavior of our model. While these issues do not necessarily undermine the model's validity, they suggest caution in extrapolating the results or making predictions.

Table 5.4: Diagnostic Tests

LM Test	0.083
Heteroskedasticity Test	0.277
Normality Test	$< 2.2e-16^{***}$

Note: p-values from Breusch-Godfrey LM Test, Engle's Test for Residual Heteroscedasticity, and Jarque–Bera Normality Test.

5.3.2 Variance Decomposition & Impulse Response Function

To enhance our understanding of the relationship between the number of IPOs and the macroeconomic factors, we conducted an analysis using Forecast Error Variance Decomposition (FEVD) and Impulse Response Function (IRF). Both FEVD and IRF are useful analytical mechanisms in autoregressive models (Lütkepohl, 1990).

This part of our analysis is built upon the underlying VAR specification of the VECM. The VECM was transformed to a VAR model using the *vec2var* function from the *urca* package in R.[12] In our context, we used IRFs to investigate how the number of IPOs react to a shock in the macroeconomic variables. The IRFs were calculated two years (24 months) ahead.

Table 5.5: Variance Decomposition

Period	N_IPO	LT	IP	VOL	INDEX	$\sum$
1	100.000	0.000	0.000	0.000	0.000	1.000
2	88.368	0.287	0.799	8.177	2.370	1.000
3	80.704	0.323	0.892	14.193	3.888	1.000
4	75.852	0.410	0.998	18.138	4.602	1.000
5	72.226	0.447	1.115	20.987	5.225	1.000
6	68.407	0.446	1.186	24.163	5.798	1.000
7	64.741	0.440	1.217	27.280	6.322	1.000
8	61.438	0.447	1.230	30.078	6.806	1.000
9	58.428	0.464	1.238	32.636	7.234	1.000
10	55.664	0.481	1.239	35.010	7.605	1.000
11	53.128	0.497	1.232	37.212	7.931	1.000
12	50.797	0.512	1.220	39.249	8.223	1.000
13	48.649	0.528	1.204	41.135	8.485	1.000
14	46.663	0.544	1.186	42.886	8.721	1.000
15	44.825	0.561	1.167	44.514	8.933	1.000
16	43.122	0.577	1.147	46.030	9.124	1.000
17	41.541	0.593	1.126	47.442	9.298	1.000
18	40.070	0.609	1.105	48.760	9.456	1.000
19	38.698	0.624	1.085	49.993	9.600	1.000
20	37.418	0.639	1.064	51.146	9.732	1.000
21	36.221	0.653	1.044	52.227	9.853	1.000
22	35.100	0.667	1.025	53.243	9.965	1.000
23	34.048	0.680	1.006	54.197	10.068	1.000
24	33.060	0.693	0.988	55.095	10.164	1.000

Notes: Variance decomposition based on the underlying VAR representation of the VEC Model. Numbers in %.

Our results reveal that VOL and INDEX substantially contribute to the variance in the forecast error of the number of IPOs (Table 5.5). After 24 months, these factors account for 55.09% and 10.64% of the variance, respectively. Specifically, for both VOL and INDEX, we observe a month-to-month increase.[13]

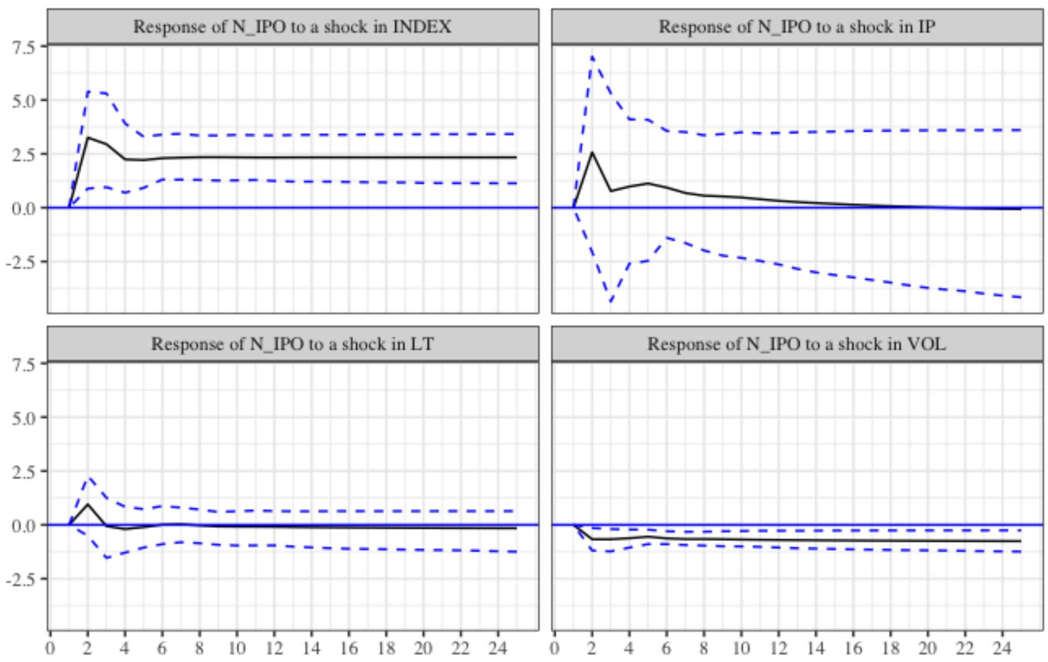
Figure 5.1 demonstrates the response of N_IPO to shocks in the macroeconomic factors. Vector Error Correction models, unlike their VAR models, do not

[12]See Table A3.6 in Appendix for the underlying VAR representation of the VECM

[13]Visualisation of the FEVDs are presented in Figure A3.2 in Appendix

necessarily have IRFs that converge to zero, which corresponds to our results (Lütkepohl and Reimers, 1992). This may be attributed to the presence of unit roots in the system, indicating the non-stationary property of the variables. Observing that some of the IRFs do not stabilize around zero suggests that the shocks in the system appear to have permanent effects on the number of IPOs. This implies that changes in the macroeconomic factors may lead to long-term shifts in the number of IPOs, rather than temporary deviations. Upon closer examination of the graphs, it becomes evident that INDEX exhibits a consistently positive impact on N_IPO, indicating a long-term effect. Conversely, VOL displays a negative influence. As for LT and IP, they initially contribute positively in the short term, but eventually stabilize at values around zero.

Figure 5.1: Impulse Response Functions



Note: The figures show impulse response to a one standard deviation shock, with dotted blue lines representing a 95% confidence interval.

