ERASMUS UNIVERSITY ROTTERDAM
ERASMUS SCHOOL OF ECONOMICS
MSc Economics & Business
Specialization Financial Economics

Convertible Bond Arbitrage: An Analysis of Liquidity, Pricing and Investor Sentiment

Author: QPP Hilbers
Student number: 545911
Paper supervisor: dr. J. Lemmen
Second reader: dr. L. Swinkels
Finish date: July 2024

PREFACE AND ACKNOWLEDGEMENTS

I would like to extend my sincere gratitude to my supervisor, Dr. Jan Lemmen, for his guidance and support throughout this entire process. His insightful feedback and thoughts about possible additions have made the development of this work more comprehensive and more robust. I appreciate the time he has invested in providing direction for my work, which ultimately enhanced the quality of my research.

ABSTRACT

This paper investigates the impact of convertible bond arbitrage on liquidity and pricing efficiency in equity markets, with a particular focus on the influence of investor sentiment. Utilizing a comprehensive dataset of U.S. convertible bond issues from May 2009 to June 2023, I analyze changes in short volume around issuance dates to proxy for arbitrage activity. My findings indicate that convertible bond arbitrage significantly enhances market liquidity, evidenced by increased turnover and trading volumes, as well as reduced bid-ask spreads. Contrary to expectations, I also find a positive correlation between arbitrage activity and price efficiency, suggesting that arbitrageurs may possess some degree of informational advantage. However, these findings do not hold in additional tests. Furthermore, my analysis reveals that investor sentiment may play a role in amplifying the observed market quality effects, contributing to higher liquidity but showing no direct impact on price efficiency. The results provide new insights into the dynamic interaction between hedge fund strategies, market quality, and psychological factors in financial markets, highlighting the evolving nature of convertible bond arbitrage in market environments.

Keywords: Convertible Bond Arbitrage, Hedge Funds, Liquidity, Market Efficiency, Investor Sentiment

JEL Classification: G11, G23, G12, G14

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CHAPTER 1 Introduction

Over recent decades, the U.S. has seen a remarkable growth in the issuance of convertible bonds by corporations. In the beginning of this century, Choi, Getmansky and Tookes (2009) reported an increase from $7.8 billion in 1992 to over $50 billion by 2006 in this debt market. This period is also marked by a significant rise in the involvement of hedge funds applying convertible bond arbitrage strategies: Pulliam (2004) outlined that hedge funds purchased an estimated 80% of convertible bonds in 2004, while Mitchell, Pedersen and Pulvino (2007) reported an estimation of 75% in 2007 - both studies confirming a significant role. This period[1] stands in stark contrast to the aftermath of the 2008 financial crisis, when the issuance of such bonds as good as halted. Currently, after the COVID-19 global crisis, the convertible debt market has experienced a jump again. Companies refinance their existing convertible notes and use these securities to lower borrowing costs. U.S. companies have issued more than $40 billion of convertibles in 2023, up from $29 billion in the previous year[2]. The rise in the issuance of these securities can be partly credited to the increasing availability of capital facilitated by hedging strategies (Choi, Getmansky and Tookes, 2009).

This research aims to explore the influence of convertible bond arbitrage strategy on the liquidity and pricing efficiency of the underlying stock, while simultaneously test the specific influence of investor sentiment in this relation. For these purposes, the following research question is formulated:

"Are liquidity and price efficiency in markets affected by convertible bond arbitrage, and are these effects influenced by investor sentiment?"

Although the examination whether arbitrage behavior influences market dynamics is not new, hedge funds have increasingly been active in the convertible bond market in the past years - which raises ongoing questions about their influence. Besides influencing markets, hedge funds can play a significant role in shaping the design of the securities involved: convertible bonds. Convertible bonds are dynamic instruments with a variety of provisions that evolve continuously to adapt to the ever changing financial markets. Numerous studies have described the dynamic characteristics of these hybrid instruments. Lewis and Verwijmeren (2011) examined the design of convertible bonds, particularly noting that settlements - the process of fulfilling the terms of a convertible bond - are frequently conducted in cash. They find that fixed income claims are chosen by firms for multiple reasons, such as the reduction of corporate taxes and refinancing costs. Grundy and Verwijmeren (2018) later demonstrated how the design of these securities is shaped by the interaction between hedge funds, as primary capital providers, and preferences of the issuers. They find that observed drops in call provision features in convertible bonds may be the direct cause of the market dominance of arbitrage hedge funds. Verwijmeren and Yang (2020) further analyzed this subject and found that

[1]The 2000s upon the financial crisis (2008) [2]According to Goldman Sachs (2023)

recently issued convertible debt instruments have typically short maturities, to substitute for these call provisions.

