RAISING CAPITAL DURING A CRISIS

AN INVESTIGATION ON MARKET REACTIONS TO EQUITY RAISES THROUGH RIGHTS OFFERINGS AND PRIVATE PLACEMENTS IN PUBLIC EQUITY BEFORE AND DURING THE PANDEMIC

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Raising Capital During a Crisis: An Investigation on Market Reactions to Equity Raises Through Rights Offerings and Private Placements in Public Equity Before and During the Pandemic.

Abstract:

This study examines returns following announcement of upcoming private placements and rights offerings, before and during the Covid-19 pandemic, to measure investor preferences in method of equity financing. The results produced did not differ significantly between the time periods. An increase in preferences for private placements in public equity over rights offerings was noted but could not be statistically proven. We used a matching algorithm to identify announcements and corresponding returns of companies that shared similar qualities, a method that we believe can be expanded upon to yield more elaborate and significant results in future applications.

Keywords:

Private Placements in Public Equity, Rights Offerings, Market Sentiment, Covid-19, Machine Learning

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1. Introduction & Background

The Covid-19 pandemic impacted the world in many ways, and the financial markets were no exception. The spread of the virus and the following economic impact created considerable uncertainty. Governments and central banks responded in numerous ways to maintain economic and financial stability, wherein several actions were directed to ensure continued liquidity and predictability in financial markets. This paper aims to investigate whether investor preferences regarding equity financing changed during the pandemic as opposed to the years before it. We measure the relative returns of matched pairs of private placements in public equity ("PIPEs") and rights offerings, which aggregated provide how the transactions were received in the market before and during the pandemic. If relative reactions change significantly, this should imply a shift in preferences, with implications on how investors interpret signals implied by the offerings regarding, among other things, corporate governance, investment opportunities, and firm financial health. It is our hope that such insight can be leveraged to better understand investor behavior in times of uncertainty.

Earlier papers have examined the performance of companies announcing PIPEs and rights offerings, upon which we extend the existing research by adding a temporal comparative dimension, as well as a larger emphasis on comparing returns through matching. We also conduct four regressions, one on each final dataset, to control the integrity of transaction type as key in explaining announcement day returns.

The study did not produce statistically significant changes in relative returns between the two time periods examined. We can therefore not with certainty conclude that investor preferences regarding method of equity financing changed during the pandemic, though the results indicate that such a shift did take place in favor of PIPEs. Both average and median relative returns yield this implication, supported by a strong performance of PIPEs during the pandemic which was not counteracted by a similarly strong trend among rights offerings. The volatile markets of the pandemic might have valued the signaling made available by PIPEs. It is possible that an improved matching algorithm and corresponding larger final datasets would produce similar results at significant levels.

1.1 Private Placements in Public Equity

PIPEs are a way of raising capital through the issuance of primary equity to a select group of investors. Non-participating shareholders, which in publicly traded firms are the majority, thus suffer from dilution. The firm issuing equity can, together with its advisors, effectively choose its new shareholders. This, in conjunction with their relative time advantage due to a discretionary book building process as opposed to a subscription period, makes them a preferable method of raising capital when the firm in question desires flexibility. The ability to control what new shareholders gain influence in the company has several implications. Firstly, it allows the selection of strategically more advantageous shareholders, with regards to stated intentions, investment horizon, reputation, and expertise. Secondly, this power to select investors allows management to shift the distribution of votes in what direction they deem desirable, thus entailing effects on corporate governance-related matters. This stems from that the capital raised is distributed among a smaller number of investors, resulting in those investors partaking to greater extents acquire considerable voting rights. The selective targeting of investors enables companies and potential investors to enter discussions during the book building process, before public announcements of upcoming transactions. While no binding agreements are to be reached before such announcements, details and corresponding intentions can be indicated. PIPEs are common among relatively smaller firms that seek quick access to capital and lower issuance costs. These lower costs are offset by higher expected returns from investors in contrast to other forms of equity financing (Lim et al., 2021).

1.2 Rights Offerings

Rights offerings are a more conventional method for raising capital via primary equity, wherein existing shareholders receive subscription rights at a predetermined pro rata number which in turn is based on shareholding at a set and publicly announced date. Subscription rights can in turn be traded during a subscription period, after which the rights can be exchanged for the right to subscribe for new shares at a fixed exchange rate. This method of equity issue allows existing shareholders to preserve their ownership share, as subscribing the entire stock of subscription rights given pro rata fully protects from dilution. Transactions can be structured in several ways, with or without underwriting and guarantors, including solutions where the transaction is not carried through if a certain threshold of subscribed shares is not reached, that a subscription period where no subscription rights are needed to subscribe for new shares is held after the initial subscription period, or that the transaction is completed regardless of participation. Rights offerings entail a more complicated structuring process than PIPEs as the timeline of any given transaction is longer and includes a significantly larger number of participants. As opposed to

PIPEs, changes in shareholding structure are decided by the market rather than the issuing firm, since firms do not control what investors hold subscription rights at the control date.

1.3 Signaling Through Financing

The matter of asymmetric information is highly present in the context of equity issues, stemming from the superior insight and understanding of the firm in question that management possesses as compared outside investors. As illustrated by Akerlof (1970), the effects of a seller and buyer not acting upon the same level of information creates the risk of no buyer being willing to pay more than the expected value in the worst state. In terms of equity, this would imply that investors would in theory only participate in an offering of new equity if the worst possible expected return would be positive. Myers & Majluf, (1984) elaborate on this reasoning, pointing out that management that operate with the aim to maximize shareholder value will choose financing alternatives in a certain order based wherein equity is to be used as a last resort, preceded by retained earnings and debt, known as the pecking order hypothesis. This reasoning is based on several considerations, but most relevant for this paper are the implications of information asymmetry. In an effort to minimize cost of capital, management is only incentivized to issue equity when no other financing is available at reasonable conditions, or when the share price is exceeding levels that can be motivated by intrinsic value. Both conclusions imply that the announcement of an equity issue signals to investors that the outlook of the firm has hindered it from financing operations or new projects through other means, or that the implied valuation of the offering exceeds intrinsic value. The pecking order hypothesis does not differentiate between different types of equity offerings, but rather the different levels of information asymmetry in terms of investment opportunities and firm health. For the sake of this paper, such reasoning could be applied to the market reaction to announcements of PIPEs and rights offerings, wherein shifts in relative reactions in the market could imply a corresponding shift in either how signals are interpreted among investors, or what details the choice of equity offering signals to investors.

1.4 Financial Markets during Covid-19

Relevant for this paper, and a significant basis for the reasoning on possible shifts in investor sentiment, are the market conditions that have prevailed in the wake of the Covid-19 pandemic. As yields (CNBC, 2022) and stock indices dropped (S&P Dow Jones Indices, 2022), The Federal Reserve countered by announcing decreases to the federal fund's rate on two occasions, on the third and fifteenth of March 2020, of which the latter was accompanied by the announcement of an expansion of the Federal Reserve balance sheet through asset purchases. These and other measures taken were intended to provide sufficient liquidity and demand in the financial markets to ensure their continued functioning, to in turn support economic outlook (The Federal Reserve, 2020). The asset purchases were as significant in magnitude and at their most intensive during the remainder of March until early June, though the program of quantitative easing is still ongoing as of March 2022 (The Federal Reserve, 2022).

Considering the market uncertainty and government and central bank stimulus, Jha, Liu and Manela (2021) investigate sentiment towards finance during natural disasters, including epidemics, using data from 1870 to 2009. By combining quantified linguistic trends in literature and natural disaster data, general interest and sentiment towards the financial markets are estimated to decrease and worsen following their occurrence. This shift is counteracted by positive stock market performance induced by large government and central bank interventions. When applying this methodology to finance sentiment in the US during the Covid-19 pandemic, the authors find a noticeable decrease following the outbreak of the pandemic, followed by a rebound shortly after. They relate this to the strong performance of the generally forward-looking equity markets, which through government intervention-induced performance regained legitimacy. They conclude by pointing out a weak but positive correlation between fiscal responses to the pandemic and news-based finance sentiment. The initial decrease and subsequent increase of trust in the financial markets among the public is mirrored by the development of sentiment among institutional investors, as highlighted by BCG's series of surveys Covid-19 Investor Pulse Check (2020, 2021). In its early editions, a majority of investors expressed a pessimistic outlook for the remainder of the year. Investors sought firms that could act with flexibility, with a majority seeking revised earnings guidance as well as transparent and increased communication on short-term plans. A majority also expressed that firms should prioritize investments rather than margin retention or expansion, as well as dividends and share repurchases. Initial preferences for financing were in line with the pecking order hypothesis. By the end of 2020, on the other hand, only a quarter of respondents were bearish, with an increasing share expecting positive developments from the economy and the stock market. The sentiment towards issuing equity as a means for financing investments had also grown more positive, equaling preference for debt. Institutional participants in the market thus revised their expectations upward, with an increased emphasis on the importance of equity financing.

