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IPO Activity and the Impact of Macroeconomic Factors: An Empirical Analysis of the Italian Market

Course of Econometric Theory

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Abstract

This thesis aims to examine the relationship between macroeconomic factors and IPO activity in Italy from January 2000 to December 2023. By employing models capable of handling count data and a classical linear time series methodology, our analysis found evidence of an existing relationship between the macroeconomic factors and IPO activity. Moreover, 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. The Granger causality test was employed to determine any potential causal relationship between the variables. Furthermore, an out-of-sample forecasting exercise was used as an instrument to compare the predictive power of the relevant models.

Notably, our findings confirm an existing positive relationship between the stock market returns and IPO activity, as it resulted relevant in all the models employed. However, we encountered limited statistical evidence to support a relationship between the other variables and IPO activity. Although market volatility demonstrates a closer connection to IPO activity compared to the other variables, the statistical support for this relationship remains relatively weak.

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1 Introduction

Initial Public Offerings (IPOs) have long been recognized as a crucial mechanism for firms to access public capital, transform their ownership structure, and signal quality to market participants. Globally, IPOs play a pivotal role in the evolution of capital markets by facilitating resource allocation, enhancing liquidity, and promoting corporate transparency. Seminal studies have documented the multifaceted drivers of IPO activity. For instance, early work by Ibbotson and Jaffe (1975) highlighted the "hot issue" phenomenon, while Pagano, Panetta, and Zingales (1998) provided empirical evidence on how firm-specific and market-wide factors interact in the decision to go public. More recent contributions published in leading journals, such as the insights on market cycles by Lowry (2003) and the analysis of underpricing and investor sentiment by Ritter and Welch (2002) , further emphasize that IPO volumes are subject to considerable fluctuations, reflecting both cyclical dynamics and evolving economic conditions.
Beyond firm-level determinants, the broader macroeconomic environment has been shown to exert significant influence on IPO activity. Studies have established that variables such as interest rates, inflation, and economic growth have the theoretical basis to be linked to the timing and volume of IPOs (Bernanke and Blinder 1979); (Lowry and Schwert 2002). Similarly, further research has underscored the importance of monetary policy and market activity (returns and volatility) in shaping investors' willingness to participate in new equity issues (Chemmanur and Fulghieri 1999); (Jovanovic and Rousseau 2004). With these basis, different country or geographical specific studies have been performed to analyze this links, such as the one performed on the US market by Tran and Jeon (2011) and on the UK one by Angelini and Foglia (2018). While these studies provide valuable insights into how macroeconomic variables affect IPO activity across various geographical areas and countries, there remains a notable gap in the literature regarding the Italian market. This study addresses this gap by examining the effect of macroeconomic variables on IPO activity in Italy, aiming to assess whether the Italian case aligns with or deviates from the patterns observed in other contexts. In light of this, the current thesis addresses the following research questions: How do key macroeconomic variables, namely monetary policy, inflation, economic growth, and stock market activity, influence IPO activity over time? What are the dynamic interrelationships between these macroeconomic factors and the frequency of IPOs, both in the short and long run? In what ways do the unique

structural features of a national market, such as Italy's reliance on bank-based financing and the prevalence of small and medium-sized enterprises, modify these relationships?
To answer these questions, this study employs a comprehensive time series analysis spanning the period 2000–2023. The methodological framework integrates autoregressive models for count data, including Poisson and Negative Binomial specifications, with a vector autoregressive (VAR) approach to capture both contemporaneous and lagged effects among the variables. This dual-method strategy not only addresses potential issues of autocorrelation and non-stationarity but also enables an in-depth investigation into how shocks in macroeconomic conditions propagate through IPO activity.
The main empirical results indicate that, consistent with studies performed in other countries and geographies, stock market performance and market volatility are the most significant indicators driving IPO activity in Italy. In contrast, other macroeconomic variables, such as interest rates, inflation, and economic growth, do not exhibit statistically significant effects on the number of IPOs. These findings suggest that investor sentiment and liquidity conditions, as reflected by the performance and volatility of the stock market, play a more crucial role in shaping IPO activity than broader macroeconomic fundamentals. This result both reinforces and extends the theoretical predictions and empirical evidence documented in the literature.
From 2000 to 2023, Italy witnessed a total of 591 Initial Public Offerings (IPOs), excluding cases involving mergers, acquisitions, or business combinations where companies were listed without a direct decision to go public. This period of IPO activity showcases substantial fluctuations influenced by global economic events, local macroeconomic conditions, and structural developments within the Italian market. These fluctuations underline the importance of understanding the dynamics and determinants of IPO activity, particularly in a market like Italy, where structural reliance on bank-based financing has historically influenced the decision to access equity markets (Zingales 2000).
As previously anticipated, IPOs represent a transformative milestone for firms, enabling them to raise equity capital from public investors and transition into publicly traded entities. This process provides companies with access to a broader capital base, enhances their credibility, and improves their visibility in competitive markets. However, the decision to go public is complex, reflecting the interplay of internal and external factors, including firm-specific needs, market sentiment, and broader macroeconomic conditions (Espinasse 2014). In Italy, the small and medium-sized enterprises (SMEs) that dominate its economic landscape have increasingly turned to IPOs as a mechanism for raising capital, particularly since the establishment of platforms like AIM Italia (now Euronext Growth Milan), that was introduced to fit the specific needs of these firms.
The study of IPO activity in Italy is particularly relevant due to its distinctive market structure and the diverse macroeconomic challenges faced by the country over the years. Italy's reliance on small and medium-sized enterprises (SMEs) and its tradition of bank-

based financing create a unique context for IPO activity. Over the last two decades, IPO markets in Italy have been shaped by both global economic trends and local market dynamics, experiencing significant fluctuations in response to macroeconomic shocks, policy shifts, and evolving investor sentiment.

Globally, the IPO market from 2000 to 2023 underwent a series of pronounced cycles, which were mirrored, even though on a smaller scale, in Italy. The early 2000s were marked by a recovery from the dot-com bubble (1997-2000), which had significantly dampened investors trust in the financial markets and, thus, appetite for equity offerings (Ritter and Welch 2002). In this period, IPO activity was relatively subdued as markets globally, and in Italy, grappled with the aftereffects of speculative excess and overvaluation in the tech sector.

The 2008 financial crisis and the subsequent Eurozone debt crisis represented again a pivotal downturn for IPO markets worldwide. As liquidity dried up and investor risk aversion surged, IPO activity contracted sharply, and Italy was no exception. The crisis highlighted vulnerabilities in its financial system and exacerbated reliance on traditional forms of financing, stalling IPO issuance across sectors. However, following this period of contraction, the global post-crisis recovery from 2010 to 2019 brought renewed optimism to equity markets. In Italy, this period was characterized by an increasing number of SME listings, facilitated by the development of the Alternative Investment Market in 2009 (AIM Italia, now Euronext Growth Milan), which was created specifically to address the financing needs of smaller enterprises. This market reform was instrumental in diversifying the types of firms participating in IPO activity and reducing dependence on bank financing.

The onset of the COVID-19 pandemic in 2020 introduced unprecedented challenges for the global economy, but it also led to a paradoxical surge in IPO activity in certain sectors. Ultra-low interest rates, substantial fiscal stimulus, and increased investor interest in technology and health-related sectors drove an unexpected boom in IPOs during 2020 and 2021. In Italy, the pandemic underscored the resilience of the IPO market, particularly for firms operating in innovative and high-growth industries. However, this recovery was uneven, reflecting Italy's ongoing structural and fiscal challenges.

Overall, the Italian IPO market, while smaller in scale compared to global leaders like the United States and United Kingdom, has been shaped by a confluence of global trends and local developments. From 2000 to 2023, the market exhibited significant variability, with periods of expansion driven by economic recovery and market reforms, and contractions linked to global financial crises and regional instability.

This thesis situates the study of Italian IPOs within this broader theoretical and historical context, focusing on the interplay between macroeconomic variables and IPO activity. By exploring the unique dynamics of the Italian market from 2000 to 2023, it aims to contribute to the understanding of how systemic and firm-level factors shape IPO decisions,

providing insights for both academic research and policy-making.
In this chapter we will further explore the functioning of IPOs and focus on the structure of the Italian Stock Market. The remainder of this thesis is organized as follows. Chapter 2 reviews the relevant literature and establishes the theoretical framework. Chapter 3 details the data and variable selection, while Chapter 4 outlines the methodological approach. Chapter 5 presents the empirical analysis and discusses the findings, and Chapter 6 concludes with implications for policy and future research.

1.1 Background

1.1.1 Understanding Initial Public Offerings

An Initial Public Offering (IPO) refers to the process through which a privately held company offers its shares to the public for the first time (Espinasse 2014). It marks a pivotal moment in a company's evolution, transitioning from a private to a public entity by offering shares to investors on a stock exchange. This process enables firms to access public capital markets, providing essential funding for growth, innovation, and long-term strategic initiatives (Espinasse 2014). By going public, companies gain not only financial resources but also increased visibility, credibility, and a broader shareholder base, which can facilitate subsequent capital-raising efforts. The IPO mechanism is deeply embedded in the functioning of modern financial markets, serving as both a financing tool for companies and a critical pathway for investors to participate in corporate growth (Espinasse 2014).
There are primarily two types of IPOs: primary offerings and secondary offerings. In a primary offering, the company issues new shares to the public, with the proceeds directed toward the firm itself. This form of IPO is predominantly aimed at raising fresh capital to finance growth, invest in new projects, or reduce existing debt. On the other hand, a secondary offering involves the sale of shares by existing shareholders, such as founders, private equity firms, or other early-stage investors. In this case, the company does not receive any proceeds; instead, the offering provides liquidity to the existing shareholders (Espinasse 2014). Most IPOs in Italy involve a mix of these types, with both primary and secondary shares offered, allowing firms to raise capital while providing an exit strategy for initial investors.
The IPO process in Italy follows a structured sequence of steps governed by the regulatory framework of Consob (Commissione Nazionale per le Società e la Borsa), the Italian financial markets authority, and the listing requirements of Borsa Italiana, the country's primary stock exchange. The process begins with the company's internal preparation and strategic decision-making. At this stage, the firm evaluates its readiness to go public, including considerations of its financial performance, governance structure, and compli-

ance with regulatory requirements. Companies often engage legal and financial advisors to assist in this evaluation. Once a company decides to proceed, it selects underwriters, typically investment banks, which play a pivotal role in managing the IPO process. The underwriters are responsible for conducting due diligence, structuring the offering, determining the initial price range, and marketing the shares to potential investors. In Italy, the underwriters collaborate with the company to prepare the prospectus, a comprehensive document outlining the firm's business model, financial performance, risk factors, and strategic goals. The prospectus must be approved by Consob, ensuring compliance with regulatory standards and providing transparency for potential investors (Borsa-Italiana n.d.[a]).

The pricing of the IPO is then a critical phase, often determined through a process known as book-building. During this process, the underwriters solicit bids from institutional investors, such as asset managers and pension funds, to gauge demand and establish an appropriate price range for the shares. The final offer price is typically set at the higher end of the range if demand is strong, reflecting market interest and confidence in the company's prospects.

Following the pricing, the IPO enters the roadshow phase, where the company's management presents its investment case to institutional investors. These presentations are essential for building confidence and generating interest in the offering (Borsa-Italiana n.d.[a]). Retail investors in Italy also play a significant role in IPOs, and shares are often allocated also to this segment to ensure broad market participation.

The culmination of the IPO process is the listing of the company's shares on Borsa Italiana. This happens once the company's admission has been approved by the Stock Exchange's admission team. Trading begins on the designated launch date, marking the firm's official transition to a publicly traded entity. Post-listing, the company is subject to ongoing reporting and disclosure obligations, including the publication of periodic financial statements and adherence to corporate governance standards. This transparency is essential for maintaining investor confidence and compliance with Italian and European Union regulations (Borsa-Italiana n.d.[a]).

Despite its advantages, the IPO process also involves significant costs and risks. The direct costs, such as underwriting fees, legal expenses, and compliance costs, can consume a substantial portion of the funds raised, often amounting to 5–10% of the total proceeds. Additionally, public companies must adhere to rigorous reporting standards and governance requirements, which can strain internal resources and expose sensitive information to competitors. Another common challenge is market pressure, as public companies face heightened expectations from investors and analysts, often emphasizing short-term performance at the expense of long-term strategy. Furthermore, IPOs frequently experience underpricing, a phenomenon where shares are sold below their true market value, resulting in significant first-day price increases. While underpricing benefits initial investors,

it represents a cost to the issuing company, as it reduces the proceeds raised during the offering.
In summary, the IPO process involves a series of carefully regulated steps, from preparation and regulatory approval to pricing, marketing, and eventual listing. The process not only provides companies with access to capital but also requires significant effort to meet the expectations of regulators, investors, and the broader market. By understanding the types of IPOs and the procedural intricacies, one can better appreciate the strategic and operational considerations that companies face when going public.

1.1.2 Overview of Borsa Italiana

Borsa Italiana, Italy's main stock exchange, has a history that reflects the evolution of the country's financial markets and its integration into the broader European economic landscape. Established in 1808 in Milan, the exchange originally served as a local trading hub, facilitating transactions in bonds and shares for regional businesses and governments. Over time, it grew in significance, becoming the centerpiece of Italy's financial system as industrialization spurred economic development and capital needs expanded (Borsa-Italiana n.d.[b]).
The modern era of Borsa Italiana began in 1998 with the unification of the 10 regional Italian stock exchanges in the Milan stock exchange and its privatization, transitioning from a public institution to a privately managed company. This change was part of broader financial reforms aimed at increasing efficiency, transparency, and competitiveness in Italian markets. As part of these reforms, the exchange adopted advanced electronic trading systems to replace traditional floor trading, aligning itself with international standards and improving market accessibility (Borsa-Italiana n.d.[b]). In 2007, Borsa Italiana merged with the London Stock Exchange Group (LSEG), a move that enhanced its global visibility and facilitated cross-border investment opportunities. This partnership integrated Italy into one of Europe's leading financial market infrastructures, fostering greater collaboration and technological innovation (Borsa-Italiana n.d.[b]). More recently, in 2021, Borsa Italiana became part of the Euronext Group, a pan-European exchange operator that now controls 7 main stock exchanges, following its acquisition from LSEG. This development further embedded Italy's financial markets within a broader European framework, enabling Italian companies to access a wider pool of investors and benefit from harmonized listing requirements and services across the Euronext network (Borsa-Italiana n.d.[b]).
Borsa Italiana is organized into several distinct markets and segments, each designed to serve the diverse needs of companies and investors. Its structure ensures that businesses of various sizes and industries can access appropriate capital-raising platforms while pro-

viding investors with a broad range of opportunities.
The Euronext Milan (previously Mercato Telematico Azionario or MTA) is the principal market of Borsa Italiana, dedicated to medium and large-cap companies. It is subdivided into segments that target specific types of issuers and investors. The most norable is the STAR segment (Segmento Titoli ad Alti Requisiti), created in 2001, that caters to medium-sized companies that adhere to higher standards of corporate governance, transparency, and liquidity, making it particularly attractive to institutional investors. It is represented by the FTSE Italia STAR index and now includes 75 titles.
Many market indices have been created to represent the Italian stock market, the most important one being the FTSE MIB. It includes the most capitalized and liquid companies listed on Borsa Italiana.
For smaller companies, Borsa Italiana operates Euronext Growth Milan, previously known as AIM Italia. Established in 2009, this market provides a streamlined pathway for small and medium-sized enterprises (SMEs) to access capital markets. With simplified listing requirements and regulatory obligations, it is designed to encourage entrepreneurship and innovation while offering growth opportunities to smaller firms. Euronext Growth Milan has become a vital platform for Italy's economy, given the country's reliance on SMEs. Every company listed on this market is also included in the FTSE Italia Growth index.
In addition to equity markets, Borsa Italiana includes the MOT (Mercato Telematico delle Obbligazioni) for fixed-income securities, which facilitates the trading of government bonds, corporate bonds, and other debt instruments. The EuroTLX market operates alongside the MOT, offering additional liquidity for bonds and certificates. The IDEM (Italian Derivatives Market) provides a platform for trading derivatives, including options and futures on individual stocks and indices, such as the FTSE MIB. This market plays a key role in risk management and speculative strategies for institutional and retail investors alike. Lastly, the ETFplus market specializes in Exchange-Traded Funds (ETFs) and Exchange-Traded Commodities (ETCs), offering investors easy access to diversified and sector-specific portfolios. This segment supports the growing demand for passive investment vehicles in Italy.

