NAVIGATING THE STORM: AN EXAMINATION OF IPO UNDERPRICING IN 21ST CENTURY CRISES

A STUDY ON IPO UNDERPRICING BETWEEN 1999 TO 2023

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Abstract:

IPO underpricing is a phenomenon studied by many, with theories explaining the reason for this mispricing problem. However, there is little to no research examining how IPO underpricing reacts in different crises during the 21st century. This paper focuses on companies issuing in the US market on NYSE and NASDAQ. The data set contains the period from January 1999 to September 2023 and explore four modern crises, Dot.com bubble, Global Financial Crisis, Covid-19 crisis and the crisis associated with the Ukraine invasion. We show that there is no significant positive correlation between general crises and IPO underpricing however we reach the result that Covid-19 exhibits a significant positive correlation with average monthly initial returns and its standard deviation, showing that during this period the IPOs tend to be lower priced, and their average return are very volatile. We thus conclude that there is no general correlation between crises and underpricing but there can be in specific crisis.

Keywords:

Initial public offering, IPO, IPO underpricing, Financial Crisis

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1. Introduction

Initial Public Offering is a common type of equity financing however the actual pricing of the underlying stocks is not always easy. When the offer price is lower than the market price of the stock, the IPO is considered to be underpriced. IPO underpricing is highly autocorrelated; hence companies tend to precisely point their IPOs in a certain time period in the interest of maximizing their offering price, Young, Colak & Wang (2006). The reason not only being information asymmetry but a pricing problem for underwriters with the reason being both market conditions and firm specific factors Lowry, Officer & Schwert (2010).

The IPO market has been hot the past two decades, between 1999-2023 there were 2923 IPOs issued on either Nasdaq or NYSE in the US, with a number of underpriced IPOs on average approximately 32% with a standard deviation of 73.5% which is more underpriced than studies conducted with larger time periods, see for example, Loughran, Ritter & Rydqvist (1994)[1] who found an initial return of 17.5%.

The market is underpriced on average, and issuers must consider the long-term performance of underpriced IPOs. Ritter (1991) shows substantial negative long term returns in underpriced IPOs. Three-year performance is measured for IPO to distinguish the correlation between the long- and short-term gains in underpriced IPOs. The short term of day one is consistent and well documented, however, Ritter discovers that the three-year performance for firms issuing illustrates an underperformance contrary to certain different benchmark.

There are various underlying theories and research papers that try to explain and contribute to conclusions of why IPOs are underpriced. Rock (1986) describes information asymmetry and winners' curse that is a crucial part of understanding the reason for underpricing. It is argued that there are investors with superior information, who act and invest in these more attractive priced securities. It creates information asymmetry between the informed and uninformed investors, therefore issuers price their IPO lower to capture both subgroups of investors. The price thus reflects the aggregate demand of the market's information which creates pricing inconsistency. Beatty and Ritter (1986) extended Rocks paper and demonstrated that companies that are subject to more information asymmetry are open to more underpriced on average.

Ritter & Welch (2002) note that information asymmetry is a contributing factor, however it does not explain how the Dot.Com bubble experienced 65% initial return hence there are other factors to affect underpricing. More recent research such as, Lowry et al (2010), one of the most prominent papers in the IPO underpricing field conduct an in-depth analysis and find a correlation between average monthly returns and standard deviation, not tested by previous research. Our finding confirms that these results still stay true today. With information asymmetry as a base Lowry et al (2010) argue that underpricing comes from underwriters’ ability to price issues correctly, which are based on both

[1] The paper by Loughran, Ritter & Rydqvist was initially published in 1994, updated their data September 2023. The updated data is the data that we are referring to.

market-wide conditions, (also found in previous research Pástor & Veronesi (2005) and Pástor, Taylor and Veronesi (2009)) and firm-specific factors.

Even though the IPO literature is quite substantial there is little to no information on how underpricing reacts in different types of crises such as the Dot.Com crash in the beginning of the 21st century, the Global Financial Crises, Covid-19 and crisis associated with the Ukraine invasion (the time periods for each crisis are defined such as in James & Menzies (2023)). This article examines the effect that both general and specific crisis has on IPO underpricing. We believe that there will be little evidence to support a significant correlation between crises in the 21st century and underpricing. Our reasoning is built on the fact that numerous of papers including Young et al (2006) examines the IPO cyclicality which exhibit a wave pattern that consists of higher initial return in “hot” markets and lower in “cold”, complementing frameworks such as Helwege, Liang (2004) and Lowry & Schwert (2002). Since the crises are mostly during periods with lower economic standards where fewer IPOs are issued, crises contain most of the cold markets, it is thus reasonable that this is found in our dataset too. However, papers that have conducted this type of research have not primarily focused on the 21st century, hence our research might reach other conclusions.

In this paper we find that general crises have little explanatory value of IPO underpricing and that issuers should not base their timing decision on how IPO underpricing reacts in all crises. Our results confirm our predictions, and research such as Helwege & Liang (2004) and Lowry & Schwert (2002), during all crises there is no positive relation to IPO underpricing. However, we do find that there is a large positive correlation between specific crises and IPO underpricing which we did not predict. Our model illustrates that during Covid-19 there seems to be higher average initial return and higher volatility in those returns. This suggests that the Covid-19 reacts differently from other crises which would be interesting to further analyze to see what type of underlying specifics contribute to that.

2. Data & Methodology

In this section, we provide an overview of our dataset and discuss our data selection process. We also describe the variables used and model to answer our research question.

2.1. Sample selection

Our dataset is a compilation of information gathered from various sources, namely Thomson Financial Securities Data Company (SDC) and S&P Capital IQ (CIQ). The data focuses on the US market between January 1999 through September 2023, by collecting data on IPOs issued on NASDAQ and New York Stock Exchange (NYSE). This is because of the vast availability of data and the prestigious stock exchanges, making it particularly susceptible to international economic crises.

The criterion for our dataset is based on the conditions outlined in Lowry et al (2010) study, excluding Real Estate Investment Trusts (REITs), closed-end funds, American Depository Receipts (ADRs), unit offers, IPO with an offer price below $5 and all IPO with no initial return data. In contrast to Lowry et al (2010), our data excludes Master Limited Partnerships (MLPs), and all firm's business descriptions containing at least one of the words "Non-operational", "shell", "holding" or "SPAC", by virtue of that these types of firms fundamentally differ from operational businesses in form of financial structure, objectives and market behavior, which if included would skew the result.

The data extracted from SDC includes key information such as the firm name, issue date, first month's initial returns, ticker symbol, and the CUSIP codes of the newly public firm. Between 1999 and 2023, 3959 IPOs were acquired from SDC, of which only 1870 had data for initial return. The dataset displayed 399 firms that were entered twice; hence all doubles were removed.

When extracting data from CIQ, each IPO is assigned a unique Capital IQ number. To facilitate cross-referencing and data validation between the CIQ and SDC datasets, we converted company names from the SDC dataset into unique CIQ numbers. This approach allows us to cross-examine the datasets and fill in any missing data for initial return to our SDC dataset.

Following this, all IPOs issued on the US Stock exchange between 1999 and 2023 in the CIQ database were collected, resulting in 7946 IPOs. We cross-examined the SDC database with Capital IQ through the CIQ code and filled out 1330 missing data points to our SDC data set. In cases of discrepancies or disagreements between the two datasets, we prioritize the data from SDC, resulting in a dataset of 3200 IPOs. IPOs issued over the counter as well as misleading data points that contain faulty information such as the wrong offer price or issue date were removed. This resulted in a total of 2923 IPOs in our final full sample. The data graphed every year can be found in Appendix A.