2. Literature

(Andriosopoulos & Panetsidou, 2021) evaluate announcement returns as well as long-term share price performance of companies issuing equity via PIPEs during the period 1995-2015, taking details on geography and the structure of the transactions into consideration. They find that announcements of traditional PIPEs of common stock in the United States on average yield a positive abnormal return of 2.03%, statistically significant at the 1% level. The other forms of PIPEs accounted for generally result in inferior announcement returns, apart from PIPEs of non-convertible debt and preferred stock as well as structured PIPEs of floating convertibles. Long-term share price performance was found to be significantly negative following PIPEs. They also conclude that firms issuing stock through PIPEs repeatedly see less positive market reactions on announcement. Announcement returns have decreased globally over time after 2005, though to a lesser extent in the US as compared to non-US markets. It is concluded that a growing proportion of PIPEs are issued by smaller firms that to an increasing extent have worse financial fundamentals. Furthermore, when controlling for differences in regulatory environments and government corruption, markets performing better in such regard also see greater announcement returns, implying a link between perceived quality of investor protection and market sentiment. Finally, Andriosopoulos and Panetsidou find an increasing use of PIPEs among smaller firms in the latter half of their studied period, 2005-2015. These findings are highly relevant to us as we would expect to see similar patterns in returns following announcements of PIPEs. Though we are investigating the returns on the first trading day after announcement as opposed to the longer time periods of their study, we can examine the implied signaling and market interpretation of such signals. If there is a significant shift in market reception, this could imply that market sentiment has changed.

Chen et al., (2010) investigate the rationale behind firms' choices between PIPEs and SEOs. They conclude that PIPEs are more likely to be used if a company has poor operational performance and higher levels of information asymmetry between company management and outside investors, thus having limited access to capital markets. PIPEs are in that regard to be considered a last resort for firms seeking equity financing. It is also concluded that, in terms of valuation, there is a positive correlation between use of PIPEs and stock undervaluation, implying that firms turn to private investors with the expectation that they will conduct a due diligence process which will reflect the intrinsic value of the company. Lastly, it is concluded that PIPEs are chosen due to a relative cost advantage in issuance-related costs. The authors also investigate returns in relation to SEOs and PIPEs around announcement as well as in the long-term. Returns around announcements were found to be significantly positive for PIPEs and negative for SEOs. They relate this to the undervaluation of the share price that PIPEs may signal. Long-term returns were negative for both methods, with PIPEs performing worse than SEOs. As these results are comparative in nature, they provide valuable guidance on the patterns of returns that we can expect to find in the data. As with the article by Andriosopoulos and Panetsidou (2021), we can benchmark our findings against this previous research to examine whether the market perceives the announcements of equity offerings differently during the particular market conditions of the pandemic. The article also provides a strong baseline for a continued interpretation of market reactions to equity issuances, especially with regards to the matters of performance and valuation and the choice of financing.

White & Lusztig, (1980) investigate the effects on share price that announcements of rights offerings entail. They conclude, through a regression model, that returns upon announcement of upcoming rights offerings on average are significantly negative. They defer further investigation as to why the market typically reacts negatively to such announcements to further research, but assess that rights offerings are interpreted as negative signals by investors. They also examine potential differences between returns following announcement and returns of the same stock five trading days after announcement. They conclude that these do not differ to an extent that is significant and interpret this as a sign that investors assimilate information conveyed by announcements quickly, implying support for the efficient capital market hypothesis. While the article, and the data upon which it is based, is old, its conclusions on market reaction to announcements of rights offerings is relevant to our paper. We expect our findings on returns following announcements of rights offerings to align with the findings of White and Lusztig, as well as Chen et al. (2010). We hope to expand on these insights by contrasting the magnitude of market reaction with those of PIPEs during the different time periods.

It is our aim to expand on the existing literature on market reactions to equity offerings along a temporal dimension, by examining price movements during the pandemic, while expanding on the matter by adding a comparative dimension between the two financing methods. In this way, we hope to yield new insights into the implications of choice of financing based on an evaluation from a signaling perspective. Furthermore, it is our ambition to provide additional understanding of the market conditions by evaluating and interpreting the results in a brief discussion based on signaling theory.

3. Research Question

In light of the uncertainty in the financial markets during the pandemic, the significant interventions conducted by the federal government, and those conducted by the Federal Reserve, we aim to investigate whether market sentiment shifted in terms of preference for type of equity financing during Covid-19. This has implications along two dimensions, namely what the choice between rights offerings and PIPEs signals to investors, as well as how these signals are valued by investors. The research question is therefore as follows:

How did investor sentiment regarding equity financing change during the Covid-19 pandemic, and what are the implications of such a potential change?

4. Method

4.1 Testing for Difference

4.1.1 Z-test to find difference in means

In order to find a significant answer to our research question, the aim of our method is to provide an answer to whether the market valued any of the two transaction types higher during the Covid-19 crisis than what it did before. Our method will therefore look at the market return on the first day after an announced transaction. However, in order for us to determine if the sentiment changed, we must look at the difference in returns between companies who announced a PIPE and companies who announced a rights offering during the one of the two periods. To reach such an answer, we apply a method which based on the matching of companies, or in this case, transactions, as used by Datta et al. (2001). We thus create four samples of transactions: PIPEs in the US and Canada announced between 1/7/2018 - 30/6/2019, PIPEs in the US and Canada announced between 1/7/2020 - 30/6/2021, Rights Offerings announced in the US and Canada between 1/7/2018 - 30/6/2019, and Rights Offerings which were announced between 1/7/2020 - 30/6/2021. The PIPEs' returns are compared to the returns of the rights offers for each period by subtracting the prior from the latter, which creates two new samples of differences during the two periods. We can perform a *Z-test* with the null-hypothesis:

$$H_0\colon \mu_{2018/19} = \mu_{2020/21}$$

In order to determine if the two samples are different from each other based on the mean of the samples. The null-hypothesis can then be rejected based on the probability of achieving a certain Z-score. The Z-score is calculated by:

$$Z = \frac{\left(\bar{X}_{2018/19} - \bar{X}_{2020/21}\right) - \left(\mu_{2018/19} - \mu_{2020/21}\right)}{\sqrt{\frac{\sigma^2_{2018/19}}{n_{2018/19}} + \frac{\sigma^2_{2020/21}}{n_{2020/21}}}}$$

Based on the p-value generated from the test, we can either reject our null-hypothesis or not, and thus determine if the differences in returns between the two periods are different or not.

4.1.2 Mood's Median test.

Furthermore, in order to test if the medians of the differences in first day after announcement returns are different, we use the non-parametric *Mood's Median Test*. In our calculations we will have two samples, differences in first day after announcement returns 2018/19 and 2020/21. The number of entries from each list that is greater than the median is entered into the first row of a table, and the number of entries equal or below the respective medians are entered into the second row of the table. In order to get the final p-value that tells if the medians are different or not, a Chi-squared test is performed on the table. The test-statistic is calculated:

$$\chi^2 = \sum_{i=1}^{r}\sum_{j=1}^{c}\frac{\left(n_{ij}-\hat{E}(n_{ij})\right)^2}{\hat{E}(n_{ij})}$$

Where r, c is the rows and columns in the table, and $\hat{E}(n_{ij}) = n(\hat{p}_i\hat{p}_j) = n\left(\frac{r_i}{n}\right)\left(\frac{c_j}{n}\right) = \frac{r_i * c_j}{n}$. With the degrees of freedom being $df = (r-1)(c-1)$. Finally, the p-value is calculated by comparing the test statistic with the chi-squared distribution.

4.2 Assumptions

In order to complete the Z-test, three assumptions have to be tested. Firstly, the samples must be independent from each other. Second, the samples must be large (n ≥ 30) and preferably normally distributed (although not an important assumption if the samples are large). As the Mood's Median test is a non-parametric test it does not assume normality. However, it does assume that the samples follow two distributions with the same shape.

