SPACULATIVE SENTIMENT

AN ANALYSIS OF THE IMPACT OF INVESTOR SENTIMENT ON SPAC ACTIVITY AND PERFORMANCE

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Abstract

SPACs have experienced a puzzling surge in popularity despite academics documenting their severe historic underperformance. This paper adds a new layer to previous research by investigating whether market sentiment can explain SPAC activity and performance. We find that SPAC activity rises when investor sentiment falls. Furthermore, we spot that high investor sentiment partially explains SPACs short-term underperformance over six months after a SPAC merger is made effective. Finally, we find indications of cross-sectional and conditional effects of sentiment on SPAC returns. The cross-section of returns is visible through increased fluctuations in the returns of companies that are more difficult to value and arbitrage. Further, investor sentiment displays conditional effects contingent on SPACs age, level of indebtedness, and profitability. When sentiment is high, then young, indebted, and unprofitable SPACs exhibit higher relative returns. When sentiment is low, investors alternate their preference towards older, less indebted, and profitable firms.

Keywords

Special purpose acquisition company, investor sentiment, speculative, cross-sectional variation

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1. Introduction

In recent years, special purpose acquisition companies (SPACs) have risen to the broad spotlight as fundraising breaks record after record. In short, SPACs are shell companies that raise capital through an initial public offering (IPO) for the sole intention of acquiring a private company. For their targets, SPACs represent an alternate route to traditional IPOs for going public. In 2020 alone, 248 SPAC IPOs were issued with total proceeds of $83.3bn. So far in 2021, 308 SPACs have been launched, raising $100.3bn – blowing past last year's tally within months.[1] Put into perspective, SPAC IPOs represent 77% of the total number of equity issuances in 2021 in the United States.

This ongoing boom in SPAC activity is puzzling for several reasons. Firstly, previous literature has consistently found that SPACs severely underperform the market. For example, Dimitrova (2017) finds that SPACs long-term buy-and-hold abnormal returns (BHARs) underperformed the Russel 2000 index by -60%. Thus, it would seem irrational for market participants to continue investing in SPACs. Secondly, there is an increasing risk of a SPAC oversupply. Approximately 75% of SPACs issued since 2019 are still looking for targets, leading to increased competition for quality companies. This development poses an additional risk to the future share price performance of SPAC companies. However, despite SPACs representing an increasing and substantial fraction of equity capital markets, SPAC literature has remained relatively scarce. The existing literature concentrates on deal- or company characteristics and incentive mismatches when elaborating on SPAC underperformance. Yet, rational explanations cannot fully explain the rise in SPAC activity. Particularly, when considering the persistent underperformance of SPACs.

Within the behavioral finance domain, market sentiment has been long studied as a signifier of investor irrationality (Cornelli et al., 2006). Generally, investor sentiment is viewed as investors' attitude towards financial markets. Previous literature has shown investor sentiment to be an explanatory variable for variation in number of IPOs and total volume raised (Lowry, 2003; Ljungqvist et al., 2006). Moreover, Baker and Wurgler (2006) point to investor sentiment's ability to explain and predict returns. Therefore, the idea of this paper is to investigate whether investor sentiment can explain the rise in SPAC

[1] As of April 26, 2021. Based upon numbers from https://spacinsider.com/stats/.

activity and continued underperformance of SPAC companies. We contribute to existing literature by adding a new layer to SPAC literature through investigating the relationship between investor sentiment and SPACs.

We hypothesize that SPACs may see a rise in activity when investor sentiment is low. Previous literature shows that companies avoid the traditional IPO market during contractionary periods due to increased uncertainty (Choe et al., 1993). Consequently, the demand for SPACs might increase. Further, we expect investor sentiment to predict subsequent abnormal returns as sentiment induced mispricing of SPACs reverts to the mean. Thus, following high sentiment, SPACs should exhibit lower abnormal returns (Yang et al., 2016). Finally, we hypothesize investor sentiment to have cross-sectional and conditional effects on SPAC returns. On the cross-section of returns, previous studies have found that sentiment raises and lowers prices differently across companies (Zhang, 2006). On the conditionality of returns, studies find that investors tend to alternate their preference between speculative and non-speculative companies depending on levels of sentiment (Baker and Wurgler, 2006). For example, during periods of high sentiment, investors prefer younger companies due to their potential. Meanwhile, when sentiment is low, investors shift their preference to older, more mature companies (Guidolin and Timmermann, 2004).

To test the hypotheses empirically, we construct and apply an investor sentiment index in an econometric analysis. Firstly, we regress our sentiment index against the number of SPAC IPOs, total proceeds raised, and number of SPAC acquisitions for each year from 2003 to 2018. This analysis tests whether investor sentiment has an effect on overall SPAC activity. Secondly, we run both univariate and multivariate regression of investor sentiment on buy-and-hold abnormal returns, controlling for various company characteristics. The company characteristics we consider are age, asset tangibility, beta, book-to-market, indebtedness, profitability, sales growth, and size. This analysis enables us to investigate the relationship between SPAC underperformance and investor sentiment. Thirdly, we use portfolio sorts as a non-parametric measure of the cross-section and conditionality of SPAC returns. Lastly, to add robustness, we regress investor sentiment against long-short portfolios.

The results of our analyses suggest that *investor sentiment impacts overall SPAC activity* and *returns in the short-term*. Additionally, we inconclusively find indications of *cross-sectional and conditional effects* of sentiment on SPAC returns. More specifically, regressing investor sentiment on the number of SPAC IPOs, total SPAC proceeds raised, and number of SPAC acquisitions yields a significant negative relationship. Next, the multivariate regression of investor sentiment against BHARs results in a negative short-term relationship following the six months after the merger is made effective. Moreover, we find that sentiment levels impact the returns of hard to value and arbitrage SPACs slightly more than non-speculative SPACs. Thus, the results indicate cross-sectional variation. Lastly, we spot the hypothesized conditional variation in portfolios sorted on age, indebtedness, and profitability. However, the remaining five portfolios – asset tangibility, beta, book-to-market, sales growth, and size – do not exhibit the hypothesized interaction.

We reason that the increased SPAC activity occurs due to private companies increasingly considering the SPAC route as the IPO path becomes too uncertain. In its place, SPACs provide readily available cash and fast access to public markets. Furthermore, positive investor sentiment induces overvaluation at date effective, which leads to lower subsequent returns as mispricing reverts to the mean. This mechanism is significant only within six months as inefficient prices do not persist in the long-term. Lastly, our findings suggest that investors may not treat all SPACs equally. On the one hand, investors have a harder time valuing speculative SPACs. On the other hand, opportunistic investors tend to shift their preference between speculative SPACs to non-speculative SPACs depending on sentiment levels.

This paper proceeds as follows: In *Section 2,* we elaborate on previous literature regarding investor sentiment and SPACs. *Section 3* illustrates the sample construction and descriptive statistics. *Section 4* follows with an analysis of the effect of investor sentiment on overall SPAC activity. Thereafter, in *Section 5,* we analyze the impact of investor sentiment on the historic underperformance of SPACs. *Section 6* presents the portfolio sorts and the implications on the cross-section of returns. Afterwards, in *Section 7,* we study long-short portfolios and their relationship to investor sentiment to add robustness to our findings in the prior chapter. Lastly, *Section 8* concludes the research paper.

2. Literature Review

2.1. Investor Sentiment

2.1.1. Concept of Investor Sentiment

Investor sentiment is a hotly contested subject across academic finance literature. Many researchers claim, decisively shaped by Fama (1965), that asset prices are entirely based on the rationally discounted value of expected future cash flows. Thus, cross-sectional variation of expected returns only relies on cross-sectional differences of systematic risks. Further, efficient prices persist with irrational market participants because arbitrageurs use mispricing to their advantage and eliminate pricing imbalances. This theory is known as *efficient market hypothesis*. Complementing this concept is the rather common assumption that all investors act rationally by maximizing their utility (Merton, 1973). Put differently, stock prices only reflect the fundamental value of the underlying assets based on all publicly available information. Moreover, prices deviating from fundamentals are offset by arbitrageurs.

However, market frictions and the presence of irrational investors lead to inefficient prices deviating from their intrinsic value (Grossman and Stiglitz, 1980). Accordingly, Siegel (1992) investigates the price movements around the historic stock market crash of October 1987. The crash triggered unprecedented moves in share prices, with common benchmarks such as the S&P 500 declining as much as 21% within hours. Siegel confirms that shifts in investor sentiment, and not changes in corporate profit forecasts or interest rates, drove the unusual market returns of October 1987. De Long et al. (1990) probe whether noise traders[2] pose a source of risk and explain financial anomalies like the closed-end mutual fund discounts (CEFDs). The results of the paper show that noise traders create alpha. Therefore, contradicting the efficient market hypothesis, which assumes that investors cannot beat the market. The progress in the field of behavioral finance was further solidified by books like Andrei Shleifer's Inefficient Markets (2000),

[2] Black (1986) defines noise traders as individuals who trade on inaccurate or incomplete information, often irrationally. Noise comes in many different forms but can generally be seen as uncertainty about future supply and demand. According to Black's research, noise makes financial markets running by inducing liquidity but also creates imperfections via inefficient prices.

which dismisses the idea of efficient markets. He ascribes this conclusion to limited investor rationality and limits to arbitrage.

After contesting efficient markets, literature was quick to explain how markets respond to new information instead. The concept of *underreaction* outlines that asset prices tend to underreact to fundamentally important news, e.g., earnings announcements (Barberis et al., 1998). The underreaction works both ways. If the announcement is good, prices keep going up and vice versa. Consequently, fresh information has the potency to predict subsequent returns over the short-term due to slow information processing of the market. On the other hand, the same research paper has found evidence of *overreaction*. A constant flow of news – meaning a record of good news over the past three to five years – leads securities to being more prone to overpricing. In other words, the concept of overreaction predicts that subsequent returns are going to be low based on a string of good news as valuations tend to return to the mean. High returns are expected if the opposite occurs. Both phenomena are inconsistent with the efficient market hypothesis as prices do not reflect all publicly available information in these cases.

Underreaction as well as overreaction is supported by psychological evidence, namely by both *conservatism* and *representativeness heuristic*. Edwards (1968) defines the psychological phenomenon of conservatism. Conservatism means that individuals react slowly to new information, which counteracts their initial beliefs. This psychological characteristic corresponds to the concept of underreaction. Conservatism embodies market participants' tendency to disregard the magnitude of newly released public information. Conceivably, because individuals believe the announcement only has temporary consequences. Tversky and Kahneman (1974) introduce the representativeness heuristic, which claims that individuals detect patterns in actually random contexts. This pattern relates to the overreaction evidence presented before. More specifically, market participants might (mistakenly) equate strong, historic earnings growth with overperforming companies. Yet, the historic track record could be based on luck or favorable conditions – instead of superior skill.

Albeit oftentimes discussed, there is no universally accepted definition of investor sentiment. For instance, Cliff and Brown (2004) examine investor sentiment and its relation to near-term stock market returns. According to their framework, sentiment displays market participants' expectancy relative to a benchmark. Above average expectations characterize bullish investors whereas bearish investors display below average expectations. By contrast, Baker and Wurgler (2006) investigate the effect of investor sentiment on the cross-section of returns and simply define investor sentiment as the propensity to speculate.[3] Other literature oftentimes does not further elaborate on its understanding of investor sentiment.

These definitions are rather vague and fail to incorporate specific quantitative measures. Distinctive investor sentiment measures have been introduced to better visualize the concept of investor sentiment. Generally, these measures can be split into two subgroups, *direct* and *indirect measures* (Cliff and Brown, 2004). Direct measures are based on surveys conducted across various groups with specific questions to answer. Well-known direct sentiment indices are the Consumer Confidence Index (CCI) and the Economic Sentiment Indicator (ESI). Direct indices enable surveyors to ask participants specific questions, which can be seen as an advantage of this method. However, the results of surveys run the risk of being diluted by uninformed participants, inherent priming of participants by the surveyor, or missing out on important market participants with considerable influence on price movements (Cliff and Brown, 2004).