5.4 Causality Test Results

To investigate potential short-term causalities and direction between the number of IPOs and the chosen macroeconomic factors, we performed the Granger causality test (Engle and Granger, 1987). The test was conducted on a VAR model in first difference. We chose to estimate a new VAR model, due to limitations in the *causality* function in R, as it only takes an object of class *varest*, generated by *var*, and not *vec2var* as described above.[14] Additionally, to assess each variable individually, we conducted separate linear regression analyses. In these analyses, we used lagged values of each variable as predictors. To assess the significance of each variable, we employed the *linearHypothesis* function from the *car* package. We applied the same procedure for identifying the optimal lag length as used in the VECM analysis. The number of optimal lags was based on the AIC (Akaike, 1974). The VAR model was estimated using the *VAR* function from the *vars* package (Table A3.8 in Appendix).[15]

The results of the Granger causality test provide insights on the factors' contributions to explaining changes in the number of IPOs. Each variable's null hypothesis posits that it does not Granger-cause the number of IPOs. The F−statistics are used to calculate the test's significance. Based on the results of the Granger causality test, it can be observed that there is statistically significant Granger causation between INDEX and N_IPO (Table 5.6). We also observe that the macroeconomic factors jointly Granger-cause N_IPO.

Table 5.6: Granger Causality Test

Null Hypothesis:	F−Statistic
LT, IP, VOL, INDEX do not Granger-cause N_IPO	2.881***
LT does not Granger-cause N_IPO	0.967
IP does not Granger-cause N_IPO	0.517
VOL does not Granger-cause N_IPO	1.295
INDEX does not Granger-cause N_IPO	5.463***

Note: * $p < .05$, ** $p < .01$, *** $p < .001$

The Granger causality test indicates that the relationship between INDEX and N_IPO is statistically significant. On the other hand, LT, IP, and VOL do not demonstrate significant Granger causalities with respect to N_IPO. As a

[14] Additional details and explanation can be found in subsection 4 of the methodology chapter

[15] The optimal lag length for the VAR model in first difference is 11 (Table A3.7 in Appendix)

robustness check, we reversed the ordering of the data, and obtained the same results (Table A3.9 in Appendix).

As discussed in section 4.4, the presence of cointegration implies the existence of a causal ordering in at least one direction (Engle and Granger, 1987). Given that the Johansen test indicates the presence of two cointegrating relationships, conducting a Granger causality test among the macroeconomic variables themselves could offer valuable insights.[16]

[16]Table A3.10 in Appendix reports significant Granger causalities

6 Discussion

This chapter presents and discusses the findings obtained from our analysis. Firstly, we will provide a comprehensive interpretation of our research outcomes, delving into the details. Following that, we will evaluate similarities or differences between our findings and previous studies in the field.

The coefficients within the cointegrating vector represent the relative significance or influence of each variable in establishing a long-term relationship. By considering the intuition and inherent connection between certain variables, we speculate which variables are likely to have the greatest influence towards cointegration. From an economic perspective it is plausible that a cointegrating vector may be driven by the co-movement between the stock market index and industrial production, given their shared dependency on the overall performance and growth of the economy. When the economy is expanding, industrial production tends to increase as businesses produce more goods and services to meet the rising demand. Simultaneously, the future outlook of companies improves.

The second cointegrating vector may be attributed to the relationship between the number of IPOs and the stock market index, as they are highly dependent on the overall economy. Due to these possible interconnected dynamics and dependency on the general economy, the stock market, industrial production, and IPO activity might explain a big portion of the cointegration. Tran and Jeon (2011) conducted similar tests, but with seven economic variables instead of four, and revealed four cointegrating relationships. Additionally, Angelini and Foglia (2018) examined the same set of variables as our study and found two cointegrating relationships. Our finding of two potential relationships aligns with previous studies.

Furthermore, we dive into the dynamics of the variables by estimating the VECM. The model reveals significant and expected negative coefficients for all ECTs. In the estimated VECM, we observe a relatively high absolute value for one correction term and a low absolute value for the other, suggesting the presence of a stronger cointegrating relationship in comparison to the other. The relatively high coefficient in the first ECT implies a faster response in the system and a quick adjustment, which may indicate a higher degree of market responsiveness. This finding aligns with Angelini and Foglia (2018), who also observed relatively high absolute value of the ECTs for the UK market. In contrast, Ameer (2011) obtained smaller ECT values for IPO activity in Malaysia, with substantially lower IPO volumes compared to the UK and euro area markets.

Through an examination of the lagged differences in the VECM it becomes evident that all variables, with the exception of the long-term interest rate, align with our hypothesized impact on IPO activity (Table 3.1). It is important to consider that the interpretation from level variables to lagged differences introduces a shift in perspective and interpretation. Rather than examining the absolute values, we focus on the changes between consecutive observations.

The long-term interest rate fluctuates from positive in the first lag to negative in the second, suggesting that our model encounters challenges in accurately capturing its influence on IPO activity. Alternatively, this may suggest a non-monotonic relationship (Jovanovic and Rousseau, 2004).[17] Furthermore, we observe that the changes in the number of IPOs are statistically significant in both lags, indicating a relationship between the current change and the changes in previous periods.[18] This suggests that the current change in the number of IPOs is dependent on the past changes, highlighting the influence of historical trends and dynamics in understanding the behavior of IPOs. The stock market index and the market volatility are statistically significant at their first lag and can be further evaluated.[19] It appears that higher fluctuations in change in market volatility has a negative impact on the number of IPOs, while the opposite applies for the stock market index, supporting the results found by Rees (1997) and Schill (2004).

According to Runkle (1987), interpreting impulse responses and variance

[17]Table A3.5 in Appendix
[18]Table A3.5 in Appendix
[19]Table A3.5 in Appendix

decompositions accurately is a challenging task, even with confidence intervals, as they tend to be too wide. Hence, making precise inferences becomes impossible. However, some interpretation should be drawn from these. From the variance decomposition we observe that the market volatility and the stock market index have the most substantial impact in explaining the variance in the forecast error of IPOs (Table 5.5). Specifically, after a two-year period, the market volatility accounts for 55% of the variance, while the stock price index accounts for 10%. Notably, the market volatility shows a remarkable and rapid month-to-month growth pattern. Additionally, the importance of industrial production and long-term interest rate continues to grow. However, these variables explain a considerable smaller portion of the forecast error variance in IPO activity. As the variables gradually converge or stabilize, their unexpected shock contribution to the forecast error variance becomes more or less constant. This suggests that the system has absorbed the shocks and is no longer undergoing significant adjustments. Consequently, the proportion of forecast error variance attributed to each variable remains relatively stable.

