Copenhagen Business School
Copenhagen, Spring 2019

The Dynamic Relationship between Macroeconomic Factors and Underpricing: An Empirical Study of the U.S. IPO Market

Master's Thesis 2019

Finance and Strategic Management

MSc Economics and Business Administration (Cand.merc)

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Count and Date of Submission

Characters incl. spaces: 232,137

Pages: 102.04

Date of submission: 15.05.2019

COPENHAGEN BUSINESS SCHOOL

Executive Summary

Initial Public Offerings, or simply IPOs, are fundamental in the reallocation of capital between actors in the financial markets. The listing day marks a historic event in any company's lifetime and usually receives significant attention from multiple stakeholders. The offering price of an IPO is generally valuated at 15-20 percent lower than the first closing price, hence investors tend to profit from the money being left on the table by the issuing company. The price difference also denoted underpricing or first-day returns, have long probed questions by both researchers and practitioners, as these extraordinary returns should not be achievable in an efficient market.

We seek to contribute to the academic sphere on IPOs by modeling how underpricing changes over time in correlation with transitions of the macroeconomic environment. Through the development of a statistically robust autoregressive regression model on U.S. IPOs from 2002 to 2017, we find that underpricing indeed varies according to the macroeconomic climate. More explicitly, we find that changes in financial market stress and liquidity risk, economic growth, stock returns, and long-term interest rates are all influential factors on average first-day returns. To test the predictive capability of the statistically significant variables on underpricing, we create two forecasts and find that macroeconomic indicators are highly useful in predicting IPO returns relative to a simple arithmetic average.

To shed light on our suggestions for why the correlation exists between certain macroeconomic variables and the underpricing phenomenon, the paper presents four propositions for further research. These propositions are based upon contemporary research of uncertainty in IPO-pricing as well as investor sentiment theory, yet the propositions are only subject of the authors own interpretation and therefore not prone to any explicit testing. Naturally, the paper presents useful insights, not only for researchers but also for practitioners such as investors and issuers. Amongst others, we highlight that investors should be attentive to the macroeconomic environment and the state of the financial markets before investing in IPOs.

Keywords – Initial Public Offerings, Underpricing, Macroeconomic variables, Finance

Acknowledgements

The authors would like to thank the following people for their contribution to the development of this thesis:

- Søren Ulrik Plesner, Supervisor and External Lecturer at CBS
- Benjamin Bowler, Head of Global Equity Derivates Research at Bank of America Merrill Lynch
- Professor Jay R. Ritter, University of Florida

Copenhagen Business School

Copenhagen, May 2019

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1 Introduction

At some point in time, companies need to raise capital to finance new projects and expand their operations. One of the possible methods of raising capital is to open up for the public to invest via an Initial Public Offering (IPO). IPOs are a crucial element in the reallocation of capital in the financial markets and constitute both opportunities and threats for investors and corporates alike. IPOs have persistently created above-average returns for investors on a short investment horizon, and on average the share price of a company rises approx. 15–20 percent on the listing day (Lowry et al., 2017). The phenomenon is called underpricing. The persistent underpricing in the market for equity has long provoked questions by researchers and practitioners, yet no clear theoretical consensus has been found to provide a basis for the phenomenon (Ritter and Welch, 2002). Therefore, this paper seeks to help investigate the fluctuations of underpricing in order to shed light on a perplexing paradox, as well as assist in investor decision-making regarding whether or not to buy into companies going public.

Many researchers have investigated IPO activity and the surrounding elements of what causes hot or cold IPO markets, both in terms of idiosyncratic factors such as expected growth rates, return on equity, or revenue streams (Bartov et al., 2002; Hand, 2003), but also in terms of macroeconomic factors such as economic growth, interest rate structures and so forth (Lowry and Shu, 2002; Pástor and Veronesi, 2005; Tran and Jeon, 2011). This paper seeks to contribute to the work of the macro-level researchers by analyzing IPO returns (underpricing) rather than IPO activity. To the best of our knowledge, no academic work has so far exclusively modeled underpricing as a function of macroeconomic variables, hence, we seek to investigate whether or not a correlation exists and whether this can be utilized for predicting IPO returns. Therefore, we pursue to answer the following research question:

> *What macroeconomic indicators influence IPO underpricing and in turn how well can these variables predict IPO returns?*

The analysis of this paper intends to investigate the degree to which it is possible to comprehend the underpricing phenomenon surrounding IPOs by exclusively looking at macro-environmental factors. The underlying assumption is that macroeconomic variables influence IPO returns and that IPO returns deviate from average returns contingent upon turning points within a business cycle. By utilizing data on U.S. IPOs from 1997 to 2017 and through the construction of an autoregressive distributed lag model, we indeed find evidence for the fact that macroeconomic transitions influence underpricing. Long-term interest rates, economic growth, financial market stress, liquidity risk, as well as stock market growth is found to be statistically significant predictors on IPO returns. Although the adjusted R^2 is relatively low (16.68%) we still believe that our findings have an impact on the understanding of underpricing, and additionally can help investors in their decision-making towards investing in companies going public. Furthermore, in order to test the usefulness of our findings we conduct an in-sample and a pseudo-out-of-sample forecast based on the statistically significant regressors. We find that the independent variables are advantageous in predicting IPO returns over normal arithmetic averages and that the robustness of our regression model is relatively high. Lastly, the paper discusses why the five exogenous covariates are thought to be of statistical significance, hence we derive suggestions for why the correlation exists. The suggestions can be interpreted as propositions for future research which in turn requires additional testing, as we do not claim to prove any form of causality.

1.1 Outline

The remainder of the paper is organized as follows. In Chapter 2, we present preceding theories and empirical studies examining the underpricing phenomenon surrounding initial returns. Agency theories, the effects of monetary policy on stock markets, and the existence of hot and cold IPO markets are some, amongst other, theories that we elaborate on. By combining existing literature and earlier findings, Chapter 3 lays the foundations of our problem formulation and addresses the research question we seek to answer. Taking basis in the popular Box-Jenkins framework within time series analysis, Chapter 4 presents our methodology and the econometric techniques used to analyze the question at hand, meanwhile, Chapter 5 which covers the analysis of the paper, is structured according to the model development process. As we proceed, Chapter 6 interprets and discusses the findings to disclose potential explanations of why the macroeconomic factors serve as determinants on IPO returns. In combination with contemporary literature, we seek to identify the causality of our findings and therefore provide suggestions for further research through the development of propositions. Since an ancillary objective of this paper is to present valuable insights for practitioners, the last part of Chapter 6 will discuss the practical implications of the analysis. Finally, Chapter 7 concludes with a summary of the study.

1.2 Delimitations

Naturally, the scope of the paper has been delimited and hence some boundaries of the analysis are established. Firstly, most of the preceding literature covering IPOs and the underpricing phenomenon tends to examine how macroeconomic factors affect IPO activity and not initial returns *per se*. This implies that scrutiny of the relationship between macroeconomic variables and initial returns appears to be relatively uncharted territory, hence the discussion section of this paper only provides suggestions of the dynamic causal effects between macroeconomic variables and IPO returns rather than factual statements. Secondly, whereas many researchers have paid attention to the impact of idiosyncratic company factors or perhaps industry-level elements in determining IPO returns, we limit our analysis to solely focus on macroeconomic aspects herein traditional macroeconomic variables as well as aggregated financial market indicators. We, therefore, acknowledge that sector analysis including industry-level or firm-specific considerations could have yielded interesting outcomes, other than those provided in this paper. The estimated regression model is consistent with this limitation, as our adjusted R^2 indicates that the independent variables can only explain about 16.68 percent of the variations in first-day IPO returns. Lastly, as the analysis focuses exclusively on the U.S. IPO market, the scalability of the results is subject to certain institutional constraints. Nevertheless, this paper yields unprecedented insights into the macroeconomic environment's impact on underpricing that creates value for both academics and financiers around the world.

2 Literature Review

In order to untie the dynamic effects between macroeconomic factors and IPO returns, it is imperative to thoroughly understand some basic concepts and theories related to IPOs and underpricing. Therefore, the literature review will be divided into seven subsections. Firstly, we present the concept of an IPO and the adjacent processes surrounding going-public and the most common motives for going public. Secondly, we outline what exactly constitutes underpricing, how it can be perceived, and how frequently it occurs. In extension, the third part of the literature review contains a review of the contemporary understanding of efficient markets and how abnormal returns should not be possible given certain assumptions. The fourth subsection outlines traditional underpricing theories at firstly the agency and micro-level in terms of information asymmetry and secondly in a more institutional level on information symmetry theories. The paper then proceeds to cover macroeconomic aspects of business cycles with a special focus towards what macroeconomists look for in their purpose to determine the health of an economy. By taking a point of departure in contemporary corporate finance theory, the paper shortly outlines why some firms tend to time their stock issuances with respect to the macroeconomic environment. Lastly, modern-day writing on macro-level IPO activity, especially hereunder hot and cold IPO markets, will be delineated in order to summarize the literature review and thereby lead to our problem formulation statement.

2.1 What is an IPO?

A common denominator in all types of IPOs is the aim of selling stocks to new investors. It is also referred to as going public, as the public good gains the possibility of acquiring shares of a company that was otherwise only available to institutional investors. In general, there are two types of public offerings, a primary and a secondary offering. A primary offering is an offering where a company raises cash in exchange for shares. This is the most common type of public offering and what will be considered throughout the paper. A secondary offering is, where already existing shareholders wish to unload their shares to new investors and hence no new capital is issued (Brealey et al., 2014)[1]. A recent example of a secondary offering was the offering of Spotify-stocks that went public in April 2018 without raising any cash but also with no involvement of an underwriter (Sisario and Phillips, 2018)[2]. An underwriter is typically a financial institution that generally serves three purposes; serve as an advisor towards the procedural and financial issues of the company, then buy the securities from the issuing company and lastly sell the securities to the public (Ramsinghani, 2014). The main idea behind an underwriter is that they take on the risk of holding the securities until the actual price is determined by the market. It is not uncommon to have multiple underwriters or advisors involved in larger IPOs to help transcend some of the agency problems that might arise, or simply because the issuance is too large a risk to bear for a single bank (Brealey et al., 2014). The agency problem of underwriters and investors will be covered more in-depth in Section 2.4.

Underwriters coordinate the book-building process, which is the most common method of allocating shares to new investors (Derrien and Womack, 2003). Bookrunning or book-building is the process of identifying potential buyers of the security, which often involves a roadshow where the underwriter pitches the security to institutional investors (Ramsinghani, 2014). If an investor appears willing to purchase a security, the investor is registered in "the book" with the maximum investment amount as well as the highest stock price he or she is willing to invest at. A key feature is that being registered in the book is not legally binding, so no guarantee of purchase is made or posed from the investor. It is, however, frowned upon in the investment community to not buy the shares once an investor is registered in the book. Furthermore, it may also imply future negative consequences in terms of not being offered shares in subsequent bookrunning processes (Brealey et al., 2014). Naturally, the bookrunning process is not the only method of selling newly issued shares of the company. A high-profile company with a recognizable brand sometimes goes for a Dutch auction (Derrien and Womack, 2003).

An auction is as known from other forums, a commitment to buy at the offered price, but since it is near impossible for one investor to buy a whole company, it is the lowest bidding price that attracts enough investors that settles the offering price—even though an investor initially proposed a higher bid. The Dutch auction is naturally a lot riskier than a traditional IPO, as

[1] A secondary offering is frequently denoted a seasoned offering.

[2] It is the exception to the rule that a company is taken public without the assistance of an underwriter (Jenkinson and Ljungqvist, 2001)

there is no underwriter to secure the price at a certain level, but in turn, much less expensive as the underwriter fee is quite high (Chen and Ritter, 2000). In general, Dutch auctions are quite rare as the underlying risk is quite significant (Ramsinghani, 2014). An IPO process based on the common method of raising capital through an underwriter applying a bookrunning method can overall be divided into five stages until the final IPO date is reached and the shares are floating:

Figure 2.1: The IPO Process

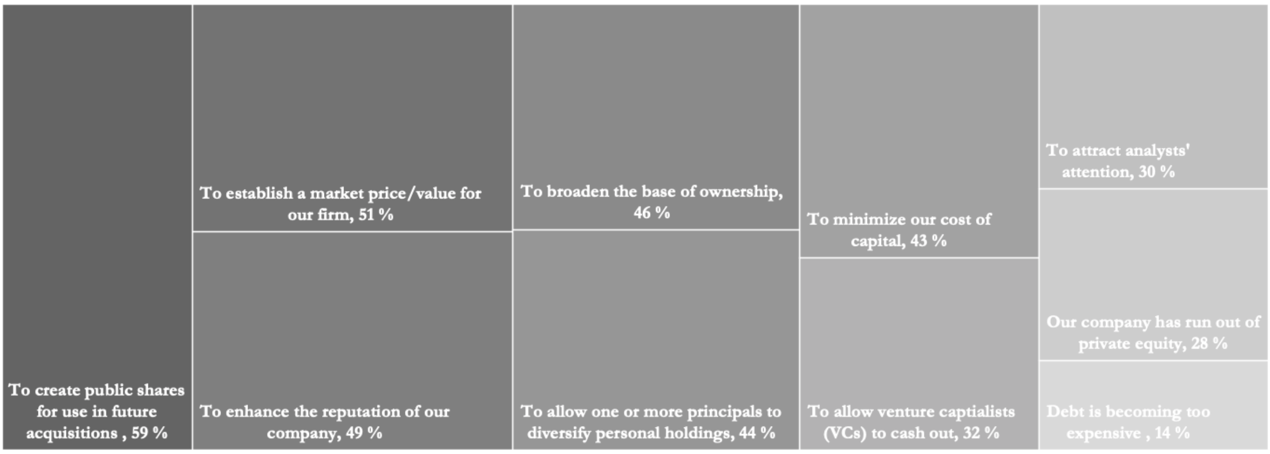
Notes: Inspired by Ramsinghani (2014). Source: Authors' own drawings.

The first step is a readiness assessment, which according to EY (2018) entails assessing the feasibility of the company towards the public market, as well as setting a long-term strategy for the IPO and the years to follow. This also entails increased spending on internal control functions, setting a plan for establishing a communication structure and investor relations setup, that can help communicate the goals of the company to the public (EY, 2018). The second step is the careful selection of the underwriter(s), sometimes referred to as the "bake-off" period, where the underwriting role is solicited for offers (Ramsinghani, 2014). Once an underwriter has been chosen, the process of filing with the Securities and Exchange Commission (SEC) begins. The SEC is an American governmental entity that seeks to protect investors in the financial markets and in relation to IPOs is responsible for granting permissions based on the submitted material regarding the issuing company. The filing with the SEC is called a S1-filing and contains very detailed descriptions of the company's finances, strategy, corporate governance as well as business risks (Ramsinghani, 2014). Once approval from the SEC has been granted, the underwriter along with key executives embark on a roadshow to gauge institutional investors' interest and accordingly the book is built. Should the underwriter deem that sufficient demand is available from the market, they will recommend proceeding with the listing. Vice versa, should demand be feeble the underwriter will suggest holding off the IPO.

2.1.1 Why Go Public?

There may be several considerations that leads a company to pursue an IPO. According to Brau and Fawcett (2006) one of the key reasons for pursuing an IPO is that of growth. According to their survey of 336 CFOs, the most pertinent reason for going public is to create public shares for use in future acquisitions, which implies that IPOs are actually used as part of an acquisition-based growth strategy:

Figure 2.2: Motives for Going Public



Notes: Study conducted by Brau and Fawcett (2006, p. 108) whom survey CFOs' motives for going public. Percent of CFOs who agree or strongly agree to the above statements. The higher the percentage the greater the size of the area. Source: Authors' own drawings.

As per Figure 2.2 there may be many different triggers for going public for a company, but it doesn't come without costs. Historically, underwriters almost always charge the same seven percent fee of the total sum raised (Chen and Ritter, 2000). A seven percent fee can rise to a significant sum that could be otherwise spent; hence corporations need to pay close consideration to the upside as well as the downside risks of going public. Furthermore, it is not only the one-off underwriter fee that makes up the total costs of an IPO. Additionally, legal fees and accountant fees also spike in the production of a prospectus and file registration with the SEC. A more long-term consideration is also the red tape that arises from the increased reporting requirements and associated monitoring and control functions needed to be a listed company. Ultimately, this leads to higher costs and a lower degree of freedom in decision-making processes (Brau and Fawcett, 2006; Brealey et al., 2014).

The company pursuing a primary offering through an IPO (seeking to raise capital) has an incentive to maximize the amount of cash raised without giving up a high percentage of ownership, or at least make sure that the valuation of the company remains high (Brealey et al., 2014). Therefore, all else equal, a company will choose an underwriter who promises to underwrite at the highest price possible. However, according to Brau and Fawcett (2006), much focus is also put on the expertise of the underwriter within the industry that the company is operating within. Furthermore, some scholars have also mentioned the reputation of an underwriter as a key factor in choosing an underwriter. This is for example highlighted by the fact that the most fee earning investment banks all have quite recognizable brands such as JPMorgan Chase, Deutsche Bank and Goldman Sachs (Brealey et al., 2014).

2.2 Underpricing or Risk-Adjusted Returns?

An investor considering buying into an IPO primarily cares about returns, and the first-day returns always get significant attention especially in terms of media coverage (Ritter and Welch, 2002). Multiple scholars have discussed how come IPOs almost always yield abnormal first-day profits. For example, a study of 12,000 IPOs in the U.S. from 1960 to 2008 found that on average IPOs yield a return of 16.90 percent on the day of listing (Brealey et al., 2014). Since the first observations of the abnormally high returns in the 1960s, scholars have been concerned with explaining the phenomenon of IPO underpricing (Anderson et al., 1995; Ibbotson and Jaffe, 1975). Underpricing can be understood as the listing of a security below its actual market value (Ibbotson and Jaffe, 1975), and is computed as the percentage difference between the first-day closing price and the offer price[3] (Rajan and Servaes, 1997). All else equal, selling a security below the actual market value naturally hurts the selling party—in this case, the company and current owners—while it benefits the buyers of the security, who can realize the appreciation in value. IPOs generally have quite significant return characteristics. Even though IPOs on average are underpriced on the day of the listing, and thus create positive returns, they surprisingly embark negative returns on a longer-term horizon, such as one-year ahead (Ritter and Welch, 2002). Longer-term returns of IPOs are beyond the scope of this paper, but still,

[3] Underpricing = (First Day Closing Price - Offer Price) / Offer Price. Throughout the paper, underpricing, first-day returns, and IPO returns are used interchangeably.

remain an interesting and insightful area of research.

In order to provide further evidence of the existence of underpricing, one can invert the question and ask how frequent negative returns have occured historically—also called overpricing (Jenkinson and Ljungqvist, 2001). For example, in Germany, there has never been a year when IPOs were overpriced on average (Jenkinson and Ljungqvist, 2001). This is actually providing very useful insights for investors. If there are little downside risk and potentially high upside gains, then why not just invest in all IPOs. In an efficient market there should be no free lunch for investors, as everything should be priced appropriately. However, underpricing opens up for the concept of "flipping" where an investor buys into an IPO and consequently sells the stocks as soon as they are open for trading (Jenkinson and Ljungqvist, 2001). This creates an extraordinary opportunity for arbitrage because the comparable average daily market return has been only around 0.05 percent (Ritter and Welch, 2002), implying an excess return of 16.85 percent when applying the data of Brealey et al. (2014).

The comparative evidence of underpricing is vast and extensive however a distinction can and should be made across countries, especially across industrialized and developing countries (Jenkinson and Ljungqvist, 2001). Developing countries on average have a higher degree of underpricing compared to the more industrialized and developed countries. For instance, in the period between 1978 and 1983 investors in Malaysia enjoyed an average first-day return of 166 percent (Dawson, 1987). The astonishing first-day returns can to some degree be explained by a weak institutional setup that leads to corruption and bureaucratic inefficiency, but naturally the same cannot be said for the U.S. and European IPO markets (Jenkinson and Ljungqvist, 2001), where underpricing is correspondingly lower. In some countries, the regulatory environment has been a main driver of significant underpricing. Until 1988, Korean firms had to price their offer price at the book value of the shares and in Taiwan the shares had to be priced at a price-to-earnings multiple equivalent to that of similar competitors driving up underpricing significantly (Jenkinson and Ljungqvist, 2001).

2.3 The Efficient Market Hypothesis

The efficient market hypothesis (EMH) stipulates that assets in the financial sector behave as they should—that is, the price of an asset deviates in value as the expected cash flow from that particular asset fluctuates over time. The embedded dynamic of the EMH is that of information. The EMH is commonly defined as the idea that asset prices, or stock prices in particular, fully reflect all available information (Burton and Shah, 2013). This is, of course a very stringent definition as no analyst or price setter in any given setting can comprehend all available information about a particular asset or company. This is because humans generally are constrained in their cognitive capacity by what Herbert Simon called bounded rationality—the limitations of humans to perceive and react based on available information (Simon, 1965). Conversely, the semi-strong definition of the EMH postulates that stock prices accurately summarize all publicly known information (Brealey et al., 2014). Under these definitions, any given market should not allow a free lunch or the opportunity to conduct arbitrage and walk away with a risk-free investment because all prices should already reflect all publicly available information. The third and last version of the efficient market hypothesis is the weak form, which has a stronger basis in reality (Burton and Shah, 2013) because it dictates that knowledge of past prices is of no value in predicting future stock prices—which is true to some degree. The concept of underpricing is however arguably defying the strong and semi-strong version of the EMH. As mentioned, in a market where prices reflect all publicly available information there should be no room for money being left on the table. However, with significant returns to investors and a corresponding loss to previous stockholders, a free lunch is arguably present.

There is another, more mathematical method of depicting the EMH. The concept of a random walk is a useful way of thinking about underpricing and the EMH. A perfectly random walk is best understood through a coin flipping game, where the heads or tails outcome has the exact same probability. A central feature is therefore that past events have no influence on the future outcomes, i.e. it is perfectly random. It is an exemplification of a martingale property (Burton and Shah, 2013), which can be written mathematically as:

$$E[X_{t+s}|X_1, X_2, ..., X_t] = X_t \text{ for any } t \text{ and } s > 0 \tag{2.1}$$

Naturally, the equation above needs to be expanded as it suggests that if you invest 100 in the stock market you receive either –1 or 1 in each trial. But since it is perfectly random you will ultimately end up with the same principal amount as you started with. The idea of a martingale property is useful as it depicts the fact that historical prices have no influence on future prices and therefore are completely isolated events (Burton and Shah, 2013). But as shown in subsection 2.2, this is not the case for IPO returns, which consistently yield above-average returns. As mentioned, it is extremely rare that average IPO returns are overpriced, i.e. yield negative first-day returns (Jenkinson and Ljungqvist, 2001). Such an observation naturally entices further investigation into the causes of underpricing. Therefore, this paper will now outline the most common theoretical foundations that are used to argue why IPOs are underpriced.

2.4 Traditional Underpricing Theories

Since Ibbotson and Jaffe (1975) proposed a list of possible explanations for why firms tend to be underpriced, many scholars have attempted to elaborate on the causal factors. The theoretical foundation was significantly increased in the aftermath of the Dotcom bubble, as the arguably irrational company valuations yielded unprecedented returns and thus enticed scholarly attention (Ritter and Welch, 2002). It is sensible to divide the literature on traditional underpricing theory into two categories: 1) the literature assuming that *information asymmetry* exists between the agents in an IPO, hereunder underwriters, investors and issuers, and; 2) the literature suggesting that *information symmetry* is present, thus implying that all parties have access to the same information, which elevates the discussion to a more institutional level. These categories will be dealt with in the following.

2.4.1 Information Asymmetry

A common theory that has sprung from traditional microeconomic thinking is that of the lemon problem. The lemon problem is the idea that the rational buyer is not certain of the quality of the product he or she is purchasing. It is called a lemon problem because the theory originates from purchases of used cars where the buyer is presumed to be uncertain of the quality of the car (Akerlof, 1970). Underlying the problem is information asymmetry between the seller and the buyer of the car, wherein the seller is assumed to have a superior level of information compared to the buyer (Hendrikse, 2003). The idea can then be transferred to the market for IPOs by arguing that high-quality firms will sell their shares at a lower price so that lower quality issuers cannot imitate the value (Ritter and Welch, 2002). This gives rise to speculation into actions that can be exercised by high-quality firms. An example could be not issuing all the intended stock in the IPO but later, or as Rajan and Servaes (1997) suggests increase analyst coverage or dividend signaling. However, according to Ritter and Welch (2002) the propensity of the lemons problem theory to provide any significant explanatory value is limited at best as signaling has been very difficult to empirically prove. That being said, it is not unthinkable that issuers would like to leave investors with a positive initial impression of the company and hence discount the value of the firm accordingly (Ritter and Welch, 2002).

Conversely, another theoretical basis has sprung from information asymmetry, namely those assuming that investors are more informed than the issuers. In that case, the issuer faces a placement problem—the issuer doesn't know at what price the market is willing to buy its stock (Lowry et al., 2017). One of the most favored theories of IPO returns within this area is that of the winner's curse, which was made famous by Rock (1986). Imagine an investor seeking to purchase shares in an IPO, they will only receive full allocation if they are amongst the highest bidders and thus face the risk of overpricing. This leads the investor to prefer a partial allocation in exchange for underpricing (positive returns). Therefore, the investor will underbid his original price and therefore only receive a partial allocation. This gives rise to a higher degree of underpricing as the lower the bid the larger the underpricing (Rock, 1986).

The theory of Rock (1986) is one of the most widely known theories within the IPO underpricing phenomenon and his work has enticed much work on information asymmetry (Ritter and Welch, 2002). However, all theories that are based on the assumption of information asymmetry imply that in case information asymmetry is not present, there will be no underpricing. Hence, scholars that are prone to favor these types of theories put much weight onto the value of information. However, the regulatory authorities apply strict rules on the issuer and underwriter about disclosing information that is not publicly available, which limits the opportunity for underpricing (Ramsinghani, 2014). Furthermore, as noted by Ritter and Welch (2002) there is agreement that some explanatory power exists within the information asymmetry literature.

However, they also argue that the explanatory power is limited, as information asymmetry most likely cannot explain variations up to 65 percent first-day returns. This is especially true because it is theories based upon inferior or superior information withheld by certain agents, which can be hard to validate or back-test (Ritter and Welch, 2002).

2.4.2 Information Symmetry

As mentioned, there are also several theories that do not base their foundation on the classical principal agent problems arising from information asymmetry. These theories are more dispersed in their unit of analysis as we move beyond the relationship between the three primary actors; issuers, underwriters, and investors. For example, a popular institutional theory concerns itself with the risk of post IPO litigation. Should an investor buy into an IPO and fairly quickly experience negative returns, the particular investor might look to the issuer or underwriter for questions regarding the negative returns. It has by some scholars been argued that by underpricing the issuance you deter the risk of bankruptcy because it requires more severe legal issues to be present, than if the issuance was not underpriced (Hughes and Thakor, 2002; Lowry and Shu, 2002). The validity of the theory is though widely debated, as for example Drake and Vetsuypens (2007) find that companies that went public with a large degree of underpricing generally experience higher amounts of lawsuits. Furthermore, Keloharju (1993) argues that the U.S. institutional setup—which has been the primary object of analysis as they generally experience more lawsuits—does not explain underpricing in other countries. Lastly, Boehmer and Fishe (2001) suggests that companies with a large degree of underpricing have a larger degree of liquidity in trading volumes in the days following the IPO. However, it is unclear why that would remain an incentive for the issuer unless the trading volume remains high over the medium to long term (Ritter and Welch, 2002).

In general, the list of scholars attempting to explain the peculiar phenomenon of consistent underpricing is vast and extensive. The abnormal returns arising from IPOs are most likely considered a multivariate analysis with many factors affecting the final outcome. We tend to agree with Ritter and Welch (2002) who argue that information asymmetry theories are lacking explanatory power in explaining average IPO returns of 65 percent in certain periods. Furthermore, the contemporary literature on information symmetrical theories could provide some value especially if the focus is shifted from the institutional setup to the allocation process and fully informed agency problems, however, it is clear that further research is still needed in order to fully illuminate the underpricing phenomenon (Ritter and Welch, 2002). This paper takes a significantly different focus from the more actors-centered theories of contemporary literature. Rather we focus on macroeconomic level tendencies and attempt to model why IPO returns fluctuate over time and hopefully identify theories from a different perspective.

2.5 The Macroeconomic Environment and Business Cycles

When economists attempt to analyze the state and health of a country, they are concerned with three basic variables, namely output growth, the unemployment rate, and the inflation rate (Blanchard and Johnson, 2013). Output growth because it is the development in the national income accounts, i.e. how much value has been added within a given period. It wasn't until the end of the second world war that focuses on having a unified system of national income accounts started to increase (Blanchard and Johnson, 2013), where the resulting tool gave economists the possibility to track the development in economic activity across jurisdictions. Output growth is usually measured in GDP growth, which can be understood as the change in the sum of income in the economy over a given period (Gartner, 2013). If GDP growth is negative it is usually referred to as a recession in the economy, while periods of positive GDP growth is referred to as expansionary periods. Naturally, expansionary periods are much more common than recessions as GDP tends to inhabit a positive long-term growth trend (Blanchard and Johnson, 2013).

The second variable of interest, that macro-economists follow closely to comprehend the health of an economy, is the level of unemployment (Blanchard and Johnson, 2013). The unemployment rate is interesting for two reasons. Firstly, because the level of welfare needed is greater if there is a higher number of unemployed people. Naturally, the level of unemployment benefits and welfare varies from country to country and over time as well, however considering all else equal, a high level of unemployment implies high financial costs to public treasuries but also psychological costs to the unemployed (Gartner, 2013). Secondly, the unemployment rate can also be considered as an indicator of efficient resource allocation. Human labor is in many macroeconomic models considered a factor of analysis. If unemployment remains high despite a high level of economic growth, then unemployment rates can be an indicator for a mispricing of human labor. (Blanchard and Johnson, 2013)

The third indicator that is relevant for macro-economists is the rate of inflation (Blanchard and Johnson, 2013). It is defined as the sustained rise in the general level of prices (Blanchard and Johnson, 2013, p. 49). As a rule of thumb, a minor positive development in inflation is positive for economic growth, meanwhile, a high degree of inflation or adverse price developments (i.e. deflation) is negative. During periods of inflation, not all prices and wages rise at the same rate, therefore income distribution is heavily affected, whereby some can't afford the same goods that they used to afford. On a longer term, inflation affects consumer and investment spending because it introduces uncertainty about future price levels and therefore spending and investments also decrease (Gartner, 2013).

While output growth, unemployment, and inflation are quintessential metrics to understand the dynamics between the macroeconomy and individuals' income distribution, these macroeconomic measures are also a result of a nation's monetary policy. In essence, monetary policy refers to the manipulation of a nation's money supply as the central bank actively intervenes within the interest rate market through issuances or buybacks of government bonds (Hull, 2015). Therefore, another metric that analysts frequently scrutinize to evaluate the U.S. economic outlay is the federal funds rate, i.e. the interest rate at which depository institutions trade federal funds with one another overnight (Bodie et al., 2014; Hull, 2015). If a depository institution has surplus balances in its reserve account, it lends money to other banks in need of larger balances—that is, banks with excess cash lends money to other banks in need to quickly raise liquidity (Hull, 2015). While the rate that the borrowing institution pays to the lending institution is determined between the two intermediaries, the weighted average rate for all of these types of negotiations is denoted the effective federal funds rate[4]. Although the federal funds rate is essentially determined by the market, it is governed by the Board of Governors of the Federal Reserve System (the Feds) through their so-called Federal Open Market Committee (FOMC) (Bodie et al., 2014).