2 Literature review

A thorough review of previous empirical and theoretical literature is indispensable for establishing the foundation of our study. This chapter not only delineates the various determinants that have been proposed to explain IPO activity but also highlights the evolution of thought on the subject. Over the past several decades, researchers have investigated the motivations behind firms' decisions to go public by examining both firm-specific characteristics and external economic conditions. This review serves to guide our selection of key variables and to frame the context in which our analysis of the Italian IPO market is conducted.

2.1 The Reasons to Go Public

The decision to go public represents a critical point in a firm's evolution, driven by a complex interplay of financial, strategic, and market-timing considerations. While the immediate need to raise capital and improve liquidity has traditionally been viewed as the primary motive for an Initial Public Offering (IPO), research over the past few decades has broadened this perspective considerably. For instance, early work by Rock (1986) and Beatty and Ritter (1986) suggest that an IPO also functions as a powerful signal to mitigate information asymmetries between the firm and the market. This signaling mechanism is essential in showing quality and future prospects to potential investors, beyond the simple provision of new funds.

Subsequent studies have deepened our understanding of this process. Baker and Wurgler (2002) and Ritter (1991) demonstrate that market timing plays a pivotal role in IPO decisions—firms often choose to go public during favorable market cycles to maximize valuation and minimize the cost of capital. Moreover, research by Carter et al. (1992) underscores the strategic dimensions of IPOs, revealing how increased market visibility can enhance a firm's competitive positioning and long-term growth prospects.

That said, the complex IPO process is influenced by a variety of firm-specific and external factors. Central to this decision are considerations related to capital needs, market timing, and strategic advantages.

2.1.1 Capital Raising and Liquidity

One of the primary motivations for going public is to raise substantial capital to finance growth, expansion, and new projects. Ritter and Welch (2002) emphasize that IPOs provide firms with access to broader capital markets, allowing them to reduce their reliance on private financing sources like venture capital or bank loans. Becoming publicly listed often grants firms the ability to secure more favorable financing terms, reflecting improved perceptions of creditworthiness post-IPO.
Additionally, IPOs offer liquidity to existing shareholders, enabling them to diversify their investment portfolios or exit their positions. Pagano et al. (1998) found that the likelihood of an IPO increases with firm size and overall industry valuations, as these factors lower perceived risks for new investors and offer better ROI to early investors. Their analysis underscores that firms use IPOs strategically to capitalize on high valuations and access cost-effective external equity financing.
This was also stated by Lerner (1994), who studied 350 privately held venture-backed biotechnology firms and came to the conclusion that these companies were more likely to go public when equity valuations were high, while they employed private financing when values were lower. Meaning that venture capitalists are pushing the companies towards an IPO when valuations are high in order to maximize their return potential.

2.1.2 Market Visibility and Strategic Goals

Going public can enhance the visibility and reputation of a company, which in turn may strengthen relationship with all the stakeholders, such as customers, suppliers, and partners. This strategic benefit is particularly significant in industries where trust and brand recognition are critical. The process also aligns the incentives of management and employees by introducing stock-based compensation mechanisms, fostering a sense of ownership and commitment (Ritter and Welch 2002).
However, the decision to go public is not without trade-offs. Zingales (1995) highlights that IPOs may reduce the control of founding shareholders because of diluition, leading to potential conflicts between ownership and management. Firms must carefully weigh the benefits of liquidity and capital access against the costs of increased disclosure and loss of operational autonomy. It's important to point out that this happens in every form of capital raise where new investors enter the cap table of the company and diluition occurs.

2.1.3 Market Cycles

Timing plays a crucial role in IPO decisions. The phenomenon of ”hot” and ”cold” markets, first ideated by Ibbotson and Jaffe (1975) and consisting in periods characterized by high and low IPO activity, respectively, has been widely studied in financial literature.

Hot markets often coincide with favorable economic conditions and investor optimism, encouraging firms to go public. Conversely, during cold markets, heightened uncertainty and low valuations discourage IPO activity. Pástor and Veronesi (2005) argue that firms treat IPOs as real options, delaying them during periods of unfavorable market conditions to maximize potential proceeds during more optimistic phases.
Research suggests that hot market cycles are often driven by technological advancements or sector-specific booms. For example, the late 1990s dot-com bubble saw a surge in IPO activity in the tech sector, as firms capitalized on heightened investor enthusiasm for internet-related businesses (Lowry 2003). These cycles are further supported by herd behavior, where firms rush to go public to avoid missing the opportunity created by temporary market exuberance.
Empirical studies support the existence of these market cycles. Loughran et al. (1994) found that IPO waves are often preceded by sustained increases in stock prices and followed by periods of below-average returns. These findings suggest that firms strategically time their public offerings to coincide with market peaks.

2.2 The Relevance of Macroeconomic Factors

The decision to go public is strongly influenced by macroeconomic conditions. Key factors such as stock market performance, volatility, interest rates, and industrial production have an impact in the timing and success of IPOs. These relationships have been previously explored in some academic literature.
The interconnections between these macroeconomic factors often results in complex dynamics. For instance, Tran and Jeon (2011) identified both short and long-term equilibrium relationships between IPO activity and macroeconomic variables, with adjustment mechanisms typically occurring within six months to a year. Their findings underscore the importance of considering both immediate and lagged effects of macroeconomic conditions on IPO decisions. Additionally, recent research suggests that factors like economic policy uncertainty and shifts in investor sentiment may further refine firms' timing strategies. In such environments, companies may delay public offerings until clearer signals emerge, reinforcing the idea that IPO decisions are shaped by a blend of quantitative indicators and market outlook(Pagano et al. 1998).

2.2.1 Stock Market Performance

A consistent finding in the literature is the positive relationship between stock market performance and IPO activity. Loughran et al. (1994) demonstrated that stock market indices, such as the S&P 500, serve as a proxy for market sentiment and economic optimism. Higher stock prices not only improve firm valuations but also encourage investors

to participate in IPOs, increasing the likelihood of successful offerings. This phenomenon is particularly pronounced in hot market cycles, where positive stock market conditions attract both firms and investors.
Ritter and Welch (2002) further emphasized that favorable market conditions reduce the cost of equity, enabling firms to raise more capital at lower dilution costs. The strategic timing of IPOs to coincide with strong stock market performance reflects the importance of external market conditions in shaping corporate financing decisions.

2.2.2 Market Volatility

While stock market performance has a positive impact on IPOs, volatility tends to have the opposite effect. Lowry and Schwert (2002) found that periods of high market volatility are associated with reduced IPO activity. This decline is attributed to increased uncertainty, which discourages firms from going public by rasing concerns about post-IPO valuations. Firms are reluctant to go public when market conditions are unpredictable, as volatility raises the risk not only of underpricing, but also poor aftermarket performance. Tran and Jeon (2011), analyzing IPOs in the US from 1970 to 2005, found that stock market volatility significantly influenced both the number of IPOs and the proceeds raised. Their findings suggest that firms delay IPOs during volatile periods to avoid adverse investor reactions and unfavorable pricing conditions.

2.2.3 Interest Rates

Interest rates play a role in influencing IPO activity from multiple points of view. On one hand, higher interest rates increase the cost of capital, making debt financing less attractive and encouraging firms to choose equity financing instead (Pagano et al. 1998). On the other hand, extremely low interest rates may delay IPOs, as the opportunity cost of waiting for more favorable market conditions diminishes (Jovanovic and Rousseau 2004). They argue that this behavior reflects a non-linear relationship between interest rates and IPO activity. While moderate interest rate reductions might encourage IPOs by lowering the cost of capital, extremely low rates can have the opposite effect, as firms find it easier and less costly to postpone going public.
Tran and Jeon (2011) highlighted that the Federal Funds rate and the 10-year Treasury yield were significant predictors of IPO proceeds, suggesting that monetary policy directly impacts firms' decisions to access equity markets.

2.2.4 Economic Growth

Economic growth, often proxied by industrial production or GDP, is another impactful determinant on IPO activity. Lowry (2003) found that periods of robust economic growth

create favorable conditions for firms to go public, as a positive investor sentiment and strong corporate earnings increase the demand for equity. Comin and Gertler (2006) noted that robust growth periods often align with strategic business investments and equity offerings, such as IPOs, as firms aim to capitalize on favorable conditions. This supports the idea that IPO volumes are positively correlated with economic expansions and cycles as firms strategically time their IPOs to align with economic expansions.
However, Loughran et al. (1994) found mixed evidence regarding the relationship between GDP and IPO activity, highlighting that while economic growth provides a favourable environment, stock market performance remains a stronger and more direct predictor.

2.2.5 Inflation

Inflation is a critical macroeconomic factor influencing IPO activity, as it affects firm valuations, investor sentiment, and the broader economic environment. High inflation often introduces uncertainty by eroding purchasing power and raising costs for businesses, which discourages IPOs as firms struggle to price shares attractively amidst volatile expectations. Ritter and Welch (2002) supported this view, observing that firms weigh inflationary pressures alongside other macroeconomic variables when considering public offerings.
Moderate inflation, on the other hand, can signal a growing economy, as indicated by the target levels of most central banks, fostering an environment conducive to IPO activity. Firms may use such periods to capitalize on positive investor sentiment and robust market conditions, aiming to secure higher valuations. Tran and Jeon (2011) noted that inflation's indirect effects, such as its influence on central bank policies and interest rates, also shape the equity market environment and the timing of IPOs.
Periods of sustained inflation may lead to stagflation-like conditions, where firms are disincentivized to go public due to deteriorating economic prospects and increasing capital costs. This interplay underscores the complexity of inflation's impact, requiring firms and investors to carefully evaluate inflationary trends within the broader macroeconomic context.

3 Data

This chapter has the objective to deep dive into the variables selected for our analysis and formulate our hypothesis. The selection is based on the conclusions and results presented in previous relevant research. The following sections will also present a descriptive analysis of all the data included in the work.

3.1 Variables Selection and Hypothesis Formulation

To adequately address our hypotheses, it is crucial to collect data from reliable sources. For the purpose of this thesis, the data collection was conducted from various reputable databases, namely Bloomberg Terminal, Organisation for Economic Co-operation and Development (OECD), Eurostat, the World Bank, European Central Bank (ECB), Borsa Italiana, and Yahoo Finance.
All currency-related data was obtained and recorded in euros. The selected timeframe for data collection extends from January 1st 2000, to December 31st 2023 in order to effectively capture multiple economic cycles. All data is reported and collected on a monthly basis.
Our variables of interest are: Number of IPOs, Industrial Production Growth, Main Refinancing Operations Rate, Inflation Rate, Stock Market Returns, Stock Market Volatility. Where the first concerns our dependent variable, which we seek to explain based on the influence of the independent variables (represented by the other five series). The specific series will be more thorougly visualized in the exploratory data analysis section.

3.1.1 IPO Activity

To provide a comprehensive analysis, we measure IPO activity using a count metric: monthly total number of IPOs. The number of IPOs reflects the frequency of firms choosing to go public within a given month. This measure captures the responsiveness of IPO decisions to changing economic and market conditions, as seen in studies like Lowry and Schwert (2002). A higher number of IPOs often indicates favorable market

environments and investor confidence.
We considered including the Total monthly IPO proceeds and the Average monthly IPO proceeds as proxies for IPO activity in Italy. However, we decided against using these measures because they were not well-suited for our analysis. Including them would have resulted in an even greater number of months with zero values, as many companies list on the market without raising capital. Additionally, the presence of a few very large listings would have skewed the values too much, making it difficult to draw meaningful conclusions.
For the purpose of our analysis, the listings made through Special Purpose Acquisition Companies (SPACs) have been counted only at the vehicle listing and not at the moment of the company acquisition, as the number of listed companies doesn't change.
Data relative to IPO activity have been gathered both on the Bloomberg Terminal and from Borsa Italiana. The range is from January 2000 to December 2023.

3.1.2 Industrial Production Growth

Economic growth, typically measured by changes in GDP, captures the overall health and performance of an economy. For this study, we use the Industrial Production Index (IPI) growth rate as a proxy for economic growth. The IPI reflects changes in the production levels of industrial sectors, offering a more frequent and sector-specific indicator of economic activity.
Empirical studies, such as those by Lowry (2003), have demonstrated a positive correlation between economic expansions and IPO volumes. The underlying theoretical rationale is that periods of robust industrial production signal stronger economic performance, leading to increased investor confidence, higher firm valuations, and improved financing conditions. This, in turn, makes it more attractive for firms to go public. The market timing theory, supported by work from Baker and Wurgler (2002) and Ritter (1991), suggests that firms strategically choose to issue IPOs during favorable economic conditions to maximize valuation and minimize financing costs.
Testing the hypothesis that Industrial Production Growth is positively related to IPO activity is important for several reasons. First, it serves as a validation of the market timing and signaling theories in the context of Italy's unique financial system, which is characterized by a strong reliance on bank-based financing and a predominance of small and medium-sized enterprises. A positive sign in this relationship would confirm that improved industrial output—a proxy for overall economic health—indeed boosts IPO activity. Conversely, if the expected positive relationship were not observed, this might indicate that additional market imperfections or institutional constraints are influencing IPO decisions in Italy, thus challenging or refining existing theoretical models.

Hypothesis 1 (H1):
There is a **positive** relationship between Industrial Production and IPO activity in Italy.