2.2 Period definition

We have grouped the data to facilitate the examination of four distinct economic crises and their impact on IPO underpricing. The specific periods under consideration are as follows:

Dot.Com bubble: 2000-03-01 - 2002-10-01
Global Financial Crises: 2007-01-03 - 2010-03-03
Covid-19: 2020-03-11 - 2020-08-31
2022 Crises associated with Ukraine invasion 2022-01-03 - 2022-05-13**.**

Defining the periods of economic crises has been done in several different ways across previous research and crises are not distinctly defined in one way. Some papers refer to crises by looking at changes in monetary policy, sovereign default rates or other metrics; however, the results are usually a period of a few months and would contain few data points. Due to the structure of our dataset, our model reaches better predictions with a broader definition, thus we have decided to follow the structure appointed above by James & Menzies (2023) as it is a relevant definition of financial crises for our intended research.

2.3 Descriptive Analysis

Initial return for IPO is the main measurement to examine underpricing. As in Lowry et al (2010), the model measures the percentage of initial return from the issue date to 4-week closing price, instead of the one-day initial return that most previous research uses, (see for example Young et al (2006) and Lowry (2003)). By virtue of Ruud (1993) and Hanley, Kumar & Seguin (1993), who argue that monthly returns better represent the stabilized market value of the stock. Any data collected from SDC will have a monthly return as it was not possible to retrieve the 4-week closing price however it still represents the true market value of the stock.

The returns are grouped together on a monthly basis in order to measure the correlation between the average monthly initial return and its standard deviation. They are measured over both the entire dataset and the different crises. By bundling the returns into monthly averages, the standard deviation within each month can be measured which otherwise would be infeasible with one data point. Months with fewer than 4 IPOs are excluded in the cross-sectional standard deviation nevertheless the average initial returns are presented as long as it contains at least 1 IPO. Due to this, there are fewer observable months in the cross-sectional standard deviation compared to the average initial returns.

Equation (1) calculates the average monthly initial return of an IPO. Where u denotes months, n denotes total number of IPO being issued that month and z denotes IPO of firm z in equation (1), (2) and (3)

$$\overline{IPO\ IR_u} = \frac{1}{n} \sum_{ui=1}^{un} \frac{Four\ week\ closing\ price_{ui} - Offer\ price_{ui}}{Offer\ price_{ui}} \qquad \textbf{(1)}$$

Equation (2) calculates the average standard deviation of the monthly initial return of the IPO.

$$IPO\ IR\sigma_u = \sqrt{\frac{\frac{1}{n}\sum_{ui=1}^{un}(IPO\ IR_{ui} - \overline{IPO\ IR_z})}{n-1}} \qquad \textbf{(2)}$$

Equation (3) calculates the initial return for the firm specific IPO.

$$IPO\ IR_u = \frac{four\ week\ closing\ price_u - Offer\ price_u}{Offer\ price_u} \qquad \textbf{(3)}$$

The autocorrelation is tested, to show the cyclicality of underpricing by calculating the relation between the average initial return and the standard deviation measures, up to 6 different lags. The Covid-19 and Ukraine invasion crises are defined with a narrower time period only containing 6 and 3 months. Therefore, to test autocorrelation up to six lags are not possible.

2.4 Cross-Sectional Model

To examine the different effects crisis and other independent variables have on underpricing, a correlation matrix and an ordinary least squared (OLS) regression is conducted, to further examine the relationship between the independent and dependent variables. In the OLS, through the defined variables we can control for exogenous and endogenous factors affecting our dependent variables Lowry (2003). The OLS regression is based on the model of Lowry et al (2010) to analyze our two different subsets, the full data set from 1999-01-01 to 2023-09-30 and the omitted data set (excluding the bubble period) from 2000-03-01 to 2023-09-30.

2.4.1 Descriptive Evidence

Our dependent, independent and dummy variables used to examine the effect crisis has on IPO underpricing, are as follows:

1. *Average initial return (Dependent Variable)* is the percentage difference between the offer price and the four-week closing price during a month.
2. *Standard deviation of initial return* measures *(Dependent Variable)* the standard deviation of the percentage difference in the offer price and the four-week closing price during a month.
3. *Number of listed firms (Dependent Variable)* measures the number of firms listed during a month.
4. *Average adjusted initial return (Dependent Variable)* measures the percentage difference of average initial return and the S&P 500 average initial return for a given amount. S&P 500 is used as a control metric since it takes overall market

performance into account, and therefore works as a metric for overall market movements.

5. *Adjusted standard deviation (Dependent Variable)* measures the standard deviation of average initial return and the S&P 500 average initial return for a given amount.
6. *Nasdaq Dummy (Independent Variable)* equals one if the firm is issued on Nasdaq, and zero otherwise. It is more common for small, young and tech firms to be listed on Nasdaq. Which has a higher risk of underpricing due to the lack of information making it harder for underwriters to value these firms. Lowry et al (2010).
7. *NYSE Dummy (Independent Variable)* equals one if the firm is issued on the New York Stock Exchange, and zero otherwise. NYSE is common for more established firms to go public on, which gives underwriters a higher chance of better estimating the firm value prior to the IPO Lowry et al (2010).
8. *Dot.Com Dummy (Independent Variable)* equals one if the IPO is issued during the Dot.com crisis from 2000-03-01 to 2002-10-01, and zero otherwise.
9. *Global Financial Dummy (Independent Variable)* equals one if the IPO is issued during the Global Financial crisis from 2007-01-03 to 2010-03-03, and zero otherwise.
10. *Covid-19 Dummy (Independent Variable)* equals one if the firm IPO is issued during the Covid-19 crisis from 2020-03-11 to 2020-08-31, and zero otherwise.
11. *Ukraine Dummy (Independent Variable)* equals one if the firm IPO is issued during the 2022 crises associated with Ukraine invasion from 2022-01-03 to 2022-05-13, and zero otherwise.
12. *Crisis Dummy (Independent Variable)* equals one if the IPO month is characterized as a crisis, and zero if not.
13. *Bubble Period Dummy (Independent Variable)* equals one from 1999-01-01 to 2000-02-29, and zero if not.

We will run several regressions on our five different dependent variables, monthly initial return, standard deviation of monthly initial return, number of IPOs, adjusted initial return and the adjusted standard deviation of initial return to measure the effect crises has on IPO underpricing. Adjusted initial return is calculated by taking the difference between the average initial return and the average S&P 500 initial return during the same months. S&P 500 is used for both adjusted initial returns and adjusted standard deviation of initial return since it takes the overall market performance into account, and therefore works as a metric for overall market movements.

The independent variables are all categorized as dummy variables. Percentage Nasdaq and Percentage NYSE shows the relationship between the underpricing on their exchange versus the rest of the data set. Established firms often go public on NYSE, which makes it easier to value them due to the higher accessibility of information, hence less underpricing. Less established firms tend to list on Nasdaq, thus a higher risk for underpricing, Lowry et al (2010). Due to this, we will use Percentage Nasdaq and Percentage NYSE as dummy variables. It will further be examined with our crises as dummy variables to view their influence on the dependent variables.