Furthermore, the impulse response functions offer insights into the dynamics within our system. By shocking the stock market index we observe a consistent positive impact on the IPO activity, suggesting a long-term effect. Considering the lagged variables within the VECM, indicating the same direction, offers further evidence that a positive change in the stock market index has a positive impact on changes in IPO activity. It is plausible that these findings can be attributed to the effect of increased investor sentiment on IPO volume (Lowry, 2003).

Initially, a shock in the long-term interest rate and the industrial production index contribute positively, but eventually they stabilize around zero. This indicates that the markets have incorporated the shock. This observation aligns with the lagged coefficients obtained from the VECM. Based on our evaluation of the dynamics so far, we have not been able to confirm a positive relationship between the business cycle and the number of IPOs, as suggested by Lowry (2003). Through our analysis, we have observed that the industrial production index aligns with our anticipated and hypothesized direction. However, we have not obtained statistically significant evidence to support this relationship, and it appears to have a smaller impact than initially assumed, contrary to what has been observed in similar studies.

Long-term interest rate has a positive but smaller effect on IPOs. In order to reduce capital expenses, corporations may opt to go public when interest rates are high and, conversely, decide to not do so when rates are low, according to Angelini and Foglia (2018). One interesting observation regarding the IPO activity, when sending a standard deviation shock into the long-term interest rate, is the fact that the response in number of IPOs goes from positive to negative twice before stabilizing. This observation is similar to what we found in our VECM, which showed that the long-term interest rate fluctuates between positive and negative coefficients for the first and second lag, respectively. Without giving the impulse response function too much interpretation, this can be linked to the proposition of long-term interest rate being non-monotonic (Jovanovic and Rousseau, 2004). This may imply that the long-term interest rate does not exclusively affect the IPO activity in one certain direction. It is highly plausible that this relationship is sensitive to the surroundings, and must be considered in the light of other factors.

When sending a shock into the market volatility, we observe a negative and consistent spike in the number of IPOs. This can be attributed to investors exercising caution and being hesitant in investing in newly public companies. This persistence may be explained by the clustered occurrence of both market volatility and IPO activity, historically observed to persist over extended periods, as suggested by He et al. (2016) and Ibbotson and Jaffe (1975).

It reasonable to assume that there are some overlapping effects between some of our explanatory variables. For example, lower interest rates yield more favorable valuations, potentially stimulating IPO activity. Such an increase in valuations would also be reflected in a rise in the stock market index. Therefore, when both variables are included in the model, the coefficient estimate might be more correct, but it may have less statistical power. However, we maintain our belief that the interest rate retains its distinct information and economic significance, serving as a direct indicator of the impact of monetary policy on IPO activity.

Based on the results of the Granger causality test, there is a statistically significant relationship between the stock market index and the frequency of IPOs, confirming our hypothesis and the importance of the overall stock market in the process of going public. On the other hand, the long-term interest rate, industrial production, and market volatility do not demonstrate a significant Granger causality with respect to the number of IPOs. The claim of causality between the stock market index and the number of IPOs is consistent with the findings of Tran and Jeon (2011) and Rees (1997) for the US and UK market, respectively. However, we were not able to claim Granger causality between the long-term interest rate and industrial production and the number of IPOs as Ameer (2011) and Angelini and Foglia (2018) were able to.

7 Conclusion

Through the application of time-series econometric techniques, our analysis reveals evidence of two long-run equilibrium relationships between the macroeconomic factors and IPO activity. These relationships are possibly rooted in the interdependence of these variables with the overall performance and growth of the economy.

We formulated four hypotheses regarding the impact and direction of the macroeconomic factors on IPO activity in the euro area from January 2000 to December 2022. Based on our acquired knowledge and findings from previous research, we expected the stock market, market volatility, and industrial production to be significant. Our analysis confirms that the stock market index exhibits a significant positive relationship with IPO activity. However, we lack sufficient statistical evidence to establish a relationship between the other three variables and IPO activity. Although market volatility appears to have a closer association with IPO activity compared to industrial production and the long-term interest rate, the evidence is not statistically strong. It is worth noting that the long-term interest rate, as previously discussed, may exhibit a non-monotonic relationship with IPO activity. Consequently, our model struggles to capture this fluctuating relationship. It may explain the lack of statistical evidence supporting the influence of interest rates.

By addressing the knowledge gap in the literature and examining the relationship between macroeconomic factors and IPOs in the euro area, our study contributes to a better understanding of how these factors influence IPO activities. Our results may hold implications for investors, investment banks, and IPO-planning firms, providing valuable insights into the impact, the persistence, and the degree to which they influence new equity issuances. It is worth noting that the influence of macroeconomic factors on IPO activity may vary across countries due to distinct institutional and regulatory contexts. Our findings should be interpreted within the context of the euro area. This study may serve as inspiration to comparative studies outside the euro area. However, such studies should pay attention to contextual constraints.

8 Limitations & Suggestions for Further Research

In this chapter, we will present limitations and suggestions for further research as we find it crucial to enhance the quality and integrity of our work, and to provide context for better understanding our findings.

One potential variable limitation of our study is the reliance on monthly data. While analyzing the variables at a monthly frequency may provide valuable insights into their relationships with IPO activity, it is important to acknowledge that the dynamics and effects of these variables may operate on different time scales. Monthly data might not capture short-term fluctuations or fully capture the real-time response of IPO activity to changes in the macroeconomic variables. Further, the analysis covers the period from January 1^{st}, 2000 to December 22^{nd}, 2022. While this time frame allows for a substantial analysis, it is still limited to just over two decades. The inclusion of a longer time series can provide a more comprehensive understanding of the relationships between the variables, capturing dynamics and trends between the variables more precisely.

Our study only focuses on the number of IPOs and does not consider the proceeds raised. Examining the proceeds raised together with the number of IPOs may provide a more comprehensive understanding of the financial impact and market conditions associated with IPO activity. By not considering proceeds, important variations in economic implications and market dynamics associated with IPOs might be overlooked. Future studies should explore this aspect for a more complete picture of the relationship between macroeconomic variables and IPO activity.

Investigating the difference between the announcement day and listing date for IPOs can potentially hold significant value as it provides insights into the timing dynamics of the IPO process. By examining this difference, researchers can gain a deeper understanding of the factors influencing timing decisions, assess the efficiency of the IPO process, analyze market impact during the pre-listing period, and provide valuable implications for market participants and policymakers.