An important objective of the FOMC is to adjust the federal funds rate so that the tradeoff

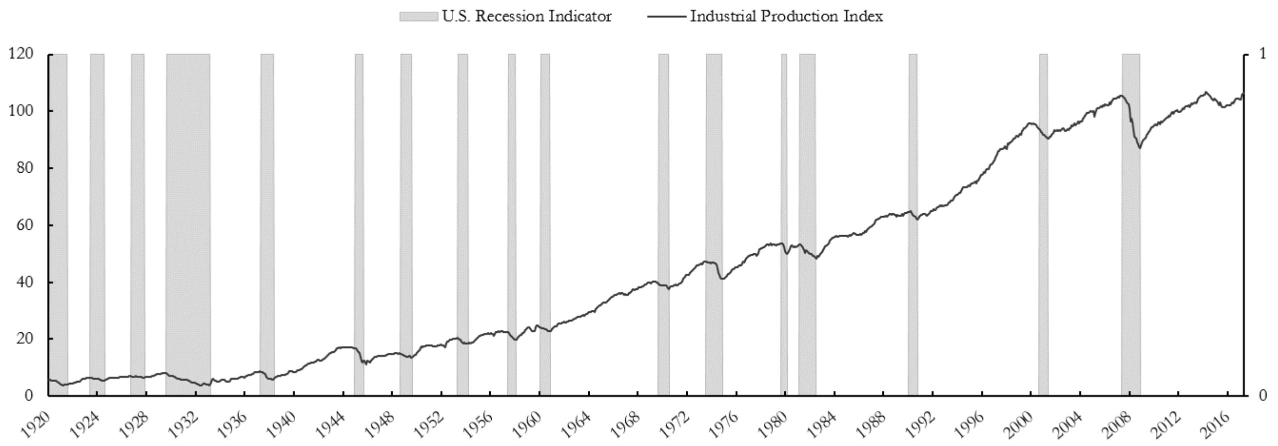
[4]The federal funds rate target is of March 2019 set to 2.25 – 2.50 percent (Board of Governors of the Federal Reserve System, 2019)

between production output and inflation is in accordance with the Feds long-term inflation target. Whether the Fed wishes to buy or sell government bonds depends on the state of the economy. If the FOMC envision that tighter monetary policy is needed to obey with their dual mandate of maximizing employment and stabilizing prices, liquidity can be reduced by selling government bonds if the proceeds are consequently retained from further circulation within the economy. As this will eventually decrease the aggregated money supply, depository institutions will necessarily readjust their spreads by increasing outbound lending rates (Hull, 2015). In the opposing scenario, the FOMC can decrease the federal funds rate by increasing overall market liquidity through the purchase of government bonds. This way the aggregated money supply increases and therefore reduces interest rates as interbank lending becomes relatively cheaper. Moreover, the U.S. interest rate environment is dictated by the Feds who determines the level of the interest rates according to various factors, nonetheless with a primary focus on the long-term inflation target. (Simpson, 2014)

Although central banks apply different tools to steer the national economy, they repeatedly seem to pass through good and bad times (Simpson, 2014). These economic fluctuations, referred to as business cycles, are of vital importance when investors are to establish specific investment strategies as deviations from consensus will most certainly affect asset prices (Bodie et al., 2014). One way of understanding the business cycle is to think of a nation's economy as the sum of each of its sectors and industries. Sectors and industries are always expanding and contracting at different time intervals (Grant, 2016). However, when some industries grow more than those that recede, it will result in a period of expansion, where GDP growth will be a positive figure and vice versa (Grant, 2016). According to Okun's Law, this will result in a decreased level of unemployment because the demand for labor is increasing (Blanchard and Johnson, 2013). Effectively, this will according to the Philips curve imply that inflation also will start to rise, because unemployment is low and hence the price of labor increases (Blanchard and Johnson, 2013). Until the central bank starts to interfere in the money market by increasing the cost of money, interest rates and aggregate output starts to dampen off. This depiction is perhaps the most simplistic illustration of a business cycle and how the aggregate economy behaves. As Schumpeter (1939, p. 5) described them: *"Cycles are not, like tonsils, separable things that might be treated by themselves, but are, like the beat of a heart, of the essence of the organism that displays them."*.

In modern economic theory, the industrial production index is perceived as a leading indicator of business cycles (Ameer, 2012), and by inspecting Figure 2.3 one clearly sees that output growth and business cycles are strongly correlated, wherein a diminution of economic output tends to serve as a precursor of economic contractions.

Figure 2.3: The Industrial Production Index



Notes: The industrial production index is steadily increasing throughout the timespan, however one clearly sees that prior to economic contractions, the index plunges. The grey shaded areas indicate U.S. recessions based on a mathematical derivation by the National Bureau of Economic Research. The recession indicator is binary; values of zero (no recession) or one (recession) to indicate economic disturbances. Source: Authors' own drawings. Data: NBER (2019).

However, many scholars argue that when conducting macroeconomic analysis it is equally important to be attentive to financial market indicators as they are known to contain macro-level information that is not necessarily included in traditional macroeconomic metrics (Angelini and Foglia, 2018; Benaković and Posedel, 2012). One of the measures closely related to output growth is the availability of money. If the price of money goes up (interest rates rises), the general availability of funds also decreases, which is also referred to as liquidity. As a general definition, an asset is considered liquid if market participants perceive that they can sell large amounts of the asset without adversely affecting its price (Lybek and Sarr, 2002; Hull, 2015). While there is no unified and theoretically correct methodology of measuring liquidity in the aggregated financial markets, liquidity can overall be divided into five focus areas that are interesting to investors and regulators alike; 1) *tightness* which refers to low transaction costs measured in for example bid-ask spreads; 2) *immediacy* which refers to the speed at which an order can be executed; 3) *depth* which refers to how many orders both above and below the price have been given; 4) *breadth* which implies that the number of orders and their volume are large with minimal price impact, and; 5) *resiliency* which implies that market imperfections are quickly rebalanced by a new flow of orders (Lybek and Sarr, 2002). When discussing liquidity, the subject usually surrounds financial institutions as they are responsible for relocating funds between stakeholders. Hence, the liquidity of financial intermediaries is often of vital importance to the liquidity of the rest of the financial system. For example, the cause of Lehmann Brothers' collapse was not due to solvency issues, but rather due to illiquidity problems and when the institution was not able to rely on funds from the interbank market it was thus declared bankrupt Mcdonald (2016).

Since the 1980s, several scholars have contributed to the popular literature covering the macroeconomic climate and its impact on stock returns (Benaković and Posedel, 2012). Liquidity is according to Hull (2015) such a variable. He argues that one should adjust the expected return of a stock according to the average liquidity of an asset, however many other macroeconomic variables seem to have an impact on stock returns. The most notable study on stock returns and macroeconomic factors was conducted by Chen et al. (1986). By leveraging the concept of factor models, the authors investigated how macroeconomic and financial market variables affect U.S. stock returns, and in particular, identified to what extent the risk entailed in innovations in macroeconomic variables was rewarded within stock prices. They developed an economic factor model including industrial production, inflation, interest rates, and oil prices and found that these sources of macroeconomic risks were significantly priced from 1953 to 1983.

In general, the macroeconomic environment has positive and negative effects on the stock market. Therefore, it is also useful to analyze the current status of for example the stock market. The most common way of measuring financial stress, at least within the equity market, is by analyzing the implied volatility of an asset—most commonly a derivative (Bodie et al., 2014). The VIX index is the most widely used measure of financial stress in the financial system today, where in fact some media reporters denote the VIX index as the fear gauge of the U.S. stock market (Edwards, 2019). It tracks the implied volatility of options based on the S&P 500 index as the underlying asset and helps provide an indication into the returns of not only stocks but also other asset classes (Hull, 2015).

Section 2.5 provided a fundamental basis of this paper by presenting the most common approaches to measuring macroeconomic developments. The most important factors for pure macroeconomists are amongst others aggregated economic output, inflation, and unemployment but perhaps equally important for this paper is the nature of interest rates and how these fit into the business cycle. Furthermore, the section also shed light onto the fact there is information that is not embedded in the mere traditional macroeconomic variables and hence additional information can be found within the financial markets. Therefore, the paper has presented three indicators of the financial markets that other authors have found to be of significant interest in explaining macroeconomic developments. The next section will outline how company valuations and business cycles interplay, and thereby provide insights not only into stock returns and how they are affected but also why companies choose to go public at certain points in time.

2.6 Monetary Policy and Company Valuation

Unsurprisingly owners of firms want to maximize the value of their holdings and the value of firms varies according to the macroeconomic environment. The most fundamental method of determining the value of a company can according to Brealey et al. (2014) be assessed by the discounted cash flow (DCF) model. Typically, when an investor is to decide whether or not to invest in a particular stock, he or she is concerned with the so-called fundamental value of the company—that is, a company's intrinsic value (Brealey et al., 2014). To discover the value of a company's common equity, investors may choose to discount expected net future cash flows (i.e. future dividends) so that the present value of common equity, P_e, is a result of expected earnings minus corresponding costs:

$$P_e = \sum_{t=1}^{\infty} \frac{d_t}{(1 + r_e)^t} \tag{2.2}$$

where,

P_e *is the value of common equity*

d_t *is the net cash distributions to common equity holders*

r_e *is the cost of equity capital, i.e. investors' expected return*

By applying the DCF model, analysts have to forecast future earnings and costs to derive the present value of all future net cash flows (or, alternatively by predicting future dividends).

However, as it is impossibly time-consuming to compute the present value of an infinite series on a term-by-term basis, it is common to add a terminal value which corresponds to the present value at the horizon of all subsequent cash flows beyond a given time (Brealey et al., 2014; Lundholm and Sloan, 2013):

$$P_e = \sum_{t=1}^{T-1} \frac{d_t}{(1+r_e)^t} + \frac{d_T}{(r_e - g)(1+r_e)^{t-1}} \tag{2.3}$$

where,

g is the growth rate of the cash flows

As one can derive from both equations above, the net cash flows are discounted by the cost of equity, r_e. Moreover, for higher levels of r_e the present value of a company decreases, and vice versa. The question, therefore, becomes how can stakeholders calculate a company's cost of equity? From the popularized CAPM theory within finance, the cost of equity is a composition of the risk-free rate that can be obtained in the market (r_f), a company's systematic risk relative to the market (β), and the expected return of the very same market (r_m):

$$r_e = r_f + \beta(r_m - r_f) \tag{2.4}$$

where,

r_f equals the risk-free interest rate

r_m equals the return on the market portfolio, e.g. the S&P 500 index

β equals the systematic risk of a particular stock

The CAPM-theory stipulates that investors are compensated for risk beyond the systematic risk embedded in the market, and in turn that the expected risk-free rate is of vital importance when companies and investors are to establish the cost of equity (Brealey et al., 2014).

In the previous section, we postulated that economists frequently scrutinize changes within the macroeconomy, which, in turn, are affected by central banks who actively participate in the interest rate market to stimulate the economic outlook. In relation to asset prices, monetary policy plays an important role in determining equity returns, either by the alteration of the discount rates used by market participants (e.g. the risk-free rate) or by influencing market participants' expectations regarding future economic activity (Christos and Alexandros, 2006). To exemplify how the risk-free rate affects asset prices, consider the following scenario; the Feds realizes that the U.S. economy is faltering towards a recession and that the monetary policy has to be adjusted accordingly. Recall that the central bank is faced with the tradeoff between maintaining inflation levels while simultaneously optimizing production activity and that their ultimate objective is to achieve a long-term inflation target by adjusting overall production activity through intervention within the interest rate market. To ease the probability of a recession, the Feds may choose to decrease the federal funds rate, i.e. increase production capacity at the cost of deviating from their long-term inflation target[5]. By doing so, interbank lending becomes relatively cheaper as the overnight interest rate on short-term loans declines, which results in a reduction of both long and short-term interest rates.

From the CAPM equation, the cost of equity should all else equal, decrease if the risk-free rate declines and accordingly increase the present value of a company[6]. This follows from the fact that a decrease in interest rates ultimately reduces the denominators of all cash flows and therefore leads to an increase in P_e. On the other hand, if the economy is booming and the central bank recognizes the need for reducing economic output by increasing interest rates so that the inflation level converges towards the long-term inflation target, it is latent to believe that P_e decreases if the denominators in Equation 2.3 increase.

Taking the basis in these arguments, contemporary corporate finance theory dictates that it is not uncommon that firms seek to issue and repurchase equity at certain points in time (Brealey et al., 2014). Issuers will most likely attempt to issue as much equity as possible when valuations are high so that they can get the most cash into the business for the smallest percentage of ownership. Vice versa, companies are more likely to repurchase outstanding equity if the owners of the firm believe that the shares are undervalued (Brealey et al., 2014). The timing decision is also highlighted in the IPO literature which will be covered below with particular attention to hot and cold IPO markets.

[5]Theoretically speaking, a decrease in interest rates will, ceteris paribus, increase the risk of inflation as production activity increases (Christos and Alexandros, 2006).

[6]This idea builds upon the fact that investors demand to be compensated for the risk they undertake beyond what is obtainable by investing in risk-free assets. Therefore, if the risk-free rate declines, investors generally accept a lower return on their placements (Brealey et al., 2014).

2.7 Hot and Cold IPO Markets

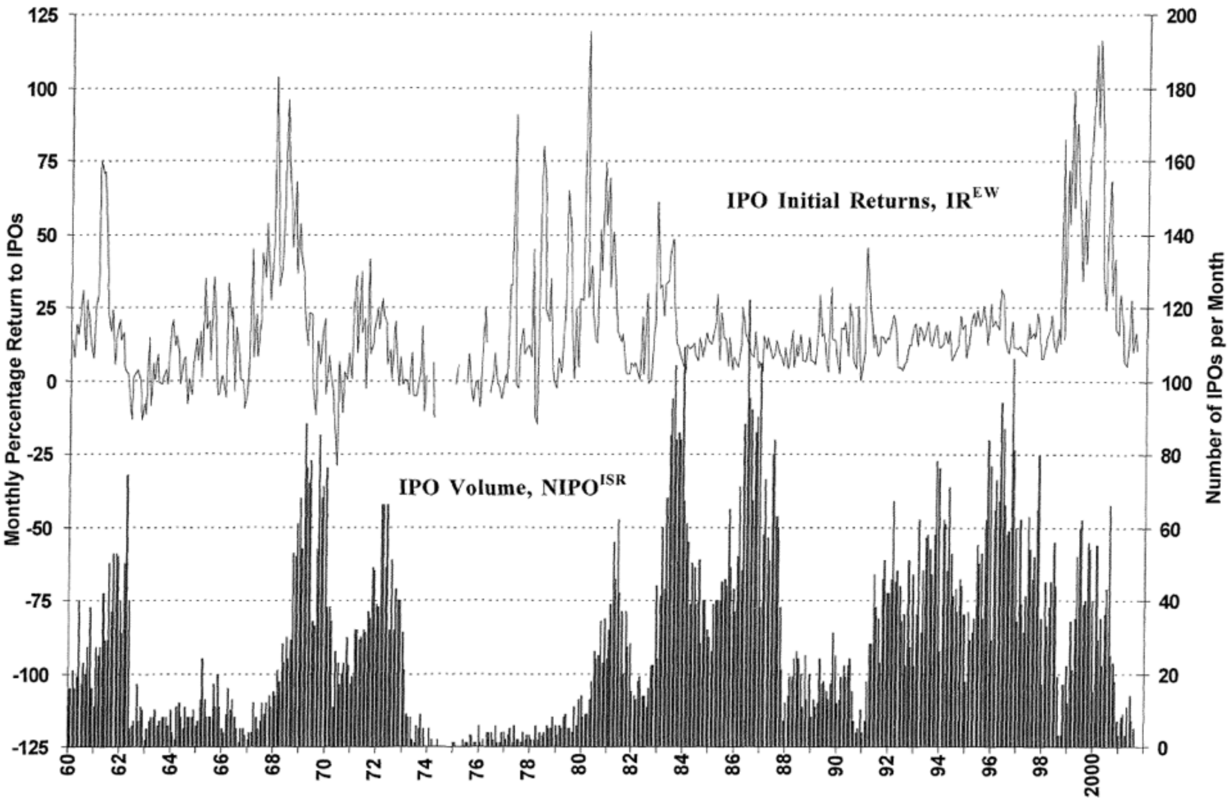
One of the most interesting observations of Ibbotson and Jaffe (1975) was the fact that they noted that firms tended to go public in clusters. This implies that one can divide IPO periods into two categories; one where *many* firms go public at the same time, the other where *few* firms go public at the same time, or so-called hot and cold IPO markets respectively. It is bewildering for why hot and cold IPO market exists as there, in an efficient market, should be no difference towards going public in a hot or a cold period. The puzzle of hot and cold IPO markets becomes much more significant when considering that a bulk of new IPOs follow a period of high IPO returns (Lowry and Schwert, 2002), implying that IPO returns are a precursor for future IPO activity. Assuming that companies attempt to time their public offering, this is equivalent to an issuer identifying high underpricing and consequently go public, which appears to be an irrational decision (Ritter and Welch, 2002). Therefore, much research has been put into identifying the trends that explain the hot or cold aspect of IPO activity. According to Lowry et al. (2017), the research on hot and cold IPO markets can be divided into five main arguments.

The first theory as to why IPO markets are sometimes hot or cold has to do with that of the investor sentiment. The argument is seemingly practical as it states that very high investor sentiment will cause investors to overbid stock prices compared to their actual value (Lowry et al., 2017). Underlying the argument is the idea that market participants are not always rational and therefore subject to behavioral and psychological factors that affect their decisions. Lowry (2003) attempts to model IPO volume using investor sentiment and finds a positive correlation between the two. She also finds support for the second argument of IPO markets, which deals with the demand for capital. By applying GDP as a proxy for the demand for capital, the regression output showed that there is a significant explanatory power in applying GDP to model IPO activity. The second argument is derived from the idea, that more investment opportunities arise during times of higher economic growth which in turn fuels the need for additional cash to invest in projects with positive net present values and hence more IPOs are conducted. Thirdly, Lowry (2003) also highlights the role of information asymmetry as highlighted by more traditional underpricing theories, which increase the cost of issuing equity (Akerlof, 1970; Hendrikse, 2003; Ritter and Welch, 2002; Rock, 1986). By applying announcement effects on the stock price as a proxy for information asymmetry, she does find statistical significance in determining IPO underpricing albeit, unfortunately, she doesn't appear to find a very evident relationship between information asymmetry on IPO activity. In conclusion of her very acknowledged paper, Lowry (2003) suggests that investor sentiment has almost double the effect that the demand for capital has during hot or cold IPO periods.

The fourth argument towards understanding the variation in IPO activity is by treating an IPO as a real option (Benninga et al., 2005; Pástor and Veronesi, 2005). Per definition, a real option gives the holder an opportunity to choose to conduct a certain action or not (Brealey et al., 2014), and by taking a company public the option is exercised. Consider a situation, where an issuer has received a patent on a certain innovation but requires capital to initiate full-scale production. In case that capital markets are constant, the issuer will immediately pursue an IPO. However, capital markets are not constant and therefore the issuer will speculate into the factors that most optimally provide him with the desired amount of cash (Pástor and Veronesi, 2005). The factors that the issuer will consider is the expected market return, expected aggregate profitability, and ex ante uncertainty, all of which make up the market conditions (Pástor and Veronesi, 2005). When market conditions are good more issuers will exercise the option to go public and vice versa. Ex ante uncertainty is not only a factor in IPO activity but has also been proven by Beatty and Ritter (1986) to influence underpricing. The argument they propose is that the larger the degree of uncertainty, the higher a discount is required from investors as the risk of overpricing goes up along with uncertainty. Hence, the idea is founded in the problems of lemons as later described by Akerlof (1970) in section 2.4.1. Benninga et al. (2005) extends the argument of Pástor and Veronesi (2005) by arguing that the option to exercise is also influenced by the ownership and control impacts of the issuer. Their sayings imply that if an issuer goes public, the issuer will receive funds at the cost of handing over some control of the company. Hence, when cash-flow rates are high, the potential advantages of diversification are also higher and hence the issuer will exercise and become a publicly listed company (Benninga et al., 2005).

With very few exceptions almost all IPOs in the U.S. are based on the book-building model (Loughran et al., 1994). Therefore, Benveniste and Spindt (1989) developed a model that focused on information sharing during the book-building period. Their argument is that underwriters obtain valuable information from investors when they face an uncertain demand curve whereby investors require to be compensated for the information they share (Ritter and Welch, 2002). Moreover, investors will receive favorable treatment in terms of greater allotment or perhaps even underpriced shares (Benveniste and Spindt, 1989). However many authors have also pointed to the fact that exogenous information during the book-building period is not always reflected in an adjustment of the offering price (Bradley and Jordan, 2002; Lowry and Schwert, 2002).

Figure 2.4: The Relationship between IPO Activity and IPO Performance



Notes: "Ibbotson, Sindelar and Ritter's (1994) monthly data on aggregate U.S. initial public offerings per month (NIPOISR) and average initial returns to IPO investors (IREW)". Source: (Lowry and Schwert, 2002, p. 1172).

In general, what exactly constitutes a hot or cold IPO market remain opaque, however looking back at the data of the past 60 years of IPO activity and returns, it is easy to visually identify IPO clusters as illustrated in Figure 2.4 (Lowry and Schwert, 2002). Nevertheless, the theories on hot and cold IPO markets, which yields interesting insights for practitioners and scholars alike, can roughly be divided into two groups. Either the theory is based upon fluctuations in investor sentiments that implicitly influence IPO returns, which in turn influence IPO activity, or, the theory is based upon the idea that demand for capital is the most useful predictor for activity (Lowry et al., 2017). However, as Tran and Jeon (2011) notes, the insights from the hot and cold perspective sometimes undervalue the total fluctuations that are determined at the macroeconomic level. The theories yield interesting acumens but are based on predicting clusters that might not be so relevant in the post Dotcom bubble era as noted by Lowry et al. (2017).

In summary, this paper has firstly outlined how the process of IPOs functions in practice with particular attention paid towards the book-building process, as this is the most common underwriting method in the western world (Ritter and Welch, 2002). Secondly, the paper put forth some stylized facts about what underpricing entails for both investors and issuers, and how extensive underpricing actually is. This led to a discussion of what an efficient market actually calls for and how one can assume that underpricing is a violation of at least the strong and semi-strong definitions of the EMH. The paper has then outlined the theories of underpricing. Firstly, with respect to the traditional underpricing theories, that deal with information asymmetry and secondly by the theories that deal with information symmetry. This paper has then outlined some of the basic phenomena surrounding business cycles and macroeconomic development while being especially attentive towards how to measure macroeconomic developments and how that affect company valuations. In extension, this paper has outlined contemporary research on the more macroeconomic aspects of hot and cold markets and outlined the five most prominent explanations of such occurrences. In general, the traditional theory on hot and cold IPO markets are facing some constraints as they are not thoroughly analyzing macroeconomic variables as argued by Tran and Jeon (2011).

3 Problem Formulation

So far, existing literature on IPOs has primarily focused on the following two areas of analysis; 1) traditional underpricing theories, and; 2) the theories that seek to explain hot and cold IPO markets even though the two areas naturally interlink. Tran and Jeon (2011) applies a significantly different approach of modeling macroeconomic variables as regressors towards IPO activity and proceeds, whereby they argue that *"Given the importance of market conditions for conducting IPOs, very few authors have examined in depth the macroeconomic determinants of IPOs."* (Tran and Jeon, 2011, p. 3188). That argument we tend to agree with as many authors states that the macroeconomic environment dictates the demand for capital and investor sentiment and, therefore, is of vital importance to IPO activity and underpricing (Lowry et al., 2017; Lowry and Schwert, 2002; Ritter and Welch, 2002). Tran and Jeon (2011) models output growth, stock market returns, market volatility, market liquidity as well as interest rates on the number of IPOs and proceeds raised from 1970 to 2005. The methodology of analyzing IPO developments by applying time series techniques that utilize macroeconomic variables is ultimately similar to the approach of this paper.

At this point, one vital distinction must be made. Rather than modeling IPO activity by applying selected macroeconomic variables, this paper attempts to model IPO returns or underpricing if you will. The distinction is significant as one must assume that the factors that cause underpricing are not necessarily the factors that cause IPO activity. The lack of emphasis on underpricing should be further highlighted as multiple scholars have found that underpricing is actually a precursor for IPO activity rather than a result of it (Ritter and Welch, 2002; Lowry et al., 2017). Thereby more emphasis should be put on the factors that influence underpricing than vice versa. However, as outlined in the literature review, we argue that the current theoretical basis of IPO underpricing does not seem to capture the entirety of the phenomenon and, hence we turn to the basis of macroeconomics. Macroeconomic factors might yield interesting insights into the underpricing phenomenon, which to the best of our opinion has not been covered adequately in contemporary research. On that basis the research question of this paper is as follows:

What macroeconomic indicators influence IPO underpricing and in turn how well can these variables predict IPO returns?

By applying the theoretical foundations as outlined in Section 2.5, this paper seeks to explain how IPO returns vary over time by combining macroeconomic data and financial market indicators. Thus far, our argument has been that the traditional underpricing theory, which can be divided into information asymmetry and symmetry, has limited explanatory power in elucidating how and why IPO returns vary over time. Therefore, the focus has shifted towards the macroeconomic perspective in which time series analysis opens up for. The initial perception is that business cycles and theory on hot and cold IPO markets has a stronger explanatory power for the relation between macroeconomic variables and IPO returns and hence the structure of the paper adopts that idea.

As outlined, macroeconomic factors can cover a large range of indicators of varying importance to IPO returns. However, this paper relies on the work of former scholars in choosing the variables of interest. Since a very limited number of prior studies model IPO returns and macroeconomic factors, it is reasonable to base our choice of factors on authors, who have covered other aspects of IPOs. Studies on macroeconomic factors' impact on IPO activity and proceeds is of great interest as we believe there is some sort of transferability between the number of IPOs and proceeds raised vis-à-vis the underpricing phenomenon. Furthermore, the selected variables are based on an all-encompassing approach meaning that in order to avoid omitted variables bias, the idea has been to include more areas of interest than perhaps might be needed. In that way, the analysis limits the possibility of overlooking or ignoring variables that are of significance in explaining returns. The selected macroeconomic variables and the authors who have written about them as well as the implementation in our analysis is dealt with in subsection 4.2.1.

In Chapter 6 the paper will provide suggestions of why the results of the analysis appear the way they do. This is done with the notion in mind that correlation does not imply causality and therefore our suggestions of why certain variables are significant or not will be presented in a discussion format. By utilizing contemporary research on hot and cold IPO markets and traditional corporate finance theory, we provide suggestions as to why certain coefficients appear correlated with first-day returns in our model. These suggestions are presented in a proposition format intended for future research.

Lastly, the research question has been derived with the aim of providing an informative framework to better understand how macroeconomic determinants may affect IPO returns. As shown in Section 2.2 covering preceding literature on IPO underpricing and risk-adjusted returns, we demonstrated that investors can indeed achieve superior returns by investing in IPOs. However, returns vary over time and, therefore, a secondary objective of this paper is to provide investors with tools to analyze when to invest in an IPO or not. Taking basis in the macroeconomic climate the secondary objective of this paper is to provide investors with more informed insights into the question of whenever IPOs is likely to have positive or negative returns. The outcome of the analysis from an investor perspective will be covered in depth in Chapter 6.

4 Research Design, Data and Methodology

4.1 Research Design

The derivation of the research question has now been outlined with respect to how the peculiar phenomenon of underpricing keeps persisting over time. We have argued that there are limitations to the traditional approach of information-based theories and therefore we seek other means to explain underpricing. Implicitly such a method implies an inductive approach to the philosophy of science as made famous by Francis Bacon in 1620 (Moses and Knutsen, 2012). This approach is characterized by detecting a myriad of observations and then consequently deriving a type of truth. On the other hand, is the deductive approach to science. The fundamental difference lies in the approach to the already existing knowledge, while the inductive approach is more prone to reject former knowledge and proceed according to where patterns and irregularities lead, the deductive approach to a greater extent builds upon pre-existing knowledge of a phenomenon. The approach of this paper is therefore arguably an inductive approach, as we to a great extent refute pre-existing knowledge and therefore seek our own path to come up with suggestions for potential causal factors. (Moses and Knutsen, 2012)

The inductive vs deductive approach discussion primarily exists within the naturalist philosophy of science, which stands in sharp contrast to for example the constructivist approach (Rosenberg, 2011). The methodology of this paper is also highly statistical and mathematical, which implies a naturalist approach. At the core of the naturalist philosophy of science is the assumption that a Real World exists even though it might not always be observable to the human eye nor mind (Rosenberg, 2011). The statistical method is by nature very data-driven and in an extension of that, the subsequent sections will describe the data used, how it is been collected and thereafter outline the methodology surrounding the modeling work of the proposed regression model. (Moses and Knutsen, 2012)

4.2 Data

The aggregated worldwide IPO market is quite extensive with over 1624 IPOs and over 189 bn. USD in total issuance volume in 2017 with China being the most active region (EY, 2018). In choosing the region in scope for the analysis, multiple factors were considered. Firstly, to comply with the law of large numbers, a country or region with many annual IPOs were deemed necessary (Agresti and Franklin, 2013). A minimum of 10 years of monthly data on all variables was required to conform a well-functioning regression model. However to be certain we increased the timespan to 20 years for more accurate estimates. This is also in line with the recommendations of Box and Tiao (1975) who argue that a minimum of 100 observations is required for time series regression. Secondly, a country with a uniform currency was also needed to exclude currency fluctuations from skewing the analysis in either direction. Thirdly, it was important to choose a country with relatively well-established institutional structures that haven't changed radically over the given timespan. Given these factors, it was a natural choice to select the U.S. IPO market, which is the only country that lives up to all requirements, while at the same time having extensive and transparent information available regarding the IPO market (Brealey et al., 2014). However, it should be noted that applying data from the U.S. only naturally gives rise to complications with regards to the scalability of the results, as the characteristics of the U.S. IPO market might differ from that of other markets as outlined by La Porta et al. (1997). The scalability of the results will be further discussed in Section 6.2.

4.2.1 Dataset Description

Variables of Interest

Until now the paper has outlined the theoretical foundations of the interplay between IPOs and the macroeconomic environment. A criterion for a variable to be included in our analysis is if former scholars have utilized that particular variable with respect to either IPO returns, proceeds or activity. Yet, not all variables are deemed relevant to model IPO returns and therefore the following section will describe why certain variables have been chosen, how the data is structured and the source of origin.

The list of exogenous variables has been divided into two sub-subsections; one covering traditional macroeconomic factors, one covering financial market indicators. As argued by many scholars, there is an information loss in macroeconomic modeling if one limits oneself to real-economy indicators. Hence by including financial markets indicators on a macroeconomic level, a higher degree of information is included as it is assumed that informed investors provide more information than what the mere traditional macroeconomic indicators do (Benaković and Posedel, 2012).

For a list of all indicators applied in the analysis of this paper please refer to Table 4.1, which contains an overview of the unit of measurement, the symbol used in Stata[7], the source of the data as well as the expected sign. The expected sign is included to help structure the analysis and provide a perspective for the modeling work. The expected sign is by no means derived through economic intuition but rather by simply computing the correlation amongst the variables. If there is a negative correlation between two variables the expected sign will be negative and vice versa (see Appendix A1 for full output).

IPO Returns

The data on IPO returns (IPO_RET) has been derived from a Bloomberg Terminal by utilizing its integrated IPO module (Bloomberg, 2019). Before extracting the data, a few constraints were put onto the search in order to align the results as much as possible. In line with Ritter's seminal work (1984) all IPOs with issuance size less than 1 million USD were excluded and so were the various other offer types except regular IPOs based on common equity or Class A shares. Moreover, we exclude offerings of preferred stock and other types of liabilities. The reasoning for only including common stock is that we want to identify if macroeconomic factors affect IPO returns, and it is easier for private investors to buy pre-listed common stocks than for instance preferred stock, although we acknowledge that including preferred stock could have yielded interesting insights. The final data extract consists of data from 1997 to 2017 on 4,016[8] IPOs, including the name of the issuer, ticker, IPO date, offer size and offer to first close. The latter implies the percentage change between the offering and closing price at the end of the first trading day. The data is then converted into monthly equally weighted average returns

[7]Stata is a statistical software for data science (StataCorp, 1985).

[8]Approximately 15 percent of the population of IPOs was omitted from the data sample due to missing observations.

consisting of the IPOs that went public within a given month so that the data is comparable to the exogenous variables. Moreover, the monthly first-day returns are calculated as a simple arithmetic average of the initial returns of all new issues within the same calendar month—a common practice if we follow the work of earlier authors such as Ritter (1984) and Loughran and Ritter (2004).

Macroeconomic Factors

Economic Growth

Economic growth, being equivalent to that of the development in aggregate production output is as mentioned one of the most widely used metrics of macro-economists. Multiple authors have found a correlation between IPO activity and economic growth. For example, Lowry (2003) applies GDP as a proxy for demand for capital and finds that there exists a strong significant relationship between IPO activity and GDP. The approach and aim of applying economic growth in our methodology are somewhat different as we want to model IPO returns and underpricing. Bearing in mind that the implications surrounding the variable should not be understated and is therefore included in our analysis.