To better understand how the convertible bond arbitrage strategy can influence liquidity and pricing in stock markets, an overview of the tactics and rationale behind the strategy is helpful. The arbitrageur, in this case the hedge fund, seeks for a convertible bond that is priced in a way that does not reflect the value of the underlying stock (often underpriced bonds: Henderson, 2005). To gain from this inefficiency, the arbitrageur will buy the mispriced convertible bond and sell short the stock, in which the bond can be converted. If the price of the bond increases, the arbitrageur profits from the long position in the bond – if the stock price decreases, the arbitrageur profits from the short position in the equity. In this scenario, hedge funds often apply a strategy known as delta-neutral hedging. “Delta” is referred to as a “Greek,” which is a term used to describe the different measures of sensitivity of the price of an option to various factors. All relevant Greeks can be found in Appendix B. Delta refers to the ratio that compares the change in the price of the convertible to the change in the price of the underlying equity. The primary goal is, as the name of the strategy suggests, to adjust the hedge ratio to maintain a neutral position. This means adjusting the ratio of the shorted stock to the owned convertible bonds such that the overall position of the portfolio delta is zero. This implies that when the price of the stock increases, the value of the conversion option of the bond also increases, making the bond behaving more like a stock. To maintain neutrality, the hedge fund will increase the short position (i.e. short sell more stocks). Conversely, when the stock declines, the bond behaves more like a straight bond, and the fund would buy shares back. This trading behavior tends to move in opposite directions from aggregate market movements.

By constantly executing trades, to pursue a delta-neutral strategy, the aim is to set up a position where small movements in the stock price do not affect profits, but cash flows are rather achieved by the convertible bond yield (coupon payments) or the short position’s interest rebate. Achieving cash flows on the interest rebate can be explained as follows. When a hedge fund establishes a short position, it borrows securities from other owners, providing cash collateral to the lender. This cash can be placed in interest-bearing accounts, generating an "interest rebate". The rebate provides additional income for the lenders, and the investor who sold short the stock (i.e. the hedge fund) is entitled to receive a portion of this rate. To make the subject more tangible, Figure (1) demonstrates the critical elements of a delta-neutral strategy.

