BI Norwegian Business School - campus Oslo

GRA 19703

Master Thesis

Thesis Master of Science

The Predictability of Future IPO Volume Through Initial Returns, a Study of the European Market

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Start: 15.01.2020 09.00

Finish: 01.09.2020 12.00

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by
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MSc in Finance

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Oslo, July 1, 2020

ABSTRACT

IPO volume is highly autocorrelated in the European market, unlike initial returns. We find more companies tend to go public the following quarter after periods of high initial returns, as well as some characteristics with significant contribution towards explaining initial returns. However, the explanatory power of these characteristics are too low to yield sufficient predictions for the eventual underpricing of an IPO. We observe some differences in explanatory power of characteristics from the beginning to the end of an IPO's registration period, which imply an increase in knowledge for the issuing firms and their underwriters, in the statistical sense, however this has little economical impact.

Acknowledgements

We would like to express gratitude to our thesis supervisor, NFI Professor of Finance Samuli Knüpfer from the Department of Finance at BI Norwegian Business School. He has provided us with steady guidance throughout the process, supporting our decision making and analysis, as well as writing. His contribution has been highly appreciated. We would furthermore like to extend our thanks to Sigrid Noer Gimse and Ole Andreas Solberg, senior librarians at BI Norwegian Business School, which has provided us with mobile support during the Covid-19 lockdown. Their contribution has enabled us to access data and to progress at a comfortable pace throughout our thesis. Finally, we would like to thank our families and friends. While they have not contributed to our scientific work, they have provided us with moral support and motivation during these strange times.

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1 Introduction and Motivation

In order to understand the reasonings behind initial public offerings (IPOs) clustering over time, we are going to examine; if there is a significant relationship between initial returns and the future number of IPOs; what characteristics can explain underpricing for offerings; and identify potential drivers of first day returns. This analysis is done to evaluate if firms and their underwriters use information from the IPO market to learn and time their own offering. We will focus on the European market over the time-period from January 1999 to December 2019, as a similar study is done for the US market by Lowry and Schwert (2002). Their main findings are (1) firms with similar characteristics tend to go public at the same time and (2) information learned during the registration period is used to decide the final offer price. However, they are not able to find evidence of firms being able to reduce their underpricing through timing their IPOs.

IPO clusters are documented to follow periods of high initial returns by several researchers. While investors stand to gain from underpriced initial public offerings, for the company going public this means money left "on the table". Their goal should thus be to minimize initial returns in order to obtain a fair value on their offering. We will analyse if this type of clustering is caused by firms and their underwriters observing an IPO-friendly market, with investors being more optimistic towards their valuation of offerings, creating an opportunity to obtain a higher price for offerings to come. However, due to information asymmetry investors cannot fully trust the offer price and some systematic underpricing is needed to attract investors, as famously described by Akerlof (1978).

Using a second-order vector autoregression model we find initial returns to have a significant impact on the number of IPOs, suggesting one percentage point increase in initial returns will contribute to an additional 0.2 IPOs the following quarter. Our classical linear regression models, using characteristics to explain initial returns, yield low explanatory power of 0.005 – 0.009 from the beginning until the end of the registration period. The change in explanatory power suggest issuing companies and their underwriters obtain more knowledge during the registration period, however it has little economical impact when used to estimate the eventual underpricing of an IPO.

Going forward, this thesis will give a brief literature review covering key findings of relevant research in section 2. This will also give an introduction into our research topic if you, the reader, are unfamiliar with initial public offerings and related research. Further, we will introduce the dataset and methodology for our thesis in section 3 and 4 respectively. Our analysis will be presented in section 5, giving an easily accessible overview of our results accompanied by discussions surrounding our key findings. Finally, we will give some concluding remarks in section 6, followed by opportunities for further work (section 7).

2 Literature Review

Since the mid 70's initial public offerings have been researched extensively, both with regards to market anomalies and its volume cyclicality. Underpricing and the "hot issue" market phenomenon was discovered early on, with Ibbotson and Ritter being amongst the pioneers in the field. A variety of prominent researchers have tried to understand, bring arguments and findings to why such trends seem to repeat themselves, and have accumulated into a wide list of contributions to explain the phenomenon. We will use this section to provide the reader with an overview of the most recognized research papers relevant to our research question.

2.1 Underpricing of Initial Public Offerings

Ibbotson (1975) is recognized as the first to find significant evidence of IPO underpricing and their followingly positive initial returns. His research indicates this to be caused either by offer prices being too low or a systematic overvaluation by investors in the short-term (first month). Ibbotson illustrates several plausible scenarios related to the involved parties; underwriters, issuing corporation and investors, however all possible explanations for underpricing is conflicted by "unknown legal constraints, needlessly complicated indirect compensation schemes, or irrational behavior" (Ibbotson, 1975). In other words, he finds supportive evidence of initial underpricing, but are unable to give a reason for the phenomenon.

In more recent years Lowry and Schwert (2002) commented on the underpricing phenomenon, suggesting firm characteristics such as industry, size and information which becomes available during the registration period are only partly incorporated in the offering price. As firms themselves cannot control these characteristics or predict future information, it should not be possible for management to strategically time their IPOs in order to gain lower underpricing. Further, they go on to investigate initial return and IPO volume cycles leading to two puzzling questions. First, while sequential learning from other issues should enable firms to avoid high initial return bubbles, their research suggests underwriters to be unable or unwilling to fully price recent valuations into new issues. Secondly, issuing companies have a harder time seeing the benefits from initiating an IPO process during periods of high initial returns due to serial correlation of initial returns. Lowry and Schwert explain the serial correlation as a part of the underwriters' learning process and overlap between registration periods of several IPOs. They highlight new positive information to be an advantage from issuing in periods with high initial returns, as the issuers may be able to raise larger amounts of capital than previously expected.

In contrast, Benveniste, Ljungqvist, Wilhelm, and Yu (2002) suggest initial returns to decrease as a function of IPO bundling for companies with a common valuation factor. They argue investment bankers responsible for public offerings are able to use information obtained across offerings simultaneously. This makes for a more complete level of information and leads to less issues with underpricing. This result contradicts the documented positive correlation between IPO volume and initial returns. They go on to investigate a smoothening hypothesis of bundling effects, which leads to: "(a) lower percentage discounts on average as the total cost of information production is spread across a larger bundle of firms, and (b) a relatively smooth distribution of discounts across bundled firms" (Benveniste et al., 2002). However, with no precise definition of transactions where bundling is feasible, testing for such hypothesis is complicated.

Ritter (1991) extended his research from short-run to long-run performance. He points out IPOs are usually underpriced, reflected through high initial returns. However, their long-run performance is most commonly poor compared to the market. Further, he argues high initial returns to be driven by excessive first day aftermarket prices, rather than the issuers and underwriters' valuations being too low. Additionally, Ritter finds the long-run underperformance to be more significant for younger firms and firms issuing at IPO volume peaks and argues this to be a result of companies taking advantage of the "window of opportunity". This relates to "hot issue" markets (section 2.3), and suggest investors to be overly optimistic in "hot" markets, which can induce a more advantageous offering outcome for the firm.

2.2 Asymmetric information

Several researchers have tried to explain IPO underpricing arguing information asymmetry to be the root of all problems. Rock (1986) explains the relation between informed and uninformed investors through the winner's curse and free rider problem. He goes on to say uninformed investors face a winner's curse, as informed investors will withdraw from offerings when issues are perceived to be priced above their fair value. Consequently, an increased number of shares will be allocated to uninformed investors in such scenarios, and only when issues are relatively underpriced will informed investors receive the greater amount of shares. In order to relate this to IPO underpricing, Rock highlights the rationing of shares done by underwriters on the day of offering. As underwriters are likely to deny this, research into this topic is difficult, and Rock uses information from tender offer premiums to compare with IPO underpricing in order to support stronger empirical evidence. He finally argues issuing firms have to underprice their IPOs to compensate uninformed investors for the bias and adverse selection.

With regards to information asymmetry, Welch (1989) points out offering firms have a wider horizon when deciding their price and proportion offered. He describes it as a game to gain the most from multiple issues, combining an IPO with seasoned offerings (SO). He suggests a strategy where high-quality firms intentionally underprice their IPOs in order to receive higher prices through later SOs. This argument follows the significantly lower marginal cost of underpricing for high-quality firms and the ability to provide superior information following an IPO. For the same strategy to work for low-quality firms, they need to imitate the characteristics of higher quality firms. Given the probability of being revealed in between offerings, signaling and other costs exceed benefits. Welch concludes high-quality firms have a favorable position to be compensated later on, which is a potential explanation for a higher degree of underpricing.

Baron (1982) explores the agency problem arising from the issuer and underwriter relationship. He argues unseasoned issuing firms are willing to accept a lower market price due to their lack of information about the market, in comparison to a firm doing a seasoned offering. His study is based on the demand for investment banking services, dependent on the contribution the issuer senses the underwriter can bring. He finds demand for investment banking services to increase with market uncertainty. Baron argues the optimal offering price to be a decreasing function of uncertainty, which implies a greater probability of underpricing in times of high market uncertainty.

Benveniste and Spindt (1989) try to find evidence supporting underwriters' contribution to reduce inefficiency in IPO pricing. Their base scenario is an issuing firm completing their IPO without an underwriter, yielding a natural underpricing. This underpricing stems from asymmetric information between issuer and investors, as investors will assume the firm excludes some private information in the prospectus. Investors need to be compensated in order to invest, which is shown through investors indicating a lower valuation than their intrinsic share value. However, when investment bankers are present, they can introduce an incentive trade-off to investors which will make underpricing less frequent. Despite this, investors benefit from a lower price, and might not be incentivized to reveal their private information to underwriters, in order to gain attractive abnormal returns in the aftermarket. They assume all information eventually will be incorporated in the price. However, it is crucial for investors to reveal enough information, as underwriters mainly decide which investors receive shares. As a final remark; this sort of equilibrium, created by introducing underwriters, should result in a decreased amount of underpriced issues according to Benveniste and Spindt (1989).

Hanley (1993) presents findings which indicate a relationship between information gathered during the pre-issue period, the following initial return and allocation of shares. She suggests a positive price update, from the average offering price range, leads to higher initial return and an increased number of shares issued. Further, she comments on the asymmetric benefits from information gathered during "road shows", as it mostly benefits investors, not the issuing companies. This concept is defined as the "partial adjustment" phenomenon by Ibbotson et al. (1988), where underwriters only partially revise the offering price based on the information gathered. The underwriters' motivations are connected to potential profits which depend on returns and share allocations. Followingly, underwriters are willing to compensate investors for truthful information by issuing highly underpriced shares at a lower quantity.

Opposed to the above-mentioned contributions, Ritter and Welch (2002) argue agency problems and asymmetric information to be an insufficient explanation for underpricing. They argue future research into behavioral explanations and agency conflicts is needed. In addition, they emphasize the importance of share allocation. To this date, a lack of insight into the micro level data on share allocations in the US have led to an unsatisfactory level of empirical evidence. As this data has gradually become more accessible, it immediately gives a more fundamental layer of information and sheds light on issues of importance. As such, share allocations stand out as a research topic for further investigation.

2.3 "Hot Issue" Markets

The decision to go public is for the majority of companies based on several years of strategic decision-making, maturity of business model and a clear market for its products and services. However, when a firm is ready to go public the question of timing arises in order to achieve favorable pricing for their offering. This decision gives rise for the discussion surrounding "hot" and "cold" markets. Issuers might be better off issuing in "cold" markets according to Ibbotson and Jaffe (1975) as "issuers may obtain a higher offering price relative to the efficient price when they issue in cold issue markets.". This finding contradicts the opinion of several researchers and professionals. Investment bankers will usually advise firms to go public in "hot" markets, and Ibbotson and Jaffe argue this is to assure a guaranteed interest and successful offerings. Time series need to be stable and predictable for different states of the market and for companies, in order to strategically time "hot" or "cold" markets. Ibbotson and Jaffe (1975) find these patterns in their research, together with serial dependency in the data, and believe past data can be used to predict "hot issue" markets.

Ritter (1984) tried to explain the "hot" and "cold" market effect by the level of uncertainty and risk, however he finds the hypothesis to have low explanatory power. He finds the volume of similar IPOs to be an important factor in his study. While Ritter's study investigates the six-year period between 1977-82, it focuses mainly on findings from the 1980's, which have a higher level of underpricing. However, he finds the natural resources industry to be the main driver of these results, and is a consequence of underwriters exploiting issuers in this industry. While the difference in initial returns between "hot" and "cold" markets are exceptionally large for the natural resources industry, in other industries the "hot issue" market is barely observable. Though the overall result leads to arguments supporting "hot issue" markets, it is mostly driven by segmented market conditions.

Lowry (2003) finds a distinct variation in IPO volume over time and argues the need for financing is not the only motivation for going public as the variation does not follow cycles in capital expenditures. She gives three explanations, (1) business cycle variation, (2) changes in investor optimism and (3) the lemons problem. However, only required additional capital together with investor optimism yield significant results as drivers of IPO volume, both statistically and economically. She observes clustering of IPOs following high initial returns for similar offerings, and suggests firms benefit by learning from each other's book-building to lower underpricing.

Ibbotson, Sindelar & Ritter are highly renowned within the field of research and have through a combined effort published two articles (1988 & 1994) trying to elaborate further on IPO underpricing, cycles and long-run underperformance. They show a consistent pattern of both high initial returns and IPO clustering, and present a variety of potential explanations for "hot issue" markets. They argue "hot" markets follow periods of uncertainty, assuming issues with greater uncertainty generate higher initial returns.

Further, Ibbotson, Sindelar & Ritter suggest another explanation can be "momentum" strategies, saying investors believe in a positive autocorrelation in initial returns. As such, their demand for IPOs and willingness to pay a premium price depend on the outcomes of recent issues. This assumption in combination with the difficulty of shorting IPOs allow for the "momentum" hypothesis to hold. An alternative explanation is "the window of opportunity"; when investors are bullish and willing to pay higher relative prices, issuers are tempted to go public. However, with firms rushing to complete their issue, they are susceptible to accept slightly lower prices to time the market, which contribute further to drive underpricing.