The most frequently used metric for economic growth is the GDP indicator, which is a measure of the total value of all sold goods within a given country. However, GDP is a very extensive task for national authorities to calculate and hence it is only reported on a quarterly basis (Simpson, 2014). This gives reason to question if there are too few observations within the given timespan, which is why an adjacent index has been chosen, namely the Industrial Production (IP) index. The IP index is a metric that tracks the real output of the manufacturing, mining, and electric and gas utility industries in the U.S. It is indexed to 2012 and reported on a monthly basis and thus referred to as the short-term indicator of the real economy. There is however an underlying assumption implied with the use of the IP index, namely that using it as a proxy for the real economy ignores the value added in the retail sector (Board of Governors of the Federal Reserve System, 2018). Nevertheless, scholars have found the same statistical relationship between industrial production indices and GDP growth rates on IPO data, thus implying that the measures yield more or less the same results (Meluzín and Zinecker, 2014). Data on the U.S. IP index has been downloaded from the Federal Reserve Board of St. Louis's database called FRED and entails seasonally adjusted data from 1997 to end of 2017, with the ticker "INDPRO". The seasonal adjustment is performed by the Federal Reserve Board by applying an ARIMA model to adjust for variations during the year (Board of Governors of the Federal Reserve System, 2018).

Inflation

As outlined in Section 2.5, another key variable macro-economists rely on when determining the state of an economy is the developments in inflation (Blanchard and Johnson, 2013). Inflation is by definition the price-appreciation of goods and can, therefore, be both a positive and negative figure (Brealey et al., 2014). The influential paper of Tran and Jeon (2011) utilizes an inflation indicator in their model as a regressor towards IPO activity and money left on the table. While they only find statistical significance in their model when predicting proceeds raised and not on IPO activity, we argue that since inflation is arguably more of a monetary and financial metric than a demand indicator, it is reasonable to assume that inflation might have an impact on IPO returns. This way we include inflation in our model as well.

There are many different measures of inflation but the most commonly used is the Consumer Price Index (CPI), which measures the amount of dollars required to pay for a typical basket of consumer goods. Moreover, the monthly percentage change in the index is an indicator of inflation. The CPI is calculated by the Bureau of Labor Statistics in the U.S., who gathers data from sources in different cities throughout the country (FRED, 2019). Like the IP index, the CPI is seasonally adjusted and computed on a monthly basis. The CPI is derived from the FRED database and indexed to 1983 (FRED, 2019).

Oil Price

The oil price (CRUDE) is often seen in relation to the state of an economy as oil shocks have proven to be a precursor to changes in for example unemployment levels (Mishkin, 2015). By utilizing the price of oil as a dummy variable in conjunction with other macroeconomic variables, Lowry (2003) attempted to model why IPO volume fluctuates so significantly over time. Based on her approach we also employ the oil price as a macroeconomic indicator albeit we do not include it as a binary variable but rather as a normal integer. Therefore, it is hypothesized that a relationship between the oil price and IPO returns could exist. The price of oil is usually measured in crude oil, which is unrefined oil when extracted from the ground. Because crude oil is traded on a daily basis, the price changes are on an intraday basis. The FRED database publishes end-of-month figures, which is the last quoted price within a given month, implying that the price might have deviated significantly intra-month, but that won't be revealed in our data (FRED, 2019). The price is denominated in USD per barrel.

Employment Level

The third variable that macroeconomists rely on when analyzing the state of a nation's economy is the unemployment rate (UNEMP) as it is perceived as a vital indicator for the well-being of the general public (Blanchard and Johnson, 2013). Not only does the unemployment level contain vital macroeconomic information, but it is also a variable in scope for our analysis as Hrnjic and Sankaraguruswamy (2010) applies the unemployment rate as a proxy for market-wide consumer confidence and sentiment, and finds correlation with underpricing. The level of unemployment is measured by the unemployment rate, which is the percentage of unemployed people relative to the total labor force defined by the U.S. Bureau of Labor Statistics. The labor force is limited to people who live in either of the 50 states in America, are above 16 years old and who do not reside in any type of penalty, mental or pension facility (FRED, 2019). The indicator is being published on a monthly basis by the Bureau of Labor Statistics and is seasonally adjusted, or "detrended" if you will. The data is downloaded from the FRED database.

Interest Rate Environment

The federal funds rate is essentially the central benchmark interest rate in the U.S. economy as it influences interest rates with varying maturities. The federal funds rate indirectly influences long-term interest rates such as mortgages, loans, and savings, all of which are important to consumer wealth and confidence (Board of Governors of the Federal Reserve System, 2019). However, companies and investors commonly use the yields on government bonds as the risk-free rate when pricing assets and future cash flows (Brealey et al., 2014). For instance, Bodie et al. (2014, p. 501-02) and Chen (2009, p. 216) postulates that as a consequence of the expectation theory of the term structure of interest rates, long-term rates equals the average of future short-term rates plus a premium which essentially implies that long-term rates contain greater information than short-term rates:

$$f_n = E(r_n) + \text{liquidity premium} \tag{4.1}$$

where,
$E(r_n)$ is expected future short-term rates
f_n is equal to the forward rate of a long(er) term bond

Although the federal funds rate may be useful in portraying the Feds' perception of the future U.S. economy, investors price these expectations into long-term interest rates (Fuhrer, 2006). Because FOMC meets eight times a year to discuss whether an adjustment of the federal funds rate is needed to steer the U.S. economy, the level of information pertaining long-term interest rates becomes more relevant for financial analysts to scrutinize as the yield curve is continuously adjusted through the supply and demand of long-term government bonds (Bodie et al., 2014).

Much literature on IPO activity has paid special attention to the level of interest rates at varying maturities (Angelini and Foglia, 2018; Meluzín and Zinecker, 2014; Tran and Jeon, 2011). Once again we highlight the paper of Tran and Jeon (2011) as they find significance in utilizing the yields on 10-year government bonds as a regressor towards IPO proceeds. Based on that, it is not unlikely that the same correlation is present with IPO returns. Because investors and companies commonly treat the yields on 10-year government bonds as a benchmark of the long-term risk-free interest rate (Grabowski et al., 2014) and this paper is trying to imitate the viewpoint of a private investor, the yields on 10-year government bonds (GBOND10Y) is used as a variable to analyze the impact of the interest rate environment on first-day returns. The GBOND10Y is quoted as a percentage yield to maturity at the end of each month. Once more the data is collected from the Board of Governors of the Federal Reserve System of St. Louis' database (FRED, 2019).

Taking into account that the federal funds rate is quite complex as it is affected by inflation levels and unemployment rates, as well as the series, affect yields on long-term bonds, we find it reasonable to assume that including the federal funds rate will cause our regression model to suffer from unnecessary multicollinearity. For instance, Martin (2016) reports that long-term interest rates are highly correlated with the federal funds rate, which may lead the finalized regression model to suffer from imperfect multicollinearity (Stock and Watson, 2015). Although imperfect multicollinearity does not prohibit us from estimating a regression model, it may lead to imprecisely estimated coefficients. Based on this argument we choose to exclude the federal funds rate from the analysis whilst simultaneously acknowledging that the variable itself may pertain interesting implications on first-day returns.

Financial Market Indicators

Market Liquidity

As mentioned many financial indicators contain information that is not captured in the traditional macroeconomic variables and liquidity in the financial markets is one of such (Benaković and Posedel, 2012). Liquidity risk, which is often measured by the bid-ask spread of assets, should theoretically be reflected in increased returns so that an investor is compensated for the increased risk he or she undertakes (Hull, 2015). This is also supported by the findings of Pástor and Stambaugh (2003) who report that liquidity is indeed an important factor when pricing equities. The concept of market-wide liquidity has also been presented to have an impact on IPO activity. As an example, Tran and Jeon (2011) apply a liquidity metric based on the mathematical derivation proposed by Pástor and Stambaugh (2003). They find significance in predicting IPO activity and argue that liquidity is a useful indicator in the timing of IPOs. Based on those findings we tend to believe that there might also exist a relationship between liquidity and IPO returns.

Bank of America Merrill Lynch (BAML) has created an index that tracks the funding stress in the global financial system by measuring the tightness of spread-based relationships in rates, credit and currencies called the liquidity risk index (LIQUIDITY) (Bloomberg, 2019). It was developed in 2010, but backtesting reveals that it has been able to serve as a good predictor for sell-offs in global equities, commodities and high yield bonds (Business Wire, 2010). It is a sub-index that together with others makes up the more commonly known Global Financial Stress Index (GFSI). The liquidity risk index is based on averages, hence if the index is above zero then there is implied liquidity risk in the market and vice versa if the index is below zero (Bloomberg, 2019). A caveat should though be highlighted, namely that the liquidity risk index is based on global assets and therefore not specific to the U.S. market alone. However, the U.S. is notably the most influential financial market in the world and hence any development in U.S.

liquidity should also be reflected in global values. Therefore, the index has been found viable despite this deficiency. While the range of the data does not stretch back beyond 2000—and thereby limits the applicability of the variable—the final timespan of the proposed regression model will be determined through structural break testing in subsection 5.2.1. Finally, it should be mentioned that the index has been derived from a Bloomberg Terminal with the ticker: GFIRSLIQ. For further information regarding the composition of the index please see Appendix A5.

Stock Market Returns

The significance of the stock market in determining investor appetite should not be discarded as several authors report that stock market increments tend to increase investment spending (Chen et al., 1986). Since IPOs are as an asset class equivalent to that of equity, it is natural that several authors have modeled IPO activity and proceeds raised by using the stock market as an exogenous regressor. According to Brau and Fawcett (2006) stock market developments is one of the key determinants that managers look to when deciding to go public, cf. Section 2.1.1. Since the stock market is a principal factor for CFOs, it is likely to assume that there exists a correlation, not only with IPO activity as found by Ljungqvist (1997) or Tran and Jeon (2011) but also with IPO returns. It is therefore a principal factor for our analysis, thus we include the stock market as a regressor on IPO returns.

When determining what mirrors the stock market in various textbooks it is often suggested to apply the S&P 500 index as a proxy (Bodie et al., 2014). Because the S&P 500 index (SP500) tracks the 500 largest companies in the U.S. covering approx. 80 percent of the available stock market capitalization, it is a well-diversified portfolio with weighting according to the market capitalization of each share every quarter. (S&P Dow Jones Indices, 2019). The monthly data are derived from Thomson Reuter's Datastream by extracting the closing value at the end of each month (Datastream, 2019).

Financial Market Stress

As pointed out the most common method of measuring stress in financial markets is through utilizing the implied volatility of the future value of the stock market. Volatility or stress in the financial markets has proven to have a significant impact on IPO activity but not on the amount of proceeds raised (Tran and Jeon, 2011). To the best of our knowledge, it has not yet been applied as an independent regressor towards underpricing, nevertheless, we include financial stress as a factor in our analysis because we find it reasonable to assume that some of the variations in average IPO returns are explainable vis-à-vis financial stress. The most widely applied index that measures stress in the financial sector is the VIX index. However, since the VIX index is limited to only analyzing derivatives on the S&P500, this paper relies on a financial stress indicator (STRESS) developed by the Federal Reserve Bank of St. Louis.

The financial stress indicator, with the ticker "STLFSI", includes 18 different input factors that all can be used to identify stress in the financial markets. The index has three overall categories of input factors; various interest rates, yield spreads and other indicators, whereas the VIX index is featured within the "other" category. Therefore, the financial stress indicator is very broad and covers more aspects of the financial markets than the VIX index does (Kliesen et al., 2010). Although the stress index can be thought of as a coincident index because it merely tracks market developments as they occur, Kliesen et al. (2010) argue that the index can potentially serve as a leading indicator because rising levels of financial stress may indicate future economic turmoil and disruptions. Like the liquidity risk indicator of BAML values above zero can be interpreted as showing heightened financial market stress and vice versa for values below zero. For a complete overview of the input used in the financial stress indicator please see Appendix A1.

Table 4.1: Variables of Interest

Indicators/Factors	Unit/Level	Exp. Sign	Symbol	Retrieved From
IPO Performance Indicators				
IPO Returns	Percent	+	IPO_RET	Bloomberg's Integrated IPO Module
Macroeconomic Factors				
Economic Growth	Index	+	IP	FRED, Federal Reserve Bank of St. Louis
Inflation	Index	-	CPI	–" "–
Oil Price	USD/Barrel	+	CRUDE	–" "–
Unemployment Level	Percent	-	UNEMP	–" "–
Long-term Interest Rates	Percent	-	GBOND10Y	–" "–
Financial Market Indicators				
Global Market Liquidity	Index	-	LIQUIDITY	Bloomberg
Stock Market Returns	Index	+	SP500	Datastream
Financial Market Stress	Index	-	STRESS	FRED, Federal Reserve Bank of St. Louis

Notes: 4.1 portrays the selected macroeconomic and financial variables selected to answer the research question. The expected signs are based upon the correlation matrix found in Appendix A2. Source: Authors' own drawings.

4.2.2 Dataset Limitations

To ensure that the extracted dataset is valid for inference and statistical computation some configurations had to be made. First of all, some of the observations did not contain information on first-day closing returns, hence these observations had to be excluded. These IPOs were for the most part relatively small in terms of issuance size, so the overall impact should not be significant. Secondly, the data on IPO returns have been computed to monthly averages, so that the data is comparable to the other exogenous variables. Having said that, some months had very few observations which might skew the computations in either direction as one must assume that the more observations within a given month, the more accurate the estimate of true IPO returns becomes.

During times of financial turmoil, fewer IPOs are listed (Katti and Phani, 2016). This phenomenon is also present in our data, where we even had months where no new stock issuances were made. In September 2001, which is the month of the terror attacks in New York City, there were no new offerings. No companies were neither listed in December 2008, which is most likely due to significant financial stress in the aftermath of the bankruptcy of the investment bank, Lehmann Brothers (Bodie et al., 2014). Altogether, the IPO returns of September 2001 and December 2008 has been set equal to zero, despite the modeling complications that this might give rise to.

It should also be noted that there might be overlap across the independent variables used in the analysis. For example, the financial stress indicator and the liquidity risk index both include yield spreads as risk factors, which might give rise to modeling complications. However, the regional scope of the two indices are different wherein the financial stress indicator generally contains a myriad of inputs which probably factors out the issues of perfect multicollinearity. Furthermore, the yields on 10-year government bonds are also utilized as an input variable of the stress index by the Federal Reserve Bank of St. Louis (see Appendix A1). This might inflate the coefficients of the model which emphasize the need to test for multicollinearity across the independent variables (Stock and Watson, 2015).

4.3 Methodology

This paper has so far presented the data selected to answer whether macroeconomic variables can be used to predict IPO returns. Naturally, this paper applies data that is given within a defined time interval, which creates the opportunity for the use of time series analysis. Data collected for a single entity at multiple points in time (i.e. time series data) can be applied to answer quantitative questions such as the causal effects on a variable of interest, Y, of changes in another exogenous variable, X, over time (Stock and Watson, 2015). Given that our study tries to identify macroeconomic determinants on IPO returns, it becomes necessary to apply time series theory within the field of econometrics.

While there is a plethora of time series models the "optimal" model must be selected based on a combination of theoretical justification and economic intuition (Stock and Watson, 2015). Therefore, the methodology is divided into four subsections as a way of illustrating the popularized time series framework proposed by Box and Jenkins (1970). In their seminal work on time series models, Box and Jenkins (1970) advocated that researchers undergo three overarching phases to obtain an optimal time series model, namely an identification phase, an estimation phase, and lastly model diagnostics checks (Enders, 2015).

The first subsection, which corresponds to the identification stage in the Box-Jenkins approach, present theory on how to determine a time series' autocorrelation structure, underlying assumptions of covariance-stationarity and its implications for practice. Further, the concept of Granger causality is presented to showcase a method for detecting whether a variable has marginal explanatory power beyond those included in a regression function. The concept of Granger causality is essentially considered useful to discover feedback effects between the dependent and independent variables in a regression function. Next, the idea of cointegration is elaborated upon to understand how variables may share a long-run relationship and finally we present a specific time series model which will be applied to help answering the proposed research question, and thoroughly elaborate upon how to estimate "optimal" regression models from a broad spectrum of variables.

4.3.1 Autocorrelation, Lags and Information Criterions

The observation on the time series variable Y made at date t is denoted Y_t, whereas the total number of observations are typically denoted T. The period of time between observation t and $t+1$ corresponds to a unit of time, which in our case equals months as the paper address the impact of macroeconomic factors on monthly average IPO performance. Because both the dependent and the independent variables may be correlated with their prior values respectively, lags of the variables are often included to integrate these effects. In econometric terms Stock and Watson (2015) defines the correlation of a variable between current and prior values as the variables' autocorrelation or serial correlation structure. The value of the dependent variable Y in the previous period (simply its first lag) is denoted Y_{t-1}, whereas the first lag of the independent variable X is denoted X_{t-1}. The change in the value of Y between period $t-1$ and period t equals Y_t - Y_{t-1} which refers to the first difference of variable Y[9].

While the first difference represents the changes between current and prior values of a variable, the autocorrelation displays the correlation coefficient between current and prior values of the very same variable. Because lagged values of both the dependent and the independent variables may yield valuable insight regarding the evolution of the time series, exclusion of statistically significant lags may reduce the explanatory power of the model and potentially induce omitted variables (Stock and Watson, 2015). It is therefore utmost important to understand how one can derive a series autocorrelation and lag structure.

According to Stock and Watson (2015) the choice of lag length must balance the benefit of using additional information against the cost estimating additional coefficients. While an overparameterized model may increase estimation uncertainty as a result of including too many lags, the alternative of excluding relevant lags may decrease forecast accuracy as valuable information is potentially lost although the model becomes more parsimonious (Enders, 2015)[10]. To determine the optimal lag structure given the variables of interests, scholars often apply Akaike's Information Criterion (AIC) or Bayes' Information Criterion (BIC) as portrayed in

[9]Implying that the first difference of Y equals $\Delta Y_t = Y_t - Y_{t-1}$, second difference equals $\Delta^2 Y_t = \Delta Y_t - Y_{t-2}$ and so forth.

[10]A parsimonious model refers to the principle of deriving the best possible model with as few parameters as possible (Enders, 2015)

Equation 4.2 (Akaike, 1974; Schwarz, 1978):

$$AIC(K) = ln\frac{SSR(K)}{T} + K\frac{2}{T} \text{ and } BIC(K) = ln\frac{SSR(K)}{T} + K\frac{ln(T)}{T} \tag{4.2}$$

where,

$SSR(K)$ is the sum of squared residuals with K coefficients

T is the total sample size

Because the regression coefficients in a given time series model are estimated through Ordinary Least Squares (OLS), the sum of squared residuals will decrease, by the inclusion of additional lags (Stock and Watson, 2015). However, the second term of both criteria serves as a penalty term as it increases by the increasing number of regressors. By incorporating both terms in Equation 4.2, the information criterions trade off these two forces so that the number of lags that minimizes the AIC- or BIC-score turns out to be a consistent estimator of the optimal lag length (Stock and Watson, 2015). The major difference between the AIC and the BIC criterion is that the latter substitutes $K\frac{2}{T}$ with $K\frac{ln(t)}{T}$, hence imposing an even stricter penalty term which evidently results in more parsimonious regression models (Enders, 2015). In general the lag-length with the lowest value of either criterion is said to be the preferred lag structure in terms of serial correlation[11]. Additionally, information criterions can be used to detect an optimal regression model. This will be further elaborated upon in subsection 4.3.5.

4.3.2 Stationarity

When estimating dynamic regression models to capture interesting relationships between economic time series data, one assumes that the past may be a good indicator of the future and that historical relationships can be used to forecast the future (Stock and Watson, 2015). For this assumption to hold econometricians stress that the observed time series must be covariance-stationary which implies that the probability distribution of the time series does not change over time (Stock and Watson, 2015). Simply put covariance-stationarity proclaim that the series'

[11] In practice, a convenient shortcut is to require all the regressors to have the same number of lags, that is, to require that $p = q_1 = ... = q_k$, so that only $p_{max} + 1$ models need to be compared (corresponds to $p = 0, 1, 2, ..., p_{max}$).

mean, variance and autocorrelation structure prevail constant throughout time (Enders, 2015). However economic time series data tend to fluctuate over time due to structural changes within economies and thereby violate the assumption of covariance-stationarity. Non-stationary time series may easily lead to spurious regressions, whereby two series give the impression of being correlated with one another, despite being fictitious (Stock and Watson, 2015). Under such circumstances, the regression output "looks good" as the t-statistics appear significant, however, spurious regressions tend to yield unexpected model behavior and unreliable hypothesis tests, confidence intervals and forecasts under OLS-estimation (Enders, 2015; Stock and Watson, 2015). It is therefore crucial to examine the series' properties to identify whether any transformations are needed to fulfill the assumption of covariance-stationary[12].

While there may be several reasons to why economic time series fail to be stationary, two especially prominent issues are that of trends and breaks. First and foremost, if the time series have persistent long-run movements, the time series is said to be affected by trends. In such occurrences, the mean of the series fluctuates around its trend and is therefore not constant over time, which is an important assumption in OLS-estimation (Enders, 2015; Stock and Watson, 2015). Secondly, if the series is discretely changing over the course of analysis, the series is said to be suffering from structural breaks as the population regression behaves unstable over time (Stock and Watson, 2015). In these cases, the coefficients may either be over- or underestimated and therefore not display the true relationship between the variables of interest. The following two sub-subsections will further elaborate upon these two phenomena.

Trends and The Augmented Dickey-Fuller Test

If a time series is inhabiting a persistent long-term movement, it is said to include trends (Stock and Watson, 2015). While trends can be either be upwards or downwards, time series containing a trend may either follow a deterministic or stochastic process. In its purest form, deterministic trends are non-random functions of time, thus implying that the trend may be linear with a constant growth factor throughout a given time frame. On the other hand, stochastic trends are randomly varying over time, thus implying that the evolvement of the time series is unpredictable (Stock and Watson, 2015). Given the fact that our data is economic of nature, it is plausible to

[12]In the jargon of econometrics, a variable that is stationary at levels form is denoted I(0) whereas a variable that are stationary after first difference are denoted I(1). Moreover, I(d) represents the "d" order of integration necessary to make the variable stationary.

assume that the trends included in our data sample are unpredictable with a random component (Stock and Watson, 2015). To exemplify the development of aggregated unemployment is quite dependent upon several factors such as demographic and structural changes within the economy, hence the variability in aggregated unemployment is somewhat random. Therefore in cases where a trend is present, we choose to refer to this as a stochastic trend rather than a deterministic trend.

Stock and Watson (2015, p. 598-99) argue that *"the simplest model of a variable with a stochastic trend is the random walk"* and that a time series, Y_t, is said to follow a random walk if the change in Y_t and u_t are identically and independently distributed:

$$Y_t = Y_{t-1} + u_t \tag{4.3}$$

The idea of the random-walk-model is that the value of the series tomorrow equals the value today plus an unpredictable change, and if this is the case, the best forecast of Y_{t+1} is simply the value today, Y_t. However, some series contain an obvious upward or downward trend, meaning that the best forecast of the series has to include an adjustment factor that incorporates these effects. By including an adjustment factor, we simply extend the random walk model to include a drift-term:

$$Y_t = \beta_0 + Y_{t-1} + u_t \tag{4.4}$$

where,
β_0 *denotes the drift-term; and,*
the expectations of u_t *given prior values of* Y_t *equals zero:* $E(u_t \mid Y_{t-1}, Y_{t-2}, ..., Y_{t-p}) = 0$.

In cases where the drift-term is positive, Y_t increases on average and vice versa. Hence, random walk with drift simply states that the best forecast of the series tomorrow is the value of the series today plus the drift-term, β_0. (Stock and Watson, 2015, p. 599)

There are several ways to identify whether a time series is stationary. However, most scholars tend to apply the Augmented Dickey-Fuller (ADF) test for a unit regressive root when dealing with autoregressive regression models (Stock and Watson, 2015; Enders, 2015). In their seminal paper Dickey and Fuller (1979) addressed how to identify whether time series have stochastic trends or not. While the null hypothesis stipulates that the time series has a stochastic trend (i.e. a unit regressive root), the alternative hypothesis depends on whether one chooses to include a trend or not. If the variable of interest does not include any sort of trends, the alternative hypothesis states that Y_t is stationary:

$$H_0 : \delta = 0 \text{ against } H_1 : \delta < 0 \text{ in } \Delta Y_t = \beta_0 + \delta Y_{t-1} + \gamma_1 \Delta Y_{t-1} + ... + \gamma_p \Delta Y_{t-p} + u_t \tag{4.5}$$

As stipulated above the series may comprise a trend which implies that a modification of the ADF-test is needed. To identify if this is the case, it is useful to derive the series' autocorrelation structure and inspect the time series plot. In cases where the autocorrelation at lag one is approximately equal to one (in terms of magnitude) and the following autocorrelation structure is *gently* decaying over time, the series is possibly encompassing a trend. Otherwise, if the first autocorrelation coefficient appears relatively small whereas the time series plot has no apparent trend characteristics, it is legitimate to believe that the series does not have a trend (Stock and Watson, 2015). By conducting an ADF-test that includes a trend-term, α_t, the alternative hypothesis stipulates that Y_t is trend-stationary:

$$H_0 : \delta = 0 \text{ against } H_1 : \delta < 0 \text{ in } \Delta Y_t = \beta_0 + \alpha_t + \delta Y_{t-1} + \gamma_1 \Delta Y_{t-1} + ... + \gamma_p \Delta Y_{t-p} + u_t \tag{4.6}$$

It should be noted that under the null hypothesis of a unit regressive root, the ADF statistic has a non-normal distribution even in large samples. Conventional critical values from the normal distribution cannot be used when using the ADF statistic to test for a unit root. A different set of critical values must be applied instead. These critical values are given in Table 4.2. (Stock and Watson, 2015, p. 606)

Table 4.2: Critical Values of the Augmented Dickey-Fuller Statistic

Deterministic Regressors	$\alpha =$ **10 percent**	$\alpha =$ **5 percent**	$\alpha =$ **1 percent**
Intercept only	-2.57	-2.86	-3.43
Intercept and time trend	-3.12	-3.41	-3.96

Notes: Large-sample critical values of the ADF Statistic. Source: Stock and Watson (2015, p. 606)

In summation, the ADF-test is a formal statistical procedure for detecting whether the series pertain a unit root, and accordingly whether they appear stationary or not. Therefore, it becomes necessary to include an optimal lag structure of the variable, so that the serial correlation amongst the residuals are incorporated in the ADF-test. This stems from the fact that if the series is autocorrelated, then the errors are most likely autocorrelated as well. This may eventually lead the ADF-test to falsely reject the null hypothesis of a unit regressive root, although the opposite may be true (Stock and Watson, 2015). While the lag lengths p and/or q is unknown, it can be estimated using the information criterions in Equation 4.2, cf. subsection 4.3.1. Preceding studies investigating the ADF-statistics suggests that it is better to include too many lags than too few when testing for a unit root (Stock and Watson, 2015) and for that reason, scholars frequently recommend using the AIC criterion as a measurement of the lags to be included in the ADF-test (Haldrup and Jansson, 2005; Stock, 1994). Endwise series that are affected by stochastic trends is usually non-stationary. One solution is therefore to transform the series into its first-difference, cf. subsection 4.3.1. This follows from the fact that if Y_t follows a random walk whereby $Y_t = \beta_0 + Y_{t-1} + u_t$ is non-stationary, then $\Delta Y_t = \beta_0 + u_t$ is stationary[13]. Moreover, first-differences eliminates the trends in a series (Stock and Watson, 2015, p. 607).

Structural Breaks and the sup-Wald Statistics

The second type of non-stationarity arises when the population regression function significantly changes over the course of the sample, and as pointed out breaks may occur as a result of discrete changes in the population regression function (Stock and Watson, 2015). Enders (2015, p. 102) describes how structural breaks may affect the population regression function of U.S. GDP as a result of discrete changes within the U.S. economy. If this is the case, then the series is said to include structural breaks that deviate from the assumption of constant long-run mean and variance, and if not taken into consideration the regression model can easily provide a misleading basis for inference. This results from the fact that an OLS regression over the full sample will estimate a relationship that holds "on average" (Stock and Watson, 2015). Depending on the location and the size of the break the average regression function can be substantially different from the true regression function at the end of the sample, and thereby inflate or deflate the estimated coefficients which ultimately leads to poor estimates (Stock and Watson, 2015).

[13] Recall that $\Delta Y_t = Y_t - Y_{t-1}$, hence, $\Delta Y_t = Y_t - Y_{t-1} = \beta_0 + u_t$ (Stock and Watson, 2015, p. 607).

One way to identify whether the variables suffer from structural breaks can be done by applying the so-called Chow (1960) test. Stock and Watson (2015, p. 609) demystifies the Chow test through the following example; imagine that we expect a break at time τ between date τ_0 and τ_1 and let $D_t(\tau)$ be a binary valuable that is equal to 0 before the break date and 1 after, hence $D_t(\tau) = 0$ if $t \leq \tau$ and $D_t(\tau) = 1$ if $t > \tau$. By including this term in the regression function, we get the following interaction[14]:

$$Y_t = \beta_0 + \beta_1 Y_{t-1} + \delta_1 X_{t-1} + \gamma_0 D_t(\tau) + \gamma_1 [D_t(\tau) \times Y_{t-1}] + \gamma_2 [D_t(\tau) \times X_{t-1}] + u_t \tag{4.7}$$

By inspecting Equation 4.7, one can derive that the population regression function is unaffected by any structural breaks if $D_t(\tau)$ equals zero throughout the time period τ_0 to τ_1. The null hypothesis states that there is no structural break in the observed period which is equivalent to $\gamma_0 = \gamma_1 = \gamma_2 = 0$. If however, the population regression function is different between two periods—that is, different before and after a break at date t—then one of the γ's is nonzero which evidently results in a structural break. Therefore, the existence of a structural break can be tested by computing the F-statistics of the full sample. (Stock and Watson, 2015)

Often the date of a possible break is unknown for the researcher implying that some sort of modification of the Chow test is needed (Stock and Watson, 2015). By modifying the Chow test to handle several breaks at all possible dates between τ_0 and τ_1, the test enables us to identify structural breaks at unknown dates. By running several Chow tests for every data point throughout a predefined sample, one can identify structural breaks without testing for specific breakpoints (Stock and Watson, 2015). This modification is often denoted the sup-Wald statistics (which is the term we shall use) or the Quandt Likelihood Ratio (QLR) statistics (Quandt, 1960). To ensure that the large-sample approximation is statistically good, the researcher assigns a pre-specified upper and lower trim in which the sup-Wald test "disregards". Enders (2015) postulates that a 10 percent trim of the sample is common for applied research, meaning the F-statistics is computed for all possible breaks in the central 80 percent of the sample, i.e. $\tau_0 = 0.1T$ and $\tau_1 = 0.9T$[15].

[14] Equation 4.7 is based upon an ADL (1,1) model that incorporates the binary variable $D_t(\tau)$ to detect whether the population regression function is affected by a structural break between τ_0 and τ_1. Note that ADL models will be further elaborated upon in subsection 4.3.5

[15] The critical values of the sup-Wald test is dependent upon the number of regressors included in the regression function and the trim. These values can be found in Andrews (2003).

4.3.3 Granger Causality Test

One way to determine the extent to which a regressor have explanatory power on the dependent variable can be done through the Granger causality test. Granger causality identifies whether the regressors have predictive power on Y_t beyond that contained in past values of the dependent variable (Stock and Watson, 2015). The independent variable, X, is said to Granger-cause Y if past values of X and Y are useful for predicting Y_t. Moreover, by regressing X on its own lagged values and the lagged values of Y, the Granger causality test identifies whether the estimated coefficients on the lagged values of X are jointly zero (Stock and Watson, 2015). The test can be algebraically written as follows:

$$Y_t = \beta_0 + \beta_1 Y_{t-1} + ... + \beta_1 Y_{t-j} + \gamma_1 X_{t-1} + ... + \gamma_k X_{t-j} + u_t \tag{4.8}$$

where,

$\gamma_1 = ... = \gamma_k = 0$

It should be noted that Granger causality does not imply causality in the sense of an ideal randomized controlled experiment, where one may inspect the causal links on how changes in X affects Y. Instead, if X Granger-causes Y, then X is said to be a useful predictor of Y, given the other variables in the regression (Stock and Watson, 2015). The null hypothesis postulates that the regressors have no predictive power on Y_t, whereas the alternative hypothesis postulates that the regressors have predictive power on Y_t.