Indirect measures rely on proxies or indices that mimic investor sentiment. Such an approach is beneficial as it allows market participants to observe shifts and movements in sentiment based on 'true' actions. This paper chooses to follow the investor sentiment index by Baker and Wurgler (2006).

2.1.2. Baker and Wurgler's Sentiment Index

Motivated by the increasing importance of investor sentiment on the cross-section of market returns, Baker and Wurgler (2006) provide evidence that mispricing occurs in consequence of both an uninformed demand shock and an arbitrage constraint. Consequently, changes in sentiment impact asset prices differently as long as one of these two channels varies across stocks. This effect is known as cross-sectional variation, meaning that prices of stocks do not rise or fall equally. Cross-sectional variation in sentiment is especially apparent in cases which the range of valuations is wide, known as

[3] Following this definition, market sentiment is high if the propensity to speculate is high. Interestingly, Hausch and Ziemba (1995) prove based on bias in sports and racetrack betting that individuals with the propensity to speculate exhibit a tilt towards high-risk bets, leading to the most negative expected returns. Suggesting that investor sentiment might affect the cross-section of returns as speculative investors favor riskier stocks.

degree of valuation subjectivity or *valuation uncertainty*. Imagine companies exhibit characteristics such as negative profitability in combination with extreme sales growth. Irrational market participants could reasonably argue for the high end as well as the low end of valuations, depending on their current sentiment. Alternatively, companies with characteristics such as long earnings history, stable growth, and healthy margins display a much lower plausible range of valuations and are therefore less affected by shifts in sentiment. Baker and Wurgler (2006) summarize companies with elevated valuation uncertainty as *speculative* whereas *non-speculative* companies display low valuation uncertainty.

One could argue that waves in sentiment influence the market in general rather than a specific subset of stocks. Then the second channel of mispricing, *limits on arbitrage*, still affects the cross-section as long as arbitrage forces vary across stocks. Shleifer and Vishny (1997) study to what extent textbook arbitrage (no capital and risk requirement) works. They point out that arbitrage is malfunctioning under immoderate market conditions as inefficient prices persist, especially when fundamentals and asset prices disperse significantly. These conditions oftentimes require arbitrageurs to deploy capital as well as to take on risk, ultimately making arbitrage trades less attractive. Furthermore, research also indicates that *arbitrage is riskier and more costly for speculative stocks*, which display a broader range of possible valuations (Shleifer, 2000). Several properties of speculative stocks drive this observation. Speculative stocks exhibit general difficulties to short-sell (D'Avolio, 2002), larger downside due to elevated idiosyncratic risks (Wurgler and Zhuravskaya, 2002), higher transaction costs (Amihud and Mendelson, 1986), and subdued liquidity makes this market segment vulnerable to erratic price moves (Brunnermeier and Pedersen, 2005). Interestingly, Mitchell and Pulvino (2012) note that *SPACs are among companies that are hard to arbitrage*, largely for financial engineering issues concerning shareholder voting practices, which triggers high margin requirements.

It is important to note that both channels, variation in sentimental demand shocks and varying limits to arbitrage, feature overlapping properties. Put another way, stocks with high degrees of valuation subjectivity are oftentimes the most difficult to arbitrage. Therefore, investor sentiment has the biggest impact on securities which feature both characteristics (Baker and Wurgler, 2006). In order to draw robust conclusions, Baker and Wurgler (2006) build a composite index based on five proxies, all of which are known for their ability to closely track investor sentiment.[4] The five indicators include the closed-end fund discount (CEFD), the number of IPOs (NIPO), the average first-day returns of IPOs (RIPO), the equity share in new issues (S), and the dividend premium ($P^{D\text{-}ND}$).

The CEFD is computed as the average variation between the price of closed-end fund shares and the net value of all the fund's assets after deducting liabilities. Zweig (1973) tests whether closed-end fund discounts have predictive power in forecasting subsequent returns. His results confirm that Dow Jones stocks revert to the mean if closed-end funds trade at a premium, implicating negative, significant correlation between CEFD and subsequent returns. Consequently, the correlation between CEFD and sentiment is positive as high investor sentiment induces overvaluation.

RIPO is added to the index since the IPO market is traditionally seen as a good sentiment barometer. During hot markets, suggesting investor optimism, first-day returns tend to be larger (Ritter, 1984; Loughran and Ritter, 1995). Therefore, the correlation between RIPO and sentiment is positive. Subsequently, the overshooting of security prices on the first trading day implicates lower future returns.

The next indicator, number of IPOs, follows the same intuition, driven to some extent by the high autocorrelation between RIPO and NIPO (Lowry and Schwert, 2002). Further, Lowry (2003) examines the reasons for the time-series variation of NIPO, discovering that sentiment partly drives the total number of primary issues. Thus, the correlation between investor sentiment and NIPO is positive. Afterwards, returns are expected to be low, another indicator of the resemblance with RIPO.

Another proxy that captures market sentiment well is the equity share as a fraction of total equity and debt issues. The rationale behind S is the following: According to Kim and Weisbach (2008), corporations favor equity over debt as long as their equity is overvalued compared to their fundamentals. Thus, the equity share in new issues and sentiment exhibit a positive correlation as equity tends to be particularly overvalued during positive sentiment periods. Moreover, Baker and Wurgler (2000) examine whether S has the power to predict subsequent stock market returns. They find that periods with

[4] Baker and Wurgler dropped NYSE turnover as one of the six sentiment indicators in subsequent years due to the meteoric rise of high-frequency trading. Hence, high liquidity is not necessarily driven by investor optimism as institutional traders drive more and more of demand and supply. This paper adapts to five proxies for its own purposes.

high equity shares are followed by muted returns, indicating a negative correlation between S and subsequent returns.

Lastly, the fifth sentiment indicator is the so-called dividend premium, computed as the log difference between market-to-book ratios of dividend and non-dividend payers. Baker and Wurgler (2004) investigate the driving force behind the decision to pay dividends. Their main finding implies that the payout decision is dependent upon investor demand, which in turn is powered by investor sentiment. As a consequence, negative dividend premia suggest higher demand for small firms with low margins and high growth. On the contrary, demand for mature companies is high when the dividend premium is positive, hinting at investor pessimism. Pursuant to Fama and French (2001), dividend-paying companies are oftentimes bigger and command higher margins with less growth potential. This interconnected relationship results in a negative correlation between P^{D-ND} and sentiment.

2.2. SPACs

2.2.1. Structure of SPACs

SPACs, a special form of blank-cheque companies, are set up to raise funds for, yet unidentified, one or multiple business combinations with operating businesses.[5] Although SPACs surged to the broad attention only in recent years, the concept is not new. However, this paper focuses on modern SPACs introduced in 2003 by a then niche investment bank, EarlyBirdCapital. After a fraudulent period in the 1980s and 1990s, several legislative adjustments and the pioneering work of EarlyBirdCapital paved the way towards modern-day SPACs (Shachmurove and Vulanovic, 2018). For example, legislative adjustments such as Rule 419-a included the requirement for SPACs to disclose more financial information. EarlyBirdCapital, conversely, advised SPACs to raise more than $5m to avoid stricter penny stock rules (Heyman, 2007).

Nowadays, the instrument of choice for SPAC IPOs is the sale of units, which are comprised of common stock and in-the-money warrants (Riemer, 2007). Schultz (1993) shows that issuing units is beneficial for public offerings with greater uncertainty about future prospects. Thus, agency costs decrease as warrants do not provide funds at the IPO

[5] https://www.investor.gov/introduction-investing/investing-basics/glossary/blank-check-company.

but rather in the future given the business is performing well. Nonetheless, both literature and professionals have doubts on whether deeply in-the-money warrants sufficiently incentivize founders to look for quality business combinations.

Typically, the transaction has to be completed within a pre-fixed time span of up to 24 months and the target has yet to be recognized. To add credibility and increase the likelihood of an acquisition, a SPAC is oftentimes incorporated by well-known managers.[6] The managers count on their reputation to float a shell company with no operating business via an IPO. Accordingly, Kim (2009) finds that knowledge and reputation of the management team is a crucial factor in determining whether a SPAC is going to perform well.

It is important to note that founders work through the highly regulated, traditional IPO process – including roadshows, prospectuses, and SEC filings – with the non-operating shell company. The traditional IPO filings rarely contain forward-looking statements such as financial projections as issuers are liable for their projections. SPAC acquisition targets, conversely, routinely add financial projections to their proxy statements when it comes to a proposed business combination (Klausner et al., 2021). Acquisition targets are allowed to engage in *regulatory arbitrage* since de-SPAC transactions[7] qualify as mergers, an exemption specified in the Private Securities Litigation Reform Act. This act protects private companies, which use the SPAC route to go public, from lawsuits in case forward-looking statements turn out to be wrong. This rule is not applicable to the traditional IPO process.

Subsequent to the primary offering, historically around 96% of the net proceeds are transferred into an escrow account until the founders complete a business combination (Cumming et al., 2014). In the meantime, the trust account earns interest on safe securities such as U.S. Treasury bills. The remainder of the proceeds is used for covering ongoing expenses until an acquisition has been made. However, expenses do not include compensation for sponsors. Instead, Dimitrova (2016) finds that sponsors oftentimes receive a 20% stake for an investment as little as $25,000. Further, the sponsors also obtain warrants, which are valued at a steep discount.

[6] The literature does not differentiate between managers, founders, and sponsors. This paper will follow the interchangeable usage.
[7] A de-SPAC transaction describes an acquisition of or a merger between a SPAC and a private operating company. We treat it as a synonym of SPAC acquisition.

As the time frame is limited, founders start looking for potential targets immediately after the public listing. Although managers normally have the mandate to invest across all industries or geographies, they try to focus on their respective segment of expertise. However, sponsors are not entirely free in their choice since at least 80% of the net assets in the escrow account needs to be spend on the transaction to avoid liquidation (Boyer and Baigent, 2008). In case the target's valuation exceeds the available capital of the SPAC, the founders can arrange additional funds. Private investment in public equity (PIPE) is oftentimes the vehicle of choice to raise further capital. PIPEs could consist of both equity and debt financing (Lenahan et al., 2018).

If managers propose a target company, SPAC shareholders are entitled to vote in favor of the business combination or to make use of their share redemption right. An investor who redeems its shares receives the respective pro rate share of the trust account.[8] Thus, the transaction proposed by the sponsors goes through if a majority of shareholders votes in favor. Otherwise, a significant percentage of investors (60%-80%) needs to decide against redeeming its shares (Hale, 2007). If shareholders approve the business combination, the target company goes public via a reverse merger.

If founders are unable to identify a suitable target within the specified time period, the SPAC is forced to liquidate its holdings and distribute them to investors on a pro rata basis (Heyman, 2007). As a consequence of liquidation, managers lose both founder shares and warrants in case of liquidation.

From a shareholder perspective, it can be beneficial to sell shares in the open market instead of redeeming. This is the case as long as the market capitalization exceeds the net asset value in the escrow account (Gose, 2006). However, selling shares in the open market instead of redeeming shares creates a loophole for founders. Dimitrova (2017) shows that 50% of the managers scoop up shares in the open market prior to the Special Meeting of Shareholders. Managers then use the additional shares to vote in favor of the transaction – ultimately attempting to ensure the approval of the proposed business combination.

[8] Investors who opt to redeem their shares can keep or exercise their warrants.

2.2.2. Rationale of SPACs

The above outlined SPAC process includes three major stakeholders: investors, management, and private companies. Naturally, every stakeholder has its own incentives – sometimes in contradistinction to each other.