2.4 Pseudo market timing

Not only has research found IPOs to cluster over time, they cluster around market peaks. In other words, it seems to be a correlation between the general performance of financial markets and the willingness to go public. Schultz (2003) refers to this phenomenon as pseudo market timing and suggests it is caused by firms going public when the market itself is doing well, in order to obtain higher prices. He points out market peak clustering cannot be observed at the time of an offering, but is caused by availability of funds and positive NPV projects.

Schultz finds such timing easily leads to long run underperformance of IPOs, as pseudo market timing per definition leads to more peak valuation offerings. Issuers themselves cannot predict whether they are at a peak. They will followingly be attracted by a higher price level, enabling larger proceeds and lower dilution. Issues will keep on rising until valuations start to slope downwards, together with prices and returns. However, pseudo market timing bias can be avoided by using calendar-time returns rather than event-time, and is a limitation to his hypothesis.

Similarly, Lucas and McDonald (1990) suggest firms which consider themselves to be undervalued, will postpone upcoming IPOs to receive a higher price under better market conditions. They continue by stating any postponement decision has to be seen together with the level of information asymmetry, as well as project and firm durability, in order to evaluate the willingness to accept underpricing. Postponement can be avoided if the firm can provide favorable information to receive a better outcome. In addition, they find the sum of average asset quality to be a driving factor, having a positive correlation with both issue volume and market returns. This result might explain clusters of high-quality firms.

3 Data

This section covers our dataset, starting with a discussion of the data collection process, as well as providing a definition of our variables. Thereafter, we present our method for data processing and an overview of descriptive statistics central to our analysis.

3.1 Data Collection

We use three databases to collect data: SDC Platinum, Datastream and Eikon. From SDC, we extract: issuer, filing date, issue date, offer price and in which currency it is denoted, number of shares, filing range, SEDOL and ISIN numbers, nation of issuer, industry, business description, high-tech classification, exchange, marketplace and underwriters. This is done for IPOs from the European market filed between 1981 and 2019. Our method of matching companies from SDC to either Datastream or Eikon is primarily through SEDOL numbers, while ISIN numbers are used for companies without SEDOL, as company tickers cannot be coordinated across databases.

Historical stock prices are gathered through a time series request spanning from two months prior to the issue date and ending at 30 days after the issue (180 days when file- and issuing dates are equal). We use Excel add-ins for Datastream and Eikon for this extraction process. However, both databases struggle with some SEDOL numbers. Datastream does not accept alphanumeric numbers, while the Eikon add-in is not able to retrieve data when companies are merged, acquired or dead. As such, we supplement our core company identifying methods with Eikon RIC codes to complete our dataset.

To make data comparable across countries and time, we use Datastream to extract the following historical data: exchange rates for European currencies against the US dollar, US inflation rates and MSCI Europe Index price, our proxy for the European market return.

3.2 Definitions

Initial return is calculated as the percentage change from the offering price to the first closing price of the issuing company. Further, we differentiate between two types of initial return portfolios: equal-weighted quarterly initial return IR^{EW} and proceed-weighted quarterly initial return IR^{PW}. The number of IPOs issued per quarter is denoted as $NIPO$, while number of withdrawals per quarter is NWD. We specify withdrawals as IPOs with no closing price available within the first month, or six months if the offering- and filing dates are the same. Time in registration, $REGTIME^{PW}$, is the number of days between the filing and offering date, calculated as a proceed-weighted measure for issues completed in a given quarter. Lastly, $NFIL$ is the number of new filings per quarter.

3.3 Processing the Data Set

A selection of the data contains observations outside the scope of interest; real estate investment trusts (REITs), closed-end funds, venture capital trusts (VTCs), unit IPOs and “false positives”, and are excluded from our dataset. “False positives” usually stem from companies switching exchange and are characterized by one of two criteria; (1) IPOs with their first trading day two months prior to the planned issue date (Gajewski and Gresse, 2006), or (2) IPOs with first trading day prior to the filing date, as registration time by nature is non-negative.

Extreme observations, defined as IPOs where the ratio between the first closing price and the offer price is greater than 5 (Gajewski and Gresse, 2006), are removed as a precaution against non-reliable data from SDC. Further, we remove IPOs with a ratio less than $1/5$, as we observe extremes in the opposite direction as well.

The starting point of our dataset is 1999. We rely upon a steady stream of IPOs and a high rate of viable observations for our analysis. As seen in figure 3.1 the study should start no earlier than 1994 based on number of observations. However, given the second criteria we choose to start in 1999, as the early 90s have a high ratio of non-viable observations (figure 3.2).

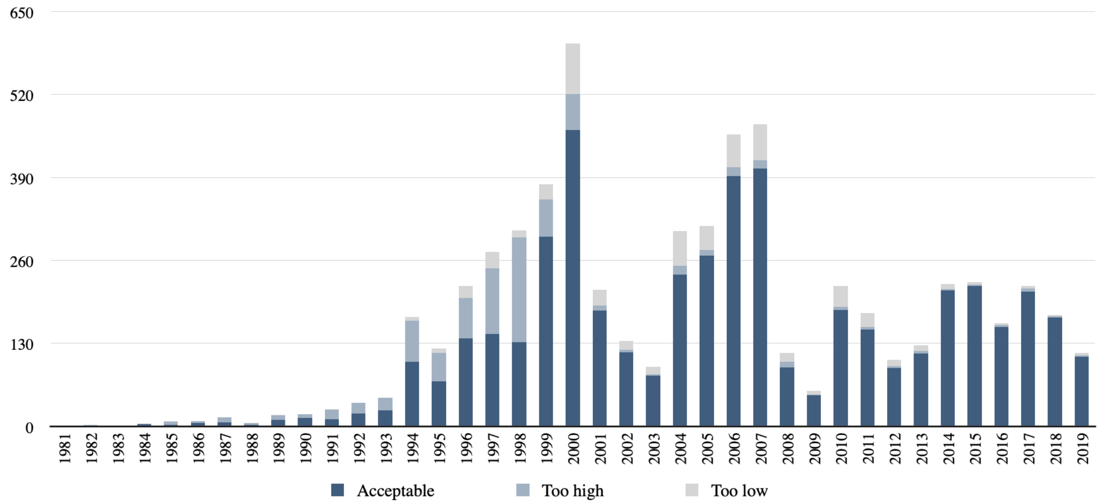


Figure 3.1: Number of IPOs per year, between 1981 and 2019. The figure shows the number of viable observations, the number of observations deemed too high, the ratio between first price and offer price greater than 5, and observations deemed to low, observations where the ratio between first price and offer price is less than $1/5$.

While our initial idea were to operate at a monthly level, as evident from figure 3.3 (a), monthly based portfolios run the risk of periods with few observations creating an additional level of noise. While this is still a risk for quarterly portfolios (figure 3.3 (b)), it occurs less frequently. The drawback of using quarterly portfolios is an information reduction. We see a clear pattern of smoothening in the quarterly portfolios when comparing the aforementioned figures. However, we argue excessive noise is worse than reduced information.

3.4 Descriptive Statistics

On average, 39 IPOs are issued per quarter, achieving an average of 3.05% in proceed-weighted initial returns, and somewhat higher returns (4.96%) for equal-weighted portfolios, as seen in table 3.1, which suggests larger IPOs on average obtain less underpricing. This pattern is also seen when excluding UK. Further, we observe some autocorrelation in the second quarter lag of the equal-weighted portfolios, while there is no autocorrelation for the proceed-weighted portfolios. When looking at monthly data, there is some autocorrelation for both equal-weighted and proceed-weighted initial returns (table B.3 - B.4).

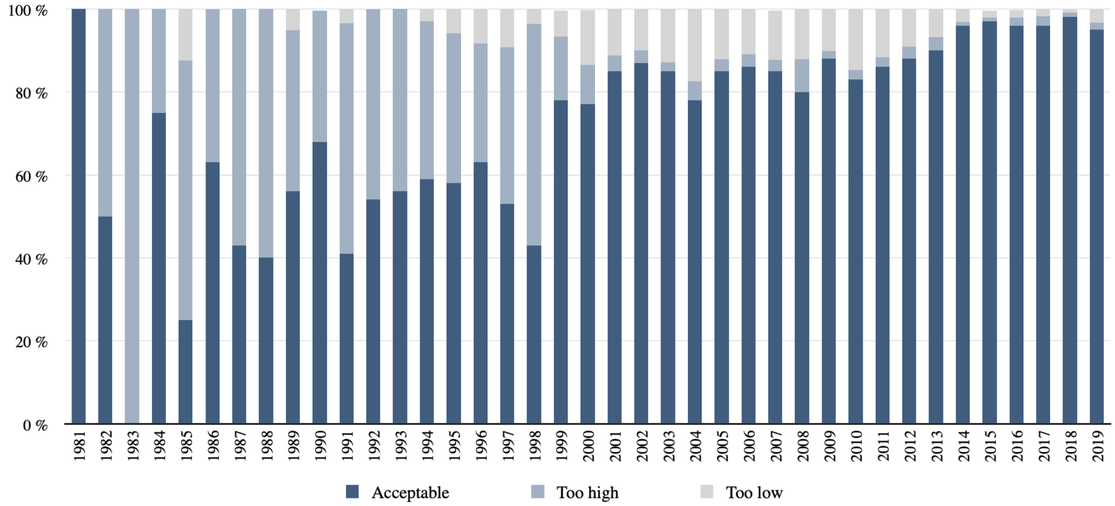
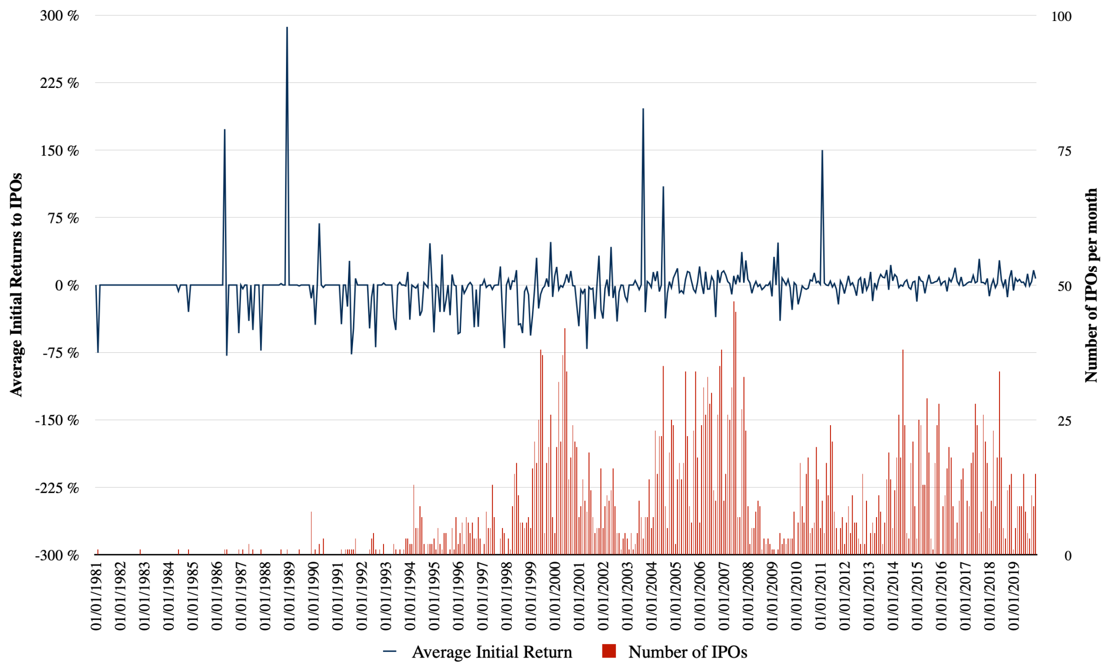


Figure 3.2: Ratio of viable and non-viable observations between 1981 and 2019. The graph shows the percentage of viable observations versus observations deemed to high, the ratio between first price and offer price greater than 5, and observations deemed to low, observations where the ratio between first price and offer price is less than $1/5$.

The number of IPOs ($NIPO$), new filings ($NFIL$) and withdrawals (NWD) are highly autocorrelated. This can be explained by a steady stream of IPOs, which is a selection criteria for our dataset. We observe autocorrelation for the registration time ($REGTIME^{PW}$) as well. This measure averages around two months, however it shows a considerable variation, suggesting its potential as a timing measure in IPO proceedings.

(a) Monthly IPO Volume and Initial Returns



(b) Quarterly IPO Volume and Initial Returns

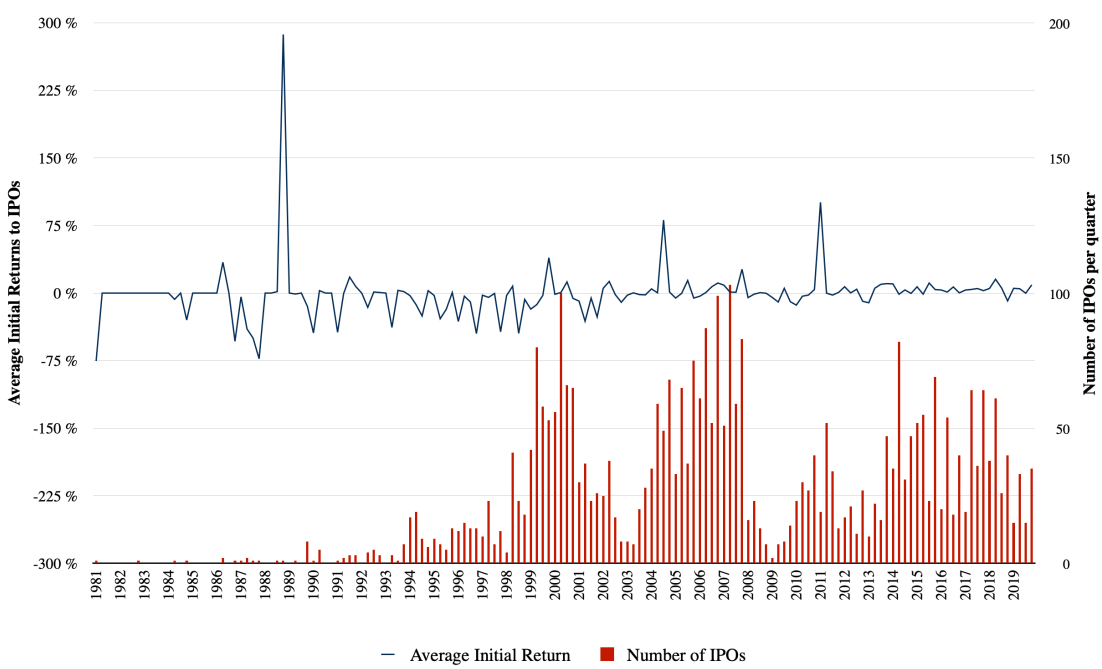


Figure 3.3: IPO Portfolio Volume and Initial Return, 1981 - 2019. A graphical illustration of the number of IPOs per portfolio and proceed-weighted initial return (IR^{PW}). Subplot (a) shows portfolios constructed at a monthly basis, while subplot (b) shows portfolios constructed at a quarterly basis.