The Industrial Production Index data is sourced from Eurostat, covering the period from January 2000 to December 2023. The index measures changes in industrial output relative to a base year (2021) and is seasonally adjusted to account for recurring patterns in production. We calculated the Year-on-year percentage changes of the index. The decision not to use the GDP growth is due to the non availability of GDP data on a monthly basis.

3.1.3 Long-Term Interest Rate

The long-term interest rate represents the yield on long-term government bonds, often reflecting the cost of capital and market expectations for inflation and growth. It is a critical factor influencing corporate financing decisions and economic activity. The long-term interest rate is essential for understanding the cost of financing alternatives to equity, such as debt. Studies, such as those by Tran and Jeon (2011), highlight its importance in shaping IPO activity, as firms may prefer equity financing during periods of high interest rates to avoid costly borrowing. Conversely, very low rates may delay IPOs, as suggested by Jovanovic and Rousseau (2004), due to reduced urgency in securing funds.
We use the 10-year yield of BTP (Buoni del Tesoro Poliennali), Italian government bonds, as the long-term interest rate. The data is sourced from the OECD and spans January 2000 to December 2023, reflecting the average monthly yield of these bonds. This variable was initially included in our analysis, but eliminated due to multicollinearity concerns during the preliminary analysis. For that reason, it will not be included in our explorations in the rest of this work.

3.1.4 Central Bank's Interest Rate

The Governing Council of the European Central Banks (ECB) sets the key interest rates for the euro area. These rates are the Deposit facility rate, the Main refinancing operations rate, and the marginal landing facility rate. The Deposit facility (DF) is the rate on the deposit facility, which banks may use to make overnight deposits with the Eurosystem at a pre-set interest rate (ECB n.d.). The Main refinancing operations (MRO) is the interest rate on the main refinancing operations. In these operations banks can borrow funds from the ECB against broad collateral on a weekly basis at a pre-determined interest rate. The rate is set above the deposit facility rate (ECB n.d.). Last, the Marginal lending facility (MLF) is the rate on the marginal lending facility, which offers overnight credit to banks against broad collateral at a pre-set interest rate. The rate is set above the main refinancing operations rate (ECB n.d.).

We utilize the MRO rate as it is the European Central Bank's (ECB) benchmark interest rate, governing the cost at which commercial banks borrow short-term liquidity from the ECB and it significantly influences market liquidity, credit conditions, and borrowing costs in the Eurozone, reflecting in a direct impact on the Italian financial system. A lower MRO rate typically boosts liquidity, reducing borrowing costs and enhancing investor confidence, which can positively influence IPO activity. Ritter and Welch (2002) emphasized the importance of monetary policy in shaping equity market conditions and IPO timing.
Testing the hypothesis that the ECB's MRO rate is negatively related to IPO activity is important for several reasons. First, it provides a means to validate theoretical predictions from monetary policy and credit market theories, such as those discussed by Bernanke and Blinder (1979), which argue that lower short-term borrowing costs improve market liquidity and lower the cost of financing. This, in turn, can delay the urgency for firms to access public markets since cheaper bank financing becomes more attractive. A negative relationship would confirm that monetary easing enhances market conditions for IPOs. Conversely, an unexpected sign or insignificance in this relationship might indicate the presence of unique institutional factors in the Italian market—such as its heavy reliance on bank-based financing—that could alter the typical dynamics observed in other contexts.

Hypothesis 2 (H2):
There is a **negative** relationship between the ECB's MRO and the IPO activity in Italy.

The MRO rate data is sourced from the European Central Bank (ECB), covering January 2000 to December 2023. It is reported monthly and reflects the primary monetary policy stance of the ECB, acting as our measure of short-term borrowing costs.

3.1.5 Inflation Rate

Inflation is the general increase in the overall price level of goods and services typically bought by households. It is measured as the average price change over a given period of time for a basket of goods and services that are typically bought in the economy. It is a crucial macroeconomic indicator that affects purchasing power, firm costs, and investor behavior. Inflation influences IPO activity through its impact on firm valuations and market conditions. High inflation creates uncertainty and raises the cost of capital, often discouraging IPOs, while moderate inflation may signal robust economic activity, encouraging firms to go public (Ritter and Welch 2002).
Testing the hypothesis that there is a negative relationship between the inflation rate and IPO activity is important for several reasons. First, from a theoretical perspective, higher inflation increases uncertainty regarding future cash flows and raises financing costs, mak-

ing equity financing less attractive. This is consistent with the notion that stable price levels foster better market conditions and higher investor confidence (Fama 1990). A negative sign in this relationship would confirm that firms are less inclined to launch IPOs during periods of high inflation, thereby supporting models of market timing and risk assessment in capital markets. Conversely, if the relationship were insignificant or even positive, it might suggest that other factors—such as compensatory mechanisms in the Italian market—are at play, warranting further investigation. Ultimately, validating this hypothesis enhances our understanding of how macroeconomic stability influences IPO decisions, a subject of central importance in both academic research and policy-making.

Hypothesis 3 (H3):
There is a **negative** relationship between the inflation rate and the IPO activity in Italy.

Our reference for measuring inflation is the Harmonised Index of Consumer Prices (HICP). The HICP is compiled by Eurostat, the statistical office of the European Union, and the national statistical institutes of EU Member States. The same methodology is used across all european countries. To calculate the inflation rates, national statistical institutes regularly collect prices for a "basket" of goods and services, representing the consumption of all private people in the country. These national values are then compiled into an inflation rate for the euro area. Prices are collected from different places, like stores, restaurants and online shops, to get a broad overview of how prices evolve for different goods and services.
The source of our data is the European Central Bank and spans January 2000 to December 2023.

3.1.6 Stock Market Returns

Stock market indices serve as proxies for overall market performance and investor sentiment, both of which are crucial for assessing IPO activity. A strong-performing index indicates favorable conditions for raising capital, improved firm valuations, and enhanced investor confidence. Empirical research, such as that by Loughran et al. (1994), has documented a robust positive relationship between stock market levels and IPO volumes, with higher index values fostering greater investor demand for equity offerings. Similarly, Pástor and Veronesi (2005) argued that strong market conditions reduce uncertainty and facilitate better pricing of IPOs.
Testing the hypothesis that the FTSE MIB index performance is positively related to IPO activity is important for several reasons. First, from a theoretical standpoint, market timing and signaling theories suggest that robust market performance, as captured by rising stock market indices, enhances investor sentiment and lowers uncertainty, thereby

encouraging firms to go public. A positive relationship would indicate that improved market conditions translate into higher IPO volumes—confirming that firms strategically time their offerings to capitalize on favorable market environments. Conversely, if the expected positive sign is not observed, it may imply that unique institutional or structural factors in the Italian market, such as regulatory constraints or a pronounced reliance on bank-based financing, are influencing the IPO process differently than in other contexts. In this way, verifying the direction and significance of this relationship not only supports established empirical findings, such as the ones of Baker and Wurgler (2002) and Pástor and Veronesi (2005), but also provides valuable insights for both policymakers and market participants regarding the determinants of IPO timing and success.

Hypothesis 4 (H4):
There is a **positive** relationship between the FTSE MIB index performance and the IPO activity in Italy.

The FTSE MIB is the primary benchmark index of the Italian stock market, managed by FTSE Russell. It comprises the 40 largest and most liquid companies listed on the Borsa Italiana. The index represents approximately 80% of the market capitalization of all listed companies in Italy, making it a reliable proxy of market sentiment and market performance.
Monthly returns were calculated based on monthly closing values of the FTSE MIB index, sourced from Yahoo Finance and covering January 2000 to December 2023.

3.1.7 Stock Market Volatility

Stock market volatility reflects the degree of uncertainty and risk in the financial markets, significantly influencing investment decisions and IPO activity. High volatility typically discourages firms from going public due to the increased uncertainty surrounding post-IPO valuations and aftermarket performance. Underpricing risk, which refers to the likelihood of IPO shares being sold below their market value, becomes more pronounced during volatile periods. For instance, Lowry and Schwert (2002) documented that high volatility reduces IPO volumes as firms delay offerings to avoid pricing challenges and weak investor demand. Their findings align with theories positing that uncertainty disrupts efficient price discovery, discouraging IPO issuance.
Testing the hypothesis that the FTSE MIB volatility is negatively related to IPO activity is important for several reasons. First, theoretical models of information asymmetry and risk suggest that high market volatility increases uncertainty, leading to a higher cost of capital and a corresponding reluctance among firms to enter the public markets (Lowry and Schwert 2002). This negative relationship supports the view that volatility acts as

a proxy for market uncertainty, hindering accurate valuation and efficient price discovery during IPOs. Second, confirming a negative relationship would reinforce the notion that elevated volatility signals deteriorating market sentiment, thereby reducing investor appetite for new issues. Conversely, if the expected negative relationship were not observed, it might imply that mitigating factors, such as robust investor sentiment or supportive institutional frameworks, are at work in the Italian market, potentially challenging conventional theories. Understanding these dynamics is crucial for both refining existing theoretical models and informing policy decisions aimed at fostering a stable capital market environment.

Hypothesis 5 (H5):
There is a **negative** relationship between the FTSE MIB volatility and the IPO activity in Italy.

As there is no official volatility index for the Italian market, we calculated monthly historical volatility for the FTSE MIB index. This approach aligns with methods used in empirical finance to measure realized market volatility. Monthly historical volatility of the FTSE MIB index was calculated using daily closing prices obtained from Yahoo Finance. The calculation involved standard deviation methods, reflecting the percentage volatility of prices each month for the period January 2000 to December 2023.

3.2 Exploratory Data Analysis

Table 3.1 summarizes the distributional properties of the variables under study. The dataset spans 288 monthly observations (January 2000 – December 2023), capturing Italy's IPO activity and key macroeconomic indicators.

Table 3.1: Summary Statistics

	Count	**Mean**	**Std Dev**	**Min**	**Max**	**Skewness**	**Kurtosis**
Number of IPOs	288	2.052	2.191	0	12	1.504	2.652
Ind. Prod.	288	−0.411	8.367	−44.050	79.245	2.261	33.039
MRO Rate	288	1.576	1.559	0.000	4.750	0.567	−1.076
Inflation	288	2.190	2.134	−1.000	12.600	2.255	7.083
FTSE MIB Ret.	288	0.120	6.089	−22.439	22.950	−0.140	1.388
FTSE MIB Vol.	288	6.097	3.256	1.749	26.003	2.214	7.970

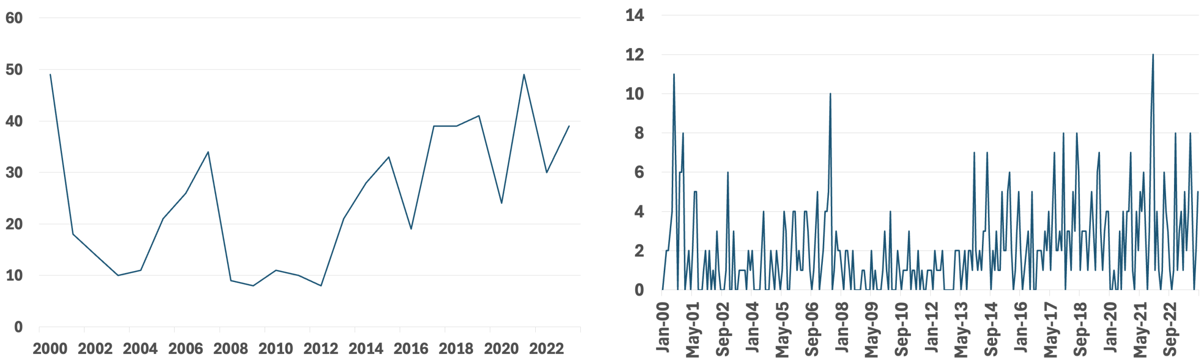
The IPO series exhibits pronounced overdispersion, with a variance (4.80) exceeding its mean (2.05), violating the Poisson assumption of equidispersion. This justifies the exploration of Negative Binomial or INAR models in subsequent analyses. The distribution is right-skewed (skewness = 1.50), with monthly IPO counts ranging from 0 to 12, and 27.1% of observations recording zero IPOs.

Macroeconomic variables display substantial heterogeneity. Industrial production and inflation show high volatility, with the former experiencing extreme fluctuations (minimum = -44.05, maximum = 79.25). The monetary policy rate reflects the European Central Bank's accommodative stance post-2008, ranging from 0% to 4.75%. Stock market volatility is leptokurtic (kurtosis = 7.97), indicating heavy-tailed behavior consistent with financial time series.

Figure 3.1 illustrates the annualized trend in IPO activity in Italy from 2000 to 2023. The plot reveals pronounced fluctuations in IPO volumes, reflecting macroeconomic and regulatory shifts during this period.

The annual trajectory of Italian IPO activity, depicted in Figure ??, reveals a dynamic

Figure 3.1: IPO trends over time in Italy



Annual Number of IPOs

Monthly Number of IPOs

interplay of macroeconomic cycles, regulatory reforms, and global financial shocks over the 24-year period. IPO volumes exhibit pronounced volatility, with annual counts ranging from 8 listings during crisis years to peaks of 49 IPOs, reflecting Italy's evolving equity market landscape. The early 2000s were marked by subdued IPO activity, a legacy of the dot-com bubble collapse and Italy's protracted economic stagnation, where GDP growth averaged just 0.8% annually. Family-owned firms, which dominate Italy's corporate sector, largely eschewed public listings due to cultural preferences for retained control and fragmented regulatory frameworks. This inertia began to dissipate in the mid-2000s, as harmonization with EU capital market directives spurred modest growth in listings, particularly among financial institutions and industrial firms. The Global Financial Crisis (2008–2009) and subsequent Eurozone debt crisis (2011–2012) precipitated a near-collapse in IPO activity, with annual counts plummeting to historic lows. Investor risk aversion, epitomized by the FTSE MIB index's 55% decline from 2007 to 2009, compounded by soaring sovereign bond yields, rendered equity fundraising untenable for most firms. Austerity measures further constrained small and medium enterprises (SMEs), which faced

heightened collateral requirements and diminished access to venture capital. A structural shift emerged post-2015, as ECB quantitative easing and Italy's banking sector reforms revitalized investor confidence. IPO volumes rebounded, peaking in 2021 with over 40 annualized listings, a resurgence fueled by the EU's Next Generation EU recovery funds and the Borsa Italiana's launch of the dedicated "SME Growth Market" segment. The COVID-19 pandemic induced a transient contraction in 2020, yet the swift policy response, including targeted liquidity injections and debt moratoria, facilitated a rapid recovery. By 2023, IPO activity stabilized at pre-pandemic levels.
The correlation matrix provides initial insights into the relationships between IPO activity and key macroeconomic variables. While correlation does not imply causation, it helps identify potential linkages that will be further explored through econometric modeling.