2.4.2 Cross-sectional regression model

In this section, we examine the correlation between each dependent and independent variable with a correlation matrix. This will be calculated by the monthly average characteristics of firms going public. The purpose of this matrix is to understand the relationship between each dependent and independent variable. We will investigate more in detail the relationships from the correlation matrix, through an OLS regression. First, we will look at the effect all crises combined through our crisis dummy, have on IPO underpricing, which will be done by using equation (4). Equation (4) will be run individually on our five dependent variables.

$$Dependent\ Variable = \beta_0 + \beta_1 Crisis\ Dummy_u + \varepsilon_u \qquad \textbf{(4)}$$

To examine the individual effect each crisis has on IPO underpricing we will use all crises as individual dummy variables as well as using relevant independent variables such as bubble period, Percentage Nasdaq and Percentage NYSE as in Lowry et al (2010). The cross-sectional OLS regression will be applied on equation (5) and (6). We will also run the regression with our omitted data sample on equation (6). The difference between equation (5) and (6) is that equation (5) includes the bubble period dummy.

$$Dependent\ Variable = \beta_0 + \beta_1\, Percentage\ NYSE_u + \beta_2\, Percentage\ Nasdaq_u + \beta_3 Dot.Com_u \qquad \textbf{(5)}$$
$$+\beta_4\, Global\ Financial\ Crisis_u + \beta_5\, Covid19\ Crisis_u + \beta_6\, Ukraine\ Crisis_u + \beta_7\, Bubble\ Period_u + \varepsilon_u$$

$$Dependent\ Variable = \beta_0 + \beta_1\, Percentage\ NYSE_u + \beta_2\, Percentage\ Nasdaq_u + \beta_3 Dot.Com_u \qquad \textbf{(6)}$$
$$+\beta_4\, Global\ Financial\ Crisis_u + \beta_5\, Covid19\ Crisis_u + \beta_6\, Ukraine\ Crisis_u + \varepsilon_u$$

2.4.3 Assessment of multicollinearity and heteroskedasticity

Two assumptions underlie the OLS regression, no multicollinearity or heteroskedasticity. We test for these to achieve as descriptive a model as possible.

If two independent variables are dependent the results become unreliable Lowry et al (2010). To examine the presence of multicollinearity amongst our independent variables, we perform a variance inflation factors (VIF) test on our variables. If the VIF results in a score above five, it indicates a strong multicollinearity.

If the data set exhibits heteroskedasticity with inefficient estimators, the reliability of the hypothesis being tested decreases Lowry et al (2010). To test for heteroskedasticity we perform White's test which examines if the variance in errors in the regression model are dependent on the independent values.

In the presence of heteroscedasticity, we will conduct a Weighted Least Square (WLS) regression which uses the variance of error from the regression model in equation (5).
It is assumed that u has a connection with the independent variables that are positive to affect the dependent variable. Through that assumption we use the log variance of the regression model presented in equation (7) and (8). The difference on equation (7) and

(8) is the presence of the bubble dummy variable in equation (7). The WLS regression will follow the method presented in Lowry et al (2010). The standard deviations of the regression error σ (u) will be used as weighted least square.
estimation in equation (7) and (8).

$$Log_1(\sigma^2(\varepsilon_u)) = Y_0 + Y_1\, Percentage\ NYSE_u + Y_2\, Percentage\ Nasdaq_u + Y_3 Dot.Com_u$$ **(7)**
$$+Y_4\, Global\ Financial\ Crisis_u + Y_5\, Covid19\ Crisis_u + Y_6\, Ukraine\ Crisis_u + Y_7\, Bubble\ Period_u$$

$$Log_2(\sigma^2(\varepsilon_u)) = Y_0 + Y_1\, Percentage\ NYSE_u + Y_2\, Percentage\ Nasdaq_u + Y_3 Dot.Com_u$$ **(8)**
$$+Y_4\, Global\ Financial\ Crisis_u + Y_5\, Covid19\ Crisis_u + Y_6\, Ukraine\ Crisis_u$$

3. Empirical results

3.1 Descriptive statistics

Figure 2

Figure 2. Frequency distribution of first month IPO returns, 1999 to 2023. Black bars show distribution of percentage change in initial returns from the offer date to the 4-week trading day. Normal distribution is presented in the dotted line.

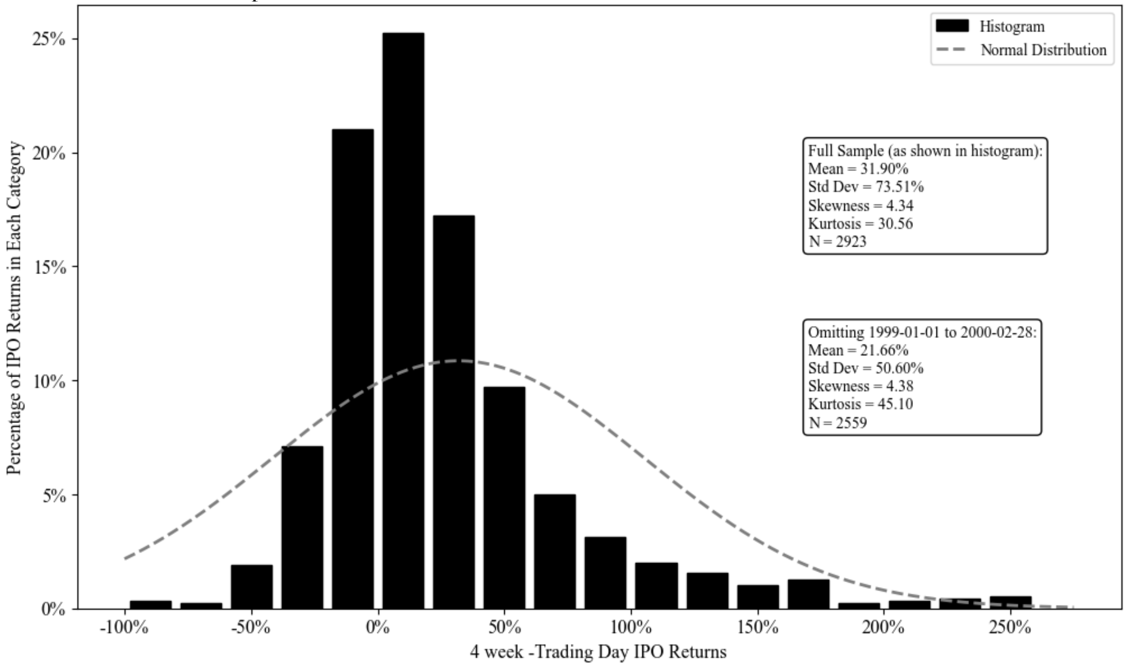


Figure 2 exhibits the percentage of the 2923 IPO returns issued in the interval 1999-2023. The result shows that the average return is 31.9% and a standard deviation of 73.51%. The values are substantially higher than the values in Lowry et al (2010). This can be explained due to the different periods in our dataset only overlapping from 1999 to 2005 in which it is noted that there is an unusual dispersion in the years 1999-2000. Figure 2 also displays a high skewness and heavy-tailed distribution in initial returns with a normal distribution demonstrated with the same mean and standard deviation. Our omitting data shows a significant decrease in both mean and standard deviation showing the big impact the two irregular markets caused.

Figure 3 shows the mean, standard deviation and number of IPOs plotted in the period of 1999-2023, displaying high cyclicality in number (hot and cold markets) and the dispersion of IPOs. We see a clear distinction that the initial 4-week return is higher in hot markets and lower in cold markets. It is noticeable that our dataset exhibits somewhat a correlation between average initial returns and the volatility in line with Lowry et al (2010), thus we further examine this in Table 1.

Figure 3

Figure 3. Mean, standard deviation of initial return and number of IPOs per month, 1999 to 2023. Initial monthly return (mean) defined as the percentage change between offer price and 4-week return, and standard deviation of those returns are calculated on a monthly basis. The blue line represents the average initial returns and the yellow line the standard deviation of those returns. The number of IPOs are displayed in the green line.