Table 3.1: Descriptive Statistics for IPO Related Measures in Europe, between 1999 and 2019

The mean, median (med.), standard deviation (std.), minimum, maximum, sample size T, autocorrelations for 4 lags, ρ_1 to ρ_4, and the standard errors of correlations assuming no autocorrelation $S(\rho)$. The first grouping is for volume related measures; the number of IPOs per quarter ($NIPO$), the number of new filings per quarter ($NFIL$) and the number of withdrawals per quarter (NWD). The second grouping is time in registration $REGTIME^{PW}$, consisting of the average time in registration per quarter weighted by IPO proceeds. The last grouping is for initial returns, and consist of two portfolios; the proceed-weighted average initial return per quarter (IR^{PW}) and the equal-weighted average initial return per quarter (IR^{EW}). Panel A shows statistics for the full sample, while panel B shows statistics when excluding UK.

	Mean	Med.	Std.	Min	Max	T	ρ_1	ρ_2	ρ_3	ρ_4	$S(\rho)$
(A) Full Sample of European Countries											
Number of IPOs per month											
$NIPO$	38.98	35.00	24.19	2.00	103.00	84	0.42	0.69	0.21	0.42	0.20
$NFIL$	40.36	40.00	24.12	3.00	122.00	84	0.60	0.55	0.30	0.40	0.14
NWD	1.60	1.00	2.27	0.00	11.00	84	0.47	0.49	0.21	0.20	0.16
Time in registration in days											
$REGTIME^{PW}$	67.53	57.49	38.72	17.25	224.47	84	0.52	0.37	0.22	0.20	0.15
Average initial returns											
IR^{EW}	4.96	4.86	9.18	-13.15	43.97	84	0.16	0.22	-0.08	0.01	0.14
IR^{PW}	3.05	0.60	16.80	-31.20	100.76	84	0.04	-0.05	-0.06	-0.01	0.05
(B) Sample of European Countries Excluding the United Kingdom											
Number of IPOs per month											
$NIPO$	25.92	21.00	18.49	2.00	84.00	84	0.39	0.69	0.20	0.43	0.20
$NFIL$	27.25	25.00	18.82	2.00	98.00	84	0.59	0.55	0.31	0.38	0.13
NWD	1.54	1.00	2.27	0.00	11.00	84	0.47	0.48	0.22	0.18	0.16
Time in registration in days											
$REGTIME^{PW}$	83.41	68.67	56.63	16.00	279.47	84	0.35	0.25	0.13	0.02	0.14
Average initial returns											
IR^{EW}	2.09	1.43	12.91	-30.22	59.63	84	0.22	0.04	-0.09	-0.03	0.14
IR^{PW}	0.91	0.11	16.08	-33.09	110.91	84	0.09	0.05	-0.04	-0.06	0.07

4 Methodology

Market timing is often perceived as the dynamic of IPO clustering following periods of high initial returns. However, it is not a sufficient measure to say firms indeed time the market. As such, we execute our study in several parts, enabling us to establish if there is a relationship between initial returns and future IPO volume, followed by an investigation into what drives such a relationship.

4.1 Predictive Power and Causality from IPO Initial Returns

We use a higher-order vector autoregressive ($VAR(n)$) model, accompanied by a Granger F-test, to investigate if there is any predictive relationship between initial returns and IPO volume in Europe. We use the cross correlation between the variables as a guiding measure to decide the appropriate number of lags, n.

Using a VAR model has a clear advantage when determining the predictability between initial returns and the number of IPOs, as all variables are considered endogenous (Sims, 1980). Variables are known ahead of time as they exclusively depend on each other's lagged terms. However, VAR models have limitations linked to stationarity (Brooks, 2019). Even though initial returns are perceived as stationary, such an assumption is not necessarily similar for the number of IPOs. There has been an increase in initial public offerings, outside of clusters, when comparing the last 20 years to the 1980's, as seen in figure 3.3. However, by limiting our time-frame to achieve a steady flow of IPOs, we believe there is support for stationarity in the number of IPOs.

Even though our study mainly focuses on the timing relationship between initial returns and subsequent IPO volume, there are other relevant timing measures to investigate. The selected variables of interest are the relationship between IPO initial returns and (1) the number of new filings, (2) the time in registration and (3) the number of withdrawals. We examine if initial returns cause any of the above-mentioned timing measures using Granger causality. If initial return drive the number of IPOs, we expect changes to all these measures as a part of the timing process.

We expect both $NFIL$ and NWD to increase as high initial returns will expedite firms' thought-process of filing for new IPOs, while firms nearing their offering date are more likely to withdraw to wait for better states of the market, leaving less cash "on the table". $REGTIME$ is linked to both new filings and existing processes. We argue firms with IPOs coming up shortly after high initial return will postpone, while firms with a longer time-frame, and new filings, will prefer a shorter registration time. Followingly, we expect $REGTIME$ to decrease.

4.2 Information Content Contributed to Initial Returns

We need to look beyond general findings in order to explain underpricing. As such, we make a thorough investigation into firm characteristics, and examine information content and its connectedness with initial returns over the registration period. This is done in order to determine whether firms and underwriters learn during the registration period.

We propose two regression models: equation 1 is the initial return explained by characteristics known at the time of registration, while equation 2 is initial return explained by characteristics and factors known at the time of offering. This two-step format is used to incorporate the learning process and see if information gathered during the registration period contributes to explain initial returns to a greater extent.

$$\begin{aligned} IR_i = \alpha + \beta_1 RANK_i + \beta_2 TA_i + \beta_3 TECH_i + \beta_4 LSE_i \\ + \beta_5 DEB_i + \beta_6 EUR_i + \varepsilon_i \end{aligned} \tag{1}$$

$$\begin{aligned} IR_i = \alpha + \beta_1 RANK_i + \beta_2 TA_i + \beta_3 TECH_i + \beta_4 LSE_i \\ + \beta_5 DEB_i + \beta_6 EUR_i + \beta_7 MKT^- + \beta_8 MKT^+ + \varepsilon_i \end{aligned} \tag{2}$$

Where:

1. IR is the initial return of an IPO, calculated as the percentage change from the offer price to the first closing price. The variable is given in percentage points.

2. $RANK$ is the ranking of the senior underwriter of the IPO, ranging from 1 to 5, and is based on an underwriter's total proceeds the year of a given IPO. If no underwriter is listed, the IPO is assigned a zero-ranking.

3. TA is the logarithmic total assets in US dollars, adjusted for inflation (base year is set to 1999).

4. $TECH$ is a dummy variable, it equals one if the IPO is in a high-tech industry, as defined by SDC, and zero otherwise.

5. LSE is a dummy variable, it equals one if the IPO is listed on London Stock Exchange, and zero otherwise.

6. DEB is a dummy variable, it equals one if the IPO is listed on Deutsche Boerse, and zero otherwise.

7. EUR is a dummy variable, it equals one if the IPO is listed on Euronext, and zero otherwise.

8. MKT^- is the return, in percentage points, of the MSCI Europe Index during a 15 day period leading up to the IPO if the market return is negative and zero otherwise.

9. MKT^+ is the return, in percentage points, of the MSCI Europe Index during a 15 day period leading up to the IPO if the market return is positive and zero otherwise.

The market return, where MSCI Europe Index is used as a proxy, is connected to two variables MKT^- and MKT^+ rather than one single variable. This is done to uncover any asymmetric effects the market condition might have on initial returns.

The main goal of this regression is to indicate which characteristics and factors explain underpricing, not necessarily providing an accurate prediction. We see a clustering of IPOs over time from figure 3.3 (b). Such patterns may cause correlation of error terms which yields less reliable results.

4.3 Drivers of Initial Return Cycles

In finalizing the investigation of our main hypothesis we examine the dynamics of actual initial return, expected initial return from the two regression models explained in section 4.2 and unexpected initial return, calculated as the difference in actual and expected initial returns. We analyse the autocorrelation in actual, expected, and unexpected initial returns of proceed-weighted IPO portfolios on a quarterly basis to examine the underlying drivers of initial returns. Such an analysis is important to confirm whether serial correlation is driven by expected or unexpected initial return. Lowry and Schwert (2002) see serial correlation in actual returns as underwriters' lack of incorporating all information into the final offer price. However, clusters of firms with similar characteristics can cause serial correlation in expected initial returns and consequently affect actual initial returns. We do not expect to observe autocorrelation in the unexpected returns, i.e the regression error terms, as it violates the homoskedasticity assumption of no serial correlation of error terms for classical linear regression models.

4.4 Robustness Check

We perform a secondary set of linear regression to test the robustness of our results, by checking if coefficients remain constant and significant when controlling for time. Even though our inspirational paper performs a Fama-Macbeth (Fama and MacBeth, 1973) we see such a method as inferior in appropriately reflecting time-effects in our sample due to the lower number of IPOs.

We implement a range of dummies to see if time-variation disturb regression results. The dummies equals one if the IPO is issued in $year_i$ and zero otherwise, for $i \in$ [2000, 2019]. Dummies start in 2000 as time-variation attributed to 1999 is captured in the constant term α, and is done to avoid multicollinearity between the time-dummies and the intercept. The time-controlled regressions are given in equation 3 and 4 and corresponds to 1 and 2 respectively. X_{year} is a $N \times 20$ matrix containing all the time dummies from 2000 to 2019, and β_{year} is a 20×1 vector containing the time-dummy coefficients. N is the total number of IPOs.

$$\begin{aligned} IR_i = \alpha + \beta_1 RANK_i + \beta_2 TA_i + \beta_3 TECH_i + \beta_4 LSE_i \\ + \beta_5 DEB_i + \beta_6 EUR_i + X_{year}\beta_{year}\varepsilon_i \end{aligned} \tag{3}$$

$$\begin{aligned} IR_i = \alpha + \beta_1 RANK_i + \beta_2 TA_i + \beta_3 TECH_i + \beta_4 LSE_i \\ + \beta_5 DEB_i + \beta_6 EUR_i + \beta_7 MKT^- + \beta_8 MKT^+ + X_{year}\beta_{year} + \varepsilon_i \end{aligned} \tag{4}$$

4.5 Subsampling at Country Level

As a final analysis, we perform our methodology at a country-level to complement our cross-continental findings. This is done to make results more comparable to US studies. As Europe consists of several different countries, opposed to the United States, a cross-European study might not yield the same results. We observe several differences, such as European companies usually list at their local exchange (table A.1), and even after the introduction of the Euro, a wide range of currencies are still in circulation. Based on the number of IPOs (figure A.1), we are left with three countries with a sufficient sample size for our analysis: United Kingdom, Germany, and France.

5 Results

Our main results come from two core samples: the full dataset and a sample excluding the United Kingdom. UK has approximately $1/3$ of our observations (figure A.1) and can potentially drive the cross-continental results. This is the reasoning behind working with two separate samples. We structure the analysis into the following subsections: initial returns predictive power on timing measures, information content in initial return and drivers of initial returns, followed by a robustness check and a country-level analysis. We summarize our results with a wide range of descriptive statistics, figures and tables. Unless otherwise mentioned, all statistical significance refers to a 5% significance-level.

5.1 IPO Initial Returns Predictive Power on Timing Measures

To some extent, we see a monotonic pattern from left to right (figure 5.1), which indicates an increasing level of cross correlation between initial returns and both the number of IPOs ($NIPO$) and new filings ($NFIL$). We observe similar patterns when excluding UK, which suggest UK firms behave similarly to other European firms when proceeding with their IPOs. These results demonstrate companies' increased willingness to pursue IPOs in the aftermath of high initial returns. However, the monotonic pattern is weaker than seen in US studies. This is no surprise, as the US and its financial markets is a more integrated marketplace, while the European market is more segmented and foreign IPOs might not drive decision-making across countries.

To show a predictive relationship between initial returns and the number of IPOs we use a $VAR(2)$ model. We use two lags, i.e two quarters, as we find it to be the most convenient time-period to investigate. Looking at figure 5.1 we expect to find significance in lag 1, rather than lag 2.