Furthermore, we assume that the returns are an indicator of market sentiment. This means that we assume that the return cannot be explained by another factor, such as industry effect nor time specific effects. As the dataset is represented by transactions announced over the course of 12 months, we assume that the randomization solves the potential problem of time specific effects over the whole dataset, such as news stories that might affect the daily returns or macro-events that would affect overall daily market returns.

4.3 The Matching Problem

Due to the heterogeneity among companies in the original four samples, the data must be sorted in a way that generates the most representative samples possible. The problem is that the return after an announced PIPE and an announced rights offerings will be vastly different if the companies themselves are vastly different. Since smaller companies are potentially more dependent on the transaction, an announcement might cause a far bigger reaction in the market return than what the announcement of an equal transaction would for a large company. Therefore, it is necessary to match the companies who announced a rights offering in 2018/19 to similar companies who announced a PIPE in 2018/19, as illustrated in fig 1.

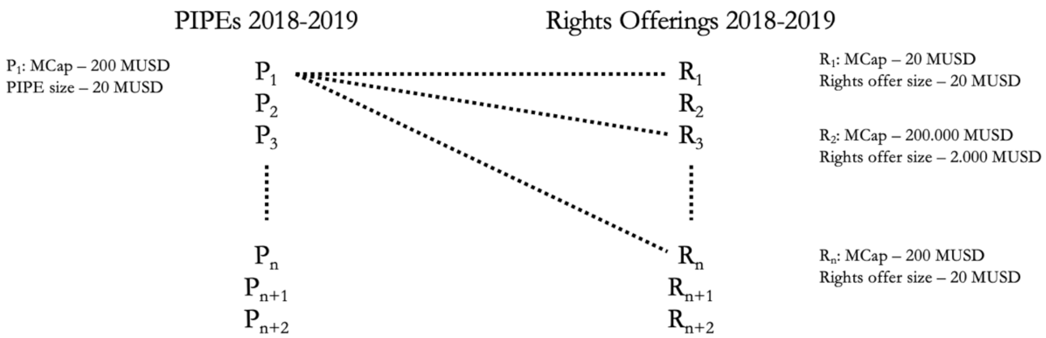

fig 1. Illustration of the matching-problem. It is evident that R_n would be the best match for P_1

4.3.1 K-Means++ Machine Learning Algorithm

In order to solve the matching-problem, we are using the *K-Means++ algorithm* (Arthur & Vassilvitskii, 2007), which is an improved version of the K-Means algorithm. The K-Means algorithm divides a set of data points into clusters of points which are similar to each other based on the selected properties of the data. First, the algorithm chooses an initial K centers $C = \{c_1, \dots, c_K\}$. Then for every $i \in \{1, \dots, K\}$ it changes C_i in order for the data points χ to be closer to the centers based on the Euclidean distance to each point from the center $C: c_i = \frac{1}{|c_i|}\sum_{x \in \chi} x$, where the Euclidean distance is calculated by:

$$\|a-b\|_2^2 = \sum_{i=1}^{n}(a_i - b_i)^2$$

The algorithm returns the clusters that have the minimum sum of squared distances, i.e., the cluster of points which are most like each other. However, the K-Means algorithm shares two common problems for any machine learning algorithm, speed, and accuracy. For the K-Means algorithm, given a set of n data points $\chi \subset \mathbb{R}^d$, it chooses K centers C to minimize the function:

$$\phi = \sum_{x\in\chi} \min_{c\in C} \|x - c\|^2$$

The steps are repeated until C no longer changes. This results in the optimization problem being NP-hard. The variable ϕ refers to the corresponding potential. The K-Means algorithm chooses the starting center point at random, which thus increases the difficulty of the optimization problem making it NP-Hard. The K-Means++ algorithm, on the other hand, is $\Theta \log(K)$ $-$competitive, meaning that the solution is at most $8(\ln k + 2)$ times the potential of the best solution. The algorithm works by initially choosing a center c_1 uniformly at random from χ, however it then goes on to choose the next center c_i, selecting $c_i = x' \in \chi$, with the probability:

$$\frac{D(x')^2}{\sum_{x\in\chi} D(x)^2}$$

where $D(x)$ is the shortest distance from the data point to the closest center. These steps are repeated until K centers are created, where it continues with the traditional K-Means algorithm. By adding this simple randomized seeding algorithm to the original K-Means algorithm, Arthur and Vassilvitskii proves that the K-Means++ algorithm is a faster and more accurate way of creating clusters.

4.3.2 Matching the datasets

In order to find similar companies between our Rights Offerings 2018/19 and PIPEs 2018/19 and between Rights Offerings 2020/21 and PIPEs 2020/21, we run the machine learning algorithm (K-Means++) with 1,000 iterations based on market capitalization and transaction size. Furthermore, we run a meta-algorithm, *Multi K-Means++* that runs 1,000 trials of the K-Means++ and chooses the best trails. These two steps will create four sets of clusters, one for each dataset. Then, in order to find the matched transactions, we overlap the rights offerings clusters with the PIPE clusters from the equivalent time period such as: $Cl_{PIPE} = \{cl_{p1}, \dots, cl_{pK}\}$ and $Cl_{RO} =$

$\{cl_{r1}, \ldots, cl_{rK}\}$. The cross section between the sets will equal all transactions which could be seen as matched M for each time period $j = \{2018/19,\ 2020/21\}$:

$$M_{RO_j} = Cl_{RO_j} \cap Cl_{PIPE\,j} \quad M_{RO_j} \in Cl_{RO_j}$$

$$M_{PIPE_j} = Cl_{PIPE_j} \cap Cl_{RO_j} \quad M_{PIPE_j} \in Cl_{PIPE_j}$$

By taking the post-announcement returns from M_{RO_j} and subtracting the first day after announcement returns from M_{PIPE_j}, we create two new datasets of matched returns. The cross sections are approximated by making an ellipse from a cluster by subtracting the centroid's, or the final center of the cluster's, market cap from the maximum market cap as the major axis of the ellipse. Similarly, the semi-minor axis is calculated by subtracting the centroid's transaction size from the cluster's maximum transaction size.

To check if two ellipses intersect, the program begins to estimate their shape with two rectangles. If a rectangle intersects another ellipse, it calculates the probability that the intersected points are also a part of the ellipse, and not in the area between the ellipse and the rectangle. This results in a time-conserving and unaltering method to find the intersected area, opposing the potential method of calculating the intersections using linear algebra. Naturally, the method results in an approximation of the cross section instead of a perfect match, however it reduces the computational power needed to run multiple trials efficiently.

The complete algorithm is summarized below:

1. Read data files.
2. Run K-Means++ and Multi K-Means++ to create clusters of the datasets.
3. Approximate clusters with ellipses.
4. Check if the ellipses from one datasets overlap with the ellipses from another dataset.
5. Extract the points in the cross sections from the intersected ellipses.
6. Create new dataset with the transactions that are found by the points that are in the cross sections, i.e., the samples of matched transactions.

4.3.3 Finding the optimal K

The K-Means++ machine learning algorithm comes with a limitation in relying on how many clusters K to create. A potential solution to finding an appropriate value for K is to use the *Elbow Method*, where the squared sum of the distances (SSD) to the centroid for each optimal cluster is plotted for each K, in a range of n values of K. Where the SSD is calculated for each point $p \in Cl_j$ where $Cl_j = \{cl_1, \dots, cl_K\}$:

$$SSD = \sum_{i=1}^{n} \sum_{j=1}^{K} \left(p_j - cl_j\right)_i^2$$

The graph that is generated will have points where the trend breaks (i.e., the elbow of the graph), which is a potential optimal value for K.