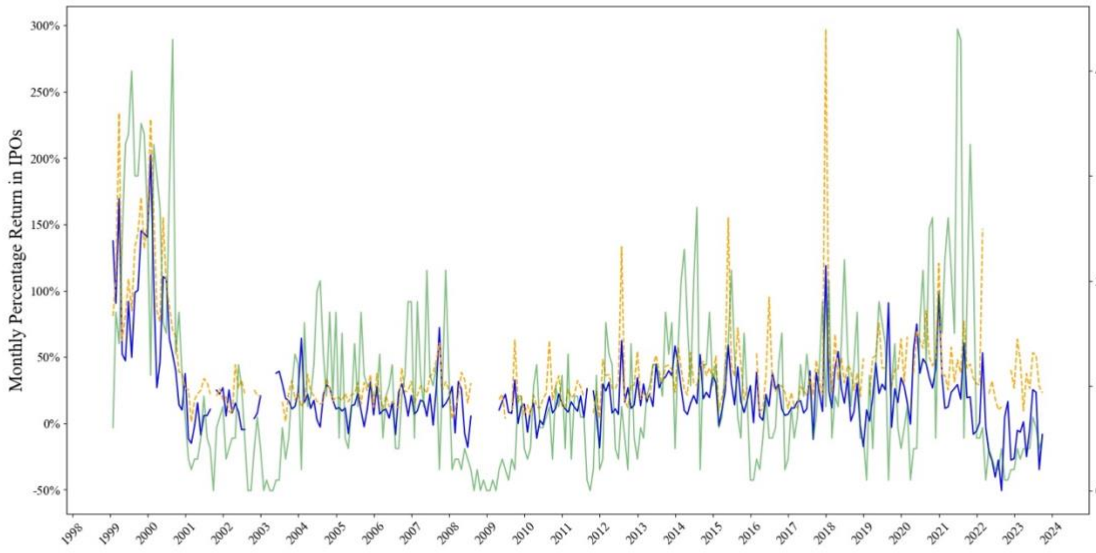


Table 1 includes the descriptive statistics that the graph in figure 3 displays. In column 1 we calculate the average 4 week return and standard deviation in each month. The mean, median, Standard deviation and correlation of those months are respectively shown in column 2,3,4 and 5. The metrics are calculated over the entire data set, omitted data set and across the four crises.

The average cross-sectional standard deviation is almost twice as big as the average IPO initial return in the dataset provided in the periods 1999-2023. The results closely follow the findings in Lowry et al (2010). We find a correlation of 0.831 confirming the visual correlation in figure 3. This relationship provides a strong reason why the distribution in Figure 1 is highly skewed.

Table 1

Table 1. Descriptive Statistics on the Monthly Mean and Volatility of IPO Initial Returns. The table consists of six different time periods with average IPO initial return and Cross-sectional standard deviation of those returns. Number of months with average initial return, mean, median, standard deviation are calculated for both average IPO initial return and Cross-sectional standard deviation of those returns. Correlation and autocorrelation between the average return and standard deviation are also estimated. Months with at least one IPO is calculated in Average IPO initial return but not in standard deviation. Months with at least four IPOs are calculated for Cross-sectional standard deviation.

						Autocorrelations: Lags					
	N	*Mean*	*Median*	*Std.Dev.*	*Corr.*	*1*	*2*	*3*	*4*	*5*	*6*
1999-2023											
Average IPO initial return	297	22.5%	16.2%	31.4%		0.609	0.521	0.503	0.483	0.462	0.422
Cross-sectional of IPO IRs	230	42.4%	30.5%	39.3%	0.831	0.469	0.410	0.487	0.442	0.408	0.364
1999–2023 (omitting January 1999 – February 2000)											
Average IPO initial return	283	17.9%	15.5%	22.2%		0.385	0.263	0.271	0.251	0.174	0.172
Cross-sectional of IPO IRs	216	36.5%	28.8%	29.8%	0.700	0.200	0.160	0.230	0.141	0.103	0.076
Dot.Com Bubble March 2000 - October 2002											
Average IPO initial return	32	22.7%	14.6%	31.2%		0.736	0.490	0.413	0.339	0.037	0.004
Cross-sectional of IPO IRs	23	46.3%	32.6%	35.8%	0.847	0.774	0.700	0.677	0.656	0.468	0.408
Global financial crises January 2007 - March 2010											
Average IPO initial return	39	13.1%	11.4%	17.3%		-0.035	-0.055	0.117	-0.032	-0.162	0.148
Cross-sectional of IPO IRs	16	24.9%	25.3%	11%	0.226	0.531	0.421	0.011	0.068	-0.304	-0.420
Covid-19 March 2020 - September 2020											
Average IPO initial return	6	43.5%	46.7%	25.1%		-0.222	-0.800	0.825	-1.000	NA	NA
Cross-sectional of IPO IRs	5	62.4%	62.4%	17.3%	-0.063	-0.354	0.102	1.000	NA	NA	NA
Ukraine Invasion January 2022 to May 2022											
Average IPO initial return	5	0.3%	-2.9%	31.9%		0.152	-0.199	-1.000	NA	NA	NA
Cross-sectional of IPO IRs	3	66%	29%	70%	0.971	-1.000	NA	NA	NA	NA	NA

There is an even greater correlation 0.847 in the Dot.Com bubble 2000-2002, which is self-explanatory due to the irregular market. The global financial crisis of 2007-2010 finds little support for correlation and also exhibits a lower mean than the total sample. However, by cross-examining it with figure 2 it is clear that the number of IPOs in this period is very low, hence consisting of a lot of cold markets, therefore supports previous research Ibbotson and Jaffe (1975), Ibbotson, Sindelar & Ritter (1988, 1994), Lowry et al (2010), and Lowry and Schwert (2002). To further examine correlations among crises and different industries see appendix B.

The contribution of this result is that we see somewhat of a divergence in the Covid-19 period and a clear difference in the Ukraine crisis. This is interesting and it is worth mentioning that the average return in the Ukraine crisis is very low at 0.3 % showing small signs of underpricing, with a standard deviation in average initial returns of 31.9 %, which is close to the full sample. The correlation is just below 1 at 0.971 demonstrating a close co-movement. On the other side of the spectrum, the correlation is slightly negative in the Covid-19 period. Something that we need to consider is that these two periods are only a couple of months, thus when they are measured against a data set over two decades it can be somewhat misleading. Nevertheless, the result raises questions about whether the uncertainty in these crises has an extraordinary effect on underpricing thus tested in part 4.

4. Linear regression

The variable description in descriptive evidence data summarizes our dependent, independent and dummy variables for our correlation and regression test. Table 2 plots the correlation of IPO market characteristics against five metrics, average initial return, standard deviation of initial return, number of listed firms, average adjusted initial return and adjusted standard deviation. They are shown in both the full sample and the omitted sample. At first both the NASDAQ and NYSE variables were plotted however there seemed to be a correlation between the two variables thus tested and confirmed in Table 2. We therefore chose to only include NYSE over NASDAQ as it is the less volatile stock exchange exhibiting fewer underpriced IPOs according to Lowry et al (2010).

We expect to find a negative correlation of the average initial return during our crises and companies listed on NYSE. As predicted, we see a clear negative correlation between firms listed on NYSE and their average initial return and standard deviation, confirming that in Lowry et al (2010), firms listed on NYSE are less subject to underpricing. The results regarding crises however were not predicted, two positively and two negatively correlated. The Global Financial crisis seems to have a significant negative correlation with both average initial return and standard deviation, however, during Covid-19 there is a significantly positive correlation in both average initial return and its standard deviation suggesting that during this period IPOs tend to be more underpriced and more volatile. The reason for this could be that there was a rare market boom in IPOs compared to different financial markets at the time, caused by a surge in tech and healthcare IPOs, with a possible explanation that these two markets were overvalued as a result of the pandemic Baig & Chen (2022). Nevertheless, we further test the impact of the crises in the regression in Table 3 and Table 4. The Dot.Com and Ukraine crisis show a small positive and negative correlation however the results are statistically insignificant and should be interpreted with caution. The results are consistent and only exhibit minor changes over adjusted average initial returns and standard deviation and with the omitted data sample.