4.3.4 Cointegration

In 1983, Clive W.J. Granger postulated that two time series with stochastic trends that moves closely together over the long-run may share a common trend factor. Through their seminal papers, Granger (1983) and Engle and Granger (1987) argued that if two series, X_t and Y_t, are integrated of order one I(1) and there is some coefficient, θ, that makes $Y_t - \theta X_t$ integrated of order zero I(0), the series are said to be cointegrated. Consider for example the 10-year interest rates and 3-month interest rates. Because both series are dependent upon the same monetary policy it is latent to believe that the series appears to fluctuate with a common trend, although with different rates. If we then calculate the term spread which equals the difference between long- and short-term interest rates—and the term spread is integrated of order zero I(0)—then the series appear to be cointegrated. In such cases, θ, resembles a cointegrating coefficient between the two variables as $Y_t - \theta X_t$ eliminates the common stochastic trend between the variables. (Stock and Watson, 2015)

To identify whether two (or more) variables are cointegrated, Stock and Watson (2015) presents three ways that may unveil the long-run relationship between the variables of interest. First and foremost the authors stress that applying expert knowledge and economic theory can justify whether it is latent to believe that the series are cointegrated or not. Going back to the example of the term spread, the authors stress that these series indeed are cointegrated as a result of the *"expectations theory of the term structure of interest rates"* (Stock and Watson, 2015, p. 704). Unless this was the case, investors could make money without being exposed to risk by holding either Treasury notes or a sequence of 3-month T-bills, and thereby bid up prices until the expected returns were equalized (Stock and Watson, 2015). Secondly, the authors suggest that graphing the series may reveal if the variables seem to share a common stochastic trend. They stress that graphing the series itself is insufficient to detect the value of the common stochastic trend and that statistical computation is needed. This can be done by applying the Engle-Granger Augmented Dickey-Fuller test for cointegration, or simply the EG-ADF test (Engle and Granger, 1987; Stock and Watson, 2015).

An EG-ADF test is a two-step approach that first identifies the cointegrating coefficient between two variables and accordingly conducts an ADF-test on the residuals between the variables. The intuition behind these tests is as follows; if Y_t and X_t are cointegrated with a cointegration coefficient, θ, then $Y_t - \theta X_t$ is stationary I(0). However, because θ in most cases are unknown prior to testing for a unit root in the residuals, it has to be estimated through an OLS-estimation of the following regression specification:

$$Y_t = \alpha + \theta X_t + z_t \tag{4.9}$$

Once θ is identified, an ADF-test including intercept without trends (cf. Equation 4.5) is used to test for a unit root in the residuals estimated from Equation 4.9 (Stock and Watson, 2015).

Moreover, the ADF statistics impose the same critical values as illustrated in Table 4.2. In this occasion, the null hypothesis postulates that $Y_t - \theta X_t$ contains a unit regressive root which implies that rejection of the null hypothesis results in the fact that Y_t and X_t are cointegrated.

4.3.5 Model Selection and Estimation Techniques

While there are a plethora of time series models, the Autoregressive Distributed Lag (ADL) model is frequently used in empirical time series research (Stock and Watson, 2015; Kripfganz and Schneider, 2017). Depending on the research design and the question one seeks to answer, every time series model carries both its strengths and deficiencies. Moreover, it is imperative to justify the model selection based on economic intuition and the desired goal (Enders, 2015). This sub-subsection will deliberately focus on the so-called ADL model as this is the model used to infer the dynamic relationship between macroeconomic factors and IPO returns. Model estimation techniques, hereunder specific-to-general and general-to-specific, are hereafter discussed.

Model Selection: The Autoregressive Distributed Lag Model

One way to unveil the dynamic relationship between numerous variables can be done by applying a multivariate regression function such as the Autoregressive Distributed Lag model[16]. Because the ADL model allows for the inclusion of lags of the dependent variable, Y_t, and successive lags of independent variables, X_{kt}, Kripfganz and Schneider (2017) argue that the model is useful when inferring economic relationships. The authors postulate that ADL models become especially applicable when inferring short- and long-run dynamics between the variables of interest, as the model may include a so-called error-correction term. In short, the error-correction term enables us to identify the existence of a long-run relationship amongst the variables if cointegration is present. The ADL model with p lags of Y_t and q lags of X_{kt} denoted $ADL(p, q_1, ..., q_k)$ as portrayed in Equation 4.10, allows for k additional predictors, where q_1 lags of the first predictor are included, q_2 lags of the second predictor are included, and so forth[17]. The model can

[16] Autoregressive as it includes lagged values of the dependent variable, and distributed lag as it incorporates multiple lags of the independent variables (Stock and Watson, 2015).

[17] $ADL(p, q)$ is frequently denoted $ARDL(p, q)$

algebraically be written as:

$$Y_t = \beta_0 + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + ... + \delta_{k1} X_{k_{t-1}} + \delta_{k2} X_{k_{t-2}} + ... + \delta_{k,qk} X_{k_{t-qk}} + u_t \tag{4.10}$$

Underlying the ADL model four general assumptions needs to be upheld for the model to provide a valid and interpretable result under OLS estimation. (Stock and Watson, 2015, p. 588):

1. $E(u_t|Y_{t-1}, Y_{t-2}, ..., X_{1t-1}, X_{1t-2}, ..., X_{kt-1}, X_{kt-2}) = 0$;
2. *(a) the random variables* $(Y_t, X_{1t}, ..., X_{kt})$ *have a stationary distribution, and;*
   (b) $(Y_t, X_{1t}, ..., X_{kt})$ *and* $(Y_{t-j}, X_{1t-j}), ..., X_{kt-j})$ *become independent as* j *gets large*;
3. *Large outliers are unlikely:* $X_{1t}, ..., X_{kt}$ *and* Y_t *have nonzero, finite fourth moments; and*
4. *There is no perfect multicollinearity.*

The first assumption implies that the model necessitates a conditional mean of zero given all past values of Y and X, hence no additional lags of either Y or X belong in the ADL model. In other words, the chosen lag length p and q are the true lag lengths, meaning the coefficients on additional lags are zero. The second assumption postulates the importance of stationarity, thus that the series needs to be either I(0) or I(1), cf. subsection 4.3.1. Akin to cross-sectional analysis, the third assumption stipulates that large outliers are unlikely. Finally, for the ADL model to be valid under OLS-estimation, absence of perfect multicollinearity is vital. By definition, perfect multicollinearity implies that one of the regressors is a perfect linear function of the other regressors in the regression function. (Stock and Watson, 2015)

Model Estimation: Specific-to-General and General-to-Specific

A fundamental idea within the Box-Jenkins framework is the principle of parsimony (Enders, 2015). The authors stress that parsimonious regression models produce better estimates and forecasts than overparameterized models, as they ultimately fit the data well without encompassing unnecessary coefficients (Enders, 2015). While there are several ways to identify an optimal regression model using time series data, two especially popular methods are; specific-to-general, and; general-to-specific[18].

[18]Specific-to-General is often denoted a forward selection process, whereas General-to-Specific is renowned as

Specific-to-general modeling implies that the researcher starts off with a simple model specification and successively identifies whether adding new covariates will lead to better regression estimates. While the specific-to-general approach appears fairly logic, it is unarguably prone to yield inflated or deflated regression coefficients due to the possibility of omitted variables. This phenomenon denoted omitted variable bias (OVB), occurs when an excluded variable in the error term is correlated with the included regressors and if the omitted variable is a determinant of the dependent variable (Stock and Watson, 2015). If the regression function is affected by OVB, the finalized regression model easily become spurious and lead to inadequate results.

To reduce the probability of the so-called OVB phenomenon researchers may start off with a generalized regression model including several variables and their respective lags. In this occasion, the lag length should be justified through economic intuition and logical reasoning, rather than relying on the lag structure as proposed by the information criterions (Campos et al., 2005). By successively examining whether the included covariates are statistically significant—that is, useful predictors of the dependent variable—the researcher can exclude variables who appear statistically insignificant. This process is renowned as general-to-specific (GETS) modeling and enables the researcher to start with a General Unrestricted Model (GUM) including maximum p lags of the dependent variable and q lags of the independent variables. By ascertaining that the GUM is statistically valid[19] the first phase of the selection process is to stepwise eliminate covariates that do not fulfill a predefined significance level within a specific search-path (Clarke, 2014). The researcher can explicitly restrict the finalized regression model to only include coefficients that satisfy a predefined significance level. The next step is then to check whether the simplified model remains congruent after the removal of statistically insignificant variables and/or lags. Finally, by continuing these steps until none of the remaining variables appear statistically insignificant, the researcher has found a final regression model that is valid for inferring the dynamic relationship amongst the variables (Campos et al., 2005).

We exemplified earlier how the information criterions may be used to determine optimal lag structures prior to testing for covariance-stationarity. Building upon the same logic these criteria may be used to determine, amongst a wide variety of candidate models, the one with

backward selection process (Clarke, 2014).

[19]Prior to initiating general-to-specific modeling, one must ascertain that the GUM is statistically valid by the means of; error-normality, stationarity, ARCH effects, and homoscedasticity. This is deemed necessary to ensure avoidance of "garbage-in, garbage-out" effects (Campos et al., 2005).

optimal fit. Because GETS modeling searches for and defines several regression models through complex mathematical algorithms, the terminal specification that has the lowest BIC-score is deemed the preferred model (Clarke, 2014). Furthermore Clarke (2014, p. 897) postulates that *"GETS is a prescriptive way to select a parsimonious and instructive final model from a large set of real-world variables and enables the researcher to avoid unnecessary ambiguity or ad hoc decisions"*. Therefore, and in contrast to the specific-to-general approach, GETS modeling is less liable to suffer from OVB as the researcher initiates the elimination process on a broad spectrum of independent variables in the GUM (Clarke, 2014). That being said, GETS modeling is more likely to yield overparameterized regression functions as backward selection processes generally lead to the inclusion of more variables and lags contrary to forward selection processes (Campos et al., 2005).

4.4 Econometric Delimitations

While the purpose of this paper is to scrutinize the financial aspects between macroeconomic variables and IPO returns, we find it elementary to support the findings through statistical justification—hence much space has been devoted to the econometric methodology. Econometrics, and time series analysis, in particular, are quite extensive in terms of modeling capabilities and techniques to derive the statistical properties between variables. In other words, the analytical methods including stationarity tests, test for structural breaks, Granger causality, and cointegration presented above are by no means fully exhaustive. This subsection will, therefore, put emphasis on econometric delimitations that could have an impact on the analysis.

First and foremost, the paper presented the ADF-test as a way of identifying whether the series used in the analysis are covariance-stationary or not. While we addressed some of the potential flaws of the ADF-test—in particular, that it tends to reject the null hypothesis of a unit regressive root although it might be untrue—we did not mention other statistical tests that could be supportive on the subject. For instance, the Phillips-Perron or the KPSS tests could probably yield different results than the ADF-statistic albeit including quite similar logical application (Phillips and Perron, 1988; Kwiatkowski et al., 1992). Furthermore, instead of only adopting the EG-ADF test to showcase how two (or more) variables can share a long-run relationship, the test for cointegration could be supplemented by the canonical findings of Johansen (1988, 1991) or the newer Bounds-test for Cointegration developed by Pesaran et al. (2001). That said, we feel that these econometric trade-offs are beyond the scope of this assignment, as we implicitly leverage literature on econometrics to better understand how macroeconomic factors affect IPO returns.

In terms of model selection, we seek to create a time series model that enables us to accommodate several independent variables and their respective lags. While we "semi-concluded" that the specifications, assumptions, and properties following the ADL model were sufficient with respect to our overall mission, one could argue that Vector Autoregressive Models (VAR) or Vector Error Correction Models (VECM) could yield better results. As a matter of fact, most studies inferring how fluctuations in IPO volume changes in response to changes in macroeconomic variables tend to adopt VAR or VECM models (see for instance; Tran and Jeon (2011) or Ameer (2012)). That way, the researchers are able to induce macroeconomic "shocks" through so-called Impulse Response Functions and thereby inspect how these disturbances affect the number of companies going public. Additionally, such modeling concepts may identify if there is any adjustment towards a "steady state" between the variables.

However, we believe that such relationships are difficult to capture once the analysis is shifted from IPO activity towards returns, especially when considering that stock returns ideally should follow a random walk. Additionally, because we're more interested in examining how underpricing varies according to the macroeconomic climate—and not necessarily how the interdependence amongst the macroeconomic variables evolve—we argue that a simple multivariate ADL model is easier to interpret. In support, Stock and Watson (2015) stress that VAR models become inefficient if the variables included in the analysis are unrelated to one another, and that the inclusion of unrelated variables will increase overall estimation error without adding predictive content. In line with their sayings, we believe that IPO returns is not a sufficient metric to explain the evolution of the selected macroeconomic variables—at least not from a financial perspective—hence we chose to treat the selected macroeconomic factors as exogenous predictors on IPO returns.

5 Analysis

Following the Box-Jenkins framework, the first parts of this section will analyze each series' statistical properties. In essence, we aim to identify the variables' autocorrelation structure and identify whether the variables need to undergo any transformations to fulfill the criterion of covariance-stationarity. We will then estimate a regression model through general-to-specific modeling. Then, we move onto model diagnostics to ensure that the estimated regression model is unaffected by structural breaks, check for feedback effects and determine whether cointegration is present or not. Subsequently, we comment on the statistical results in terms of significance and implications that will be addressed in the following chapter. We then proceed with the estimated regression model in order to identify whether the statistically significant variables may serve as useful predictors of future IPO returns through out-of-sample forecasting. We end the chapter by reviewing to what extent the estimated regression model appears valid and reliable—that is if the residuals resemble a white noise process—and whether the regression model fulfills the aforementioned OLS assumptions.

5.1 Preliminary Findings and Descriptive Statistics

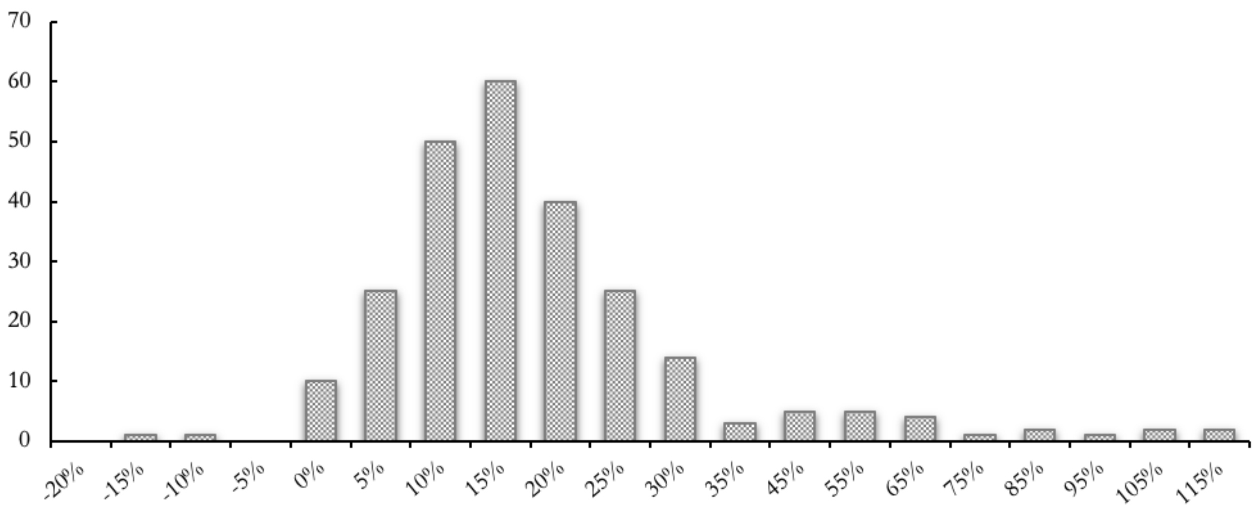
Table 5.1: Descriptive Statistics 1997 - 2017

Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
IPO Performance Indicators					
IPO_RET	252	17.47	19.40	-19.92	118.90
Macroeconomic Indicators					
GBOND10Y	252	3.85	1.42	1.50	6.89
IP	252	97.01	6.14	79.82	106.66
CPI	252	204.31	27.29	159.40	247.91
CRUDE	252	55.60	29.74	11.35	133.88
UNEMP	252	5.89	1.72	3.80	10.00
Financial Market Indicators					
SP500	252	1391.89	426.26	700.82	2673.61
STRESS	252	-.05	1.03	-1.55	4.70

Notes: Descriptive statistics using Stata's inbuilt "summarize" command. Source: Authors' own drawings.

Table 5.1 portrays an overview of the descriptive statistics on monthly IPO performance and the selected macroeconomic variables. From 1997 to 2017, 4016 firms were listed with an average first-day return of approx. 17.5 percent. The average number of IPOs corresponds to approx. 15.94 listings each month because of the 252 months in question, while the aggregated amount of proceeds raised sums up to 823 bn. USD. Average monthly return ranges from -19.9 percent to 119 percent indicating that the spread is quite significant with a high standard deviation. This is further depicted in Figure 5.1, which is a histogram that shows the distribution of the returns using 20 bins. From 1997 to 2017 only nine months experienced average first-day returns below zero, thus implying that overpricing is quite uncommon and therefore in line with preceding empirical literature, cf. Section 2.2. The distribution is somewhat skewed with some outliers such as an average first-day return of 119 percent in December 1999. The findings of this paper actually significantly differ from the first findings of underpricing. For instance, Ibbotson (1975) disclosed that there is an approximately equal chance of having positive or negative returns in a given IPO but because of significant positive outliers, the risk-adjusted average return was reported around 11.4 percent. Our findings indicate the likeliness of having positive first-day returns is much greater than zero as the median of the average monthly returns equals 12.57 percent. The first-day return distribution in Figure 5.1 also highlights that fact:

Figure 5.1: Distribution of IPO Returns



Notes: Distribution of IPO Returns from 1997 – 2017. Y-axis = monthly IPO volume/activity, X-axis = avg. first-day returns. Source: Authors' own drawings.

In terms of the macroeconomic climate, the 10-year Treasury bond is quite stable hitting a record high yield of 6.89 percent in April 1997 with a 21-year average of 3.85 percent. The evolution of the IP and CPI indices are of little interest in this context, as it is the monthly changes that are of significance for the analysis. The monthly standard deviation of the price of oil is surprisingly large with the lowest observable price of 11.35 and the highest of 133.88 USD per barrel. The unemployment rate has an average of 5.89 percent during the 21-year timespan, and peaks in the aftermath of the financial crisis in October 2010 with 10 percent. The S&P 500 index has grown from the sample minimum of 700 up to 2673 points, thus implying remarkable returns for the investors who bought in at the lowest point. The stress indicator has a mean of -0.05 which implies that throughout the period of interest, there has been marginally lower stress than what is considered during normal financial market conditions. The variable stretches from -1.545 to a maximum of 4.7 when the global financial crisis was at its height.

5.2 Regression Results

Before identifying the series' order of integration—that is, whether the variables are stationary or not—a good starting point is to determine the optimal lag structure based on either information criterion discussed in subsection 4.3.1. By doing so the ADF-test incorporates the serial correlation between the estimated residuals and is, therefore, less likely to incorrectly reject the null hypothesis of a unit regressive root (Enders, 2015; Stock and Watson, 2015). To determine the optimal lag length, we ran multiple tests using Stata with respect to both the AIC and BIC criterions. In addition, we plotted the so-called partial autocorrelation functions (PACF) of each series to visualize the number of lags to be included in the ADF-test (see Appendix A2). As displayed in Table 5.2, the AIC criterion allows for the inclusion of more lags contrary to the BIC criterion, which seems intuitive due to the stricter penalty term that the BIC criterion imposes, cf. Equation 4.2.

Table 5.2: Optimal Lag Structure 1997 - 2017

Variable	**Akaike Information Criterion**	**Bayes Information Criterion**
IPO Performance Indicators		
IPO_RET	2	2
Macroeconomic Factors		
IP	8	5
CPI	3	3
CRUDE	2	2
UNEMP	7	7
GBOND10Y	6	2
Financial Markets Indicators		
SP500	5	1
STRESS	4	3

Notes: Optimal lag structure using Stata's inbuilt "varsoc" command. The command uses the AIC and BIC criterions as displayed in Equation 4.2 to determine the optimal lag structure for each variable. This test is run for each variable to determine the optimal lag structure. Moreover, the command is used to determine how many lags to be included in the Augmented Dickey Fuller test as described below. Source: Authors' own drawings.

Although the suggestions from the AIC criterion could result in an overparameterized model in general, Enders (2015) stipulates that including too few lags when testing for a unit regressive root is ill-advised. Following Enders' (2015) argumentation we choose to include the lag structure proposed by the AIC criterion when conducting the ADF-test with the results following in Table 5.3:

Table 5.3: Augmented Dickey-Fuller Statistics 1997 – 2017

Variable	**Lags**	**Prop.**	**Level**	**First/Sec Diff.**	**Interpretation**
IPO Performance Indicators					
IPO_RET	2	Drift	-3.727(***)	-13.715(***)	Unit Change
Macroeconomic Factors					
IP	8	Drift	-1.982	-4.249(***)	Percent
CPI	3	Trend	-2.125	-8.408(***)	Percent
CRUDE	2	Drift	-2.403	-8.862(***)	Percent
UNEMP($\perp$)	7	Drift	-2.287	-10.090(***)	Curvature
GBOND10Y	6	Trend	-2.991	-7.631(***)	Unit Change
Market Performance Indicators					
SP500	5	No Cons.	1.611	-5.920(***)	Percent
STRESS	4	Trend	-2.886	-7.870(***)	Unit Change

Notes: The Augmented Dickey Fuller test statistics using Stata's inbuilt "dfuller" command. (***), (**), (*) denotes significance at the 1%, 5%, and 10% significance level respectively. All variables except IPO_RET, STRESS and GBOND10Y are transformed to their log-first-difference. When calculating the first-difference and deriving the ADF statistics we reduce the optimal lag selection with one lag to preserve the ADF statistics. ($\perp$) implies that the variable is I(2) and is therefore stationary after secondary differencing. Source: Authors' own drawings.

In cases where the series visually had a trend with an unchanging autocorrelation structure—that is, approximately constant autocorrelation coefficients over time—the ADF-test were performed by integrating a trend-term. If the series otherwise appeared to have a gradually decaying autocorrelation structure, we used the specification which includes a drift-term as discussed in subsection 4.3.2 (see Appendix for plots of the series). Furthermore, because time series quite frequently exhibits exponential growth over time, it is useful to compute the logarithm of the series Stock and Watson (2015). By doing so the logarithm of the series grows roughly linearly which implies that the standard deviation of the time series is approximately constant over time. In our case, some variables tended to inhabit exponential growth, which is why we applied the first-log-difference of all variables except for the ones quoted in percentages at levels form.

When inspecting the outcome of the ADF-test we find it legitimate to apply first differences, either as *log-differences* or *level-differences*, as most variables appear stationary after first differencing. By transforming a variable into its first-log-difference we derive the percentage change of the variable. Likewise, the first-difference of a variable that is expressed in percentages such as GBOND10Y simply refers to the percentage change in long-term interest rates. As illustrated in Table 5.3, the unemployment rate appears non-stationary after first difference. To transcend this issue we computed the second-order difference. While the direct interpretation becomes "the change of a change", second-order differences refer to the series' curvature. Therefore, if the coefficients of UNEMP is positive the series is "curving" upwards at that time, and vice versa.

Because the intention of this paper is to unravel the dynamic relationship between macroeconomic factors and IPO returns, we need to conform a regression model that allows for the inclusion of several variables including their respective lags. Since we believe that both contemporary and historical values of the independent variables might affect first-day returns, we find it intuitive to fit an ADL model for two reasons: firstly, it enables us to include an autoregressive term of the dependent variable as additional regressors; secondly, it allows for the inclusion of both contemporary and lagged values of the selected independent variables. As for the lag structure, several scholars suggest including somewhere between 2 to 12 lags when dealing with time series data. This should be dependent upon the total observations available and the economic intuition behind the lag selection (Enders, 2015; Hendry and Juselius, 2000; Liew, 2004). Although our data sample is greater than 250 observations, we believe that no more than four lags seem appropriate to be included in the final regression model. This is based upon the argumentation of prior studies modeling macroeconomic factors and IPO activity (see for instance Tran and Jeon (2011)), the outcome of using the "varsoc" command on all variables in Stata and the fact that we believe that macroeconomic factors' impact on IPO returns are determined on a short horizon, i.e. max four months before an IPO (see Appendix A2 for full output of the "varsoc" command).

In subsection 4.3.5 we highlighted that specific-to-general and general-to-specific modeling poses both advantages and disadvantages. While the former estimation technique may lead to OVB, the latter may induce the final regression model to suffer from overparameterization. Because we initially include a broad spectrum of independent variables to analyze macroeconomic determinants on first-day returns, we believe that specific-to-general poses greater estimation uncertainty than GETS for two reasons. First, it is quite time-consuming to estimate a regression model whereby as much as four lags of each variable will have to be included in different orders. Secondly and more importantly the costs of OVB is greater than overparameterization. Since our overall mission is to untangle and infer the dynamic relationship between macroeconomic variables and first-day return, we argue that GETS modeling is in line with our approach of choosing variables of interest, which can be characterized as an all-encompassing maneuver, whereby we attempt to avoid OVB in our selection process. We make up for the risk of overparameterization by applying the more strict penalty term, which is present in the BIC score in the final model selection. Therefore, we ultimately start with a wide selection of variables and narrow these down in the final model selection, by utilizing a stricter penalty term.

To estimate an appropriate ADL model, we apply a GETS-procedure using Stata's inbuilt "genspec" command and restrict the GUM to include a maximum of four lags of all variables[20]. We restrain the selection process to search for optimal regression models through 50 different paths with a requirement that all included coefficients should at least be statistically significant at the 10 percent significance level. To comply with the principle of parsimony (Box and Jenkins, 1970), we censor the command to determine the model with the lowest BIC-score[21] and achieve

[20]It should be noted that four months of the total sample will be deducted from the regression output due to the criterion of applying maximum four lags in the regression model. Hence the actual samples range from May 2002 to December 2017.

[21]The significance level of 10 percent corresponds to a critical t-value of 1.64. The "genspec" command in Stata is using BIC as the final model selection criterion, as this will eventually lead to a more parsimonious regression model and is therefore considered beneficial (Enders, 2015).

the following results:

Table 5.4: Estimated ADL Model 1997 - 2017

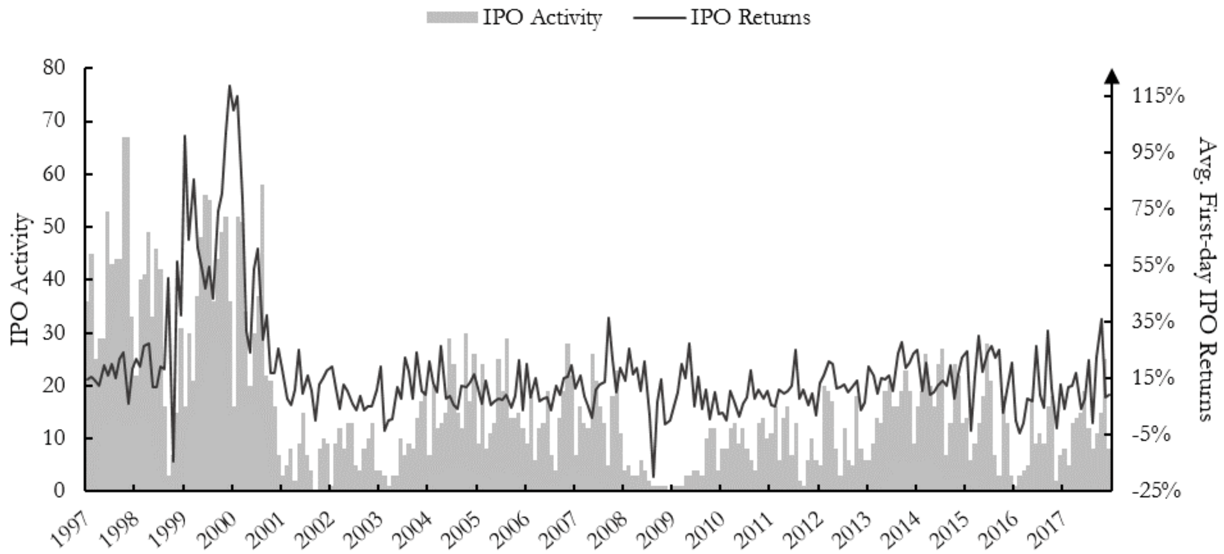
Variable	Intercept	IPO_RET	ΔGBOND10Y	ΔSTRESS	ΔIP
$t-0$	.0268261** (0.012)		8.551254** (0.017)		
$t-1$		.4957172*** (0.000)			
$t-2$		.3433381*** (0.000)			
$t-3$			-7.342571** (0.037)	.0643211** (0.033)	1.945663* (0.089)

Notes: Estimated ADL model using Stata's inbuilt "genspec" command on data ranging from 1997 to 2017. Values outside parentheses equals the estimated coefficient-value for each variable respectively. Values inside parenthesis represents the corresponding p-values. The notation $t-1$ corresponds to the first lag, $t-2$ the second lag and so forth. Δ indicates that the variable is first-differenced. Δip is log-first-differenced. (***), (**), (*) symbolize significance at the 1%, 5%, and 10% significance level respectively. For full output, see Appendix A2. Source: Authors' own drawings.

5.2.1 Test for Structural Breaks

Given the fact that our data covers a time period that includes two financial crises, we find it necessary to examine whether these incidents will bias our estimates. What is renowned as the Dotcom bubble within the field of finance was a period characterized by extreme IPO activity and returns, mostly resulting from underwriters' inappropriate valuations and investors' ambiguous and surrealistic market perception (Bodie et al., 2014). As pointed out earlier, the descriptive statistics displayed that the highest average first-day return throughout the timespan equaled astonishing 119 percent in December 1999 based on 36 different public offerings. In contradiction to the staggering results from the Dotcom bubble, and after the collapse of Lehman Brothers and the beginning of the Global Financial Crisis, a sharp decrease on both IPO activity and IPO performance is observed. For instance, the lowest average first-day return equals -20 percent in August 2008, whereas the lowest number of IPOs in the dataset corresponds to as little as four in the fourth quarter of 2008:

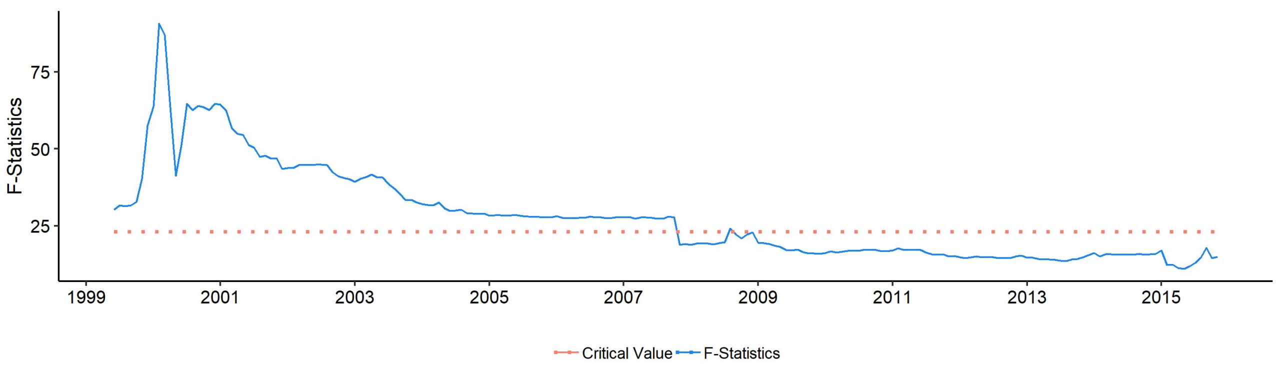
Figure 5.2: Structural Breaks?



Notes: Comparison of IPO activity relatively to first-day IPO returns. Left axis denotes IPO Activity, right axis denotes IPO Returns. Source: Authors' own drawings.