We see initial returns with one lag IR_{t-1} have a positive, statistically significant, effect on the number of IPOs, $NIPO_t$ (table 5.1, panel A). This result suggests high initial

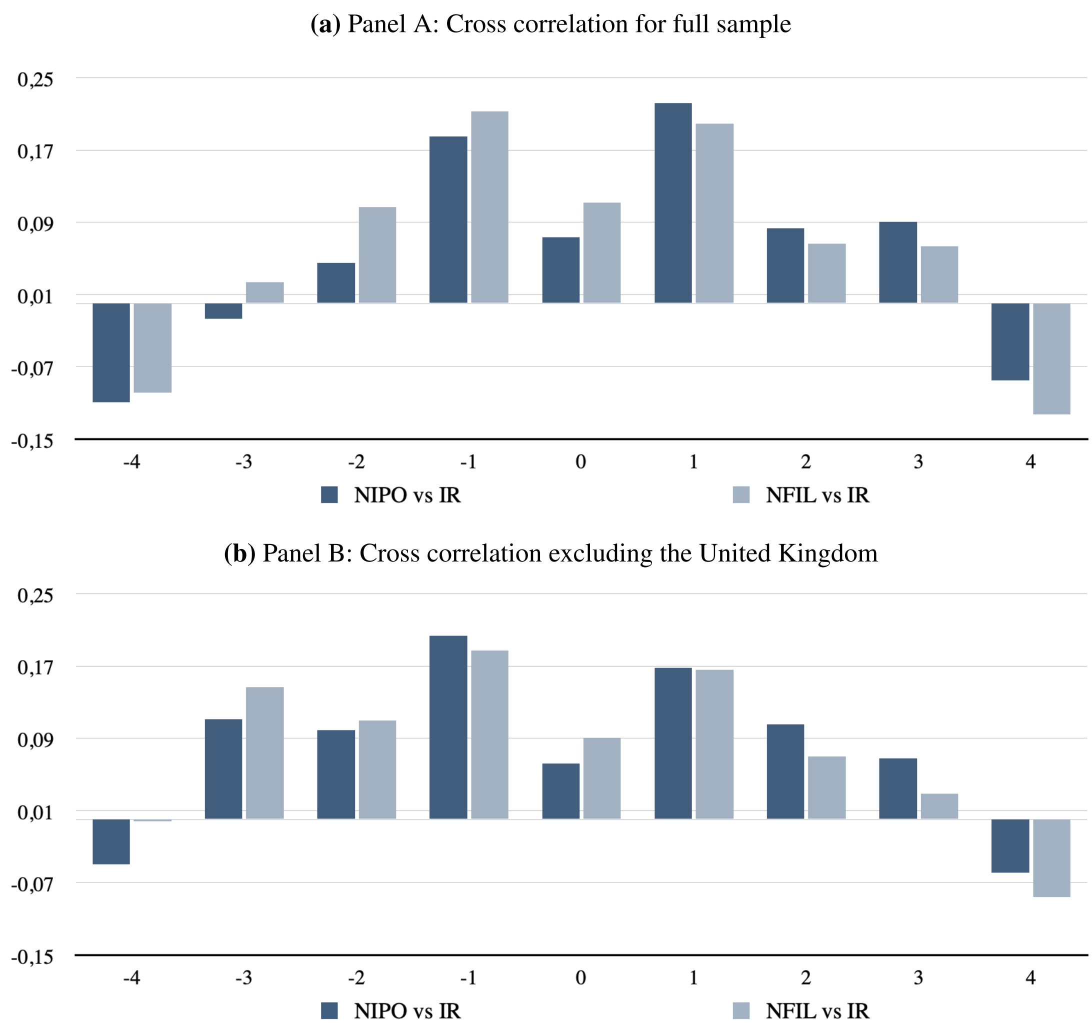


Figure 5.1: The cross correlation between initial returns and two timing measures; (1) the number of initial public offerings, and (2) the number of new filings. The data is for quarterly observations between 1999 and 2019 for the European market. IR is the proceed-weighted initial return in quarter t. $NIPO$ is the number of IPOs and $NFIL$ is the number of new filings, both in quarter $t+k$ for $k \in [-4, 4]$. In Panel A the large sample standard errors of correlations are 0.037 for $NIPO$ and 0.039 for $NFIL$. These standard errors are 0.028 and 0.029 respectively for Panel B.

returns can predict an increase in number of IPOs the following quarter, which makes sense as IPO processes take time and thus will show a delayed effect in the number of IPOs. The same relation is less statistically significant when excluding UK, achieving significance only at a 10% level, an indication of UK's effect on the full sample. Initially we ran the analysis at a monthly level, yielding significance in the third month lag (table B.5), which is consistent with our first quarter findings. Further, we observe a statistically significant relation between $NIPO_{t-1}$ and IR_t, suggesting higher initial returns follow quarters with many IPOs. However, the low explanatory power of this relationship makes it hard to form a conclusion regarding its economical significance.

When analysing the predictive power of initial returns on other timing measures, only the relationship with number of withdrawals (NWD) shows statistical significance, as seen in table 5.2. This finding suggests those in active IPO processes tend to withdraw offerings more often following quarters with high initial returns, and is arguably done to raise more proceeds at a later stage. The number of new filings ($NFIL$) and the time in registration ($REGTIME$) show no statistically significant causation between initial returns and these measures.

5.2 Information Content in Initial Return

To explain initial returns, we analyse deal- and firm characteristics as potential drivers. Logarithmic total assets (TA) have a statistically significant effect on initial returns with a negative coefficient, for the full data sample (table 5.3). In other words, companies with more assets tend to have lower initial returns. This relation is likely because asset-heavy firms are able to provide a more complete information package, decreasing the risk of essential information entering the market at a later stage. We observe similar results, across all variables, at the time of registration and offering, both with regards to coefficients' size and significance.

When excluding UK from the sample, logarithmic total assets are no longer statistically significant, suggesting the significant impact UK has on our results. However,

Table 5.1: Predictability Between IPO Initial Returns and Number of IPOs

Second order vector autoregressive, VAR(2), model for proceed-weighted initial return (IR) and number of initial public offerings ($NIPO$) on a quarterly basis for the European market between January 1999 and December 2019. Panel A use the full sample of all European countries, while panel B excludes the United Kingdom from the analysis. The VAR(2) model uses White's heteroskedasticity-consistent standard errors and uncorrelated error terms. Additionally is a Granger F-test for incremental predictability (granger causality) included, using the same number of lags and assumptions for standard errors and correlations as the VAR model. R^2 is the coefficient of determination, adjusted for degrees of freedom, while $S(u)$ is the standard error of the regression.

	PANEL A: Full Dataset				PANEL B: Excluding UK			
Dependent variable	IR_t^{PW}		$NIPO_t$		IR_t^{PW}		$NIPO_t$	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
Regressors								
$Constant$	−1.049	−0.38	7.875	2.67	−3.310	−1.23	5.785	3.00
IR_{t-1}	0.021	0.42	0.178	2.66	0.052	0.90	0.104	1.66
IR_{t-2}	−0.099	−1.50	−0.002	−0.01	0.008	0.12	0.041	0.69
$NIPO_{t-1}$	0.156	2.55	0.154	1.81	0.175	2.46	0.105	1.47
$NIPO_{t-2}$	−0.034	−0.47	0.610	6.58	0.006	0.07	0.633	6.81
R^2	0.075		0.551		0.091		0.607	
$S(u)$	16.565		16.607		15.717		11.885	
Granger F-test								
Lagged $NIPO$	10.548				6.975			
(p-value)	0.005				0.031			
Lagged IR			3.546				0.592	
(p-value)			0.170				0.744	
Sample Size	84		84		84		84	

Table 5.2: Relations between IPO Initial Returns and IPO Filings, Timing, and Withdrawals, 1999 to 2019

Granger F-test for incremental predictability (granger causality) for two lags, assuming White's heteroskedasticity-consistent standard errors and uncorrelated error terms. The data are for quarterly observations in the European market between January 1999 and December 2019. Panel A is the full sample of all European countries, while panel B excludes the United Kingdom from the analysis. IR^{PW} is the proceed-weighted initial returns on a quarterly basis, $NFIL$ is the number of new filings per quarter, $REGTIME$ is the average proceed-weighted time in registration for IPOs issued within a quarter and NWD is the number of IPO withdrawals per quarter.

	Initial Return Measures (IR^{PW})			
	(A) Full Dataset		(B) Excluding U.K.	
IPO Timing Measures	F-test	p-value	F-test	p-value
$NFIL$				
(1) Returns predict filing	2.393	0.302	1.386	0.500
Sample Size	84		84	
$REGTIME$				
(2) Returns predict timing	2.420	0.298	5.407	0.067
Sample Size	84		84	
NWD				
(3) Returns predict withdrawals	6.390	0.041	2.299	0.967
Sample Size	84		84	

the Deutsche Boerse-dummy (DEB) obtain statistical significance. The coefficient is highly positive, 7.3 at offering, indicating issues listed at Deutsche Boerse achieve considerably higher initial returns. As UK is a major part of our full sample, the sudden significance in DEB might be caused by companies listed on this exchange having more in common with several UK, opposed to other European, IPOs and make them stand out when excluding UK.

We observe a statistically significant relationship between market performance leading up to an IPO and initial returns for both datasets. Both market variables have positive coefficients, which is a consistent and logical result, as increased initial returns follow positive market returns and vice versa. However, we do not detect any market asymmetry as there is no significant difference in the coefficient size for these variables.

Further, we observe a statistically significant relationship at a 10% level between high-tech companies ($TECH$) and initial returns. A curious note from this result is the negative coefficient. In general, the assumption for tech companies is their ability to achieve high initial returns, which is inconsistent with our result. However, when looking at the distribution of our tech issues (figure A.3) they are evenly distributed and most likely driven by certain negative spikes throughout our time period.

Despite several variables being statistically significant, the explanatory power of the models are low. With R^2 smaller than 0.01, initial return estimations will have low accuracy and a hard time contributing to explain the "bigger picture".

5.3 Drivers of Initial Returns

We analyse whether the information underwriters and issuing companies obtain during the book-building process is reflected in initial returns and contributes to drive initial return cycles. This is done by investigating the behaviour of expected initial returns and initial return surprises.

We see our regression models capture the data poorly when comparing actual and expected initial returns (table 5.4). Expected initial returns have a notably lower variance and capture extreme values at a low degree, as we observe significantly lower minimum and maximum values. Neither datasets show significant serial correlation for actual-, expected- nor unexpected initial returns. However, we observe significant autocorrelation, for expected initial returns at the time of registration, if portfolios are built on a monthly basis (table B.6 - B.7). As we estimate expected returns based on firm characteristics, the monthly results can simply be a reflection of the type of firms going public.

The absence of serial correlation in initial returns makes it hard to infer expected- and unexpected initial returns' effect on initial return cycles. With regards to underwriters and issuing companies' learning process, we see an increase in explanatory power throughout the registration period. However, due to the low explanatory power, the economical impact of this result is limited.

Table 5.3: IPO Returns' Relation to Deal and Firm Characteristics

Regression model for initial returns of IPOs issued between January 1999 and December 2019 in Europe to determine the information content in IPOs given deal and firm characteristics. Panel A is regression results for the full sample of European countries, while panel B excludes the United Kingdom from the sample. The dependent variable is initial return, while the independent variables are *RANK* – the ranking of the IPO's underwriter (scoring 1-5 based on total proceeds to each underwriter within the year the IPO is issued), *TA* – the logarithmic total assets in place prior to going public (given in USD adjusted for inflation), *TECH* – a dummy for high-tech companies as defined by SDC, and dummies for three major exchanges in the eurozone; London Stock Exchange (*LSE*), Euronext (*EUR*) and Deutsche Boerse (*DEB*). These independent variables are all known at the time of registration, and is run in the first (leftmost) regression for each panel. The second regression has the same independent variables, but additionally includes variables for the market return over the 15 day period prior to the IPO. MKT^- equals the market return, if the return is negative and zero otherwise. MKT^+ equals the market return, if the return is positive and zero otherwise. The MSCI Europe Index is used as a proxy for the market return. R^2 is the coefficient of determination, adjusted for degrees of freedom, while $S(u)$ is the standard error of the regression.

	(A) Information Content, Full Dataset				(B) Information Content, Excluding UK			
	Registration		Offering		Registration		Offering	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Constant	19.971	3.77	19.984	3.77	10.365	1.52	9.948	1.46
RANK	−1.394	−1.47	−1.377	−1.45	−1.352	−1.17	−1.328	−1.15
TA	−0.848	−2.76	−0.851	−2.77	−0.459	−1.20	−0.438	−1.15
TECH	−2.602	−1.70	−2.578	−1.69	−1.670	−0.83	−1.626	−0.81
LSE	2.615	1.00	2.573	0.99	8.479	1.19	8.263	1.16
EUR	−2.541	−0.95	−2.718	−1.02	−1.211	−0.41	−1.430	−0.49
DEB	5.108	1.62	5.105	1.62	7.335	2.13	7.307	2.13
MKT^-			0.818	2.58			0.894	2.18
MKT^+			0.794	2.42			0.848	1.99
R^2	0.005		0.009		0.004		0.008	
$S(u)$	40.513		40.432		43.521		43.428	

Table 5.4: Autocorrelation of Initial Returns to IPOs Issued in Europe, 1999 – 2019

Descriptive statistics for proceed-weighted initial return portfolios constructed at a quarterly basis for initial public offerings in the European market between January 1999 and December 2019. The measures reported are actual initial return (IR), expected initial return at the time of registration ($E_F[IR]$) and offering ($E_O[IR]$) and unexpected initial returns at the time of registration ($IR - E_F[IR]$) and offering ($IR - E_O[IR]$). The key results in this table are the autocorrelation of returns for four lags ρ_1 to ρ_4 of the different return measures. Additionally are mean, median (med.), standard deviation (std.), minimum, maximum, sample size T and the standard errors of correlations assuming no autocorrelation $S(\rho)$ reported. Panel A is the full sample of European countries, while panel B excludes the United Kingdom. Measures related to the time of registration are based on equation 1 and time of offering are based on equation 2. Coefficients for these regression models are available in table 5.3