Table 2: Correlation matrix: Plots the correlation of IPO market characteristics against five metrics, average initial return, standard deviation of initial return, number of listed firms, average adjusted initial return and adjusted standard deviation. They are shown in both the full sample and the omitted sample.

	1999–2023					1999-2023 (omitting bubble)				
	Average IPO Initial Return	Std. Dev. of IPO Initial Returns	Number of Listed Firms	Average Adjusted Initial Returns	Adjusted Std.Dev Initial Returns	Average IPO Omitting Bubble	Std. Dev. of IPO	Number of Initial Returns	Average Adjusted Listed Firms	Adjusted Std.Dev Initial Returns
Crisis Dummy	-0.02	-0.01	-0.06	-0.01	-0.01	0.11	0.09	0.00	0.14	0.09
	(0.697)	(0.847)	(0.409)	(0.894)	(0.806)	(0.199)	(0.215)	(0.975)	(0.099)	(0.234)
Percentage NYSE	-0.27	-0.37	-0.33	-0.27	-0.37	-0.18	-0.32	-0.24	-0.18	-0.32
	(.000)	(.000)	(.000)	(.000)	(.000)	(0.022)	(0.000)	(0.000)	(0.020)	(0.000)
Percentage Nasdaq	0.27	0.37	0.33	0.27	0.37	0.17	0.32	0.24	0.18	0.32
	(.000)	(.000)	(.000)	(.000)	(.000)	(0.023)	(0.000)	(0.000)	(0.020)	(0.000)
DotCom Dummy	0.03	0.03	0.02	0.05	0.03	0.14	0.11	0.07	0.18	0.11
	(0.641)	(0.594)	(0.794)	(0.410)	(0.645)	(0.160)	(0.164)	(0.473)	(0.069)	(0.188)
Financial Crisis Dummy	-0.12	-0.13	-0.06	-0.12	-0.13	-0.11	-0.12	-0.03	-0.11	-0.12
	(.000)	(.000)	(.208)	(.000)	(.000)	(0.001)	(0.000)	(0.555)	(0.001)	(0.000)
Covid19 Dummy	0.13	0.08	-0.01	0.11	0.08	0.24	0.13	0.00	0.22	0.14
	(.000)	(.024)	(.827)	(.000)	(.027)	(0.000)	(0.003)	(0.979)	(0.000)	(0.003)
Ukraine Invasion Dummy	-0.05	0.07	-0.10	-0.03	0.07	-0.05	0.12	-0.11	-0.02	0.12
	(.595)	(.630)	(.000)	(.738)	(.613)	(0.749)	(0.546)	(0.000)	(0.907)	(0.526)
Bubble Period Dummy	0.69	0.60	0.44	0.70	0.60	—	—	—	—	—
	(.000)	(.000)	(.000)	(.000)	(.000)	—	—	—	—	—

Table 3

Table 3. An OLS Regression on crises full sample: Relation between crises and Average initial return, Standard deviation of IPO initial return, Number of IPO's Adjusted initial return and adjusted standard deviation by using full sample. Calculated trough:

$$IR_u = \beta_0 + \beta_1 Crisis\ Dummy_u + \varepsilon_u$$
$$IR\sigma_u = \beta_0 + \beta_1 Crisis\ Dummy_u + \varepsilon_u$$
$$Number\ of\ IPO_u = \beta_0 + \beta_1 Crisis\ Dummy_u + \varepsilon_u$$
$$Adjusted\ IR_u = \beta_0 + \beta_1 Crisis\ Dummy_u + \varepsilon_u$$
$$Adjusted\ IR\sigma_u = \beta_0 + \beta_1 Crisis\ Dummy_u + \varepsilon_u$$

	Average IPO Initial Return	Std. Dev. of IPO Initial Return	Number of IPOs	Average Adj. IPO Initial	Std. Dev. of Adj. IPO Initial Return
Intercept	23.891 (.000)	41.848 (.000)	10.958 (.000)	23.058 (.000)	45.693 (.000)
Crisis Dummy	-5.267 (.217)	-8.170 (.111)	-2.738 (.015)	-3.712 (.374)	-12.340 (.034)
R^2	0.005	0.009	0.021	0.003	0.020

Table 4:

Table 4. An OLS Regression on crises omitted sample: Relation between crises and Average initial return, Standard deviation of IPO initial return, Number of IPO's Adjusted initial return and adjusted standard deviation by using omitted sample. Calculated trough:

$$IR_u = \beta_0 + \beta_1 Crisis\ Dummy_u + \varepsilon_u$$
$$IR\sigma_u = \beta_0 + \beta_1 Crisis\ Dummy_u + \varepsilon_u$$
$$Number\ of\ IPO_u = \beta_0 + \beta_1 Crisis\ Dummy_u + \varepsilon_u$$
$$Adjusted\ IR_u = \beta_0 + \beta_1 Crisis\ Dummy_u + \varepsilon_u$$
$$Adjusted\ IR\sigma_u = \beta_0 + \beta_1 Crisis\ Dummy_u + \varepsilon_u$$

	Average IPO Initial Return	Std. Dev. of IPO Initial Return	Number of IPOs	Average Adj. IPO Initial	Std. Dev. of Adj. IPO Initial Return
Intercept	17.632 (.000)	34.778 (.000)	9.879 (.000)	16.829 (.000)	37.645 (.000)
Crisis Dummy	0.991 (.745)	-1.100 (.781)	-1.660 (.097)	2.517 (.391)	-4.291 (.339)
R^2	0.000	0.000	0.010	0.003	0.004

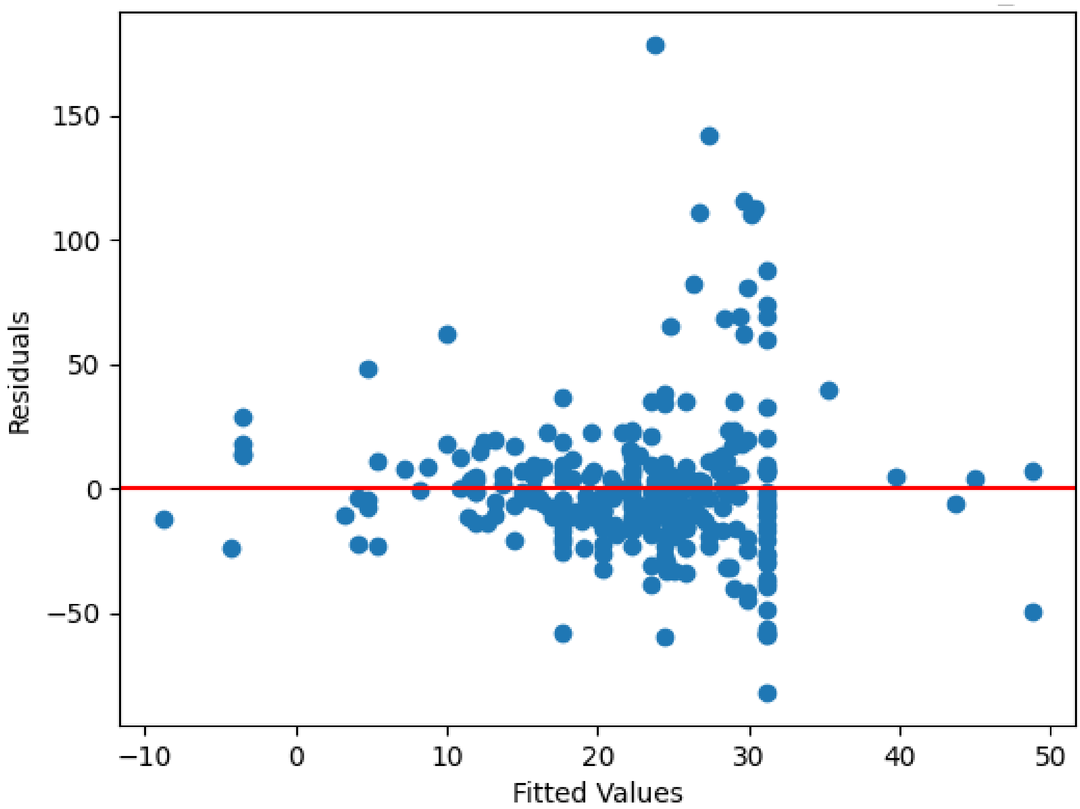
In table 3 and 4 the output of the OLS regression with and without the omitted period is plotted. Interpreting table 3 the intercept seems to be positive and statistically significant, and the average IPO initial return is 23.89% in the "normal" state. During crises both the adjusted average and average initial return decreases however we note that it is interpreted with caution as the dummy variable is statistically insignificant. It could imply that different crises have different effects on initial return and adjusted initial return. Although the model can, with significance, predict that during crises the standard deviation of adjusted IPO initial return decreases by 12.34 percentage points thus, the IPO market relative to the overall market seems to be less volatile. We also find that the number of IPOs seem to decrease showing less IPO activity in crises.