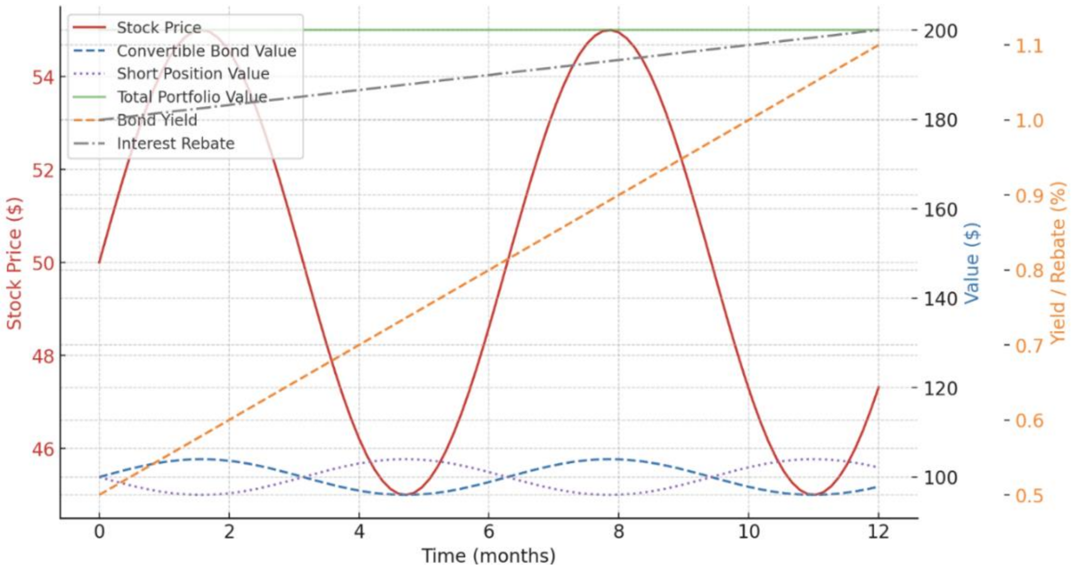

Figure (1) Visualization of the delta-neutral strategy. All prices and values are purely indicative. The red line (stock price) shows how the stock price fluctuates over time. The blue dashed line (convertible bond value) and the purple dotted line (short position value) demonstrate where the gains in the convertible bond's value due to increasing stock prices offset losses in the short position value, and vice versa (neutralization of market volatility). The green line (total portfolio value) shows that the overall portfolio value remains relatively stable. The grey and orange dotted line show income derived from interest earned on the cash collateral and the bond yield, both steady income streams that enhance the profitability of the hedge fund.

Having explained the relevance and technical aspects of this subject, I will now discuss the rationale and expected outcomes of my research question. The main focus of this paper will be to provide an analysis on how convertible bond arbitrage strategies influence liquidity and price efficiency of the underlying equity (Choi, Getmansky, Henderson, Tookes, 2007; Faulkender and Petersen, 2006). Moreover, this paper seeks further by being the first, to my knowledge, to give a subsequent analysis on whether investor sentiment in the market as a whole affects the outcomes. This sentiment can influence buying and selling decisions, which can significantly affect market liquidity and pricing.

As mentioned before, hedge funds have increasingly been involved in the convertible bond market, where they employ strategies that involve trades, which are expected to move in the opposite direction of the market (Choi, Getmansky and Tookes 2007). This raises questions about their influence on market liquidity and efficiency. The expectations guiding the first part of this research are as follows. First, I expect improved liquidity due to their presence. Whether hedge funds engaging in convertible bond arbitrage are informed or uninformed investors, ostensibly determines their impact on price efficiency. I expect hedge funds to be uninformed investors, as they seemingly do not have specific negative information but use short selling for hedging. In this context, describing hedge funds as "uninformed" does not necessarily imply that they lack information or financial acumen. Instead, it suggests that their trading decisions, particularly regarding short selling, are not primarily driven by specific negative insights into the companies whose shares they decide to sell short. This distinguishes them from informed investors, who short-sell based on (superior) information or analyses predicting a downturn. If hedge funds are truly uninformed, also suggested by Choi et al. (2007), I anticipate that those employing convertible bond arbitrage strategies will not affect price efficiency.

The relevance of the exploration of investor sentiment is now highlighted. Recent literature (Bouteska, 2020; Ryu, Ryu and Yang, 2023; Liu, 2005) has found investor sentiment to be a great factor in determining liquidity and price efficiency in capital markets. Given the sensitivity of convertible bonds to fluctuations in the equity market, incorporating investor sentiment is in particular valuable. When investor sentiment is positive, equity markets tend to perform well, thereby enhancing the value of convertible bonds. Conversely, negative sentiment can depress stock prices and, consequently, the value of convertible bonds. Incorporating an analysis of this sentiment provides a more nuanced understanding of how these securities react to market conditions, and it offers insights into potential strategies for managing them effectively in fluctuating markets. By incorporating this factor, the paper adds a layer of depth on existing literature examining psychology effects in financial markets. The expectation that further analysis of investor sentiment will significantly alter my results is ambiguous. In this paper, I capture real-time emotions and attitudes that significantly can impact investor behavior and, consequently, market liquidity and quality. Given that hedge funds are typically sophisticated investors, I first expect their behavior to be less influenced by investor sentiment than the market as a whole. This enables them to impact, or not impact, market liquidity and price efficiency consistently, regardless of the sentiment state of the market. However, it is important to note that varying market conditions, influenced by shifts in investor sentiment, can complicate the execution of arbitrage strategies. Even though hedge funds are generally less sensitive to immediate fluctuations in sentiment, this sentiment can still pose significant challenges to the effective implementation of these strategies. If this is the case, it could lead to notable variations in the results of my main analysis (not controlling for investor sentiment) and the subsequent analysis (controlling for investor sentiment).