Because the sup-Wald statistics investigates whether the regression coefficients are different for split datasets through multiple F-tests, it detects whether a single or two separate regression lines best fits the data, cf. subsection 4.3.2. By performing the sup-Wald test on the estimated ADL model with a pre-specified trim of 10 percent as proposed by Enders (2015), we find that the dataset includes a structural break at March 2000 with a p-value less than 5 percent. By inspecting Figure 5.3, the F-statistics of the estimated regression function is exceeding the critical value:

Figure 5.3: The sup-Wald Statistics for Structural Breaks 1997 – 2017



Notes: The dotted line in red denotes the critical value taken from Andrews (2003). The blue line represents the F-statistics of the estimated regression function. Because the blue line exceeds the dotted line, the regression function suffers from a structural break. Source: Authors' own drawings.

This implies that we can reject the null hypothesis of no structural break. Moreover, the estimated coefficients might be biased as the period before the structural break are most likely non-representative for the period after the break (see Appendix A2 for sup-Wald statistics). The significant interference coincides with the fact that the Dotcom bubble busted around this time-period, hence a significant drop in average first-day returns remarked the period (Jenkinson and Ljungqvist, 2001). One way to circumvent the issues of structural breaks could be to include a dummy variable in March 2000. Because IPO returns are gradually declining from early 2000 to ultimo 2001 as seen in Figure 5.3, we find it more convenient to exclude the Dotcom bubble from further analysis. Hence, we conclude that the Dotcom bubble has a too significant impact on average IPO returns and that a readjustment of the time period is pivotal to achieve a statistically valid model.

5.2.2 New Time Horizon

Given the fact that our dataset ranging from 1997 – 2017 contains a structural break around March 2000 and that IPOs prior to this date experienced tremendous first-day returns, a regression function including the proposed structural break would definitely lead to inflated coefficients (Stock and Watson, 2015). Therefore, we decided to reduce the observation period to cover 2002 – 2017, as it is commonly perceived that the Dotcom bubble ended around 2002 (Angelini and Foglia, 2018). Because of the reduction in the data sample, we have to re-estimate an ADL model by following the aforementioned steps—that is, to determine a new lag structure and then identify whether or not the variables appear stationary.

Before moving onto the pre-estimation of a new ADL model, recall from the dataset description in subsection 4.2.1 that BAML released their so-called market liquidity index in 2010. Because this index tracks the funding stress in the global financial system in terms of the tightness on spread-based relationships in rates, credit, and currencies and backdates as far as 2000, we can include this variable as an additional predictor when examining the question at hand. For example Tran and Jeon (2011) find that market liquidity serves as a useful precursor of total proceeds raised after an IPO, hence implying that market liquidity to some extent affect IPOs. Although their studies cover IPO activity and "money left on the table" and their proxy for liquidity is different, we find it natural include the liquidity index as there is evidence pointing to the fact that liquidity risk affects IPO in some shape or form. Table 5.5 below presents new descriptive statistics from 2002 to 2017:

Table 5.5: Descriptive Statistics 2002 - 2017

Variable	Obs.	Mean	Std. Dev.	Min	Max
IPO Performance Indicators					
IPO_RET	192	11.87	8.10	-19.92	36.64
Macroeconomic Indicators					
GBOND10Y	192	3.28	1.08	1.50	5.28
IP	192	99.19	4.82	87.07	106.66
CPI	192	215.67	20.48	177.70	247.91
CRUDE	192	66.06	26.22	19.72	133.88
UNEMP	192	6.33	1.73	4.10	10.00
Financial Market Indicators					
SP500	192	1456.65	456.09	700.82	2673.61
STRESS	192	-0.32	1.05	-1.55	4.70
LIQUIDITY	192	0.26	0.51	-0.40	2.84

Notes: Descriptive statistics using Stata's inbuilt "summarize" command. Source: Authors' own drawings.

Given the new time horizon, the variables of interest seem more "normalized". Naturally, the number of observations has decreased from 252 to 192 and therefore the sample size is smaller. However, the values of the macroeconomic indicators and the financial market indicators do not yield significantly different results than before, which is also a supplementary indicator for a structural break during the Dotcom bubble as the macroeconomic variables does not change significantly when excluding that period (Stock and Watson, 2015). Nevertheless, the observations on first-day returns differ substantially. The mean return decreases from 17.5 percent to 11.9 percent, which seems to be a "better" estimate as one excludes extreme outliers. This is supported by the fact that the maximum monthly observation declines from 119 percent to 36.6 percent, meanwhile, the standard deviation drops from 17.5 to 8. Hence the data on IPO returns appear more stabilized, while the macroeconomic and financial market factors remain more or less constant. The main difference between the two time horizons is the inclusion of the liquidity metric, which has a maximum value of 2.8 that occurred during the financial crisis in late 2008. Because the metric is construed in such a way that zero is supposed to be the mean—that is, normal liquidity risk—this implies that there has been elevated liquidity risk during the new time horizon.

In subsection 4.3.2 we stressed the importance of including variables' serial correlation to reduce the probability of falsely rejecting the null hypothesis of a unit root when applying the ADF-statistics to test for stationarity. Therefore, we re-estimate the optimal lag length using Stata's inbuilt "varsoc" command, and as illustrated below we achieve a slightly different lag structure in terms of both information criterions relative to the period of 1997 to 2017. It should also be noted that we include the liquidity index as well:

Table 5.6: Optimal Lag Structure 2002 - 2017

Variable	**Akaike Information Criterion**	**Bayes Information Criterion**
IPO Performance Indicators		
IPO_RET	3	1
Macroeconomic Factors		
IP	5	5
CPI	3	3
CRUDE	3	2
UNEMP	7	6
GBOND10Y	3	2
Financial Markets Indicators		
LIQUIDITY	3	1
SP500	1	1
STRESS	4	4

Notes: Optimal lag structure using Stata's inbuilt "varsoc" command. The command uses the AIC and BIC criterions as displayed in Equation 4.2 to determine the optimal lag structure for each variable. This test is run for each variable to determine the variables' serial correlation. Without any further commenting, we observe that some of the variables' autocorrelation structure is reduced contrary to the period covering 1997 – 2017. Source: Authors' own drawings.

Following the above-mentioned process, we conduct a new ADF-test to identify whether the time series appear stationary or not using the lag structure anticipated by the AIC criterion above. For tractability reasons, we have also derived new characteristics of the series as shown in Appendix A3.

Table 5.7: Augmented Dickey-Fuller Statistics 2002 – 2017

Variable	Lags	Prop.	Level	First/Sec-Diff.	Interpretation
IPO Performance Indicators					
IPO_RET	3	Drift	-5.218(***)	-12.124(***)	Unit Change
Macroeconomic Factors					
IP	5	Drift	-2.212	-3.269(**)	Percent
CPI	3	Trend	-1.942	-7.511(***)	Percent
CRUDE	3	Drift	-2.578(*)	-7.659(***)	Percent
UNEMP(⊥)	7	Drift	-2.023	-8.687(***)	Curvature
GBOND10Y	3	Drift	-2.019	-7.500(***)	Unit Change
Market Performance Indicators					
SP500	1	No Cons.	2.123	-12.770(***)	Percent
LIQUIDITY	3	Drift	-3.234(**)	-6.973(***)	Unit Change
STRESS	4	Trend	-2.111	-6.766(***)	Unit Change

Notes: The Augmented Dickey Fuller test statistics using Stata's inbuilt "dfuller" command. (***), (**), (*) denotes significance at the 1%, 5%, and 10% significance level respectively. All variables except IPO_RET, STRESS, GBOND10Y and LIQUIDITY are transformed into their equivalent log-first-difference form when testing for stationarity at first differences. (⊥) implies that the variable is I(2) and is therefore stationary after secondary differencing. Source: Authors' own drawings.

By applying the general-to-specific command in Stata with respect to a predefined critical t-value of 1.64 and BIC as the final model selection criterion, we achieve the following regression results:

Table 5.8: Estimated ADL Model 2002 - 2017

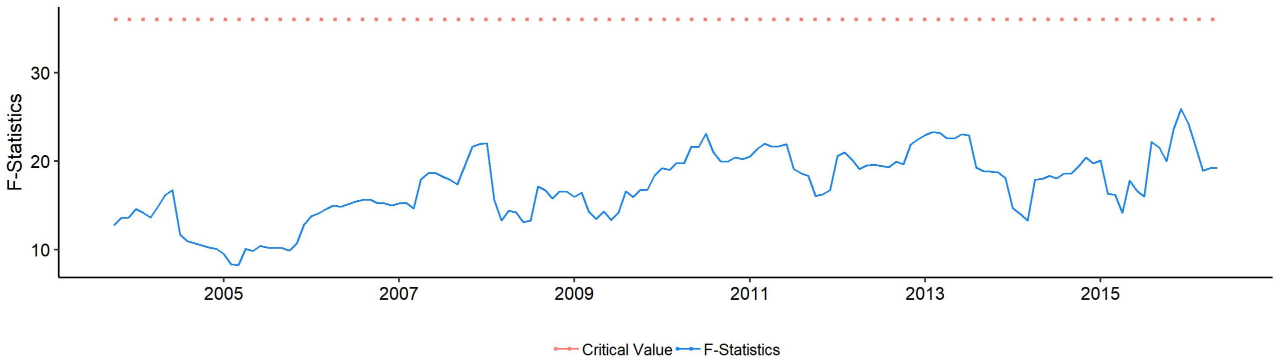
Variable	Intercept	IPO_RET	ΔGBOND10Y	ΔSTRESS	ΔLIQUIDITY	ΔIP⊥	ΔSP500⊥
$t-0$	.0746135*** (0.000)			.0787578** (0.021)	-.1119495** (0.033)	2.195074** (0.021)	.25769* (0.090)
$t-1$		.1558932** (0.028)		.1047017*** (0.005)	-.0888803* (0.069)		.2872344* (0.054)
$t-2$			-5.8919** (0.027)				.3848221*** (0.006)
$t-3$		.2086772*** (0.004)		.047431** (0.035)		-2.028267** (0.039)	
$t-4$						-1.744906* (0.058)	

Notes: Estimated ADL model using Stata's inbuilt "genspec" command on data ranging from 2002 – 2017. Values outside parentheses equals the estimated coefficient-value for each variable respectively. Values inside parenthesis represents the corresponding p-values. The notation $t-1$ corresponds to the first lag, $t-2$ the second lag and so forth. Δ indicates that the variable is first-differenced. ⊥ implies that the variable is log-first-differenced. (***), (**), (*) symbolizes significance at the 1%, 5%, and 10% significance level respectively. For full output, see Appendix A3. Source: Authors' own drawings.

5.2.3 A New Test for Structural Breaks

Since the financial crisis had a momentous impact on global stock markets and the worldwide economy, we find it quintessential to test for structural breaks vis-à-vis the period covering 1997 to 2017. When running a new sup-Wald test with a pre-specified trim of 10 percent on the estimated ADL model, a structural break is suggested around February 2008. However, the proposed structural break is statistically insignificant at every conventional significance level with a p-value of 0.4491 (see Appendix A3 for full output). In opposition to the first regression model, we fail to reject the null hypothesis of no structural break, and by inspecting the graphical representation of the sup-Wald statistics, one clearly see that the regression function gives the impression of being unaffected by any disruptions:

Figure 5.4: The sup-Wald Statistics for Structural Breaks 2002 – 2017



Notes: In this occasion, the blue line (the F-statistics of the estimated regression function) is persistently below the dotted line throughout the time-period. We therefore conclude that the regression model is unaffected by structural breaks. It should be noted that the critical value have increased contrary to the period covering 1997 - 2017 due to more covariates included in the new regression model. Source: Authors' own drawings.

As we do not find any statistical evidence proving that the re-estimated regression model appears biased in terms of structural breaks, we proceed with the ADL model for further analysis. However, the sup-Wald test actually reveals something extremely interesting in terms of contemporary IPO literature. Recall that the test for structural breaks when the Dotcom era was included showed a significant structural break in March 2000. Given the fact that the Dotcom bubble is the last known "hot IPO period" in the U.S. (Jenkinson and Ljungqvist, 2001) and the sup-Wald statistics was insignificant when excluding this time period, it implies that we do not find evidence of any hot IPO periods since. This means that, according to our estimates, there is no indication of a hot IPO market over the 15-year period in question. This can also be derived from Figure 5.2, where the period after 2002 appears almost constant with slightly diminutive fluctuations. It may therefore imply a large shift in regards to prevailing literature, which is focused IPO waves, as there doesn't appear to be any hot or cold markets present anymore. On average, each IPO wave happens around every 10-15 years (Lowry and Schwert, 2004) but at the time of writing, the IPO market has been remarkably quiet since the burst of the Dotcom bubble. This may imply that either a hot/cold IPO market is underway or perhaps that the fundamental developments in IPO activity and returns over time has changed. Lowry et al. (2017) suggest the same observation in their relatively recent publication, contributing and supporting the notion of a changed IPO market structure.

5.2.4 Granger Causality Test for Feedback Effects

Prior to inferring the estimated coefficients, we find it sensible to scrutinize whether first-day returns reside any feedback effects on the selected macroeconomic variables. Recall from Section 4.3.3 that a Granger-causality test is generally used to assess whether a variable has marginal explanatory power on the dependent variable beyond the other variables included in the same regression function. To identify whether IPO returns embodies any feedback effects on the selected macroeconomic variables, we find it advantageous to carry out a Granger causality test. Using a maximum of four lags of each variable, we discover that the selected macroeconomic variables Granger-causes IPO returns, and to our big surprise that IPO returns Granger-causes the U.S. industrial production index. This is unexpected as it seems improbable to believe that IPO returns plausibly affect the overall U.S. macroeconomic environment, as the industrial production index tracks the real output of U.S. manufacturing, mining, and electric and gas utilities (see Appendix A3 for full output).

While it is latent to claim that the S&P 500 index may be affected by IPOs if the "money left on the table" is of a considerable amount, we argue that this is not the case in our study. Firstly, there are formal requirements that have to be fulfilled before a company can become a member of the S&P 500, in which one of these prerequisites is that a company has to be traded for several months before even being considered a potential candidate (S&P Dow Jones Indices, 2019). Secondly, we are exclusively focusing on first-day IPO returns, which means that seasoned offerings are excluded from the analysis. This implies that none of our companies are existing members of the S&P 500 index.

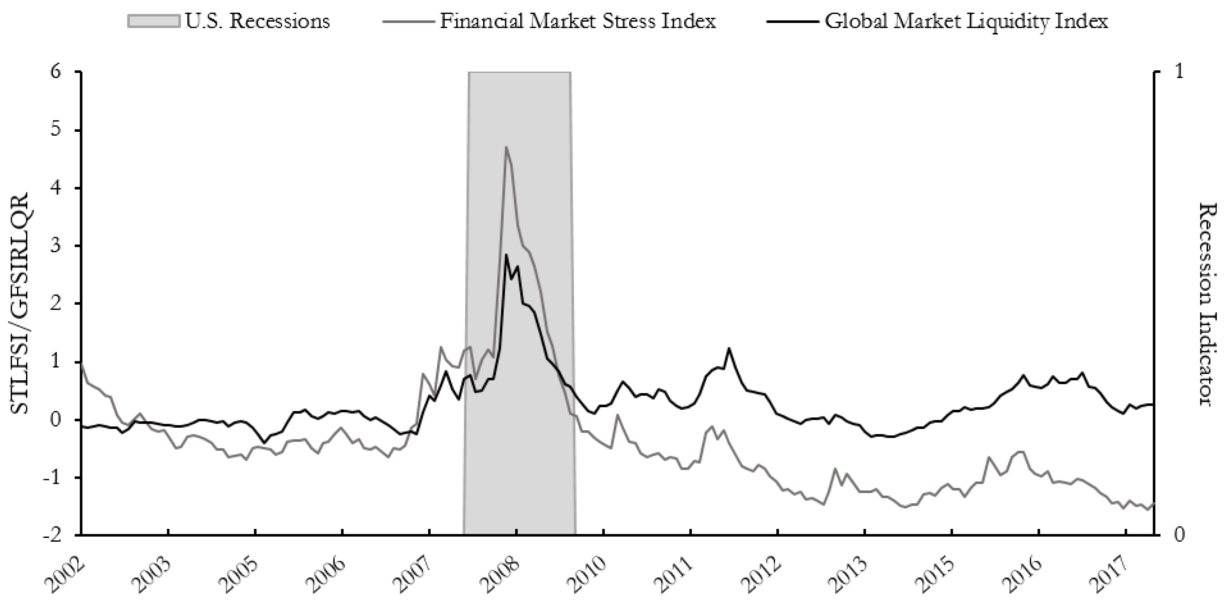
5.2.5 Test for Cointegration

Given that we have identified an ADL model that is unaffected by structural breaks, we would like to determine whether the coefficients included in the regression function share a long-run relationship. To do so, we leverage Stock and Watson's (2015) three-step-approach of theoretical reasoning, visualization and statistical computation. Since we found that IPO_RET are integrated of order zero I(0) through the ADF-test above, we cannot derive any long-run relationship between first-day returns and the selected macroeconomic variables through the EG-ADF test (Engle and Granger, 1987; Shumway and Stoffer, 2011). The logic is simply that we cannot find a cointegrating coefficient that will make the combination of IPO_RET and the independent variables stationary as IPO_RET are stationary in levels form. Additionally, we find little economic rationale supporting the existence of a long-run equilibrium between IPO returns and macroeconomic factors *per se*, as we know from the literature that IPO-pricing is sensitive to idiosyncratic company features.

However, because the independent variables are first-difference-stationary—that is, they are integrated of order one I(1)—these variables may be cointegrated. For instance, when inspecting Figure 5.5, we clearly see a tendency towards a common stochastic trend between the STRESS and LIQUIDITY series. By utilizing the EG-ADF test, we fail to reject the null hypothesis of no cointegration, and accordingly we are unable to identify a long-run relationship between any of the independent variables in our ADL model. Although two series may appear to visually share a common stochastic trend, it can only be fully determined through statistical computation and economic intuition. To do so, we apply Stata's inbuilt "egranger" function including four lags of each variable and as illustrated in Appendix A3, the results from the EG-ADF test are statistically insignificant.

Despite the fact that some authors have found a long-run relationship between IPO activity and macroeconomic factors (see for instance; Tran and Jeon (2011); Ameer (2012) or Angelini and Foglia (2018)), this seems not to be the case when shifting the analysis towards macroeconomic factors' impact on first-day IPO performance.

Figure 5.5: Cointegration amongst the Financial Stress Index and Global Market Liquidity?



Notes: Values above zero implies that there is elevated financial stress within the U.S. market and greater global liquidity risk. Source: Authors' own drawings.

5.2.6 Commentary on Regression Output

In the following section, we present the statistical interpretation of the estimated ADL model. We find it interesting to see the differences between the regression functions from 1997 to 2017 and from 2002 to 2017, as we observe a considerable reduction in the estimated coefficients on lagged initial returns. This subsection will therefore put more emphasis on this finding relative to those of the macroeconomic variables, while the next chapter will to a greater extent focus on the intuition of why some macroeconomic factors serve as determinants on first-day returns.

The Goodness of Fit

Before interpreting the estimated coefficients in Table 5.8, we find it important to discuss the model's goodness of fit. We can inspect the estimated R^2 which simply is the fraction of the sample variance of Y_i explained by the included regressors, k. However, because R^2 increases whenever a regressors is added to the regression model, Stock and Watson (2015) stress that the adjusted R^2 (*adj.* R^2) is a better measure of overall model fit[22]. In essence adding predictors without explanatory power would not result in a better fit and consequently, the R^2 may become somewhat artificial. Following the argument of Stock and Watson (2015) we explicitly focus on the *adj.* R^2. In our case, we achieve an *adj.* R^2 of 0.1668 which implies that 16.68 percent of the variance in average first-day returns are explained by changes in the macroeconomic factors incorporated in the regression model. Put differently 83.32 percent of the variation in average initial returns is explained by other factors than those included in the regression function.

While one may argue that such a R^2 value is disappointingly low, we find it intuitive for several reasons. As outlined in Section 2.4 on traditional underpricing theories, there are multiple concepts that perhaps can help shed some light on the remaining variance that is not covered in the model as they do not fall into the category of macroeconomic variables. Rather, these are firm-specific or information-based factors that do not fluctuate according to the macroeconomic environment. Analysis of such considerations is naturally beyond the scope of this paper which, all else equal, affects the R^2 value. Additionally, by limiting the GETS modeling to only include statistically significant variables and their successive lags at a critical t-value of 1.64, we ultimately create a time series model whose objective is to examine the relationship between the variables of interest, rather than being built for the purpose of forecasting. For example, Stock and Watson (2015) argue that forecasting models do not necessarily need to have a causal interpretation. In short, we are more concerned about the dynamics between IPO returns and macroeconomic variables than we are of maximizing the R^2 value.

The Intercept

The constant or the intercept, β_0, of a linear regression communicates the expected value of the dependent variable when the independent variables are held constant at zero. In other words, by restricting all other variables to be zero the intercept implies that the regression line intersects the Y-axis at 0.0746135. Simply put, if all of the coefficients in the regression function is held constant at zero, which implicitly implies that independent variables experience zero growth, the expected first-day return equals approx. 7.5 percent. This further implies that the statistically significant variables, on aggregate, have a positive contribution towards explaining IPO returns. Again, as the average IPO return throughout the period equals approx. 11.9 percent, it seems

[22]This is true if the estimated coefficient of the added regressor(s) is exactly zero (Stock and Watson, 2015)

legitimate to suggest that other factors than those included in the regression model impact IPO returns, hereunder idiosyncratic factors as hinted above. (Stock and Watson, 2015)

Autocorrelated First-day Returns

Ritter (1984) and Bradley and Jordan (2002) confirms that initial returns appear to be highly autocorrelated as they evidence that periods of high persistence in first-day returns are inclined to last for several months. In line with their remarkable results, we observe a strong, positive relationship between contemporary and past IPO returns. While Bradley and Jordan (2002) reports that previous underpricing of less than 5 percent induces contemporary initial returns to averages about 16 percent, or more extreme, that previous underpricing greater than 30 percent induce current first-day returns to exceed astonishing 60 percent, our findings appear more conservative. We find that a percentage increase in preceding average initial returns increase underpricing today by approximately 1.5 percent and that a percentage increase in initial returns three months ago induce contemporary returns to increase by roughly 2.1 percent[23]. That being said, we believe that the differing results extrapolate from the fact that their data encompass IPOs from 1990 to 1999, and that the Dotcom bubble could potentially inflate their findings[24].

To support our argumentation, we observed a distinctive reduction in the coefficients encompassing lagged initial returns when comparing the ADL models ranging from 1997 to 2017 and from 2002 to 2017. We found a significant structural break in March 2000 and argued that this was potentially resulting from the striking first-day returns that investors could achieve relative to the returns following after the burst of the Dotcom bubble. Amid being a plausible suggestion, for instance Lowry et al. (2017) argue that IPO waves appear more muted in the post-2000 period with "hot markets" being "less hot" compared to the markets of the late-1990s, we cannot necessarily conclude on the causality of our observed structural break with respect to the Dotcom bubble[25]. Additionally, it should be noted that Bradley and Jordan (2002) applies a substantially different method than we do as their findings are based upon a moving average regression model; and because ADL models cannot include a moving

[23]It should be noted that our study implies how much the average initial return deviate for an increase in previous returns. We can therefore not discard the authors' findings.

[24]At the time Bradley and Jordan (2002) wrote their initial paper, the term "Dotcom bubble" were not popularized.

[25]As much as the structural break appears to be discrete, it could be a result of a gradual change in the population regression. Additionally, we do not specifically test for the causality between IPO returns and the Dotcom bubble (Stock and Watson, 2015).

average term, our results may not appear as precise as theirs. Nonetheless, it is believed that our regression results support earlier evidence, namely that initial returns appear serially correlated at which point past returns may affect initial returns today.

Long-Term Interest Rates

In line with our preliminary expectations derived from our correlation matrix, long-term interest rates pose a negative impact on IPO returns with a coefficient equal to -5.8919. Since GBOND10Y is expressed in first-differences, the interpretation becomes as follows: "an increase of hundred basis points in long-term interest rates decreases contemporary IPO returns with approx. 5.9 percent". Furthermore, the estimated coefficient is statistically significant at the 5 percent significance level with a p-value of 0.47 and therefore considered relatively reliable as an estimate.

Financial Stress Index

Recall that the financial stress metric measures the stress in both bond, currency, stock and interbank markets. According to our regression model, there are three significant lags of the stress variable that has explanatory power on IPO returns. Since the variable at $t-0$ equals 0.0787578, a percentage increase in STRESS increase average IPO returns by approx. 7.9 percent. It is interesting to see that there is a positive relationship at all three lags between stress in the financial market and first-day returns. Intuitively, this might seem a little contradictory as one should assume that returns on a "stock-like-asset" should go down during times of stress and uncertainty. However, the opposite appears true. We will thoroughly present our understanding of the phenomenon in subsection 6.1.2.

Global Market Liquidity Index

The global liquidity risk index developed by BAML is statistically significant with opposite signs of the financial stress index. Meanwhile the stress index appeared positively correlated with IPO returns, increments in global liquidity risk have a negative impact on first-day returns. Statistically, the metric is only significant at $t-0$ and $t-1$ at the 5 percent and 10 percent significance level respectively. Because the index tracks the liquidity risk of the global financial market, we find that heightened liquidity risk decreases IPO returns. There is arguably a close relationship between the liquidity index and the stress index which makes the opposing signs of the lag operators even more interesting. Once again, subsection 6.1.3 attempts to delineate on the causing factors of these relationships.

The Industrial Production Index

Our proxy for economic growth—the industrial production index—is also correlated with first-day returns, however with differing signs. At $t-0$, the IP index is statistically significant at the 5 percent level with a positive figure implying that if industrial production goes up by one percent, then average IPO returns will soar by approx. 2.2 percent. The coefficient at $t-1$ is not significant at the 10 percent significance level and is therefore excluded from 5.8. The index is significant at the 5 percent significance level at lag 3 and at the 10 significance level at lag 4. Interestingly enough a contemporaneous growth in the index is positively correlated with IPO returns, but negative beyond until lag 4. This implies that if the IP index increases with one percent four months prior to an IPO, then average contemporary IPO returns will go down by approx. 1.74 percent. On the contrary, if output growth has been *negative* for a couple of months before a company goes public, then it would be wise of investors to invest in IPOs.

The Stock Market

The best proxy for stock returns is arguably the monthly changes in the S&P 500 index. In line with some scholars that have used the index as a benchmark in terms of stock market returns towards IPO activity, we also find that the index is a robust predictor of IPO returns. The proxy is statistically significant at lags 0, 1 and 2, which all have positive signs, thus implying the existence of a positive correlation between stock market returns and IPO returns. More specifically all three lag operators are positively correlated with IPOs return within the range of 0.26 to 0.38 percent which implies that as a minimum over the three time-periods, a percentage change in S&P 500 increase average IPO returns by at least 0.26 percent. Thereby all the financial market indicators included in the analysis hereunder; financial market stress, liquidity risk, and stock market returns have a statistically significant impact on IPO returns.

Variables of Insignificance

From Table 5.8 it should by now be clear that not all variables originally included in the analysis have a significant impact on underpricing. Inflation, as measured by the CPI index, has shown not to be statistically significant at the 10 percent level and therefore it is not included in the model. This does not mean that we can rule out that inflation will have no impact on IPO returns, rather that we are unable to identify any predictive capabilities at the 10 percent significance level given our data. The same goes for changes in the unemployment rate as well as crude oil. The fact that the unemployment rate is insignificant at the 10% level is actually surprising given the fact that Hrnjic and Sankaraguruswamy (2010) apply the unemployment level as one of the proxies for investor sentiment and finds that correlation actually exists. This is not supported by our findings but might be attributable to a different time period in scope and different model setup. Hence without any further commenting, the insignificant variables are excluded from further analysis.

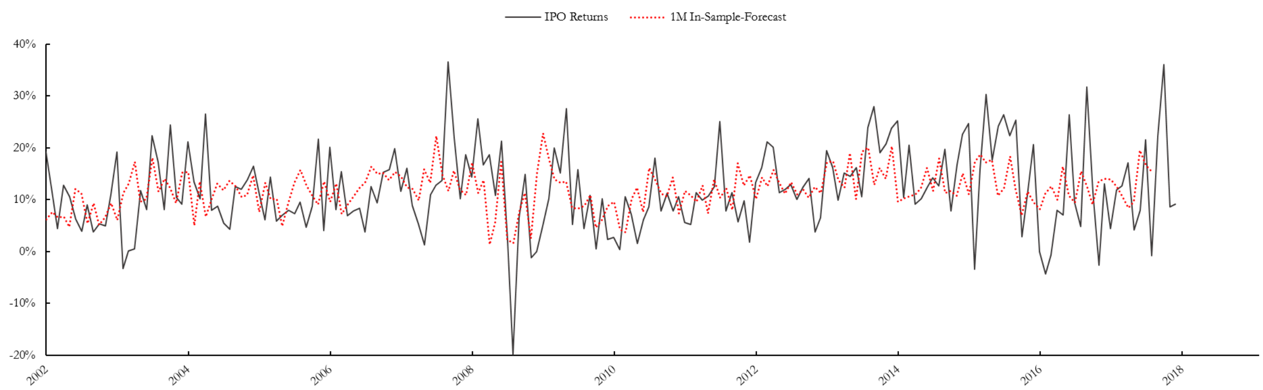
5.3 Sub Conclusion I

At this stage, the paper is able to conclude on the first part of the research question, namely what macroeconomic factors influence IPO underpricing. By utilizing time series techniques to model initial returns using macroeconomic variables, the paper has found that several macroeconomic indicators indeed influence IPO underpricing. Throughout the literature review, contemporary theories on IPO activity and returns have been covered, and as argued we find that macroeconomic modeling is a useful and academically stipulated subject that necessitates additional focus. By systemically choosing variables that have been proved by preceding literature to have an influence on IPO returns, proceeds or activity, we found eight variables of interests that are all deemed informative on a macroeconomic level. The sup-Wald test on our preliminary regression model indicated a structural break around the burst of the Dotcom bubble, hence the timespan of the data was narrowed from 2002 to 2017. By creating a new regression model, no structural break was consequently found, perhaps suggesting that a hot IPO market has not been present since the Dotcom bubble. The final model presented five exogenous variables that are all correlated with the underpricing of IPOs. Long-term interest rates, Federal Reserve's stress index, the liquidity risk metric of BAML, the industrial production index, as well as the S&P 500 index, have lag operators that are statistically significant at the 10 percent significance level, while unemployment, inflation, and crude oil did not turn out significant. Even though the *adj.* R^2 of the model is only 16.68 percent we still believe that the data is of significance as, to the best of our knowledge, no other authors have realized this type of macroeconomic modeling outcome. For now, it has been investigated which macroeconomic factors influence IPO underpricing, thus the remaining steps are to examine how useful these indicators are in predicting first-day returns and subsequently test the validity of the results.

5.4 Forecasting Results

Earlier we postulated that time series analysis assumes that the past can be a good approximation of the future and that time series models may be used to predict the future if properly modeled. While our main goal was to build a model with the notion of inferring the dynamic relationship between the macroeconomy and IPO returns, this section will apply the very same model to delineate how good the macroeconomic variables predict future IPO returns. To do so we construct, firstly a one-month in-sample forecast, and secondly a twelve-month pseudo-out-of-sample forecast. The in-sample forecast serves as a way of illustrating how good the model is to predict prior realized returns given the corresponding macroeconomic data. Technically speaking, in-sample forecasting evaluates the predictive capabilities of the regression model by measuring how effective the model is to reproduce actual data (Enders, 2015). And as depicted in Figure 5.6 the fitted values of the regression model portrays a tendency wherein the model appears to follow fluctuations in IPO returns, however with a differing amplitude relative to realized IPO returns.

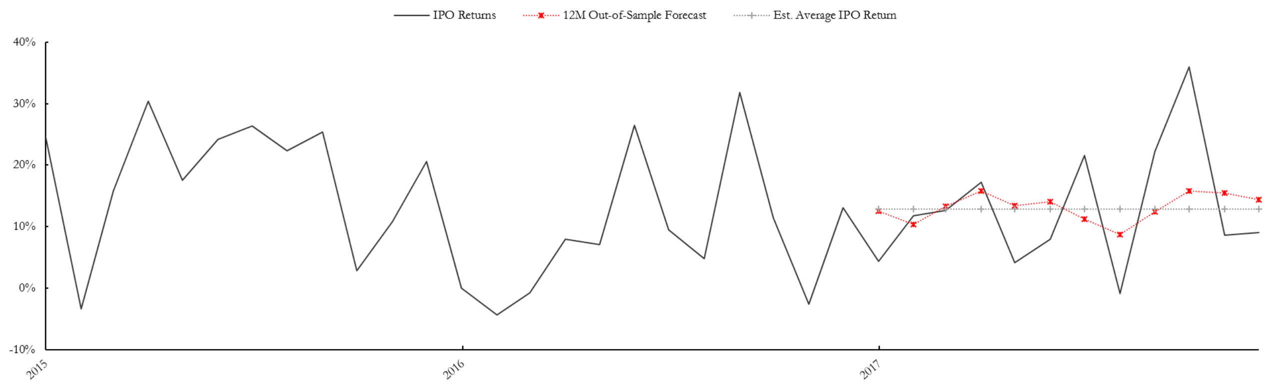
Figure 5.6: In-sample Forecast



Notes: The in-sample-forecast is created utilizing the inbuilt function "predict, xb" in Stata. Source: Authors' own drawings.

