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Agency Problems In Special Purpose Acquisition Companies

Master Thesis

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MSc in Finance

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ABSTRACT

Special Purpose Acquisition Companies (SPACs) are publicly held shell companies with no operations, formed with the sole purpose of acquiring a single private company. With a sample of 342 SPAC mergers between July 2016 and February 2022, we find that the average 3-month buy-and-hold abnormal return (BHAR) is -16.7 percent, and only a quarter of SPAC's produce positive returns. We attribute these results to agency problems such as conflicting interests between the participants and adverse selection problems for the target shareholders. By analyzing SPAC data with the state-of-the-art tabular machine learning algorithm, XGBoost, we identify previously undiscussed features that can help investors predict the performance of SPACs and understand the conflicting interest. Our results may indicate that outside investors are unaware of the true determinants of SPAC performance. Furthermore, our evidence suggests that the SPAC structure leads to optimistic valuations of target companies and primarily benefits the parties that sell or redeem their shares before the merger. We suggest new regulations that align the interest of the parties involved in the SPAC transaction with the publicly traded target firm.

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Contents

Abbreviations

ABHAR Average Buy-and-Hold Abnormal Return

API Application Programming Interface

BHAR Buy-and-Hold Abnormal Return

IPO Initial Public Offering

IRR Internal Rate of Return

NPV Net Present Value

OLS Ordinary Least Squares

PIPE Private Investment in Public Equity

RMSE Root Mean Squared Error

SEC Securities and Exchange Commission

SHAP Shapley Additive Explanations

SPAC Special Purpose Acquisition Company

1 Introduction & Motivation

Special Purpose Acquisition Company (SPAC) are blank-check companies whose only objective is to raise capital in an Initial Public Offering (IPO) to acquire a target company through a business combination (Heredia et al., 2021). Going public through a SPAC offers an alternative path for companies to raise public equity. The main motivations for issuing public equity are raising capital for the firm, providing liquidity to company founders and early investors, and taking advantage of a higher valuation (Ritter and Welch, 2002).

The key research question in this thesis is how agency problems associated with the SPAC structure and SPAC participants affect the performance of the new publicly-traded company. Due to a lack of data regarding SPAC sponsors and Private Investment in Public Equity (PIPE) investors, the thesis primarily focuses on the SPAC IPO investors and the deSPAC investors. We address our research question by testing eight hypotheses related to the SPAC structure and asymmetric information. Our findings complement earlier research and bring new insights to the emerging literature on SPACs. Furthermore, the state-of-the-art tabular machine learning algorithm XGBoost has provided us with hitherto unexplored methods for evaluating and presenting SPAC data.

Our findings reveal that several SPAC features cause agency problems and that the deSPAC investors bear the costs. As a result, the deSPAC investors, on average, receive a negative 3-month abnormal return of 16.7%, while the SPAC IPO investors achieve a risk-free Internal Rate of Return (IRR) of 14%. We also disclose that IPO investors' payoff primarily comes from the warrants, which may lead to a conflicting interest with the deSPAC investors because the IPO investors value volatility as well as the quality of the deal. Additionally, our thesis provides some evidence that target companies do not prefer to merge with SPACs with a high fraction of warrants because of the increased dilution of the deSPAC company.

Issues discussed in this thesis will interest SPAC investors, regulators, and people interested in learning about SPACs. The thesis finds evidence of how the fundamental structures of a SPAC can lead to costs and inefficiencies related to asymmetric information. The Securities and Exchange Commission (SEC) has, during the writing of this thesis, on March 31, 2022, proposed new rules regarding SPACs. The SECs proposed new rules focus on the disclosure of the SPAC sponsors, conflicts of interest, and sources of dilution, which are similar issues that we discuss in our thesis.

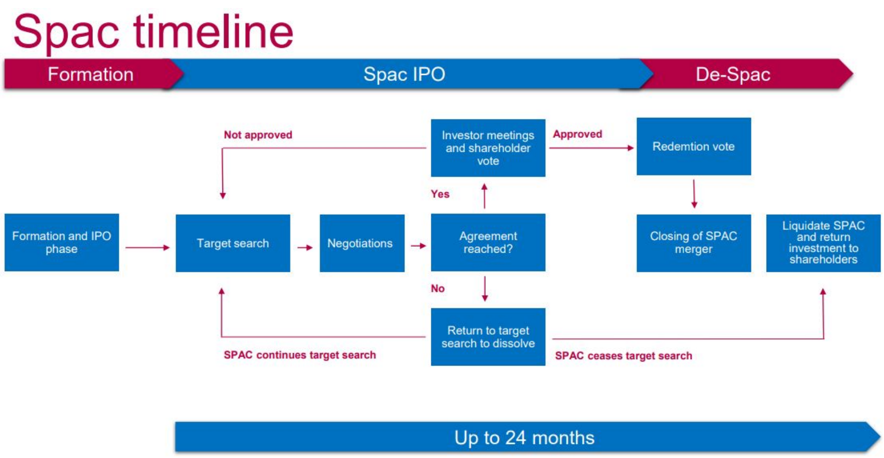
While SPACs have existed since the early 1990s, they have seen a boom in the US markets over the past years. More than 50% of SPAC IPOs have taken place after 2020, and SPACs have become the most popular way to take a private company public in the US, according to SPACresearch.com (2022). Europe has lagged behind the US on SPAC issuance, partially explained by regulation and liquidity in the capital markets being more favorable to SPACs in the US. However, in 2021 there were some large SPAC transactions at the stock exchange in Amsterdam and Frankfurt. In addition, the Norwegian battery cell company Freyr, went public on NASDAQ in 2021 through a SPAC merger. Norwegian Finanstilsynet is currently considering if SPACs should be allowed at the Oslo Stock Exchange but is also evaluating the issues related to investor protection and asymmetric information before making a decision.

Changes in the regulations on SPACs, volatile capital market, and the high growth of SPACs IPOs makes trends in the SPAC market change fast. Our thesis will contribute to prior literature by analyzing more updated and larger data samples and using a more complex model suited for the low signal-to-noise SPAC data.

2 SPAC Structure

A SPAC is a publicly held investment vehicle created to merge with a private company to bring it public. The lifetime of a successful SPAC consists of two separate transactions: First, the SPAC sells shares in an IPO and goes public. The SPAC has no operations but a group of sponsors that organize and manage the company. Secondly, the SPAC merges with a private company in a "deSPAC," to form a public listed company. If the SPAC fails to identify and merge with a private company, the proceeds from the IPO is returned to shareholders. The timeline of a SPAC is illustrated in figure 1. We define the period between the IPO and merger as the SPAC period and the time after the merger as the deSPAC period. It also makes sense to distinguish between the SPAC and deSPAC because the SPAC IPO investors are almost entirely large institutional investors, while the deSPAC investors are often retail investors. Klausner et al. (2021) finds that there is near 100% turnover of shares between the time of a merger announcement and the closing of the merger, indicating that SPAC IPO investors have little intention of remaining invested through the merger.

Figure 1: SPAC timeline



This figure illustrates a typical timeline for a SPAC transaction. Reproduced from PWC (2022).

In our research, we aim to explain the performance of the deSPAC based on how the SPAC is structured. Therefore we first need to understand some aspects of the SPAC structure and the identities of the participants in a SPAC transaction.

2.1 Participants

There are primarily four different participants that are involved in the SPAC transactions:

1. **The sponsors** are the team that establishes the SPAC. The sponsors range from large private equity, venture capital, or hedge funds, to former Fortune 500 executives, to individuals with no relevant background (Klausner et al., 2021). The sponsors will fund offering expenditures, including the up-front component of the underwriting discount and a small amount of working capital. The sponsors are also in charge of analyzing and acquiring a private firm in a time frame of 18 to 24 months. They will subsequently merge the private company with the SPAC after the acquisition (Layne and Lenahan, 2018). As compensation for the costs, the sponsors get a block of shares equal to 25% of the SPAC IPO proceeds, or 20% of the shares outstanding of the merger, called the sponsors "promote."

2. **SPAC IPO investors** are usually large institutional investors and is defined as the investors that take part in the SPACs IPO. The unit price of each issued share is usually $10, and the proceeds are placed in an escrow account that earns interest. A couple of days before the merger, the IPO investors can redeem their share and get back their investment instead of taking part in the deSPAC. The proceeds in the escrow account are the money used to acquire the private company. The investors in the SPAC IPO are also compensated with a warrant that is a fraction of the

unit share that trades separately from the stock. The investor keeps the warrant even when the share is redeemed.

3. **deSPAC investors** are the SPAC IPO investors or investors that buy the shares from the IPO investors and do not redeem their shares, the 20% sponsor promote, and shareholders from the private company in the merger.

4. **PIPE investors** is like the SPAC IPO investors, large institutional investors. PIPE refers to a private placement of shares of an already listed company to a selected group of accredited investors, usually at a discounted price. PIPE deals are often seen in SPAC transactions because sponsors need to raise more money to compensate for the redeemed money. PIPEs have been popular because they are efficient and can quickly raise capital compared to other secondary offerings.

2.2 Structure

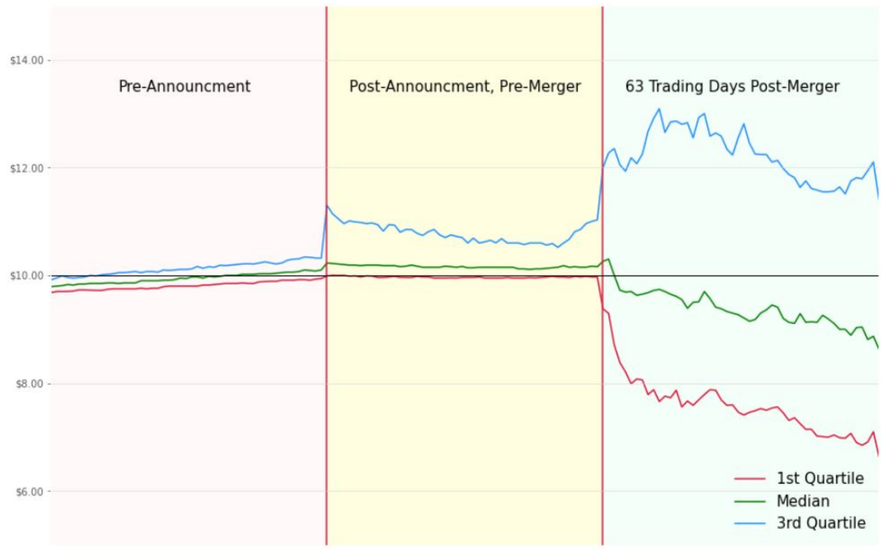
SPAC timeline. SPACs typically have a timeline between 18-24 months, as shown in the figure below. From our dataset, the average time between the SPAC IPO and the announcement of a business combination is just under 12 months, while the average time between the announcement and merger is less than six months.

Prior to the IPO, the sponsor purchases a block of shares at a nominal price that will be adjusted to equal 25% of the IPO proceeds or, in other words, 20% of post-IPO equity. This block of shares, known as the sponsor's promote, is the sponsor's pay for forming the SPAC and supporting its management while it looks for a private firm to take public. While searching for a merger target, the SPAC uses the proceeds of the sponsor's investment to cover the cost of the IPO and its running expenses. The sponsors will always be motivated to get a deal through because they will only get compensated in case of a merger. If the SPAC liquidates, the sponsors lose their investment. In certain SPACs, part of those proceeds is added to the trust to subsidize the return to IPO investors (Klausner et al., 2021). Once a SPAC has identified a target company and reached an agreement on a merger, the IPO investors vote on whether or not to approve the proposed merger. If the merger is approved, the IPO investors have a second vote where each shareholder must determine whether or not to redeem their shares at a price equal to $10.00. This means that the redemption option is as a money-back guarantee for the IPO investors. Even if their shares are redeemed, unitholders can keep (or sell) their warrants since they will trade separately. In some cases, the SPAC requires additional funds to complete the merger and may issue debt or additional shares, such as PIPE.