In my analysis of convertible bond arbitrage, liquidity, pricing, and investor sentiment, two other important factors should be considered. First, that shorting behavior of hedge funds may contribute to negative investor sentiment in the market. This sentiment is reflected in the overall level of shorting at any given moment, as shorting across the market may serve as a proxy for (part of) the investor sentiment. Second, I need to consider that shorting stocks can be relatively costly, and relatively few investors have the ability to short sell certain stocks. While investors who believe a stock is undervalued can easily purchase it, those with bearish thoughts may face constraints. As a result, there may be an upward bias in stock prices due to the incomplete reflection of negative information. This bias is especially evident in equities without (call or put) options. Figlewski and Webb (1993) examined the idea that options markets may eliminate such short selling constraints. They find evidence that stocks with options attached have no constraints on shorting, which makes the upward bias disappear. To account for these two factors – firstly, that short selling may act as a proxy for investor sentiment and second, that stocks without options exhibit upward bias - additional tests in this research are made.

The first initial dataset comprises convertible debt issues from U.S. firms from May 2009 to June 2023. This data is combined with an extensive daily short volume dataset and several datasets containing variables related to the underlying equity. Furthermore, I integrate a dataset of investor sentiment. For the methodology, an event study as outlined by Brown and Warner (1985) is exploited in conjunction with further regressions. To conduct this research, the arbitrage behavior needs to be identified as direct data on convertible bond arbitrage activity, which is not directly available to me. Therefore I need to establish certain proxies.

The proxy for convertible bond arbitrage activity, which is the change in short volume in the equity of issuing firms around the issue date, offers several benefits compared to relying on databases of hedge funds to identify this activity (according to Choi, Getmansky and Tookes, 2007). First, it measures the positions arbitrageurs take in individual securities directly, providing a more precise insight into their activities. In contrast, data from hedge funds are self-disclosed and thus may offer a distorted image of arbitrage activities. Second, hedge fund databases often suffer from style misclassification and have the issue of funds reporting multiple strategies simultaneously, which can mask the true extent of arbitrage activity. Third, even with accurate measurements of fund assets, the actual positions remain hidden due to the usage of leverage. Furthermore, my dataset has several benefits over previous literature. My constructed proxy for convertible bond arbitrage (i.e. short volume around the issuance) is derived from daily stock data, in contrast to previous literature (Choi et al. 2007), using monthly data. This enhances the precision of the research. Furthermore, my proxy is based on trading volume rather than short volume interest, offering several advantages, which will be discussed later in the paper. The method to identify convertible bond arbitrage is simple, but effectively captures the strategy of interest, given the significant rises in short selling near convertible debt issues that I find. As I want to capture the (abnormal) change in short volume of the underlying equity, these changes are examined against a normalized shorting volume (Desai, Ramesh, Thiagarajan and Balachandran, 2002). The rationale for constructing my proxy will further be elaborated in Sections 2 and 4.

After the identification of the convertible bond arbitrage activity, an event study is conducted (univariate analysis) to examine the relationship between convertible bond arbitrage, liquidity and price efficiency. Furthermore, to control for factors other than the short-volume and to assess the influence of investor sentiment in this relationship, a multivariate analysis is conducted. Lastly, I conduct an analysis of long-run returns of the equity positions of the arbitrageurs. This is an additional test to examine the effect of arbitrage behavior on price-efficiency.

I find substantial evidence of arbitrage activity (unusual shorting volume in the equity) coinciding with the issuance dates of the bonds. This short-selling around the issuance is significantly positively related to liquidity in the stock market. My results further show that convertible bond arbitrage has an ambiguous effect on price-efficiency. Specifically, I find in my main analysis, contrary to expectations, a significant relationship between arbitrage activity and price-efficiency, but this relation does not hold in the additional test of long-run returns. Lastly, I conclude that the results are robust to, and may be amplified by, the inclusion of investor sentiment.