Regarding investors, SPACs present several appealing propositions. Firstly, SPACs offer investors the opportunity to invest in renowned founders with stellar records of success in the past. Further, SPACs can be seen as a private-equity style investment, which is more liquid and transparent (Riemer, 2007). Additionally, Mitchell and Pulvino (2012) find that institutional investors take advantage of apparent mispricing in SPACs until the date of announcement. For instance, prior to the financial crisis, SPACs yielded 4.7% on average, compared to 3.1% on Treasury bills. Since the money in the escrow account is invested in Treasury bills, which bear no credit risk, the SPAC yield can be viewed as risk-free excess return.[9] The mispricing persisted because SPACs traditionally have high margin requirements, largely due to technical matters in connection with shareholder voting processes. Hence, weaker arbitrage forces due to high margin requirements lead to inefficient prices.

Considering the payoff structure of SPACs to investors, Lewellen (2009) notes the resemblance with a riskless zero-coupon bond (money in the escrow account earns interest on Treasuries) including a call option (business combination with the option to redeem shares as floor). This strategy is oftentimes applied by hedge funds. The appeal of SPACs towards institutional investors is further underlined by the fact that they own 78% of SPAC equity on average (Lakicevic and Vulanovic, 2013). However, it is unclear why investors are attracted by SPACs in the long-term, especially since the historic performance of this asset class is mediocre.

On the contrary, founders do not need to rely on arbitrage to turn profit. First and foremost, the management team acquires all of the pre-IPO securities for $25,000 or $0.017 to $0.047 per share (Jog and Sun, 2011). As the management team typically only sells 80% of its shares, it keeps 20% of total shares, the so-called founder shares. In combination with heavily discounted warrants, managers earn a whopping 1900% in

[9] Indeed, even during the bankruptcy of Lehman Brothers, escrow accounts held at Lehman Brothers were not impaired (Mitchell and Pulvino, 2012). Instead, the trust accounts were simply transferred to other financial institutions.

annualized returns. As a consequence, strong incentives arise for managers to favor any kind of deal to avoid liquidation (Lewellen, 2009). This incentive is magnified by the fact that sponsors lose both founder shares and warrants in case of liquidation. This pattern is in line with the observation that founders buy additional shares in the open market before shareholder votes to secure approval (Shachmurove and Vulanovic, 2018). Ultimately, Dimitrova (2017) shows that sponsors also tend to overpay for targets as they need to spend at least 80% of the net assets in the escrow account.

Incentives for private companies to merge with SPACs are manifold. Sjostrom (2008) finds that both cost and time requirements decrease if a private company chooses to go public via a reverse merger. A traditional IPO costs up to 31.9% of realized market value, considering sizeable direct expenses such as underwriting fees combined with indirect expenses like underpricing (Ritter, 1987). SPAC IPOs as well as reverse mergers can be cheaper, even if taking the dilution into account. However, the alleged cost reduction is contested (Levine, 2020). Regarding time, traditional IPOs can consume up to 18 months of preparation whereas reverse mergers can be completed within weeks.

Moreover, Berger (2008) identifies that reverse merger characteristics such as readily available cash, renowned management teams, and flexible capital structure solutions appeal to private companies. Additionally, private companies use the ability to issue financial projections to create an exciting business case in a forward-looking way (Klausner et al., 2021). This particularly appeals to early-stage companies, which cannot issue forward-looking statements as part of the standard IPO prospectuses without fearing litigation in the future. Lastly, SPACs provide an alternative to going public during periods of low IPO activity and volatile markets (Kolb and Tykvová, 2016).

All in all, mainly smaller and unseasoned firms are attracted by the SPAC route. Bigger and seasoned firms usually go public via the traditional IPO path without experiencing considerable disadvantages compared to reverse mergers. The above outlined stakeholders show misaligned incentives, e.g., the fact that founders are incentivized to find a target at all costs in order to reap in their equity compensation. The question is, however, whether these misalignments have a value-destructive effect on the share performance.

Indeed, academic literature homogenously finds that SPACs underperform their peers post-acquisition. Lakicevic and Vulanovic (2013) investigate short-term returns around the day of merger completion. They report -3.81% abnormal return on the day of completion and -9.59% cumulative abnormal return over one week following the acquisition. Extending the time period post-acquisition leads to even lower returns. Jenkinson and Sousa (2011) find -30% and -46% buy-and-hold returns six months and twelve months post-acquisition, respectively.

The suggested reasons for the constant underperformance are diverse and still subject to debates. Recent literature distinguishes between deal and company characteristics when investigating SPAC underperformance. Dimitrova (2017) argues that the 80% net asset value threshold results in founders to paying too much for business combinations. In addition, she points out that the performance of SPACs decreases the closer to the deadline deals are consummated. On the other hand, Kolb and Tykvová (2016) show that smaller, highly levered firms choose to go public via SPACs. This observation indicates a tilt towards lower quality firms when it comes to SPAC acquisitions. This tilt towards smaller, lower quality companies was further magnified by the introduction of the JOBS Act in 2012 (Rodrigues, 2012).[10] As previously mentioned, Mitchell and Pulvino (2012) add that SPACs are hard to arbitrage because of technical reasons related to shareholder voting procedures. A speculative tilt of SPACs in combination with limits to arbitrage and misaligned incentives are potential explanations for the continued underperformance of SPACs.

To sum up, SPACs display appealing characteristics to managers, investors, and target companies. Managers have the opportunity to make a lot of money with consummated business combinations. Investors can participate in a private-equity like investment with an interesting payoff structure until the date of a merger announcement. Private companies, especially smaller and unseasoned ones, can take advantage of getting readily available capital, exposure to experienced managers, and faster access to public markets, even during times of greater turmoil. Furthermore, early-stage companies use the option to issue forward-looking statements to attract investors – which is not feasible when using the traditional IPO path.

[10] The intention behind the Jumpstart Our Business Startups Act (JOBS) is to convince small-cap companies to go public by slashing disclosure requirements and federal regulation. The legislation, signed into law by the Obama Administration, pushed the SPAC market due to an easier and cheaper IPO process.

3. Data

3.1. SPAC acquisitions

We retrieved data on SPAC acquisitions from various databases. First, we identify all SPACs that have gone public over the period from 2003 to 2018. Subsequently, these SPAC IPOs are matched with all consummated de-SPAC transactions over the same period. The SPAC IPO and de-SPAC datapoints are primarily drawn from SDC Platinum. Between January 2003 and December 2018, we observe 286 SPAC IPOs and 136 SPAC acquisitions in the US. The difference in the number of IPOs and acquisitions is driven by the fact that SPACs have two years to complete the merger. Thus, many SPACs which went public in 2017 and 2018 are excluded. In addition, a fraction of SPACs was liquidated as no suitable target was found until the deadline. Lakicevic et al. (2014) find that the liquidation rate reached 35.3% from 2003 to 2012. Considering both influences, the size of the SPAC acquisitions sample is in line with our expectations.

Table 1

Descriptive statistics of number of SPAC IPOs, number of SPAC acquisitions, and total proceeds raised

The table presents sample statistics for the period from July 2003 to December 2018. The following metrics are included: number of SPACs that completed an IPO; number of SPACS that consummated a business combination; the total capital raised based on all observed SPAC IPOs in USDm; average volume raised per IPO transaction during the respective year.

Variable	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	
Number of SPAC IPOs	1	6	19	26	55	14	3	8	
Number of SPAC acquisitions	0	1	1	7	25	19	17	10	
Volume (USDm)	24	159	1,463	2,420	9,644	3,225	40	492	
Mean (USDm)	24	27	77	93	175	230	13	62	
Variable	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**Total**
Number of SPAC IPOs	14	10	11	11	18	13	34	43	286
Number of SPAC acquisitions	0	5	11	3	6	4	9	17	135
Total Volume (USDm)	725	435	1,333	1,155	3,497	3,239	8,996	9,205	46,051
Mean (USDm)	52	44	121	105	194	249	264	214	161

Table 1 displays the development of SPAC IPOs over the sample period. The successful listing of Millstream Acquisition Corporation in August 2003 by

EarlyBirdCapital marked the starting point of the rise in SPAC activity. Afterwards, the number of SPAC IPOs, total proceeds raised as well as average proceeds raised took off. More precisely, SPAC IPOs accounted for 34% of total number of IPOs during a cooling market in 2008 (Ritter, 2008). The peak in number of SPAC IPOs and total volume raised was reached in 2007 with 55 and $9.6bn, respectively. A similar rise can be seen after the financial crisis, after a slump to three small SPAC IPOs during the final phase of the financial crisis in 2009. In 2018, number of SPAC IPOs reached 43, raising a total of $9.2bn. Meanwhile, average proceeds raised also increased to $214m. Interestingly, the average proceeds raised peaked at $230m during the midst of the financial crisis, indicating robust demand and supply of SPAC IPOs during greater market turmoil.

As previously mentioned, SPAC acquisitions exhibit a lag compared to SPAC IPOs, which is not surprising as managers normally have two years to close a business combination. For instance, the number of de-SPAC transactions exceeded the number of SPAC IPOs from 2008 to 2010. Nonetheless, SPAC acquisitions seem harder to close than SPAC IPOs during economic downturns as large SPAC backlogs cannot be entirely dissolved. An important driver of this observation, next to the oversupply of empty shells, is the dependency of SPAC acquisitions on additional institutional capital in the form of PIPEs. PIPEs are more difficult to obtain during greater market turmoil. However, many private companies still resort to SPACs to go public during periods of turbulent markets.

Table 2

Variables, descriptions, and sources

Variable	**Unit**	**Description**	**Source**
Age	Years	Differential between date effective and date of incorporation	Eikon
Asset tangibility	%	Property, plant, and equipment divided by total assets, six months after date effective	Compustat
Beta	Ratio	Covariance of returns of the respective security with the market divided by the variance of market returns	Eikon
Book-to-market	Ratio	Book value divided by market value, six months after date effective	Compustat, Eikon
Indebtedness	%	Total liabilities over total assets, six months after date effective	Compustat
JOBS Act	Dummy	1 if the JOBS Act has been active during the respective year, 0 if otherwise	SEC
Profitability	%	EBIT divided by total assets, six months after date effective	Compustat
Sales Growth	%	Sales one year after date effective divided by sales at date effective	Compustat
Size	USDm	Market capitalization six months after date effective	Eikon

We add firm-specific variables and daily closing prices to the SPAC acquisitions data. The data is mainly extracted from the Center for Research in Security Prices (daily closing prices), Compustat (accounting data), and Refinitiv Eikon (market data). Table 2 presents an overview of variables the analyses are based on and the respective sources they are retrieved from. Almost all firm-specific variables are measured six months after date effective.[11] The intuition behind this date is the following: We ensure that the collected data points refer to the financial statements of the operating target company instead of the non-operative shell company.

Table 2

Variables, descriptions, and sources

Variable	Unit	Description	Source
Age	Years	Differential between date effective and date of incorporation	Eikon
Asset tangibility	%	Property, plant, and equipment divided by total assets, six months after date effective	Compustat
Beta	Ratio	Covariance of returns of the respective security with the market divided by the variance of market returns	Eikon
Book-to-market	Ratio	Book value divided by market value, six months after date effective	Compustat, Eikon
Indebtedness	%	Total liabilities over total assets, six months after date effective	Compustat
JOBS Act	Dummy	1 if the JOBS Act has been active during the respective year, 0 if otherwise	SEC
Profitability	%	EBIT divided by total assets, six months after date effective	Compustat
Sales Growth	%	Sales one year after date effective divided by sales at date effective	Compustat
Size	USDm	Market capitalization six months after date effective	Eikon

Table 3 shows the statistical properties of all firm-specific variables. Winsorization on the 0.5 and 99.5 percentiles makes the observations more robust as we account for outliers. On average, SPAC firms display characteristics that resemble speculative firms. Asset tangibility is low, indebtedness is high, profitability is negative, sales growth is high, and the companies tend to be small. This observation is in line with previous literature. For instance, Kolb and Tykvová (2016) find that SPAC companies tend to be of less quality. On the contrary, high book-to-market values are usually an indicator for quality companies. Further, high average age and betas below one represent rather non-

[11] Date effective is the day on which the de-SPAC transaction is officially consummated.

speculative characteristics.[12] However, a number of outliers seem to drive the mean of book-to-market as the median is considerably lower. Therefore, we see indications of a speculative tilt within the SPAC sample.