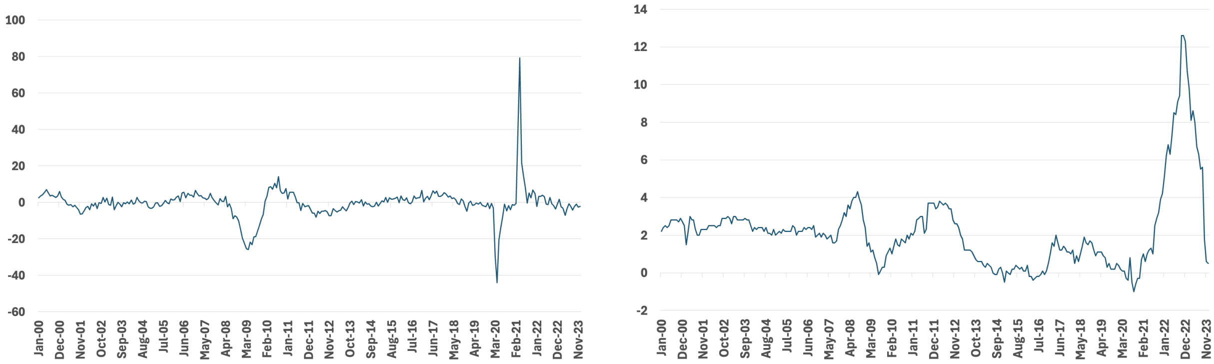
Table 3.2: Correlation Matrix

	Number of IPOs	**Ind. Prod.**	**MRO Rate**	**Inflation**	**FTSE MIB Ret.**	**FTSE MIB Vol.**
Number of IPOs	1.000	0.198	−0.051	0.030	0.003	−0.220
Ind. Prod.		1.000	−0.048	0.013	0.037	−0.342
MRO Rate			1.000	0.322	−0.110	−0.028
Inflation				1.000	−0.023	−0.020
FTSE MIB Ret.					1.000	−0.397
FTSE MIB Vol.						1.000

The number of IPOs shows a weak positive correlation with industrial production, suggesting that stronger economic activity may support IPO issuance. Conversely, its correlation with the MRO rate is slightly negative, indicating that higher interest rates may discourage IPO activity, though the effect appears minimal. Regarding stock market variables, IPO activity is largely uncorrelated with FTSE MIB index returns but negatively correlated with FTSE MIB volatility, implying that firms prefer going public in stable market conditions. Other macroeconomic interdependencies align with expectations, such as the positive correlation between inflation and interest rates and the negative relationship between market volatility and index returns.
The time series analysis of key macroeconomic and financial indicators showed in Figure **??** reveals distinct patterns and interlinkages across variables. Industrial production growth exhibits pronounced cyclicality, with periods of expansion, such as the mid-2000s recovery, interrupted by severe contractions during the Global Financial Crisis of 2008–2009 (-25.5% year-on-year in March 2009) and the COVID-19 pandemic (-44% in April 2020).

These downturns coincided with heightened market stress, as evidenced by the FTSE MIB index, which plummeted by 22.4% in March 2020, and volatility surging to 26%

Figure 3.2: Time Series of Macroeconomic Indicators (1)

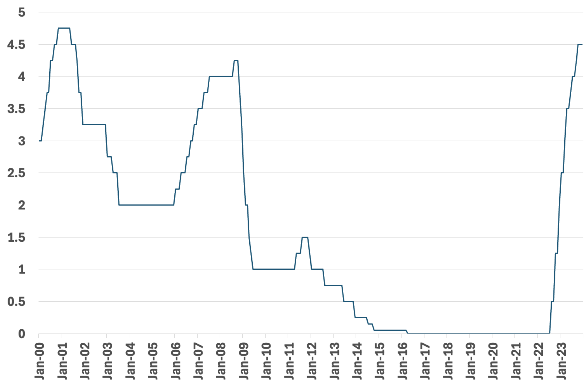


Industrial Production Growth

Inflation Rate

during the same period. The European Central Bank's main refinancing rate followed a downward trajectory, declining from 3% in early 2000 to near-zero levels post-2014, reflecting prolonged accommodative monetary policy to counter economic shocks.

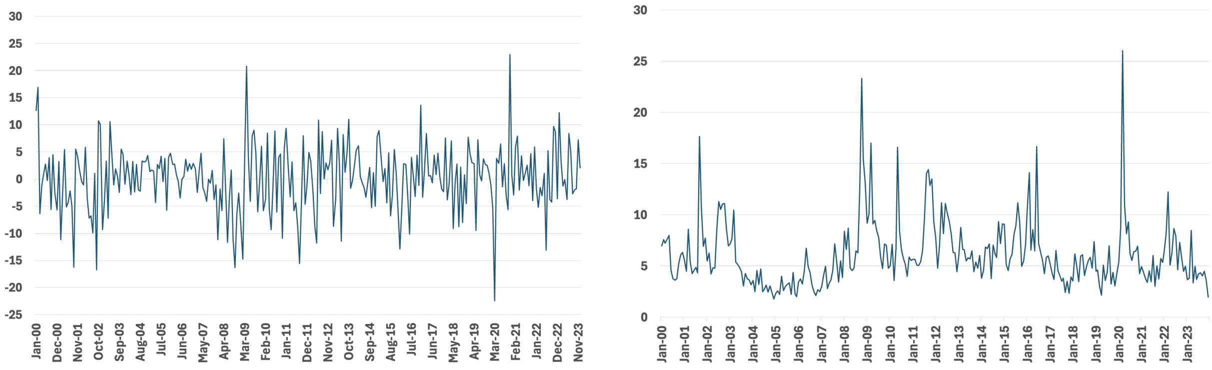
Figure 3.3: Time Series of Macroeconomic Indicators (2)



MRO Rate

Inflation displayed moderate stability until 2021, when supply-chain disruptions and energy crises drove a sharp rise to 12.6% in late 2022, followed by rapid decline of the inflation rate to 0.5% by December 2023.

Figure 3.4: Time Series of Macroeconomic Indicators (3)



FTSE MIB Returns FTSE MIB Volatility

The FTSE MIB index growth mirrored broader economic sentiment, with sustained declines during the Eurozone debt crisis (e.g. -13.1% in June 2022) and recoveries aligning with policy interventions. Volatility spikes, such as the 23.3 reading in October 2008, underscored systemic risks during crises, while subdued levels post-2021 suggested gradual market normalization. Collectively, these series highlight the interplay between monetary policy, industrial activity, price dynamics, and financial market behavior over two decades of structural and cyclical challenges.

4 Methodology

4.1 Preliminary Analysis

A thorough preliminary analysis is crucial to ensure the validity of the time-series modeling techniques employed in this study. This section addresses three key aspects of time-series data: multicollinearity, stationarity, and autocorrelation. Ensuring the independence of each variable is essential for the reliability of the results, while testing for stationarity is a prerequisite for many time-series models. Examining autocorrelation further aids in understanding the structure of dependencies within the data.

4.1.1 Multicollinearity Check

Prior to estimating the count data models, it is essential to assess the potential presence of multicollinearity among the predictor variables. Multicollinearity occurs when two or more independent variables in a regression model are highly correlated, which can lead to unstable and unreliable coefficient estimates. To diagnose this issue, this study employs the Variance Inflation Factor (VIF) as the primary diagnostic tool.
The VIF quantifies the severity of multicollinearity by measuring the inflation in the variance of estimated regression coefficients relative to what would be observed if the predictor variables were uncorrelated. For each predictor variable X_i, the VIF is calculated through an auxiliary regression where X_i is regressed against all other predictors:

$$X_i = \beta_0 + \sum_{j \neq i} \beta_j X_j + \epsilon_i \tag{4.1}$$

The R-squared (R_i^2) from this auxiliary regression is then used to compute the VIF:

$$VIF_i = \frac{1}{1 - R_i^2} \tag{4.2}$$

This calculation is performed independently for each macro-economic predictor variable in our dataset. The interpretation of VIF values follows established guidelines in the econometric literature: values between 1 and 5 suggest minimal collinearity, values between 5 and 10 indicate moderate multicollinearity that warrants attention, and values exceeding 10 signal severe multicollinearity that requires remedial action. A VIF of 10 corresponds to an R_i^2 of 0.90, indicating that 90% of the variance in that predictor is explained by other predictors.

For variables exhibiting concerning levels of multicollinearity (VIF > 5), several remedial strategies are considered. The first approach involves removing one of the highly correlated predictors from the model specification. Alternatively, variable transformation techniques may be employed, such as creating composite indicators or applying mathematical transformations to the affected variables. In cases where multiple variables show high correlation, Principal Component Analysis can be utilized to combine correlated variables into orthogonal components while preserving the underlying information content.

The selection among these remedial strategies is guided by a careful balance between statistical considerations and the theoretical importance of each variable to the model. This diagnostic process ensures that the subsequent count data models (Poisson AR, Negative Binomial AR, and INAR-NB) are built on a foundation of statistically sound predictor variables, thereby enhancing the reliability of the estimated coefficients and the overall model inference.

4.1.2 Testing for Unit Roots

In practice, econometric time series based on real data are often non-stationary, meaning that their statistical properties (such as mean, variance, and autocorrelation) change over time, often due to trends or seasonality. To assess whether the variables used in this study exhibit stationarity, the Augmented Dickey-Fuller (ADF) test is employed. The ADF test is based on the null hypothesis that a unit root is present in the series, indicating non-stationarity. Rejection of the null hypothesis suggests that the series is stationary. The ADF estimation equation is given as follows:

$$\Delta y_t = \mu + \beta t + \gamma y_{t-1} + \sum_{i=1}^{p} \alpha_i \Delta y_{t-i} + \varepsilon_t \tag{4.3}$$

In this equation, Δy_t denotes the first difference of the series, μ is the intercept, β captures a deterministic trend, γ is the coefficient on the lagged level y_{t-1} (whose significance is tested to determine stationarity), and α_i are the coefficients on the lagged differences. The null hypothesis is $\gamma = 0$, indicating a unit root.

Given the nature of the dependent variable in this study, the monthly count of IPOs in Italy, stationarity will be addressed differently depending on the type of analysis. For the Poisson, the Negative Binomial Autoregression, and the INAR NB models, stationarity transformations will not be applied to the dependent variable, as these models are designed to handle count data directly. However, for Granger causality tests and the Vector

Autoregression (VAR) model, the dependent variable will be differenced if it is found to be non-stationary. This ensures that the assumptions of these models are met. The ADF test will also be applied to the macroeconomic covariates, and any non-stationary covariates will similarly be differenced for inclusion in the Granger causality and VAR models.

4.1.3 Autocorrelation Analysis

Autocorrelation measures the degree of dependency between a time series and its lagged values. To examine the autocorrelation structure of the dependent variable, the Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) will be computed. The ACF provides an overall view of the correlation at different lag levels, while the PACF isolates the correlation at each lag, removing the influence of intervening lags. These diagnostics are essential for identifying the appropriate lag structure for the autoregressive models.

In addition to autocorrelation within the dependent variable, cross-correlation between the dependent variable and each covariate will be examined using the Cross-Correlation Function (CCF). This analysis will assist in selecting the appropriate lags of the covariates to include in the models. Identifying significant cross-correlation at specific lags ensures that the temporal relationships between variables are accurately captured.

4.2 Autoregressive Models for Count Data

Given the characteristics of the dependent variable in this study, the monthly number of Initial Public Offerings (IPOs) in Italy, a modeling framework tailored to count data is essential. The number of IPOs is a discrete variable, often characterized by small counts and a high number of zero observations. We need models that are suitable for such data with the ability to accommodate the discrete and non-negative nature of the dependent variable. To address these challenges, this study employs Poisson Autoregression and, once the overdispersion of such data is explored, Negative Binomial Autoregression models. These models are typically estimated via maximum likelihood estimation and are sometimes referred to as log-linear autoregressive count models.

4.2.1 Poisson Autoregression

The Poisson autoregression model with covariates assumes that the dependent variable Y_t at time t follows a Poisson distribution:

$$Y_t \sim \text{Poisson}(\lambda_t) \tag{4.4}$$

where the conditional mean λ_t is modeled as:

$$\lambda_t = \exp\left(\beta_0 + \sum_{k \in K} \beta_k Y_{t-k} + \mathbf{X}_t^\top \boldsymbol{\gamma}\right). \tag{4.5}$$

Here, Y_t represents the count of IPOs at time t. The parameter β_0 is the intercept term, and the summation $\sum_{k \in K} \beta_k Y_{t-k}$ captures the autoregressive dynamics via selected lags (e.g., if $K = \{1, 12\}$, only Y_{t-1} and Y_{t-12} are included). The vector $\mathbf{X}_t$ comprises macroeconomic covariates at time t with corresponding coefficients $\boldsymbol{\gamma}$. The exponential link function $\exp(\cdot)$ ensures that λ_t remains strictly positive, which is essential for modeling count data.

This specification builds upon a robust body of literature. Freeland and McCabe (2004) provide an analysis of low count time series data using Poisson autoregression, highlighting its suitability for sparse count data. Fokianos et al. (2009) offer a comprehensive treatment of Poisson autoregression models, while Jung and Tremayne (2002) discuss coherent forecasting in integer time series models. Moreover, Fokianos (2012) reviews count time series models in depth, underlining the importance of the exponential link in ensuring a positive conditional mean.

After estimating the Poisson Autoregression model, it is essential to evaluate whether the underlying assumptions of the model hold. Specifically, the Poisson model assumes that the mean and variance of the dependent variable are equal. To test this assumption, overdispersion diagnostics will be conducted. Overdispersion occurs when the variance of the dependent variable exceeds its mean, which can result in underestimated standard errors and biased statistical inferences in the Poisson model.

If significant overdispersion is detected, the Negative Binomial Autoregression model will be employed. The Negative Binomial model extends the Poisson model by introducing an additional parameter that explicitly accounts for overdispersion. This adjustment allows the variance of the dependent variable to exceed the mean, accommodating the variability typically observed in count data like IPO activity. The flexibility of the Negative Binomial model makes it more robust when dealing with datasets characterized by small counts, large variability, and an excess of zero observations Hilbe 2012.

4.2.2 Negative Binomial Autoregression

The Negative Binomial autoregression model with covariates assumes that the dependent variable Y_t at time t follows a Negative Binomial distribution:

$$Y_t \sim \mathrm{NB}(\mu_t, \phi), \tag{4.6}$$

where μ_t is the conditional mean and ϕ is the dispersion parameter that allows for overdispersion (i.e., when the variance exceeds the mean). The conditional mean μ_t is modeled as:

$$\mu_t = \exp\left(\beta_0 + \sum_{k \in K} \beta_k Y_{t-k} + \mathbf{X}_t^\top \boldsymbol{\gamma}\right). \tag{4.7}$$

In this formulation, Y_t represents the count of IPOs at time t, β_0 is the intercept, and the term $\sum_{k \in K} \beta_k Y_{t-k}$ captures the influence of lagged dependent variables (e.g., if $K = \{1, 12\}$, then only Y_{t-1} and Y_{t-12} are included). The vector $\mathbf{X}_t$ comprises macroeconomic covariates with corresponding coefficients $\boldsymbol{\gamma}$, and the exponential link function ensures that μ_t remains strictly positive.