My paper sheds new light on the influence of hedge funds' strategies on market dynamics, if market dynamics are defined as changes in liquidity and price efficiency. The paper contributes to the literature in three ways. First, my research contributes to the ever-evolving literature on convertible bond arbitrage and its impact on liquidity and market efficiency, focusing on a novel time frame that has not yet been explored. This is highly important because convertible bonds (as stated before) are dynamic financial instruments and hedge funds can play a significant role in shaping them. Since financial markets have changed drastically over the years, especially with the adoption of new rules and technology developments, a lot could have changed. Second, my dataset comprises daily short-selling data, in terms of volume to identify convertible bond arbitrage. Previous research has primarily focused on monthly data of short selling, in terms of short interest. The accuracy of daily data can give more empirical exactness, whereas volume data can give a superior image compared to interest data, which will be argued upon later in the paper. Third, I am the first to give a comprehensive analysis for the incorporation of investor sentiment in the field of convertible bond arbitrage, stock market liquidity, and price efficiency. Previous research controls for market-wide variables, but these are mainly general time-specific effects such as year and month dummy variables. In my paper, the unique contribution of investor sentiment is isolated.

The remainder of the paper is organized as follows: in Section 2, I describe the relevant literature and outline my main hypotheses. Section 3 reports the data and sample. Section 4 describes the methodology and the construction of the arbitrage proxy. Section 5 outlines the results, and in Section 6 the paper is discussed. Lastly, I will conclude my findings in Section 7.

CHAPTER 2 Related Literature

2.1 The reasoning for convertible debt and the role of hedge funds

Understanding the fundamental reasons why companies issue convertible debt and how hedge funds exploit these securities into lucrative strategies is vital for my research. Previous empirical research (Green, 1984; Mayers, 1998; Constantinides and Grundy, 1989) has underscored one plausible reason for issuance: convertible bonds give investors the chance to capitalize on the prospective appreciation of the underlying equity. Conversely, if the stock of the company does not perform well, the bond remains more debt-like, offering protection to the holders. The “protection” mentioned refers to the downside protection inherent in the bond aspect: unlike equity, where the value can drop to zero, bonds have a maturity date at which the principal is paid, bonds have regular interest payments, and bonds often have seniority over equity in cases of default. The lower price barrier is often referred to as the “bond floor”, which is the minimum value that a specific bond should trade for. In essence, it is equal to the present value of the future cash flows if the conversion option is not exercised. Therefore, because convertible bonds exhibit features of both debt and equity, they serve as an effective financial tool when assumptions have to be made by investors – for example, the riskiness of a company (Brennan & Kraus, 1987; Brennan & Schwartz, 1988).

The equity-related theories of Stein (1992) give another incentive for firms to issue bonds. He states that companies may use convertible bonds as an indirect way to incorporate equity into their capital structures, particularly in situations where conventional stock issuance is deterred by adverse selection issues. This can be explained as follows. Investors, that do not have full information about a company’s financial health, may suspect that new shares are being issued because the stock is overvalued. When a company issues new equity, investors may interpret this as a signal that the stock is currently priced too high, leading them to discount the price. This concern may prevent a company from issuing new equity, particularly when they believe their stock is not overvalued or when management has favorable information not yet reflected in the market price. To avoid the negative perception associated with new equity issues, companies might choose convertible bonds. This allows companies to raise capital immediately while potentially delaying equity dilution and mitigating the adverse selection costs associated with straight equity issuance. For banks, there is an additional reason to issue convertible debt. Banks are required to maintain capital adequacy ratios to increase their resilience against potential losses. During times of financial stress, the ability to convert bonds into equity strengthens their capital base, helping them meet these regulatory requirements.