Comparing the results to table 4 we see a clear drop in all intercept values in the omitted data. In this dataset we recognize that both the adjusted average, and average initial return instead increase in crises, although these variables do not show statistical significance. The dummy variable explains little variation in IPO performance thus other explanatory parameters have to be further investigated. To capture a better model, we further examine and plot each specific crisis against our dependent variables, shown in table 5.

Due to the statistically insignificant result for the crisis dummy variable, we use the White's test to look if our cross-sectional OLS regression shows indications of Heteroscedasticity. Standard deviation of initial return, number of listed firms or adjusted standard deviation results in a p-value above 0.05 which suggest that there is not enough evidence to reject the null hypothesis of homoscedasticity. Therefore, we assume these variables to have homoscedasticity. However, both average initial return and adjusted average initial return shows a p-value close to 0.00 which is below the conventional p-value of 0,05, we therefore reject the null hypothesis. Thus, there is significant statistical evidence of heteroskedasticity in the model with average initial return and adjusted average initial return. Due to this we will use a WLS regression to fit the data since it enables us to measure both the level and uncertainty of independent variables affecting average initial return and adjusted average initial return. We believe the WLS regression will be a better fit for these two dependent variables since heteroscedastic predicts the amounts of the residual values in the fitted OLS model as seen in figure 4. The OLS model will be used as a benchmark against the WLS regression as also done by Lowry et al (2010).

Figure 4

Figure 4. Residual values plotted: Residual values from OLS regression vs the fitted values plotted to examine heteroskedasticity in the average initial return for data between 1999-2023.



Due to the fact that standard deviation of initial return, number of listed firms and adjusted standard deviation indicates no heteroscedasticity and the independent variables indicate no multicollinearity, we will perform a cross-sectional OLS regression. Table 5 shows the OLS regression for three different periods, the full sample period from 1999-01-01 to 2023-09-30, the full sample period and adding the bubble dummy variable indicating one if the IPO occurs from 1999-01-01 to 2000-02-29, and zero otherwise.

The last column shows the omitted data set (excluding 1999-01-01 to 2000-02-29 from the full data set). When interpreting table 5, the coefficients of all independent variables of the full sample differ considerably from the result of the full sample with bubble dummy and omitted sample. This leads to the same conclusion presented in Lowry (2010) that, restricting coefficients on all independent variables through the entire data period, leads to misinterpretations and biased interference. Due to this and the significantly higher r-squared value when the bubble dummy is included, we will focus the discussion on the full sample with bubble dummy to avoid misinterpretations.

Table 5

Table 5. An OLS regression using Variance, Number of IPO and Adjusted standard deviation as dependent variables. An OLS regression calculated by using Standard deviation of initial return (Variance), Number of IPO and Adjusted standard deviation as dependent variables. Each regression is done through three different sets: Full sample including all data, Full sample with Bubble Dummy includes the Bubble Dummy and the Omitted Sample omitted 1999-01-01 to 2000-02-29 from the full data.

	Full Sample			Full sample with Bubble Dummy			Omitted Sample		
	Variance	Number of IPO	Adjusted Std.Dev	Variance	Number of IPO	Adjusted Std.Dev	Variance	Number of IPO	Adjusted Std.Dev
Intercept	49.179 (.000)	12.741 (.000)	46.433 (.000)	38.039 (.000)	10.970 (.000)	34.970 (0.000)	38.375 (.000)	10.791 (.000)	35.299 (.000)
Percentage NYSE	-37.776 (.000)	-6.579 (.000)	-36.202 (0.001)	-20.571 (0.009)	-3.844 (0.020)	-18.498 (0.022)	-21.757 (0.005)	-3.214 (0.052)	-19.658 (0.014)
Crisis DotCom	2.029 (0.748)	-0.027 (0.988)	0.771 (0.910)	8.593 (0.172)	1.017 (0.583)	7.525 (0.270)	8.572 (0.172)	1.028 (0.581)	7.505 (0.270)
Crisis Global Financial	-13.178 (0.001)	-3.975 (.000)	-20.876 (.000)	-8.349 (0.011)	-3.207 (0.003)	-15.906 (0.000)	-8.251 (0.013)	-3.259 (0.003)	-15.810 (.000)
Crisis Covid19	10.140 (0.459)	-1.798 (0.561)	12.717 (0.356)	17.944 (0.152)	-0.558 (0.854)	20.746 (0.099)	17.837 (0.157)	-0.501 (0.868)	20.642 (0.102)
Crisis Ukraine	3.143 (0.888)	-7.844 (.000)	-0.674 (0.977)	11.417 (0.613)	-6.529 (.000)	7.839 (0.738)	11.278 (0.617)	-6.455 (.000)	7.703 (0.742)
Bubble period	Nan (.000)	Nan (.000)	Nan (.000)	98.080 (.000)	15.591 (.000)	100.921 (0.000)	Na (.000)	Na (.000)	Na (.000)
R-squared	0.078	0.075	0.090	0.383	0.233	0.388	0.069	0.051	0.084

We find that IPOs issued during the Dot.Com tend to be more volatile, displayed with statistically insignificant positive standard deviation of initial return. The NYSE variable confirms previous findings with a negative coefficient, companies issuing on NYSE tend to experience less volatility in their average initial returns also found in Lowry et al (2010). We see that when including the bubble period, the variance and adjusted standard deviations increases significantly and confirms that the bubble period affects the volatility in underpriced IPOs with statistical significance.

We perform a WLS regression due to the heteroscedasticity in our data set in average initial return and adjusted initial return. Table 6 also presents the OLS regression as a benchmark against the WLS. Table 6 presents the data in three subsets, full Sample, full sample with bubble dummy and omitted sample. The WLS regression illustrates the same as the OLS, the coefficients of all independent variables of the full sample differ considerably from the result of the full sample with bubble dummy and omitted sample.

With the same reasoning, will we focus this discussion on the output from the full sample with bubble period.

Table 6

Table 6. An OLS and WLS regression calculated by using average initial return (Mean) and adjusted initial return (Adjusted Mean) as dependent variables. Each regression is done through three different sets: Full sample including all data, Full sample with Bubble Dummy includes the Bubble Dummy and the Omitted Sample omitted 1999-01-01 to 2000-02-29 from the full data.