This specification builds upon a substantial body of literature. Davis and Wu (2009) introduce a Negative Binomial model for time series of counts, demonstrating its suitability for data exhibiting overdispersion. Chen et al. (2016) extend this framework by incorporating autoregressive dynamics in overdispersed count data. The approach is also thoroughly discussed by Cameron and Trivedi (1996) and further elaborated in Hilbe (2012) , which highlight the flexibility of the Negative Binomial framework. Notably, as the dispersion parameter ϕ approaches zero, the Negative Binomial model converges to the Poisson model, thereby linking this model to the Poisson autoregression discussed earlier. This flexibility makes the Negative Binomial Autoregression model especially robust for datasets characterized by small counts, substantial variability, and a potential excess of zeros, as is often observed in IPO activity.

Both models will be estimated using maximum likelihood estimation.

4.2.3 Integer-Valued Autoregressive Negative Binomial

Following our earlier analyses using Poisson and Negative Binomial Autoregression models, we now introduce the Integer-Valued Autoregressive Negative Binomial (INAR-NB) model as a refined approach to capture both the overdispersion of IPO counts and their temporal dependencies. Its development is grounded in early work by Steutel and van Harn (1979) and was formalized for first-order processes by Al-Osh and Alzaid (1987). The model has later been extended to include covariates, see the works of Du and Li (1991) and Al-Osh and Aly (1992). In our context, the INAR-NB model, originally advanced by Al-Osh and Aly (1992) and recently applied by Wamwea et al. (2023) , is adopted to capture both temporal dependence and overdispersion in IPO counts while preserving the integer nature of the data.

In contrast to the Negative Binomial Autoregression (NB-AR) model, where lagged dependent variables are directly included as covariates, effectively treating the counts as continuous, the INAR-NB model employs a thinning operator ($\circ$) to explicitly account for the discrete retention of past events. This operator ensures that only a random subset of past events, each retained with probability α, influences the current count, thereby better modeling the inherent discreteness of IPO activity.

The INAR-NB model is specified as follows. Let Y_t denote the count of IPOs at time t. The model is given by:

$$Y_t = \alpha \circ Y_{t-1} + \varepsilon_t, \tag{4.8}$$

where $\alpha \in [0, 1]$ is the autoregressive parameter and the thinning operator is defined as

$$\alpha \circ Y_{t-1} = \sum_{i=1}^{Y_{t-1}} \xi_{t,i}, \tag{4.9}$$

with $\{\xi_{t,i}\}$ being independent Bernoulli random variables with success probability α [6]. This formulation captures the idea that each event in Y_{t-1} is retained with probability α. To incorporate the effect of macroeconomic covariates and to address overdispersion, we assume that the innovation term ε_t follows a Negative Binomial distribution. Its conditional mean is modeled using a log-linear function:

$$\mu_t = \exp\left(\beta_0 + \mathbf{X}_t^\top \boldsymbol{\gamma}\right), \tag{4.10}$$

where β_0 is the intercept, $\mathbf{X}_t$ is a vector of covariates at time t, and $\boldsymbol{\gamma}$ is a vector of corresponding coefficients. It is important to note that equation (4.10) specifies the conditional mean of the innovation term ε_t, not the overall conditional mean of Y_t. The overall conditional expectation of Y_t given Y_{t-1} and $\mathbf{X}_t$ is given by:

$$\mathbb{E}(Y_t \mid Y_{t-1}, \mathbf{X}_t) = \alpha\, Y_{t-1} + \exp\left(\beta_0 + \mathbf{X}_t^\top \boldsymbol{\gamma}\right). \tag{4.11}$$

Thus, the autoregressive component (equation 4.8) and the covariate-driven innovation (equation 4.10) are linked in that the overall expected count is the sum of the retained counts from the previous period and the new counts generated by exogenous factors.
Both the autoregressive parameter α and the covariate effects $\boldsymbol{\gamma}$ are estimated simultaneously, via maximum likelihood estimation, as discussed by Freeland and McCabe (2005). Lag selection for the autoregressive term and for the inclusion of covariates is guided by the autocorrelation function (ACF), partial autocorrelation function (PACF), and cross-correlation function (CCF) analyses performed during preliminary model diagnostics.
In summary, the complete INAR-NB model with covariates can be written as:

$$Y_t = \alpha \circ Y_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim \mathrm{NB}\left(\mu_t, \phi\right), \tag{4.12}$$

with μ_t defined in equation (4.10). This specification effectively separates the contribution of past IPO activity from the influence of macroeconomic conditions, making it a robust framework for analyzing count data that exhibit both overdispersion and temporal dependency.

4.3 Vector Autoregressive Framework Analysis

In this section, we present an alternative approach to analyzing IPO activity by employing linear time series techniques. Unlike the Poisson and Negative Binomial autoregressive models discussed earlier, which are specifically designed to handle the discrete and overdispersed nature of count data, the linear approach is based on the Vector Autoregression (VAR) model. In addition, we use Variance Decomposition (VD) and Impulse Response Functions (IRF) to assess the impact of shocks, as well as Granger Causality tests to investigate predictive relationships.
While these methods are valuable for exploring dynamic interactions among variables, it is important to note that linear models are not ideally suited for count data. Therefore, the results from the linear analysis should be interpreted as complementary to the insights gained from the count data models.

4.3.1 Vector Autoregressive Model

The Vector Autoregression (VAR) model is employed to analyze the dynamic interdependencies between the monthly number of IPOs in Italy and the selected macroeconomic variables. Unlike the Poisson and Negative Binomial models, which focus on modeling count data, the VAR model is applied to stationary and continuous time series, providing a broader understanding of the relationships between variables in a multivariate framework.
The VAR model is well-suited for this study because it treats all variables as endogenous, allowing for the exploration of feedback loops and interactions between IPO activity and macroeconomic indicators. By capturing these interdependencies, the VAR model enables the study of how shocks to one variable propagate through the system over time. This is particularly relevant for understanding how changes in particular variables influence others and vice versa.
The VAR model expresses each variable as a linear function of its own lagged values and the lagged values of all other variables in the system. The general form of a VAR(p) model, where p represents the number of lags, is as follows:

$$\mathbf{Y}_t = \mathbf{c} + \mathbf{A_1}\mathbf{Y_{t-1}} + \mathbf{A_2}\mathbf{Y_{t-2}} + ... + \mathbf{A_p}\mathbf{Y_{t-p}} + \mathbf{e_t} \tag{4.13}$$

In that model, $\mathbf{Y}_t$ represents the vector of endogenous variables at time t. The equation allows each variable to be predicted by its own lagged values and lagged values of other variables in the system. The constant vector $\mathbf{c}$ provides the baseline intercept, while the

coefficient matrices $\mathbf{A}_i$ capture the dynamic interdependencies between variables across different lags. The number of lags is determined by p, with each lag matrix describing how past values influence current values. The error term $\mathbf{e}_t$ captures the unexplained variation, reflecting the stochastic nature of the time series interactions.
The process of choosing the maximum lag p in the VAR model requires special attention because inference is dependent on correctness of the selected lag order.
Moreover, while the VAR model is a powerful tool, it relies on several assumptions, including stationarity and the absence of multicollinearity between variables. It is also assumed that the error terms are homoscedastic and serially uncorrelated (i.e., they behave as white noise), which is critical for the validity of statistical inference.
Additionally, the model does not impose theoretical constraints on the relationships between variables, meaning that results are purely data-driven. Therefore, care must be taken when drawing conclusions, as the VAR model captures statistical relationships but does not imply causality in a structural sense.

4.3.2 Variance Decomposition and Impulse Response Function

The Variance Decomposition (VD) and Impulse Response Function (IRF) analyses are essential tools for interpreting the results of the Vector Autoregression model. These methods provide deeper insights into the dynamic interactions between the variables of interest, highlighting the relative importance of each variable in explaining variations and tracing the propagation of shocks through the system. Variance Decomposition quantifies the contribution of each variable in the VAR model to the forecast error variance of the dependent variable over different time horizons. In this study, VD helps to identify which macroeconomic variables have the largest explanatory power for variations in IPO activity over time.
On the other hand, the Impulse Response Function traces the dynamic response of a variable to a one-unit shock in another variable in the VAR system. In the context of this study, the IRF is used to examine how IPO activity reacts to exogenous shocks in the macroeconomic variables over time. Typically, the IRF is computed using a Cholesky decomposition to orthogonalize shocks.
Both VD and IRF analyses rely on the correct specification of the VAR model, including stationarity and the appropriate lag structure. Additionally, the results may be sensitive to the ordering of variables if the Cholesky decomposition is used to orthogonalize shocks. This potential sensitivity will be addressed by considering alternative orderings as part of the robustness checks.
By combining VD and IRF analyses, this study aims to provide a comprehensive understanding of how macroeconomic shocks influence IPO activity in Italy, offering valuable insights into the dynamic interplay between financial markets and the broader economy.

4.3.3 Granger Causality Test

The Granger causality (GC) test is implemented to examine whether the macroeconomic variables considered in this study can provide predictive information about the monthly number of IPOs in Italy. Unlike the Poisson and Negative Binomial Autoregression models, which are designed for count data, the GC test and subsequent Vector Autoregression (VAR) analysis rely on the assumption of stationarity and are applied to transformed data when necessary. These analyses are conducted after completing the modeling with Poisson and Negative Binomial methods, providing complementary insights into the relationships between variables.

If any of the variables, including the dependent variable (Number of IPOs), are found to be non-stationary, they will be differenced to achieve stationarity. This step ensures that the assumptions of the test are met and that spurious causality due to trends in the data is avoided.

The Granger causality test evaluates whether lagged values of one variable can provide statistically significant predictive information about another variable, beyond what is explained by the variable's own past values. In this study, the test is applied to determine whether the macroeconomic variables Granger-cause IPO activity.

The results of the Granger causality test will provide insights into the potential predictive relationships between macroeconomic variables and IPO activity. However, it is important to emphasize that Granger causality does not imply true causation in a structural sense; it only identifies temporal precedence and predictive capability. Additionally, the test is sensitive to the choice of lag length, and incorrectly specifying the lag structure can affect the reliability of the results.

4.4 Forecasting

To assess the predictive performance of the models, an out-of-sample forecasting approach was employed. This method allows for the evaluation of how well the models generalize to new, unseen data, providing a robust measure of their forecasting capabilities beyond the sample used for estimation.

The data was divided into two distinct sets: an in-sample period used for model estimation (Jan 2000 - Dec 2022) and an out-of-sample period reserved for forecast evaluation (Jan 2023 - Dec 2023). The models were trained on the in-sample data, capturing the underlying patterns and temporal dependencies, and then used to generate forecasts for the out-of-sample period. The out-of-sample period consisted of monthly IPO counts, and the forecasted values were compared against the actual observed data to assess the accuracy of each model.

Three different models were utilized for this forecasting exercise: the Poisson Autoregressive (Poisson AR) model, the Negative Binomial Autoregressive (Negative Binomial AR) model, and the Vector Autoregression (VAR) model. The Poisson AR and Negative Binomial AR models are specifically designed to handle count data, with the former assuming equidispersion and the latter accommodating overdispersion. The VAR model, in contrast, is a multivariate time series model that captures linear interdependencies among multiple variables but is not inherently tailored to count data characteristics.

The forecast accuracy was evaluated using two standard error metrics: Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). RMSE measures the square root of the average squared differences between the predicted and actual values, giving greater weight to larger errors. MAE, on the other hand, computes the average absolute differences, providing a more straightforward interpretation of the average forecast error. Both metrics offer complementary insights into model performance, with lower values indicating better predictive accuracy.

The use of out-of-sample forecasting ensures that the evaluation of the models is not biased by overfitting to the training data. By comparing the forecasts to actual IPO counts in the holdout period, the analysis provides a clear indication of how each model performs in a real-world predictive context. This methodology is critical in determining the practical applicability of the models for forecasting IPO activity and identifying which modeling approach offers the most reliable predictions.

5 Analysis

5.1 Preliminary Analysis Results

5.1.1 Multicollinearity Check

To ensure the robustness of regression estimates, variance inflation factor (VIF) analysis was conducted to detect multicollinearity among predictor variables. VIF quantifies the severity of linear dependencies between regressors, with values exceeding 5 indicating moderate multicollinearity and values above 10 signaling severe issues that warrant variable exclusion or transformation.

The test was first performed on all the variables, inclusive of the IPO counts and the six macroeconomic ones. However, the results indicated values of the Long-Term Interest Rate and the MRO rate higher than the critical levels. Thus, the variable of the long-term interest rate was eliminated from all the future analysis to avoid multicollinearity issues. The test was then performed again on the remaining variables to confirm that the potential issues were eliminated.

The results, presented in Table 5.1, demonstrate that all variables exhibit VIF values well below the conservative threshold of 5. Industrial production and the monetary policy rate show minimal inflation (VIF = 1.17 and 1.15, respectively), while market volatility registers the highest VIF at 1.42. These findings confirm that multicollinearity does not pose a significant threat to the validity of coefficient estimates in subsequent models.

Table 5.1: Variance Inflation Factor Test

Variable	**VIF**
N. of IPOs	1.084
Ind. Prod.	1.171
MRO Rate	1.149
Inflation	1.119
FTSE MIB Ret.	1.237
FTSE MIB Vol.	1.424

Notes: Values with $VIF < 5$ were considered reliable.

Given these results, no variables were excluded or transformed to address multicollinearity. The low VIF values reflect the orthogonal design of the macroeconomic predictors, which capture distinct dimensions of Italy's economic environment. This outcome reinforces the suitability of the selected variables for inclusion in autoregressive and vector autoregression (VAR) models, as they provide complementary information without redundant explanatory power.

5.1.2 Testing for Unit Roots

The Augmented Dickey-Fuller (ADF) test was employed for each variable in the dataset. The ADF test evaluates the null hypothesis that a unit root is present in the series, against the alternative hypothesis of stationarity. The test equation includes a constant term and a lagged dependent variable to account for serial correlation. 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.
The results of the ADF tests, summarized in Table 5.2, reveal mixed stationarity properties across the variables. The IPO activity series and the monetary policy rate exhibit non-stationarity, failing to reject the null hypothesis at the 5% significance level. In contrast, industrial production, the stock market index, and market volatility show strong evidence of stationarity, with ADF statistics well below the 5% critical value. The inflation rate presents a borderline case, rejecting the null hypothesis at the 5% level but remaining close to the 10% critical threshold, suggesting cautious interpretation in subsequent models.