Redemption option. A study by Gahng et al. (2021) shows that the average redemption rate is 37%. However, our data set, which includes mergers to February 2022, shows that the average redemption has increased to 48%. Even when little capital is left after the redemption, a SPAC can complete a transaction and take a target business public. As a result, SPACs usually bring less capital to the merger than the proceeds raised at the IPO. However, the most common case is that a minimum amount of cash is negotiated, and the sponsors must look at alternatives to fund the gap between the proceeds left after the redemption, and the minimum amount promised. In some cases, the sponsor invests additional cash; in others, target shareholders may invest. In addition, SPAC and target management actively market proposed mergers to potential investors, going on what is referred to as SPAC roadshows (Klausner et al., 2021). Another alternative is to fill the gap through PIPE investments.

Trading price. SPAC IPOs are typically priced at a nominal $10 per unit. Because the SPAC is just a blank check company and has no operations, it is valued based on the expected economic success of the SPAC. At the same time, the ability to redeem the shares just before the merger protects the downside. Figure 2 shows our return data's median, 25th- and 75th percentile. The SPACs are traded at a slight discount in the pre- announcement period, which reflect the discounted share redemption.

Figure 2: SPAC Return Profile



The figure illustrates 1st, 2nd, and 3th quartile returns in our data set. "pre-announcement" and "post-announcement, pre- merger" illustrate the period we define as the SPAC period and "63 traiding days post- merger" is what we have defined as the deSPAC period.

Between the announcement and merger, we see the best quartile trade at a premium. In this case, we will have 0% redemption because investors who do not want to participate in the deSPAC are better off selling their shares in the market rather than collecting the $10 redemption. The lower quartile shows that the share price falls right after the redemption vote, usually a few days before the merger. After this date, there is no more downside protection for the investors. We also see that the median SPAC in our data sample loses about $1.5 of its value in the first 63 trading days after the merger.

Warrants. The SPAC IPO is often structured to offer investors a unit of securities consisting of (i) shares of common stock and (ii) warrants. The warrants usually have a strike price of $11.50 (SEC, 2021). In our data sample, the IPO investors receive 0.5 warrants for each common stock on average. The most common SPAC warrants are either public warrants or private placement warrants. The warrants can typically be exercised after the business combination event or at least 12 months after the SPACs IPO (Veal, 2021). Therefore, the nature of the warrants is comparable to American options.

2.3 Agency problems

The recent boom in the SPAC market combined with poor performance and some frauds related to deSPACs has highlighted a process with conflicting interests where fees and compensations have been extracted at the expense of the shareholders. The complex SPAC structure gives room for sophisticated methods to dilute shareholders and sometimes lead to competing incentives as a result of both **moral hazard** and **adverse selection** problems. As a result, different participants in the industry have asked for better mechanisms that lead to lower levels of information asymmetry to improve the pricing of SPACs. Earnouts have been one of the suggestions to solve the inadequate sponsor incentives but Michael Klausner (2022) recently revealed that the way earnout is structured today had no, or little effect.

The biggest moral hazard problem related to SPACs is the conflict of interest between the sponsors and the deSPAC shareholders and between the SPAC IPO investors and the deSPAC shareholders. The sponsors promote gives the sponsors significant financial incentives to pursue a merger even though the transaction could result in lower returns for public shareholders. Given the lack of data on the sponsor's payoff, we will primarily focus on the conflicting interest between the deSPAC shareholders and the SPAC IPO investors.

The moral hazard problem between the SPAC IPO investors and deSPAC shareholders is related to the SPAC IPO investors' ability to redeem their stock share while retaining their warrant. When the warrant is retained and exercised, the deSPAC shareholders are diluted relative to what they would be absent from such exercise. In addition, the SPAC IPO investors can sometimes vote in favor of a merger but then redeem their shares after the vote, furthering the conflict. Warrants have a similar payoff to a call option and are enhanced by greater volatility of the underlying security. This gives the SPAC IPO investors incentives to vote for high-risk mergers in conflicting interests with deSPAC shareholders.

The SPAC structure also leads to adverse selection problems. The use of due diligence and forecasts regarding earnings and performance of the target company is a mechanism that helps investors price a company correctly. However, SEC (2022) states that the due diligence and forecasts of SPACs also create some conflicting interest. The need to secure shareholder approval and meet the exchange listing's requirements may imply that the target company presents the most optimistic projections of its future performance. The sponsors' and SPAC IPO investors' interest in completing the merger to receive their compensation could also affect the degree to which they would be motivated to question the target's projections. If the SPAC vote against the merger, the alternative could be that the sponsor would not get any compensation, and the IPO investors would lose their warrant value.

3 Literature Review

SPACs have been present since the early 1990s but have not caught the researcher's interest before the recent boom in the market. This section will go through several studies that have looked at concerns related to our research. The facts discussed in this part will be the foundation for our hypothesis and tests. In this section, we will also explain the theoretical motivation for our hypothesis. The hypothesis testing will be further explained in section "Methodology & Hypothesis." The ideas we utilize are non-mutually exclusive and may be used to complement one another.

3.1 Efficient market hypothesis

The efficient market hypothesis is defined as the idea that competition among investors works to eliminate all positive Net Present Value (NPV) opportunities. It implies that securities will be reasonably priced, based on their future cash flows, given all information available to investors (Berk and DeMarzo, 2016). The assumption that markets collect information from many investors and that this information is reflected in asset prices is a natural result of investor competition. If the information suggested that buying a stock had a positive NPV, investors possessing that knowledge would opt to buy the shares, causing the stock price to rise. We could also have the same case the other way. Investors who discovered that selling a stock had a positive NPV would sell it, causing the stock price to decline. The amount of competition, and the validity of the efficient markets hypothesis, will be determined by the number of investors who have access to this information.

In the 1960s, the theory of efficient markets evolved from a Ph.D. dissertation by U. S. economist Eugene Fama. Fama (1970) suggested that the efficient market hypothesis existed in 3 forms: Weak, semi-strong, and strong. The Strong form is concerned with whether individual investors or groups have monopolistic access to any information relevant to price formations. The second form of market efficiency was the semi-strong form. Fama (1970) explained it as: In a semi-strong efficient market, prices reflect all publicly available information about economic fundamentals, including the public market data (in weak form), as well as the content of financial reports, economic forecasts, company announcements, and so on. The difference between the weak and semi-strong forms is that observing public market data is virtually free, whereas if prices are to fully reflect all publicly available information, such as public accounting data, public competition information, and industry-specific knowledge, a high level of fundamental analysis is required (Jones and Jeffry, 2008).

The last form is the strong form of efficient markets. (Fama, 1970, p. 409) defined the strong form as: "In strong form, the highest level of market efficiency, prices reflect all public and private information." This extreme form serves primarily as a limiting example since it would necessitate the inclusion of even corporate officials' confidential information about their own business in stock pricing (Jones and Jeffry, 2008).

Although the efficient market hypothesis should hold, many scholars are interested in the subject. According to several studies, the expenses of a SPAC structure outweigh the costs of a standard IPO. Klausner et al. (2021) finds that the costs associated with SPACs as currently structured are far higher than the costs of an IPO, even considering the IPO pop. Gahng et al. (2021) also finds the same results. The total cost of the median company going public via a SPAC merger between January 2015 and March 2021 was 14.6% of the post-issue market cap, while it was 3.2% for traditional IPOs (Gahng et al., 2021). The question regarding if SPACs are a better way to go public remains. (Klausner et al., 2021, p.85) answers the question in his paper: "however, a SPAC can be a cheaper means of going public than an IPO from the perspective of a target. So long as the target negotiates merger terms that leave the non-redeeming SPAC shareholders bearing the cost of the merger, the SPAC is a good deal for them." Without knowing if Ritter agrees with Klausner that the costs are passed on to deSPAC investors, he defends the high costs by touting all of the SPACs benefits. Despite the high expenses, an intriguing study issue may be to see if the benefits of the SPAC genuinely lead to efficient markets. According to Gahng et al. (2021), entrepreneurs who went public through a SPAC are ready to bear more significant expenses because of the additional financial considerations the sponsor brings to the firm in terms of experience. Entrepreneurs who decided to go public via merging with a SPAC often mention the business insight that sponsors can bring into their companies, mentioning that the cost was a secondary consideration. Comparing this to research on venture capital, Hsu (2004) documents that startup companies take offers with 10-14% pre-money valuation discounts made by venture capital funds with a high reputation because many startup companies consider extra-financial considerations to be important.

According to the efficient market hypothesis, the true value of the merger deal should, on average, be reflected in the deal price. Therefore, theory indicates that we should not find abnormal returns for investing in the average SPAC IPOs or deSPACs. Earlier research indicates that deSPAC investors, often associated with retail investors, earn a negative abnormal return. In contrast, SPAC sponsors and IPO investors often associated with institutional investors earn positive abnormal returns. This can indicate a transfer of wealth from retail investors to institutional investors. In our thesis, we first want to test whether this is true by calculating the abnormal returns of the deSPAC investors and the IPO investors in hypotheses 1 and 2. Further, we try to explain the results with the asymmetric information in the SPAC structure through hypotheses 3 to 8.

Hypothesis 1: deSPAC investors do not receive abnormal returns.

Klausner et al. (2021) find that there is a near 100% turnover of shares between the merger announcement and the merger's closing, indicating that the institutional investors nearly always redeem or sell their shares prior to the merger. Therefore, to test hypothesis 2, we construct a risk-free redemption strategy for the SPAC IPO investors explained further in section "Stage 1 - Calculate abnormal return and volatility".

Hypothesis 2: SPAC IPO investors do not receive abnormal return

3.2 Agency problems

The sponsor of a SPAC is an important part of the structure. The sponsors have several potential upsides because of how the SPAC is structured. The incentives for the sponsors to complete a merger are widely acknowledged to cause moral hazard. Both Klausner et al. (2021), and Gahng et al. (2021), agree that the incentives are insufficient, although their justifications differ somewhat.

SPACs have three options, according to Gahng et al. (2021): a good merger, a bad merger, or no merger at all. As the deadline approaches it creates an agency problem that encourages a sponsor to pursue an unpromising acquisition because if the SPAC is liquidated, the sponsor shares and warrants become worthless. Essentially this means that sponsors who cannot come up with a decent merger has an incentive to suggest a bad merger, which Klausner et al. (2021) also agrees on. Dimitrova (2017) also finds strong evidence that much of the SPAC value destruction through bad acquisitions is a result of certain contractual features that give SPAC manager's incentives to pursue any acquisition over no acquisition. (Gahng et al., 2021, p.6) instead counterattacks it with: "The redemption option is designed to address this agency problem - by redeeming, public shareholders do not suffer losses on their shares, and they may force the SPAC to liquidate." However, our research reveals that incentives for the IPO investors are more in line with the sponsors than the deSPAC shareholders, which makes Gahng et al. (2021) argument weaker. The SPAC must liquidate if it fails to merge, in which case the sponsor will get nothing and lose its initial investment. According to Klausner et al. (2021), the sponsor prefers a transaction that benefits deSPAC shareholders, but it will choose an unfavorable deal for the shareholders over no agreement at all. This puts the sponsor in a position where they may be hesitant to disclose a proposed merger's specifics to shareholders fully.

Based on earlier literature and the agency problems discussed in section 2.3 Agency problems we conduct four hypothesis related to the asymmetric information:

Hypothesis 3: High redemption rates signals a poor merger deal.

Gahng et al. (2021) claims that the redemption option is a mechanism to discourage sponsors from carrying out a poor deal. This indicates that a higher redemption rate should lead to a worse merger deal. We want to investigate if this mechanism applies on our data and leads to lower returns.

Hypothesis 4: A late merger indicates a poor deal since the sponsors fear liquidation.