	Full Sample				Full sample with Bubble Dummy				Omitted Sample			
	OLS		WLS		OLS		WLS		OLS		WLS	
	Mean	Adjusted Mean	Mean	Adjusted Mean	Mean	Adjusted Mean	Mean	Adjusted Mean	Mean	Adjusted Mean	Mean	Adjusted Mean
Intercept	31.226 (.000)	30.296 (.000)	29.112 (.000)	28.443 (.000)	20.698 (.000)	19.813 (0.000)	20.326 (.000)	19.538 (.000)	21.555 (.000)	20.280 (0.000)	20.731 (.000)	19.994 (0.000)
Percentage NYSE	-27.061 (.000)	-26.720 (.000)	-24.168 (0.000)	-24.571 (0.000)	-10.803 (0.075)	-10.512 (0.075)	-10.605 (0.013)	-10.622 (0.011)	-12.412 (0.038)	-12.160 (0.036)	-11.864 (0.006)	-12.030 (0.004)
Crisis DotCom	-1.320 (0.825)	1.478 (0.792)	-1.763 (0.761)	0.686 (0.904)	4.883 (0.402)	7.655 (0.162)	2.477 (0.671)	4.975 (0.383)	4.855 (0.404)	7.625 (0.162)	2.208 (0.699)	4.682 (0.402)
Crisis Global Financial	-7.736 (0.037)	-6.941 (.045)	-0.191 (.965)	0.932 (0.827)	-3.172 (0.324)	-2.397 (0.414)	-0.982 (0.727)	-0.039 (0.989)	-3.039 (.347)	-2.261 (0.443)	-0.383 (0.898)	0.612 (0.834)
Crisis Covid19	17.563 (0.111)	-14.390 (0.159)	28.204 (0.010)	24.628 (0.024)	24.937 (0.013)	21.733 (0.018)	30.798 (0.002)	27.350 (0.004)	24.792 (0.014)	21.585 (0.020)	31.481 (0.001)	27.985 (0.004)
Crisis Ukraine	-26.461 (0.021)	-21.170 (.069)	-32.132 (0.03)	-26.530 (0.07)	-18.643 (0.127)	-13.385 (0.277)	-24.688 (0.031)	-19.226 (.084)	-18.832 (0.121)	-13.578 (0.266)	-25.570 (0.030)	-20.077 (0.081)
Bubble period	Na (.000)	Na (.000)	Na (.000)	Na (.000)	92.682 (.000)	92.291 (0.000)	96.097 (.000)	95.715 (.000)	Na (.000)	Na (0.000)	Na (0.000)	Na (0.000)
R-squared	0.067	0.062	0.107	0.099	0.454	0.464	0.155	0.149	0.067	0.063	0.086	0.076

In the Dot.Com bubble there seems to be more underpricing due to the positive coefficient on average initial return. In Global Financial Crises there seem to be a negative coefficient showing less underpricing. These results are statistically insignificant and should be interpreted with caution. However, the average initial return and adjusted average initial return show with statistically significance a positive impact with 30.8 percentage points during the Covid-19 crisis confirming results from table 2 that there is a positive correlation between Covid-19 and IPO underpricing. During Covid-19 IPOs tend to be more underpriced. Furthermore, we also see that there is a negative correlation between the Ukraine Crisis and IPO underpricing. This was expected and is in line with our predictions that crises will not have a positive impact on IPO underpricing. Overall, our findings confirm our predictions, crises do not have a positive effect on IPO underpricing except in Covid-19.

5. Conclusion

The primary objective of this paper was to extend the findings and complement Lowry et al (2010) with a different data set ranging from 1999 to 2023 to see if their findings stay true still today. Our results affirm this, there is a correlation between dispersion of initial returns each month and the average initial monthly return. The volatility of the average monthly initial return shows great significance and varies over time, confirming the cyclicality pattern explored by Young et al (2006).

To deeper compliment Lowry et al (2010) we further examine the relationship that general crises have with IPO underpricing. The correlation of general crises to underpricing seems to be insignificant in our results and our model explains little of the underlying variables in this stage. We find that there is a negative correlation and that during crises there seems to be less underpricing complementing theories such as Helwege & Liang (2004) and Lowry & Schwert (2002) however our findings are not statistically significant. These results show that there are other variables better explaining this relationship.

Due to no general correlation, we instead check if there are any specific crises that affect IPO underpricing. We find a noticeable exception, there is a positive correlation between Covid-19 and IPO underpricing. During the Covid-19 crisis IPOs tend to be more underpriced shown in both the average initial return but also the adjusted plotted against the S&P 500 index. This raises a series of questions, why is there a difference in IPO underpricing between Covid-19 and other crises? This could further be looked at by examining other valuables across crises such as our table in the appendix.

Issuers undergoing an IPO based on our results should not fear underpricing as much during crises in general due to the fact that they tend to be less underpriced and less volatile. However, it should be noted that unordinary circumstances where there is a lot of uncertainty such as Covid-19 might be different.

6. Limitations

This study aims to look at how different crises affect IPO underpricing in the US market in the 21st century. The outputs show how different crises have different effects on IPO underpricing. However, when using different crises as a combined variable, it is important to acknowledge that different crises have unique characteristics. Therefore, one limitation to this study is the way crises are combined but also in the way the different crisis periods are defined. Instead, further research could look at different measurements to determine a crisis, for example by measuring GDP growth, inflation rate and IPO activity.

The IPO market is a dynamic market influenced by several different exogenous factors, which is hard to capture in just a few independent variables, therefore another limitation is that we only used the S&P 500 index as a market adjuster, another approach would be to include several market adjusters to further capture the dynamic market influencers. One could also look further into different industries and what effect these crises have on IPO underpricing in specific industries. Another approach to capture more market dynamic influences is to use a larger sample and not only focus the data on the US market. All of these areas could be used for further research in how crisis affect IPO underpricing.

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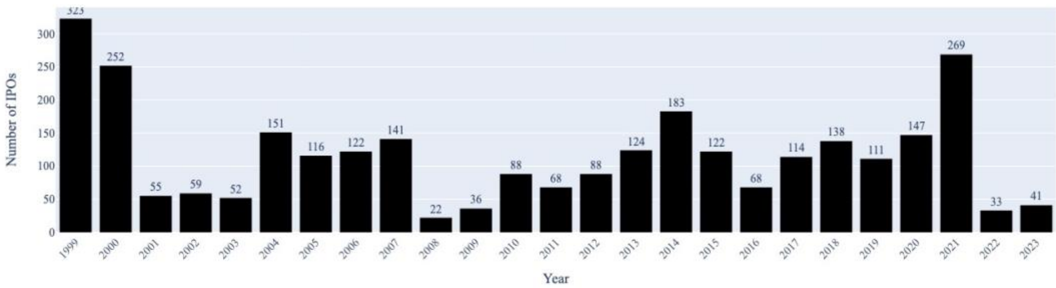
8. Appendix

Appendix A: Figure 1

Figure 1: Issued IPOs: 1999-2023 in the US Stock Market



Appendix B

We note that a lot of research looks at firm specific variables for underpricing and that there might be a correlation between industries and underpricing in IPOs. Thus, we plotted a table of different sectors to see the average initial return, median and standard deviation across the full sample, omitted sample and across the crises.

The tech sector especially stands out and has high initial return and standard deviation in every time period except the Ukraine crisis. This is not surprising, and in line with previous research, Lowry et al (2010) finds that tech firms experience a lot of pricing problems and are underpriced on average. Consumer Cyclicals are also above the mean and standard deviation for all sectors in every period except the Ukraine crisis and could experience a lot of information asymmetry causing a lot of high average initial returns that are very volatile. It is worth mentioning that Healthcare and Industrials exhibit substantial greater average initial return in Covid-19 crisis, compared to all other periods. This could be a base for further research to recognize the correlation between industries and IPO underpricing in crises to see if there is a pattern. The results of such further research could be of great importance for issuers when pricing their IPOs in order to price them correctly.