Table 5.2: Augmented Dickey-Fuller Test

Variable	**ADF Statistic**	**p-value**
N. of IPOs	−2.646	0.0838
Ind. Prod.	−4.644	0.0001***
MRO Rate	−2.223	0.1979
Inflation	−2.900	0.0454**
FTSE MIB Ret.	−4.777	0.0001***
FTSE MIB Vol.	−3.504	0.0079***

Notes: Critical values for the ADF test at 1% (***), 5% (**), and 10% (*) significance levels are -3.454, -2.872, and -2.572, respectively.

The treatment of non-stationary variables depends on the modeling framework employed. For autoregressive models explicitly designed for count data, such as Poisson AR, Negative Binomial AR, and INAR NB, non-stationarity in the IPO series (num_ipos) will not be addressed via differencing. In fact, these models inherently account for temporal dependencies through autoregressive terms and exogenous predictors, preserving the integer-valued structure of the dependent variable while capturing trends via covariates or lagged effects. This approach aligns with the theoretical interpretation of IPO activity as a discrete process influenced by lagged macroeconomic conditions.

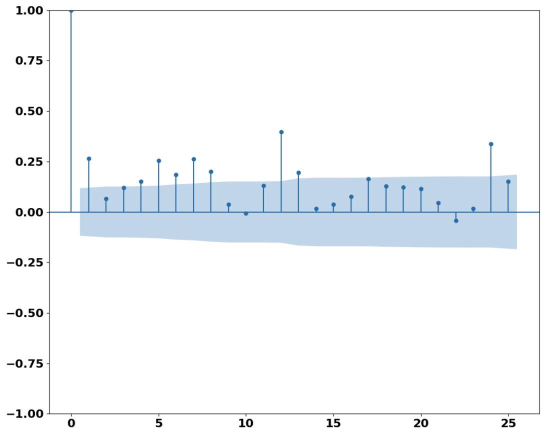
By contrast, Granger Causality tests and Vector Autoregression (VAR) models require strict stationarity for valid inference. To satisfy this precondition, the number of IPOs and the monetary policy rate will be first-differenced in these analyses, enabling their inclusion in VAR frameworks. This could create some distortion of the original count structure, but it is necessary when working with these models.

5.1.3 Autocorrelation and Cross-Correlation Analysis

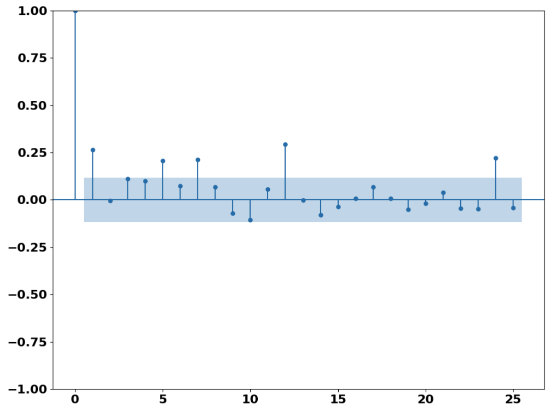
The autocorrelation (ACF) and partial autocorrelation (PACF) functions, displayed in Figures 5.1a and 5.1b, provide critical insights into the temporal dependence structure of monthly IPO activity in Italy. These functions help determine whether past IPO counts influence future values and inform the selection of autoregressive components for count data models while validating earlier findings on non-stationarity.

Figure 5.1: Autocorrelation and Partial Autocorrelation Functions of Monthly IPO Counts

(a) ACF of the Number of IPOs



(b) PACF of the Number of IPOs



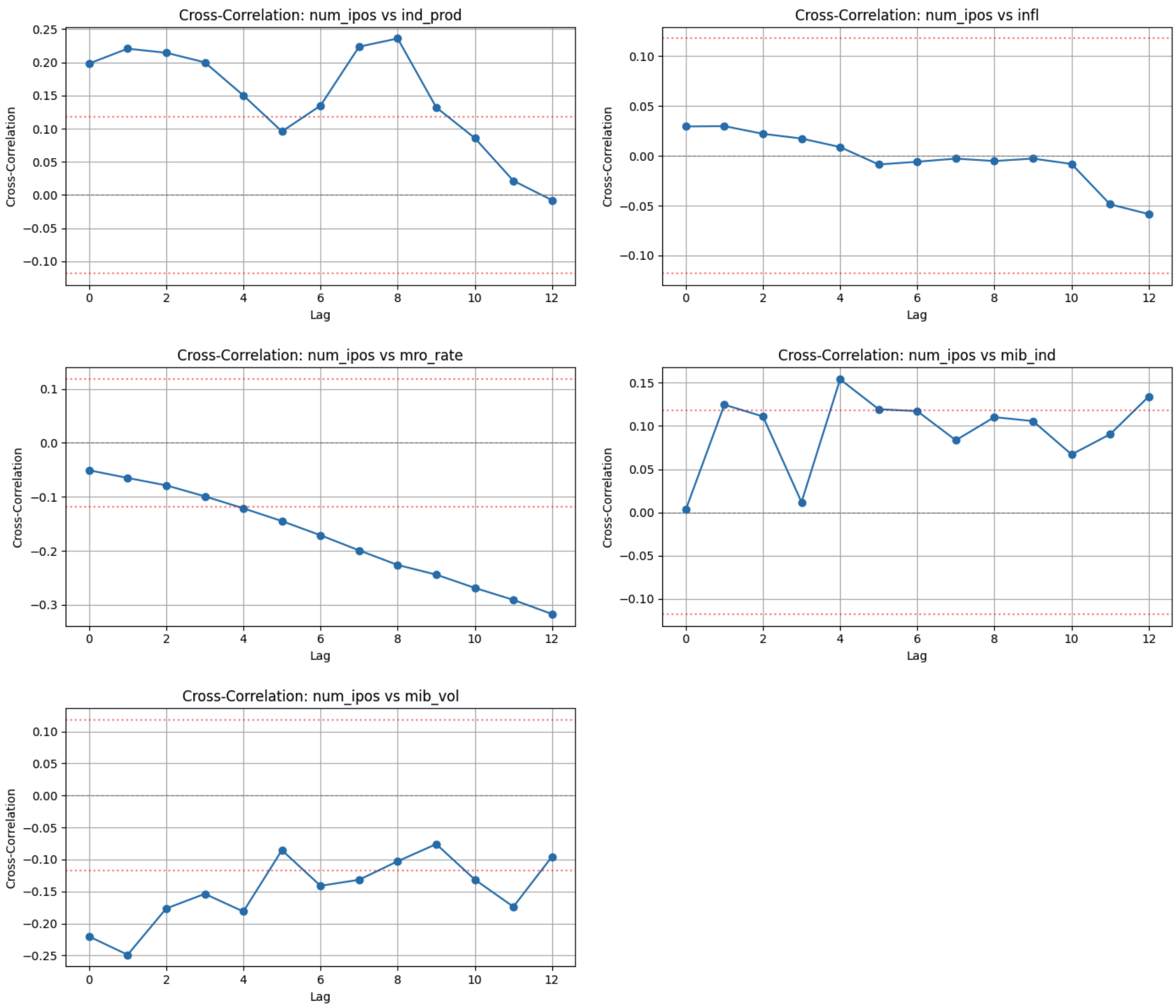
Notes: Dashed lines denote 95% confidence intervals.

Both cases show relevant autocorrelation at the lags 12 and 24, signaling strong seasonal patterns and long-term cyclical dependencies in the data.

The ACF plot shows significant positive autocorrelations at several lags, particularly in the first few months, indicating that IPO activity exhibits persistence over time. This suggests that months with high IPO counts tend to be followed by months with similarly high counts. Some spikes beyond the confidence bands imply statistically significant autocorrelations at specific lags.

The PACF plot exhibits significant partial autocorrelations at shorter lags, particularly at lags 1, 5, 7, suggesting that IPO activity may be best modeled using an autoregressive process in which past IPO levels influence future values. The significant drop in partial autocorrelations after a few lags suggests that an autoregressive structure with a limited number of lags may be appropriate.
The cross-correlation functions (CCFs) between monthly IPO counts and macroeconomic variables, showed in Figure 5.2 reveal distinct lagged relationships critical to understanding the drivers of IPO activity.

Figure 5.2: Cross-Correlation Functions



Notes: Dashed lines denote 95% confidence intervals.

Industrial production exhibits a significant positive correlation peaking at lag 8, indicating that improvements in economic output precede IPO surges by approximately eight months, a delay consistent with firms' strategic timing to align listings with post-recovery growth phases. Conversely, the ECB monetary policy rate shows a strong negative correlation at lag 12, underscoring the deterrent effect of rising interest rates on equity issuance over extended horizons. Market volatility demonstrates an immediate negative impact, reflecting issuers' aversion to launching IPOs during turbulent periods, while stock market returns exhibit sporadic positive correlations, notably at lag 4, suggesting equity market booms indirectly stimulate listings after short delays. Inflation, however, shows no statistically significant contemporaneous or lagged relationship with IPO activity, aligning with mixed theoretical expectations about its role. These results advocate for incorporating variable-specific lag structures into autoregressive models, with industrial production and monetary policy rates prioritized at lags 8 and 12, respectively, while contemporaneous market volatility is treated as an immediate deterrent. These insights directly inform the lag selection for exogenous predictors in subsequent count data models, ensuring alignment with observed temporal dynamics.

5.2 Autoregressive Models for Count Data Results

The analysis of monthly IPO counts necessitates specialized autoregressive frameworks, as traditional models inadequately capture the discrete, overdispersed, and autocorrelated nature of the dependent variable. Building on the temporal dependencies identified in Section 5.1.3, notably the persistent autocorrelation (ACF) and dominant AR(1) structure (PACF), this section evaluates three count data models: the Poisson Autoregression, its Negative Binomial extension to address overdispersion, and an Integer-Valued Autoregressive (INAR) formulation that explicitly preserves the discrete evolution of IPO counts. Each model incorporates lagged values of the dependent variable and macroeconomic covariates, enabling a granular assessment of how past IPO activity and economic conditions jointly shape listing behavior, while avoiding the interpretational distortions of differencing or continuous approximations. Considering this models can handle count data, for this part of the analysis we didn't apply any transformation to the non-stationary data.

5.2.1 Poisson Autoregression

In order to model the dynamics of IPO listings over time, we begin our analysis with autoregressive models for count data, starting with a Poisson autoregression. The choice of lags and variables was driven by a thorough examination of the cross-correlation function (CCF) as well as the autocorrelation (ACF) and partial autocorrelation (PACF) functions. This preliminary analysis suggested that the first and twelfth lags of the number of IPOs capture important autoregressive patterns, while several other economic and market variables also exhibit meaningful lagged relationships with IPO listings. In particular, we included both the contemporaneous and lagged values of industrial production, the mortgage rate, FTSE MIB returns, and trading volumes to account for potential delayed

effects.
The Poisson autoregression model was chosen as an initial approach because it provides a straightforward framework to handle count data while incorporating autoregressive components. By assuming that the number of IPOs follows a Poisson distribution, the model expresses the logarithm of the expected count as a linear function of the selected covariates. This specification is not only computationally simple but also appropriate given the discrete and non-negative nature of the dependent variable.

Table 5.3: Poisson Autoregression Model Results

Variable	**Coefficient**	**Std. Error**	**p-value**
const	1.0082	0.157	0.000***
N. of IPOs L1	0.0325	0.020	0.097*
N. of IPOs L12	0.1536	0.016	0.000***
Ind. Prod.	-0.0011	0.007	0.875
Ind. Prod. L1	0.0132	0.006	0.027**
MRO Rate L12	-0.1820	0.035	0.000***
FTSE MIB Ret. L4	0.0247	0.008	0.003***
FTSE MIB Vol.	-0.0408	0.021	0.050**
FTSE MIB Vol. L1	-0.0620	0.023	0.006***

Notes: Significance levels at 1% (***), 5% (**), and 10% (*)

Table 5.3 summarizes the estimation results. The findings reveal a pronounced autoregressive structure: the twelfth lag of IPO listings is highly significant and positive, implying that past IPO activity, possibly reflecting seasonal or delayed effects, is a strong predictor of current listings. Moreover, the significant positive coefficient on the lagged industrial production variable indicates that higher levels of industrial output are associated with increased IPO activity, whereas the negative coefficient for the lagged mortgage rate suggests that tighter credit conditions adversely affect the likelihood of listing. Notably, the lagged FTSE MIB returns also appear as a significant predictor, reinforcing the notion that stock market performance exerts considerable influence on firms' listing decisions. In contrast, the contemporaneous measure of industrial production does not show a significant effect, suggesting that the market and economic conditions impacting IPO listings manifest with a delay.
The estimated marginal effects from the Poisson autoregression model are shown in Table 5.4. The results indicate that past IPO activity has a positive and significant impact on current IPO volumes, with the 12-month lag showing a particularly strong effect. Economic indicators also play an important role: lagged industrial production positively influences IPO activity, while tighter monetary conditions, as captured by the ECB's MRO rate—exert a significant negative impact. Moreover, the FTSE MIB index and market volatility measures reveal that stronger market performance boosts IPO activity,

whereas increased volatility dampens it.

Table 5.4: Average Marginal Effects from the Poisson AR Model

Variable	**Coefficient**	**Std. Error**	**p-value**
N. of IPOs L1	0.0638	0.039	0.098*
N. of IPOs L12	0.3015	0.034	0.000***
Ind. Prod.	-0.0021	0.013	0.875
Ind. Prod. L1	0.0259	0.012	0.028**
MRO Rate L12	-0.3575	0.070	0.000***
FTSE MIB Ret. L4	0.0486	0.016	0.003***
FTSE MIB Vol.	-0.0800	0.041	0.051*
FTSE MIB Vol. L1	-0.1218	0.045	0.007***

Notes: Significance levels at 1% (***), 5% (**), and 10% (*)

These results underscore the dynamic interplay between past market conditions and current IPO decisions.
It's important to state that the Poisson model assumes that the mean and variance of the count variable are equal. However, our analysis indicates that this assumption does not hold for our data. Specifically, the Pearson residual-based dispersion statistic was calculated to be approximately 1.44, while the average number of IPOs is 2.05 and the variance is 4.80. This excess in variance relative to the mean is a clear indication of overdispersion. To address this issue and ensure the reliability of our results, we proceed by estimating a Negative Binomial autoregression model, which is better suited for handling count data with overdispersion.

5.2.2 Negative Binomial Autoregression

In light of the evidence of overdispersion in our count data, we proceeded to estimate a Negative Binomial autoregressive model. This approach is better suited to accommodate the extra-Poisson variation observed in the data. We maintained the same covariate specification used in the Poisson autoregression, including the first and twelfth lags of the number of IPOs, as well as selected lagged economic and market variables. Estimating the model via a generalized linear model framework with a Negative Binomial family, we obtained results that largely confirm the importance of past IPO activity and other macroeconomic indicators in predicting current IPO listings.