	Mean	Med.	Std.	Min	Max	T	ρ_1	ρ_2	ρ_3	ρ_4	$S(\rho)$
(A) Full Sample of European Countries											
Actual initial returns											
(1) IR	3.15	0.59	16.77	-31.20	100.76	84	0.03	-0.05	-0.04	-0.01	0.13
Expected initial returns based on information known at the time of filing											
(2) $E_F[IR]$	2.74	2.69	1.93	-2.32	7.64	84	0.03	0.03	0.01	-0.01	0.13
(3) $IR - E_F[IR]$	0.41	-1.95	16.57	-34.68	93.81	84	0.03	-0.04	-0.08	0.01	0.13
Expected initial returns based on information known at the time of offering											
(4) $E_O[IR]$	2.78	2.71	3.24	-5.02	14.17	84	0.14	0.07	-0.19	-0.04	0.13
(5) $IR - E_O[IR]$	0.37	-1.60	16.54	-33.79	91.70	84	0.04	-0.04	-0.07	0.01	0.13
(B) Sample of European Countries Excluding the United Kingdom											
Actual initial returns											
(1) IR	1.18	0.13	15.90	-33.09	110.91	84	0.08	0.04	0.00	-0.07	0.13
Expected initial returns based on information known at the time of filing											
(2) $E_F[IR]$	1.37	0.97	2.61	-7.41	9.51	84	-0.02	0.12	0.20	0.09	0.12
(3) $IR - E_F[IR]$	-0.19	-0.16	15.84	-35.70	104.79	84	0.01	0.02	-0.07	-0.05	0.13
Expected initial returns based on information known at the time of offering											
(4) $E_O[IR]$	1.42	0.96	3.70	-11.09	13.80	84	0.16	0.07	-0.01	0.02	0.12
(5) $IR - E_O[IR]$	-0.23	-0.26	15.71	-34.64	102.45	84	0.03	-0.01	-0.02	-0.07	0.13

Table 5.5: Time Controlled Regression for IPOs Issued Between 1999 and 2019

Regression model for initial returns of IPOs between January 1999 and December 2019 in Europe controlling for time variation as a robustness check of results in table 5.3. Panel A is regression results for the full sample of European countries, while panel B excludes the United Kingdom from the sample. The dependent variable is initial return, while the independent variables are $RANK$ – the ranking of the IPOs' underwriter (scoring 1-5 based on total proceeds to each underwriter within the year the IPO is issued), TA – the logarithmic total assets in place prior to going public (given in USD adjusted for inflation), $TECH$ – a dummy for high-tech companies as defined by SDC and dummies for three major exchanges in the eurozone; London Stock Exchange (LSE), Euronext (EUR) and Deutsche Boerse (DEB), these independent variables are all known at the time of registration, and is run in the first (leftmost) regression for each panel. The second regression includes the same independent variables, but additionally includes variables for the market return over the 15 day period prior to the IPO. MKT^- equals the market return, if the return is negative and zero otherwise. MKT^+ equals the market return, if the return is positive and zero otherwise. The MSCI Europe Index is used as a proxy for the market return. Additionally, for both regression models are 20 time-related dummies included ($year_i$ for $i \in$[2000, 2019]) equals 1 if the IPO was issued in year i and zero otherwise. R^2 is the coefficient of determination, adjusted for degrees of freedom, while $S(u)$ is the standard error of the regression. Coefficients and statistics for time-related dummies, are reported in appendix C, table C.1

	(A) Information Content, Full Dataset				(B) Information Content, Excluding UK			
	Registration		Offering		Registration		Offering	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
$Constant$	12.030	2.05	11.454	1.95	5.380	0.74	4.370	0.46
$RANK$	−0.997	−1.04	−1.013	−1.06	−0.890	−0.77	−0.883	−0.76
TA	−1.010	−3.20	−0.989	−3.14	−0.627	−1.59	−0.586	−1.49
$TECH$	−2.052	−1.31	−2.083	−1.33	−1.477	−0.71	−1.473	−0.71
LSE	3.114	1.19	2.929	1.12	6.075	0.85	5.868	0.82
EUR	−2.795	−1.03	−3.006	−1.11	−0.023	−0.01	−0.246	−0.08
DEB	4.761	1.51	4.786	1.52	7.041	2.03	7.065	2.04
MKT^-			0.720	2.22			0.798	1.91
MKT^+			0.759	2.29			0.802	1.87
R^2	0.011		0.013		0.005		0.006	
$S(u)$	40.265		40.201		43.165		43.091	

5.4 Robustness Check of Regression Results

We perform a robustness check, as public offerings tend to cluster by nature, to test if our regression models are affected by time variation. We do this to verify if our coefficients in 5.3 remain both significant and constant. To control for time we use several time-dummies, and run a second panel regression, with these dummies, as a robustness check.

For the full sample (panel A, table 5.5), significant variables stay significant when controlling for time and we observe minor changes to the size of the coefficients. The market variables do make an interesting change through the control, as the MKT^{+} coefficient now is greater than MKT^{-}, suggesting a larger effect following positive market conditions, opposed to negative. Regardless, coefficients are still not significantly different from each other and do subsequently not represent any market asymmetry. For panel B, excluding UK, the market dummy for Deutsche Boerse remain reasonably constant and significant, while market coefficients yield statistical significance only at a 10% level after controlling for time.

In conclusion, full sample results from the regression models in equation 1 and 2 are robust to noise created by time variation. With a purpose of exclusively estimating initial returns based on characteristics, the models are reliable, however due to the low explanatory power it is not advisable for economical purposes.

5.5 Findings on a Country Level

We perform country-level analysis for the United Kingdom, Germany and France, to obtain complementary results to our cross-continental analysis. As European firms tend to list locally (table A.1), with few cross-border IPOs, we argue a firm's IPO decisions are more likely to be affected by local market conditions.

The United Kingdom stands out in this analysis as it shows stronger cross-correlation than the full sample data or any other countries in the country-level analysis for quar-

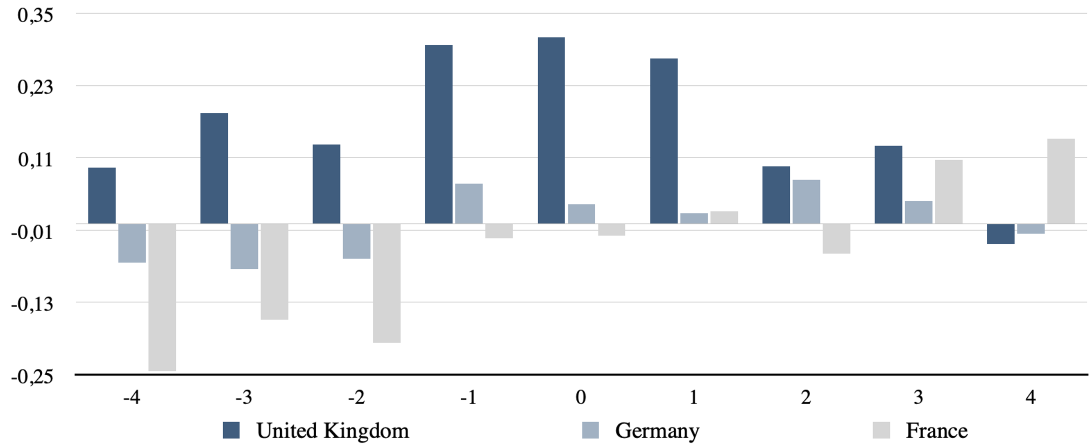


Figure 5.2: The cross correlation between proceed weighted initial returns IR^{PW}, in quarter t and the number of IPOs, $NIPO$ in quarter $t+k$ for $k \in [-4, 4]$ for the United Kingdom, Germany and France.

terly lags and leads (figure 5.2). Germany and France present weaker cross-correlation, while their left to right pattern is to a larger extent in line with the original US study. France shows no statistically significant ability to predict IPO volumes from our VAR(2) model, while Germany in contrast shows evidence of statistically significant predictability for the second lag of IR on $NIPO$. The relationship has no support from Granger-causality, which makes the result less powerful.

A thorough look into our VAR(2) analysis for the United Kingdom (table 5.6) shows a significant relationship for initial returns predicting future number of IPOs at the second lag. However, the negative coefficient is inconsistent with most research as it indicates a relation where higher initial returns lead to a decreasing number of IPOs. We do further analysis to explain why such results emerge, and by looking at initial returns and IPO volumes historically for the United Kingdom (figure 5.3) we notice substantial spikes in initial returns leading up to the financial crisis in 2008. As the aftermath of 2008 shows a lower number of IPOs, we expect correlations during the particular period to disturb our overall results. We perform two separate VAR (2) analyses for the United Kingdom, ranging from 1999-2007 and 2009-2019 (table B.1). In those analyses we find the positive relation we expect.

Table 5.6: Predictability Between IPO Initial Returns and Number of IPOs at Country Level.

Second order vector autoregressive, VAR(2), model for proceed-weighted initial return (IR) and number of initial public offerings ($NIPO$) on a quarterly basis for the selected between January 1999 and December 2019. Panel I is a subsample of IPOs from the United Kingdom, panel II from Germany and panel III from France. The VAR(2) model uses White's heteroskedasticity-consistent standard errors and uncorrelated error terms. Additionally is a Granger F-test for incremental predictability (granger causality) included, using the same number of lags and assumptions for standard errors and correlations as the VAR model. R^2 is the coefficient of determination adjusted for degrees of freedom, while $S(u)$ is the standard error of the regression.

	(I) United Kingdom				(II) Germany				(III) France			
Dependent variable	IR_t^{PW}		$NIPO_t$		IR_t^{PW}		$NIPO_t$		IR_t^{PW}		$NIPO_t$	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Regressors												
Constant	−0.339	−0.12	2.827	2.71	3.582	0.77	0.527	1.51	−1.366	−0.69	1.738	3.57
IR_{t-1}	−0.079	−1.40	0.012	0.18	−0.215	−4.43	0.000	0.04	0.042	0.64	0.016	0.57
IR_{t-2}	0.092	1.17	−0.082	−2.84	−0.141	−4.19	0.009	1.97	−0.019	−0.32	−0.014	−0.43
$NIPO_{t-1}$	0.653	1.42	0.406	3.43	1.426	2.18	0.527	3.73	0.253	0.58	0.248	2.34
$NIPO_{t-2}$	−0.194	−0.78	0.415	3.53	−1.303	−1.68	0.228	1.92	−0.732	−1.25	0.302	2.37
R^2	0.110		0.533		0.089		0.803					
$S(u)$	18.028		7.366		32.623		2.886					
Granger F-test												
Lagged $NIPO$	7.916				7.734				2.287			
(p-value)	0.019				0.021				0.319			
Lagged IR			10.509				2.927				0.333	
(p-value)			0.005				0.231				0.847	
Sample Size	84		84		84		84		84		84	

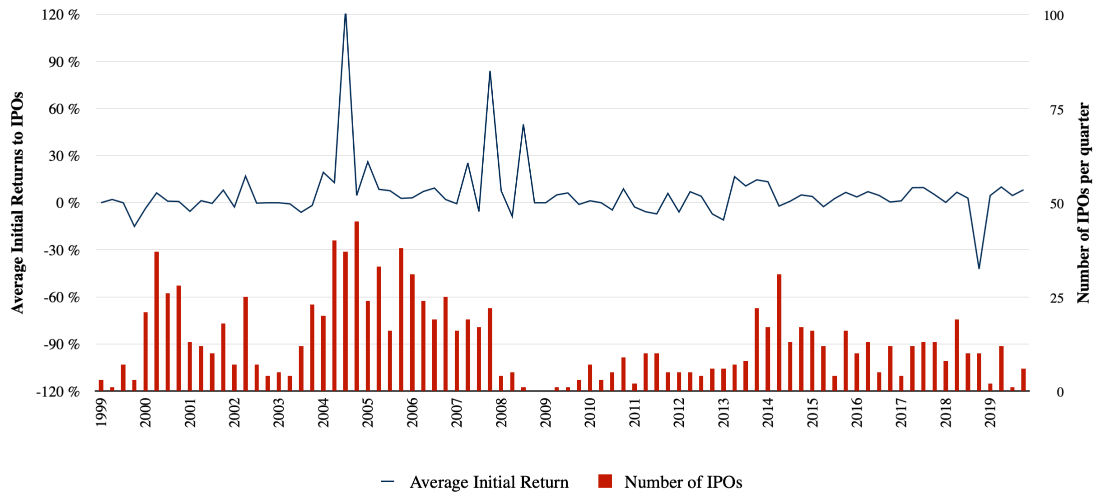


Figure 5.3: IPO Portfolio Volume and Initial Return for UK, 1999 - 2019. A graphical illustration of the number of IPOs per portfolio and proceed-weighted initial return (IR^{PW}) in the United Kingdom. Portfolios are constructed on a quarterly basis.

We perform a country-level analysis with respect to deal- and firm characteristics to see whether they drive initial returns for the respective countries. The analysis follows the same principles, however the models in section 5.2 are slightly altered. Rather than having three exchange dummies LSE, DEB and EUR, we use one exchange dummy per country EXC_i. For the United Kingdom the exchange dummy is London Stock Exchange ($EXC_i = LSE$), for Germany it is Deutsche Boerse ($EXC_i = DEB$) and for France it is Euronext ($EXC_i = EUR$). This is done to avoid multicollinearity with the intercept in the case of a zero-vector.

Initial returns in France demonstrate a statistically significant negative relationship with the underwriter ranking $RANK$, indicating initial returns in France are expectedly lower for highly ranked underwriters. Such a pattern makes sense, as we assume more qualified underwriters to provide less underpriced IPOs. There is furthermore a statistically significant relation for positive market returns MKT^+, which yields a positive coefficient, suggesting an increase in initial return following positive market returns. To some degree, we observe a market asymmetry as MKT^- is not statistically significant, and has a considerably smaller coefficient. After performing a time-controlled linear regression model $RANK$ remains significance, while MKT^+ is only significant at a 10 % level as seen in table 5.9. The $RANK$ term increased from -4.0 to -2.3, suggesting even though a good underwriter helps to decrease the amount of money a company leaves “on the table”, it is not as much as we indicate in the original model. Finally, we observe no significant characteristics, neither for the UK nor the German sample.

There is no significant autocorrelation in initial returns (table 5.8) on a country-level. We observe improvements in explanatory power from the beginning to the end of the registration period across all countries, when regressing initial returns on firm- and deal characteristics. This result speaks to underwriters and issuing companies’ learning process. However, neither UK nor Germany have any significant regression results, and followingly France is the only country where we can clearly identify drivers of initial return.