Nummer	Period	Sector	N	Mean	Median	Standard Deviation
0	1999-2023	All Sectors	285	22.5	16.2	31.4
6	1999-2023	Technology	201	41.4	24.8	76.7
7	1999-2023	Consumer Cyclicals	160	19.0	15.6	43.8
8	1999-2023	Academic & Educational Services	24	22.5	15.1	44.0
9	1999-2023	Financials	156	17.0	11.0	38.2
10	1999-2023	Industrials	144	20.8	12.9	32.1
11	1999-2023	Healthcare	230	22.3	14.7	56.4
12	1999-2023	Consumer Non-Cyclicals	61	28.2	18.1	57.7
13	1999-2023	Basic Materials	56	11.8	8.7	28.2
14	1999-2023	Energy	83	5.5	5.3	20.5
15	1999-2023	Utilities	16	6.2	10.8	26.3
16	1999-2023	Real Estate	48	4.0	0.6	17.5
17	1999-2023	Institutions, Associations & Organizations	2	-10.5	-10.5	0.1
18	1999-2023	Government Activity	1	14.3	14.3	NaN
1	1999-2023 omitting specified periods	All Sectors	271	17.9	15.5	22.2
19	1999-2023 omitting specified periods	Technology	187	33.4	22.5	70.6
20	1999-2023 omitting specified periods	Consumer Cyclicals	147	17.3	14.9	41.4
21	1999-2023 omitting specified periods	Academic & Educational Services	19	18.0	20.9	31.7
22	1999-2023 omitting specified periods	Financials	145	12.3	10.3	22.6
23	1999-2023 omitting specified periods	Industrials	132	16.1	12.4	25.4
24	1999-2023 omitting specified periods	Healthcare	222	16.7	13.8	27.5
25	1999-2023 omitting specified periods	Consumer Non-Cyclicals	55	26.7	18.4	54.4
26	1999-2023 omitting specified periods	Basic Materials	53	13.0	11.0	28.6
27	1999-2023 omitting specified periods	Energy	79	5.7	5.3	20.6
28	1999-2023 omitting specified periods	Utilities	16	6.2	10.8	26.3
29	1999-2023 omitting specified periods	Real Estate	48	4.0	0.6	17.5
30	1999-2023 omitting specified periods	Institutions, Associations & Organizations	2	-10.5	-10.5	0.1
31	1999-2023 omitting specified periods	Government Activity	1	14.3	14.3	NaN
...						

Nummer	Period	Sector	N	Mean	Median	Standard Deviation
2	Dot-Com Bubble	All Sectors	28	22.7	14.6	31.2
32	Dot-Com Bubble	Technology	21	36.1	27.0	42.7
33	Dot-Com Bubble	Consumer Cyclicals	10	2.7	0.9	29.9
34	Dot-Com Bubble	Academic & Educational Services	0	NaN	NaN	NaN
35	Dot-Com Bubble	Financials	12	6.9	13.1	24.3
36	Dot-Com Bubble	Industrials	14	26.4	22.1	26.3
37	Dot-Com Bubble	Healthcare	26	16.8	13.4	31.2
38	Dot-Com Bubble	Consumer Non-Cyclicals	6	52.2	42.8	39.3
39	Dot-Com Bubble	Basic Materials	4	51.5	27.4	67.4
40	Dot-Com Bubble	Energy	7	-15.6	-14.3	20.4
41	Dot-Com Bubble	Utilities	2	0.5	0.5	34.8
42	Dot-Com Bubble	Real Estate	0	NaN	NaN	NaN
43	Dot-Com Bubble	Institutions, Associations & Organizations	0	NaN	NaN	NaN
44	Dot-Com Bubble	Government Activity	0	NaN	NaN	NaN
3	Global Financial Crisis	All Sectors	34	13.1	11.4	17.3
45	Global Financial Crisis	Technology	19	18.1	15.3	30.4
46	Global Financial Crisis	Consumer Cyclicals	13	14.5	19.9	19.3
47	Global Financial Crisis	Academic & Educational Services	6	38.9	33.4	41.5
48	Global Financial Crisis	Financials	15	9.1	3.2	27.8
49	Global Financial Crisis	Industrials	18	17.1	13.8	24.5
50	Global Financial Crisis	Healthcare	18	5.5	4.9	14.8
51	Global Financial Crisis	Consumer Non-Cyclicals	2	3.7	3.7	9.9
52	Global Financial Crisis	Basic Materials	6	13.1	14.1	27.8
53	Global Financial Crisis	Energy	13	-0.9	-0.4	15.1
54	Global Financial Crisis	Utilities	1	-1.6	-1.6	NaN
55	Global Financial Crisis	Real Estate	1	0.2	0.2	NaN
56	Global Financial Crisis	Institutions, Associations & Organizations	0	NaN	NaN	NaN
57	Global Financial Crisis	Government Activity	0	NaN	NaN	NaN
...						

Nummer	Period	Sector	N	Mean	Median	Standard Deviation
4	Covid-19	All Sectors	6	43.5	46.7	25.1
58	Covid-19	Technology	3	72.1	85.6	61.5
59	Covid-19	Consumer Cyclicals	2	-10.4	-10.4	15.7
60	Covid-19	Academic & Educational Services	1	-13.7	-13.7	NaN
61	Covid-19	Financials	4	42.9	42.2	10.5
62	Covid-19	Industrials	2	82.4	82.4	20.6
63	Covid-19	Healthcare	6	49.9	56.0	35.6
64	Covid-19	Consumer Non-Cyclicals	1	73.3	73.3	NaN
65	Covid-19	Basic Materials	1	35.2	35.2	NaN
66	Covid-19	Energy	0	NaN	NaN	NaN
67	Covid-19	Utilities	0	NaN	NaN	NaN
68	Covid-19	Real Estate	1	-48.0	-48.0	NaN
69	Covid-19	Institutions, Associations & Organizations	0	NaN	NaN	NaN
70	Covid-19	Government Activity	0	NaN	NaN	NaN
5	Ukraine Invasion Crisis	All Sectors	5	0.3	-2.9	31.9
71	Ukraine Invasion Crisis	Technology	1	-50.0	-50.0	NaN
72	Ukraine Invasion Crisis	Consumer Cyclicals	1	-47.2	-47.2	NaN
73	Ukraine Invasion Crisis	Academic & Educational Services	1	-4.6	-4.6	NaN
74	Ukraine Invasion Crisis	Financials	1	6.8	6.8	NaN
75	Ukraine Invasion Crisis	Industrials	2	-5.8	-5.8	8.6
76	Ukraine Invasion Crisis	Healthcare	5	11.3	-2.9	50.9
77	Ukraine Invasion Crisis	Consumer Non-Cyclicals	1	-65.2	-65.2	NaN
78	Ukraine Invasion Crisis	Basic Materials	0	NaN	NaN	NaN
79	Ukraine Invasion Crisis	Energy	0	NaN	NaN	NaN
80	Ukraine Invasion Crisis	Utilities	0	NaN	NaN	NaN
81	Ukraine Invasion Crisis	Real Estate	0	NaN	NaN	NaN
82	Ukraine Invasion Crisis	Institutions, Associations & Organizations	0	NaN	NaN	NaN
83	Ukraine Invasion Crisis	Government Activity	0	NaN	NaN	NaN
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Appendix C

AI has been used in this research to help produce a framework for python code, graphs, regressions and models. It has also been used for reference formatting and grammar/spell-check.