In contrast to in-sample forecasts, pseudo-out-of-sample forecasting involves the task of dividing the total data sample into two subsets; the first one is a training set which forms the basis for estimating a forecast model, the latter being an "unexplored" dataset in which the forecast model use to predict future values of the dependent variable. By splitting the total data sample into two subsets, we simply use historical data to determine the relationship between the dependent and independent variables to construct a predictive model. This model is then used to predict future IPO returns based upon transitions in the statistically significant macroeconomic variables, and consequently, we are able to compare the forecasting results in terms of forecast errors:

Figure 5.7: Out-of-sample Forecast



Notes: Out-sample-Forecast are made in Stata using the inbuilt function "forecast". The figure portrays 12M out-of-sample forecast of IPO returns; the straight line equals realized IPO returns; the dotted red line represents pseudo out-of-sample forecast, and; the dotted gray line denotes the simple arithmetic of average first-day returns in 2017. The area between the lines represent forecasting errors. Source: Authors' own drawings.

Moreover, we model a 12-month pseudo-out-of-sample forecast on a training set encompassing observations from 2002 to 2016 and compare this to the arithmetic average first-day returns in 2017. By choosing a 12-month period to forecast, we find the length of the training set to be adequate (14 years or 168 observations) for the model to learn. At the same time, 12 months is also a reasonable duration of a forecast as it allows for at least some graphical and computational interpretation. To understand whether our regression model produce insightful results we estimate and compare the mean squared error (MSE) of the ADL model (*red line*) and the arithmetic average returns (*grey line*) relative to realized IPO returns (*black line*)[26]. When comparing the MSE of each prediction, we find that the ADL model yields a lower forecasting error over the arithmetic average with an MSE of 0.0081 compared to 0.0093. Albeit having a

[26]Mean Squared Error is calculated as follows: $MSE = \frac{1}{n}\sum_{i-1}^{n}(Y_i - \hat{Y}_i)^2$

lower forecasting error, some model characteristics have to be outlined.

As our main objective is to unravel the dynamic effects between macroeconomic indicators and IPO returns, contemporary values of the macroeconomic variables are incorporated in the forecasting model. This implies that our forecasting model is built upon values that should be "unknown" when running the forecasting-exercise. This may seem counterintuitive as these values should, from a theoretical standpoint, be predicted themselves. To illustrate, we found that contemporary changes in industrial production have a positive impact on IPO returns. Subsequently, the forecast uses $t - 0$ values of the industrial production index (amongst others) to forecast initial returns in 2017. However, when forecasting returns the next twelve months, the industrial production index should be unknown at $t - 0$ as this number is published approx. two weeks later than the first calendar day in the following month. Secondly, when inspecting Figure 5.7 we observe a significant spike in realized IPO returns ultimo 2017. This may lead to a higher forecasting error between realized and simple arithmetic first-day returns, and thereby skew the findings.

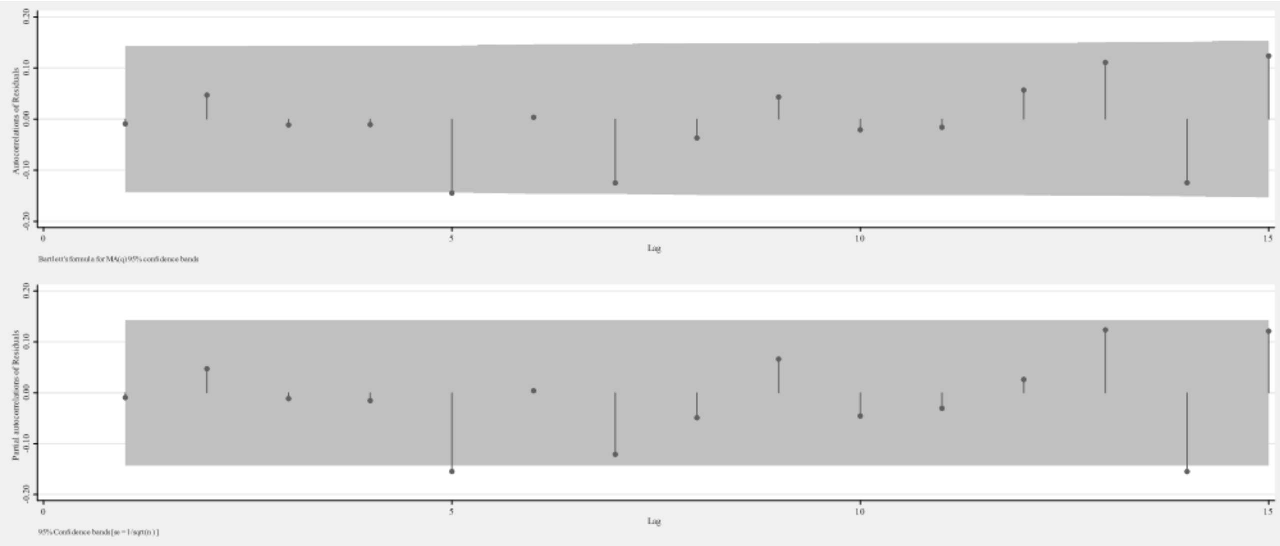
Altogether, the forecasting model entails a lower MSE relative to the estimated average return throughout the same time period, which *de facto* showcase that applying macroeconomic variables to better understand fluctuations in underpricing is plausible. Nevertheless, because the forecasting model relies on contemporary values of the independent variables it becomes inefficient to apply our regression model to purely forecast first-day returns—unless the independent variables are predicted themselves.

5.5 Post-Estimation: Diagnostic Checks

Following the last stage within the Box-Jenkins framework, we will now identify to what extent the regression model appears statistically valid through several diagnostic checks (Enders, 2015). In Section 4.3.5 we presented four assumptions that need to be upheld in order for the ADL model to be valid in terms of OLS estimation. The first assumption, $E(u_t|Y_{t-1}, Y_{t-2}, ..., X_{1t-1}, X_{1t-2}, ..., X_{kt-1}, X_{kt-2}) = 0$, pinpoints that sometimes Y_t is above the population regression line and sometimes Y_t is below the regression line, but on average Y_t falls on the population regression line (Stock and Watson, 2015). It is therefore assumed that the error term, u_t, is uncorrelated with the regressors, and accordingly that the model does not suffer from omitted variables. This is anticipated to not be the case as the Ramsey (1969) regression specification-error test for omitted variables are statistically insignificant with a p-value of 0.2668 (see Appendix A4 for full output). While the second assumption stresses that the model should be stationary, the third assumption emphasizes that extreme outliers should be unlikely, hence we need to examine if this is the case or not. The last conjecture pinpoints that the existence of perfect multicollinearity invalidates OLS estimation, therefore, careful scrutiny is needed. Finally, we wish to identify whether the residuals appear to be white-noise or not. As mentioned earlier, this is the very basic building block of time series analysis which assumes that the sequence of a series should have a mean of zero, constant variance, and a constant autocorrelation structure (Enders, 2015). This section departs with an analysis of the error-term to discover if the residuals appear to be white-noise or not. Next, we inspect if extreme outliers are prevalent, and then move onto two tests for multicollinearity. Lastly, we end our diagnostic section by analyzing the parameter stability of the regression model.

The first step to understanding whether the residuals resembles a white-noise process can be done by plotting its autocorrelation (ACF) and partial autocorrelation (PACF) functions. Theoretically speaking, white-noise processes imply that the residuals (errors) are random and thereof normally distributed with means equal to zero and constant variances, i.e. $N(0, \sigma^2)$. A neat way to investigate whether this is the case or not can be done by inspecting the serial correlation amongst the residuals; if the residuals follow a white-noise process, then the ACF and the PACF should be approximately zero (Enders, 2015). In our case, we observe a spike at the fifth lag in both the ACF and PACF plots:

Figure 5.8: ACF and PACF of Residuals

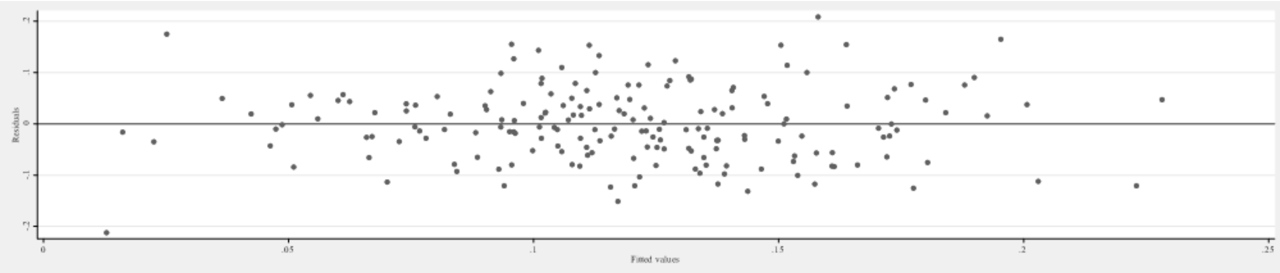


Notes: Upper plot displays the residuals' autocorrelation structure, lower plot displays the residuals' partial autocorrelation structure. The gray-shaded area represents the 95% confidence bands. Dots exceeding the 95% confidence band implies that the residuals may suffer from serial correlation. Source: Authors' own drawings.

This may imply that the residuals suffer from serial correlation and in turn invalidate the estimated regression coefficients. However, the p-values are greater than the 5 percent significance level and are therefore statistically insignificant. When running the Ljung and Box (1978) Q-statistics to test for white-noise we fail to reject the null hypothesis which implies that the error-term (residuals) follows a white-noise process. Additionally, by employing the widely used Breusch-Godfrey test for serial correlation, we fail to reject the null hypothesis of no serial correlation amongst the residuals (Breusch, 1978; Godfrey, 1978). Taking these tests into account, we argue that the residuals resemble a white-noise process despite the ACF and PACF plots (see Appendix A4 for full test statistics).

To ensure that the estimated regression model is statistically valid, we have to isolate whether the residuals seem to have homoscedastic or heteroscedastic features. By definition, homoscedasticity implies that the sequence of a variable has the same finite variance, whilst heteroscedasticity indicates the opposite. Simply put, homoscedasticity indicates that the residuals pertain a constant variance throughout the period of interest, which is a necessity under OLS estimation (Stock and Watson, 2015). By inspecting the plot of the residual-vs-fitted values, we observe a minor tendency towards greater distance between the residuals and the straight line as we move from left to right in Figure 5.9:

Figure 5.9: Residuals vs. Fitted Values



Notes: Residuals vs. Fitted Values. The straight line at the Y-axis equals a mean of zero. Source: Authors' own drawings.

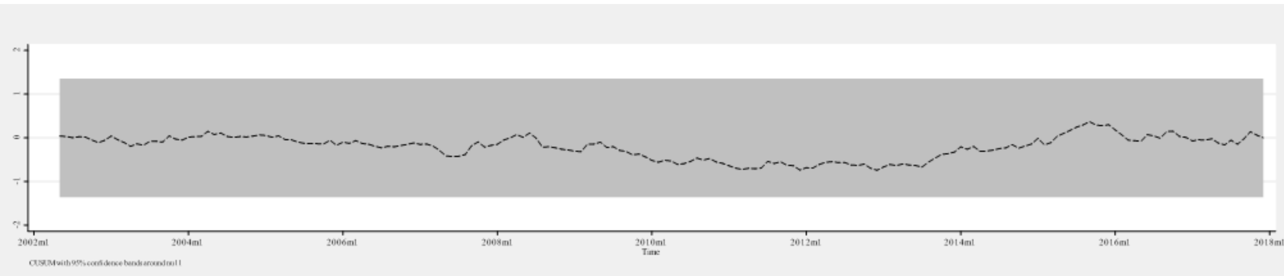
This may indicate that the regression model is comprising heteroscedastic errors and thus lead to invalid regression results. Because this can have serious consequences for the estimated regression model—OLS estimation assumes that the residuals are drawn from a population with a constant variance—we choose to apply Breusch-Pagan's test for heteroscedasticity (S. Breusch and Pagan, 1979; Enders, 2015). Since this test identifies whether the variance of the error-term is dependent upon the independent variables, the null hypothesis stipulates that the variance of the errors appear constant. In our case we fail to reject the null hypothesis of constant variance (see Appendix A4 for full output). Moreover, we find evidence proving that the estimated regression errors embody homoscedastic features, thus pointing out that the regression model is statistically valid in terms of OLS estimation. Additionally, the plot does not give the impression of extreme outliers being present within the dataset, hence we argue that the third OLS assumption is fulfilled.

Next, we want to discover if the estimated regression function suffers from perfect multicollinearity. As previously stipulated, perfect multicollinearity implies that some of the independent variables are "perfectly" correlated with one another and that one of the variables can be seamlessly predicted by the other variables in the regression function (Stock and Watson, 2015). Gujarati and Porter (2009) argues that a correlation above $|0.8|$ may induce multicollinearity issues within a regression model. According to our estimates, there is no pair of variables with an absolute correlation coefficient greater than 0.8. In fact, the highest correlation factor we achieve, which is between LIQUIDITY and STRESS, equals approx. 0.62. Hence the correlation matrix does not show any sign of perfect multicollinearity.

To further examine the degree of multicollinearity within our regression model, we apply the concept of variance-inflation-factors (VIF). The VIF estimates the degree to which the variance of a specific predictor is inflated by other predictors within the regression model. By indexing the variance inflation amongst the explanatory variables within a regression function, the VIF measures how much the variance of an estimated coefficient is increased due to collinearity (Stock and Watson, 2015). Although there is no unified consensus on a critical VIF-score in terms of multicollinearity (StataCorp, 2015), some scholars report that a VIF-score above ten implies severe multicollinearity (see for instance Hair et al. (2014)). In our case, the highest VIF-score equals 3.62 with a mean VIF-value of 1.83. Hence, we do not find evidence proving that our regression model suffers from perfect multicollinearity, thus the fourth OLS assumption is satisfied (see Appendix A4 for full output).

Lastly, we want to ensure that our regression model appears stable over time—that is, whether or not the model is dramatically changing over the course of the analysis. To identify whether this is true for our model, we can simply run a test for structural breaks on the estimated residuals. By using Stata's inbuilt "sbcusum" command, we achieve the following cumulative sum of residuals:

Figure 5.10: OLS Cumulative Sum Control Chart



Notes: Grey-shaded area represents the 95% confidence bands around a mean of zero. If the dotted line exceeds the threshold-values of ± 1.64, the regression model is suffering from structural breaks which consequently leads to model instability. Source: Authors' own drawings.

The null hypothesis stipulates that the cumulative sum of OLS residuals has a mean of zero and as Figure 5.10 illustrates, the dotted line does not exceed the 95 percent confidence bands. This implies that the residuals are unaffected by structural breaks and that the model performs steadily throughout the period of analysis. This is supported by the fact that our test statistics is less than the critical values at every conventional significant level, thus implying that we cannot reject the null hypothesis of no structural break (see Appendix A4 for full output).

5.6 Limitations of the Study

Before we proceed with interpretations of our findings and suggestions for why certain variables influence underpricing, some limitations have to be outlined. First and foremost, a particularity highlighted in subsection 5.2.4 was the Granger causality test indicated that IPO returns *Granger causes* changes in the industrial production index. We argued that it seemed improbable and counterintuitive to believe that first-day returns cause increments in industrial production and that this relationship should, at least from a theoretical standpoint, be the other way around. While this may potentially point towards some sort of modeling deficiencies, we believe that analysis over a greater timespan than 16 years could yield different results. In addition, it is worth noting that Granger causality does not imply causality in the sense that changes in X cause Y, it simply implies that IPO returns may prove useful in disclosing the evolution of economic growth (Stock and Watson, 2015). Despite being aware of the discovery, the paper progressed with the IP index as a predictor on IPO returns whilst acknowledging that the estimated coefficients might be distorted as a consequence.

The stress indicator of the Federal Reserve Bank of St. Louis and the liquidity risk index of BAML are quite closely correlated. In fact, the two series have a correlation coefficient of 0.6234 which implies a relatively strong positive relationship, thus making it is reasonable to assume that the variables should retain the same expected sign towards IPO returns. However, and as mentioned, the metrics have an inverse impact on IPO returns, which might be due to underlying issues with the regression model. This discussion will be picked up in the following chapter. Furthermore, underlying the use of indices entail the risk of including the same input-variables between the covariates in the regression function, which in turn may affect the validity of the estimated coefficients. For example, the yields on 10-year government bonds is an input variable in the calculation of the stress indicator (FRED, 2019). This might skew the result and amplify the coefficients as they might be exaggerated in value. In addition, the liquidity index overlap—to some degree—with the stress index in terms of input data as the Libor OIS spread is used in both indices. However, the VIF test for multicollinearity showed no sign that any of the variables appeared perfectly multicollinear, thus implying that all variables remain valid as regressors on IPO returns.

In terms of forecasting, the regression model included lags at $t-0$ which limits the practical applicability as some variables are not available on an intraday basis but rather published after a given period. To circumvent the issues of including $t-0$ values, we could derive a new regression model that only include lagged values of the explanatory variables, however doing so implies that we do not leverage our initial regression model to determine its predictive capabilities. Additionally, it may lead to omitted variables or biased estimates as we already know from Table 5.8 that some of the coefficients are statistically significant at $t-0$ (Stock and Watson, 2015). Another approach—which presumably would be the ultimate way of inspecting the regression model's ability to predict initial returns—should take a basis in forecasting the independent variables themselves and then use these forecasts as inputs to predict future returns. Amid producing better forecasts, at least from a theoretical standpoint, such an exercise is quite extensive and would constitute an unsustainable use of our time. Furthermore, as the aim of this paper is to identify the dynamic effects between the macroeconomic variables and IPO returns and not necessarily to improve forecasting *per se*, it is deemed beyond the scope of this paper.

5.7 Sub Conclusion II

The second part of the research question requires investigating how well our model is in term of predicting IPO returns. This question is twofold as one firstly needs to investigate how useful the forecast is and secondly examine the validity of the regression model. The first part of the analysis revealed that five exogenous macroeconomic variables had a significant impact on IPO returns, hence the forecasting exercise took a basis in these variables. By creating a one-month in-sample forecast and a twelve-month out-of-sample forecast, this paper has demonstrated that changes in long-term interest rates, financial market stress and liquidity risk, economic growth, and the stock market indeed have predictive power on first-day returns. This is supported by computing the MSE of the forecast model relative to an estimated arithmetic average, wherein our model yielded a lower forecasting error. However, the forecast is based on the assumption that the values of the independent variables are known at $t-0$, which is not necessarily the case in practice. Lastly, we presented some of the deficiencies of the model, which to a large extent surrounds the intra-correlation between some variables, where the input factors to the stress and liquidity indices overlap each other to a smaller degree. Because these interdependencies can potentially affect one another, the estimated coefficients can somewhat become artificially high or low. Nevertheless, the model diagnostics check indicated a statistically robust model with little to no deficiencies.

6 Discussion and Interpretation

Through the application of time series analysis, we found that some macroeconomic variables can serve as predictors on first-day returns, yet we have not uncovered any of the underlying fundamentals that may indicate why these variables influence underpricing. The outcome of the analysis has opened up for an interesting discussion into why some variables appear statistically significant. By taking a point of departure in the notion that correlation does not mean causation and building upon earlier work on macroeconomic factors' impact on IPOs, we will now present our suggestions towards why correlation exists. This section will, therefore, outline four propositions to summarize why we believe certain variables appear statistically significant on the underpricing phenomenon surrounding initial returns. However, it should be noted that the propositions are by no means subject to any further testing than as interpretations of our regression results and hence should be read as such. Additionally, we present our thoughts on the implications that our findings may have in terms of practical applicability—that is, how our results may provide valuable insights for practitioners.

6.1 Implications for Research

Since the availability of data tends to be non-experimental within social science, it must be admitted that testing theories of finance and distinguishing between the results is a challenging task. Information provided by the observed market behavior necessarily arises from a process in which the researcher knows all too little, thus pointing towards the fact that the line of argumentation may be on uninformed grounds. Although econometric techniques are precisely formulated to cater the problem of analyzing data, lack of experimental control implies that certain errors in the form of uncertainty become an unavoidable principle that must be attached to all conclusions—we stress that the reader should bear this in mind. Although the propositions may point towards interesting contributions that can supposedly deepen researchers' knowledge of the underpricing phenomenon encircling IPOs, we acknowledge that they remain purely theoretical and only after empirical testing one can examine their relevance. (Anderson et al., 1995)

6.1.1 Long-term Interest Rates and Initial Returns

Our regression results indicate that first-day returns are negatively correlated with long-term interest rates, whereby an increment of hundred basis points in long-term interest rates two months prior to the listing day decreases first-day returns by approximately 5.9 percent. While there may be several reasons to why long-term interest rates decrease underpricing, we find it fruitful to link our empirical findings with preceding research on the effects between monetary policy, stock market returns and IPO activity.

Several authors note that a tight monetary policy is associated with a contemporaneous decline in stock market value, thus implying that returns tend to depreciate when interest rates spike (see for instance Fama (1970) or Jensen et al. (1996)). In relation to the outcome of our regression, we find that the same development is present with first-day returns, i.e. that increased interest rates negatively influence IPO returns. The same trends have found to be true for IPO activity (Jovanovic and Rousseau, 2004; Ameer, 2012) and for IPO proceeds (Tran and Jeon, 2011). The authors argue that the cost of going public when interest rates are high negatively affects the present value of future cash flows which ultimately reduce company valuation, and consequently that IPO-ing firms are rewarded by postponing the IPO until the market conditions appear more profitable. Tran and Jeon (2011) pinpoint that when interest rates increase in the U.S., investors find debt markets more attractive than equity markets, and subsequently the amount of proceeds raised through IPOs becomes less in periods of high interest rates.

Our suggestion towards why interest rates are negatively correlated with IPO returns is grounded in the notion of the partial adjustment anomaly as first proposed by Hanley (1993). She finds that new information introduced after the first version of the prospectus is published is not fully incorporated in the offering price, and that positive adjustments in the offering price above the one quoted in the prospectus leads to greater underpricing. Furthermore, Hanley (1993, p. 232) denotes that *"offerings that decrease the offer price to below the lowest anticipated price quoted in the preliminary prospectus have an average initial return of 0.6%"*. Linking her findings to our results and those of other authors—that is, if interest rates rise, overall valuations decrease (Cutler et al., 1988)—the adjustment in the offering price is not fully representative of the broader decrease in company valuations. Only a partial downward adjustment of the offering price will be present, which leads to a smaller gap between the offering price and the final trading price. Therefore when a company is taken public, ceteris paribus, underpricing will be lower, when interest rates rise.

This is naturally reliant on a number of factors. Firstly, the rate of the partial adjustment is dependent on the reputation of the investment bank where the adjustment factor should be higher for highly reputable banks because they are better at grasping investor interests through a broader network (Wang and Yung, 2011). More importantly, some authors have found that publicly available information like changes in interest rates and general equity valuations are not subject to the same trade-off between information flowing from the investors to the underwriter. Therefore, the compensation in the form of underpriced shares should not be present as the underwriter can simply observe the condition of the markets and set the offering price accordingly (Lowry and Schwert, 2004) which serves as a strong counterargument for our postulation. Nevertheless, authors are still disputing the impact of public vs private information on underpricing and hence the outcome is not clear (Lowry et al., 2017). Thirdly, a more fundamental issue arises in our modeling work namely, that there are many interdependencies in the macroeconomic environment that might affect our argumentation. The basis of the partial adjustment argument is founded in valuations, which is impacted by interest rates (Cutler et al., 1988). General stock valuations are captured in our S&P 500 variable and therefore might already contain the given developments and thus distort our regression results. Having said that, we still find the partial adjustment argument plausible and argue that this is an interesting area for further research. We therefore propose the following:

Prop. 1 *Given that increments in interest rates decrease company valuations, IPOs become generally less underpriced because the final offering price is only partially downgraded.*

6.1.2 Financial Market Stress and Initial Returns

The outcome of the regression analysis showed an interesting sign of the stress variable. Recall that the stress variable, which is a stress index developed by the Federal Reserve Bank of St. Louis, showed to have a positive impact on underpricing of IPOs. This is worth noting as one might be inclined to believe that increased financial market stress should decrease IPO returns.

It is at least intuitive given the fact that IPOs are an asset type closely related to stocks, which generally yield negative returns during times of stress (Edwards, 2019). That is however not the outcome of our regression analysis, which indicated that a percentage increase in financial stress at $t-0$ yielded a 0.078% higher IPO return, whereas a percentage increase one month prior to a public offering at $t-1$ gave a 0.105% higher initial return.

Since we know that underpricing increases with uncertainty (Ritter, 1984; Beatty and Ritter, 1986) and if one supposes that the financial stress metric is a proxy for uncertainty, then it is possible to argue that financial stress increases underpricing. Section 2.7 outlined contemporary theories on IPO returns with special attention towards hot and cold IPO markets. The model developed by Benveniste and Spindt (1989) was presented and it was argued that since investors are more informed about the demand for a given IPO than the issuer, they are compensated for sharing information with the underwriter with an increased level of underpricing. If there is a lot of uncertainty in the valuations of companies, the value of the information flowing from the investor to the underwriter increases. Lowry (2003) tests the adverse selection problem by using the range of analysts' earnings forecasts as well as the dispersion of announcement effects on stock returns as proxies for uncertainty, and finds that uncertainty influence IPO returns. We postulate that it is the same relationship that is present in our regression. Namely that the stress index is mere a proxy for uncertainty.

A few complications arise when arguing that the stress index is a benchmark of uncertainty. Firstly, the proxies applied by Lowry (2003) was specific to each company going public whereas the metric we apply is an aggregate measure that tracks the stress in the entire financial market. Therefore, the point of departure is significantly different and hence might not be as good as an indicator of uncertainty. Secondly, the model pioneered by Benveniste and Spindt (1989) is based on the assumption that an IPO is conducted through a book-building method. The data that we have applied is not filtered to only include "book-building IPOs", hence the data might be a little skewed. Yet, the book-building method is by far the most common method of determining the final offering price in the US (Derrien and Womack, 2003). We can therefore not foresee any obvious reason to reject our suggestion regarding uncertainty and accordingly we propose the following proposition for further research:

Prop. 2 *By treating stress indices as proxies for uncertainty, one can argue that when these indices rise ex ante, so does IPO underpricing.*

6.1.3 Market Liquidity Risk and Initial Returns

More intuitive than the results of the stress index, the coefficients of the liquidity risk index of BAML proved to have an adverse impact on underpricing. The negative coefficients of the liquidity variable were statistically significant at $t-0$ and $t-1$ at the 5% and 10% significance level respectively. Liquidity risk in the financial markets has by Tran and Jeon (2011) been proven to influence the timing of IPOs and hence we set out to investigate whether liquidity risk was an influential factor of underpricing. The short answer is, *it is.*

A compelling case for why a higher degree of liquidity risk in the financial markets negatively impacts underpricing is that of investor sentiment. Investor sentiment is a broad and encompassing terminology that seeks to capture the psychological state of mind of investors (Dorn, 2009). When applying the term of investor sentiment, it is frequently meant to concern retail investors as they, to a greater degree, are influenced by psychological biases than institutional investors are (Dorn, 2009; Barber et al., 2009). That should not be seen as an argument to neglect the power of these types of investors as they, according to Barber et al. (2009), have significant power in moving prices on a short-term basis, whereby underpricing is arguably a short-term phenomenon.

To scrutinize the interdependencies amongst liquidity risk and underpricing, it is imperative to establish a connection between liquidity and investor sentiment. This has been done by Liu (2015) who finds that investor sentiment indeed is correlated with liquidity in the aggregate financial markets. A core feature in the argument is based on the idea that investor sentiment makes overbidding on IPOs a reality and thus increase underpricing. Several authors have found that the more retail investors that submit bids on IPOs, the higher the underpricing will be (Dorn, 2009; Ljungqvist et al., 2006). Thus, the argument is based on the notion that an increase in liquidity implies a strong investor sentiment, which in turn makes overbidding of IPO-ing stocks more likely.

Recall that the preliminary correlation matrix showed a positive correlation coefficient of

0.6234 between the stress and the liquidity risk indices, whereas the output of the ADL model yielded opposite signs in the lags of the respective variables. In Section 4.4, this was argued to be somewhat conspicuous as they intuitively should retain the same positive sign in the regression output. While this may imply that the finalized regression model suffers from multicollinearity and thereby invalidate the regression results, our VIF-test indicated no such features. Additionally, the Granger causality test revealed that the liquidity metric does not Granger-cause IPO returns at any conventional significance level. As such we do not argue that the model output is false, as it is perfectly possible that they have contrasting signs despite their strong positive correlation. We just believe it is unlikely. Moreover, the propositions on both liquidity and stress should take this peculiarity into consideration. Despite the above, we still find statistical significance applying a robust regression model and thus the following proposition for future research is given:

Prop. 3 *It is the sentiment of investors that causes the correlation between market liquidity and IPO underpricing.*

6.1.4 Stock Markets and Initial Returns

As depicted in Figure 2.2, a key element that managers consider when deciding on the timing of IPOs is the condition of the stock market (Brau and Fawcett, 2006). The stock market contains an array of implied information from future macroeconomic outlook to political uncertainty, however, the psychological state of mind of investors has also been proven to have an immense impact on the stock market (Brealey et al., 2014; Smales, 2017; Barber et al., 2009). Linking these implications to the fact that we find a positive correlation between IPO returns and stock market growth at lag $t-0$, $t-1$, and $t-2$, it appears sensible to argue that human biases lead investors to irrationally invest in IPOs as soon as after-market trading begins. For instance, Shiller (1990, p. 62) found that preceding price drops (increments) in IPOs caused disbelief (encouragement) and that such waves of cognitive coherence *"appear to be related to the interpretations of what other investors are thinking..."*. In other words, it has been found that investors have a tendency to mimic the behavior of others and thereby induce contagion effects within financial markets (Hirshleifer and Teoh, 2003; Hull, 2015). We thus hypothesize that irrationality is more prevalent when the market has grown successively over time and that during these periods, retail investors are more inclined to invest in IPOs, thus driving up the first-day closing price.

As such, we base our causal argumentation for both the liquidity risk index and stock market growth on the conception of investor sentiment theory, wherein behavioral finance and investor sentiment is at the core of the discussion of an efficient market or not. Hence, we implicitly assume that the IPO market is inefficient as underpricing is a function of irrational investors' over- or underbidding of IPOs. The major cause for concern of posing such an argument is the fact that investor sentiment theories span over many different interdisciplinary fields. For example, it is intricate to determine exactly whether investor sentiment is more prevalent once liquidity risk spike in contrast to successive stock market growth, or if there is another causing factor beyond the variables included in the analysis. To a certain degree, this limits our ability to argue something tangible, as we are not explicitly testing whether investor sentiment drives up IPO returns, but merely emphasize that it is the most plausible explanation for the interrelationship with stock market changes. Inasmuch as the irrationality argument might seem straightforward, it also implies that the issuer or underwriter is unable to grasp investor demand—in particular, retail demand—and therefore can't adjust the offering price accordingly. Yet, we still believe that the theories generally fit well with our findings and therefore present the following proposition in terms of the observed correlation between stock market growth and IPO underpricing:

Prop. 4 *It is the sentiment of investors that causes the correlation between the stock market and IPO underpricing.*

6.1.5 Economic Growth and Initial Returns

As a proxy for economic growth, this paper relied on the industrial production index. The index yielded quite interesting results with coefficients being positive at $t-0$ and negative at $t-3$ and $t-4$, which implies that a positive development in industrial production three or four months ago causes a negative impact on IPO returns today. Authors like Ameer (2012); Lowry

(2003) and Tran and Jeon (2011) have all modeled economic growth as a predictor towards IPO activity in the U.S. and found statistical significance. Lowry (2003) bases her argument on the fact that firms are facing more profitable investment opportunities during high economic growth and therefore the demand for financing these activities through capital is higher (see Section 2.7). The argument is plausible and in line with existing theory on macroeconomic conditions and corporate finance (Brealey et al., 2014), yet, in terms of underpricing the equivalent demand for capital argument does not hold directly.