Dutordoir et al. (2014) also outline two main motives for firms to issue convertible debt. The first is straight-forward, which states that firms favor convertible bonds because they offer a cheaper alternative than straight debt or equity. The cost effectiveness here lies in the fact that convertible bonds usually have lower interest rates than non-convertible bonds and may allow firms to issue equity at a premium. The conversion price, the price at which the bond can be converted in stock, is usually set higher than the stocks market price. Despite skepticisms, arguing that the lower interest rates are offset by the value of the conversion option, Graham and Harvey (2001) support this theory.

The second motive is grounded in a theoretical framework, that challenges the perfect market of Modigliani and Miller (1958). In an imperfect market, firms can potentially reduce the costs associated with agency conflicts or adverse selection costs by issuing convertible bonds. Cost reduction associated with adverse selection is outlined above (Stein (1992) theory about indirect equity). Cost reduction associated with agency conflicts can be reduced due to the feature of convertible bonds to be converted into equity. First, it may align interests of shareholders and bondholders. The option to convert gives bondholders a reason to care about the stock price of the company, which is an incentive to not strictly push for policies or debt covenants at the expense of growth opportunities. Second, it may align interests of shareholders - seeking to increase stock prices - and managers. By issuing convertibles, management is signaling their confidence that the stock price will increase. Managers are then motivated to boost company performance to make the equity conversion attractive (which is amplified by the often given compensation packages of management tied to stock price performance). Additionally, the potential conversion reduces the company's debt obligations, providing managers with an extra incentive to boost stock prices.

The literature also provides substantial insights into hedge fund convertible arbitrage strategies. Choi et al. (2009) offer a perspective on the role of hedge funds in bond markets, particularly focusing on convertible arbitrage strategies and their influence as capital suppliers for convertible bond issuers. They find evidence that issuance is positively related to capital supply of hedge funds. Choi et al. (2007) investigate the relationship between convertible bond arbitrage, price liquidity and price efficiency. They find systematic liquidity improvements in the stock and no effect on price efficiency. Faulkender and Petersen (2006) also explore the impact of capital supply on the market, and find hedge funds to be significant players in the convertible bond area. Brown et al. (2019) and Dutordoir et al. (2014) further investigate this topic and state that investor demand indeed typically influences convertible bond issuance. These studies underscores the intriguing role of hedge funds in the convertible bond market. Even though hedge funds do not represent all convertible bond arbitrageurs, they play a significant role in the issuance of convertible debt.

2.2 Short selling and the proxy for convertible bond arbitrage

My fundamental empirical approach involves analyzing changes in short volume around the time of convertible bond issuances to identify arbitrage activity. Then, I investigate the influence of these changes on liquidity and price efficiency. In such manner, my study is firmly linked with the literature of short selling activity and the relationship it has on the market. First, I look at how short selling influences liquidity in financial markets. The literature has produced ambiguous results on this relationship. Blau and Whitby (2018) find that bid-ask spreads increase due to short selling, but that this only holds for small-cap stocks. Diether et al. (2009) put forward that some liquidity providers might short stock to supply liquidity, whereas Brunnermeier and Pedersen (2005) demonstrate that predatory traders can reduce liquidity. Second, I look at the relationship between short selling activity and price-efficiency. Asquith, Pathak, and Ritter (2005), Boehme, Danielsen, and Sorescu (2006), Diether et al. (2005) and Jones and Lamont (2002) all find evidence suggesting that short selling has an influence on stock prices. They argue that short selling plays a role in integrating negative information into market prices – and when these activities are restricted, it could lead to overvaluation in the stocks. Third, I look at how short selling is conceptualized to act as a proxy for convertible bond arbitrage. Researchers have different approaches to understanding and measuring the activity of convertible bond arbitrageurs. For example, Hanson and Sunderam (2014) look at changes in short interest over time to estimate how much capital is used in arbitrage strategies. Benchmann (2004) presents evidence that short selling induced by hedging contributes to some of the short-term price fluctuations around announcement dates. Similarly, Mitchell, Pulvino, and Stafford (2004) examine the trading behavior of professional investors. They find evidence of price pressure around mergers in the short-term. Furthermore, Choi, Getmansky and Tookes (2007) construct a way to identify convertible bond arbitrage by examining short selling levels around these issuances. Further work of these researchers (Choi, Getmansky and Tookes, 2009) confirms again that short selling activity around the issuance is consistent with arbitrage activity in the market. There is also extensive literature (Desai et al, 2002; Senchack and Starks, 2002) suggesting that *unexpected* short interest is a better indicator of new information. Desai et al. (2002) defines unexpected short interest as the current month's short interest minus the previous month, as a percentage of the total number of shares outstanding. Senchack and Starks (2002) define the *unexpected* short interest through a refined model with various firm-specific characteristics. However, it is important to note that both papers argue this predictor is highly effective in forecasting stock returns, rather than address its efficacy in the specific case of identifying convertible bond arbitrage.