4.3.4 Kolmogorov-Smirnov Test for Normality

In order to test the assumption of normality we use a *Kolmogorov-Smirnov* test, which test how well a dataset is fitted to a specified distribution. We use the method described by Marsaglia & Marsaglia (2004) for a one-sample KS-test evaluating the null-hypothesis that a population follows a certain distribution. We are therefore using the method to test if the population of differences during period $i = \{2018/19,\ 2020/21\}$ follows a given distribution: $diff_i \sim \mathcal{N}(\mu, \sigma^2)$. The test statistic is defined as:

$$D_n = \sup_x |F_n(x) - F(x)|$$

where F is the expected distribution and F_n is the empirical distribution. The test statistic $\Pr(D_n < d)$ is evaluated by the following method:

$d = \frac{k-h}{n}$ where k is a positive integer and $0 \leq h < 1$

$\Pr(D_n < d) = \frac{n!}{n^n} t_{kk}$ where t_{kk} is the k, k element of the matrix $T = H^n$

H is a $m \times m$ matrix where $m = 2k - 1$ whose general form can be inferred from the case of $m = 6, h \leq \frac{1}{2}$:

$$H = \begin{bmatrix} (1-h^1)/1! & 1 & 0 & 0 & 0 & 0 \\ (1-h^2)/2! & 1/1! & 1 & 0 & 0 & 0 \\ (1-h^3)/3! & 1/2! & 1/1! & 1 & 0 & 0 \\ (1-h^4)/4! & 1/3! & 1/2! & 1/1! & 1 & 0 \\ (1-h^5)/5! & 1/4! & 1/3! & 1/2! & 1/1! & 1 \\ (1-h^6)/6! & 1/5! & 1/4! & 1/3! & 1/2! & 1/1! \end{bmatrix}$$

As described by Marsaglia & Marsaglia. The Kolmogorov Smirnov test enables us to test if our differences in first day after announcement returns follow a normal distribution, which is preferred but not necessary for the Z-test.

4.3.5 OLS-Regression to test our assumptions

In order to test our assumption that the returns are an effect of the announcement of a transaction, and not an effect of for instance industry effects or time-specific events we use an *Ordinary Least Square* regression (OLS) with the depending variable Y_i representing the first day after announcement returns, $X_{i,j}$ are the dependent variables, β_i are the dependent variables' coefficients and ϵ_i are the error terms. The regression is then described by:

$$\begin{pmatrix} Y_0 \\ Y_1 \\ \vdots \\ Y_n \end{pmatrix}_{n\times 1} = \begin{pmatrix} 1 & X_{11} & X_{21} & \dots & X_{k1} \\ 1 & X_{12} & X_{22} & \dots & X_{k2} \\ 1 & \vdots & \vdots & \cdots & \vdots \\ 1 & X_{1n} & X_{2n} & \dots & X_{kn} \end{pmatrix}_{n\times k} \begin{pmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_n \end{pmatrix}_{n\times 1} + \begin{pmatrix} \epsilon_1 \\ \epsilon_2 \\ \vdots \\ \epsilon_n \end{pmatrix}_{n\times 1}$$

The method estimates the coefficients by minimizing the sum of squared residuals, where the vector of the residuals e is calculated:

$$e = y - X\hat{\beta}$$

The sum of squared residuals will then be $(e'e)^2$:

$$SSR = \begin{pmatrix} e_1 & e_2 & \cdots & e_n \end{pmatrix}_{1\times n} \begin{pmatrix} e_1 \\ e_2 \\ \vdots \\ e_n \end{pmatrix}_{n\times 1} = (e_1 * e_1 + e_2 * e_2 + \cdots + e_n * e_n)$$

Our dependent variables are transaction size, date, and industry for each individual company. The date and industry variables are expressed as dummy variables for each month and industry respectively. As a result of the use of dummy variables, we need to solve the dummy variable trap by removing one dummy for each set of dummies. The dummy variable trap means that there will be perfect multicollinearity if they are not removed since it would be possible to exactly predict one value of the dummies based on the others.

5. Data Description

The following section describes the method for gathering and delimiting the data used in the quantitative analysis conducted. Section 5.1. summarizes the sample used. The subsections to 5.2. elaborate on the variables used in the matching performed.

5.1 Summary of Sample

The relevant data was sourced from S&P Global via their Capital IQ platform. We deemed the use of a single database appropriate so as to minimize any potential systematic disruptions or errors that would hinder comparability. The data was sourced using the transaction screener and yielded a total of 7,373 transactions, after eliminations of missing values and duplicates. Of these, 1,206 and 1,541 were PIPEs and rights offerings, respectively, announced during the first time period. The corresponding numbers for the later time period were 1,659 and 2,967. The time periods were set to 1/7/2018 - 30/6/2019 and 1/7/2020 - 30/6/2021, based on their deemed fit as representative for market conditions before and during the circumstances that affected markets in the wake of the pandemic, as elaborated in Section 1.4. Only transactions that were labeled as either PIPEs or rights offerings have been considered. We have only used the returns following transactions for companies listed in the United States and Canada. This was done based on shared similarities in regulatory framework and capital market behavior, a reasoning based on the conclusions made by Andriosopoulos & Panetsidou (2021). Having run the matching algorithm, elaborated further in section 6., the sample had been narrowed down to an average of 60 transactions per iteration in the first time period, while an average of around 200 per iteration remained in the later time period. The variability in size and difference between iterations and time periods stems from the algorithm finding slightly different transactions in each iteration, and on consistently deem transactions announced in the later time period more similar an thus matchable.

In summary, we included transactions that were i) announced during our selected time periods, ii) were classified as either PIPEs or rights offerings, iii) announced by companies listed in the United States or Canada, iv) has available returns for the first trading day following announcement. The subsequent matching was done by the matching algorithm which matched a) PIPEs and rights offerings with announcements during b) the same period and with similar c) market capitalizations and d) transaction sizes.

In the controlling regressions, the same datasets were used, but with additional variables. In this implementation, the sets were the four lists of matched transactions, one for each transaction type and time period. Each time period was structured into its 12 months, with the intention to test for potential significance in the specific month of the announcement. Each issuing firm was also classified as active within an industry, retrieved from Capital IQ. Returns on announcement were chosen as the dependent variable, to measure investor sentiment and reception of the news.

5.2 Variables

5.2.1 Transaction Type

The primary variable for comparing PIPEs and rights offerings is naturally a differentiator regarding the type of transactions. We have only used transactions which upon announcement could be classified as either a PIPE or a rights offering in the Capital IQ database, excluding any other forms of transactions as well as hybrid solutions. This entails that there exists a considerable heterogeneity in the sample, as firms and advisors are able to design the details of transactions with significant discretion. While this heterogeneity does influence average returns within transaction types, as pointed out by Andriosopoulos & Panetsidou (2021), we limit our scope to only considering the broad classifications of PIPEs and rights offerings.

5.2.2 Transaction Size

We consider the size of the transactions relevant, expressed as millions of USD. The reasoning is that the signaling from the announcement of an upcoming equity transaction is influenced by the stated size of raised capital. This is due to the implications of the need for capital, wherein a larger need for equity financing should signal financial weakness in accordance with signaling theory. By matching transactions by transaction size, we hope to reduce the influence of this signaling so as to better capture the effects of choice of transaction type. The variable is also used in in the controlling regression, in order to capture a particular dependence on capital needs.

5.2.3 Market Capitalization

Market capitalization at the time of announcement should carry importance in how the market perceives the news of equity financing, as a higher market value should imply a larger and more stable organization and lower price volatility. As market reactions vary in magnitude depending on market capitalization, we deem it as material to match transactions using this metric. By matching transactions similar in both transaction size and market capitalization, we get an implicit match on the relative size of the deal value, with the ambition to rid the data of biases related to relative size.

5.2.4 Announcement Return

For each transaction conducted in the studied time periods, Capital IQ provides the return expressed in percent of the first trading day following announcement to the public. The percentage change in share price acts as an approximation of how the news was received by the investor collective. While the return could be adjusted by the return of a relevant index that would represent the broader market, we decided to not do this with the reasoning that such altering would require a subjective decision on what index to use, which further also would discriminate certain sectors and market capitalizations over others. Instead, we hope that a large set of matched pairs would compensate for any systematic market movements that coincided with the trading day following announcement.

5.2.5 Month of Announcement

The month in which an announcement was made was structured as 11 dummy variables so as to not assign numerical values to any particular month. This yielded a total of 12 outcomes, wherein all 11 variables being set to zero means that the announcement and corresponding return occurred in December. As the specific time and date of the announcement was retrieved from Capital IQ, each announcement and corresponding return could be assigned a month which in turn corresponded to one outcome in terms of the dummy variables. As both time periods correspond to 12 months, this method was applicable for both periods. In this way, a possible trend between months and returns could be illustrated. The idea was that a particular pattern could indicate a dependence on factors beyond transaction type, as well as to capture intra-period variations.