Table 3

Descriptive statistics of firm-specific variables and respective returns

The table exhibits the summary statistics for the whole data sample of SPAC firms. All variables are defined as outlined in Table 2. Daily returns are displayed as percentages.

Variable	N	Mean	Median	St. Dev.	Min	Max
Age	136	34.24	26.00	27.39	4.00	160.00
Asset Tangibility	136	28.45	18.16	28.38	0.08	92.71
Beta	136	0.84	0.80	0.37	0.16	1.76
Book-to-Market	136	0.82	0.42	1.50	-2.43	11.78
Indebtedness	136	63.22	63.32	42.27	0.06	227.91
Profitability	136	-2.61	0.31	19.12	-120.86	42.60
Sales Growth	136	21.90	8.76	53.83	-64.85	307.53
Size	136	315.43	125.41	489.59	3.73	3,412.87
Returns	10,499	2.15	-0.80	38.38	-77.40	300.00

3.2. Investor sentiment index

In this section, we outline and construct a composite index to measure market sentiment. We follow Baker and Wurgler (2006) in choice of proxies and methodology for constructing the index. The data for our sample period from 2003 to 2018 is collected from the updated investor sentiment index data from Jeffrey Wurgler's website. [13]

We begin by adjusting the raw market sentiment proxies – CEFD, NIPO, $P^{D\text{-}ND}$, RIPO, and S. First, we acknowledge that each proxy may contain a sentiment component and a business cycle component. For example, it can be entirely reasonable that the first day return of new equity issues varies with macroeconomic factors rather than investor sentiment. Hence, to account for business cycle variation, we orthogonalize the five proxies by regressing them against common macroeconomic factors. Namely, the industrial production index, durables consumption, nondurables consumption, services consumption, NBER recession indicator, employment, and inflation. The residuals from the regressions are used as cleaner proxies for investor sentiment and are labelled with

[12] In opposition to Baker and Wurgler (2006), we used date of incorporation as starting point for age and not first appearance on Center for Research in Security Prices.
[13] http://people.stern.nyu.edu/jwurgler/

the superscript "$\perp$". Notably, using the orthogonalized sentiment index yields similar results to using the raw sentiment index and controlling for the aforementioned macroeconomic factors. In reality, Baker and Wurgler (2006) find that there is no large difference between composing a raw sentiment index and an orthogonalized sentiment index. Their study notes that the macroeconomic fundamentals explain little of the common variation in the proxies. Nonetheless, controlling for macroeconomic factors allows for increased precision. Thus, the orthogonalized sentiment index is implemented in this study.

Second, the proxies may exhibit both unrelated, diversifiable risk components and distinct lead-lag relationships. Previous research shows that the volume of IPOs only increases after market participants already observe high first-day returns (Benveniste et al., 2003). Therefore, one can anticipate delayed reactions of supply-driven proxies (S and NIPO) compared to demand-driven indicators (RIPO, $P^{D\text{-}ND}$, and CEFD). Thus, to isolate the sentiment component and incorporate the relative timing of the variables, we employ a principal component analysis (PCA). This analysis allows us to reduce the dimensionality of our proxies to facilitate pattern detection.

We set up for the PCA by standardizing the proxies to ensure equal contribution to the index. Then, we run the PCA on the five proxies and their lags. This presents a first-stage index with 10 loadings. Based on the correlation between the first-stage index and the current and lagged values, we choose the five proxies' lead or lag, depending on whichever has higher correlation with the first stage index. Thus, defining the second stage orthogonalized sentiment index as the first principal component of the following five variables and their scaled coefficients:

$$Sentiment^{\perp}{}_t = 0.171CEFD^{\perp}{}_t + 0.458NIPO^{\perp}{}_t + 0.302RIPO^{\perp}{}_{t-1} + 0.350S^{\perp}{}_t - 0.364P^{\perp}{}^{D-ND}_{t-1}$$

We plot the PCA and each proxy in figure A1 and A2 in the Appendix. The results reveal that the first principal component (FPC) of the orthogonalized index explains 43% of the sample variance, capturing much of the common variation. We find that the demand driven variables (RIPO and $P^{D\text{-}ND}$) exhibit higher correlations with the sentiment index when lagged. However, similar to Baker and Wurgler (2006), we find CEFD to be the exception to the expected lead-lag relationships. Furthermore, all the variables enter with the correct relationship with the sentiment index as anticipated – CEFD, RIPO, NIPO and S exhibit a positive relationship and P^{D-ND} exhibits a negative relationship. A correlation between the first-stage index and the second-stage index is run to test how much information is lost in dropping the variables with other time subscripts. The two indexes are correlated at 0.94, suggesting that little information is lost.

Table 4 below shows the descriptive statistics and correlation matrix of the chosen proxies and the orthogonalized sentiment index. All the proxies, with the exception of P^{D-ND}, display a strong positive correlation to the sentiment index. S displays the highest correlation to the investor sentiment index at 0.82. Compared with Baker and Wurgler's (2006) sample period from 1962 to 2001, we find that S correlates much more with the index. It seems that investor sentiment is increasingly tied to new equity on the market. This points to the time-varying explanatory strength of the sentiment proxies. As hypothesized, P^{D-ND} is the only proxy that exhibits a negative correlation at -0.73.

Table 4

Descriptive statistics of investor sentiment data

The table presents the descriptive statistics and correlation matrix for measures of investor sentiment. In the first panel, we present raw sentiment proxies. The dividend premium (P^{D-ND}) is the month-end log difference between market-to-book ratios of dividend and non-dividend payers. The second indicator, first-day returns (RIPO), is the mean of monthly first-day returns on the day of the primary issue. The third measure (NIPO) stands for the monthly number of IPOs. The fourth proxy, closed-end fund discount (CEFD), is the average monthly variation between the price of closed-end fund shares and the net value of all the fund's assets after deducting liabilities. The fifth indicator, equity share across total new issues (S), is the equity share as a fraction of total equity and debt issues. $Sentiment^{\perp}$ stands for the investor sentiment, based on the five proxies and controlled for macroeconomic factors such as industrial production, growth in durable and nondurable consumption, growth in services consumption, NBER recessions, inflation, and employment data. 198 observations stand for 198 months from July 2002 to December 2018. RIPO is based on fewer observations as not every month displays an IPO.

Proxies	**N**	**Mean**	**St. Dev.**	**Min**	**Median**	**Max**
P^{D-ND}_{t-1}	198	-4.50	6.10	-16.18	-5.67	17.13
$RIPO_{t-1}$	186	13.56	10.40	-19.90	12.30	56.00
$NIPO_t$	198	14.73	8.94	0.00	14.00	39.00
$CEFD_t$	198	6.83	4.46	-6.02	7.97	18.23
S_t	198	0.11	0.05	0.04	0.09	0.27

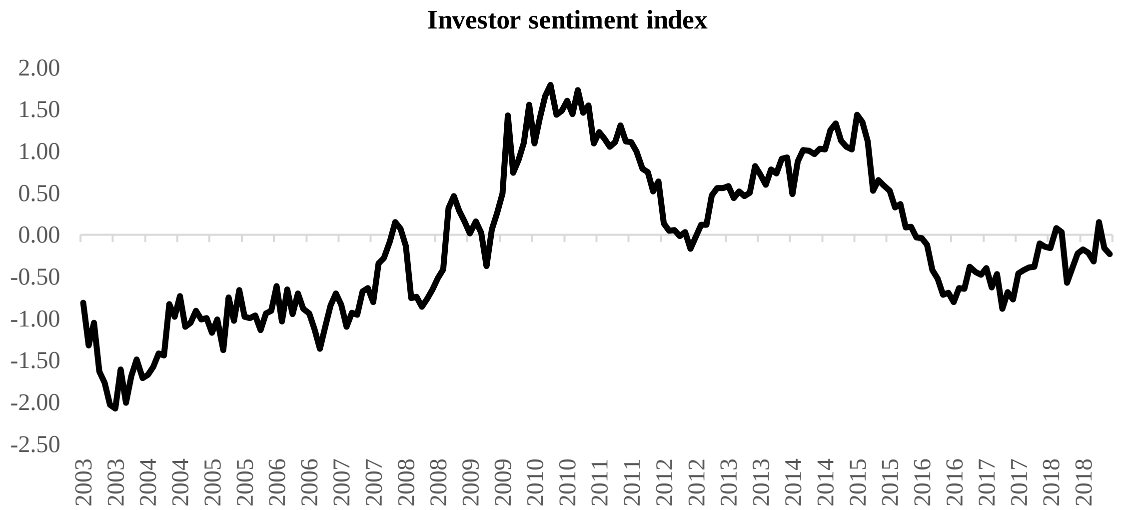
	Correlation					
Proxies	**$Sentiment^{\perp}$**	**P^{D-ND}_{t-1}**	**$RIPO_{t-1}$**	**$NIPO_t$**	**$CEFD_t$**	**S_t**
$Sentiment^{\perp}$	1.00					
P^{D-ND}_{t-1}	-0.73	1.00				
$RIPO_{t-1}$	0.62	-0.39	1.00			
$NIPO_t$	0.73	-0.41	0.33	1.00		
$CEFD_t$	0.60	-0.19	0.35	0.18	1.00	
S_t	0.82	-0.45	0.36	0.40	0.68	1.00

Figure 1 plots the orthogonalized sentiment index. The index is scaled to retain unit variance and zero mean. Hence, the index is not an indicator of the actual level of sentiment but rather variation over the specified time period. Figure 1 shows that the sentiment index roughly lines up with known accounts of sentiment fluctuations. The index starts with the aftermath of the dotcom bubble. The sentiment reached its low two years after the burst of the bubble – indicating that investors needed time to digest plummeting share prices and large equity losses. Following the dotcom bubble, we see a dip in investor sentiment that corresponds to the global financial crisis of 2007-2009. Relatively speaking, the financial crisis did have a shorter and not as severe effect on investor sentiment as the dotcom bubble. The recovery after the financial crisis was swift and strong as monetary and fiscal policy created a flourishing environment. Two additional dips in investor sentiment occurred until 2018. The first dip was triggered by the Euro crisis starting in 2010. The second one was initiated by fear over rising interest rates in 2015 communicated by the Federal Reserve.

Figure 1

Investor sentiment index

Figure 1 displays the development of investor sentiment during the sample period from 2003 until 2018. The index is based on the lagged dividend premium, lagged first-day returns, number of IPOs, closed-end fund discount, and equity share of total issues. The index is scaled to retain unit variance and zero mean.



However, the index is not without limitations. First, although the index focuses on five indicators which are considered to represent investor sentiment best, they are not universally accepted as sentiment measures. For example, CEFD tends to be controversial among academic finance literature. Some researchers, e.g., Swaminathan (1996), point towards rational reasons such as varying (rational) forecasts or fluctuating risk aversion among investors as an explanation for persistent CEFDs. Second, other variables could also be reasonably used as proxies for sentiment i.e., insider trading. Lakonishok and Lee (2001) investigate insider trades and find that insiders possess contrarian predictive power. Therefore, insiders can predict shifts in market sentiment. The reason for excluding insider trading, however, is a lack of availability and uniformity in measurement. Other variables, like NYSE turnover, cannot be used anymore because of skyrocketing high-frequency trading, which dilutes the relationship between market liquidity and investor sentiment[14]. Third, the sentiment index may not have the same predictive power it did during its inception in 2006 due to dramatic changes in the market. For example, the low interest rate environment, which was introduced as a response to the financial crisis, may affect the relationship between equity share issued and sentiment. A high equity share issuance today is a greater indicator of investor overvaluation compared with a high issuance in the 1970s. Barry et. al (2008) find that companies issue more debt compared to equity when interest rates are lower. This is also reflected in the correlations between our proxies and investor sentiment. We find that S correlates as high as 0.82 with sentiment compared with Baker and Wurgler's (2006) correlation of 0.44.