As discussed, the sponsors always prefer a merger over no merger at all. However, as the SPAC approaches the liquidation deadline, the sponsors gets more desperate to find a merger and might merge with a poor target company. This suggests that mergers announced late in the SPAC timeframe indicate a poor merger deal.

Hypothesis 5: A sponsor team with experience from earlier SPACs will increase the performance of the deSPAC.

Based on private equity theory, reputation is important for the management to get funding for future funds (Marti Pellon and Balboa, 2003). Therefore, we conduct hypothesis 5, which tests and controls for the experience of the sponsor team. The theoretical motivation for the hypothesis is that sponsors for a poor-performing deSPAC will have issues raising capital for another SPAC. Therefore, a sponsor team that has experience from earlier SPAC deals and has been able to raise new capital multiple times should be a sign of quality and lead to better deSPAC performance.

Hypothesis 6: SPAC IPO investors prefer high-risk mergers

Figure 1 showed us that the IPO investors have two voting stages. First, they vote to approve or disapprove the merger. Then, in the next stage, they decide whether to keep or redeem their shares if the merger is approved. If they decide to redeem their share, they still keep the warrant. As Klausner et al. (2021) documented almost 100% of the IPO investors have either sold or redeemed their shares before the deSPAC period. This indicates that the IPO investors either take no part in the deSPAC transaction or only have the interest to maximize the warrant value. SPAC warrants, usually structured as an American option, increases in value with increased volatility and the value of the underlying deSPAC. Therefore, the IPO investors prefers a risky deal as well as a good deal. We hypothesize that high redemption rates leads to higher volatility of the deSPAC, because the IPO investors know that the target company is risky and therefore redeem their share and maximize the warrant value. This is in conflicting interest with the deSPAC shareholders that want to maximize the share value.

3.3 Dilution of shareholders

Merging with a SPAC incurs indirect expenses from dilution and underpricing and direct costs of underwriter fees. Sponsors' promotional shares and warrants and rights owned by SPAC IPO investors and sponsors are the primary sources of dilution. According to research, merging with a SPAC is more expensive than pursuing a traditional IPO, in terms of overall cost as a percentage of cash generated and as a percentage of post-issuance market capitalization. The cost to the median company of going public, as a percentage of post-issue market cap, is 14.6% when merging with a SPAC, vs. 3.2% when using a traditional IPO (Gahng et al., 2021). Michael Klausner (2022) outlines the costs as a percent of the pre-merged equity. He finds that, on average, the dilution from the sponsors is 31%, from the warrants and rights, it is 14%, and lastly, the underwriting fees and other fees account for 14%. His findings indicate that the total costs as a percentage of the pre-merger equity is 58%, equaling 14% of the market capitalization.

Hypothesis 7: High warrant structure causes a greater share price dilution.

As Gahng et al. (2021) and Michael Klausner (2022) indicates, there is sufficient cost related to SPAC warrants. Therefore, we hypothesize that SPACs with a high warrant to common stock ratio cause greater dilution of the stocks in the deSPAC, which leads to lower deSPAC returns.

Hypothesis 8: A high fraction of warrants in the SPAC are less attractive for the target companies

The target companies are aware of the warrant structure of the SPAC companies and know that more warrants refers to greater cost and a higher dilution. Therefore, given that hypothesis 7 is true, it is less preferred for a target company to merge with a SPAC that induces higher costs through the warrants.

4 Methodology & Hypothesis

The methodology and hypothesis used in our study will be described in this section. First, we introduce the dependent and explanatory variables of interest. Following that, the steps of empirical study and the corresponding models will be discussed. The methodology section concludes by reviewing the statistical tests we use in the models to ensure that the results are reliable. Furthermore, we will present our hypotheses discussed in the literature review section and explain how they are tested.

The literature covered in the previous section is primarily based on Ordinary Least Squares (OLS) regressions. OLS can work great for finding relationships in financial data. However, OLS makes certain assumptions about the data being modeled, such as linear functional relationships and similar distributions between the dependent and explanatory variables, and assumes that outliers do not exist (Currit, 2002). Violations of these assumptions may lead to biased results. Given the nature of the data that will be explained in more detail in the data section, we have good reasons to believe that typical SPAC data violate the OLS assumptions. Therefore, we want to use a non-linear model to test some of our hypotheses, which will also serve as a robustness check of the earlier literature. We will use the gradient boosting algorithm, XGBoost. XGBoost provides results with lower bias than OLS, in exchange for higher variance. Finally, we compare the performance of the two models on our dataset by using Root Mean Squared Error (RMSE) as a loss function.

4.1 Dependent variables

The primary objective of our research is to empirically test the effect of SPACs structural properties on deSPACs return and volatility. According to previous research, there are aspects of SPACs that are not yet efficient and significantly impact abnormal returns.

The first dependent variable is the 3-month *Buy-and-Hold Abnormal Return (BHAR)* of the deSPAC, which captures the return above or below a benchmark's return. How BHAR is calculated is explained in section **4.3.1 Stage 1 - Calculate abnormal return and volatility**. We use S&P SmallCap 600 as the benchmark index to calculate the BHAR. We believe that the composition of this index best represents the size of most SPAC transactions. The second dependent variable represents the *volatility of the 3-month BHAR*.

4.2 Explanatory variables

This section contains a comprehensive list of the explanatory variables used in our analysis. The factors will be used as the primary variables to explain the abnormal return and volatility found in the study. The variables will mainly consist of structural aspects of SPACs that we believe will influence the dependent variables and fixed effects that control for time, sector, and sponsor type.

The capital which a SPAC attracts during its IPO is used to attempt to make an acquisition. In the context of an acquisition, shareholders can sell their shares back to the SPAC. This right is also referred to as a redemption right. The *redemption rate* is measured as of percentage of the IPO investors that exercise their redemption right. Redemption rates act as a money-back guarantee for SPAC IPO investors, allowing them to redeem their shares if they dislike the target company. Literature suggests that high redemption rates indicate that the business combination will yield poor abnormal returns. Our research reveals that redemption rates also is a good indicator for volatility in the deSPAC. As a result, redemption rates will be one of the variables used to explain both the abnormal returns and the volatility in our thesis.

Investors investing in the initial SPAC IPO will be rewarded with a warrant fraction per share purchased. The *warrant structure* variable is the fraction of warrants that the IPO investors receive for each share purchased in the IPO. According to Klausner et al. (2021), warrants are a cost of forming a SPAC that dilutes the value of the shares. As a result, due to dilution, a higher *warrant structure* may indicate a lower abnormal return for deSPAC stock returns.

deSPAC time is a factor calculated to capture how close to the deadline the merger is announced. According to Gahng et al. (2021), SPACs have three options: a good merger, a bad merger, or no merger at all. As the deadline approaches, an agency problem arises, encouraging a sponsor to pursue an unpromising acquisition because the SPAC would be liquidated if the transaction fails. We construct the factor: $\frac{Announcement\ date - IPO\ date}{Liquidation\ deadline - IPO\ date}$ based on the Gahng et al. (2021) argument. This variable will determine how late the merger is announced within the agreed-upon time frame. We argue that deals undertaken late in the lifespan are more likely to be constrained by the deadline. Thus, we hypothesize lower abnormal returns because we know that a sponsor will always want to complete a deal rather than liquidate. Gahng et al. (2021) attempted to capture this effect as well. However, Ritter constructed a variable that captures the log months since the IPO. We argue that Ritter's variable does not capture the remaining time until the liquidation deadline correctly because SPACs may have different time frames.

Deal value will serve as the total enterprise value of the merged company. We believe there may be a relationship between the size of the deal and the abnormal returns achieved because there usually is less uncertainty and more information related to larger companies. The variable will also control for the effects of larger (smaller) deals.

We also calculated a variable that captures how much of the total enterprise value the money raised in the SPAC account for: $\frac{SPAC\ proceeds}{Deal\ value}$. Knowing that a traditional IPO typically raises $\frac{1}{4}$ or $\frac{1}{3}$ of the expected enterprise value to minimize the effect of dilution from the founder shares and warrants (Klausner et al., 2021), we think that this relationship in SPACs also could be significant in predicting abnormal returns.

A group of sponsors always establishes the SPAC. We constructed a variable representing how many SPAC deals the sponsors had completed in the past, anticipating that experience could substantially impact abnormal returns. *Sponsor deals* will be used as an explanatory variable. Previous literature does not appear to test for the sponsor's experience with completed SPAC agreements, but only the type of sponsor.

Lastly, we include three dummy variables to the regressions to control for different periods, sectors, and types of sponsors. These dummy variables will be denoted as *Sector*, *Time* and *Sponsor* fixed effects. Throughout Covid, we saw a growth in the SPAC market and a downturn following the SEC's new regulations. Therefore, adjusting for such factors is crucial to get robust results. We also assume that the type of sponsors could influence the anticipated results. The sector variable will determine whether sector trends cause abnormal returns.

4.3 Stages of the empirical research and models

4.3.1 Stage 1 - Calculate abnormal return and volatility

In the first stage, we calculate the abnormal return on two different strategies and the volatility of the deSPAC returns. First, we use the BHAR to calculate the abnormal return on the stocks and warrants. The BHAR is calculated from the first 63 trading days of the deSPAC. 63 trading days corresponds to and will be denoted as 3 months further in the thesis. The results are robustness checked by looking at the returns for 6 months and 1 year (126 and 252 trading days). We also calculate the volatility of the deSPAC for the same period. The BHAR is defined as:

$$BHAR_{i,h} = \prod_{t=1}^{h}(1 + R_{i,t}) - \prod_{t=1}^{h}(1 + R_{m,t})$$

where $BHAR_{i,h}$ is the abnormal return of the asset i over the period h, $R_{i,t}$ is the day t simple return of the asset i and $R_{m,t}$ is the day t simple return of the benchmark portfolio m. To determine the performance of the average deSPAC we calculate the Average Buy-and-Hold Abnormal Return (ABHAR) of all the SPACs and test the significance with a t- test:

$$ABHAR = \frac{1}{N}\sum_{i=1}^{N} BHAR_i$$

The SPAC structure gives the SPAC IPO investors a fraction of a warrant when buying a common stock at the IPO. This warrant trades separately from the common stock and the investors keep the warrant, even when redeeming the stock. Therefore, redeeming the stock or selling it in the market if it trades at a premium is equivalent to a risk-free strategy because the investor will always get the proceeds from the escrow account back and keep the warrant. Next, we use the IRR to calculate the SPAC IPO investors' return on the risk-free strategy where they always redeem their common stock or sell when it trades at a premium. The warrant is sold in the market at the merger date. The redemption vote is usually a couple of days before the merger. Therefore, we choose 5 days before the merger as the date when the IPO investor decides if they sell or redeem their share.

The payoff of the strategy is inspired by Gahng et al. (2021) and calculated by multiplying the warrant price with the warrant structure of the SPAC and adding the highest value of the redemption value or the share value:

$$Payoff = C_t = max(redemption\ value_{t-5}, common\ share\ price_{t-5}) + Price\ of\ Warrant_t * Warrant\ Structure$$

We use the IRR formula on this cash flow to see if the strategy will yield a higher IRR than the risk-free rate. To compare the returns, we calculate the IRR and risk free rate on the average number of days between the SPAC IPO and merger, and annulaize the rates.

$$0 = \frac{C_t}{(1 + IRR)^t} - IPO\ investment$$

Lastly, we calculate the standard deviation (volatility) of the deSPAC:

$$S_R = \sqrt{\frac{1}{n_R - 1} \sum_{i=1}^{n} (X_{R_i} - \bar{X_R})^2}$$

4.3.2 Stage 2 - Regression

In the second stage, we run multivariate linear regressions using OLS to investigate the relationship between our dependent and explanatory variables. We run the following model:

$$BHAR_i = \beta_0 + \beta_1 Redemption\_rate_i + \beta_2 deSPAC\_time_i + \beta_3 Warrant\_structure_i + \beta_4 TEV_i + \beta_5 SPAC\_proceeds\_to\_TEV_i + \beta_6 Sponsor\_deals_i + \epsilon_i$$

The SPAC market has changed rapidly the past couple of years, so we find it reasonable to include some categorical features to control our regression for the time fixed effects, the different sectors, and the professional background of the sponsors:

$$BHAR_i = \beta_0 + \beta_1 Redemption\_rate_i + \beta_2 deSPAC\_time_i + \beta_3 Warrant\_structure_i + \beta_4 TEV_i + \beta_5 SPAC\_proceeds\_to\_TEV_i + \beta_6 Sponsor\_deals_i + \beta_7 Time\_dummy_i + \beta_8 Sector\_dummy_i + \beta_9 Sponsor\_dummy_i + \epsilon_i$$

To check the robustness of the coefficients, we conduct individual regressions with the redemption rate, deSPAC time, and warrant structure in addition to the joint regression.