Table 5.7: IPO Returns' Relation to Deal and Firm Characteristics at Country Level

Regression model for initial returns of IPOs issued between January 1999 and December 2019 in selected countries to determine the information content in IPOs given deal- and firm characteristics. Panel I is a subsample of IPOs from the United Kingdom, panel II from Germany and panel III from France. The dependent variable is initial return, while the independent variables are $RANK$ – the ranking of the IPOs' underwriter (scoring 1-5 based on total proceeds to each underwriter within the year the IPO is issued), TA – the logarithmic total assets in place prior to going public (given in USD adjusted for inflation), $TECH$ – a dummy for high-tech companies as defined by SDC, and an exchange dummy EXC_i for one of three major exchanges in the eurozone; London Stock Exchange in panel I, Deutsche Boerse in panel II and Euronext in panel III. These independent variables are all known at the time of registration, and is run in the first (leftmost) regression for each panel. The second regression includes the same independent variables, but in addition it includes variables for the market return over the 15 day period prior to the IPO. MKT^{-} equals the market return, if the return is negative and zero otherwise. MKT^{+} equals the market return, if the return is positive and zero otherwise. The MSCI Europe Index is used as a proxy for the market return. R^2 is the coefficient of determination adjusted for degrees of freedom, while $S(u)$ is the standard error of the regression.

	(I) United Kingdom				(II) Germany				(III) France			
	At Registration		At Offering		At Registration		At Offering		At Registration		At Offering	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
$Constant$	23.018	2.49	23.964	2.58	45.795	1.73	46.417	1.74	−3.170	−0.34	−4.767	−0.52
$RANK$	1.224	0.56	1.181	0.54	−5.593	−0.63	−5.294	−0.59	−4.171	−2.67	−3.999	−2.58
TA	−0.724	−1.27	−0.787	−1.38	−1.885	−1.22	−1.964	−1.26	0.139	0.25	0.230	0.41
$TECH$	−1.760	−0.79	−1.746	−0.79	−7.565	−1.07	−7.443	−1.05	−2.044	−0.78	−2.061	−0.79
EXC_i	−3.808	−1.25	−3.648	−1.20	0.697	0.09	1.368	0.17	0.086	0.03	−0.700	−0.25
MKT^{-}			0.618	1.31			−0.940	−0.61			0.762	1.44
MKT^{+}			0.778	1.62			−0.264	−0.18			1.302	2.24
R^2	0.009		0.013		0.008		0.009		0.021		0.041	
$S(u)$	33.378		33.309		59.631		59.594		24.197		23.956	

Table 5.8: Autocorrelation of Initial Returns to IPOs at Country Level, Between 1999 and 2019

Descriptive statistics for proceed-weighted initial return portfolios constructed at a quarterly basis for initial public offerings in the selected countries between January 1999 and December 2019. The measures reported are actual initial return (IR), expected initial return at the time of registration $E_F[IR]$ and at offering $E_O[IR]$ and unexpected initial returns at the time of registration ($IR - E_F[IR]$) and offering ($IR - E_O[IR]$). The key results in this table are the autocorrelation of returns of four lags ρ_1 to ρ_4 of the different return measures. Additionally are mean, median (med.), standard deviation (std.), minimum, maximum, sample size T and the standard errors of correlations assuming no autocorrelation $S(\rho)$ reported. Panel I is a subsample of IPOs from the United Kingdom, panel II from Germany and panel III from France. Measures related to the time of registration is based on equation 1 and time of offering are based on equation 2. Coefficients for these regression models are available in table 5.7.

	Mean	Med.	Std	Min	Max	T	ρ_1	ρ_2	ρ_3	ρ_4	
Panel I: United Kingdom, between 1999 and 2019											
(1) IR	5.46	2.37	19.23	-42.18	123.20	84	0.02	0.21	0.12	-0.05	0.12
(2) $E_F[IR]$	6.40	5.77	2.71	1.20	15.76	84	0.18	-0.06	0.09	0.10	0.12
(3) $IR - E_F[IR]$	-0.94	-3.89	19.09	-47.54	117.02	84	0.01	0.19	0.11	-0.02	0.12
(4) $E_O[IR]$	6.40	6.03	3.04	0.94	16.26	84	0.19	0.00	0.02	0.15	0.12
(5) $IR - E_O[IR]$	-0.93	-3.76	19.14	-47.03	117.34	84	0.01	0.20	0.11	-0.03	0.12
Panel II: Germany. between 1999 and 2019											
(1) IR	3.92	1.31	37.92	-66.52	267.13	84	-0.25	-0.11	0.03	0.07	0.14
(2) $E_F[IR]$	7.46	7.14	6.26	-7.71	26.58	84	0.08	-0.09	-0.03	-0.06	0.13
(3) $IR - E_F[IR]$	-3.53	-4.76	38.51	-74.20	260.46	84	-0.19	-0.08	0.04	0.04	0.14
(4) $E_O[IR]$	7.50	6.49	6.64	-6.55	28.12	84	0.15	-0.16	-0.04	-0.02	0.14
(5) $IR - E_O[IR]$	-3.57	-6.13	38.27	-70.01	259.83	84	-0.18	-0.07	0.05	0.04	0.14
Panel III: France. between 1999 and 2019											
(1) IR	-4.92	-0.92	14.11	-72.98	19.01	84	0.06	-0.05	0.07	-0.17	0.13
(2) $E_F[IR]$	-2.90	-2.17	3.50	-17.81	0.28	84	-0.10	-0.15	-0.11	0.05	0.14
(3) $IR - E_F[IR]$	-2.02	1.35	12.85	-60.59	18.73	84	0.07	-0.05	0.06	-0.16	0.13
(4) $E_O[IR]$	-3.25	-1.87	4.70	-18.69	3.82	84	0.01	-0.06	-0.09	0.06	0.13
(5) $IR - E_O[IR]$	-1.67	1.18	13.14	-60.23	20.73	84	0.05	-0.01	-0.01	-0.20	0.14

Table 5.9: Time Controlled Regression for IPOs Issued Between 1999 and 2019 at Country Level

Regression model for initial returns of IPOs issued between January 1999 and December 2019 in selected countries controlling for time variation as a robustness check of results in table 5.7. Panel I is a subsample of IPOs from the United Kingdom, panel II from Germany and panel III from France. The dependent variable is initial return, while the independent variables are $RANK$ – the ranking of the IPOs' underwriter (scoring 1-5 based on total proceeds to each underwriter within the year the IPO is issued), TA – the logarithmic total assets in place prior to going public (given in USD adjusted for inflation), $TECH$ – a dummy for high-tech companies as defined by SDC and dummies for three major exchanges in the eurozone; London Stock Exchange (LSE), Euronext (EUR) and Deutsche Boerse (DEB), these independent variables are all known at the time of registration, and is run in the first (leftmost) regression for each panel. The second regression includes the same independent variables, but in addition it includes variables for the market return over the 15 day period prior to the IPO. MKT^- equals the market return, if the return is negative and zero otherwise. MKT^+ equals the market return, if the return is positive and zero otherwise. The MSCI Europe Index is used as a proxy for the market return. R^2 is the coefficient of determination adjusted for degrees of freedom, while $S(u)$ is the standard error of the regression. Additionally, for both regression models are 20 time-related dummies included ($year_i$ for $i \in [2000, 2019]$) taking the value 1 if the IPO was issued in year i and zero otherwise. Coefficients and statistics for time-related dummies, are reported in appendix C, table C.2

	(I) United Kingdom				(II) Germany				(III) France			
	At Registration		At Offering		At Registration		At Offering		At Registration		At Offering	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
$Constant$	14.113	1.07	14.637	1.11	53.904	1.88	54.921	1.91	−11.373	−1.14	−13.136	−1.31
$RANK$	0.835	0.38	0.744	0.34	−5.073	−0.55	−4.707	−0.50	−3.761	−2.39	−3.536	−2.25
TA	−0.941	−1.61	−0.957	−1.63	−2.145	−1.29	−2.226	−1.34	−0.195	−0.33	−0.074	−0.13
$TECH$	−1.081	−0.47	−1.121	−0.49	−11.748	−1.55	−11.449	−1.50	−2.531	−0.94	−2.592	−0.97
EXC_i	−0.599	−0.19	−0.755	−0.24	12.062	0.98	12.573	1.02	−2.359	−0.68	−3.190	−0.91
MKT^-			0.516	1.06			−1.110	−0.66			0.699	1.27
MKT^+			0.701	1.43			−0.241	−0.15			1.065	1.78
R^2	0.016		0.016		−0.024		−0.030		0.036		0.051	
$S(u)$	32.948		32.899		58.968		58.924		23.201		23.038	

6 Conclusion

The main findings from our analysis is the significant positive impact of initial return on the number of IPOs the following quarter. This confirms the cyclicality of volume clustering following periods of high initial returns. With regards to the learning process of underwriters and information content in initial returns, we find total assets and market returns to yield significant results, however the explanatory power of these regression models is deemed too low to contribute any economical understanding of IPO underpricing.

We find similar results for samples excluding the United Kingdom and at country-level. Germany and France do not show a significant relationship between returns and IPO volume, however this may be due to an insufficient sample size. In general, as we conduct our study on a quarterly basis, we might lose some information and accuracy in our results.

7 Further Work

An interesting topic for future research is an extension of our analysis, while we cover European firms issuing to European markets it is an interesting new angle to include non-European firms issuing to European markets as well. Such an addition will first and foremost increase the sample size, and the market proxy already reflects these additional firms. Another possibility is to research the effect of price updates on the information content in IPO initial returns, which we excluded due to limited data.

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A IPO Distribution Across Europe

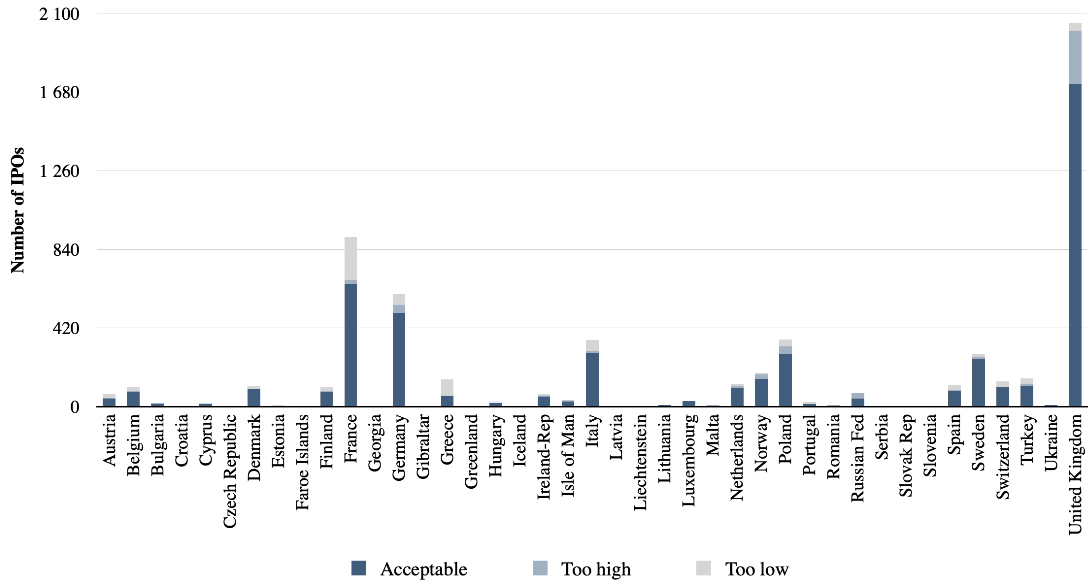

Figure A.1: Number of IPOs per Country between 1981 and 2019. The figure shows the number of viable (acceptable) observations, the number of observations deemed too high and number of observations deemed too low. i.e the ratio between first price and offer price greater than 5 or lower than $1/5$ respectively.

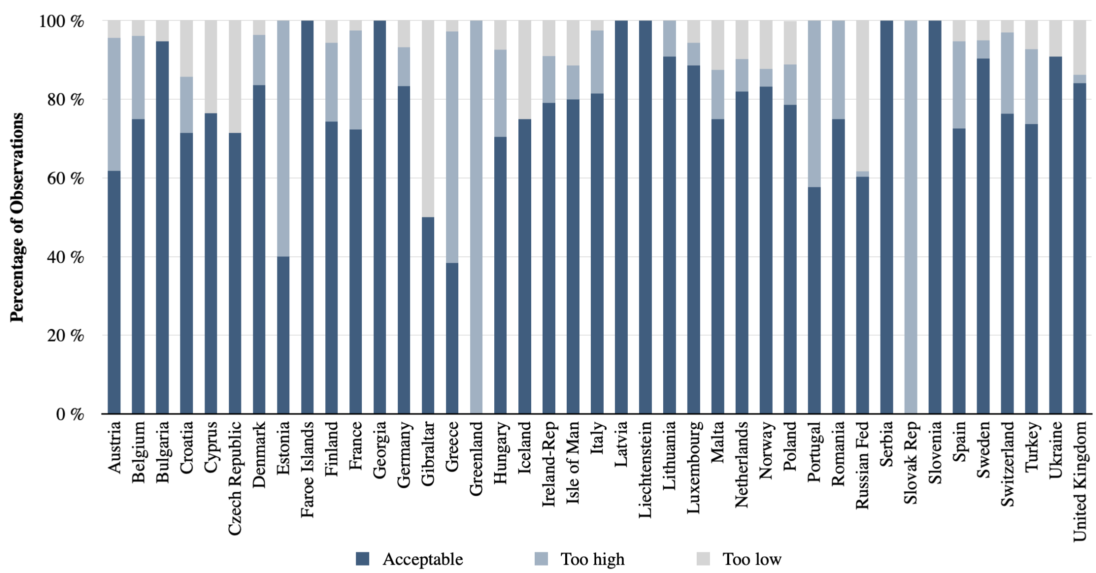

Figure A.2: Ratio of viable and non-viable observations per Country between 1981 and 2019 The figure shows the number of viable observations (acceptable), the number of observations deemed too high and number of observations deemed too low, i.e the ratio between first price and offer price greater than 5 or lower than $1/5$ respectively.