The estimation results indicate that the twelfth lag of IPO listings remains a highly significant predictor, reinforcing the notion of a persistent and delayed influence on current listing activity. In contrast, the immediate autoregressive term (lag 1) is not statistically

Table 5.5: Negative Binomial Autoregression Model Results

Variable	**Coefficient**	**Std. Error**	**p-value**
const	1.0811	0.269	0.000***
N. of IPOs L1	0.0101	0.038	0.792
N. of IPOs L12	0.1788	0.034	0.000***
Ind. Prod.	-0.0010	0.014	0.943
Ind. Prod. L1	0.0135	0.013	0.302
MRO Rate L12	-0.1880	0.058	0.001***
FTSE MIB Ret. L4	0.0270	0.014	0.056*
FTSE MIB Vol.	-0.0457	0.033	0.171
FTSE MIB Vol. L1	-0.0710	0.036	0.049**

Notes: Significance levels at 1% (***), 5% (**), and 10% (*)

significant, suggesting that the effect of IPO activity is more pronounced over a longer horizon. Additionally, the lagged MRO rate exhibits a significant negative effect, which implies that tighter monetary policy conditions are associated with a lower likelihood of firms going public. The effect of FTSE MIB returns, captured by mib_ind_lag4, is marginally significant, which supports the interpretation that stock market performance continues to exert an influence on IPO decisions, although with somewhat reduced statistical strength compared to the Poisson specification. Last, both the FTSE MIB volatility variables show statistical significance, confirming the theory that supports the high influence of the financial markets stability on the listing decisions. Overall, these findings from the Negative Binomial autoregression provide a more robust estimation in the presence of overdispersion, ensuring the reliability of our inference regarding the determinants of IPO listings.

The marginal effects from the Negative Binomial autoregression model are shown Table 5.6.

The results reveal that the 12-month lag of IPO activity exerts a strong positive influ-

Table 5.6: Average Marginal Effects from the Negative Binomial AR Model

Variable	**Coefficient**	**Std. Error**	**p-value**
N. of IPOs L1	0.0201	0.076	0.792
N. of IPOs L12	0.3570	0.083	0.000***
Ind. Prod.	-0.0019	0.027	0.943
Ind. Prod. L1	0.0270	0.026	0.306
MRO Rate L12	-0.3754	0.125	0.003***
FTSE MIB Ret. L4	0.0538	0.029	0.063*
FTSE MIB Vol.	-0.0913	0.068	0.177
FTSE MIB Vol. L1	-0.1418	0.074	0.054*

Notes: Significance levels at 1% (***), 5% (**), and 10% (*)

ence on current IPO volumes. In contrast, the short-term IPO lag and the production measures exhibit statistically insignificant effects. Notably, the ECB's MRO rate (lagged 12 months) shows a significant negative effect, underscoring that tighter monetary conditions reduce IPO activity. Additionally, FTSE MIB returns (lagged 4 months) display a positive effect that is marginally significant, while both the current and lagged measures of market volatility tend to dampen IPO activity, with the lagged volatility being nearly significant. These findings highlight the nuanced role of macroeconomic and market variables in shaping IPO dynamics.

5.2.3 Integer-Valued Autoregressive Negative Binomial

The Integer-Valued Autoregressive Negative Binomial (INAR(1)-NB) model represents another valuable approach for analyzing our IPO count data. This model combines two crucial characteristics that make it particularly suitable for our analysis: the ability to handle integer-valued time series and the capacity to account for overdispersion in the data.

While the Poisson AR and Negative Binomial AR models previously discussed provide valuable insights, the INAR-NB model offers additional advantages by explicitly accounting for the discrete nature of IPO counts. Unlike continuous-valued autoregressive models, INAR models use a binomial thinning operator to ensure that the predicted values remain integer-valued, which better reflects the actual count process of IPO occurrences.

Overall, the INAR-NB model could address both the issues simultaneously, potentially offering a more accurate representation of the underlying IPO generation process.

For this study, an INAR(1) model with Negative Binomial innovations (INAR(1)-NB)

Table 5.7: INAR(1)-NB Model with Covariates Results

Variable	**Coefficient**	**Std. Error**	**p-value**
alpha	0.3316	0.120	0.012**
Innov. Interc.	1.5854	1.032	0.112
Ind. Prod.	-0.0043	0.003	0.151
Ind. Prod. L1	0.0105	0.007	0.234
MRO Rate L12	-0.2284	0.151	0.128
FTSE MIB Ret. L4	0.0156	0.012	0.119
FTSE MIB Vol.	-0.0444	0.036	0.139
FTSE MIB Vol. L1	-0.0714	0.041	0.155
phi	1.5341	0.530	0.017**

Notes: Significance levels at 1% (***), 5% (**), and 10% (*)

was implemented to account for both the overdispersion of IPO counts and their inherent temporal dependence while explicitly modeling the discrete nature of the data. The

results indicate that the thinning parameter α and the dispersion parameter ϕ are statistically significant (with estimates of 0.3 and 1.53, respectively), suggesting that there is a persistent component in IPO activity and that the data indeed exhibit overdispersion. However, the coefficients for the macroeconomic covariates are not statistically significant, implying that these exogenous factors do not have a strong detectable effect on IPO counts within this model specification.
One possible explanation for the lack of significant covariate effects is the relatively small sample size, which may contribute to instability in the parameter estimates and reduce the power to detect subtle relationships. Moreover, the INAR(1)-NB model, with its more complex structure incorporating the thinning operator, may be overly sophisticated relative to the characteristics of our dataset. In light of these findings and limitations, it appears more appropriate to rely on the simpler models,namely, the Poisson Autoregressive and Negative Binomial Autoregressive models, that were explored earlier in the analysis, as they may provide more stable and interpretable insights into the determinants of IPO activity.

5.3 Vector Autoregressive Framework Analysis Results

5.3.1 Vector Autoregressive Model

In constructing the Vector Autoregressive (VAR) model for this analysis, it was essential to ensure that all included time series variables were stationary, as non-stationarity can lead to unreliable and spurious results. Initial tests indicated that both num_ipos and mro_rate exhibited non-stationary behavior. To address this, we applied first differencing to these variables, a common technique to achieve stationarity in time series data.
However, it is critically important to note that differencing count data can introduce significant methodological challenges. While differencing is a standard approach for achieving stationarity, it can potentially distort the inherent characteristics of count data, which typically follow discrete, non-negative distributions. The statistical literature emphasizes the potential problems associated with differencing count series, including potential loss of important information about the underlying data-generating process and the introduction of artificial negative values. These concerns guided our primary modeling choices, which were carefully analyzed in the previous chapter.
Subsequent testing confirmed that the differenced series were stationary, validating their suitability for inclusion in the VAR model. This approach aligns with standard econometric practices, which recommend differencing non-stationary variables to ensure the robustness of VAR model estimations.

To determine the optimal lag structure for our Vector Autoregressive (VAR) model, we conducted a comprehensive lag selection process using multiple information criteria. The selection was based on four key statistical measures: Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Final Prediction Error (FPE), and Hannan-Quinn Information Criterion (HQIC). The lag selection results revealed nuanced insights into the model's optimal configuration. After examining the information criteria across different lag orders, we ultimately selected a lag order of 4 for our VAR model.

Table 5.8: VAR Order Selection

Lag Order	AIC	BIC	FPE	HQIC
0	9.378	9.457	1.182×10^4	9.409
1	5.030	**5.583***	153.0	5.252
2	4.753	5.778	115.9	**5.164***
3	4.611	6.110	100.7	5.212
4	**4.463***	6.436	**87.05***	5.255
5	4.475	6.921	88.28	5.456
6	4.496	7.415	90.52	5.667
7	4.548	7.942	95.96	5.910
8	4.654	8.521	107.5	6.206
9	4.797	9.137	125.1	6.538
10	4.694	9.507	114.3	6.625
11	4.492	9.779	94.80	6.614
12	4.524	10.28	99.72	6.836

*Notes: * indicates minimum value for each criteria*

The AIC criteria, which balances model complexity with goodness of fit, indicated the lowest value at lag 4. Similarly, the FPE also minimized at the 4-lag specification. While the BIC showed its minimum at lag 1 and the HQIC at lag 2, the comprehensive evaluation led us to choose lag 4 as the most appropriate specification for our analysis.
This approach ensures that we capture the most relevant temporal dynamics in the data while avoiding overfitting. The selection of 4 lags allows for sufficient exploration of the time-dependent relationships between our variables without introducing unnecessary complexity that could potentially obscure the underlying economic patterns.
Similar studies, such as the ones on Tran and Jeon (2011) and the one of Angelini and Foglia (2018) utilize 12 lags, as it's the suggested lag length when dealing with monthly data. However, in this thesis we will use 4 lags to avoid problems caused by the short series, given that using more lags could cause overparameterization, unstable coefficient estimates, and reduced degrees of freedom, which ultimately can compromise the reliability of the results.

The Vector Autoregressive model results for the number of Initial Public Offerings re-

Table 5.9: VAR Model Results

Variable	**Coefficient**	**Std. Error**	**t-statistic**	**p-value**
Constant	-0.155580	0.476325	-0.327	0.744
L1 Number of IPOs	-0.667588	0.058978	-11.319	0.000***
L1 Ind. Prod.	0.000483	0.025677	0.019	0.985
L1 MRO Rate	-1.277142	1.125757	-1.134	0.257
L1 Inflation	0.074283	0.279053	0.266	0.790
L1 FTSE MIB Ret.	0.033172	0.027260	1.217	0.224
L1 FTSE MIB Vol.	-0.045103	0.064067	-0.704	0.481
L2 Number of IPOs	-0.655487	0.066567	-9.847	0.000***
L2 Ind. Prod.	-0.002794	0.032533	-0.086	0.932
L2 MRO Rate	1.026789	1.061579	0.967	0.333
L2 Inflation	-0.148655	0.411835	-0.361	0.718
L2 FTSE MIB Ret.	0.021514	0.027681	0.777	0.437
L2 FTSE MIB Vol.	-0.008622	0.068661	-0.126	0.900
L3 Number of IPOs	-0.467369	0.068108	-6.862	0.000***
L3 Ind. Prod.	0.029109	0.032811	0.887	0.375
L3 MRO Rate	0.892520	1.024274	0.871	0.384
L3 Inflation	0.210527	0.431814	0.488	0.626
L3 FTSE MIB Ret.	-0.007079	0.026832	-0.264	0.792
L3 FTSE MIB Vol.	0.043415	0.066402	0.654	0.513
L4 Number of IPOs	-0.311220	0.061362	-5.072	0.000***
L4 Ind. Prod.	-0.033287	0.024847	-1.340	0.180
L4 MRO Rate	0.790761	1.092530	0.724	0.469
L4 Inflation	-0.175483	0.316339	-0.555	0.579
L4 FTSE MIB Ret.	0.047273	0.024623	1.920	0.055*
L4 FTSE MIB Vol.	0.049838	0.058854	0.847	0.397

Notes: Significance levels at 1% (***), 5% (**), and 10% (*)

veal a complex and nuanced relationship between the variables. The most statistically significant finding is the strong negative autoregressive effect, with lagged values of IPO counts consistently showing significant negative coefficients across multiple lags. Specifically, the first four lags of num_ipos have t-statistics ranging from -5.072 to -11.319, all with probability values of 0.000, indicating a robust and statistically significant negative autocorrelation.
This persistent negative autocorrelation suggests a mean-reversion tendency in the IPO market, where periods of high IPO activity are systematically followed by periods of reduced activity. The magnitude of these coefficients implies that each previous period's IPO count has a dampening effect on the subsequent period's IPO volume. For instance, the first lag (L1.num_ipos) shows a coefficient of -0.667, suggesting that a higher number of IPOs in the previous period is associated with a significant reduction in IPO activity in the current period. Interestingly, while most of the other variables show weak or statistically insignificant relationships with the number of IPOs, the lagged values of the FTSE MIB returns at the fourth lag approach statistical significance, with a t-statistic of 1.920 and a probability of 0.055. This near-significant result hints at a potential subtle influence of the stock market index on IPO activity, though the relationship is not conclusive at conventional significance levels.
The model's results underscore the complex and somewhat unpredictable nature of IPO markets, where past performance appears to be a more reliable predictor of future activity than contemporaneous macroeconomic indicators. The strong autoregressive pattern suggests that market dynamics and investor sentiment play a crucial role in determining IPO volumes, with a tendency towards mean reversion that could be valuable for understanding market behavior and potential investment strategies.
It's important to remember that, however, these results may not include all the characteristics of our variables and be inaccurate due to loss of information in differencing the count number of IPOs.

5.3.2 Variance Decomposition and Impulse Response Function

The variance decomposition serves as a complementary analytical tool to the VAR model, offering a sophisticated lens through which to interpret the complex interdependencies within the financial and economic system. By quantifying the proportion of forecast error variance attributed to each structural shock, we can discern the relative importance of different economic factors in explaining IPO market fluctuations. This approach not only enhances our understanding of the underlying mechanisms driving IPO activity but also provides a robust framework for interpreting the systemic relationships embedded within the economic landscape.

Table 5.10: Forecast Error Variance Decomposition for Number of IPOs

Period	Number of IPOs	Ind. Prod.	MRO Rate	Inflation	FTSE MIB Ret.	FTSE MIB Vol.
0	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000
1	0.985761	0.000342	0.002485	0.000178	0.009947	0.001287
2	0.976406	0.000335	0.011699	0.000624	0.009581	0.001355
3	0.965453	0.001868	0.011526	0.000764	0.016883	0.003505
4	0.951604	0.006127	0.011329	0.000876	0.026346	0.003719
5	0.949442	0.005998	0.011046	0.000938	0.028094	0.004481
6	0.949305	0.005937	0.011444	0.001016	0.027744	0.004554
7	0.947730	0.005919	0.011627	0.001736	0.028241	0.004746
8	0.947179	0.006015	0.011638	0.001811	0.028574	0.004784
9	0.946671	0.006521	0.011646	0.001809	0.028548	0.004806
10	0.946606	0.006517	0.011655	0.001831	0.028571	0.004821
11	0.946500	0.006524	0.011733	0.001842	0.028550	0.004851
12	0.946439	0.006523	0.011773	0.001861	0.028539	0.004865

Interpreting the Forecast Error Variance Decomposition (FEVD) for the number of Initial Public Offerings (num_ipos) reveals a complex and evolving narrative of systematic influences over a twelve-period horizon. The analysis provides a granular perspective on the relative contributions of different economic variables to the forecast error variance of IPO market activity.