Furthermore, the potential presence of model specification issues, omitted variables, and assumptions underlying the estimation techniques might be other limitations of our study. The use of lag lengths in the Johansen cointegration test may also have implications for the interpretation of the results. While we have accounted for two cointegration relationships and incorporated short-term dynamics through the VECM, it is important to acknowledge that different lag lengths and modeling choices may yield different outcomes, even though the overall picture does not change dramatically. Furthermore, the generalizability of our findings may be limited to the specific time period and frequency of our data set.

Additionally, when interpreting the results of our Granger causality test, it is crucial to exercise caution and avoid placing excessive weight on the causality relationships identified. Even though the test aims to examine the predictive power of one variable on another, it does necessarily imply a "real-life" causal relationship. The ordering of variables may also affect the direction of causality, and the test does not establish the true direction. Actually, the causality may be bi-directional, reverse, or influenced by other factors. This test is also data-driven and do not inherently incorporate economic theory. Hence, it crucial to consider potential underlying economic mechanisms when interpreting the results.

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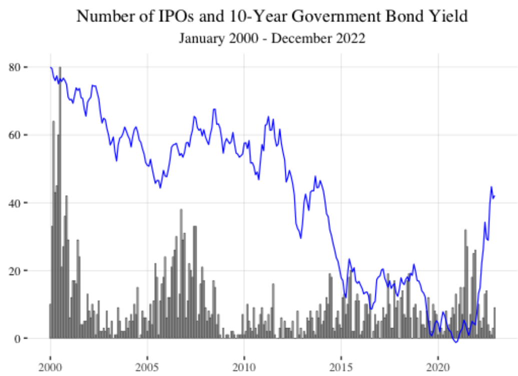
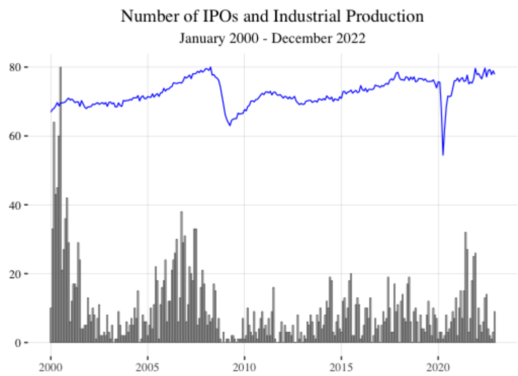
Appendix

A1 Descriptive Statistics

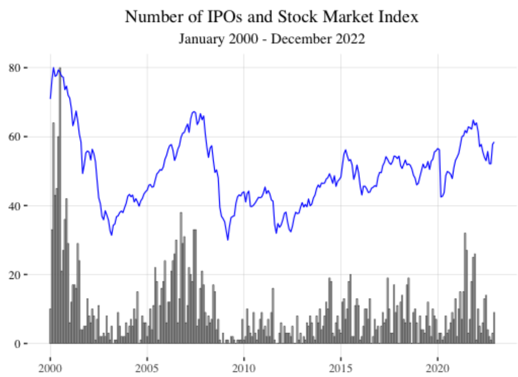
Figure A1.1: Number of IPOs and Macroeconomic Factors



A1.1.1: Number of IPOs and Long-Term Interest Rate

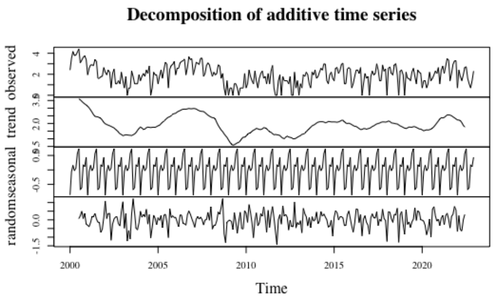


A1.1.2: Number of IPOs and Industrial Production Index

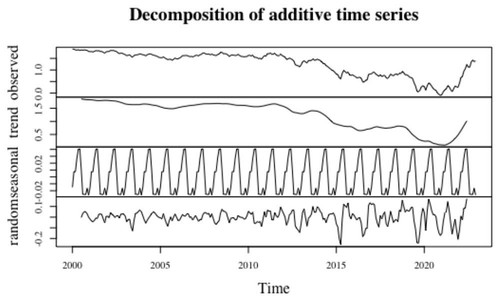


A1.1.3: Number of IPOs and Stock Market Index

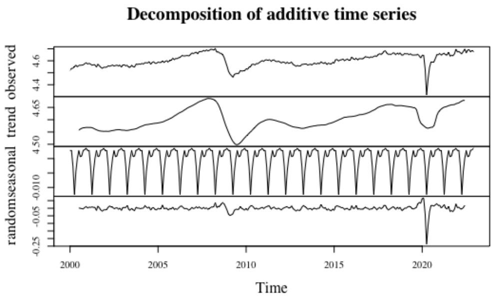
Figure A1.2: Decomposition of Log Time Series



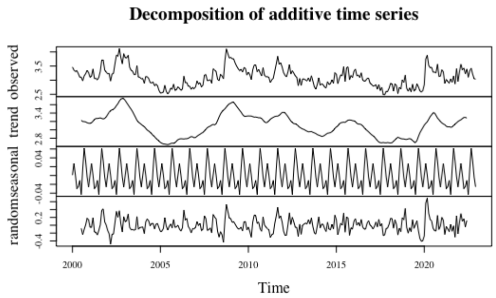
A1.2.1: Decomposition of Number of IPOs



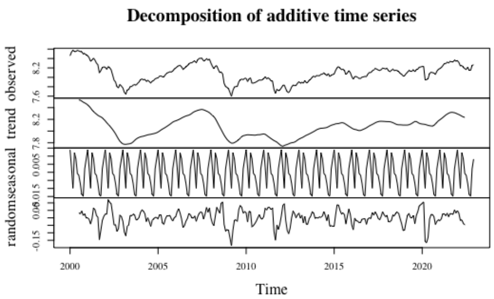
A1.2.2: Decomposition of Long-Term Interest Rate



A1.2.3: Decomposition of Industrial Production Index



A1.2.4: Decomposition of Market Volatility



A1.2.5: Decomposition of Stock Market Index

A2 Methodology

A2.1 Stationary Test

Employing a confirmatory data analysis will give us an comprehensive assessment of the time series properties, providing a more robust and reliable analysis of the data. The null and alternative hypotheses under each testing approach are as follows (Brooks, 2019, p. 452):

ADF / PP	KPSS
H_0: $y_t \sim I(1)$	H_0: $y_t \sim I(0)$
H_1: $y_t \sim I(0)$	H_1: $y_t \sim I(1)$

This approach has four possible outcomes:

(1) Reject H_0 and Do not reject H_0
(2) Do not reject H_0 and Reject H_0
(3) Reject H_0 and Reject H_0
(4) Do not reject H_0 and Do not reject H_0

where the conclusive outcomes observed in cases (1) and (2) contribute to a better understanding of the stationarity characteristics of the time series, while the inconclusive results obtained in cases (3) and (4) highlight the complexity surrounding the stationarity assessment.