5.2.6 Industry of Issuer

Each issuing company could be assigned an industry definition by Capital IQ. These were then condensed into a selection of broader industries. With 16 industries in total, this yielded 15 dummy variables. It should be noted that the industries provided by the Capital IQ database likely are blunt in the sense that they do not account for any potential heterogeneity in operations. Each issuing firm is thus only classified as active within one single industry. The issue is partly resolved by broader definitions, yet these are still limiting for potential conglomerates or other companies active in more than one industry. The reasoning behind the inclusion of industry as a dependent variable is the potential differences in implications of the announcement of an upcoming equity financing transaction based on industry.

6. Results & Discussion

6.1. Descriptive Statistics

To generate the clusters to match the data point, the number of clusters has to be decided for each dataset. The elbow method shows the optimal *K* when run for each set and resulted in the following number of clusters: K=13 for Rights Offerings 2018/2019, K=11 for Rights Offerings 2020/21, K=10 for PIPE 2018/2019 and K=13 PIPE 2020/2021. A potential case could be made for K-values around 8 as the trends break there as well. However, in order to differentiate our clusters enough, we have chosen the later break in trend. Figure 2-5 shows the elbow graphs for each dataset.

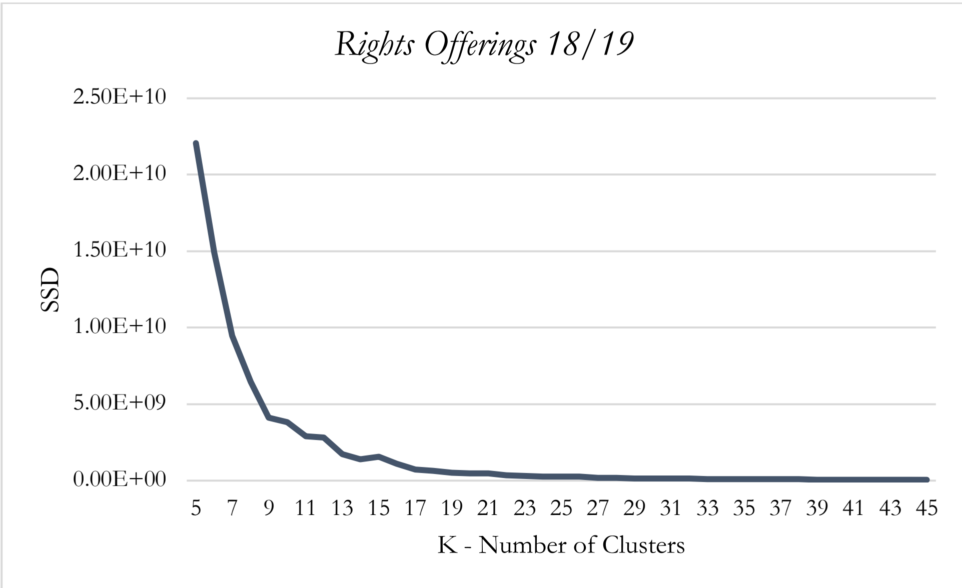

fig 2. Shows the elbow-graph for Rights Offerings 2018/2019. Sum of Squared Distances are plotted on the Y-axis, and K is plotted on the X-axis.

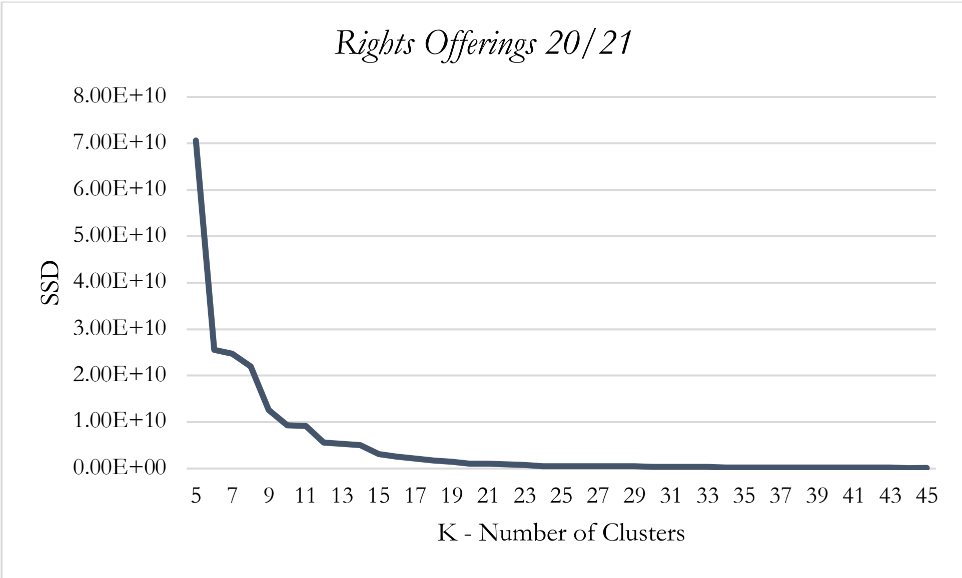

fig 3. Shows the elbow-graph for Rights Offerings 2020/2021. Sum of Squared Distances are plotted on the Y-axis, and K is plotted on the X-axis.

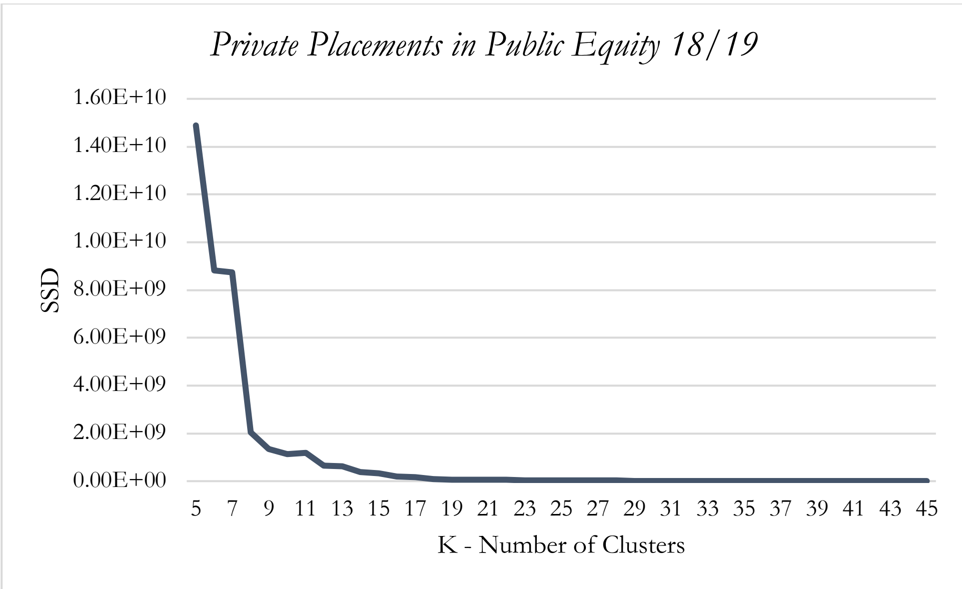

fig 4. Shows the elbow-graph for PIPEs 2018/2019. Sum of Squared Distances are plotted on the Y-axis, and K is plotted on the X-axis.

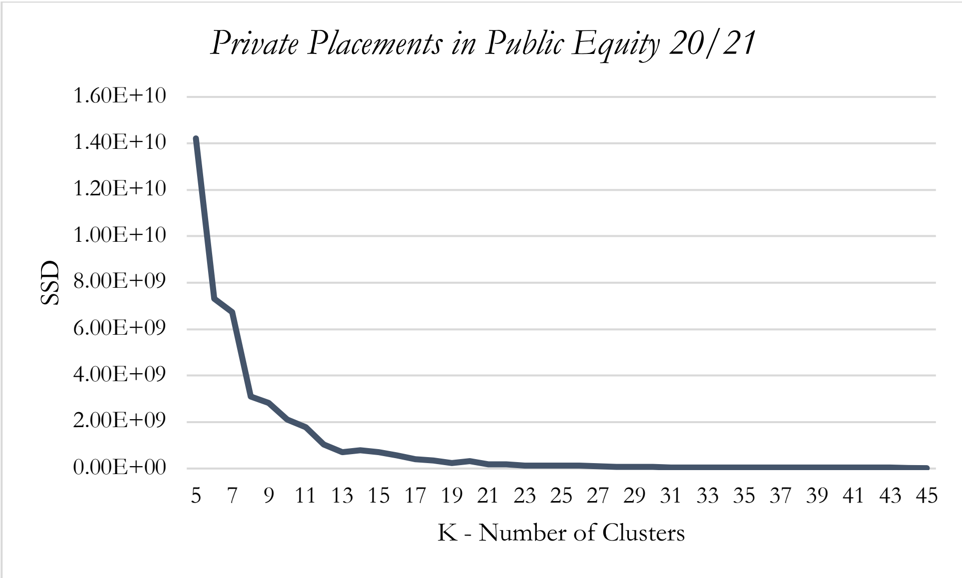

fig 5. Shows the elbow-graph for PIPEs 2020/2021. Sum of Squared Distances are plotted on the Y-axis, and K is plotted on the X-axis.