[14] http://people.stern.nyu.edu/jwurgler/

4. Investor sentiment and SPAC activity

4.1. Hypothesis

We begin the investigation of market sentiment's influence on SPACs by measuring the relationship between market sentiment and SPACs activity. We hypothesize that when general market sentiment is negative, demand and supply of SPACs increases. We assume this relationship as the SPAC route provides more certainty for private companies in an otherwise uncertain environment. Thus, the volume of investments in SPACs, the number of SPAC issuances, and subsequently the number of SPAC acquisitions should rise. The opposite pattern applies to positive sentiment. This hypothesis is in line with previous studies. The studies show that investor sentiment is an explanatory variable for the fluctuations in volume raised and number of traditional issuances in the public market (Lowry, 2003; Ljungqvist et al., 2006). However, unlike IPOs, the hypothesized relationship between SPAC IPOs and market sentiment is reversed. SPAC literature has indicated an inverse relationship between SPAC activity and the state of the market. Kolb and Tykvová (2016) show that during periods of above-average market volatility, companies with less access to the public market will prefer the SPAC route. Thus, we seek to measure whether the investor sentiment index yields a negative relationship with SPACs activity.

4.2. Methodology

To investigate whether market sentiment has any predictive power over the number of SPAC IPOs, volume of investments in SPACs, and number of SPAC acquisitions, we will run the following univariate regressions:

$$V_t = \beta_0 + \beta_1 SENT^{\perp}_{t-1} + \varepsilon_t \qquad (1)$$
$$N_t = \beta_0 + \beta_1 SENT^{\perp}_{t-1} + \varepsilon_t \qquad (2)$$
$$A_t = \beta_0 + \beta_1 SENT^{\perp}_{t-1} + \varepsilon_t \qquad (3)$$

where *t* stands for time and is measured monthly, $SENT^{\perp}$ is the orthogonalized market sentiment index, *V* stands for volume invested in SPACs, *N* for number of issuances, and

A for number of acquisitions. We measure lagged sentiment to allow for the time required to file for an IPO and to close a business combination. As sentiment is orthogonalized, the regression is similar to regressing the raw sentiment index and controlling for macroeconomic factors. Hence, we inherently check for important macroeconomic drivers of the IPO market such as recessions.

4.3. Results

Table 5 exhibits the results of the regressions of market sentiment on overall SPAC activity. The results display negative significant correlations between sentiment and number of SPAC IPOs, total SPAC IPO volume, as well as number of SPAC acquisitions. More specifically, if sentiment rises by one standard deviation, the number of SPAC IPOs decreases by 0.32, volume shrinks by $75.84m, and number of SPAC acquisitions falls by 0.16. These results are all significant at the 5% level.

Table 5

Results of univariate regressions of sentiment on SPAC IPOs, SPAC IPO volume, and SPAC acquisitions

This table presents the time-series regressions of SPAC IPOs (N), SPAC acquisitions (A), and total volume (V) raised during the period 07/2003 – 12/2018, using a single-factor model. The independent variable is the orthogonalized investor sentiment. Sentiment$^{\perp}$ stands for the investor sentiment, based on the five proxies, and controlled for macroeconomic factors such as industrial production, growth in durable and nondurable consumption, growth in services consumption, NBER recessions, inflation, and employment data.

$N_t = \beta_0 + \beta_1 SENT_{t-1}^{\perp} + \varepsilon_t$ (1) $A_t = \beta_0 + \beta_1 SENT_{t-1}^{\perp} + \varepsilon_t$ (2) $V_t = \beta_0 + \beta_1 SENT_{t-1}^{\perp} + \varepsilon_t$ (3)

Number of observations stands for the number of months within our sample period. Standard errors are shown in parentheses. *, **, and *** suggest statistical significance at the 10%, 5% and 1% levels, respectively.

Variable	SPAC IPOs	Volume (USDm)	SPAC Acquisitions
Sentiment$^{\perp}$	-0.32**	-75.84**	-0.16**
	(0.14)	(31.28)	(0.08)
Constant	1.52***	242.18***	0.72***
	(0.13)	(29.45)	(0.07)
Observations	186	186	186

The increase in SPAC activity during low sentiment levels may be due to SPACs filling the vacuum that traditional IPOs leave. Periods of low investor sentiment have been labelled as cold markets induced by deteriorating market conditions, which lead to the increased unwillingness of private companies to go public (Helwege and Liang, 2004). Hence, SPACs provide an appealing proposition towards private companies, offering readily available cash and fast access to public markets. These characteristics of the SPAC route provide more certainty than the traditional IPO route, especially amid a low sentiment period. This explanation is in line with previous literature. For instance, Schill (2004) shows a significant decline in the frequency and volume of IPOs amid tumultuous market environments of 13% and 21%, respectively. Moreover, he finds that these market conditions dampen the accessibility to public markets, particularly for small and unseasoned companies. Interestingly, small and unseasoned companies happen to be the same companies that oftentimes use the SPAC route (Kolb and Tykvová, 2016).

The impact of shifts in market sentiment on the number of SPAC acquisitions is relatively lower than on the number of SPAC IPOs. The difference can be attributed to the following: SPAC acquisitions are oftentimes dependent on additional capital provided by institutional investors via PIPEs. During more turbulent times, institutional investors might be reluctant to provide additional capital for business combinations. However, institutional investors value the SPAC IPO payoff structure, which also appeals to them during tumultuous times (Lewellen, 2009). The intuition is that a zero-coupon bond without credit risk in combination with a call option in the future acts as a hedge during turbulent times. Simultaneously, the call option offers upside when markets look more appealing again.

Our findings confirm the hypothesis that SPAC activity has a negative relationship with investor sentiment. We suggest that the main drivers of this observation are the following. First, private companies value the increased certainty attached to the SPAC route. This is particularly appealing when the traditional IPO path is less accessible, which oftentimes coincides with market downturns. Furthermore, market participants value the payoff structure of SPACs. More precisely, the downside protection in combination with the option to participate in the future business combination suits investors during uncertain market conditions.

5. Investor sentiment and underperformance

5.1. Hypothesis

We hypothesize that market sentiment at the date a SPACs acquisition is made effective explains SPAC's historic underperformance. More precisely, we anticipate that sentiment should exhibit a negative correlation with BHARs. This phenomenon is known as mispricing correction, which follows overvaluation induced by positive sentiment (Yang et al., 2016). We look for patterns of mispricing correction, as a measure of mispricing, due to difficulties in identifying fundamental value. Additionally, we hypothesize that sentiment influences abnormal returns for a set period of time. Afterwards, we expect the sentiment at date effective to become less significant in explaining abnormal returns. This theory is in line with findings of Fama (1998), which suggest that market inefficiencies disappear over the long-term. We are, however, aware of the joint hypothesis problem. This concept postulates that testing for market efficiency is not possible. Thus, any predictability patterns we find reflect compensation for systematic risks. Lastly, we control for company characteristics to investigate whether they influence sentiment's impact on underperformance.

5.2. Methodology

To assess underperformance, we follow extant SPAC literature convention and use buy-and-hold abnormal returns for our event-time analysis. We begin with daily share prices of our sample and compute the corresponding daily returns. The daily returns are then converted into buy-and-hold returns for periods of 6, 12, 24, 36, and 60 months after date effective. The different time periods allow us to distinguish between the short and long-term effects of investor sentiment on SPAC underperformance. We follow the same approach for our choice of benchmark, the Russel 2000 index. [15] We apply best practice in SPAC literature by choosing the small stocks index (Kolb and Tykvová, 2016; Dimitrova, 2017). We use the following formula to find SPAC's buy-and-hold abnormal returns:

[15] The Russell 2000 index is a small-cap stock market index of the smallest 2,000 stocks in the Russell 3000 index, which is made of the 3000 largest U.S. stocks.

$$BHAR_{i,t_1,t_2} = \prod_{t=t1}^{t2}[(1 + R_{it})] - \prod_{t=t1}^{t2}[(1 + R_{bt})] \qquad (4)$$

where R_{it} is the return of a SPAC firm and R_{bt} is the return of the benchmark portfolio. t_1 is the date effective. t_2 corresponds to the end of the measurement period or the delisting date, depending on what occurs first.

After calculating the BHARs for our SPAC sample, we regress the abnormal returns against the market sentiment as of date effective. First in a univariate regression and then in a multivariate regression. The multivariate regression controls for company characteristics that may influence the degree sentiment impacts returns. The regression formulas are presented below:

$$BHAR_{i,t_1,t_2} = \beta_0 + \delta_1 SENT_{t1}^{\perp} + \varepsilon_t \qquad (5)$$

$$\begin{aligned} BHAR_{i,t_1,t_2} = {} & \beta_0 + \delta_1 SENT_{t1}^{\perp} + \beta_1 Age + \beta_2 Asset\ Tangibility + \beta_3 Beta \\ & + \beta_4 Booktomarket + \beta_5 Indebtedness + \beta_6 Profitability \\ & + \beta_7 Sales\ Growth + \beta_8\ Size + \varepsilon_t \end{aligned} \qquad (6)$$

5.3. Results

Table 6 displays the results of the univariate regression of investor sentiment on buy-and-hold abnormal returns. The relationship between investor sentiment and abnormal returns is negative across all periods. This pattern suggests that positive investor sentiment yields negative abnormal returns over subsequent periods as valuations revert to the mean. However, the negative relationship displays no statistical significance at any point. Therefore, it is difficult to draw any definitive conclusions from the results of the univariate regression. Additionally, the explanatory degree of the univariate regression is limited. Thus, we introduce control variables through a multivariate regression to add robustness. Further, the variables enable us to control whether company characteristics influence the effect of investor sentiment on SPAC underperformance.

Table 6

Results of univariate regression of investor sentiment on buy-and-hold abnormal returns

This table shows the results of the univariate regression of sentiment on BHARs. Orthogonalized sentiment is the independent variable.

$$BHAR_{i,t_1,t_2} = \beta_0 + \delta_1 SENT_{t1}^{\perp} + \varepsilon_t$$

Standard errors are shown in parentheses. *, **, and *** suggest statistical significance at the 10%, 5% and 1% levels, respectively.

	BHAR				
Variable	**6 months**	**12 months**	**24 months**	**36 months**	**60 months**
Sentiment$^{\perp}$	-0.0655	-0.0176	-0.0682	-0.0241	-0.0625
	(0.0420)	(0.0523)	(0.0619)	(0.0755)	(0.0852)
Constant	-0.1996***	-0.3453***	-0.5136***	-0.5943***	-0.7347***
	(0.0312)	(0.0389)	(0.0461)	(0.0562)	(0.0634)
Observations	135	135	135	135	135
R^2	0.018	0.001	0.009	0.001	0.004
Adjusted R^2	0.011	-0.007	0.002	-0.007	-0.004

Table 7 depicts the results of the multivariate regression of investor sentiment on buy-and-hold returns. If sentiment rises by one standard deviation, returns decrease by 8% in the following six months. This result is significant at the 5% level. For longer periods, the relationship between investor sentiment and BHARs remains negative but without statistical significance. Regarding the control variables, profitability and size are significantly, positively linked with abnormal returns until twelve months after date effective. Beta exhibits a positive relationship with BHARs, which becomes more significant the longer the period. The remaining company characteristics – indebtedness, book-to-market, size, asset tangibility, and sales growth – show no clear pattern and no statistical significance.

Table 7

Results of multivariate regression of investor sentiment on buy-and-hold abnormal returns

This table displays the results of the multivariate regression of sentiment on buy-and-hold abnormal returns (BHAR). The independent variable is the orthogonalized sentiment and the control variables are the company characteristics. The company characteristics are defined as outlined in Table 2. We adjust age and size by logging age and dividing size by 1 million.

$$BHAR_{i,t_1,t_2} = \beta_0 + \delta_1 SENT_{t1}^{\perp} + \beta_1 Age + \beta_2 Asset\ Tangibility + \beta_3 Beta + \beta_4 Booktomarket + \beta_5 Indebtedness + \beta_6 Profitability + \beta_7 Sales\ Growth + \beta_8\ Size + \varepsilon_t$$

Standard errors are shown in parentheses. *, **, and *** suggest statistical significance at the 10%, 5% and 1% levels, respectively.