2.3 Market quality and firm characteristics

Besides the findings of Choi et al. (2007) as stated in Section 2.1, there is more literature on the influence of debt issuances and market effects. Kumar et al. (1998) and DeTemple and Jorion (1990) find a positive impact of debt issuances on liquidity (and no impact on price efficiency) when they explore the effects of the derivatives market on the market of the underlying asset. This may be attributed to the impact of short sale restrictions. Short sale restrictions can skew market prices because they asymmetrically affect investors with favorable and unfavorable information. Figlewski (1981) found that these restrictions prevent negative information from being fully incorporated in the market. Further analysis on this study concluded that options markets is able to eliminate such short selling constraints (Figlewski and Webb (1993)). Moreover, Ross (1976) and later works (Grossman (1988); Biais and Hillion (1994); Easly, O'Hara and Srinivas (1998)) all show that the implementation of (convertible) options exhibit liquidity improvements in the markets due to more completeness and/or more informativeness in stock prices. However, they find that this introduction has no negative impact on price efficiency.

To further see in which kind of issuers convertible bond arbitrage is most evident, I should also examine the literature on firm characteristics where this strategy is often applied. Choi et al. (2009) suggest that arbitrageurs tend to favor stocks with lower conversion premia, as these are indicative of reduced credit risk and lower interest rates. Credit risk is reduced as lower conversion premia indicate that the bond is closer to its bond floor value. This floor value (the minimum the bond should trade for, see Section 2.1) provides a safety net because, in the event of the issuer's financial distress, the bondholder still has the claim to the principal and interest payments of the bond. As the bond is priced closer to the value of the underlying stock, lower risk is implied, which in turn reduces interest rates.

Choi et al. (2009) also find increased dynamic hedging activity in stocks with higher volatility. This indicates that investors are more likely to employ convertible bond arbitrage when stocks have large price fluctuations. In volatile markets, prices of convertible bonds can deviate more significantly from their fundamental value. This mispricing can be exploited by arbitrageurs. Hirshleifer, Teoh, and Yu (2011) find that constraints on shorting arbitrage differ across exchanges. D'Avolio (2002) addresses the size component and finds that short-selling is more constrained for smaller firms (limited availability of shares and thus higher cost of borrowing shares to short).

2.4 Investor sentiment

During my research, it is possible that the findings of liquidity and price efficiency in the underlying equity are influenced by broader market trends rather than the activity of convertible bond arbitrage. Previous research differs in the way it examines such potentially important issues. Yet, the gross of the studies control for sets of firm specific or year fixed effects in the form of dummy variables. However, to my knowledge, there is no great attention paid to the growing literature of the impact of investor sentiment on liquidity and market quality in the field of convertible bond arbitrage. Time fixed effects control for all global and national factors over time, but do not specifically gauge the exact influence of the fluctuating psychological factors of investor sentiment. Year or month fixed effects could encompass macroeconomic policies and other cyclical factors, such as GDP or CPI levels, or interest and inflation rates. These cyclical factors will likely intersect with investor sentiment (just as the degree of short selling in the market, as outlined in Section 1), but there is an important distinction. Identifying this distinction allows me to examine psychological factors in financial markets separately, without the influence of the cyclical factors mentioned above. This reasoning is further explained in Section 4.