Figure 6 describes the first day return after announcements for the data sets. The means increase substantially for PIPEs between the two periods, although the medians experience a lesser increase which indicates a higher variance during the COVID-19 period (2020/2021). However, based on the medians alone, it is indicated that the returns from rights offerings decreased from 2018/2019 to 2020/2021 while the returns increased for PIPEs.

	RO 18/19		RO20/21		PIPE 18/19		PIPE 20/21
Mean	Median	Mean	Median	Mean	Median	Mean	Median
-4.29%	-2.33%	-2.49%	-2.80%	2.60%	0.38%	7.38%	0.60%

fig 6. Shows the Mean and Median first day returns after announcement for each dataset.

The summary of the tests carried out on the difference in returns from the matched sets of transactions are presented in fig.7 below. Since the K-Means++ algorithm does not return a static set of transactions, the table below shows the 1st, 2nd and 3rd quartile as well as the average of the results gathered from 250 runs of the algorithm. The Z-value and the P-value connected to it shows how likely it is that the means of the samples of differences in returns between 2018/2019 and 2020/2021 are the same. As evident from the low median p-value (2nd quartile) we can only reject the null-hypothesis that the two samples are in fact the same at a 11.5% significance level.

Furthermore, the p-value from the Mood's Median test is not significant enough in order for us to reject the null hypothesis that the medians are in fact the same.

Since the relative returns are calculated by taking the returns from rights offerings and subtracting the matched return from the PIPE during the same period, the relative result is an expression of the difference in potential return an investor can capture by holding either share on announcement. A larger difference implies a greater relative return within the matched pair. As illustrated in fig.7, the negative mean and median returns are the result of returns of PIPEs on average exceeding the returns of the matched rights offerings. Similarly, to the summary of returns from the full datasets, does the mean and median differ. The median is seen as the more important indicator of the market sentiment due to the potential of extreme values affecting the mean of both samples and shows that the absolute value of differences increased during the Covid-19 time period. Furthermore, the fact that the median of the returns becomes more negative for each quartile indicates that the returns from the PIPEs increased more than the returns from the rights offerings.

Summary of Statistics on Differences in Returns (RO-PIPE)

	3rd Quartile	**2nd Quartile**	**1st Quartile**	***Average***
Z-Value	1.685	1.199	0.777	*1.209*
P-Value (Z-test)	0.207	0.115	0.046	*0.143*
Mood's P-Value	0.321	0.321	0.314	0.319
Mean 18/19	-3.35%	-3.82%	-4.18%	*-3.53%*
Mean 20/21	-6.10%	-6.95%	-7.90%	*-6.79%*
Median 18/19	-2.53%	-2.98%	-3.41%	*-2.79%*
Median 20/21	-3.83%	-4.96%	-5.77%	*-4.49%*
P-Value (KS-test) 18/19	0.000	0.000	0.000	*0.000*
P-Value (KS-test) 20/21	0.000	0.000	0.000	*0.000*

fig 7. Shows summarized statistics from the tests on the differences from the matched transactions from 250 runs

Fig 7. also shows the p-values from the Kolmogorov-Smirnov tests to test our assumptions regarding normality. The p-value is approximately zero for both periods which shows that it is almost certain that the samples are not normally distributed. This test underlines the importance of having larger datasets in order to get a statistically valid result.

Fig 8. describes the summarized statistics from four OLS-regressions carried out on the matched transactions from the *RO18, RO20, PIPE18* and *PIPE20* datasets. The regressions are run 100 times on the matched sets. The adjusted R Squared values show that the regressions do not have a high explanatory value which tells us that our assumption that the returns is based on the announced transactions, and not due to transactions size, industry effects and dates is potentially correct. However, the possibility remains that the returns could be explained by an unknown variable, although unlikely. Furthermore, the F-statistics and the associated P-values shows that we are unable to reject the null-hypothesis that all factors to the variable could be equal to zero. Thus, the OLS-regressions further strengthen our assumption that the return is a reaction to the announcement of a transaction and not based on other factors such as industry effects or time specific events. This is further confirmed by the regressions based on either only dates, industry or another combination of the variables found in the Appendix (Appendix B-F).

Summary of OLS-Regressions

	R Squared	Adj. R Squared	F Statistric	P-Value
RO18/19 3rd Quartile	0.624	0.280	0.081	1.000
RO18/19 2nd Quartile	0.565	0.196	0.072	1.000
RO18/19 1st Quartile	0.507	0.080	0.060	1.000
Average	*0.562*	*0.180*	*0.068*	*1.000*
RO20/21 3rd Quartile	0.174	0.024	0.035	1.000
RO20/21 2nd Quartile	0.157	0.004	0.032	1.000
RO20/21 1st Quartile	0.138	- 0.025	0.028	1.000
Average	*0.159*	*0.001*	*0.036*	*0.999*
PIPE18/19 3rd Quartile	0.290	- 0.143	0.117	1.000
PIPE18/19 2nd Quartile	0.290	- 0.143	0.117	1.000
PIPE18/19 1st Quartile	0.290	- 0.143	0.117	1.000
Average	*0.290*	*- 0.143*	*0.107*	*1.000*
PIPE20/21 3rd Quartile	0.098	- 0.026	0.234	0.993
PIPE20/21 2nd Quartile	0.098	- 0.026	0.234	0.993
PIPE20/21 1st Quartile	0.098	- 0.026	0.234	0.993
Average	*0.097*	*- 0.026*	*0.220*	*0.993*

fig 8. Shows summarized statistics from the OLS-regressions carried out on the matched datasets.

6.2 Discussion

6.2.1 Market Reactions on Announcement

Neither the increase in average, nor median, returns on announcement could be proven significant. This means that any discussion and implication based on the results should be interpreted as indicative and be subject to adequate skepticism. Nevertheless, both average and median return yield results that, while not significant, provide a foundation for discussion on a potential increase in preference towards PIPEs over rights offerings. While the general trend was, as with broader investor sentiment, a more optimistic market, our matched data shows a particular preference for PIPEs over rights offerings in the time period encompassing the pandemic. The matched returns for the first period yielded an average difference between PIPEs and rights offerings of 3.54%, a number that increased to 6.79% in the market affected by the economic effects of the pandemic. The corresponding numbers for the medians were 2.79 and 4.49. The increase was smaller in the median, implying a notable volatility in returns. Also noteworthy is the decrease in the median for rights offerings alone, which in conjunction with a slight increase in the median of PIPEs resulted in the increase in relative returns. In terms of averages, both transaction types were received with more optimism in the market, but the increase was greater for PIPEs. When returns are considered in both matched and de-matched form, the development is clarified. The relative returns increased as a consequence of the returns following announcements of PIPEs increasing to a greater extent than those for rights offerings, though both transactions were received more positively. Investor sentiment regarding methods of equity financing can be interpreted as having shifted towards a preference for PIPEs over rights offerings during the Covid-19 pandemic, though this development cannot be significantly proven.

The indicated increase in relative preference for PIPEs over rights offerings demands several considerations on the matter of implications. It is unlikely that a possible shift was due to an arbitrary shift in preferences among the larger investor collective. It is possible that the announcement returns, and thus investor sentiment, reflects what the method of financing signals. Signaling theory predicts that a firm issuing equity implicitly signals that the valuation of the firm exceeds its intrinsic value, as the cost of equity exceeds the cost of capital of both retained earnings and debt. The fact that the market on average responds negatively to rights offerings, and positively to PIPEs, implies a discrimination between equity issuances and thus a problematization of the typical three-step pecking order in signaling theory. What our data indicates, though not significantly, is that this tendency was reinforced in the wake of the pandemic, as the relative returns of PIPEs over rights offerings increased. The matter of information asymmetry, which is a key feature in signaling theory, could provide a partial explanation for this shift.