	BHAR				
Variable	**6 months**	**12 months**	**24 months**	**36 months**	**60 months**
Sentiment$^{\perp}$	-0.0803**	-0.0372	-0.0681	-0.0223	-0.0704
	(0.0404)	(0.0518)	(0.0630)	(0.0776)	(0.0871)
Profitability	0.4320***	0.3949**	0.2273	0.0727	-0.0202
	(0.1471)	(0.1886)	(0.2295)	(0.2827)	(0.3172)
Indebtedness	0.0037	0.0292	-0.0059	-0.0148	-0.0117
	(0.0740)	(0.0949)	(0.1155)	(0.1423)	(0.1596)
Age	-0.0210	0.0668	0.2198	0.2884	0.4365*
	(0.1041)	(0.1335)	(0.1625)	(0.2002)	(0.2246)
Book-to-market	-0.0143	0.0064	0.0194	0.0173	0.0284
	(0.0136)	(0.0175)	(0.0213)	(0.0262)	(0.0294)
Size	0.0001***	0.0001**	0.0000	0.0000	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Asset Tangibility	-0.0211	0.0828	-0.0027	0.1057	0.3008
	(0.1081)	(0.1385)	(0.1686)	(0.2077)	(0.2330)
Growth	0.0825	0.0557	-0.0143	-0.0314	-0.0288
	(0.0527)	(0.0676)	(0.0822)	(0.1013)	(0.1136)
Beta	0.1641*	0.2165**	0.3701***	0.4184***	0.3737**
	(0.0832)	(0.1067)	(0.1298)	(0.1599)	(0.1794)
Constant	-0.3394**	-0.7183***	-1.1455***	-1.3910***	-1.7923***
	(0.1696)	(0.2175)	(0.2646)	(0.3260)	(0.3658)
Observations	135	135	135	135	135
R^2	0.2115	0.14	0.19	0.16	0.16
Adjusted R^2	0.1547	0.08	0.13	0.10	0.10

First, we postulate that prices are inversely related to sentiment due to mispricing correction. Market participants tend to overvalue SPACs when sentiment is high as valuation uncertainty and limits to arbitrage induce inefficient prices in the short-term. Then, mispricing correction arises in the subsequent period when sentiment shifts. Baker and Wurgler (2006) also show this to be the case. In the long-term, investor sentiment's impact on underperformance diminishes as stock prices revert to the company's fundamental value. This interpretation is in line with Fama (1998), who already notes that market anomalies reverse towards efficient prices in the long-term.

Second, more profitable and larger companies do not underperform as much as their peers in the short-term. This observation indicates that investors value profitable and larger companies more than their less attractive peers. Consequently, more profitable and larger companies are less affected by swings in market sentiment. On the other hand, beta suggests the opposite relationship. The higher the beta, the lower the underperformance in subsequent periods. This observation indicates that riskier companies are not as prone to overvaluation during periods of high investor sentiment as less risky companies. Moreover, the influence of beta on investor sentiment's impact on underperformance is more durable. More specifically, mispricing correction takes up to 60 months. The other characteristics do not significantly influence investor sentiment's effect on SPAC underperformance. Overall, we observe that the entire sample tendentially acts in unison as the controls do not majorly alter the impact of investor sentiment on underperformance.

In line with our hypotheses, the multivariate regression suggests that investor sentiment explains the abnormal returns of SPACs in the short-term. Mispricing correction leads to lower abnormal returns after periods of high sentiment. In addition, mispricing correction occurs rather quickly as inefficient prices do not persist in the long-term. However, cross-sectional effects are limited to three controls, indicating homogeneity among the SPAC sample. We further assume the homogeneity of the SPAC sample to tilt towards speculative companies. This conclusion is in line with previous literature. Kolb and Tykvová (2016) derive that SPAC firms tend to be of less quality, therefore, rather speculative. Besides, Mitchell and Pulvino (2012) emphasize that SPACs are hard to arbitrage. As a consequence, both channels which catalyze mispricing – *valuation uncertainty* and *limits to arbitrage* – are satisfied. These circumstances explain the results of the analysis. Periods of positive investor sentiment are followed by relatively swift mispricing correction when sentiment shifts.

6. Portfolio sorts

6.1. Hypothesis

In this section, we apply a non-parametric analysis to investigate how market sentiment impacts SPACs returns. First, we hypothesize that overall SPAC returns are partly explained by sentiment. Such that, when sentiment is positive, investors should value both speculative and non-speculative firms more than when sentiment is negative. Thus, SPACs should exhibit higher returns during positive sentiment periods relative to negative sentiment periods. In the same way that Yang and Copeland (2014) find that bullish sentiment leads to higher market returns while bearish sentiment leads to lower returns.

Our second hypothesis follows extant literature on the cross-sectional impacts of sentiment. Postulating that market sentiment influences the pricing of speculative, hard to arbitrage companies more than the pricing of non-speculative companies (Baker and Wurgler, 2006; Zhang, 2006). Especially since idiosyncratic risk increases the costs of arbitrage, more so for speculative companies (Pontiff, 2006). Thus, we should see speculative SPACs returns fluctuate more than non-speculative SPAC's returns through shifts in investor sentiment.

Finally, we hypothesize that when market sentiment is positive, investors are likely to overestimate the value of speculative SPACs more than the value of non-speculative SPACs. Meanwhile, when market sentiment is negative, risk averse investors will prefer safer, non-speculative investments. Thus, the sentiment conditioned returns should be higher for speculative SPACs during positive sentiment periods and higher for non-speculative SPACs during negative sentiment periods. This hypothesis is in line with Guidolin and Timmermann's (2004) findings. They point out that investors tend to reallocate their investments depending on the market states, such that risky assets are found to be unattractive during bear states.

6.2. Methodology

To investigate the cross-sectional impact of market sentiment, we base our methodology on Baker and Wurgler (2006)'s conditional characteristics model:

$$E_{t-1}[R_{it}] = \beta_0 + \delta_1 SENT_t^{\perp} + \beta_1 Char_{i,T+6} + \beta_2 SENT_t * Char_{i,T+6} \quad (7)$$

where *t* stands for time, *i* represents the firm index, $SENT^{\perp}$ is the orthogonalized proxy for market sentiment, *Char* is a vector of characteristics, and *T* stands for date effective. The model is first sorted on characteristics and then on sentiment. Sentiment is measured as a bivariate variable based on the deviation from average sentiment. Such that, above average sentiment represents positive sentiment periods and vice versa. The coefficient δ_1 picks up the generic effect of sentiment, and the vector β_1 picks up the generic effect of characteristics. β_2 measures the interaction between sentiment and the characteristics vector. The null hypothesis reveals that any nonzero effect is rational compensation for systematic risk. The alternative, $\beta_2 \neq 0$, shows cross-sectional patterns in sentiment-driven mispricing.

To apply this model, we test the effects of conditional characteristics in a non-parametric way. We look at eight characteristics: age, asset tangibility, beta, book-to-market, indebtedness, profitability, sales growth, and size. We are mindful that looking at SPACs may introduce a sample bias since companies that choose the SPAC route are more likely to exhibit speculative characteristics (Kolb and Tykvová, 2016). Yet, we still expect to see some cross-sectional variation of returns between less speculative and speculative SPAC companies.

We create equal-weighted portfolios of monthly returns sorted on company characteristics, placed into uniformly distributed groups of speculative and non-speculative. We choose uniform distribution to allow comparability between the two groups. This is because the sample's summary statistics indicate mostly speculative SPACs. The alternative, sorting the portfolios based on characteristic cut-offs, would limit the reliability of the non-speculative group due to a small group size. All characteristics, with the exception of sales growth, are sorted by least speculative to most speculative depending on their definition. For example, leverage is sorted smallest to largest while size is sorted largest to smallest. Sales growth is seen to exhibit speculative characteristics on both extremes. For example, a company with negative sales growth or very high sales growth is more difficult to value. Thus, we distribute the non-speculative group between the 25th and 75th percentiles. We then sort the returns into subgroups depending on the sentiment in which the returns occurred. The average return of each subgroup is subsequently calculated. The returns are equally weighted rather than value weighted as large firms tend to be less affected by sentiment obscuring relevant patterns (Baker and Wurgler, 2006).

6.3. Results

Table 8

Results of portfolio sorts

This table shows the results of the various portfolio sorts. The returns are reported as percentages. For every month within our sample, we form two equal-weighted portfolios that are equally distributed according to the company characteristics. The characteristics are defined as outlined in Table 2. Afterwards we display average portfolio returns over months in which Sentiment$^{\perp}$ is positive and negative. Below positive and negative sentiment returns, we display the difference between the respective returns. A positive difference confirms the first hypothesis that SPAC returns should be higher during positive sentiment periods compared to during negative sentiment periods. Comparing the absolute value of the difference of speculative groups versus non-speculative groups measures the second hypothesis, postulating that speculative groups should exhibit greater absolute difference between their returns. The column, labelled comparison, compares the returns between speculative and non-speculative groups for each sentiment period. If the comparison exhibits alternating signs, then the portfolio indicates a pattern of returns conditional on sentiment, measuring the third hypothesis. The p-values relate to *t*-test performed on the group means.

		Portfolios			
Variable	**Sentiment$^{\perp}$**	**Speculative**	**Non-Speculative**	**Comparison**	**p-value**
Age	Positive	1.62	0.10	1.52	0.464
	Negative	0.44	1.23	-0.79	0.496
	Difference	**1.18**	**-1.13**		
Asset Tangibility	Positive	2.07	-0.35	2.42	0.227
	Negative	1.35	0.10	1.25	0.295
	Difference	**0.72**	**-0.45**		
Beta	Positive	-1.17	2.29	-3.47	0.083
	Negative	0.07	1.63	-1.56	0.227
	Difference	**-1.24**	**0.67**		
Book-to-market	Positive	0.20	1.16	-0.96	0.672
	Negative	0.49	0.99	-0.50	0.670
	Difference	**-0.29**	**0.17**		
Indebtedness	Positive	1.31	0.38	0.93	0.653
	Negative	-0.39	1.55	-1.93	0.128
	Difference	**1.70**	**-1.16**		
Profitability	Positive	2.25	-0.45	2.69	0.175
	Negative	-0.05	1.80	-1.85	0.107
	Difference	**2.29**	**-2.25**		
Sales Growth	Positive	0.72	0.82	-0.10	0.955
	Negative	1.28	0.33	0.96	0.444
	Difference	**-0.57**	**0.49**		
Size	Positive	1.94	-0.90	2.83	0.149
	Negative	1.07	0.79	0.28	0.810
	Difference	**0.87**	**-1.69**		

Table 8 displays the characteristic on which the portfolios are sorted, the sentiment on which the subgroups are conditioned, and the average returns for the corresponding speculative and non-speculative portfolios. Below each characteristic sort is a row displaying the difference of returns following positive and negative sentiment for each subgroup. The difference is used as a measure of the direction and degree of impact sentiment has on the characteristic sorts, testing our first and second hypotheses, respectively. The final column displays a comparison between speculative and non-speculative returns for each sentiment level. This metric allows us to test our third hypothesis regarding conditional variation. The p-values indicate whether there is a significant difference between the means of the speculative and non-speculative groups.

Our first hypothesis suggests that during periods of positive sentiment all SPAC returns should be higher than returns during periods of negative sentiment. This can be seen through the sign of the difference between returns. If the difference is positive, then returns during positive sentiment periods are higher than during negative sentiment periods. The results confirm this only for one sub-group per portfolio sort. Although the majority of non-speculative sub-groups follow the hypothesis, the results alternate and are not consistent enough to draw an affirmative conclusion towards the hypothesis.