The contemporary literature on hot and cold IPO markets indicates that higher underpricing is timely correlated with a higher number of IPOs and hence it might be prudent to assume that the same relationship exists between economic growth and underpricing. However, the relationship between IPO activity and underpricing is lagged according to Ritter and Welch (2002). The argument relies on the idea that many issuers, who observe a high level of underpricing might also be keen to go public because valuations are surprisingly high (Lowry et al., 2017). Our findings do not necessarily support this development because underpricing serves a precursor to the number of IPOs and hence the timing of our results is not consistent with the literature. On the contrary, if economic growth has been positive three or four months prior to a given IPO date, it will result in a lower degree of underpricing. Hence, the demand for capital argument simply does not correspond to our data. Fundamentally it is an outcome of our regression that we do not find very reasonable in terms of causality. It seems unlikely that such significant changes in IPO returns (from positive to negative) changes over such a short timespan. Consequently, it appears implausible to us that the industrial production index actually has any explanatory power on underpricing, at least when analyzing our data sample. Yet, if an argument had to be put forward it would again be based on the idea of investor irrationality, where an investor overbid on the exact month, where there is aggregate growth and underbid if there were positive growth three to four months prior. Yet, it does not seem like a plausible and logical explanation and furthermore, the investor irrationality is arguably better captured through other indicators than the industrial production index.

At this stage, we simply do not possess credible evidence sufficient to derive a proposition based on the industrial production index and hence we are reluctant to do so. This is further reinforced by the findings in subsection 5.2.4, where it was discovered that IPO returns Granger-causes the industrial production index. Intuitively, it does not make sense that the higher IPO returns, the higher the economic activity of a whole nation. Additionally, it should be noted that by applying GETS modeling, the feasibility of justifying the statistical results through economic intuition can sometimes become difficult as such selection processes identifies optimal regression models based on complex mathematical algorithms (Campos et al., 2005). Therefore the outcome of the modeling efforts also supports our reluctance to suggest any proposition. That being said, there is still valuable insight from including industrial production in our analysis. It provides a better model because including a significant variable increases the predictive power of the regression function and secondly it provides investors with useful insights into when to invest in IPOs. This will be further elaborated upon in the following section.

6.2 Implications for Practice

The fact that the analysis of this paper has practical applicability should hopefully be clear by now. However, it is useful to recapitulate how practitioners can use and apply the outcome of our regression results. One of the first findings of the analysis revealed that IPO returns appear serially correlated. Moreover, the inspection of previous returns may provide useful information in determining whether upcoming IPOs are more likely to be underpriced or not. Brau and Fawcett (2006) analyze the perception of 336 CFOs of newly listed companies and argue that practitioners are more attentive to the performance of the stock market when deciding to go public, whereas they are less observant to the performance of recent IPOs. Our results indicate that practitioners, hereunder investors and managers, should be much more focused on recent IPO performance when determining whether they should buy into any given IPO. From the investor's perspective, one could make above-average returns from investing in IPOs if there have been recent increases in average IPO returns. From the issuer's perspective, one could perhaps increase the sum of money raised if the timing of the IPO is right.

The main outcome of our analysis indicated that it is truly imperative for investors and asset managers to be extra observant towards macroeconomic conditions when deciding whether or not to buy into an IPO. Our paper has proved that a macroeconomic analysis of both the real economy and the financial markets should be an integral part of the decision. Interest rates, the stress and liquidity risk of the financial markets, economic growth, as well as the "state" of the stock market all are decisive factors in obtaining abnormal returns. It is reasonable to assume that economic growth and leading indicators are already ingrained into the investment decision process of asset managers and other investors, but conversely, it is also sensible to undertake that investors do not look at, for instance, aggregated stress indices when deciding to invest in IPOs. However, our thesis has shown that when stress is high in the financial markets, the greater becomes underpricing, which is most likely a surprise to most practitioners.

Additionally, a supplementary point of interest was also highlighted during the modeling development. In subsection 5.2.3 we identified no additional structural breaks in our dataset when limiting the analysis from 2002 to 2017. The importance for investors arises because no hot or cold IPO markets was implicitly found in our dataset. This has a tremendous impact on practitioners and investors alike. No longer does it seem to be beneficial to await going public during a hot or cold IPO period as the IPO market appear much more stabilized. The same phenomenon is also reflected in the visual inspection of Figure 5.2 in subsection 5.2.1, which indicates that the presence of hot or cold IPO markets after 2002 is, to a great extent, not found. Generally, scholars have agreed that during hot IPO markets underpricing will be higher and vice versa (Ibbotson and Jaffe, 1975; Loughran et al., 1994; Ritter and Welch, 2002). However, that does no longer seem to be the case and hence investors should refrain from waiting on a hot IPO market to invest, but rather invest continually throughout cycles (albeit being considerate to the significant indicators found in this analysis). It should be mentioned that this paper has not attempted to test the presence of hot or cold IPO markets, it is merely an observation derived from our structural break test and should be interpreted as such.

The discussion suggested two interesting details that may be relevant to practitioners. First and foremost, underpricing tend to be heavily influenced by investor sentiment. This is in line with what other scholars have found to be true for other asset classes, hence investors should take this into consideration when investing in IPOs. In short, it implies that the investor sentiment surrounding IPOs opens up the opportunity for even larger than "normal" first-day returns. Secondly, investing in IPOs during a period of significant market uncertainty is profitable. It is rare to find an asset class wherein increased uncertainty surrounding valuations increase average returns, however, IPOs might appear to be of such. Many authors have highlighted that when firm-specific factors make valuations difficult, underpricing increase (Ljungqvist et al., 2006; Ramsinghani, 2014), but, perhaps even more interesting, we find that when market-wide uncertainty increases so does underpricing. This is an important finding for practitioners because, during periods of elevated market uncertainty, it is probably more strenuous to identify well-performing securities relative to conventional periods.

7 Conclusion

An IPO is perhaps the most significant event in any company's lifespan and from an investor perspective, the success of an IPO is often measured by the degree of underpricing. The underpricing phenomenon is a widely debated subject by scholars and practitioners because it seems irrational of the issuers to leave about 15 percent of total proceeds raised on the table for investors to grasp. The theoretical foundation for explaining underpricing is arguably somewhat incomplete as scholars are still seeking answers to why the degree underpricing is so great. Taking a basis in this perplexing phenomenon, this paper set out to investigate whether macroeconomic indicators could shed some light onto the variations of the observed underpricing. The brief summary is *yes* they can.

The application of time series techniques has provided the tools to analyze the developments in underpricing over time. We started out with eight variables that, by other scholars, had been found to contain valuable information in relation to IPO activity, proceeds or even underpricing. Through general-to-specific modeling, we obtained an autoregressive regression model where five variables appeared correlated with IPO returns. To ensure that the regression function was unaffected by any disruptions, we conducted a test for structural breaks wherein the sup-Wald statistic implied that we needed to exclude observations prior to 2002 in order to normalize the data and circumvent the abnormalities of the Dotcom bubble. While the exclusion of the Dotcom bubble produced a more statistically sound model, it revealed that the presence of hot and cold IPO markets might not be as prevalent in the twenty-first century as previously.

Our results revealed that changes in long-term interest rates, economic growth, financial market stress, liquidity risk, as well as stock market growth, appeared correlated with first-day returns. Based on these findings the paper constructed two forecasts to examine whether these variables could be used to predict future IPO returns. An in-sample forecast and secondly a twelve-month pseudo-out-of-sample forecast demonstrated that the regression model indeed had predictive power towards the level of underpricing. Even though the forecasts were not perfect in explaining all of the monthly variations in IPO returns, it did perform better than the simple arithmetic average of realized returns throughout the same time interval. The implications for investors and issuers are evident; before going public, issuers should be attentive to the macroeconomic environment and so should investors before they "jump on the bandwagon".

The discussion section of this paper included reflections concerning why we believe that correlation exists amid the variables. We presented four propositions for further research on the underpricing phenomenon surrounding IPOs. The propositions are primarily based on contemporary literature within IPO underpricing pertaining to either investor sentiment theory or market uncertainty. According to investor sentiment theory, which stands in sharp contrast to the EMH, market anomalies induce overbidding of newly listed securities thereby driving underpricing up. However, it is difficult to establish whether investor sentiment is heavily influenced by macroeconomic indicators or if it is the reflection of the investor sentiment that is disclosed in the regression output. The second argument acclaims that the greater *ex ante* uncertainty is, the more ambiguous company valuations become, which in turn leads to a greater discount in the offering price of IPOs. This is aligned with contemporary IPO research, yet our main contribution hereto stems from the fact that we find that uncertainty is not necessarily an idiosyncratic feature but subject to observable macro-level developments. That being said, we have not tested any specific theories nor attempted to prove any given stance. Thereby, we do not postulate that the variables applied in this analysis are the most pertinent indicators of the effects between underpricing, uncertainty, and investor sentiment.

We have argued that the implications of the analysis for practitioners are quite significant. Needless to say, an analysis of the macroeconomic environment should be an ingrained part of any investment decision-making process related to IPOs. We have though highlighted that certain variables, like stress and liquidity risk in the financial markets, are perhaps more surprising as they assumably aren't as integrated with decision-making processes relative to other variables. Furthermore, and in line with other scholars, we find that when deciding to invest in an IPO, one should be particularly attentive to the development in former IPO performance as they remain serially correlated. Lastly, we highlighted that the absence of hot and cold IPO markets should induce investors to invest in IPOs continually throughout periods and not wait for either a hot market or cold market to resurrect, while simultaneously being vigilant towards the macroeconomic variables presented in our model.

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Appendix

A1 The Financial Stress Indicator

Interest Rates	Yield Spreads	Other Indicators
Effective Federal Funds Rate	Yield Curve: 10+-year Treasury minus 3-month Treasury	J.P. Morgan Emerging Markets Bond Index Plus
2-year Treasury	Corporate Baa-rated bond minus 10-year Treasury (corporate credit risk spread)	Chicago Board Options Exchange Market Volatility Index (VIX)
10-year Treasury	Merrill Lynch High-Yield Corporate Master II Index minus 10-year Treasury (high-yield credit risk spread)	Merrill Lynch Bond Market Volatility Index (1-month)
30-year Treasury	3-month London Interbank Offering Rate – Overnight Index Swap spread (3-month LIBOR-OIS spread)	10-year nominal Treasury yield minus 10-year Treasury Inflation Protected Security yield (breakeven inflation rate 10-year)
Baa-rated Corporate	3-month Treasury-Eurodollar spread (TED spread)	S&P 500 Financials Index
Merrill Lynch High-Yield Corporate Master II Index	3-month commercial paper minus 3-month Treasury Bill (commercial paper spread 3-month)	
Merrill Lynch Asset-Backed Master BBB-Rated		

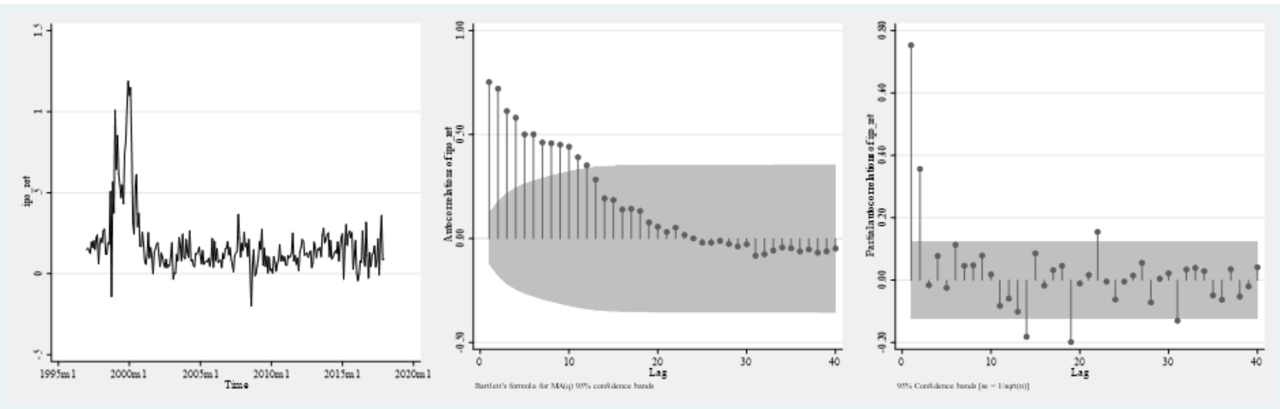
Source: FRED (2019)

A2 Time Series Analysis 1997 - 2017

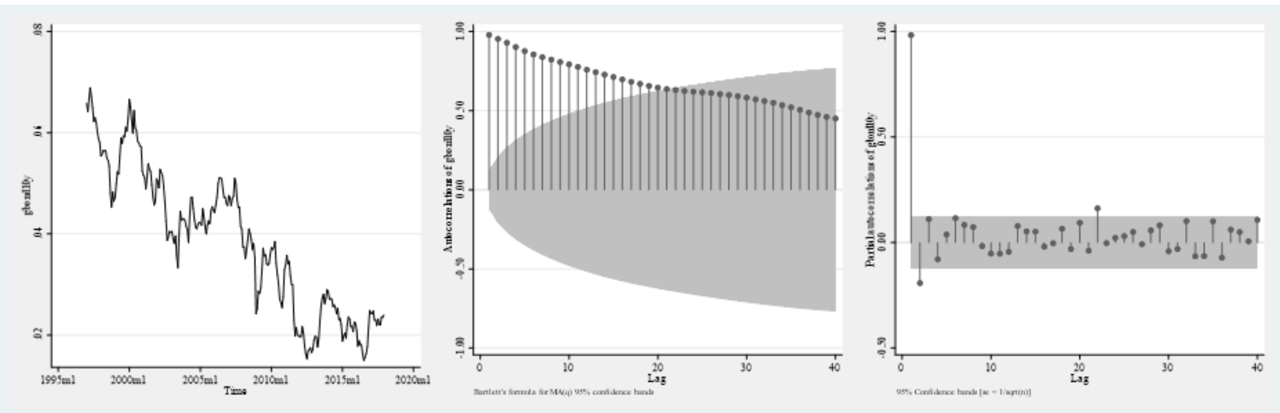
A2.1 Time Series Plots, ACF and PACF

To plot each series and derive their equivalent ACF and PACF structures, we use Stata's inbuilt "tsline, ac, and pac" commands respectively. These representations are at the levels form of each variable–that is, without any transformations from 1997 to 2017. By inspecting the time series plots, autocorrelation structures, and partial autocorrelation functions one may understand whether the series appear to be stationary or not. For instance, a slowly decaying autocorrelation structure indicates that the series possibly include a trend term, and if this the case, the ADF-specification in Equation 4.6 are used.

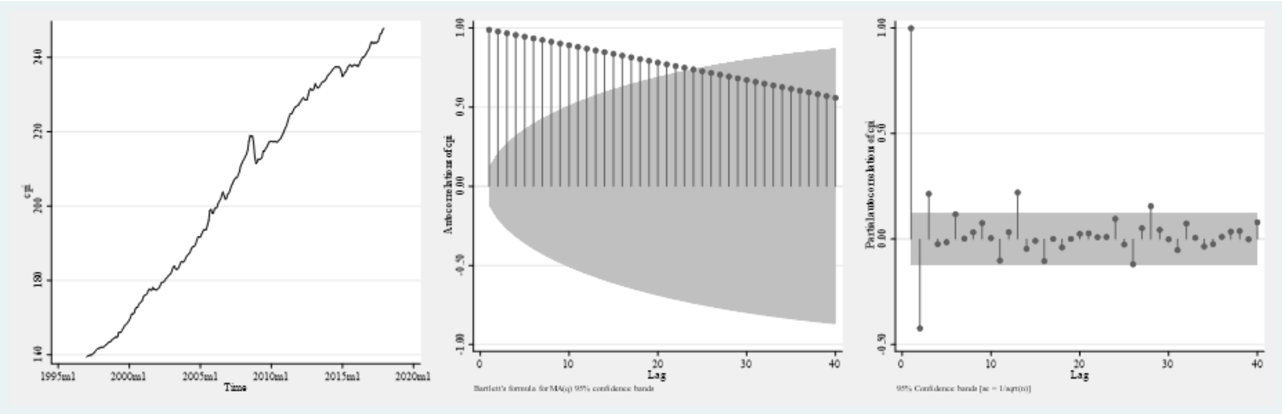
A2.1.1 IPO Returns



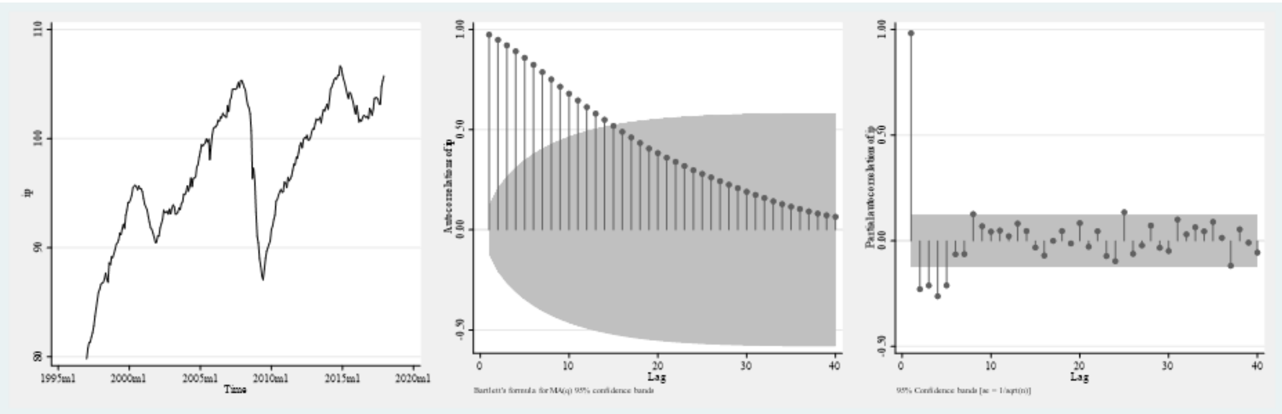
A2.1.2 Long-term Interest Rates



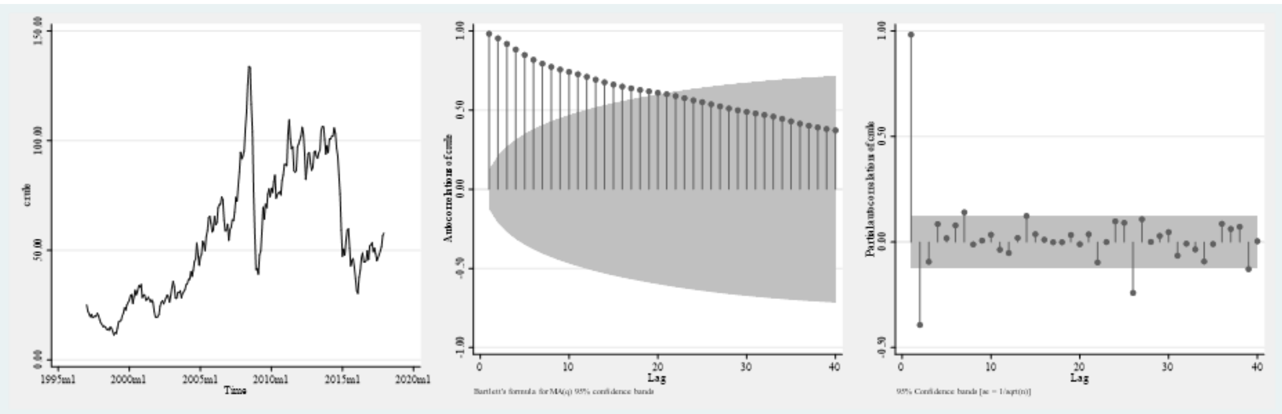
A2.1.3 Consumer Price Index



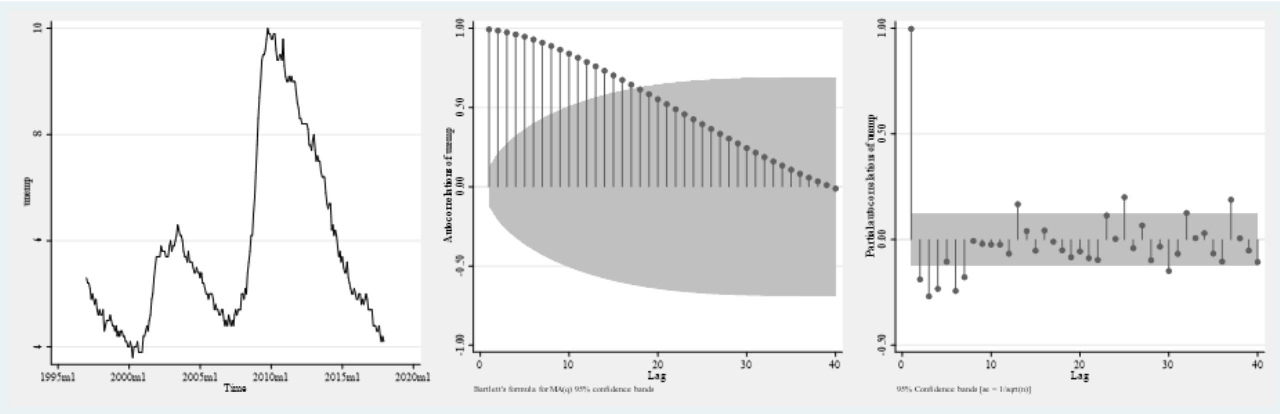
A2.1.4 Industrial Production Index



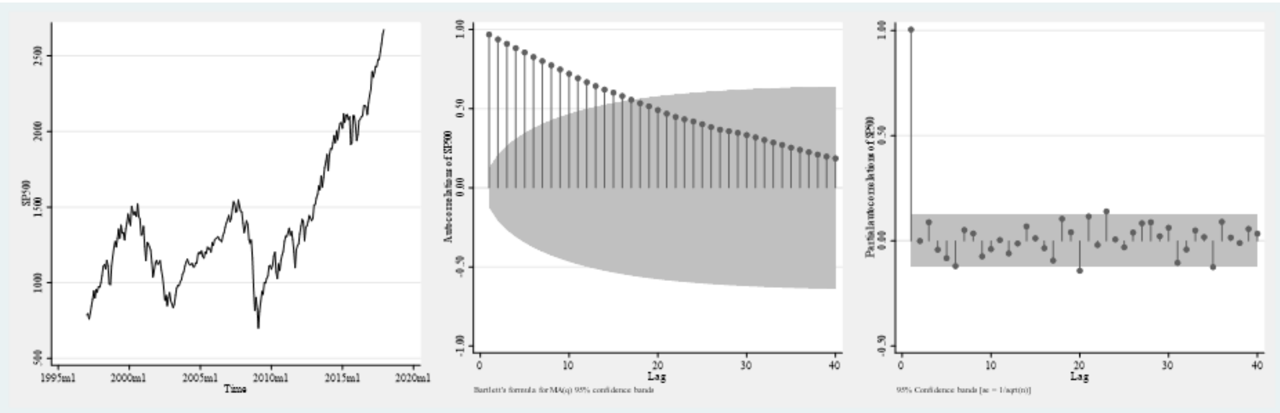
A2.1.5 Crude Oil



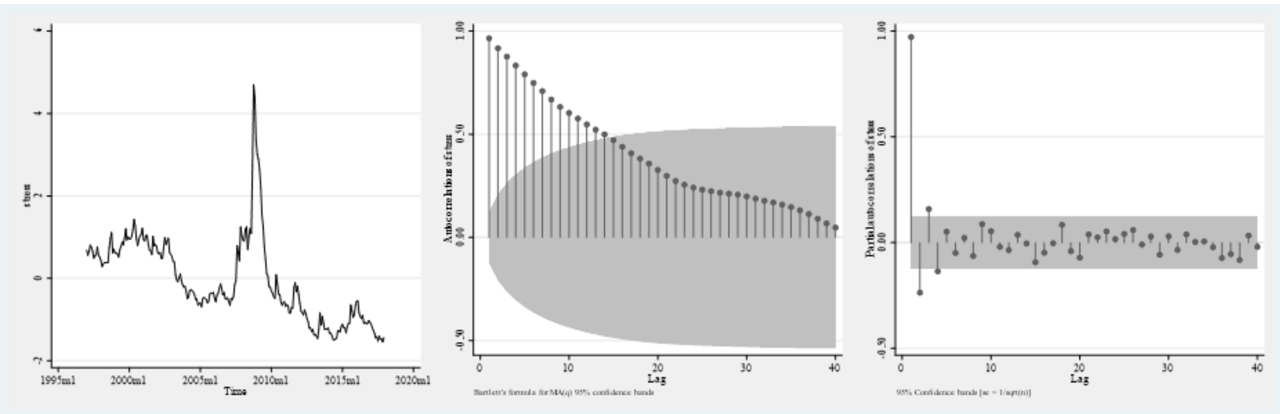
A2.1.6 Unemployment Rates



A2.1.7 S&P 500 Index



A2.1.8 The Stress Index



A2.2 Correlation Matrix

The correlation matrix is derived from Stata using the inbuilt "correlate" function. This function derives the correlation between every variable included in the analysis. Correlation coefficients near one imply that the variables are strongly positively correlated, and vice versa.

A2.2.1 Correlation Matrix (w/o transformations)

	ipo_ret	gbond10y	stress	ip	cpi	crude	unemp	SP500
ipo_ret	1.0000							
gbond10y	0.3795	1.0000						
stress	0.1989	0.5645	1.0000					
ip	-0.1686	-0.6143	-0.5677	1.0000				
cpi	-0.3530	-0.9111	-0.5999	0.7568	1.0000			
crude	-0.2962	-0.5740	-0.3664	0.5947	0.7093	1.0000		
unemp	-0.3184	-0.4862	-0.1228	-0.0894	0.4089	0.5666	1.0000	
SP500	0.0331	-0.5608	-0.6343	0.7358	0.7017	0.2350	-0.2529	1.0000

A2.3 Model Estimation

To identify how many lags to be included in GETS modeling, we use Stata's "varsoc" command. This command runs a regression of all the variables of interest on the dependent variable and thereby identifies how many lags to be included according to various information criterions. As one can see from the output below, the AIC criterion suggests including a maximum of four lags of each variable.

A2.3.1 Lags included in GETS modeling

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	3854.86				1.40E-24	-32.1913	-32.1444	-32.0749
1	4134.5	559.29	64	0	2.40E-25	-33.9958	-33.5738	-32.9485*
2	4253.18	237.35	64	0	1.50E-25	-34.4534	-33.6562*	-32.4752
3	4320.64	134.91	64	0	1.50E-25	-34.4823	-33.31	-31.5731
4	4387.07	132.87	64	0	1.5e-25*	-34.5027*	-32.9552	-30.6626
5	4436.26	98.372	64	0.004	1.70E-25	-34.3787	-32.4561	-29.6077
6	4486.69	100.85	64	0.002	1.90E-25	-34.2652	-31.9674	-28.5632
7	4534.01	94.654	64	0.008	2.20E-25	-34.1256	-31.4528	-27.4927
8	4599.08	130.13	64	0	2.30E-25	-34.1346	-31.0865	-26.5707
9	4649.01	99.858	64	0.003	2.70E-25	-34.0168	-30.5937	-25.522
10	4693.92	89.819	64	0.018	3.40E-25	-33.8571	-30.0588	-24.4313
11	4742.18	96.512	64	0.005	4.20E-25	-33.7253	-29.5519	-23.3687
12	4802.19	120.02*	64	0	4.80E-25	-33.6919	-29.1434	-22.4043

A2.3.1 Regression Output

Table A2.3.1.1 portrays the final output after applying GETS modeling in Stata. As one can see from the R-squared and the t-statistics, the values appear relatively high which may indicate a spurious regression model, cf. subsection 4.3.2.

A2.3.1.1 Regression Output after GETS modeling

Source	**SS**	**df**	**MS**	**Number of Obs**	=	**248**
				F(6,241)	=	73.54
Model	6.1064542	6	1.01774237	Prob >F	=	0
Residual	3.33540422	241	0.013839852	R-squared	=	0.6467
				Adj R-squared	=	0.6379
Total	9.44185842	247	0.038226147	Root MSE	=	0.11764

ipo_ret	**Coef.**	**Std. Err.**	**t**	**P>t**	**[95% Conf.**	**Interval]**
ipo_ret						
L1.	0.4957172	0.0584967	8.47	0	0.380487	0.6109473
L2.	0.3433381	0.0590018	5.82	0	0.2271131	0.4595631
Dgbond10y						
L0.	8.551254	3.569996	2.4	0.017	1.518875	15.58363
L3.	-7.342571	3.503639	-2.1	0.037	-14.24424	-0.4409055
Dstress						
L3.	0.0643211	0.0300298	2.14	0.033	0.0051668	0.1234755
Dln_ip						
L3.	1.945663	1.14064	1.71	0.089	-0.3012339	4.19256
_cons	0.0268261	0.0105742	2.54	0.012	0.0059964	0.0476559

A2.3.2 sup-Wald test for Structural Breaks

The test for unknown structural breaks is initiated through Stata's inbuilt "sbsingle" command with a trim of 10%. This test computes the F-statistics for a predefined subsample, cf. subsection 4.3.2.

A2.3.2.1 Test for Structural Breaks

```
Test for a structural break: Unknown break date

                             Number of obs =        248

Full sample:                  1997m5 - 2017m12
Trimmed sample:               1999m6 - 2015m12
Estimated break date:         2000m3
Ho: No structural break

     Test           Statistic         p-value
---------------------------------------------
     swald            90.7785          0.0000
---------------------------------------------
Exogenous variables:          L.ipo_ret L2.ipo_ret Dgbond10y L3.Dgbond10y L3.Dstress L3.Dln_ip
Coefficients included in test: L.ipo_ret L2.ipo_ret Dgbond10y L3.Dgbond10y L3.Dstress L3.Dln_ip _cons
```

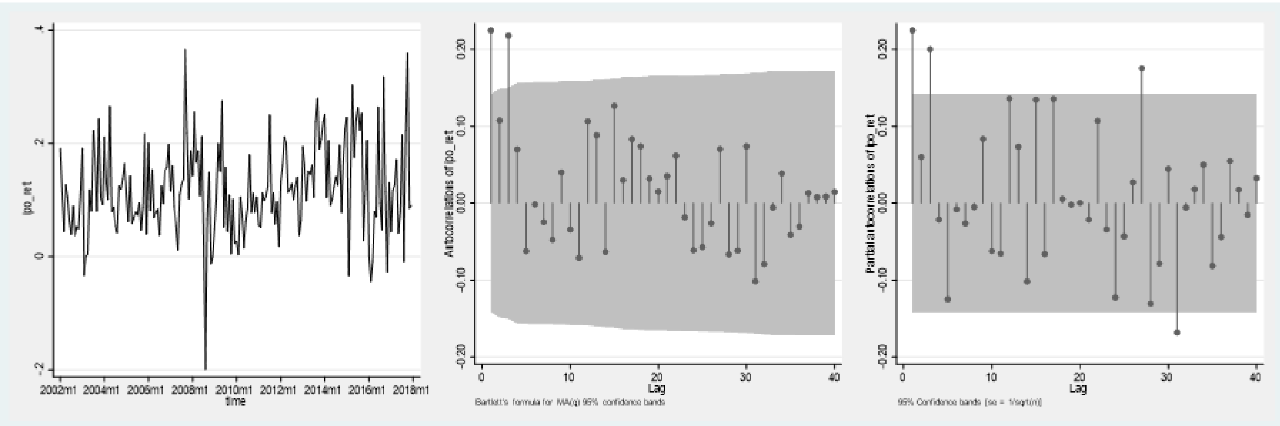
Conclusion: p-value < 0.05, i.e. we reject the null hypothesis of no structural break, i.e. a structural break is present.