A2.2 Cointegration Test

The testing procedure is carried out systematically, considering a sequence of null hypotheses for the number of cointegrating vectors, denoted as $r = 0, 1, ..., g-1$. Specifically, the hypotheses for λ_{trace} can be stated as follows:

$$\begin{gathered}
H_0 : r = 0 \text{ vs. } H_1 : 0 < r \leq g \\
H_0 : r = 1 \text{ vs. } H_1 : 1 < r \leq g \\
H_0 : r = 2 \text{ vs. } H_1 : 2 < r \leq g \\
\vdots \\
H_0 : r = g-1 \text{ vs. } H_1 : r = g
\end{gathered}$$

where the first test involves H_0 of no cointegrating vectors. If H_0 is not rejected, then there are no cointegrating vectors. If H_0 is rejected, then perform the second test, i.e., $H_0 : r = 1$. We increase the value of r until we no longer have sufficient evidence to reject the null hypothesis (Brooks, 2019, p. 476).

A2.3 Granger Causality Test

A multivariate VAR model with k variables and of order p will have the following representation:

$$\begin{bmatrix} y_{1,t} \\ y_{2,t} \\ \vdots \\ y_{k,t} \end{bmatrix} = \begin{bmatrix} \alpha_{1,0} \\ \alpha_{2,0} \\ \vdots \\ \alpha_{k,0} \end{bmatrix} + \begin{bmatrix} \beta_{1,1} \dots \\ \beta_{2,1} \dots \\ \vdots \\ \beta_{k,1} \dots \end{bmatrix} \begin{bmatrix} y_{1,t-1} \\ y_{2,t-1} \\ \vdots \\ y_{k,t-1} \end{bmatrix} + \dots + \begin{bmatrix} \gamma_{1,1} \dots \\ \gamma_{2,1} \dots \\ \vdots \\ \gamma_{k,1} \dots \end{bmatrix} \begin{bmatrix} y_{1,t-p} \\ y_{2,t-p} \\ \vdots \\ y_{k,t-p} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \vdots \\ \varepsilon_{k,t} \end{bmatrix} \quad (.1)$$

For simplicity and in order to briefly explain what we are interested in testing, consider the following bivariate VAR(2) model:

$$\begin{bmatrix} y_{1,t} \\ y_{2,t} \end{bmatrix} = \begin{bmatrix} \alpha_{1,0} \\ \alpha_{2,0} \end{bmatrix} + \begin{bmatrix} \beta_{1,1} & \beta_{1,2} \\ \beta_{2,1} & \beta_{2,2} \end{bmatrix} \begin{bmatrix} y_{1,t-1} \\ y_{2,t-1} \end{bmatrix} + \begin{bmatrix} \gamma_{1,1} & \gamma_{1,2} \\ \gamma_{2,1} & \gamma_{2,2} \end{bmatrix} \begin{bmatrix} y_{1,t-2} \\ y_{2,t-2} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix} \quad (.2)$$

We are interested in testing the following assumptions and examine their implications for the parameter matrices using Equation .2 above:

	Hypothesis	Implied restriction
1	Lags of $y_{1,t}$ do not explain current $y_{2,t}$	$\beta_{2,1} = 0$ and $\gamma_{2,1} = 0$
2	Lags of $y_{1,t}$ do not explain current $y_{1,t}$	$\beta_{1,1} = 0$ and $\gamma_{1,1} = 0$
3	Lags of $y_{2,t}$ do not explain current $y_{1,t}$	$\beta_{1,2} = 0$ and $\gamma_{1,2} = 0$
4	Lags of $y_{2,t}$ do not explain current $y_{2,t}$	$\beta_{2,2} = 0$ and $\gamma_{2,2} = 0$

The F−test framework can be used to test each of the four joint hypotheses, with each set of restrictions involving parameters from a single equation (Brooks, 2019, p. 421). By employing this method, we can seek answers to questions such as: "Does the variation in y_1 lead to changes in y_2?" (Brooks, 2019, p. 421)

A3 Analysis

A3.1 Stationary Test

Table A3.1: Kwiatkowski-Phillips- Schmidt-Shin (KPSS) Test

Variable	Log Level	Log Difference
N_IPO	0.581*	0.016
LT	5.452**	0.186
IP	1.513**	0.026
VOL	0.490*	0.019
INDEX	0.555*	0.154

Notes: T-statistics are reported
* $p < .05$, ** $p < .01$, *** $p < .001$

A3.2 Cointegration Test

Table A3.2: Lag Structure – Underlying VAR Model

Lag	FPE(n)	AIC(n)	SC(n)	HQ(n)
1	$5.381e-11$	$-2.364e+01$	$-2.317e+01$	$-2.345e+01$
2	$3.603e-11$	$-2.404e+01$	$-2.323e+01^{*}$	$-2.372e+01^{*}$
3	$3.298e-11^{*}$	$-2.413e+01^{*}$	$-2.298e+01$	$-2.367e+01$
4	$3.546e-11$	$-2.406e+01$	$-2.257e+01$	$-2.346e+01$
5	$3.873e-11$	$-2.397e+01$	$-2.214e+01$	$-2.324e+01$
6	$3.887e-11$	$-2.397e+01$	$-2.180e+01$	$-2.310e+01$
7	$4.078e-11$	$-2.393e+01$	$-2.142e+01$	$-2.292e+01$
8	$4.356e-11$	$-2.387e+01$	$-2.102e+01$	$-2.272e+01$
9	$4.316e-11$	$-2.388e+01$	$-2.070e+01$	$-2.260e+01$
10	$4.605e-11$	$-2.382e+01$	$-2.030e+01$	$-2.241e+01$
11	$4.784e-11$	$-2.379e+01$	$-1.993e+01$	$-2.224e+01$
12	$3.672e-11$	$-2.407e+01$	$-1.987e+01$	$-2.238e+01$

Notes: (∗) indicates the best value of the respective information criteria. FPE = Final Prediction Error, AIC = Akaike criterion, SC = Shawarz Bayesian criterion, HQ = Hannan-Quinn criterion.