Our second hypothesis concerns whether investors struggle to value speculative SPACs more than non-speculative SPACs. To measure this, we look at the difference between returns during positive sentiment periods and negative sentiment periods. The absolute value of the difference represents the degree the returns fluctuate. The results show that for all portfolios, with the exception of size, speculative SPACs fluctuate more than non-speculative SPACs. In some portfolios, such as indebtedness and beta, the difference is at 0.54% and 0.57%, respectively. Other portfolios display the distinction to a lesser extent. For example, speculative SPACs sorted on profitability fluctuate only 0.04% more than non-speculative SPACs. Overall, the results show a pattern that is consistent with the hypothesis that more speculative firms are harder to value and arbitrage. Hence, exhibiting greater difference in returns with contrasting sentiment levels. Importantly, however, we find that the difference for the more speculative subgroup is only slightly more pronounced. Thus, indicating that both groups react similarly to shifts in sentiment, with the speculative group showing a bit more fluctuation. Consistent with our previous analysis, we attribute the difficulty in spotting clear cross-sectional variation to homogeneity in the SPAC sample. Although we are able to spot cross-sectional variation in a few characteristic sorts, the inherent degree of speculation across our entire sample reduces the effect of sentiment on the cross-section of returns.

The final hypothesis relates to whether sentiment has a conditional impact on returns. This suggests that investors will alternate their preference towards speculative or non-speculative SPACs depending on the level of market sentiment. To measure this, we compare the returns of each sub-portfolio horizontally between speculative and non-speculative SPACs. If the comparison column displays alternating signs for the difference of returns, that indicates a pattern of returns conditional on sentiment. If the difference of returns shows similar signs, then investors unconditionally prefer a certain sub-group of SPACs regardless of sentiment levels. Age, indebtedness, profitability, and sales growth sorted portfolios show conditional patterns of returns. For SPACs sorted on profitability, indebtedness, and age, investors prefer speculative SPACs when sentiment is positive and vice versa. The inverse is true for growth. Investors prefer SPACs with stable growth when sentiment is positive and fast growing firms and shrinking firms when sentiment is negative. On the other hand, portfolios sorted on book-to-market, size, asset tangibility, and beta show unconditional patterns. For book-to-market and beta portfolios, investors prefer non-speculative SPACs unconditionally. Conversely, asset tangibility and size portfolios indicate that investors prefer speculative SPACs regardless of sentiment levels. Unlike Baker and Wurgler (2006), we find the small-firm effect (Banz, 1981) to appear in both sentiment periods. Furthermore, the small-firm effect is more pronounced during periods of positive sentiment. Overall, the only three portfolios that show conditionality in the hypothesized direction are age, indebtedness, and profitability sorted portfolios. The p-values further indicate that the mean differences between the speculative and non-speculative groups are statistically insignificant.

To conclude, we are unable to confirm that during periods of positive sentiment all SPAC returns are higher than during periods of negative sentiment. Moreover, the results show a pattern that is consistent with the hypothesis that more speculative firms are harder to value and arbitrage. However, the difference is marginal, suggesting that the effect on the cross-section of returns is somewhat limited. Finally, we find the hypothesized conditional variation in three of eight portfolios. Yet, the lack of significance reduces the conclusiveness with respect to conditionality.

7. Long-short portfolios

7.1. Hypothesis

Lastly, we assess the explanatory power of investor sentiment on SPAC returns. We hypothesize that long-short portfolio returns should increase when sentiment is positive and decrease when sentiment is negative. If conditional variation of investor preference holds, sentiment should be able to predict long-short portfolios formed on characteristic sorts. Hence, speculative companies should exhibit lower returns following periods of positive sentiment. This analysis adds to the non-parametric investigation conducted in Section 6 by testing significance levels and incorporating the continuous nature of the sentiment index.

7.2. Methodology

The long-short portfolios are created as *high minus low* or *speculative minus non-speculative*. First, the long-short portfolios are regressed in a univariate regression against sentiment. Second, we control for well-known factors that explain comovement as well as events that may have caused a fundamental shift in the development of SPACs. This multivariate regression allows us to add robustness and isolate the impact of sentiment from other systematic risks. We use the Carhart four-factor model (Carhart, 1997) as well as control for time series variation using a dummy variable for the JOBS act. Both regressions are outlined below:

$$R_{Xit=high,t} - R_{Xit=low,t} = \beta_0 + \delta_1 SENT_t^{\perp} + \varepsilon_t \qquad (8)$$

$$\begin{aligned} R_{Xit=high,t} - R_{Xit=low,t} = \beta_0 + \delta_1 SENT_t^{\perp} + \beta_1 MRP_t + \beta_2 SMB_t \\ + \beta_3 HML_t + \beta_4 MOM_t + \beta_5 JOBS_t + \varepsilon_{it} \end{aligned} \qquad (9)$$

Equation 8 shows the long-short portfolios as the dependent variable and the orthogonalized sentiment as the explanatory variable. Equation 9 adds the Fama French factors and dummy variable for the JOBS act. MRP is the market risk premium – market return in excess of the risk-free rate. SMB is the small minus big factor, also known as size factor. HML is the high minus low factor, commonly referred to as quality factor. MOM is the momentum factor, defined by going long on past winners and short on past losers. When regressing the size and book-to-market portfolios, the SMB and HML are excluded from the right side of the regression, respectively. We further run Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test and Augmented Dicky Fuller test (ADF Test) to measure stationarity and any need for de-trending. The tests show that the joint probability distribution remains unchanged after shifting a sequence of random variables ahead by h time periods. Consequently, our time-series data exhibits no trends, no seasonality as well as constant variance and autocorrelation. The results of the tests are shown in table A1 and A2 in the Appendix.

7.3. Results

Table 9 describes the correlations between the long-short portfolios. We find that portfolios created by age, profitability, and (to a lesser extent) beta characteristics are more positively correlated with each other than with other portfolios. This observation shows that older SPACs tend to be more profitable and have a lower beta. We also find that asset tangibility and size portfolios are correlated with a correlation coefficient of 0.57, suggesting that larger SPACs tend to have more tangible assets. Interestingly, we find that the growth portfolio is negatively correlated with most portfolios. This may be due to the difficulties exhibited in sorting our limited SPAC sample based on sales growth characteristic. Compared to Baker and Wurgler's (2006) IPO sample, we find fewer groupings of correlated portfolios and overall lower correlations. The low and varied correlations indicate that SPACs exhibit speculative traits across different characteristics. Further, it is seldom for SPACs to consistently exhibit speculative or non-speculative traits.

Table 9

Portfolio sort's correlation matrix

This table presents the correlation between various long-short portfolios. The results refer to a sample between years 2003-2018. The characteristics are defined as outlined in Table 2. The portfolios are created as speculative minus non-speculative. For age, asset tangibility, book-to-market, profitability, and size portfolios are sorted such that high values represent non-speculative and low value represent speculative groupings. Beta and indebtedness portfolios are sorted such that low values represent non-speculative and high values represent speculative groupings. Growth is an exception, where the lowest and highest 25th percentiles represent the speculative group.

Variable	Age	Asset Tangibility	Growth	Indebtedness	Size	Profitability	Beta	Book-to-market
Age	1.00							
Asset Tangibility	0.03	1.00						
Beta	0.21	-0.21	1.00					
Book-to-market	0.49	0.00	0.08	1.00				
Indebtedness	-0.08	0.14	0.09	0.08	1.00			
Profitability	0.43	0.03	0.29	0.08	0.25	1.00		
Sales Growth	-0.25	0.02	-0.31	0.07	-0.27	-0.42	1.00	
Size	0.01	0.57	-0.37	-0.03	0.27	0.16	-0.03	1.00

Table 10 displays the results from the long-short regressions. The coefficient for predicting the portfolios reflects a one-unit increase in the standardized sentiment index, which equals a one standard deviation increase. If conditional variation of investor preference holds, we expect the regressions to display a positive correlation with investor sentiment. This appears to be the case, as the majority of the results indicate coefficients in the hypothesized direction. Notably, however, the sales growth long-short portfolio displays a negative coefficient. This result follows the observations from the correlation matrix, as the sales growth portfolio is negatively correlated with other portfolios. The impact of sentiment on the long-short portfolios is largest for age, indebtedness, and profitability, which return 2.15%, 2.35%, and 1.87%, respectively.

Table 10

Results of the regressions on long-short portfolios

The table presents the regression results from equations 8 and 9. The long-short portfolios are based on firm characteristics as defined in table 2. High is defined as the speculative group of each characteristic, low as the respective non-speculative group as outlined in table 9. The first and second sets of columns show univariate regression results, the third and the fourth columns include MRP, SMB, HML, and MOM as controls. SMB (HML) is not included as a control variable when size (book-to-market) is the dependent variable. Standard errors are shown in parentheses. *, **, and *** suggest statistical significance at the 10%, 5% and 1% levels, respectively.

	Sentiment$^{\perp}$		**Sentiment$^{\perp}$** controlling for MRP, SMB, HML, MOM, and JOBS	
Variable	**β**	**p(β)**	**β**	**p(β)**
Age	0.0215**	(0.0096)	0.0213**	(0.0093)
Asset Tangibility	0.0096	(0.0103)	0.0089	(0.0099)
Beta	0.0035	(0.0115)	0.0061	(0.0114)
Book-to-market	0.0076	(0.0096)	0.0084	(0.0096)
Indebtedness	0.0235**	(0.0108)	0.0238**	(0.0110)
Profitability	0.0187**	(0.0089)	0.0204**	(0.0089)
Sales Growth	-0.0120	(0.0102)	-0.0108	(0.0104)
Size	0.0174*	(0.0099)	0.0163*	(0.0097)

We find significance across age, indebtedness, and profitability portfolios at the 5% level. This finding confirms our impression from Section 6, as these are also the portfolios that display conditional variation in the portfolio sort analysis. The small minus big (size) portfolio displays a lower significance at the 10% level. Controlling for Fama French factors as well as the JOBS act yields similar results. The levels of significance are unaffected by the controls. Although the coefficients vary slightly within the multivariate regression, the variation is not enough to change our interpretation. The minor variation in the coefficient of sentiment, between the univariate and multivariate regressions, shows that sentiment can explain returns in excess of well-known unconditional effects. The results suggest that long-short portfolios sorted on age, indebtedness, profitability, and to a lesser extent, size are capable of predicting returns conditioned on sentiment. Thus, higher sentiment forecasts relatively lower returns on young, indebted, unprofitable, and small firms. However, the other four long-short portfolios do not display any significance. Hence, we are unable to draw a definite conclusion on whether sentiment has conditional impacts on SPAC returns.

8. Conclusion

Since their revival in 2003, SPACs vast surge in activity has not been proportionally mirrored within the academic world. A considerable degree of the otherwise scarce literature has been centered around SPACs' persisting underperformance, deal and company characteristics, and the incentive mismatch created by their controversial structure. This leaves a gap in the academia that cannot fully explain the continued rise of SPAC activity considering their muted returns. Within behavioral finance, literature has shown that irrational investor behavior may be motivated by investor sentiment (Cornelli et al., 2006). Studies regarding hot and cold markets have taken a foothold in explaining cycles in the public markets (Ljungqvist et al., 2006). Thus, the recent boom in the SPAC asset class, despite their persistent underperformance, raises the question whether their cyclicality and returns could be explained by market sentiment.

With this paper, we seek to supplement gaps within the SPAC literature with a study of investor sentiment's impact on SPACs. We follow an indirect approach to measuring sentiment and construct a composite market sentiment index based on Baker and Wurgler (2006). Our findings indicate that SPAC activity rises in uncertain market conditions. When sentiment decreases by one standard deviation, the number of SPAC issuances, volume in SPAC investments, and number of SPAC acquisitions increases by 0.32, \$75.84m, and 0.16 respectively, significant at the 5% level. We postulate that the increase in SPAC activity is due to the certainty attached to their readily available cash, which allows them to fill the vacuum that traditional IPOs leave. The certainty tied to SPACs is enhanced due to the (regulatory) structure of the de-SPAC process. The structure enables private corporations to raise money quickly and issue forward-looking statements without having to fear litigation.