We also conduct the same regressions but with volatility as the dependent variable.

4.3.3 Stage 3 - Extreme gradient boosting

To complement and check the robustness of the OLS result, we build a prediction model using the supervised boosting algorithm **XGBoost** (Chen and Guestrin, 2016). XGBoost is an abbreviation of eXtreme Gradient Boosting and is an implementation of gradient boosting decision trees. Gradient boosting is a powerful supervised machine learning technique with considerable success in many practical applications (Natekin and Knoll, 2013). Gradient boosting takes a data set (x, y) where $x = (x_1, ..., x_d)$ is our explanatory variables and y corresponding labels of the dependent variable, just like when we are using OLS.

If we assume that we have K numbers of trees, our model can be written as:

$$\hat{y_i} = \sum_{k=1}^{K} f_k(x_i), f_k \in F$$

Where F is the space of Regression trees and $f_k(X)$ is the decision tree computed at iteration k. Gradient boosting uses a greedy approach that includes a penalty term, $\Omega(f_k)$ for adding more trees to avoid complexity. The objective of the model is given by:

$$Obj = \sum_{i=1}^{n} l(y_i, \hat{y_i}^{(t-1)} + f_t(X_i)) + \Omega(f_k)$$

The model is trained in an additive manner where $\hat{y_i}^{(t-1)}$ is the prediction of the i-th instance at the t-th iteration, and we add f_t to minimize the objective. XGBoost minimizes the objective by minimizing the loss function, which is the first part of the equation, while it accounts for the second part of the equation, which is the regularization term that measures the complexity of the trees. XGBoost has many hyperparameters that can be used. The tuning of the hyperparameters can be found in **appendix A.**

4.3.4 Stage 4 - Testing the reliability of regression results

To ensure the results are reliable, we test whether the OLS assumptions are met. If any of the assumptions are violated, we can get biased estimates, wrong standard errors, or wrong distribution of test statistics. First, we perform a White's test to check if the residuals are equally scattered at each level of the dependent variable. We use heteroskedasticity robust standard errors in the regression where we find evidence of heteroskedasticity. We then use the Durbin-Watson test for correlated or auto-correlated errors and the Bera-Jarque test to check for kurtosis and skewness. We do not find evidence of auto-correlation. However, the Bera-Jarque test shows strong evidence of kurtosis or skewness in our data set, which is not surprising given that our data sample is relatively small and the non-normal distribution nature of financial data. Finally, we examine the correlation between the independent variables to detect a possible multicollinearity issue in the regression. The correlation matrix in **appendix C** shows us that the highest bivariate correlation is 0.49 between the deSPAC_time and the Warrant_structure. To test for multicollinearity, we performed regressions where we excluded either of the variables, computed the variance inflation factor, and computed the condition number. Based on the analysis, we find some slight evidence for multicollinearity between the Warrant structure and the deSPAC time. We choose to keep both variables in the model to avoid any omitted variable bias. We will discuss this further in **6.5 Analysis of target companies' fear of dilution**.

4.3.5 Stage 5 - Interpret and compare the models

We use RMSE as the loss function to compare the models. RMSE is the standard deviation of the residuals and measures how concentrated the data is around the line of best fit and is given by:

$$RMSE = \sqrt{\frac{1}{n} * \sum_{i=1}^{n} (\hat{y_i} - y_i)^2}$$

$\hat{y_1}, \hat{y_2}, ..., \hat{y_n}$ are the predicted values and $y_1, y_2, ..., y_n$ are observed values. When comparing the models, we split our data set into 67% training and 33% testing samples, fit our models on the training data and use the test data to predict, $\hat{y}_i$. We compare the predicted values with the real values in the test sample by using RMSE and compare the two models.

The XGBoost model is a so-called "black-box algorithm" that can be hard to interpret. However, the use of Explainable Artificial Intelligence (Adadi and Berrada, 2018) help us create simpler explanations of the model. We use Shapley Additive Explanations (SHAP) based on the game's theoretically optimal shapley values to interpret the model. SHAP explains the model's prediction by computing the contribution of each variable to the prediction. The SHAP values from each variable of a data instance act as players in a coalition. SHAP values tell us how to fairly distribute the prediction among the different variables (Molnar, 2022). SHAP specifies the explanation as:

$$g(z') = \phi_0 + \sum_{j=1}^{M} \phi_j z'_j$$

where g is the explanation model, $z' \in \{0,1\}^M$ is the coalition vector, M is the maximum coalition size and $\phi_j \in \mathbb{R}$ is the variable attribution for a variable j, the SHAP values.

Using SHAP we create three different plots to help us unbox and interpret the model. First, partial dependence plots indicate what variables are most important for the prediction, which can relate to how we interpret coefficients and p values in a OLS regression. We can also make relative importance plots to see how a variable contributes to the prediction over the x-axis. At last, we can plot local SHAP values for a given sample to see how each variable contributes to the prediction.

4.4 Hypothesis

4.4.1 Abnormal returns

Hypothesis 1: deSPAC investors do not receive abnormal returns.

Hypothesis 2: SPAC IPO investors do not receive abnormal return

This hypothesis is tested by comparing the returns for the SPAC participants with the return of relevant benchmarks. The results from hypotheses 1 and 2 will be the baseline for the rest of our hypotheses.

Hypothesis 1 examines the first 3 months of the deSPACs abnormal return in excess of the S&P SmallCap 600 and uses a t-test to check if the ABHAR is significantly different from zero. To check the robustness of the results we also calculating the 6 month and 1 year abnormal return:

$$H_0 : ABHAR_{deSPAC} = 0,$$
$$H_a : ABHAR_{deSPAC} \neq 0$$

Hypothesis 2 test the IRR of the risk-free strategy for the IPO investors and compares it to the IRR of a 3 month T-bill that we define as the risk-free rate:

$$H_0 : \text{ IRR}_{rfStrat} = \text{ IRR}_{Tbill},$$
$$H_a : \text{ IRR}_{rfStrat} \neq \text{ IRR}_{Tbill}$$

4.4.2 SPAC structure

Hypothesis 3: High redemption rates signals a poor merger deal.

Hypothesis 4: A late merger indicates a poor deal since the sponsors fear liquidation

Hypothesis 5: A sponsor team with experience from earlier SPACs will increase the performance of the deSPAC.

Hypothesis 7: High warrant structure causes a greater share price dilution.

These hypotheses are related to the agency problems explained in the litterateur review and are tested in our main regression. We conduct the regression individually and as a joint regression for more robust results. To quantify the hypothesis, we will test if the coefficients of redemption rate, deSPAC time, warrant structure, and sponsor deal coefficients are significantly different from zero. Significant coefficients indicate the model we can explain some of the abnormal returns related to SPACs.

To test the hypothesis, we will use the following regression:

$$BHAR_i = \beta_0 + \beta_1 Redemption\_rate_i + \beta_2 deSPAC\_time_i + \beta_3 Warrant\_structure_i + \beta_4 TEV_i + \beta_5 SPAC\_IPO\_to\_TEV_i + \beta_6 Sponsor\_deals_i + \beta_7 Time\_dummy_i + \beta_8 Sector\_dummy_i + \beta_9 Sponsor\_dummy_i + \epsilon_i$$

And the following hypothesis tests:

$$\textit{Hypothesis 3}: H_0 : \beta_1 < 0, H_a : \beta_1 = 0$$

$$\textit{Hypothesis 4}: H_0 : \beta_2 < 0, H_a : \beta_2 = 0$$

$$\textit{Hypothesis 5}: H_0 : \beta_6 > 0, H_a : \beta_6 = 0$$

$$\textit{Hypothesis 7}: H_0 : \beta_3 < 0, H_a : \beta_3 = 0$$

We check the robustness of the OLS results by doing the same regression in XGBoost and comparing the results.

4.4.3 SPAC participant incentives

Hypothesis 6: SPAC IPO investors prefer high-risk mergers

To test hypothesis 6, we first test whether higher volatility of the deSPACs leads to a higher abnormal return for the warrants to confirm the basic option pricing theory on our data set. Then, we conduct the same regression as above, but with the deSPAC volatility as the dependent variable. We hypothesize that SPAC IPO investors know when they are entering a high-risk deal; in that case, they only want to keep the warrants and redeem their share. This is reasonable because the nature of the warrants in the SPAC is similar to an American option, meaning that SPAC IPO investors can execute their warrant whenever they want. This is unlike European options that limit execution to its expiration date and would give more aligned incentives with the deSPAC shareholders.

Hypothesis 8: High warrant structure in the SPAC are less attractive for the target companies

As discussed in "Stage 4 - Testing the reliability of regression results", there is a bivariate correlation between the warrant structure and deSPAC time. Therefore, if the results from hypothesis 7 are significant, we want to test if high warrant structures make SPACs less attractive for the target company because the target owners know that their shares will be more diluted if the warrants are exercised.

We will test it by examining the significance of the warrant structure coefficient. To conduct the test, we will use the following regression:

$$deSPAC\_time_i = \beta_0 + \beta_1 Warrant\_structure_i + \beta_2 Time\_dummy_i + \beta_3 Sector\_dummy_i + \beta_4 Sponsor\_dummy_i + \epsilon_i$$

And the following hypothesis tests:

$$Hypothesis\ 8 : H_0 : \beta_1 > 0, H_a : \beta_1 = 0$$

As discussed, IPO investors' payoff is usually related to the free warrant they receive. This aligns their incentives with the sponsors, who receive a payoff only if they can merge with a target company. If they fail to do so, the warrants will be worthless. This indicates that the sponsors and IPO investors prefer a short SPAC period, so they can utilize their payoff quickly and do not want to risk not being able to merge with any target company. Therefore, we do not believe there is a causality problem between the two variables in the regression.

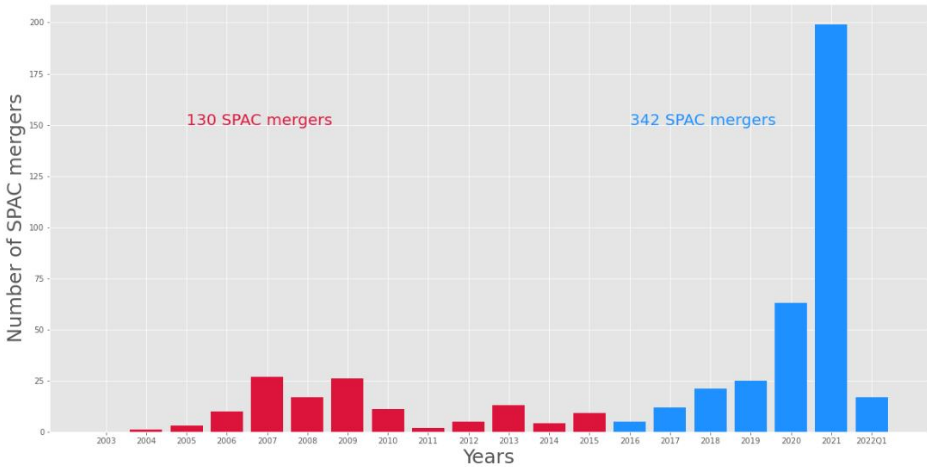
5 Data

In this section, we discuss the characteristics of our data. We present sample selection, descriptive statistics, and some of the time trends in the SPAC market.