Table A.1: Countries of Issue versus Countries of Listing

Countries of the issuing companies are given in the columns, and the rows show the countries of exchanges where the IPOs are listed.

Country of Exchange	Country of Issuing Company																																									
	Austria	Belgium	Bulgaria	Croatia	Cyprus	Czech Republic	Denmark	Estonia	Faroe Islands	Finland	France	Georgia	Germany	Gibraltar	Greece	Greenland	Hungary	Iceland	Ireland-Rep	Isle of Man	Italy	Latvia	Liechtenstein	Lithuania	Luxembourg	Malta	Netherlands	Norway	Poland	Portugal	Romania	Russian Fed	Serbia	Slovak Rep	Slovenia	Spain	Sweden	Switzerland	Turkey	Ukraine	United Kingdom	**TOTAL**
Austria	58	-	-	-	-	-	-	-	-	-	-	-	1	-	-	-	1	-	-	-	-	-	-	-	-	-	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	61
Belgium	2	104	-	-	-	-	-	-	-	-	6	-	-	-	-	-	-	1	-	-	3	-	-	-	2	-	2	-	-	-	-	-	-	-	-	-	-	-	-	-	5	125
Bulgaria	-	-	18	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	18
Croatia	-	-	-	6	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	6
Cyprus	-	-	-	-	3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1	4
Czech Republic	-	-	-	-	-	8	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	10
Denmark	-	-	-	-	-	-	104	-	1	-	-	-	-	-	-	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	106
Estonia	-	-	-	-	-	-	-	9	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	9
Finland	-	-	-	-	-	-	-	-	-	106	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	106
France	-	12	-	-	-	-	1	-	-	1	921	-	1	-	-	-	-	-	-	-	1	-	-	-	7	-	5	-	-	-	-	-	-	-	-	2	-	8	-	-	3	962
Germany	16	-	-	-	-	-	-	-	-	1	1	-	646	-	-	-	-	-	1	-	-	-	-	-	7	-	8	-	-	-	-	-	-	-	-	1	-	11	-	1	2	695
Greece	-	-	-	-	1	-	-	-	-	-	-	-	-	-	153	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	154
Hungary	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	26	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	26
Iceland	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1	2
Ireland-Rep	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	15	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	6
Isle of Man	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Italy	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1	-	-	-	-	-	366	-	-	-	2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	369
Latvia	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	4
Lithuania	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	9	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1
Luxembourg	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1	3
Malta	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	2
Netherlands	-	-	-	-	-	-	-	-	-	-	-	-	3	-	-	-	-	1	-	-	-	-	-	-	2	-	91	-	-	-	-	-	-	-	-	-	-	-	-	-	3	100
Norway	-	-	-	-	3	-	5	-	2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	204	-	-	-	-	-	-	-	-	4	-	-	-	6	224
Poland	-	-	1	-	1	1	-	1	-	-	-	-	1	-	-	-	-	-	-	-	-	-	-	5	5	-	2	-	365	-	-	-	-	1	1	-	-	-	-	7	-	391
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Serbia	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1	-	-	-	-	-	-	-	-	1
Slovenia	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	3	-	-	-	-	-	-	3
Spain	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1	-	-	-	-	-	-	-	-	119	-	-	-	-	-	120
Sweden	1	1	-	-	-	-	7	-	-	5	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1	4	1	-	2	-	-	-	-	-	-	-	311	2	-	-	1	336
Switzerland	2	-	-	-	-	-	1	-	-	-	-	-	-	-	-	-	-	-	-	-	4	-	1	-	1	-	1	-	-	-	-	-	-	-	-	-	-	116	-	-	1	127
Turkey	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	157			157
United Kingdom	2	1	3	1	11	-	-	1	-	4	2	2	3	5	3	-	-	-	50	41	8	-	-	1	7	2	17	2	2	1	-	37	-	-	-	-	4	6	4	5	2111	2336
Unknown	-	1	1	-	-	1	1	-	-	1	5	-	2	-	1	-	1	-	2	-	1	-	-	-	1	-	1	1	7	1	3	-	-	-	-	1	-	2	-	1	21	56
TOTAL	81	119	23	7	19	10	119	11	3	118	936	2	657	5	158	1	28	5	68	41	383	4	1	15	38	8	133	207	376	29	12	97	1	1	4	123	319	145	161	14	2156	6619

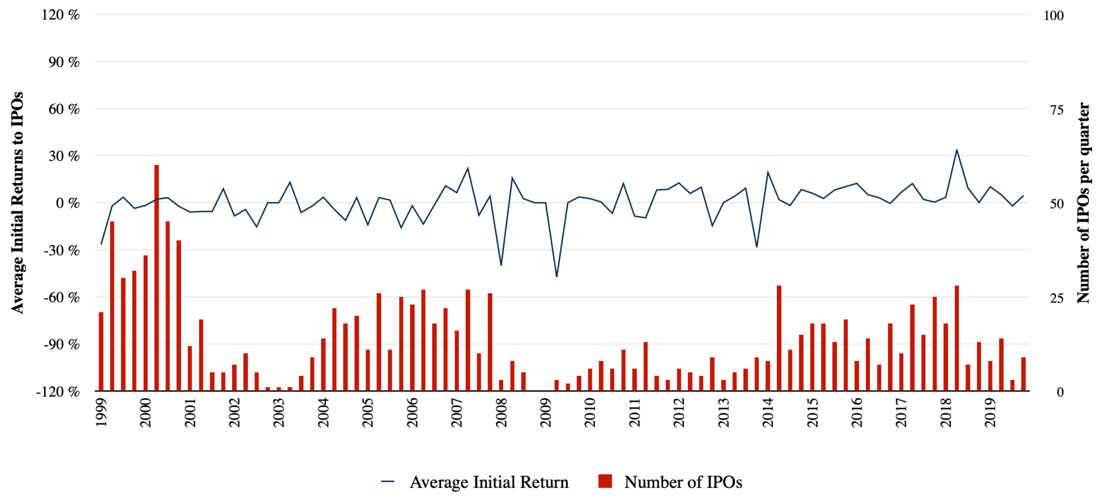

Figure A.3: High-Tech IPO Portfolio Volume and Initial Return, 1999 - 2019. A graphical illustration of the number of IPOs per portfolio and proceed-weighted initial return (IR^{PW}) for IPOs classified as high-tech. Portfolios are constructed on a quarterly basis.

B Additional Analysis

Table B.1: Predictability Between IPO Initial Returns and Number of IPOs

Second order vector autoregressive, VAR(2), model for proceed-weighted initial return (IR) and number of initial public offerings ($NIPO$) on a quarterly basis for the United Kingdom. Panel A is for IPOs between 1999-2007, while panel B is for IPOs between 2009-2019. The VAR(2) model uses White's heteroskedasticity-consistent standard errors and uncorrelated error terms. Additionally is a Granger F-test for incremental predictability (granger causality) included, using the same number of lags and assumptions for standard errors and correlations as the VAR model. R^2 is the coefficient of determination, while $S(u)$ is the standard error of the regression.

	PANEL A: UK, 1999-2007				PANEL B: UK, 2009-2019			
Dependent variable	IR_t^{PW}		$NIPO_t$		IR_t^{PW}		$NIPO_t$	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Regressors								
$Constant$	$-2,731$	$-0,45$	$7,808$	$2,71$	$3,199$	$1,51$	$3,388$	$2,62$
IR_{t-1}	$-0,141$	$-1,81$	$0,095$	$2,45$	$0,047$	$0,44$	$0,195$	$3,33$
IR_{t-2}	$0,209$	$0,96$	$-0,097$	$-2,12$	$-0,186$	$-1,63$	$0,076$	$0,73$
$NIPO_{t-1}$	$0,746$	$1,07$	$0,381$	$2,16$	$0,206$	$1,02$	$0,099$	$1,00$
$NIPO_{t-2}$	$-0,145$	$-0,40$	$0,259$	$1,52$	$-0,278$	$-0,86$	$0,486$	$3,68$
R^2	$0,164$		$0,493$		$0,068$		$0,486$	
$S(u)$	$15,296$		$5,605$		$6,486$		$3,343$	
Lagged $NIPO$	$8,740$				$10,548$			
(p-value)	$0,013$				$0,005$			
Lagged IR			$15,109$				$3,546$	
(p-value)			$0,001$				$0,170$	
Sample Size	36		36		44		44	

Table B.2: Relations between IPO Initial Returns and IPO Filings, Timing, and Withdrawals, 1999 to 2019 at Country Level

Granger F-test for incremental predictability (granger causality) for two lags, assuming White's heteroskedasticity-consistent standard errors and uncorrelated error terms. The data are for quarterly observations in selected countries between January 1999 and December 2019. Panel I is a subsample of IPOs from the United Kingdom, panel II from Germany and panel III from France. IR^{PW} is the proceed-weighted initial returns on a quarterly basis, $NFIL$ is the number of new filings per quarter, $REGTIME$ is the average proceed-weighted time in registration for IPOs issued within a quarter and NWD is the number of IPO withdrawals per quarter.

	Initial Return Measures (IR^{PW})					
	(I) U.K.		(II)Germany		(III)France	
IPO Timing Measures	F-test	p-value	F-test	p-value	F-test	p-value
$NFIL$						
(1) Returns predict filing	4.154	0.125	2.214	$0,331$	1.693	0.429
Sample Size	84		84		84	
$REGTIME$						
(2) Returns predict timing	0.610	0.737	62.813	0.000	3.920	0.141
Sample Size	84		84		84	
NWD						
(3) Returns predict withdrawals	5.500	0.064	6.044	0.049	25.293	0.000
Sample Size	84		84		84	

Table B.3: Descriptive Statistics for IPO Related Measures in Europe, between 1999 and 2019

The mean, median (med.), standard deviation (std.), minimum, maximum, sample size T, autocorrelations for 12 lags, ρ_1 to ρ_{12}, and the standard errors of correlations assuming no autocorrelation $S(\rho)$. The first grouping is for volume related measures; the number of IPOs per month ($NIPO$), the number of new filings per month ($NFIL$) and the number of withdrawals per month (NWD). The second grouping is time in registration $REGTIME^{PW}$, consisting of the average time in registration per month weighted by the IPO proceeds. The last grouping is for initial returns, and consist of two portfolios; the proceed-weighted average initial return per month (IR^{PW}) and the equal-weighted average initial return per month (IR^{EW}).

	Mean	Med.	Std.	Min	Max	T	ρ_1	ρ_2	ρ_3	ρ_4	ρ_5	ρ_6	ρ_7	ρ_8	ρ_9	ρ_{10}	ρ_{11}	ρ_{12}	$S(\rho)$
Number of IPOs per month																			
$NIPO$	13.27	10.00	10.09	1.00	47.00	252	0.57	0.21	0.24	0.41	0.37	0.27	0.33	0.31	0.11	0.03	0.27	0.44	0.04
$NFIL$	13.68	12.00	9.69	1.00	51.00	252	0.57	0.34	0.33	0.46	0.41	0.31	0.29	0.32	0.18	0.10	0.24	0.41	0.04
NWD	1.60	1.00	1.03	1.00	7.00	252	0.43	0.29	0.04	0.47	0.80	0.32	0.41	-0.14	0.02	0.12	0.03	0.07	0.08
Time in registration in days																			
$REGTIME_PW$	67.84	46.70	68.08	10.00	438.50	252	0.09	0.03	0.22	0.13	0.16	0.26	0.00	0.04	0.12	0.10	0.18	0.01	0.02
Average initial returns																			
IR_EW	4.91	3.59	14.61	-48.33	84.62	252	0.12	0.01	0.09	-0.04	0.14	0.09	0.01	-0.14	-0.02	-0.06	0.04	-0.06	0.02
IR_PW	2.47	2.21	22.17	-71.06	196.48	252	-0.07	0.01	0.03	0.08	0.05	0.02	0.06	-0.06	-0.06	0.15	-0.07	-0.05	0.02

Table B.4: Descriptive Statistics for IPO Related Measures in Europe, excluding the United Kingdom, between 1999 and 2019

The mean, median (med.), standard deviation (std.), minimum, maximum, sample size T, autocorrelations for 12 lags, ρ_1 to ρ_{12}, and the standard errors of correlations assuming no autocorrelation $S(\rho)$. The first grouping is for volume related measures; the number of IPOs per month ($NIPO$), the number of new filings per month ($NFIL$) and the number of withdrawals per month (NWD). The second grouping is time in registration $REGTIME^{PW}$, consisting of the average time in registration per month weighted by the IPO proceeds. The last grouping is for initial returns, and consist of two portfolios; the proceed-weighted average initial return per month (IR^{PW}) and the equal-weighted average initial return per month (IR^{EW}).