The investigated transaction types exhibit substantial differences with regard to how, and what, information is distributed. Rights offerings cater to all existing shareholders, while PIPEs target a select group of large and often institutional investors, with no necessary consideration for whether they own shares prior to the issue. The prior thus entails a careful consideration of what is communicated, as the information is made public. PIPEs allow for more discretion, allowing the use of NDAs and selective communication. While fewer investors partake in the information given, the information can be of higher level of detail. Participating investors in PIPEs are therefore better informed than the broader investor collective of rights offerings. It is thus possible that the announcement of an upcoming PIPE signals the trust of major and informed investors in the issuing company, as PIPEs often are backed by indicated demand. The broader investor base might interpret this as a signal of quality, relying on the judgment of the selected investors that have indicated intentions to subscribe for shares. While rights offerings can carry a similar mechanism in the form of subscription commitments, these are meant as guarantees for the deal and do not signal confidence in the same way. Non-participating investors in PIPEs could have valued the signaled support from informed investors more during the pandemic, in response to market uncertainty. This would also be in line with the implied undervaluation that PIPEs signal according to Chen et al. (2010), as the valuation-related effects would be magnified by institutional investor due diligence, providing confidence in a volatile market. Rights offerings do not allow for similar due diligence beyond what is explicitly stated in the publicly available marketing materials. Similar signaling, i.e., support from knowledgeable investors, would only become public on the close of the transactions. The pattern of stronger returns upon announcement of PIPEs might thus have been reinforced by investors finding the support of larger select investors as a more positive signaling device during the pandemic than in the earlier time period.

The implications of each method of equity financing could also be considered from a perspective of corporate governance. As illustrated by Lim et al. (2021), PIPEs allow companies to choose their new shareholders with considerable discretion. But the concentration of these new shareholders could also act as a commitment device to management teams to act in the best interest of shareholders. While rights offerings allow for existing shareholders to protect against dilution, and PIPEs do not, the latter generally entail the addition or expansion of a smaller group of shareholders with considerable interest in the continued performance of the company. Rights offerings also allow for the concentration of votes, but the outcome is not known until the transaction is finalized. As with the matter of due diligence discussed previously, investors can get indications of the outcome of PIPEs at announcement to a larger extent than with rights offerings, and can thus interpret signals on future ownership distributions immediately. The potential shift towards a favoring of PIPEs could therefore be related to the expectations among investors on the implications of the new shareholder structure, and more specifically that an addition of relatively influential owners might have been preferred during the pandemic. It is possible that the inclusion of more knowledgeable or experienced major investors conveyed a sense of security in a company's continued governance in the uncertainty of the pandemic, and similarly that improved governance would ensure correct use of funds and further investments in the prevailing environment of easily accessible capital.

To conclude the possible implications from the test for difference between average relative returns between PIPEs and rights offerings over the two time periods, we find that returns on average increased for both methods of equity financing, but that preferences shifted towards PIPEs. This can be the partial result of the strengths that PIPEs are able to convey were appreciated during the pandemic, namely the confidence of informed investors and potential positive effects on corporate governance of the issuing companies. It should once again be noted, however, that these implications are based on patterns that are not significantly proven by our applied method and are thus only indicative rather than proven.

6.2.2 Implication of Controlling Regression

As illustrated in figure. 8., the combined explanatory value of month of announcement, transaction size, and industry of the issuer cannot be assumed to be different from zero. This implies that these factors, while limited in scope, are not sufficient in explaining the shift in relative returns between the two time periods. While this does not prove that the transaction type used is the primary reason for returns, the result also leaves little room for interpretation on changes to market sentiment and preferences for financing.

7. Conclusion

This paper has examined the market reception and subsequent returns following announcements of upcoming equity raises via PIPEs and rights offerings, before and during the Covid-19 pandemic. The results indicated a shift in preferences towards PIPEs over rights offerings during the pandemic, though this change could not be statistically proven. An indicated shift in the observed direction can be illuminated with signaling theory, wherein PIPEs can be considered to better convey confidence from informed and reputable investors, as well as advantageous effects on corporate governance. The superior performance of PIPEs was expected, as it is line with previous studies, but an implied increase in relative returns would indicate that PIPEs entail characteristics that were valued to a greater extent by the market during the pandemic. In order to provide a finalizing answer to how investor sentiment on equity financing changed, further studies must be conducted.

8. Limitations & Further Research

The above presented study of shifts in investor sentiment on methods of equity financing has not considered the qualitative aspects of the companies and transactions in the sample. This means that the data might capture announcement returns that deviate from what should be considered representative in several aspects. The data has not been structured to consider any potential previous issuances of equity, nor debt, prior to the collected announcement which might influence its reception. Returns have not been adjusted for market return on the relevant date, which would isolate the effect of the announcement better. The operational health and the specifics of transaction structure beyond transaction type have not been considered, which could prove significant as in line with Andriosopoulos & Panetsidou (2021). We believe that the addition of these variables in structuring the samples, as well as the matching algorithm, could yield interesting and valuable insights. If the study were to be recreated, we suggest improving the matching algorithm in order to account for these variables. As the K-Means++ algorithm is not limited by the amount of dimensions, but limited by all dimensions $d \in \mathbb{R}$, further improvements to the method should aim to solve the problem of creating a relative scale on which to value the industries. Furthermore, as previously explained, the cross sections are approximated in the current algorithm to save time. Thus, future replications of the study are encouraged to create a more sophisticated algorithm that can calculate intersections with the correct linear algebra while keeping the optimization problem simple. Lastly, the K-value could be calculated using an evolutionary machine learning algorithm, where the fitness method is represented by the silhouette method for choosing an optimal K-value, thus calculating a more exact value.

9. Bibliography

Akerlof, G. A. (1970). *The Market for "Lemons": Quality Uncertainty and the Market Mechanism*. Macmillan Education UK. 10.1007/978-1-349-24002-9_9

Andriosopoulos, D., & Panetsidou, S. (2021). A global analysis of Private Investments in Public Equity. *Journal of Corporate Finance (Amsterdam, Netherlands), 69*10.1016/j.jcorpfin.2020.101832

Arthur, D., & Vassilvitskii, S. (Jan 07, 2007). k-means. Paper presented at the 1027-1035. http://dl.acm.org/citation.cfm?id=1283494

Board of Governors of the Federal Reserve System. Decisions Regarding Monetary Policy Implementation. 03/03/2020.

Board of Governors of the Federal Reserve System. Decisions Regarding Monetary Policy Implementation. 15/03/2020.

Board of Governors of the Federal Reserve System. "Credit and Liquidity Programs and the Balance Sheet." Federalreserve.Gov, 13 May 2022, www.federalreserve.gov/monetarypolicy/bst_recenttrends.htm.

Boston Consulting Group. BCG Investors Perspectives Series, Pulse Check #1, 3, 7, 9, 13, 15. https://www.bcg.com/publications/2020/covid-investor-pulse-survey/overview

Chen, H., Dai, N., & Schatzberg, J. D. (2010). The choice of equity selling mechanisms: PIPEs versus SEOs. *Journal of Corporate Finance (Amsterdam, Netherlands), 16*(1), 104-119. 10.1016/j.jcorpfin.2009.08.003

CNBC. "U.S. 10 Year Treasury." CNBC, 13 May 2022, www.cnbc.com/quotes/US10Y.

Datta, S., Iskandar-Datta, M., & Raman, K. (2001). Executive Compensation and Corporate Acquisition Decisions. *The Journal of Finance (New York), 56*(6), 2299-2336. 10.1111/0022-1082.00406

Deutsche Börse Group. "STOXX Europe 600." Qontigo, 15 May 2022, www.stoxx.com/index-details?symbol=SXXP.