Table A3.3: Linear Regression Results

	Estimate	Std. Error	t value	Pr(> |t|)
Dependent variable: lnN_IPO				
Constant	-21.037	4.368	-4.815	$2.44e-06^{***}$
$lnLT$	0.259	0.084	3.067	0.002^{**}
$lnIP$	0.081	0.967	0.084	0.933
$lnVOL$	-0.344	0.140	-2.458	0.014^{*}
$lnINDEX$	2.887	0.234	12.317	$< 2e-16^{***}$

Residual Std. Error: 0.6914 on 271 degrees of freedom
R^2: 0.4595, Adjusted R^2: 0.4515
F−Statistic: 57.6 on 4 and 271 DF, p-value: $< 2.2e-16$

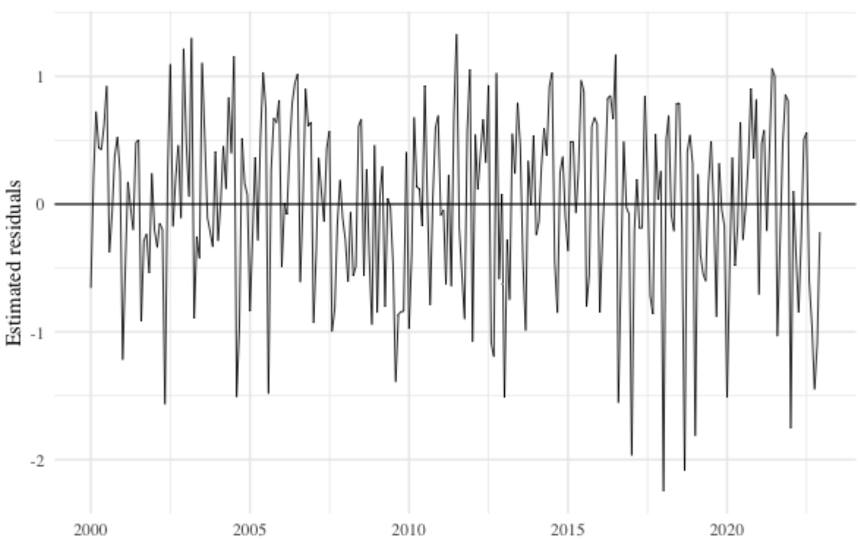
Note: * $p < .05$, ** $p < .01$, *** $p < .001$

Table A3.4: ADF Test on Estimated Residuals from Linear Regression

Variable	Test Statistics	Critical Value
$\hat{u}$	-4.923^{*}	-3.426

Notes: Critical values from MacKinnon (2010)
* $p < .05$, ** $p < .01$, *** $p < .001$

Figure A3.1: Estimated Residuals from Linear Regression



A3.3 Vector Error Correction Model

Table A3.5: VECM Estimation − Comprehensive Coefficient Estimates

	ΔlnN_IPO	$\Delta lnLT$	$\Delta lnIP$	$\Delta lnVOL$	$\Delta lnINDEX$
ECT_1	-1.121^{***}	-0.014	0.008^{**}	-0.013	0.002
ECT_2	-0.159^{***}	0.002	-0.001	-0.014^{*}	-0.003^{*}
Constant	-25.737^{***}	-1.299^{**}	0.583^{***}	2.338	0.882^{**}
ΔlnN_IPO_{t-1}	-0.883^{***}	-0.016^{**}	0.001	-0.028	0.004
$\Delta lnLT_{t-1}$	0.952	0.293^{***}	-0.014	-0.177	-0.015
$\Delta lnIP_{t-1}$	2.572	-0.199	0.012	0.201	-0.001
$\Delta lnVOL_{t-1}$	-0.669^{*}	0.029	-0.015^{*}	-0.333^{***}	-0.118^{***}
$\Delta lnINDEX_{t-1}$	3.256^{**}	0.166	0.093^{***}	-0.420	-0.062
ΔlnN_IPO_{t-2}	-1.080^{***}	-0.013	0.004	-0.009	-0.001
$\Delta lnLT_{t-2}$	-0.484	-0.076	0.076^{***}	0.198	0.043
$\Delta lnIP_{t-2}$	0.767	0.244	-0.203^{***}	-0.125	0.019
$\Delta lnVOL_{t-2}$	-0.417	0.032	-0.032^{***}	-0.225^{*}	-0.047^{*}
$\Delta lnINDEX_{t-2}$	2.092	0.264^{**}	-0.115^{***}	0.040	-0.118

Note: * $p < .05$, ** $p < .01$, *** $p < .001$

A3.4 Variance Decomposition & Impulse Response Function

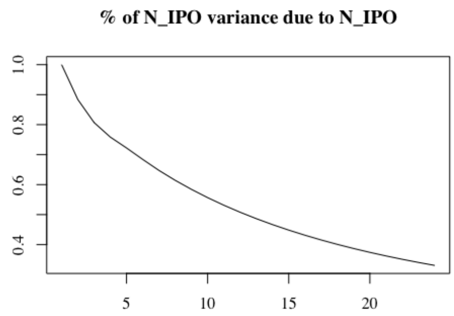
Table A3.6: Underlying VAR Representation of VECM − Coefficient Matrix of Lagged Endogenous Variables − *vec2var Transformation*

	lnN_IPO_{t-1}	$lnLT_{t-1}$	$lnIP_{t-1}$	$lnVOL_{t-1}$	$lnINDEX_{t-1}$
lnN_IPO	0.116	0.952	2.572	−0.669	3.255
$lnLT$	−0.015	1.293	−0.199	0.028	0.166
$lnIP$	0.001	−0.014	1.012	−0.015	0.093
$lnVOL$	−0.028	−0.176	0.200	0.666	−0.419
$lnINDEX$	0.003	−0.014	−0.001	-0.117	0.938