	Mean	Med.	Std.	Min	Max	T	ρ_1	ρ_2	ρ_3	ρ_4	ρ_5	ρ_6	ρ_7	ρ_8	ρ_9	ρ_{10}	ρ_{11}	ρ_{12}	$S(\rho)$
Number of IPOs per month																			
$NIPO$	9.16	7.00	7.75	1.00	40.00	252	0.56	0.20	0.23	0.40	0.37	0.28	0.32	0.29	0.08	0.04	0.23	0.41	0.04
$NFIL$	9.47	7.00	7.67	1.00	40.00	252	0.52	0.33	0.31	0.42	0.42	0.31	0.27	0.27	0.17	0.10	0.20	0.38	0.03
NWD	1.63	1.00	1.05	1.00	7.00	252	0.41	0.26	0.05	0.47	0.85	0.29	0.45	-0.15	0.00	0.09	0.03	0.06	0.08
Time in registration in days																			
$REGTIME_PW$	81.96	51.00	93.52	8.00	520.60	252	0.04	0.03	0.20	0.04	0.10	0.25	0.00	0.03	0.09	0.03	0.15	-0.02	0.02
Average initial returns																			
IR_EW	2.05	0.64	22.82	-60.23	209.66	252	0.07	0.02	0.20	-0.03	0.00	0.02	-0.05	-0.12	-0.07	-0.04	0.05	-0.09	0.02
IR_PW	-0.33	0.00	24.37	-72.40	209.66	252	0.06	-0.02	0.02	0.17	0.02	0.02	0.01	-0.06	-0.02	0.01	0.01	-0.01	0.02

Table B.5: Predictability Between IPO Initial Returns and Number of IPOs

Fourth order vector autoregressive, VAR(4), model for proceed-weighted initial return (IR) and number of initial public offerings ($NIPO$) on a monthly basis for the European market between January 1999 and December 2019. Panel A use the full sample of all European countries, while panel B excludes the United Kingdom from the analysis. The VAR(4) model uses White's heteroskedasticity-consistent standard errors and uncorrelated error terms. Additionally is a Granger F-test for incremental predictability (granger causality) included, using the same number of lags and assumptions for standard errors and correlations as the VAR model. R^2 is the coefficient of determination, while $S(u)$ is the standard error of the regression.

	PANEL A: Full Dataset				PANEL B: Excluding UK			
Dependent variable	IR_t^{PW}		$NIPO_t$		IR_t^{PW}		$NIPO_t$	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
Regressors								
Constant	0.855	0.00	3.399	0.00	−2.748	0.00	2.463	0.00
IR_{t-1}	−0.096	−1.94	−0.029	−1.22	0.034	0.55	−0.022	−1.42
IR_{t-2}	0.003	0.08	0.002	0.13	−0.021	−0.54	0.014	0.83
IR_{t-3}	0.051	1.41	0.041	2.19	0.023	0.52	0.016	1.07
IR_{t-4}	0.087	1.42	0.014	0.50	0.162	1.91	0.015	0.85
$NIPO_{t-1}$	−0.068	−0.63	0.594	8.88	0.031	0.17	0.577	7.76
$NIPO_{t-2}$	0.214	1.60	−0.207	−2.68	0.196	0.94	−0.197	−2.30
$NIPO_{t-3}$	−0.091	−0.49	0.075	1.05	0.072	0.23	0.052	0.65
$NIPO_{t-4}$	0.083	0.50	0.271	4.69	0.023	0.09	0.279	4.48
R^2	0.069		0.433		0.078		0.420	
$S(u)$								
Granger F-test								
Lagged NIPO	4.509				3.552			
(p-value)	(0.342)				0.470			
Lagged IR			6.213				4.802	
(p-value)			(0.184)				0.308	
Sample Size, T	252		252		252		252	

Table B.6: Autocorrelation of Expected and Unexpected Initial Returns to IPOs Issued in Europe Between 1999 and 2019

In addition to the autocorrelation for 12 lags, ρ_1 to ρ_{12}, of different return measures, the table reports mean, median (med.), standard deviation (std.), minimum, maximum, sample size T and the standard errors of correlations assuming no autocorrelation $S(\rho)$. The first grouping is for the proceed-weighted average initial returns in month t. The second grouping is for expected initial returns at the time of registration, based on the regression model in panel (A), column 1, in table 5.3. It gives the proceed-weighted average expected returns in month t, as well as the proceed-weighted average unexpected initial return in month t (that is the residuals of the regression model). The final grouping is for expected initial returns at the time of offering, and gives the proceed weighted average expected and proceed-weighted average unexpected initial returns, both in month t, based on the result from the regression model in panel (A) column 3, in table 5.3.

	Mean	Med.	Std	Min	Max	T	ρ_1	ρ_2	ρ_3	ρ_4	ρ_5	ρ_6	ρ_7	ρ_8	ρ_9	ρ_{10}	ρ_{11}	ρ_{12}	$S(\rho)$
Actual initial returns																			
(1) IR	2.49	1.36	21.37	-71.06	196.48	252	-0.10	0.02	0.02	0.08	0.05	0.02	0.06	-0.06	-0.05	0.15	-0.07	-0.05	0.02
Expected initial returns based on information known at the time of filing																			
(2) $E_F[IR]$	3.74	3.82	2.54	-4.40	12.18	252	0.20	0.10	0.07	0.12	0.05	0.04	0.07	0.14	-0.02	-0.03	-0.01	0.04	0.02
(3) $IR - E_F[IR]$	-1.25	-1.34	21.42	-78.53	190.97	252	-0.11	0.01	0.02	0.10	0.04	0.03	0.05	-0.05	-0.02	0.15	-0.07	-0.04	0.02
Expected initial returns based on information known at the time of offering																			
(4) $E_O[IR]$	3.51	3.75	2.70	-5.70	10.74	252	0.10	0.04	0.04	0.09	0.05	0.00	0.11	0.08	0.02	-0.04	-0.02	0.04	0.01
(5) $IR - E_O[IR]$	-1.02	-1.17	21.39	-78.16	191.22	252	-0.12	0.01	0.02	0.09	0.04	0.03	0.05	-0.06	-0.02	0.15	-0.07	-0.05	0.02

Table B.7: Autocorrelation of Initial Returns to IPOs Issued in Europe, Excluding the United Kingdom, Between 1999 and 2019

In addition to the autocorrelation for 12 lags, ρ_1 to ρ_{12}, of different return measures, the table reports mean, median (med.), standard deviation (std.), minimum, maximum, sample size T and the standard errors of correlations assuming no autocorrelation $S(\rho)$. The first grouping is for the proceed-weighted average initial returns in month t. The second grouping is for expected initial returns at the time of registration, based on the regression model in panel (B), column 5, in table 5.3. It gives the proceed-weighted average expected returns in month t, as well as the proceed-weighted average unexpected initial return in month t (that is the residuals of the regression model). The final grouping is for expected initial returns at the time of offering, and gives the proceed weighted average expected and proceed-weighted average unexpected initial returns, both in month t, based on the result from the regression model in panel (B) column 7, in table 5.3.

	Mean	Med.	Std	Min	Max	T	ρ_1	ρ_2	ρ_3	ρ_4	ρ_5	ρ_6	ρ_7	ρ_8	ρ_9	ρ_{10}	ρ_{11}	ρ_{12}	$S(\rho)$
Actual initial returns																			
(1) IR	-0.07	0.00	23.07	-72.40	209.66	252	0.04	-0.01	0.01	0.17	0.02	0.01	0.02	-0.06	-0.01	0.00	0.01	0.00	0.02
Expected initial returns based on information known at the time of filing																			
(2) $E_F[IR]$	1.95	1.43	2.64	-3.61	9.37	252	0.21	0.13	0.13	0.20	0.16	0.15	0.15	0.10	0.05	0.07	0.07	0.07	0.02
(3) $IR - E_F[IR]$	-2.01	-0.89	22.80	-77.12	206.33	252	0.02	-0.03	-0.01	0.16	0.01	0.00	0.00	-0.07	-0.01	-0.01	0.00	0.00	0.02
Expected initial returns based on information known at the time of offering																			
(4) $E_O[IR]$	1.78	1.41	2.93	-6.58	9.62	252	0.19	0.07	0.08	0.18	0.15	0.14	0.16	0.05	0.02	0.09	0.09	0.03	0.02
(5) $IR - E_O[IR]$	-1.85	-0.85	22.76	-76.48	205.99	252	0.02	-0.03	-0.01	0.15	0.01	0.00	-0.01	-0.07	0.00	-0.01	-0.01	0.00	0.02

C Time-Dummies

Table C.1: Time-Dummies for Time Controlled Regression for IPOs Issued Between 1999 and 2019

Regression model for initial returns of IPOs issued between January 1999 and December 2019 in Europe controlling for time variation as a robustness check of results in table 5.3. Panel A is regression results for the full sample of European countries, while panel B excludes the United Kingdom from the sample. This table gives the coefficients and t-statistics for the time-dummies X_{year}, i.e $year_{2000}$ - $year_{2019}$. See table 5.5 for coefficients and t-statistics for other variables, as well as R^2 and the standard error of regressions $S(u)$.

	(A) Information Content, Full Dataset				(B) Information Content, Excluding UK			
	Registration		Offering		Registration		Offering	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
$Year_{2000}$	10.479	2.87	11.330	3.09	12.187	2.70	13.030	2.88
$Year_{2001}$	5.114	1.09	6.594	1.40	−7.046	−1.12	−5.340	−0.84
$Year_{2002}$	2.917	0.56	4.489	0.87	−2.451	−0.34	−0.777	−0.11
$Year_{2003}$	8.802	1.51	7.843	1.35	16.068	1.54	15.308	1.46
$Year_{2004}$	15.159	3.84	15.063	3.82	0.375	0.06	0.291	0.05
$Year_{2005}$	16.253	4.10	16.190	4.09	7.446	1.37	7.536	1.39
$Year_{2006}$	11.627	3.17	11.157	3.04	9.133	2.06	8.661	1.96
$Year_{2007}$	14.212	3.86	14.145	3.84	12.099	2.80	12.026	2.78
$Year_{2008}$	8.932	1.49	10.466	1.75	6.851	0.98	8.405	1.20
$Year_{2009}$	15.996	2.02	14.180	1.79	16.470	1.78	14.217	1.53
$Year_{2010}$	10.072	2.17	10.044	2.17	9.423	1.73	9.576	1.76
$Year_{2011}$	18.707	4.00	19.201	4.11	19.124	3.44	19.626	3.54
$Year_{2012}$	2.311	0.43	2.599	0.48	−0.945	−0.14	−0.716	−0.11
$Year_{2013}$	8.161	1.62	8.321	1.65	2.060	0.30	2.179	0.32
$Year_{2014}$	8.086	1.99	8.431	2.07	5.346	1.04	5.572	1.08
$Year_{2015}$	8.709	2.15	9.077	2.24	7.917	1.65	8.309	1.74
$Year_{2016}$	10.434	2.31	10.606	2.35	7.872	1.42	7.992	1.44
$Year_{2017}$	13.334	3.25	13.208	3.22	12.195	2.53	12.122	2.52
$Year_{2018}$	9.959	2.36	11.056	2.61	8.424	1.66	9.535	1.87
$Year_{2019}$	13.288	1.37	12.945	1.34	14.291	1.30	13.830	1.26

Table C.2: Time-Dummies for Time Controlled Regression for IPOs Issued Between 1999 and 2019 at Country Level

Regression model for initial returns of IPOs issued between January 1999 and December 2019 in selected countries controlling for time variation as a robustness check of results in table 5.7. Panel I is a subsample of IPOs from the United Kingdom, panel II from Germany and panel III from France. This table gives the coefficients and t-statistics for the time-dummies X_{year}, i.e $year_{2000}$ - $year_{2019}$. See table 5.9 for coefficients and t-statistics for other variables, as well as R^2 and the standard error of regressions $S(u)$.

	(I) United Kingdom				(II) Germany				(III) France			
	At Registration		At Offering		At Registration		At Offering		At Registration		At Offering	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
$Year_{2000}$	4.660	0.47	4.944	0.50	4.253	0.43	3.067	0.31	12.991	2.19	13.024	2.19
$Year_{2001}$	15.984	1.52	16.578	1.58	−18.438	−1.04	−20.705	−1.14	6.819	0.84	8.416	1.03
$Year_{2002}$	4.412	0.41	5.216	0.49	−25.305	−0.69	−26.299	−0.71	13.685	1.74	15.422	1.96
$Year_{2003}$	2.447	0.23	1.022	0.10					16.835	0.69	16.990	0.70
$Year_{2004}$	18.414	1.87	17.797	1.81	16.682	0.55	16.655	0.55	7.311	0.89	6.528	0.80
$Year_{2005}$	19.714	1.98	19.070	1.92	−4.545	−0.22	−5.411	−0.26	16.488	2.34	16.291	2.32
$Year_{2006}$	11.439	1.14	10.524	1.05	−16.297	−0.99	−15.906	−0.96	22.471	4.48	21.231	4.22
$Year_{2007}$	14.614	1.43	14.117	1.38	−12.837	−0.77	−12.771	−0.76	17.133	2.99	16.396	2.86
$Year_{2008}$	13.956	0.98	15.230	1.07	−12.842	−0.29	−12.889	−0.29	20.231	1.59	18.601	1.45
$Year_{2009}$	6.602	0.37	5.812	0.33	−14.799	−0.33	−16.716	−0.37	27.316	2.48	24.510	2.22
$Year_{2010}$	8.987	0.78	8.012	0.69	−25.643	−1.28	−25.830	−1.29	17.937	2.29	17.620	2.25
$Year_{2011}$	12.613	1.10	12.704	1.11	−27.011	−1.13	−24.777	−1.02	21.466	2.99	22.539	3.14
$Year_{2012}$	7.045	0.59	7.062	0.59	−17.624	−0.67	−19.401	−0.73	14.760	1.86	14.487	1.83
$Year_{2013}$	12.185	1.15	11.865	1.12	−38.022	−1.04	−39.500	−1.07	17.244	1.96	15.707	1.78
$Year_{2014}$	8.330	0.83	8.330	0.83	−18.426	−0.81	−18.813	−0.82	15.289	2.27	15.011	2.24
$Year_{2015}$	6.222	0.59	6.113	0.58	−15.730	−0.77	−15.977	−0.78	20.994	3.32	21.045	3.32
$Year_{2016}$	11.594	1.08	11.278	1.05	−20.013	−0.61	−22.689	−0.68	16.726	2.12	16.464	2.09
$Year_{2017}$	12.332	1.15	11.620	1.08	3.417	0.15	3.386	0.15	20.546	2.52	20.550	2.53
$Year_{2018}$	9.492	0.90	10.107	0.96	−18.076	−0.95	−19.279	−1.01	15.798	2.19	17.181	2.38
$Year_{2019}$	−0.785	−0.03	−0.678	−0.03	−16.066	−0.26	−14.395	−0.23				