Jha, M., Liu, H., & Manela, A. (2021). Natural Disaster Effects on Popular Sentiment Toward Finance. *Journal of Financial and Quantitative Analysis, 56*(7), 2584-2604. 10.1017/S0022109021000466

Lim, J., Schwert, M., & Weisbach, M. S. (2021). The economics of PIPEs. *Journal of Financial Intermediation, 45*, 100832. https://doi-org.ez.hhs.se/10.1016/j.jfi.2019.100832

Marsaglia, G., & Marsaglia, J. (2004). Evaluating the Anderson-Darling Distribution. *Journal of Statistical Software, 9*(2), 1-5. 10.18637/jss.v009.i02

Myers, S. C., & Majluf, N. S. (1984). *Corporate financing and investment decisions when firms have information that investors do not have*. Elsevier BV. 10.1016/0304-405x(84)90023-0

S&P Dow Jones Indices. “S&P 500.” S&P Global, 13 May 2022, www.spglobal.com/spdji/en/indices/equity/sp-500/#overview.

White, R. W., & Lusztig, P. A. (1980). The Price Effects of Rights Offerings. *Journal of Financial and Quantitative Analysis, 15*(1), 25-40. 10.2307/2979017

Appendix

Appendix A. Industries in datasets

Industry classifications	Rights Offerings 18/19	Rights Offerings 20/21	PIPE 18/19	PIPE 20/21
Consumer Discretionary	67	163	73	114
Consumer Staples	35	73	39	56
Copper	15	22	19	10
Education Services	10	26	6	3
Energy	79	149	57	60
Financials	151	219	235	496
Health Care	713	1435	354	359
Industrials	100	337	144	185
Information Technology	78	158	95	137
Materials	58	91	87	107
Media and Entertainment	31	92	61	94
Mortgage Real Estate Investment Trusts	55	0	0	0
Oil and Gas distribution	10	0	1	1
Real Estate	133	182	29	33
Specialized Consumer Goods	2	12	0	0
Utilities	4	7	6	4

Appendix B. OLS-regression on only industries

Summary of OLS-Regressions

	R Squared	Adj. R Squared	F Statistic	P-Value
RO18/19 3rd Quartile	0.385	0.234	0.000	1.000
RO18/19 2nd Quartile	0.385	0.160	0.000	1.000
RO18/19 1st Quartile	0.385	0.097	- 0.000	1.000
Average	*0.385*	*0.177*	- *0.000*	*1.000*
RO20/21 3rd Quartile	0.058	- 0.027	0.000	1.000
RO20/21 2nd Quartile	0.058	- 0.037	0.000	1.000
RO20/21 1st Quartile	0.058	- 0.045	0.000	1.000
Average	*0.058*	- *0.034*	- *0.000*	*1.000*
PIPE18/19 3rd Quartile	0.148	- 0.061	- 0.000	1.000
PIPE18/19 2nd Quartile	0.148	- 0.061	- 0.000	1.000
PIPE18/19 1st Quartile	0.148	- 0.061	- 0.000	1.000
Average	*0.148*	- *0.061*	- *0.000*	*1.000*
PIPE20/21 3rd Quartile	0.025	- 0.055	0.000	1.000
PIPE20/21 2nd Quartile	0.025	- 0.055	0.000	1.000
PIPE20/21 1st Quartile	0.025	- 0.055	0.000	1.000
Average	*0.025*	- *0.055*	*0.000*	*1.000*

Appendix C. OLS-regression on dates only

Summary of OLS-Regressions

	R Squared	Adj. R Squared	F Statistric	P-Value
RO18/19 3rd Quartile	0.248	0.056	0.100	1.000
RO18/19 2nd Quartile	0.203	- 0.006	0.000	1.000
RO18/19 1st Quartile	0.151	- 0.080	0.000	1.000
Average	*0.208*	*- 0.005*	*0.028*	*1.000*
RO20/21 3rd Quartile	0.116	0.061	0.000	1.000
RO20/21 2nd Quartile	0.103	0.047	0.000	1.000
RO20/21 1st Quartile	0.075	0.017	0.000	1.000
Average	*0.099*	*0.041*	*0.012*	*1.000*
PIPE18/19 3rd Quartile	0.236	0.083	0.000	1.000
PIPE18/19 2nd Quartile	0.236	0.083	0.000	1.000
PIPE18/19 1st Quartile	0.236	0.083	0.000	1.000
Average	*0.236*	*0.083*	*0.025*	*1.000*
PIPE20/21 3rd Quartile	0.063	0.022	0.100	1.000
PIPE20/21 2nd Quartile	0.063	0.022	0.100	1.000
PIPE20/21 1st Quartile	0.063	0.022	0.100	1.000
Average	*0.063*	*0.022*	*0.101*	*1.000*

Appendix D. OLS-regression on industries and dates

Summary of OLS-Regressions

	R Squared	Adj. R Squared	F Statistric	P-Value
RO18/19 3rd Quartile	0.595	0.286	0.000	1.000
RO18/19 2nd Quartile	0.543	0.180	0.000	1.000
RO18/19 1st Quartile	0.476	0.066	0.000	1.000
Average	*0.542*	*0.174*	*0.011*	*1.000*
RO20/21 3rd Quartile	0.175	0.031	0.000	1.000
RO20/21 2nd Quartile	0.157	0.013	- 0.000	1.000
RO20/21 1st Quartile	0.144	- 0.003	- 0.000	1.000
Average	*0.160*	*0.011*	*0.009*	*1.000*
PIPE18/19 3rd Quartile	0.288	- 0.118	0.000	1.000
PIPE18/19 2nd Quartile	0.288	- 0.118	0.000	1.000
PIPE18/19 1st Quartile	0.288	- 0.118	0.000	1.000
Average	*0.288*	- *0.118*	*0.009*	*1.000*
PIPE20/21 3rd Quartile	0.097	- 0.023	0.049	1.000
PIPE20/21 2nd Quartile	0.097	- 0.023	0.049	1.000
PIPE20/21 1st Quartile	0.097	- 0.023	0.049	1.000
Average	*0.097*	- *0.023*	*0.049*	*1.000*

Appendix E. OLS-regression on industries and transaction sizes

Summary of OLS-Regressions

	R Squared	Adj. R Squared	F Statistric	P-Value
RO18/19 3rd Quartile	0.623	0.280	0.080	1.000
RO18/19 2nd Quartile	0.563	0.195	0.071	1.000
RO18/19 1st Quartile	0.510	0.079	0.060	1.000
Average	*0.561*	*0.179*	*0.067*	*1.000*
RO20/21 3rd Quartile	0.172	0.020	0.035	1.000
RO20/21 2nd Quartile	0.156	0.002	0.032	1.000
RO20/21 1st Quartile	0.138	- 0.026	0.028	1.000
Average	*0.158*	- *0.002*	*0.036*	*0.999*
PIPE18/19 3rd Quartile	0.290	- 0.143	0.117	1.000
PIPE18/19 2nd Quartile	0.290	- 0.143	0.117	1.000
PIPE18/19 1st Quartile	0.290	- 0.143	0.117	1.000
Average	*0.290*	- *0.143*	*0.108*	*1.000*
PIPE20/21 3rd Quartile	0.098	- 0.026	0.234	0.993
PIPE20/21 2nd Quartile	0.098	- 0.026	0.234	0.993
PIPE20/21 1st Quartile	0.098	- 0.026	0.234	0.993
Average	*0.097*	- *0.026*	*0.218*	*0.994*

Appendix F. OLS-regression on dates and transaction sizes

Summary of OLS-Regressions

	R Squared	Adj. R Squared	F Statistic	P-Value
RO18/19 3rd Quartile	0.302	0.098	0.079	1.000
RO18/19 2nd Quartile	0.242	0.010	0.069	1.000
RO18/19 1st Quartile	0.184	- 0.066	0.052	1.000
Average	*0.243*	*0.016*	*0.066*	*1.000*
RO20/21 3rd Quartile	0.128	0.068	0.034	1.000
RO20/21 2nd Quartile	0.107	0.049	0.033	1.000
RO20/21 1st Quartile	0.086	0.024	0.026	1.000
Average	*0.107*	*0.044*	*0.030*	*1.000*
PIPE18/19 3rd Quartile	0.247	0.079	0.117	1.000
PIPE18/19 2nd Quartile	0.247	0.079	0.117	1.000
PIPE18/19 1st Quartile	0.247	0.079	0.117	1.000
Average	*0.247*	*0.079*	*0.112*	*0.999*
PIPE20/21 3rd Quartile	0.063	0.018	0.234	0.992
PIPE20/21 2nd Quartile	0.063	0.018	0.234	0.992
PIPE20/21 1st Quartile	0.063	0.018	0.234	0.992
Average	*0.063*	*0.018*	*0.223*	*0.993*