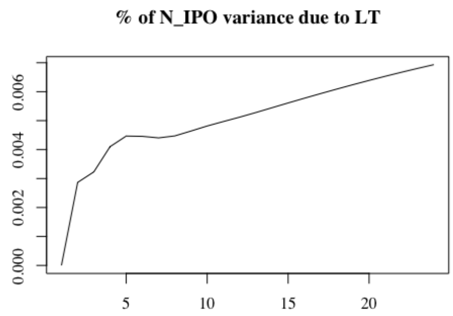
	lnN_IPO_{t-2}	$lnLT_{t-2}$	$lnIP_{t-2}$	$lnVOL_{t-2}$	$lnINDEX_{t-2}$
lnN_IPO	−0.196	−1.435	−1.805	0.252	−1.163
$lnLT$	0.002	−0.369	0.443	0.003	0.098
$lnIP$	0.002	0.089	−0.215	−0.017	−0.208
$lnVOL$	0.018	0.375	−0.325	0.108	0.459
$lnINDEX$	−0.005	0.057	0.020	0.070	−0.056

	lnN_IPO_{t-3}	$lnLT_{t-3}$	$lnIP_{t-3}$	$lnVOL_{t-3}$	$lnINDEX_{t-3}$
lnN_IPO	−0.040	0.324	0.803	−0.066	0.732
$lnLT$	−0.001	0.078	−0.051	0.000	−0.222
$lnIP$	0.004	−0.076	0.121	0.020	0.091
$lnVOL$	−0.003	−0.212	−0.329	0.112	−0.022
$lnINDEX$	0.003	−0.046	−0.170	0.015	0.107

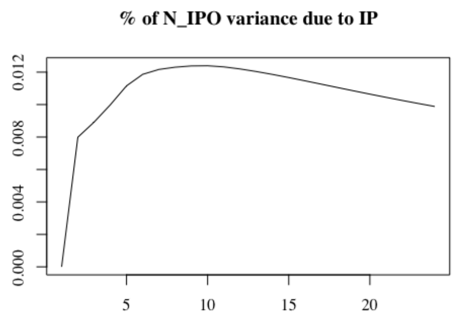
Figure A3.2: Forecast Error Variance Decompositions



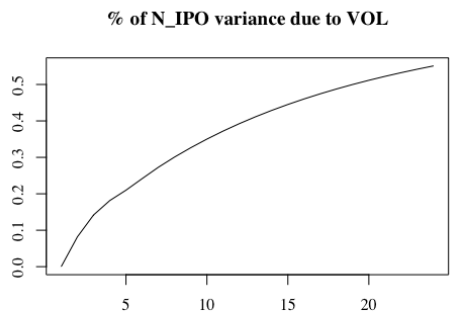
A2.1.1: % N_IPO variance due to N_IPO



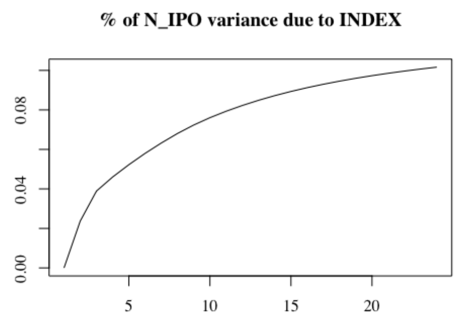
A2.1.2: % N_IPO variance due to LT



A2.1.3: % N_IPO variance due to IP

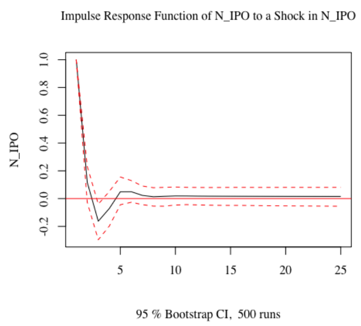


A2.1.4: % N_IPO variance due to VOL

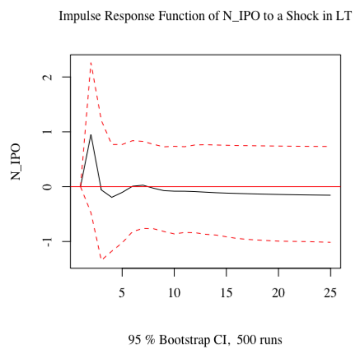


A2.1.5: % N_IPO variance due to INDEX

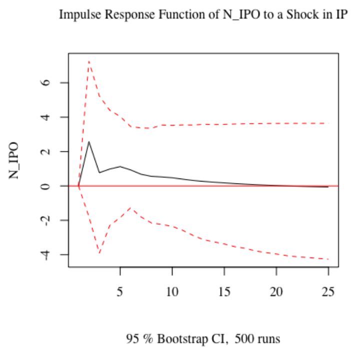
Figure A3.3: Impulse Response Functions



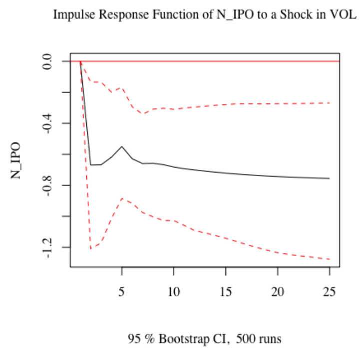
A2.2.1: Shock in N_IPO



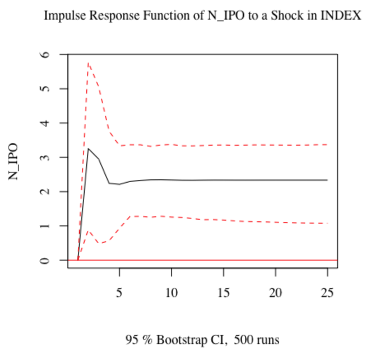
A2.2.2: Shock in LT



A2.2.3: Shock in IP



A2.2.4: Shock in VOL



A2.2.5: Shock in INDEX

A3.5 Granger Causality Test

Table A3.7: Lag Structure: VAR Model in First Difference

Lag	FPE(n)	AIC(n)	SC(n)	HQ(n)
1	$7.051e-11$	$-2.337e+01$	$-2.297e+01^{*}$	$-2.321e+01$
2	$5.668e-11$	$-2.359e+01$	$-2.285e+01$	$-2.329e+01$
3	$4.846e-11$	$-2.375e+01$	$-2.267e+01$	$-2.331e+01^{*}$
4	$4.892e-11$	$-2.374e+01$	$-2.232e+01$	$-2.317e+01$
5	$4.763e-11$	$-2.377e+01$	$-2.201e+01$	$-2.306e+01$
6	$4.903e-11$	$-2.374e+01$	$-2.164e+01$	$-2.289e+01$
7	$4.864e-11$	$-2.376e+01$	$-2.131e+01$	$-2.277e+01$
8	$5.079e-11$	$-2.372e+01$	$-2.093e+01$	$-2.260e+01$
9	$5.523e-11$	$-2.364e+01$	$-2.051e+01$	$-2.238e+01$
10	$5.950e-11$	$-2.357e+01$	$-2.011e+01$	$-2.218e+01$
11	$4.424e-11^{*}$	$-2.387e+01^{*}$	$-2.007e+01$	$-2.235e+01$
12	$4.797e-11$	$-2.380e+01$	$-1.967e+01$	$-2.214e+01$

Notes: $(*)$ indicates the best value of the respective information criteria. FPE = Final Prediction Error, AIC = Akaike criterion, SC = Schwarz Bayesian criterion, HQ = Hannan-Quinn criterion.