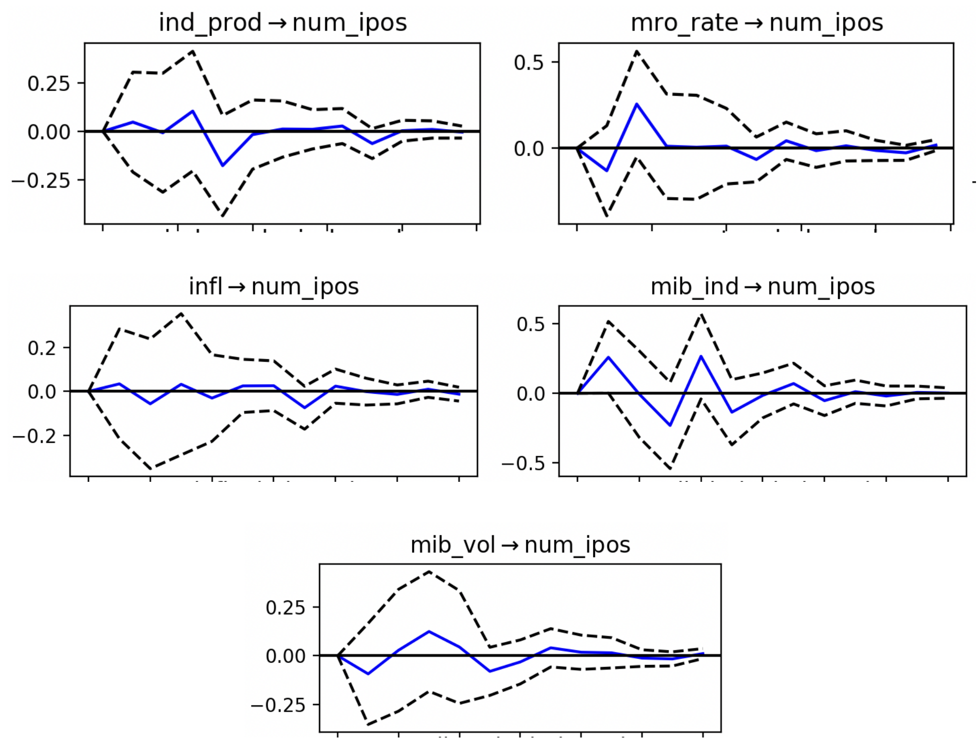
At the initial period, as expected, the variance is entirely explained by num_ipos itself, reflecting the inherent autoregressive nature of the series. However, the decomposition rapidly demonstrates the emergence of alternative explanatory factors. By the fifth period, while num_ipos continues to dominate the variance explanation, other variables begin to contribute more substantially.

The FTSE MIB emerges as the most significant external contributor, accounting for approximately 2.8-2.9% of the forecast error variance from the fourth period onward. This suggests a subtle but persistent relationship between stock market performance and IPO market dynamics. The MRO rate follows with a consistent contribution of around 1.1-1.2%, indicating a modest but stable influence of monetary policy conditions on IPO activity. Interestingly, industrial production, inflation, and market volatility demonstrate minimal explanatory power, each contributing less than 1% to the forecast error variance. This suggests that while these variables may have theoretical economic connections to IPO markets, their direct short-term predictive impact appears limited in this specific context.

Figure 5.3 displays the impulse response functions (IRFs) for the five macroeconomic variables on IPO activity. These IRFs trace the dynamic effects of a one-standard-deviation shock to each macro variable on the monthly count of IPOs over a 12-month horizon.

A closer examination of the IRFs reveals several key insights. First, the IRF for industrial production shows a significant and positive response in IPO activity immediately following the shock, which then gradually diminishes over subsequent months. This behavior

Figure 5.3: Impulse Response Functions



Notes: Dotted lines denote 95% confidence intervals.

suggests that improvements in industrial production can stimulate IPO activity, albeit with effects that fade with time. In contrast, the IRF for the MRO rate also indicates a significant response that fades with time.

The response of IPO activity to an inflation shock is characterized by a statistically insignificant response in the short term. The initial effect is not pronounced, but, as time progresses, the positive response becomes more evident. This could reflect the gradual adjustment of market participants' expectations in response to rising inflation. For the FTSE MIB index returns, the IRF reveals a strong, immediate response. The positive shock to index returns is followed by a noticeable surge in IPO activity, suggesting a close linkage between stock market performance and firms' propensity to go public. However, this effect also tends to subside over time. Finally, the IRF corresponding to FTSE MIB volatility exhibits a negative response. An increase in market volatility leads to a decline in IPO activity, which is consistent with the notion that heightened uncertainty discourages firms from entering the public market.

Overall, the IRFs underscore the heterogeneous and time-varying impacts of macroeconomic shocks on IPO activity. While some variables, such as industrial production and market returns, exert a positive influence, others like market volatility have a damping effect.

5.3.3 Granger Causality Test

To assess the dynamic interactions between our variables, we conducted Granger causality tests to determine whether the lagged values of each candidate explanatory variable help predict the number of IPOs. Consistent with the VAR model estimated earlier, we used a lag length of 4. This choice is justified by the same criteria that supported the VAR model specification.

For each candidate variable, the null hypothesis tested was that its lagged values do not Granger-cause num_ipos. The test results, based on the F-test, are summarized in Table 5.11. The results indicate that only the variable mib_ind exhibits statistically significant predictive power for num_ipos at the 5% significance level. In contrast, the other variables do not show statistically significant effects.

Table 5.11: Granger Causality Test Results

Granger Causation	**F-statistic**	**p-value**
Ind. Prod. → Number of IPOs	0.8881	0.4715
MRO Rate → Number of IPOs	0.4341	0.7840
Inflation → Number of IPOs	0.0380	0.9972
FTSE MIB Ret. → Number of IPOs	2.6548	0.0334**
FTSE MIB Vol. → Number of IPOs	1.5209	0.1963

Notes: Significance levels at 1% (***), 5% (**), and 10% (*)

Furthermore, the FTSE MIB returns was also found to be the most significant variable in the previous VAR model. This convergence of evidence indicates that the stock market performance is the most influential factor among those considered in affecting IPO listings. In practical terms, this suggests that market conditions, as reflected in FTSE MIB returns, have a substantial impact on firms' decisions to list.

5.4 Out-of-sample Forecasting

To evaluate the predictive performance of our models, Poisson Autoregression, Negative Binomial Autoregression, and Vector Autoregression (VAR), an out-of-sample forecast analysis was conducted. The models were trained on the data from 2000 to 2022 and, subsequently, tested on the 2023 data. The forecasted results were then compared against actual IPO counts, with the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) serving as key metrics to quantify model accuracy. To better reflect the nature of the predicted data, all the forecasted values were rounded to the closest integer to reflect the count nature of IPOs.

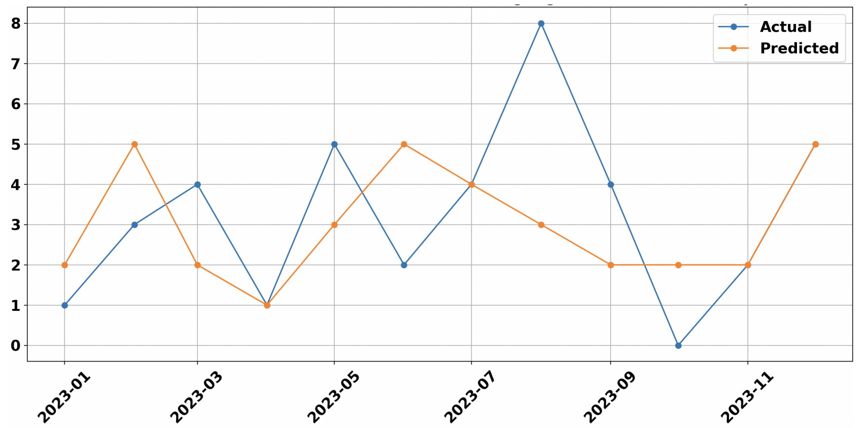
The Poisson AR model yielded a RMSE of 2.14 and a MAE of 1.58. The Negative Bi-

nomial AR model demonstrated slightly better performance, with a RMSE of 2.08 and a MAE of 1.50, while the VAR model showed the highest error values, with a RMSE of 2.43 and a MAE of 1.75. These results indicate that, among the three models, the Negative Binomial AR provided the most accurate forecasts, followed by the Poisson AR, with the VAR model lagging behind.
A visual inspection (Figure 5.4) of the forecast plots further illustrates these differences. The Poisson AR model tends to produce stable and relatively consistent forecasts, but it struggles to adapt to sudden changes in IPO activity. This is particularly evident in months with extreme variations, such as August, where the model significantly underpredicts the actual number of IPOs. The conservative nature of the Poisson AR model, stemming from its assumption of equal mean and variance, limits its ability to fully capture the volatility inherent in IPO data. As a result, its forecast line remains relatively flat in periods where the actual data exhibits more dramatic fluctuations.

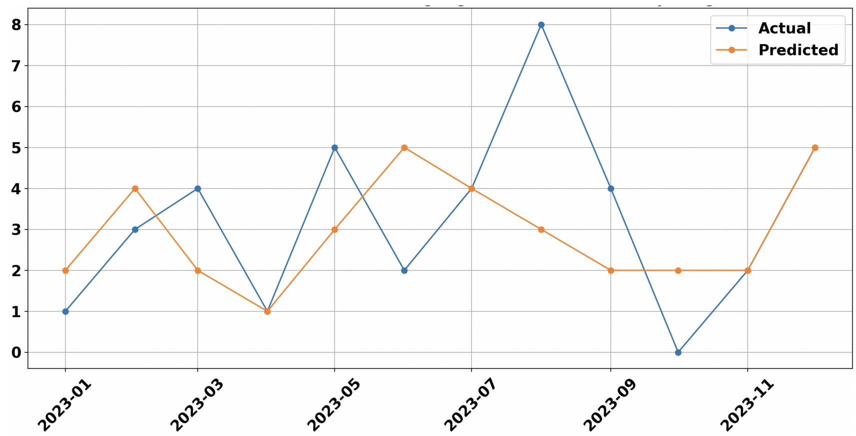
The Negative Binomial AR model, by contrast, shows improved adaptability in capturing the variability of IPO counts. Its ability to account for overdispersion allows it to better reflect the irregularities in the data. This flexibility is reflected in its superior RMSE and MAE values compared to the Poisson AR model. The Negative Binomial AR model more accurately follows the actual trend during volatile periods, though it still exhibits some limitations in capturing extreme peaks and troughs, suggesting room for further refinement.
The VAR model, despite incorporating multivariate relationships, performs the weakest in terms of both RMSE and MAE. The visual forecast indicates that the VAR model consistently underestimates the magnitude of fluctuations in IPO counts. This suggests that while the VAR framework is effective in modeling the interactions between multiple time series, it may not be well-suited to the discrete, overdispersed nature of IPO data without additional adjustments. The higher error metrics reflect this inadequacy, as the VAR model fails to capture both the trend and variability of IPO occurrences accurately.
In conclusion, the Negative Binomial AR model demonstrated the best out-of-sample forecast performance, highlighting the importance of accounting for overdispersion in count data. The Poisson AR model, while slightly less accurate, still provided reasonable forecasts, though its assumption of equidispersion limited its flexibility. The VAR model, although useful in multivariate contexts, proved less effective for forecasting IPO counts, indicating that univariate count models are more appropriate in this specific application. These results underscore the necessity of aligning model selection with the statistical characteristics of the data, particularly when forecasting time series involving discrete events like IPO activity.

Figure 5.4: Out-of-sample Forecasts

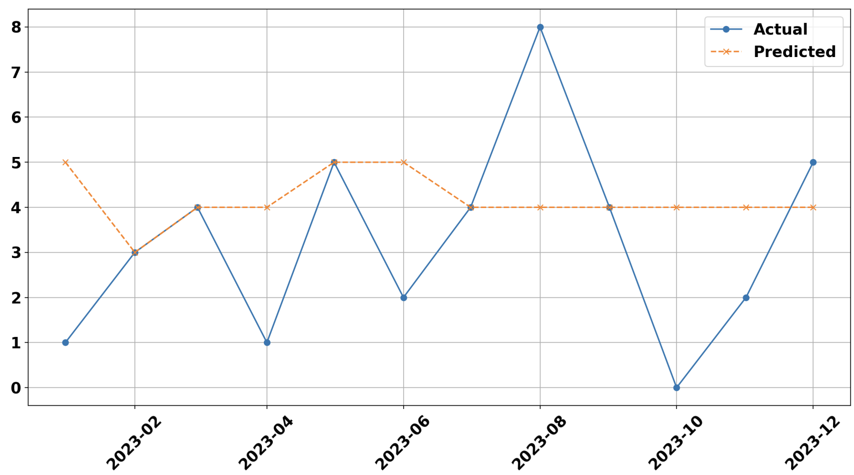
(a) Poisson AR forecasted values vs actual values



(b) Negative Binomial AR forecasted values vs actual values



(c) VAR Model forecasted values vs actual values



6 Conclusions

This study has examined the determinants of IPO activity in Italy, employing a range of econometric methodologies, including autoregressive models for count data and linear time series models. The findings offer substantial insights into the macroeconomic and financial factors influencing IPO listings and the predictive capabilities of different modeling approaches.

The autoregressive models for count data, notably the Poisson Autoregression and Negative Binomial Autoregression models, effectively captured the discrete nature of IPO activity and elucidated the impact of macroeconomic indicators. The results underscored a pronounced autoregressive structure in IPO listings, with significant influences from past IPO counts and select macroeconomic indicators. Specifically, industrial production exhibited a positive relationship with IPO activity, while the monetary policy rate and market volatility exerted negative effects. These findings are consistent with existing literature, such as Tran and Jeon (2011) , which emphasizes the role of stock market conditions and macroeconomic stability in IPO activity. However, the Integer-Valued Autoregressive Negative Binomial (INAR-NB) model did not yield reliable estimates, likely due to the relatively small sample size and the complexity of its assumptions.

Linear time series modeling, particularly the VAR framework, provided additional insights into the dynamic interactions between the inspected variables and IPO activity. The results indicated a strong negative autoregressive effect, suggesting a mean-reverting tendency in IPO markets, where periods of heightened IPO activity are generally followed by periods of decline. Among the macroeconomic predictors, the FTSE MIB index returns emerged as the most influential factor, corroborated by both Granger causality tests and impulse response function analysis. Market volatility also exhibited a deterrent effect on IPO activity but lacking statistical relevancy, reinforcing the notion that uncertainty in financial markets discourages firms from going public. This result aligns with previous literature, such as Pagano et al. (1998) , which identified stock market activity as significant predictor of new listings.

The out-of-sample forecasting exercise demonstrated that models explicitly designed for count data outperformed traditional linear time series models. The Negative Binomial Autoregressive model provided the most accurate forecasts, surpassing both the Poisson AR and VAR models. This finding underscores the importance of accounting for overdispersion and the discrete nature of IPO data when modeling such financial phenomena. Overall, this research contributes to the understanding of IPO activity in the Italian market by empirically validating the role of macroeconomic conditions in shaping listing behavior. The study highlights the necessity of selecting appropriate econometric techniques that align with the statistical properties of IPO data. While the results offer valuable insights, future research could benefit from expanding the dataset, incorporating additional financial variables, and exploring alternative non-linear modeling techniques to enhance predictive accuracy further. By refining these methodologies, policymakers, investors, and financial analysts can improve their ability to anticipate IPO market fluctuations and develop more effective investment and regulatory strategies.

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