5.1 Sample selection

In our study, we have researched 342 SPAC deals in the global market between July 2016 and February 2022. The sample selection is illustrated in figure 3 below, where the blue bars indicate our sample and accounts for about $\frac{3}{4}$ of the total SPAC mergers. Most of our data is obtained from Pythons Application Programming Interface (API) to Yahoo finance and Eikon Refinitve, and SPACresearch.com. SPACresearch will serve as our primary data source regarding the SPACs and comprises all of the information underlying the SPACs structure. The data consists of redemption rate levels, a fraction of warrants per share, total enterprise value, sector and dates for the IPO, announcements, mergers and liquidations. These variables will be decisive in answering the questions in the research. The available data at SPACresearch is why our sample selection is limited to the period after 2016. There are some pros and cons to missing out on the earlier data. Including all the merger deals in figure 3 would give a larger data sample that would reduce the variance of the output from our models. However, the structure of SPACs has evolved over the years, so the old mergers can be less relevant for how deSPAC returns if affected today. Including old data points can cause biased results, so we have a bias-variance trade-off when choosing the sample size. Table 2 shows how much the SPAC structure has changed over our sample period. We are satisfied with our sample data, and based on intuition, we believe that our sample period gives us a decent bias-variance trade-off based on what we have described above. After the merger is completed, the share price data is collected from

Figure 3: SPAC IPO Activity



The graph shows an overview of SPAC merger activity. Our data is extracted from the period with the blue bars

Yahoo finance API in Python. For the warrants, the data is gathered from the Python API to Refinitive Eikon, which provides detailed information on the warrant price development and is therefore used as the main source of data for the risk-free redemption strategy. Earlier research has used up to 1 year of returns data. However, we have chosen 3-month return data as our dependent variable because we want to maximize the data sample and believe that most of the mispricing in SPACs will be reflected in the 3-month deSPAC period.

5.2 Descriptive statistics

Table 1 presents descriptive statistics of the SPAC deals in our sample to summarize the data and provide a clear overview. As documented with the Jarque-Bera test in "Stage 4 - Testing the reliability of regression results", we can see from the difference between the mean and median that almost all of our variables are either positive or negative skewed and none of the variables are normally distributed. The return data, volatility, total enterprise value, and SPAC proceed to TEV variables have some outlier that gives the distribution fat tails. This is a common problem in financial data and creates noise in our data set. Our data is also relatively small, with 342 observations over a 7-year period, further lowering our signal-to-noise. OLS is a good model

Table 1: Continous Data Summary

Variable	Mean	Median	Std. Dev.	25%	75%
3- month abnormal return	-0.167	-0.191	0.347	-0.394	-0.005
Volatility	0.071	0.055	0.077	0.042	0.077
Redemption's	0.477	0.545	0.373	0.029	0.839
deSPAC time	0.426	0.331	0.258	0.201	0.690
Warrant structure	0.495	0.500	0.281	0.333	0.500
Number of sponsor deals	1.687	1.000	1.220	1.000	2.000
Total enterprise value (M)	1903	1127	2805	590	2086
SPAC proceeds to TEV	0.280	0.212	0.312	0.138	0.328

This table shows the summary statistic for the dependent and explanatory variable. N = 342.

to find significant relations with such data, given its ability to minimize the variance of the residuals. However, because OLS minimize the residual sum of squares, it will be driven by the outliers, and the results can be biased when large outliers are present. This is why we introduce XGBoost to our research, a non-linear model that works great on data with a low signal-to-noise ratio. XGBoost will give us a lower bias than OLS, but will have a higher variance.

5.3 Time trends

Given SPACs recent popularity, we observe from table 2 that the structure of SPACs is changing over time. When looking at the number of transactions, we see a big boom in popularity in 2020 and 2021, when the markets were recovering from Covid-19 and interest rates were low.

Despite SPACs historically poor performance, the markets were optimistic for small-cap companies with growth opportunities which led to high merger valuations and larger deals, as seen in table 2. The optimistic market also made SPACs trade at a premium pre-merger which explains the low redemption rates for the given years because the SPAC investors were better off selling their stock in the market than collecting the 10 dollar redemption. If we exclude

Table 2: Annually mean values

Year	N	Vol.	BHAR	Redemption's	deSPAC time	Warrant st.	TEV
2016	4	0.037	-0.132	0.212	0.526	0.708	1129
2017	12	0.029	-0.050	0.475	0.633	0.653	1074
2018	20	0.091	-0.066	0.579	0.611	0.688	929
2019	24	0.085	-0.076	0.594	0.604	0.656	899
2020	63	0.071	-0.119	0.377	0.614	0.597	1432
2021	198	0.063	-0.209	0.450	0.318	0.416	2376
2022Q1	21	0.150	-0.185	0.858	0.359	0.438	1556

This table examines how our data has changed over the sample period. Total enterprise value (TEV) is in a million dollars.

2020 and 2021, we see that the average redemption rate has increased from 21% in 2016 to 86% in 2022, indicating that the SPAC IPO investors are getting more skeptical of the deSPACs. The popularity of the SPACs has also led to higher competition in the SPAC market, and as of May 2022, there are about 600 SPACs searching for a target company (SPACanalysis, 2022). The competition makes the SPAC sponsors more creative on the SPAC structure to be more attractive to a target company which we can also see in the declining number of warrants for each common share.

6 Empirical Analysis

This section aims to test our hypotheses by analyzing and interpreting the outcomes of the performed tests. We perform multiple analyses to explain how agency problems in the SPAC structure affect the deSPAC return.

6.1 Analysis of the deSPAC investor's returns

This section will test hypothesis 1 to identify how the deSPAC performs. Table 3 presents the raw returns of the deSPACs common share, the abnormal return benchmarked against S&P SmallCap 600, and the adjusted abnormal return to their respective sector. All of the returns estimated are significant at a 1% level. The 3-month mean return, excess S&P 600 SmallCap, is the average BHAR and corresponds to our dependent variable.

Table 3: Buy-and-Hold Common Stock Returns

	3 months	6 months	1 year
Mean Return	-0.137***	-0.268***	-0.187***
Median Return	-0.183***	-0.363***	-0.397***
Mean Return (Excess S&P 600 SmallCap)	-0.167**	-0.313***	-0.327***
Median Return (Excess S&P 600 SmallCap)	-0.191***	-0.365***	-0.496***
Mean Return (Excess S&P 600 SmallCap Sectors)	-0.161***	-0.305***	-0.315***
Median Return (Excess S&P 600 SmallCap Sectors)	-0.188***	-0.374***	-0.490***
Observations	342	293	157

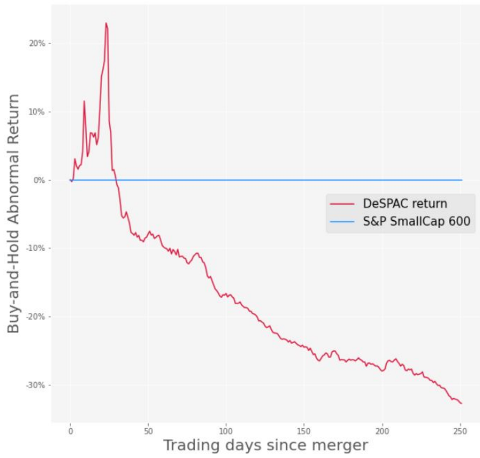
This table presents the 3, 6, and 12-month median and mean return of the deSPACs. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

As of 3 months following a merger, the average SPAC had a raw return of -13.7%. Our benchmark S&P SmallCap 600 increased on average; therefore, the deSPACs underperformed the S&P SmallCap 600 by 16.7% on average. Because the number of observations differs and the 1-year and 6-month data does not include the newest mergers, a timing effect will affect the returns and make them not entirely comparable. The 6 and 12 months abnormal return is, on average, -31.3% and -32.7%, which indicates that the average deSPAC keeps declining after 3 months. However, the number of observations declines quickly when we increase the buy-and-hold period. Therefore, we use the 3-month returns as our dependent variable to maximize the number of observations.

Our sector distribution from **appendix B** reveals that private companies in particular sectors are more interested in going public via SPACs. For example, the three sectors, Information Technology, Health Care, and Consumer Discretionary, account for 59% of our sample. As a result, we wanted to adjust the deSAPC returns for the S&P SmallCap 600 sectors to see if the sectors may explain part of the negative abnormal return. We observe that the mean return excess of the S&P SmallCap 600 and S&P SmallCap 600 sectors is relatively small and not significantly different from each other. This corresponds with the regression results in **section 6.4** where the sector dummies were not significantly different from zero.

Klausner et al. (2021) and Kolb and Tykvová (2016) reports a twelve-month negative benchmark adjusted return of -38% and -46%, respectively. Figure 4 depicts the performance of our data set's average twelve-month buy-and-hold return, which yields a negative abnormal return of 32.7%. The disparity in stated returns is due to Klausner et al. (2021) and Kolb and Tykvová (2016) using a smaller sample, and the SPAC market is relatively volatile. To calculate the twelve-month return, we have to reduce the number of observations to 157, which will result in using an earlier portion of the data set when evaluating the returns. Because of a rapidly developing market and few data points, timing will largely affect the result. From figure 4 with the data set containing 157 mergers from February 2021 and earlier, we can see that 63 trading day (3-month) abnormal return is about -10% in comparison to -16.7% for the full data set. We also observe some extreme movements in the first 50 trading days where the average deSPAC increases by more than 20% before it falls down close to negative 10%. This movement is mainly caused by two individual deSPAC that increased by hundreds of percent for a couple of days and then fell straight back. This movement is averaged out and not as significant at the whole sample.

Figure 4: Twelve-months DeSPAC returns, Excess S&P SmallCap 600



This figure shows the average 1 year deSPAC return, excess the S&P SmallCap 600 benchmark with 157 observations.

The results indicate that the deSPAC investors, on average, yield a negative return in excess of the benchmark portfolio, and we can reject the null hypothesis in hypothesis 1. In light of these intriguing findings, we will examine various explanations for why we observe such significant negative returns in the deSPAC market in the following sections.

6.2 Analysis of SPAC IPO investor's risk-free strategy in comparison with the risk-free rate

This section will look at hypothesis 2, where we have defined a risk-free strategy for the SPAC IPO investor where they always redeem their common share and sell the warrant the first day after the merger. For the calculation, we used the 194 SPACs for which we could find warrant data and calculate the IRR of the investment. As a result, the IRR of the risk-free redemption strategy is 14%, while the risk-free rate is 0.73% on average in the same period.

Our findings that the return of the risk-free redemption strategy exceeds the return on the risk-free rate provides a good indication of why Klausner et al. (2021) find a 92% selling rate in the 13-F filings, meaning that IPO institutional investors, on average, get rid of 92% of their IPO shares before the deSPAC. Our results show that it is lucrative to be a SPAC IPO investor with no intention to bear any risk in the deSPAC. This indicates that the IPO investors mainly have two priorities. First, ensure that the SPAC merges with a target company so they can utilize the free warrant. Secondly, they merge with a target company that maximizes the value of the warrant. This is a different and conflicting interest than what a deSPAC shareholder has and will serve as the foundation for the rest of the research. Comparing the results with the results from hypothesis 1, can indicate some wealth transfers from the deSPAC shareholders to the IPO investors. Earlier research discloses that the sponsors also receive a lucrative payoff, but due to the lack of data, we have not been able to calculate this.