Table A3.8: VAR(11) Model

	Estimate	Std. Error	t value	Pr(> $\|t\|$)
Dependent variable: ΔlnN_IPO				
Constant	−0.034	0.037	−0.924	0.356
ΔlnN_IPO_{t-1}	−0.867	0.059	−14.461	$< 2e-16^{***}$
ΔlnN_IPO_{t-2}	−0.852	0.079	−10.777	$< 2e-16^{***}$
ΔlnN_IPO_{t-3}	−0.789	0.095	−8.234	$1.98e-14^{***}$
ΔlnN_IPO_{t-4}	−0.736	0.109	−6.708	$1.83e-10^{***}$
ΔlnN_IPO_{t-5}	−0.616	0.116	−5.310	$2.81e-07^{***}$
ΔlnN_IPO_{t-6}	−0.613	0.117	−5.231	$4.10e-07^{***}$
ΔlnN_IPO_{t-7}	−0.528	0.117	−4.511	$1.08e-05^{***}$
ΔlnN_IPO_{t-8}	−0.452	0.109	−4.121	$5.45e-05^{***}$
ΔlnN_IPO_{t-9}	−0.524	0.096	−5.434	$1.53e-07^{***}$
ΔlnN_IPO_{t-10}	−0.579	0.078	−7.378	$3.77e-12^{***}$
ΔlnN_IPO_{t-11}	−0.574	0.060	−9.509	$< 2e-16^{***}$
$\Delta lnLT_{t-1}$	−0.047	0.659	−0.072	0.942
$\Delta lnLT_{t-2}$	−0.606	0.692	−0.876	0.382
$\Delta lnLT_{t-3}$	−0.654	0.713	−0.918	0.359
$\Delta lnLT_{t-4}$	−0.763	0.729	−1.046	0.296
$\Delta lnLT_{t-5}$	0.974	0.741	1.314	0.190
$\Delta lnLT_{t-6}$	0.435	0.769	0.566	0.572
$\Delta lnLT_{t-7}$	−0.421	0.771	−0.547	0.585
$\Delta lnLT_{t-8}$	−1.098	0.771	−1.424	0.156
$\Delta lnLT_{t-9}$	−0.665	0.821	−0.810	0.418
$\Delta lnLT_{t-10}$	0.882	0.825	1.069	0.286
$\Delta lnLT_{t-11}$	0.302	0.799	0.378	0.705
$\Delta lnIP_{t-1}$	0.063	2.437	0.026	0.979
$\Delta lnIP_{t-2}$	−1.746	2.412	−0.724	0.470
$\Delta lnIP_{t-3}$	−1.039	2.487	−0.418	0.676
$\Delta lnIP_{t-4}$	1.199	2.427	0.494	0.621
$\Delta lnIP_{t-5}$	2.408	2.352	1.024	0.307

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$\Delta lnIP_{t-6}$	3.099	2.375	1.305	0.193
$\Delta lnIP_{t-7}$	0.901	2.351	0.383	0.701
$\Delta lnIP_{t-8}$	2.101	2.362	0.890	0.374
$\Delta lnIP_{t-9}$	−0.697	2.278	−0.306	0.759
$\Delta lnIP_{t-10}$	−1.220	2.113	−0.577	0.56431
$\Delta lnIP_{t-11}$	−0.051	1.951	−0.026	0.979
$\Delta lnVOL_{t-1}$	−0.565	0.250	−2.256	0.025*
$\Delta lnVOL_{t-2}$	0.028	0.309	0.092	0.926
$\Delta lnVOL_{t-3}$	−0.020	0.317	−0.064	0.949
$\Delta lnVOL_{t-4}$	−0.314	0.317	−0.990	0.323
$\Delta lnVOL_{t-5}$	0.141	0.317	0.444	0.657
$\Delta lnVOL_{t-6}$	0.410	0.319	1.286	0.199
$\Delta lnVOL_{t-7}$	0.250	0.313	0.798	0.425
$\Delta lnVOL_{t-8}$	0.473	0.306	1.545	0.123
$\Delta lnVOL_{t-9}$	0.109	0.296	0.370	0.711
$\Delta lnVOL_{t-10}$	0.258	0.296	0.874	0.383
$\Delta lnVOL_{t-11}$	0.080	0.269	0.300	0.764
$\Delta lnINDEX_{t-1}$	3.852	1.154	3.335	0.001**
$\Delta lnINDEX_{t-2}$	2.929	1.184	2.473	0.014*
$\Delta lnINDEX_{t-3}$	1.193	1.249	0.955	0.340
$\Delta lnINDEX_{t-4}$	2.542	1.249	2.035	0.043*
$\Delta lnINDEX_{t-5}$	2.694	1.258	2.141	0.033*
$\Delta lnINDEX_{t-6}$	0.981	1.291	0.760	0.448
$\Delta lnINDEX_{t-7}$	2.473	1.256	1.968	0.050.
$\Delta lnINDEX_{t-8}$	3.411	1.291	2.641	0.008**
$\Delta lnINDEX_{t-9}$	0.827	1.279	0.646	0.518
$\Delta lnINDEX_{t-10}$	3.778	1.273	2.967	0.003**
$\Delta lnINDEX_{t-11}$	1.625	1.098	1.479	0.140

Residual Std. Error: 0.5855 on 208 degrees of freedom

R^2: 0.6896, Adjusted R^2: 0.6075

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F−Statistic: 8.4 on 55 and 208 DF, p-value: $< 2.2e - 16$
Note: * $p < .05$, ** $p < .01$, *** $p < .001$

Table A3.9: Robustness Check - Reverse Ordering

Null Hypothesis:	F−Statistic
INDEX, VOL, IP, LT do not Granger-cause N_IPO	2.881***
INDEX does not Granger-cause N_IPO	5.463***
VOL does not Granger-cause N_IPO	1.295
IP does not Granger-cause N_IPO	0.517
LT does not Granger-cause N_IPO	0.967

Note: * $p < .05$, ** $p < .01$, *** $p < .001$

Table A3.10: Granger Causality Test − Macroeconomic Factors

Null Hypothesis:	F−Statistic
LT does not Granger-cause IP	4.112***
VOL does not Granger-cause IP	2.088*
INDEX does not Granger-cause IP	4.263***
VOL does not Granger-cause INDEX	4.459***

Note: * $p < .05$, ** $p < .01$, *** $p < .001$