A3 Time Series Analysis 2002 - 2017

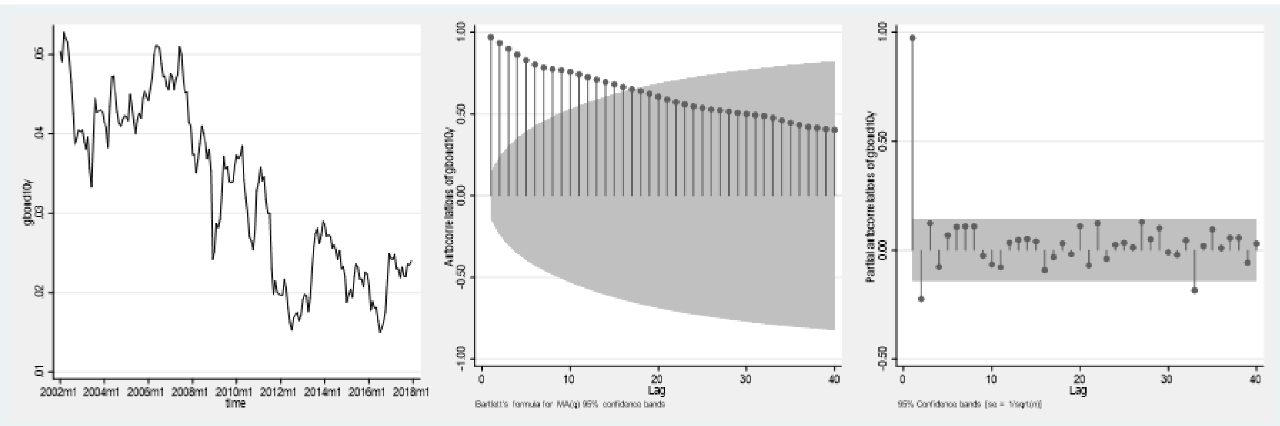
A3.1 Time Series Plots, ACF and PACF

Similar to Appendix A2 we plot each series and derive their equivalent ACF and PACF structures using Stata's inbuilt "tsline, ac, and pac" commands respectively on the new time horizon. These representations are at the levels form of each variable–that is, without any transformations from 2002 to 2017. By inspecting the time series plots, autocorrelation structures, and partial autocorrelation functions we observe a slight change in the plots contrary to the plots covering 1997 - 2017. Additionally, we include LIQUIDITY in the analysis.

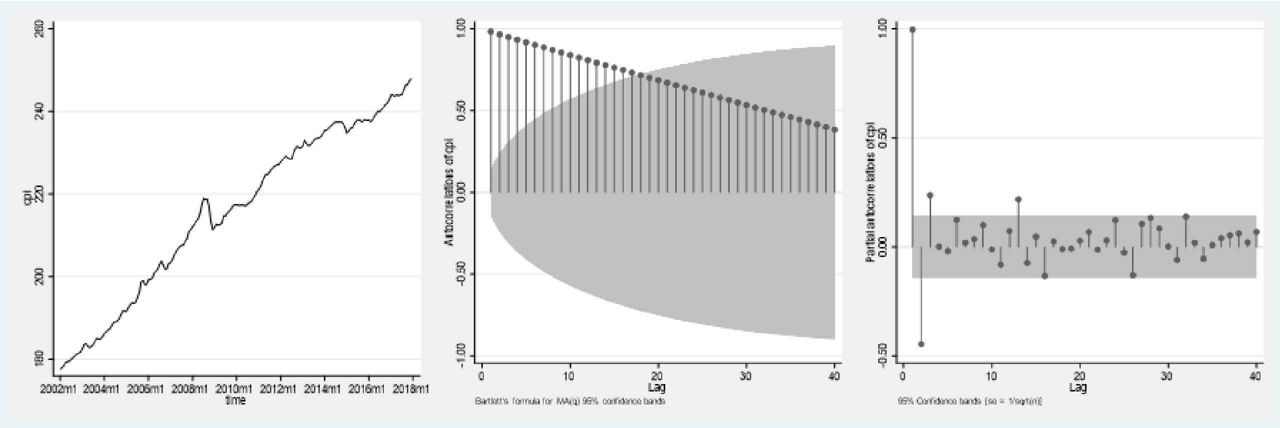
A3.1.1 IPO Returns



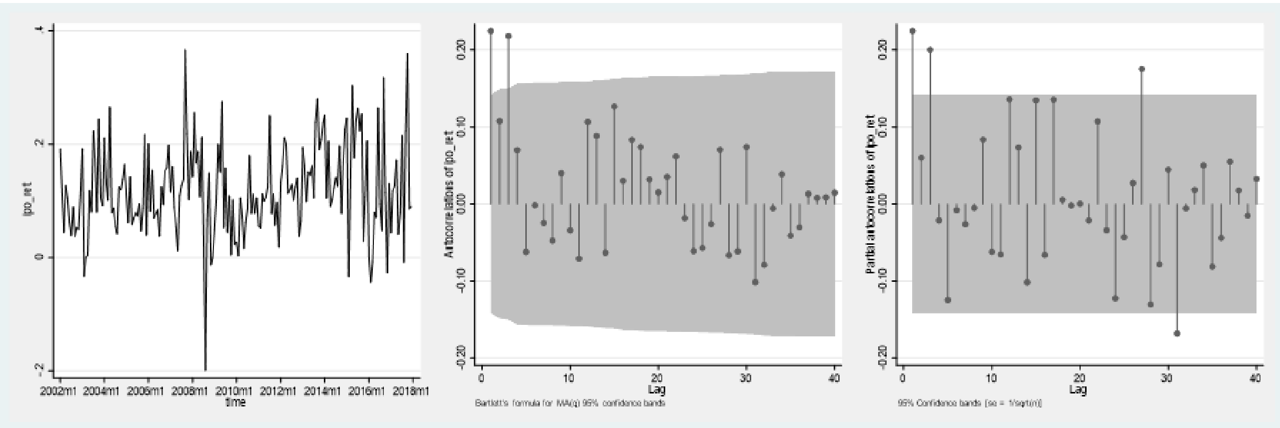
A3.1.2 Long-term Interest Rates



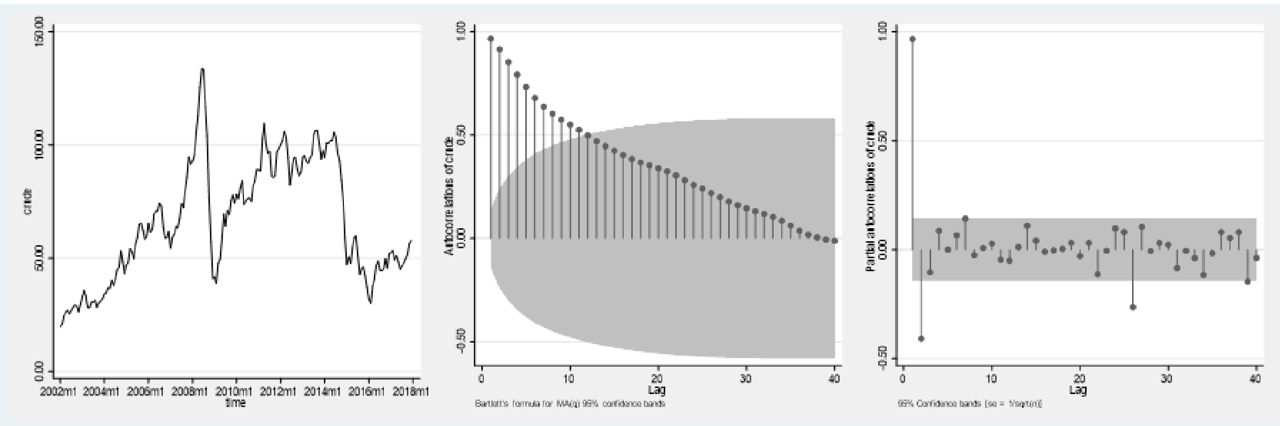
A3.1.3 Consumer Price Index



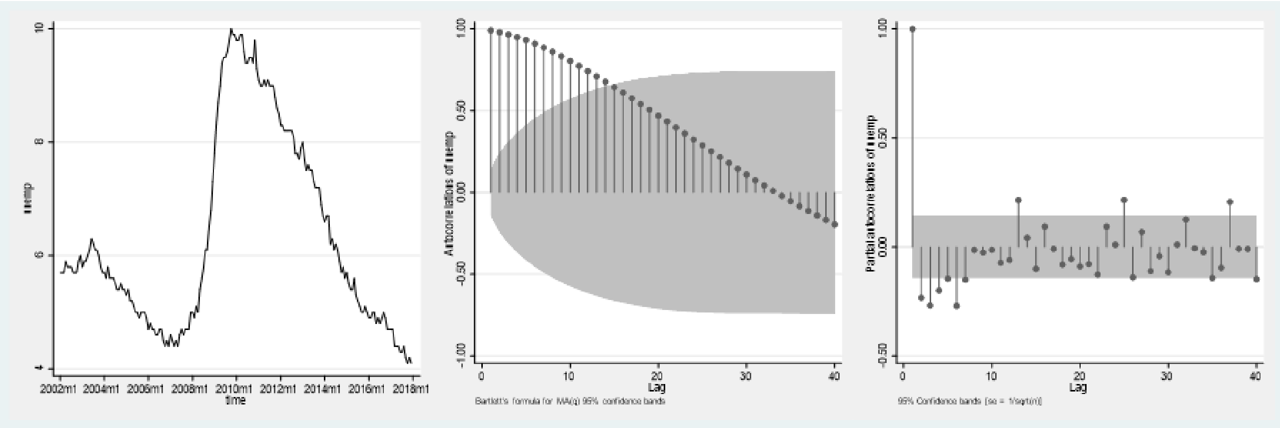
A3.1.4 Industrial Production Index



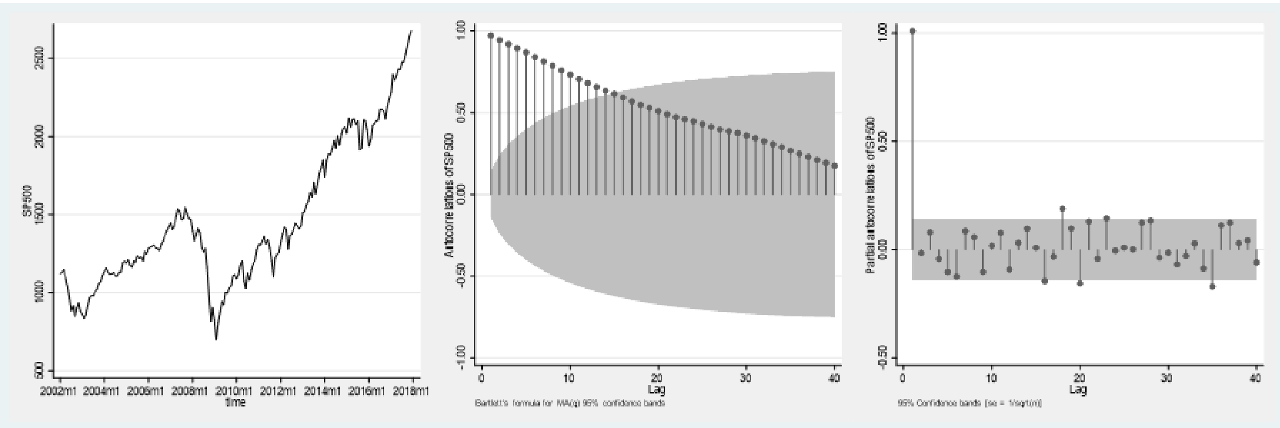
A3.1.5 Crude Oil



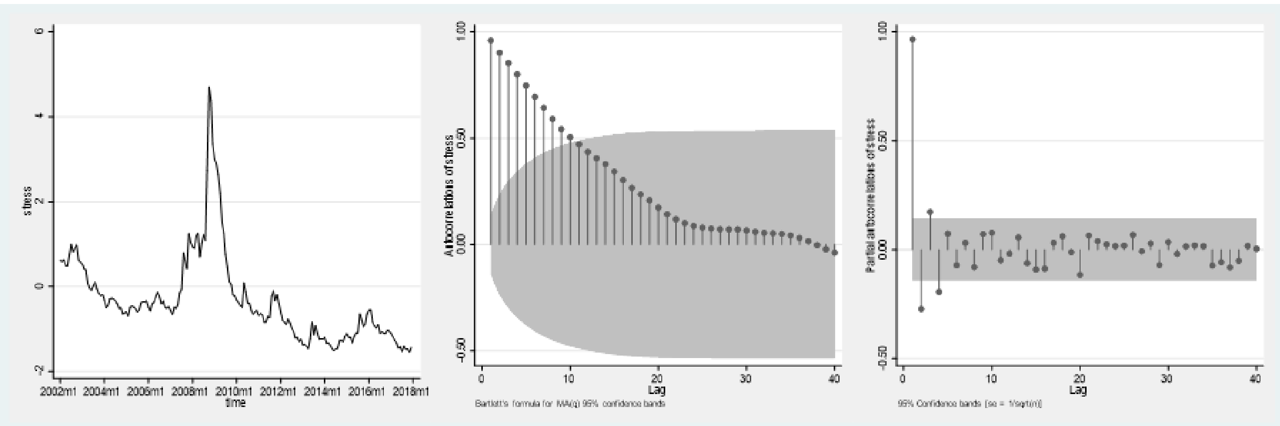
A3.1.6 Unemployment Rates



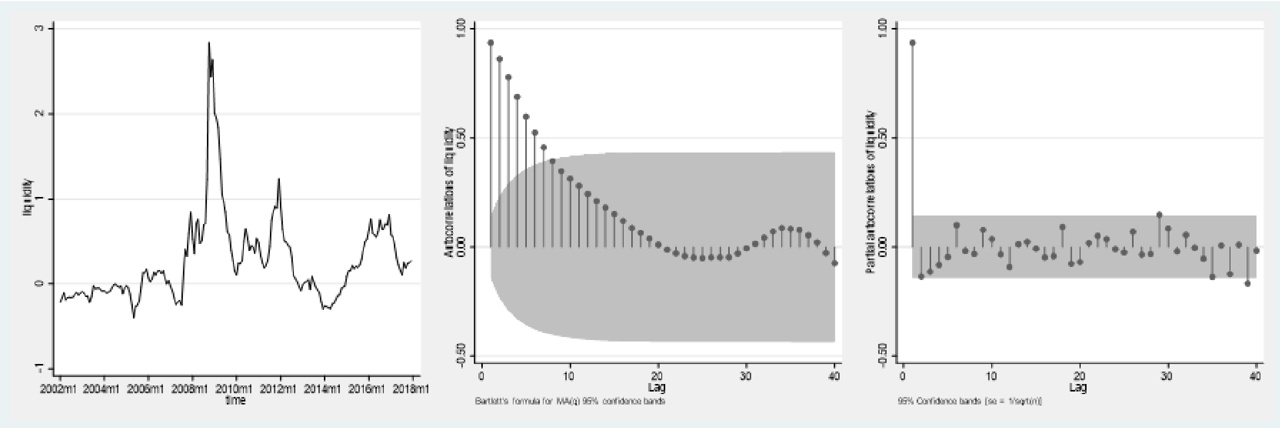
A3.1.7 S&P 500 Index



A3.1.8 The Stress Index



A3.1.9 Liquidity Risk Index



A3.2 Correlation Matrix

The correlation matrix is derived from Stata using the inbuilt "correlate" function. This function derives the correlation between every variable included in the analysis. Correlation coefficients near one imply that the variables are strongly positively correlated, and vice versa.

A3.2.1 Correlation Matrix (w/o transformations)

	ipo_ret	gbond10y	stress	liquidity	ip	cpi	crude	unemp	SP500
ipo_ret	1.0000								
gbond10y	-0.1118	1.0000							
stress	-0.1708	0.4060	1.0000						
liquidity	-0.1090	-0.2924	0.6234	1.0000					
ip	0.2504	-0.2987	-0.5068	-0.2032	1.0000				
cpi	0.1584	-0.8399	-0.4642	0.2680	0.5559	1.0000			
crude	0.1032	-0.2505	-0.1305	0.0993	0.3253	0.4567	1.0000		
unemp	-0.1016	-0.2644	0.1194	0.2815	-0.5847	0.1167	0.4149	1.0000	
SP500	0.2246	-0.5798	-0.6379	-0.0987	0.7603	0.7908	0.0726	-0.4331	1.0000

A3.3 Model Estimation

A3.3.1 Regression Output

Table A3.2.1.1 portrays the final output after applying GETS modeling in Stata for the new period. In this occasion, both the R-squared and the t-statistics appear more "normalized" relative to the output in Table A2.3.1.1.

A3.2.1.1 Regression Output after GETS modeling

Source	SS	df	MS	Number of obs	=	188
				F(14, 173)	=	3.67
Model	0.284416702	14	0.020315479	Prob >F	=	0
Residual	0.956811634	173	0.005530703	R-squared	=	0.2291
				Adj R-squared	=	0.1668
Total	1.24122834	187	0.006637585	Root MSE	=	0.07437

ipo_ret	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
ipo_ret						
L1.	0.1558932	0.0704892	2.21	0.028	0.0167636	0.2950228
L3.	0.2086772	0.0715263	2.92	0.004	0.0675006	0.3498539
Dgbond10y						
L2.	-5.8919	2.648211	-2.22	0.027	-11.11886	-0.6649375
Dstress						
L0.	0.0787578	0.0337739	2.33	0.021	0.0120958	0.1454197
L1.	0.1047017	0.0371962	2.81	0.005	0.031285	0.1781184
L3.	0.047431	0.0222852	2.13	0.035	0.0034451	0.0914168
Dliquidity						
L0.	-0.1119495	0.0521127	-2.15	0.033	-0.214808	-0.0090909
L1.	-0.0888803	0.0485115	-1.83	0.069	-0.184631	0.0068703
Dln_ip						
L0.	2.195074	0.9409869	2.33	0.021	0.3377814	4.052367
L3.	-2.028267	0.9739709	-2.08	0.039	-3.950663	-0.1058709
L4.	-1.744906	0.9161847	-1.90	0.058	-3.553245	0.0634334
Dln_SP500						
L0.	0.25769	0.1513475	1.70	0.090	-0.0410354	0.5564154
L1.	0.2872344	0.1482963	1.94	0.054	-0.0054687	0.5799374
L2.	0.3848221	0.1374049	2.80	0.006	0.1136161	0.656028
_cons	0.0746135	0.0121941	6.12	0.000	0.0505451	0.0986819

A3.3.2 sup-Wald test for Structural Breaks

Again, the test for unknown structural breaks is initiated through Stata's inbuilt "sbsingle" command with a trim of 10%, however on a new time horizon. This test computes the F-statistics for a predefined subsample, cf. subsection 4.3.2.

A3.2.2.1 Test for Structural Breaks

```
Test for a structural break: Unknown break date

                             Number of obs =        188

Full sample:                  2002m5 - 2017m12
Trimmed sample:              2003m12 -  2016m6
Estimated break date:         2016m1
Ho: No structural break

     Test            Statistic         p-value
 ----------------------------------------------
     swald            25.9223           0.4491
 ----------------------------------------------
Exogenous variables:          L.ipo_ret L3.ipo_ret L2.Dgbond10y Dstress L.Dstress L3.Dstress Dliquidity
                                  L.Dliquidity Dln_ip L3.Dln_ip L4.Dln_ip Dln_SP500 L.Dln_SP500
                                  L2.Dln_SP500
Coefficients included in test: L.ipo_ret L3.ipo_ret L2.Dgbond10y Dstress L.Dstress L3.Dstress Dliquidity
                                  L.Dliquidity Dln_ip L3.Dln_ip L4.Dln_ip Dln_SP500 L.Dln_SP500
                                  L2.Dln_SP500 _cons
```

Conclusion: P-Value $>$ 0.05, i.e we accept the null hypothesis of no structural break, i.e. a structural break is not present.

A3.4 Granger Causality Test for Feedback Effects

To determine whether feedback effects from IPO_RET affects any of the independent variables, we initiate a Granger-causality test through Stata's inbuilt "vargranger" command. As one can see from Table A3.3.1, there is, in fact, some feedback effects between IPO_RET and the industrial production index (IP). In subsection 5.2.4 we argued that it may seem counterintuitive to believe that first-day returns "causes" increments in industrial production and that this relationship should, at least from a theoretical standpoint, be the other way around. This could potentially point towards some sort of modeling deficiencies, however, we believe that analysis over a greater timespan than 16 years would probably yield other results.

A3.3.1 Granger Causality Wald Test

Equation	Excluded	chi2	df	Prob >chi2
ipo_ret	Dgbond10y	7.1729	4	0.127
ipo_ret	Dstress	7.9834	4	0.092
ipo_ret	Dln_ip	8.3561	4	0.079
ipo_ret	Dln_SP500	14.072	4	0.007
ipo_ret	Dliquidity	4.4949	4	0.343
ipo_ret	ALL	32.167	20	0.042
Dgbond10y	ipo_ret	5.5378	4	0.236
Dgbond10y	Dstress	5.6507	4	0.227
Dgbond10y	Dln_ip	5.6407	4	0.228
Dgbond10y	Dln_SP500	20.239	4	0
Dgbond10y	Dliquidity	0.81957	4	0.936
Dgbond10y	ALL	70.728	20	0
Dstress	ipo_ret	2.2168	4	0.696
Dstress	Dgbond10y	4.814	4	0.307
Dstress	Dln_ip	35.887	4	0
Dstress	Dln_SP500	0.6134	4	0.962
Dstress	Dliquidity	4.9271	4	0.295
Dstress	ALL	57.9	20	0
Dln_ip	ipo_ret	11.452	4	0.022
Dln_ip	Dgbond10y	5.5799	4	0.233
Dln_ip	Dstress	12.895	4	0.012
Dln_ip	Dln_SP500	13.674	4	0.008
Dln_ip	Dliquidity	5.579	4	0.233
Dln_ip	ALL	72.51	20	0
Dln_SP500	ipo_ret	5.13	4	0.274
Dln_SP500	Dgbond10y	3.2603	4	0.515
Dln_SP500	Dstress	6.198	4	0.185
Dln_SP500	Dln_ip	11.931	4	0.018
Dln_SP500	Dliquidity	10.666	4	0.031
Dln_SP500	ALL	68.172	20	0
Dliquidity	ipo_ret	0.61268	4	0.962
Dliquidity	Dgbond10y	2.2585	4	0.688
Dliquidity	Dstress	40.486	4	0
Dliquidity	Dln_ip	36.826	4	0
Dliquidity	Dln_SP500	1.8754	4	0.759
Dliquidity	ALL	147.28	20	0

A3.5 EG-ADF test for Cointegration

In Section 4.3.4 we argued that the EG-ADF test applies the ADF statistic to examine whether two (or more) variables appear correlated. However, the test statistic is dependent upon the number of regressors included in the analysis and the total sample size. Therefore, to analyze whether cointegration is present amongst the variables, we apply the critical values as proposed by Stock and Watson (2015, p. 705):

A3.4.1 Critical Values of the Engle-Granger ADF Statistic

Independent Variables	$\alpha = 10$ percent	$\alpha = 5$ percent	$\alpha = 1$ percent
1	-3.12	-3.41	-3.96
2	-3.52	-3,80	-4.36
3	-3.84	-4.16	-4.73
4	-4.20	-4.49	-5.07

Notes: The critical values in Table A3.4.1 are taken from Stock and Watson (2015, p. 705) which is the critical values suggested by Dickey and Fuller (1979); Phillips and Perron (1988), and Hansen (1992). The critical values are chosen so that they apply whether or not X_t and Y_t include drift components.

Note that the null hypothesis under EG-ADF tests stipulates "no cointegration" amongst the variables tested. To understand whether cointegration is present amongst the independent variables, we apply Stata's inbuilt "egranger" command with the following results:

A3.4.2 EG-ADF Statistic

Augmented Engle-Granger test for cointegration		N (1st step)	=	192
Number of lags = 4		N (test)	=	187

Z(t)	Test Statistic	1% Critical value	5% Critical value	10% Critical value
		-5.073	**-4.489**	**-4.188**
GBOND10Y	**-2.594**	_""_	_""_	_""_
STRESS	**-2.354**	_""_	_""_	_""_
LIQUIDITY	**-2.757**	_""_	_""_	_""_
IP	**-2.640**	_""_	_""_	_""_
SP500	**-1.198**	_""_	_""_	_""_

Critical values from MacKinnon (1990, 2010)

Conclusion: In all cases the t-stats < critical values at every conventional significance level, i.e we accept the null hypothesis of no cointegration in all possible scenarios.

A4 Post-Estimation: Diagnostic Checks

A4.1 Test for Omitted Variables

To identify whether our regression model suffers from any omitted variables, we apply Ramsey's RESET test using Stata's inbuilt "estat ovtest" command. We cannot reject the null hypothesis of no omitted variables, hence we argue that the model does not suffer from OVB, cf. subsection 4.3.5.

A4.1.1 Ramsey Test for Omitted Variables

Ramsey RESET test using powers of the fitted values of ipo_ret		
Ho: model has no omitted variables		
F(3, 170)	=	1.33
Prob >F	=	0.2668

A4.2 Test for White Noise Residuals

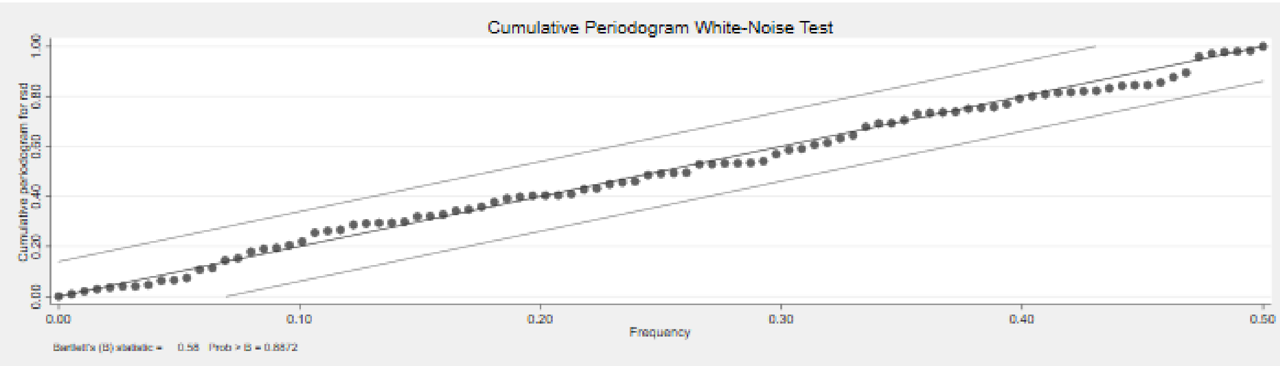
Furthermore, to analyze whether the residuals follow a white-noise process we employ the Ljung-Box Q-test through Stata's inbuilt "wntestq". To do this, we first estimate the residuals using "predict, residuals" of the estimated ADL model. Because the null hypothesis stipulates that the variable being tested is following a white-noise process whereas we fail to reject the null hypothesis at every conventional significance level (p-value < 0.1), we argue that the residuals indeed resemble a white-noise process (StataCorp, 2015).

A4.2.1 Ljung-Box Q-test for White Noise Residuals

Portmanteau test for white noise		
Portmanteau (Q) statistic	=	47.8184
Prob >chi2(40)	=	0.1850

As a way of illustrating the evolution of the residuals we construct a cumulative periodogram using Stata's inbuilt "wntestb residuals", and as depicted in Figure A4.2.2 the residuals appear relatively constant without any significant disruptions (StataCorp, 2015):

A4.2.2 Cumulative Periodogram of the Error-term



A4.3 Test for Serial Correlation and Heteroscedasticity

In Section 4.3.1 we stressed the importance of understanding how serial correlation affect a series. Additionally, we postulated the importance of examining whether the residuals (i.e. the error-term) are serially correlated as this would invalidate the estimated regression model if present. To understand whether the residuals are serially correlated we apply Stata's inbuilt "bgodfrey" command with 40 lags, and as one can derive from Table A4.3.1, we fail to reject the null hypothesis of "no serial correlation".

A4.3.1 Breusch-Godfrey Test for Serial Correlation

Breusch-Godfrey LM test for autocorrelation			
lags(p)	chi2	df	Prob >chi2
40	45.100	40	0.2671

H0: no serial correlation

One of the most important assumptions of covariance-stationarity is that the series needs to have constant variance throughout the period of analysis, cf. subsection 4.3.2. To understand whether this is the case, one can apply Breusch-Pagans test for homoscedasticity using Stata's inbuilt "estat hettest". Doing so, we achieve the following results:

A4.3.2 Breusch-Pagan Test for Heteroscedasticity

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity		
Variables: fitted values of ipo_ret		
chi2(1)	=	0.70
Prob >chi2	=	0.4019
Ho: Constant variance		

By inspecting the results in Table 4.3.2 we fail to reject the null hypothesis of "constant variance". Moreover, the regression model appears valid in terms of OLS-estimation, cf. subsection 4.3.5.

A4.4 Test for Multicollinearity

Because some of the regressors in the analysis are correlated with one another in which some of the indices share similar input variables, it is vital to understand whether our regression function is suffering from perfect multicollinearity or not. This is also, as highlighted in Section 4.3.5, one of the four assumptions that needs to be upheld for time series regressions to be valid under OLS-estimation. We therefore test for multicollinearity using Stata's inbuilt "vif" command.

A4.4.1 Variance Inflation Factors

Variable	VIF	1/VIF
Dstress		
L1.	3.62	0.276548
L0.	2.98	0.335474
Dliquidity		
L0.	2.95	0.338571
L1.	2.56	0.390268
Dln_SP500		
L0.	1.62	0.616876
L1.	1.57	0.637047
Dln_ip		
L3.	1.55	0.646127
L0.	1.47	0.67867
L4.	1.37	0.727707
Dln_SP500		
L2.	1.35	0.742631
Dstress		
L3.	1.3	0.770595
ipo_ret		
L1.	1.11	0.897287
L3.	1.1	0.911273
Dgbond10y		
L2.	1.1	0.911429
Mean VIF	**1.83**	

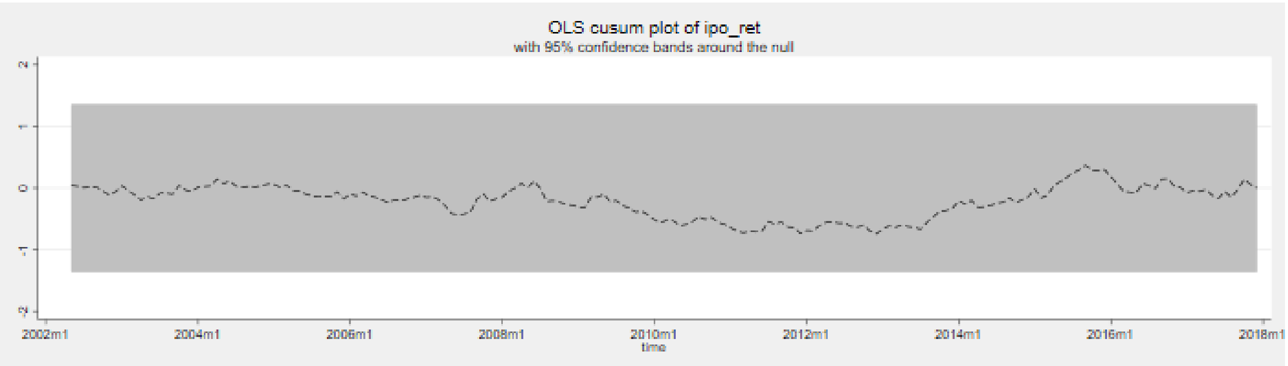
A4.5 Test for Parameter Stability

Finally, we check for parameter stability by using Stata's "estat sbcusum, ols" function. This function calculates the cusum of residuals to identify whether the model changes throughout the period of analysis. If the coefficients change after a certain time period the plot will "drift away" from a mean of zero, thus implying that model instability is present (StataCorp, 2015). As one clearly sees from both Table A4.5.1 and Figure A4.5.2 the model appearsd unaffected by any structural breaks.

A4.5.1 Cumulative Sum test for Parameter Stability

Sample:	**2002m5 - 2017m12**	**Number of obs**	=	**188**
Ho: No structural break				
Statistic	Test Statistic	1% Critical value	5% Critical value	10% Critical value
ols	0.7244	1.6276	1.3581	1.224

A4.5.2 Cumulative Sum plot of IPO Returns



A5 Attachments

The following documents, that are attachments to this paper, are not deemed required to be included in the main document:

- **Attachment 1:** A primer of the Global Financial Stress Indicator developed by Bank of America Merrill Lynch with courtesy of Benjamin Bowler.
- **Attachment 2:** A .XLS file covering the master data used in the analysis.