Given this strategy's lucrative risk-free payoff, we would expect even more IPO investors. Klausner et al. (2021) reports that the IPO investors are almost entirely institutional investors, meaning that there is a barrier for the retail investors to participate in the SPAC IPO. We also find evidence that the competition between SPACs and IPO investors is increasing. In the first quarter of 2022, there were about 600 SPACs searching for target companies, almost twice the number of mergers in the past seven years. This means that we have a seller's market and will probably see more SPACs failing to find a target company and liquidate. Table 2 also shows that the number of warrants received from each share decreased from 0.7 in 2016 to 0.44 in 2022, reducing the payoff.

Receiving fewer warrants for each share combined with a lower probability of finding a target company and utilizing the warrant can indicate that the competition is moving the payoff towards a more efficient state.

6.3 Analysis of warrant returns

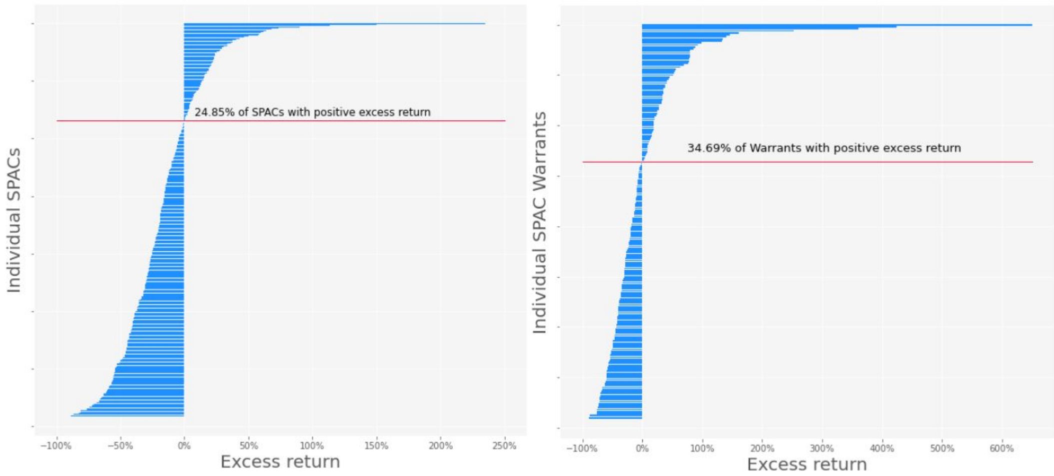
We have established that the SPAC IPO investors rarely keep their common shares in the deSPAC. However, we have also observed a lucrative risk-free strategy for the IPO investors that includes selling the warrant at the merger, but could it be a better alternative to keep the warrants in the deSPAC period? To test this strategy, we calculate the 3-month BHAR of the warrants, equal to how we calculated the $BHAR$ for the deSPAC. We find that the mean $BHAR$ of the warrants is -5.88%, excess S&P 600 SmallCap with a p-value of 0.49. The p-value suggests that the abnormal warrant returns are not significantly different from zero.

Figure 5 shows the distribution of the BHARs for the deSPAC and warrant. We observe that a larger fraction of the warrants give positive returns. The reason why the warrants, that are based on the underlying deSPAC perform better than the deSPAC is that the valuation is based on the underlying asset's volatility and price. This means that if the volatility is high, the warrant can increase in price, even when the underlying deSPAC decreases.

If the IPO investors only keep their warrants and not the share, they have incentives to vote for a high-risk merger because that will bring more volatility and maximize the warrant price. To demonstrate that the nature of option pricing is present in our data set, we test if higher volatility of the deSPACs increases the abnormal return of the corresponding warrant: The regression in table 4 provides evidence that higher volatility of the deSPACs leads to a higher BHAR of the warrants, which is consistent with option pricing theory.

Figure 5: deSPAC and Warrant returns, excess S&P 600 SmallCap

(a) deSPAC (b) Warrants



This figure shows the distribution of the 3- months buy-and-hold abnormal return for the (a) deSPACs and the (b) warrants.

Table 4: Warrant BHAR

Variable	coef	std err	t	p-value
const	-0.2010	0.079	-2.553	0.011
Volatility	2.6104	0.724	3.604	0.000

$BHAR_i = \beta_0 + \beta_1 Volatility_i + \epsilon_i$ where $BHAR_i$ is the 3 month buy-and-hold abnormal return of the warrants and the Volatility is the standard deviation of the underlying deSPAC in the same period. Adjusted R-squared = 0.058. N = 196.

Next, we test hypothesis 7 to check if the IPO investors know they are entering a high-risk merger by redeeming their shares. We test our hypothesis using an OLS and XGBoost model with volatility as our dependent variable and examine how our explanatory variables predict the volatility.

The results from the OLS and XGBoost regression in Table 5 and figure 6 provide evidence that the redemption rate can explain some of the variations in the volatility. In the OLS regression, the redemption rate coefficient is significant at a 99% level in both the individual and joint regression. The deSPAC time and warrant structure coefficient are significant at 10% level in the individual regressions, but not in the joint regression. However, while the

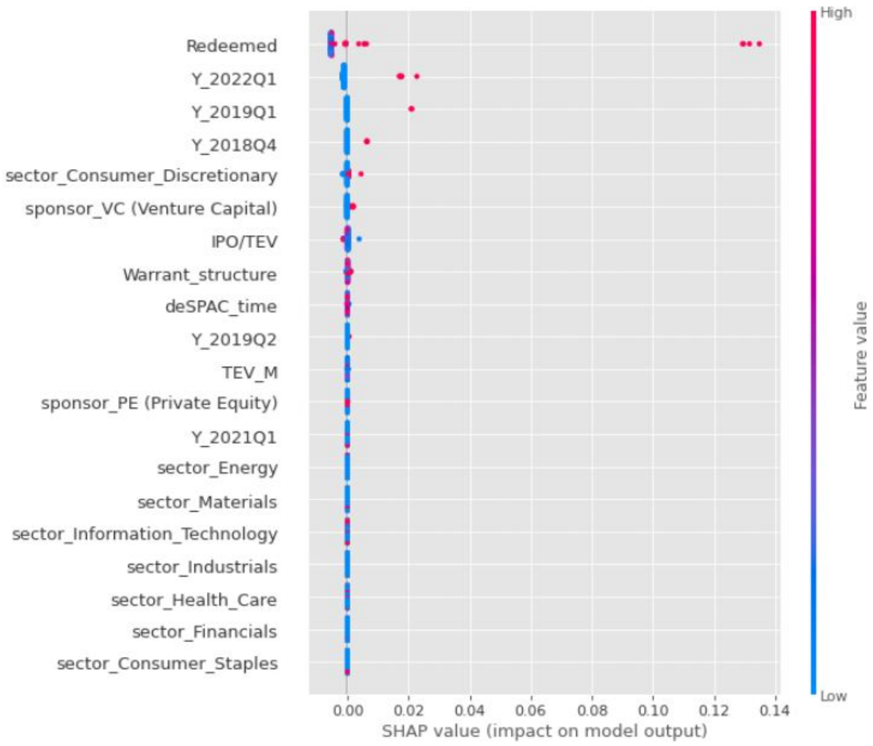
Table 5: Regression - deSPAC Volatility

Dependent Variable	1	2	3	4
deSPAC_time	0.036* (0.019)			0.016 (0.021)
Redeemed		0.041*** (0.012)		0.036*** (0.013)
Warrant_structure			0.031* (0.016)	0.012 (0.018)
TEV_M				-7.06e-07 (1.54e-06)
Sponsor_deals				-0.002 (0.003)
IPO/TEV				-0.013 (0.014)
Quarter fixed effects	Yes	Yes	Yes	Yes
Sector fixed effects	Yes	Yes	Yes	Yes
Sponsor fixed effects	Yes	Yes	Yes	Yes
Adjusted R- Squared	0.26	0.28	0.26	0.18

This table examines the SPAC structures prediction of the deSPAC volatility. Statistical significance levels: *** p-value<0.01, ** p-value<0.05, * p-value<0.10. N = 342.

OLS coefficients give us a linear relationship, XGBoost indicates a non-linear relationship between the volatility and the redemption rate as illustrated in figure 8 When we compare the performance of the two models trained on a 67% training set and evaluated on a 33% test set, we find that XGBoost predicts with a 25% lower error than OLS. The $RMSE$ of the XGBoost and OLS is 0.062 and 0.081, respectively. The tuning of the hyperparameters can be found in **appendix A**. From figure 6, it appears that XGBoost also finds redemption rate as the most important variable to explain the volatility. The figure shows the global SHAP values across the test sample. A higher SHAP value corresponds to a higher coefficient, meaning more volatility. The most important variables are presented in descending order, which means that redemption rate is the most important factor for this model. The color of the dots indicates the value of the feature. E.g., a red dot means that the redemption is equal to 1, and a blue dot means that it is equal to 0. The dummy

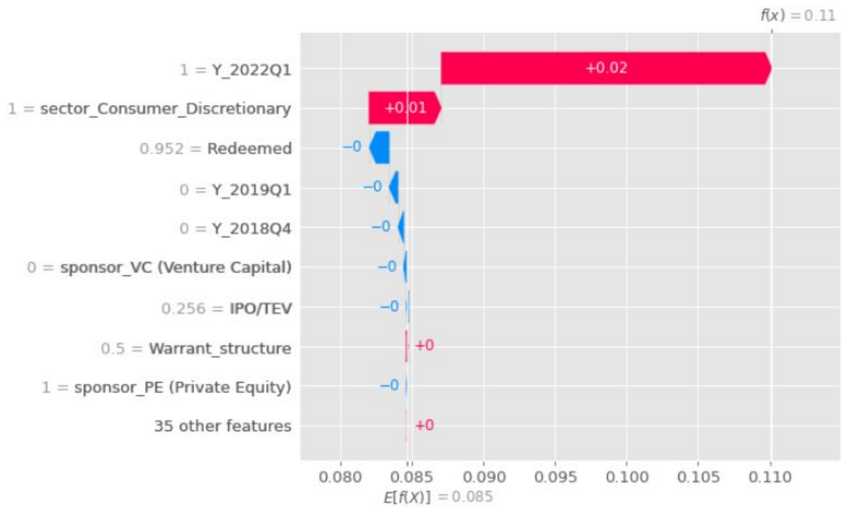
Figure 6: SHAP values across the test data



This figure illustrate the global SHAP value from the XGBoost regression with volatility as the dependent variable. The most important features of the model is presented in a descending order and the SHAP values shows the distribution of prediction from each feature. The colors indicates the features value from low to high.

variable for the first quarter of 2022 is the second most important factor due to the increasing global inflation that has caused large market movements. From the figure, we have two mergers in 2022Q1 in the test sample indicated by the two red dots, and it appears that those two dots contribute by predicting about 0.02 higher volatility for those two given samples. In figure 7, we look further at one of the samples from 2022Q1, where we examine the local SHAP values for the given test sample. The sample contains the SPAC “CITIC Capitals” merger with target company “Quanergy Systems” from the 8th of February 2022, receiving 95.2% redemption votes. The greyed-out values on the y-axis display the characteristics of the provided sample, while the red and blue bars depict the contribution of each feature to the prediction. XGBoost predicted volatility of 0.11, which is higher than the expected value of 0.085. Further, it

Figure 7: SHAP values for a given sample



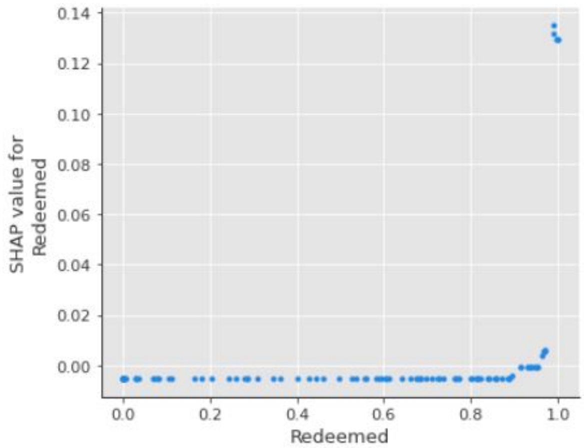
This figure illustrate a given SPAC sample. The bars indicates how each feature contribute to the prediction in a additive way. The expected volatility is 0.085 and the predicted volatility for this sample is 0.11.

becomes apparent that the merger taking place in 2022Q1 is the main reason for the high predicted volatility.