We also find that sentiment levels, at the time a SPAC acquisition is made effective, predict the underperformance of SPACs in the short-term. The buy-and-hold abnormal returns for six months are lower by 8% for each standard deviation increase of sentiment. This mispricing occurs due to sentiment induced overvaluation during high sentiment periods, which leads to mispricing correction in the subsequent period. However, this effect is limited to the six months period because inefficient prices do not persist in the long-term. Additionally, characteristic controls yielded no significant patterns, suggesting that underperformance persists regardless of the characteristics of our SPAC sample. We instead find that the entire SPAC sample performs in unison with shifts in sentiment.

Following, we seek to drill deeper into how sentiment impacts SPACs. Our conditional characteristics model finds that the returns of speculative SPACs fluctuate more than non-speculative SPACs. Suggesting that investor sentiment raises and lowers prices differently across SPACs. This observation is due to the elevated degree of valuation uncertainty in combination with limits to arbitrage tied to speculative SPACs. Although this finding confirms sentiment literature's hypothesized impact on the cross-section, the marginality in differences suggests homogeneity within the sample. The analysis also reveals a conditional shift in investor behavior found solely in age, indebtedness, and profitability sorted portfolios. We notice investors shift their preference from unprofitable, indebted, and young SPACs when sentiment is high, to profitable, less-indebted, older SPACs when sentiment is low. Our long-short portfolios confirm the impression of conditionality with respect to age, indebtedness, and profitability. However, the remainder of the characteristics do not exhibit consistent patterns. As a consequence, we cannot decisively conclude cross-sectional and conditional variation within our SPAC sample due to a lack of consistent, significant results.

While the study contributes to the existing SPAC literature by shedding light on the impact of sentiment on SPAC activity and performance, the analyses are not without their limitations. Firstly, the relative novelty of the SPAC asset class introduces constraints. Until 2018, we were only able to identify 136 SPAC acquisitions. This greatly limited our ability to analyze the cross-section. For example, sorting the characteristic portfolios into deciles rather than two groups would have enabled us to examine the cross-section in greater detail and identify non-linear patterns. A larger sample would have also enabled us to sort each portfolio based on characteristic cut-offs rather than equal distribution with enough SPACs in each group. This would allow us to circumvent the sample bias and lack of significant results to reach a more definitive answer on the conditional impacts of sentiment. Secondly, capturing a measure of sentiment suffers from an inherent limitation due to the complexity behind human decision making. Although we have relied on extensively scrutinized proxies for investor sentiment, we concede that some proxies lose their effectiveness and others become more applicable.

With this paper, we introduce the concept of sentiment onto SPACs and find a relationship that merits further probing. We initiate the investigation into the recent SPAC craze by showing that market uncertainty acts as a catalyst to SPACs activity. Yet, the outstanding rise of SPACs in 2020 suggests that a case study may add alternative explanations. For instance, the impact of forward-looking statements as part of the de-SPAC process or increased investor awareness may also explain the SPAC boom. Moreover, researchers may benefit from the abundance of observations introduced in recent years to perform a more robust analysis of the cross-sectional effects of sentiment on SPACs. Further research avenues may include incorporating other measures of market sentiment, comparing the impacts of market sentiment on the returns of SPACs and traditional IPOs or examining the type of companies that choose the SPAC route in alternating sentiment periods.

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Appendix

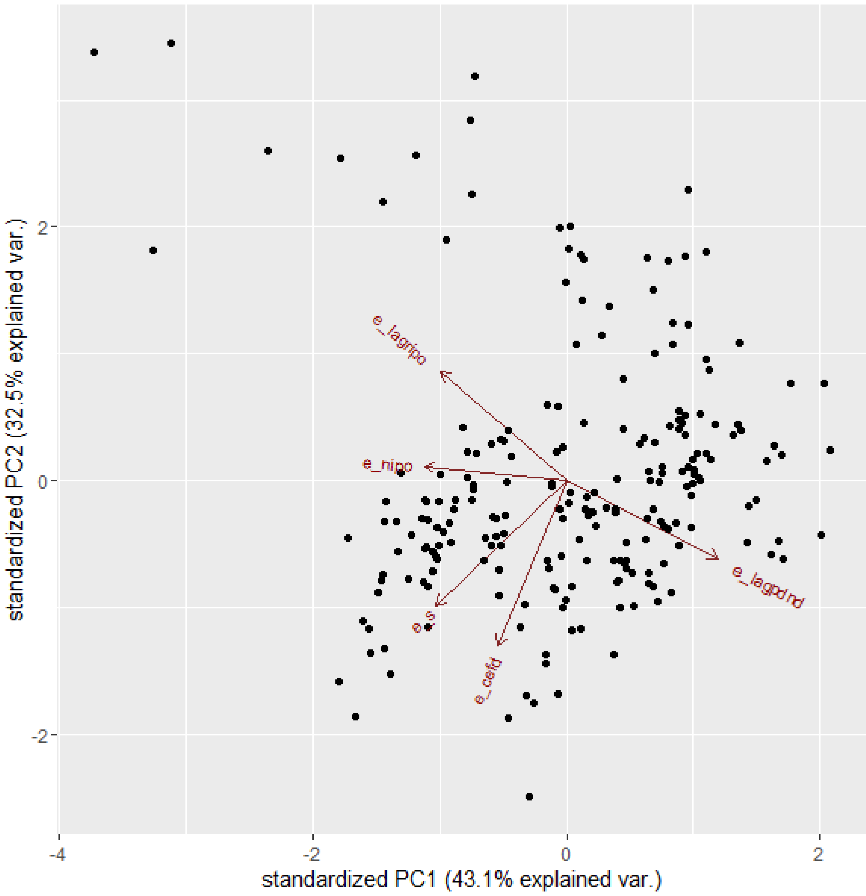

Figure A1

PCA of sentiment index proxies

The figure above plots the principal component analysis (PCA) of the investor sentiment proxies from 2003-2018. The PCA defines the second stage orthogonalized sentiment index as the first principal component of the following five variables and their scaled coefficients:

$$Sentiment^{\perp}{}_t = 0.171CEFD^{\perp}{}_t + 0.458NIPO^{\perp}{}_t + 0.302RIPO^{\perp}{}_{t-1} + 0.350S^{\perp}{}_t - 0.364P^{\perp}{}^{D-ND}_{t-1}$$

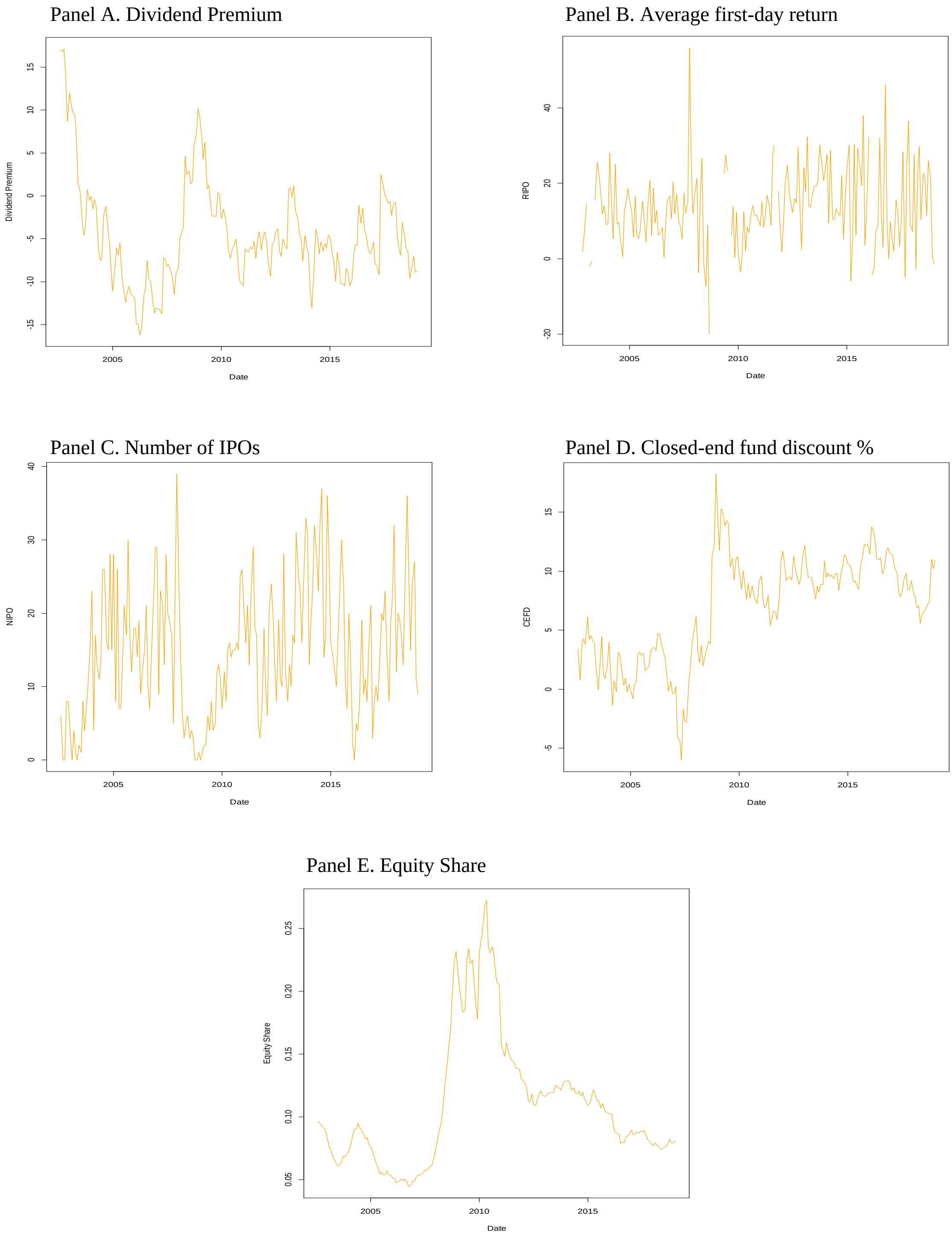

Figure A2

Investor sentiment proxies

The graphs correspond to the monthly data for years 2003-2018. Panel A illustrates the dividend premium, $P^{D\text{-}ND}$. Panel B illustrates the average first-day return, RIPO. Panel C illustrates the number of IPOs, NIPO. Panel D illustrates the closed-end fund discount, CEFD. Panel E illustrates the equity Share in new issuances, S.

	KPSS level	p-value
Age	0.216	0.100
Asset Tangibility	0.413	0.072
Beta	0.256	0.100
Book-to-market	0.106	0.100
Indebtedness	0.403	0.076
Profitability	0.418	0.069
Sales Growth	0.134	0.100
Size	1.163	0.100

Table A1

Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test
The table displays the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests conducted on the returns of the various long-short portfolios. The null hypothesis of the KPSS test is that the time-series is stationary. When the p-value is less than 0.05, we can reject the null hypothesis, suggesting that the time-series is non-stationary.

	Dickey-Fuller	p-value
Age	-5.542	0.010
Asset Tangibility	-7.133	0.010
Beta	-7.037	0.010
Book-to-market	-6.259	0.010
Indebtedness	-6.116	0.010
Profitability	-5.154	0.010
Sales Growth	-6.581	0.010
Size	-6.690	0.010

Table A2

Augmented Dickey Fuller Test (ADF test)
The table displays the Augmented Dickey Fuller Test (ADF test) conducted on the returns of the various long-short portfolios. The null hypothesis of the ADF test is the presence of unit root, that is the series in non-stationary. When the p-value is less than 0.05, we can reject the null hypothesis, suggesting that the time-series is stationary.