Figure 8 displays the partial dependence plot of the redemption rates and indicates a non-linear relationship with the volatility. The findings from XGBoost show that it makes no difference for the predicted volatility if the redemption rate is, e.g., 10% or 70%. However, the high values of redemption above 90% explain the higher volatility. These findings indicate that the relationship between the variables is non-linear, which can explain why XGBoost gives better predictions than the linear model, OLS.

The result that high redemption rates for SPACs imply significantly volatile stock returns for deSPACs indicates that IPO investors are aware of the risk when voting for redemption. This finding suggests that IPO investors may be voting for mergers to only maximize the value of their warrants and are less concerned with the performance of the deal and/ or common stock. This leads to a conflicting interest between the parties that can vote in favor of the deal and the parties that own the common stocks in the deSPAC. Further, this can lead to an adverse selection problem because the IPO investors, who

Figure 8: Partal Dependence Plot - Redemption Rate



This figure illustrates the partial dependence plot for the redemption rates in the XGBoost model. The x-axis is the feature value between 0 and 1, and the y-axis is the SHAP value that shows how much each sample feature contributes to the prediction. Redemption rates between 0% and 90% contribute to lower volatility, while redemption rates close to 100% contribute to higher volatility.

are the institutional investors and usually provide reports with valuation and due diligence of the target companies, have incentives to provide misleading or imprecise reports.

6.4 Analysis of the SPAC structure's contribution to abnormal return

The previous section told us how high redemption rates predict higher volatility and that it can lead to conflicting interests for the deSPAC investors. This section examines how the redemption rate, deSPAC time, warrant structure, and sponsor experience affect the deSPAC returns by testing hypotheses 3, 4, 5, and 7. First, we will examine table 6. Table 6 consists of four regressions where we first regress the deSPAC time on the abnormal deSPAC returns with quarter, industry, and sponsor quality fixed effects. Further, in regressions 2 and 3, we examine the dependence of the deSPAC time variable when adding variables with partial correlation. Next, we conduct our main regression with all the SPAC structure variables and examine the regression results. Finally, we check the robustness of the regression results by comparing them with XGBoost.

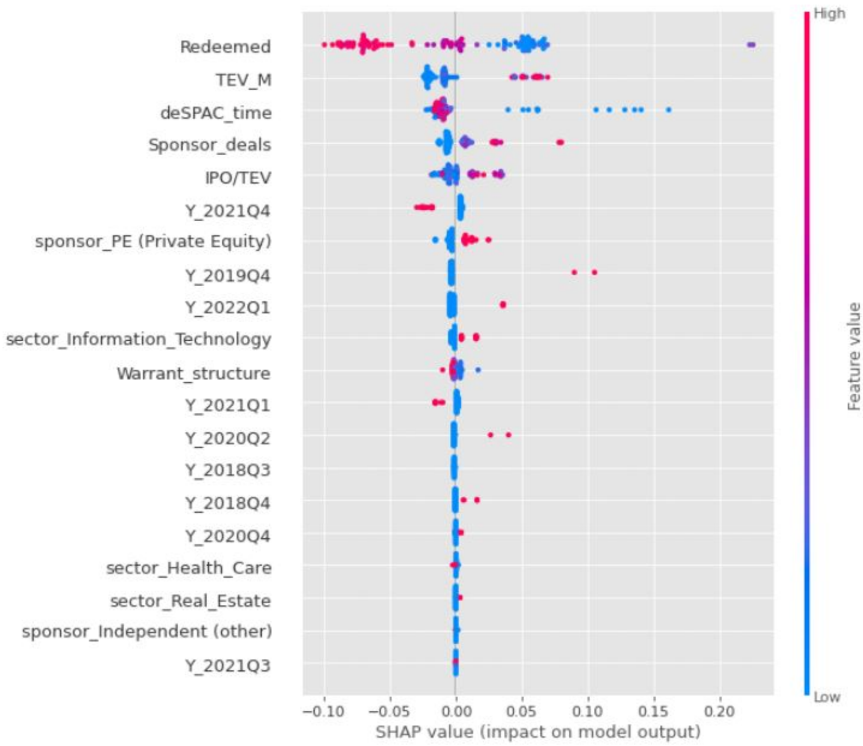
Table 6: Regression - deSPAC abnormal return

Dependent Variable	1	2	3	4
deSPAC_time	-0.288*** (0.092)	-0.202** (0.093)	-0.126 (0.097)	-0.112 (0.099)
Redeemed		-0.216*** (0.060)	-0.195*** (0.061)	-0.188*** (0.062)
Warrant_structure			-0.198** (0.082)	-0.206** (0.085)
TEV_M				-4.074e-06 7.33e-06
Sponsor_deals				0.004 (0.017)
IPO/TEV				-0.075 (0.069)
Quarter fixed effects	Yes	Yes	Yes	Yes
Sector fixed effects	Yes	Yes	Yes	Yes
Sponsor fixed effects	Yes	Yes	Yes	Yes
Adjusted R- Squared	0.027	0.064	0.078	0.073

This table examines the SPAC structures prediction of the deSPAC returns. Statistical significance levels: *** p-value<0.01, ** p-value<0.05, * p-value<0.10. N = 342.

Gahng et al. (2021) conducted a similar regression as regressions 1 and 2 in table 6, with redemption rate and the log months as the dependent variables. The SPAC period can vary between 12 and 24 months, so we believe that Gahng et al. (2021) log month variable can give misleading results because it does not control how close the SPAC is to the liquidation date. He finds that only the redemption rate is significant in his regression with both variables. Our deSPAC time variable controls for the time left to the liquidation date, and we get significant coefficients with a 95% significant level when conducting our regression with both variables. However, when we introduce the warrant structure variable, the p-value of the deSPAC time drops to 0.198, which indicates that Gahng et al. (2021) has an omitted variable in his regression. This can also imply that there could be a significant relationship between the warrant structure and the deSPAC time, as we also discussed in the methodology. We will look further at this relationship in subsection 6.5.

Figure 9: Global SHAP values for the XGBoost regression on BHAR

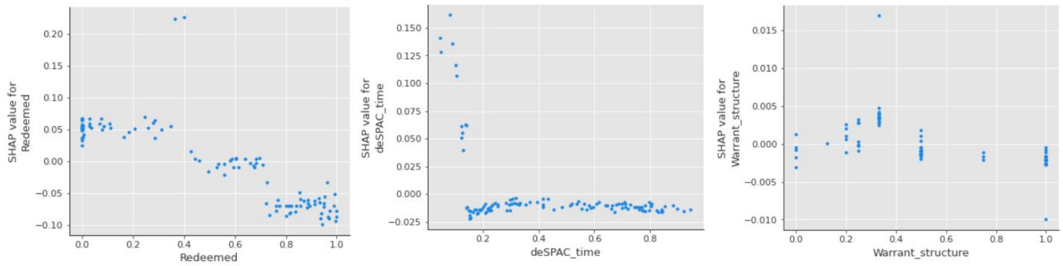


This figure illustrates the global SHAP value from the XGBoost regression with 3-month BHAR as the dependent variable. The most important features of the model are presented in descending order, with redemption rates as the most important one. The colors show that redemption rates are negatively correlated with the BHAR where the red dots (high redemption values) indicate lower SHAP values (contributions to the BHAR prediction).

Figure 9 shows that redemption rate is also the most important factor for XGBoost, and the colors indicate that higher redemption leads to lower abnormal returns. Surprisingly, and in contrast to the OLS model, deSPAC time is the second most important feature while warrant structure is quite far down. The total enterprise value and the number of sponsor deals, which have insignificant coefficients in the OLS, have a relatively significant impact on the XGboost model. The inconclusive results can be explained by XGBoost locating and using non-linear relationships between variables, whereas OLS utilizes linear relationships. XGBoost outperformed OLS by 25% in the previous regression with volatility as the dependent variable. The error of the models in this re-

Figure 10: Partial dependence plots from XGBoost

(a) Redemption (b) deSPAC time (c) Warrant structure



This figure shows the dependence plot for Redemption rates, deSPAC time and the warrant strucutre in the XGBoost model with 3-month BHAR as the depended variable.

gression is quite similar, with XGBoost outperforming OLS by only 6.25%. The RMSEs for the models are 0.400 and 0.375 for OLS and XGBoost, respectively. Next, we will test whether we should keep or reject hypotheses tested in regression 4 in table 6.

Hypothesis 3: High redemption rates signals a poor merger deal.

The redemption rate is the only OLS coefficient with a 99% significance level when all factors are included. It is also the variable that has the greatest impact on the XGBoost model. Figure 10.a illustrates that XGBoost also finds a relatively linear relationship between the redemption rate and the predicted value, where redemption rates less than 50% contribute to a positive prediction and rates over 50% give a negative prediction of the abnormal deSPAC returns. The quantitative results from our models, together with the evidence from section 6.3 that high redemptions indicate that IPO investors prefer the deSPAC deal's volatility over the offer's stock value, make us keep the null hypothesis. Therefore, high redemption rates indicate a poor merger, especially for deSPAC investors, because we expect the deal valuation to be overvalued and the target firm to be volatile. Therefore, we would not encourage an investor to invest in a deSPAC with a high redemption rate. The result is consistent with the findings from Gahng et al. (2021).

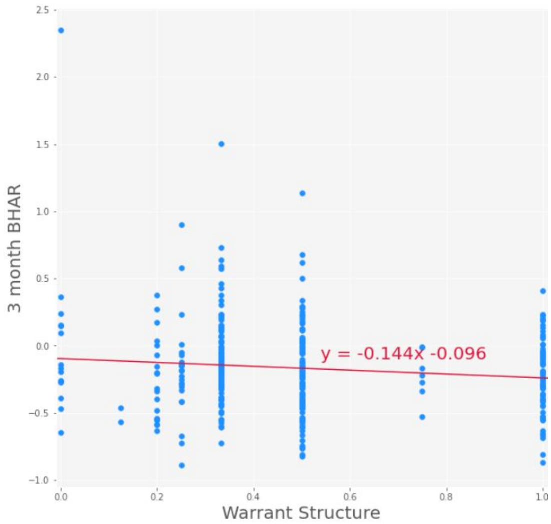
Hypothesis 4: A late merger indicates a poor deal since the sponsors fear liquidation

The regressions in table 6 showed that the deSPAC time became insignificant when we introduced the other variables in the SPAC structure. Even though the deSPAC time has the second most impact on the XGBoost model, figure 10.b predicts that there is no linear relationship between deSAPC time and the abnormal return. The SHAP dependence plot shows that a rapid merger makes a good prediction which is consistent with Kiesel et al. (2022) findings, but the plot does not show any significant trend in the interval $[0.2, 1]$. Therefore, we find no evidence indicating that the SPAC sponsors are pushing through a poor deal when they get close to the liquidation deadline and therefore reject our null hypothesis.

Hypothesis 7: High warrant structure causes a greater share price dilution.

In hypothesis 7, we test if a relatively high amount of warrants compared to the number of common stocks causes a dilution of the share price and lower abnormal deSPAC returns. The regression in table 6 concludes that the warrant structure variable is significant with a 95% significance level and has a higher coefficient than the redemption rates. On the other hand, in the XGBoost model, the warrant structure feature is just the 11th most important feature. It only contributes by increasing the prediction by ± 0.005 for almost all the observations. Looking at the scatter plot with the corresponding OLS regression line in figure 11, we can find reasons for the inconclusive results. OLS are considering the linear relationship illustrated with the regression line. If we exclude the scatter points at $x = 1$ and the outlier at $x = 0$ it would be more challenging to find the negative relationship. A potential reason why XGboost does not find the variable significant is that it would not need many trees to separate these values with decision trees. Figure 10.c shows that XGBoost does not focus on the linear relationship but instead on the clustering of x values

Figure 11: OLS Regression - Warrant structure on abnormal deSPAC returns



This figure illustrates the linear relationship between BHAR on the y-axis and warrant structure on the x-axis with the corresponding regression line.

and their interaction effects with the other variables. XGBoost's interaction effects are, unfortunately, harder to illustrate. This finding illustrates some of the weaknesses of OLS and the value of comparing the results with different models.

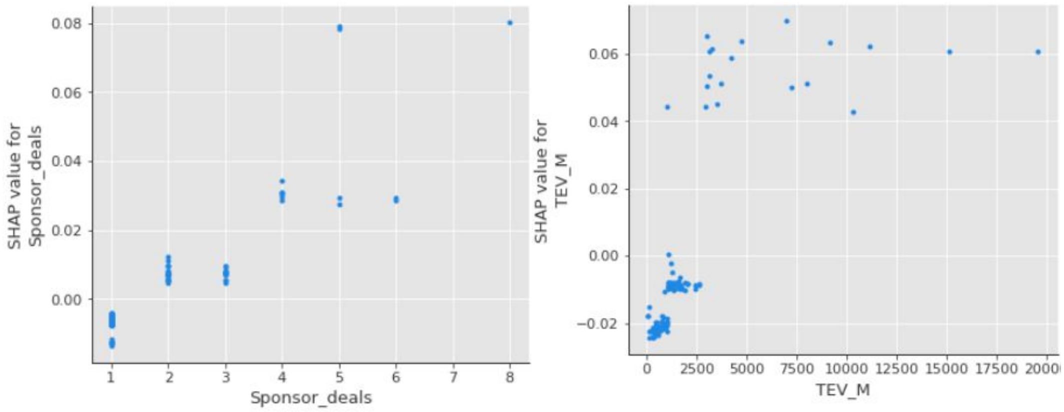
Even though the two model predictions are somewhat inconclusive, both models indicate that a SPAC structure with a 1-to-1 relationship between common stocks and warrants leads to lower abnormal returns. We fail to reject our null hypotheses and conclude that a high warrant structure causes a greater dilution of the shares and contributes to lower abnormal returns. Therefore, it is not favorable for a deSPAC investor to invest in a SPAC with a high warrant structure.

Hypothesis 5: A sponsored team with experience from earlier SPACs will increase the performance of the deSPAC.

We believe that SPAC sponsors that have successfully merged with target companies in the past would have a better experience and a good reputation based on earlier performance. This would be a quality stamp, and we hypothesize it leads to a better performance of the deSPAC. However, based on the find-

Figure 12: Partial dependence plots from XGBoost

(a) Sponsor experience (b) Total Enterprise value



This figure shows the dependence plot for sponsor experience and total enterprise value in the XGBoost model with 3-month BHAR as the dependent variable.

ings that SPAC IPO investors often have other preferences than the deSPAC investors and that the sponsors mainly need a good reputation to the IPO investors to get new funding, some arguments also go against our hypothesis. The regression shows that the coefficient is insignificant and almost equal to 0. However, in XGBoost, it is the feature with the fourth most impact. In the partial dependence plot in figure 12.a we see that the model predicts a non-linear relationship where the low number of deals, first, second and third, almost have no impact on the prediction. However, the sponsors with high experience, 4 to 8 deals, get a positive prediction. 65% of the SPACs in our data sample is managed by sponsors doing a SPAC for the first time. The clustering of observations close to zero makes it hard to find a significant linear relationship over the whole data sample. However, XGBoost can find a non-linear relationship. The total enterprise value is the second most important feature for the XGBoost model, while it gives insignificant predictions in the OLS model. The reason is the same as the sponsor deals where the distribution of observation is clustered close to zero, while there are a few points further out on the x curve. For example, figure 12 indicates that high values of both sponsor experience and total enterprise value works great to predict the abnormal deSPAC returns. In contrast, the lower values make less impact on the prediction. Again, this illustrates the value of using XGBoost, and based on the results, we keep our null hypothesis and conclude that experienced sponsors contribute to better abnormal returns.

6.5 Analysis of target companies' fear of dilution

So far, we have observed a partial relationship between deSPAC time and warrant structure. We will now look at hypothesis 8 and assess the test results. Previous research has revealed that deSPAC investors are diluted by warrants, and we hypothesize that the target company's owners are aware of this. Therefore, we anticipate a higher fraction of warrants will result in a longer deSPAC time because SPACs with many warrants are less attractive. We do not believe there is a causally problem here, because we have learned that IPO investors prefer a quick merger, so they can utilize their payoff and do not want to wait and risk that the SPAC does not find any target companies at all. As previously stated in the research, the nature of the warrant is equal to an American option and can be exercised at any time.

Table 7: Regression - deSPAC time

Variable	coef	std err	t	p-value
const	0.207	0.134	1.546	0.122
Warrant_Structure	0.310	0.058	5.341	0.000
Quarter fixed effects	Yes			
Industry fixed effects	Yes			
Sponsor quality fixed effects	Yes			

This table examines the warrant structures effect on the deSPAC time. Adjusted R-squared: 0.40. N = 342.

According to the regression results in table 7, the warrant structure is highly significant, particularly on a 1% level, and indicates that a higher warrant structure results in a longer SPAC period. When we conducted a white test on the regression results, it showed signs of heteroscedasticity, so we conducted the regression with robust standard errors. The results demonstrate that a SPAC with a high fraction of warrants has a harder time finding an agreement with a target company. It also supports our belief that the target companies' owners are aware of the structural feature problem of a SPAC.

7 Conclusion

Our research has analyzed the agency problems in the SPAC structure and how they affect the prominent participants in 342 SPAC transactions from July 2016 to February 2022. With the state-of-the-art boosting algorithm XGBoost and OLS, we have checked the robustness of previous research and found new features that help us better understand the agency costs associated with SPACs.

From the SPAC IPO investor's perspective, we find a lucrative risk-free return with an expected IRR of 14%. The return is utilized by a risk-free redemption strategy where the investor redeems or sells his share before the merger and sells the free warrant on the day of the merger. The strategy can be seen as investing in a default-free zero-coupon bond with the risk-free rate as yield to maturity, where you also receive a free call option. Although investing in the SPAC IPO is lucrative, we observe the opposite for the deSPAC investors. Buying the new publicly traded company (deSPAC) on the first day after the merger and selling three months (63 trading days) after the merger gives an average negative abnormal return of 16.7%. The distribution of the deSPAC returns reveals that 75% of the deSPACs have a negative return while a few SPACs give a very high return. Investments in deSPACs can be comparable to buying a lottery ticket, where the odds are against you, but you have a slight chance of getting a good payout, as Bali et al. (2011) discusses in his paper.

Our findings suggest that several features of the SPAC cause agency costs that affect the deSPAC investors. First, we provide evidence that the SPAC IPO investors deliberately vote in favor of SPAC mergers when they know that the target company is risky and the deal is not great for the deSPAC shareholders. Our study also disclosed that high redemption rates cause higher volatility and lower deSPAC returns. Increased volatility through high redemption rates indicates that the IPO investors are aware of the poor quality of the deals ex-ante and are enhancing warrant value by voting for high-risk deals when there are no good quality deals available.

Looking ahead, we expect deSPAC shareholders to become increasingly aware of the poor returns. The growing number of SPACs looking for target companies creates a seller market. Therefore, target companies should be able to choose SPACs with a more shareholder-friendly structure. However, given the lucrative return profile for the sponsors and IPO investors, we encourage SEC to implement the new proposed SPAC rules that require stricter disclosure of information that can reduce asymmetric information and help protect retail investors. We also recommend that the Norwegian Finanstilsynet address the discussed issues in their regulation of SPACs. We argue that the current state of SPACs transfers value from retail to institutional investors. However, we believe that a SPAC transaction with better-aligned incentives can be a good alternative to a traditional IPO.

For further research, we suggest analysis with better and broader data sets. Most of the quality SPAC data is provided by costly third parties, and our limitation to the SPACresearch.com database has limited the quality of our research. We also suggest looking more into the SPAC sponsors, whom previous literature has indicated is the most profitable participant. It would also be interesting to research the transfer of wealth from the deSPAC shareholders to the SPAC sponsors and IPO investors. At last, we suggest looking into the SPAC IPO investor's voting pattern by including voting data on the business combination to understand the IPO investors' incentives better.

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APPENDIX

A Hyperparameter Tuning

To adjust the complexity of and maximize the variance bias trade off in XGBoost, we use the Python library Hyperopt to tune the hyperparameters in the model. In our model we tune the **boosting hyperparameters** that controls how we proceed down the gradient process, **tree hyperparameters** that controls how we build the base learning decision trees, **stochastic hyperparameters** that controls the randomness of the training data during the model building and the **regularization hyperparameters** that controls the complexity of the model to prevent over fitting. We use the following hyperparameters:

Boosting hyperparameters

- learning_rate: Determines the contribution of each tree on the final outcome and controls how quickly the algorithm learns.

Tree hyperparameters

- max_depth: Explicitly controls the depth of the individual trees.
- min_child_weight: Implicitly controls the complexity of each tree by requiring the minimum number of instances

Stochastic hyperparameters

- subsample: Subsampling rows before creating each tree.
- colsample_bytree: Subsampling of columns before creating each tree

Regularization hyperparameters

- gamma: Controls the complexity of a given tree by growing the tree to the max depth but then pruning the tree to find and remove splits that do not meet the specified gamma.

- alpha: Provides an L2 regularization to the loss function, which is similar to the Ridge penalty commonly used for regularized regression.

- lambda: Provides an L1 regularization to the loss function, which is similar to the Lasso penalty commonly used for regularized regression.

We use hyperopt which is a open source bayesian optimizer to tune our hyperparameters. To tune the hyperparameter we split the 66% training data into another training and validation set, so that the model wont "cheat" and use the actually test data as validation in the learning phase. We optimized the hyperparameters by choosing the parameters that minimize the RMSE on the validation set. We get the following hyperparameter:

	BHAR Regression	Volatility Regression
learning_rate	0.001	0.001
max_depth	2	2
min_child_weight	3	0
subsample	0.997	0.693
colsample_bytree	0.594	0.503
gamma	0.016	0.097
alpha	0.201	0.358
lambda	0.058	0.042
Number of trees	2573	3979
RMSE XGBoost	0.375	0.061
RMSE OLS	0.400	0.081

This table shows the hyperparameters used when training the two main XGBoost regressions in this thesis. The hyperparameters are tuned and optimzed using hyperopt.

B Sectors

Global Industry Classification Standard Sectors

Sectors	Number of SPACs
Information Technology	57
Health Care	66
Financials	32
Consumer Discretionary	78
Communication Services	23
Industrials	34
Consumer Staples	14
Energy	23
Utilities	0
Real Estate	11
Materials	4

The table shows the sector distribution of the 342 SPACs we have examine in the thesis. The data from SPACresearch.com was distributed in 13 sectors. We converted the sectors to be aligned with Global Industry Classification Standard (GICS) that S&P uses in their sector index portfolios.

C Correlation Matrix

	3 month AR	Volatility	Redeemed	deSPAC_time	Warrant_structure	IPO/TEV	TEV_M	Deals
3 month AR	1							
Volatility	-0.101	1						
Redeemed	-0.232	0.292	1					
deSPAC_time	-0.0495	0.106	0.138	1				
Warrant_structure	-0.116	0.120	0.196	0.491	1			
TEV_M	-0.028	-0.085	-0.175	-0.271	-0.312	1		
IPO/TEV	-0.077	0.030	0.153	0.286	0.177	-0.270	1	
Sponsor_deals	0.083	-0.117	-0.117	-0.188	-0.244	0.228	-0.104	1

This table shows the correlation matrix between the two dependent variables and the explanatory variables.