Bouteska (2020) finds that sentiment-induced trading is an important determinant of stock price variation. Ryu, Ryu and Yang (2023) find that investor sentiment significantly affects futures market mispricing. Liu, Wu and Zhou (2023) show that investor sentiment affects stock market liquidity as well. They find that companies with a positive outlook increase trading activity while they reduce the impact on prices. Liu (2015) states that liquidity in asset pricing has great importance in financial markets, and that the stock market is more liquid when sentiment indices increase. In other words, liquidity is greater in a market with bullish participants.

Numerous behavioral finance studies have also documented the impact of sentiment in financial markets. Research in this field indicates that tone and sentiment correlate with market return predictability (Li, 2011; Tetlock, 2007), liquidity (Tetlock, 2010) and earnings (Tetlock et al, 2008). As my research spans over a time-frame of 14 years, it is very likely that sentiment differs around the issuances in my sample. Even more interesting, my analysis covers the COVID-19 period, during which Bai and Duan (2023) observed that rising financial investor sentiment boosted stock market returns, even during the worst of the pandemic. Higher returns can indicate improved price efficiency (higher returns can be a sign that prices are adjusting more rapidly and accurately to new information, which reflects the true value of stocks more closely). Lastly, Chau, Deesomsak and Koutmos (2016) do not only find that investor sentiment is an important determinant of stock price variation, but also that the typical investors driven by this sentiment do not need to be ‘’irrational’’, as is presupposed in classical asset pricing. They argue that sentiment-driven investors can trade against the herd and sell stocks when overinflated. These findings suggest that investor sentiment can contribute to price efficiency. They also argue that these investor sentiment-driven traders buy more aggressively during periods of declining sentiment than sell during periods rising sentiment. These findings suggest that investor sentiment can also contribute to market liquidity.

2.5 Hypotheses

The above named literature collectively investigates the reasoning behind firms issuing convertible bonds, how hedge funds influence these decisions through their strategies, and how these strategies influence the corresponding market. In this sub-section, the rationale behind my hypotheses is explained. As outlined in sub-section 2.2, most literature identifies convertible bond arbitrage by examining short selling levels. Similar to these studies, my empirical approach focusses on the short selling levels around issuance and uses this as an indicator of convertible bond arbitrage strategies. The proxy used in my research is normalized to the shorting volume of the underlying equity, adhering to the definition of *unexpected* short interest as outlined by Desai et al. (2002). The key difference is that my research utilizes daily volume data, whereas the Desai et al. (2002) study uses monthly interest data. The proxy also partly adheres to the definition of *unexpected* short interest of Senchack and Starks (2002). In their refined regression, the first explanatory variable is firm size, defined as the market value of its equity, which is also considered in the proxy used in my research. The other explanatory variables (option variable, dividend yield and beta coefficient) of their regression are not considered, since my primary objective is to capture changes in short volume related to convertible bond issuance - as this is the point where the arbitrage takes place. Taking the other three factors into account would dilute my focus on the primary relationship between issuance and short volume changes. Variables like option trading and dividend yield are more related to the characteristics and trading behaviors of the stocks themselves (so well-fitted for examining returns) rather than to the specific activity of convertible bond arbitrage. While these factors may influence short interest, they are not direct indicators of arbitrage driven by convertible bond issuance. For the reasoning above, I follow the literature on convertible bond arbitrage (Choi, Getmansky and Tookes, 2007): I determine the baseline short volume level prior to the issuance of the convertible bond, then examine the change in short volume around the time of the issuance compared to this baseline, and normalize this change by the total number of shares outstanding. Referring to my proxy as the *unexpected* short volume might be misleading, as this typically suggests a deviation from anticipated or forecasted levels, while the measure should observe direct changes, and not deviations. The calculation and reasoning will be further explained in Section 4.

After constructing the proxy for convertible bond arbitrage, three main hypotheses are tested to answer the research question in the best way possible. Initially, its relationship with changes in market liquidity is investigated. As outlined in the introduction, hedge funds that employ convertible bond arbitrage, are typically trading contrary to other market participants. This behavior is anticipated to increase market liquidity, which forms the first null and alternative hypothesis:

***$H_{0,1}$* (Liquidity):** Convertible bond arbitrage activity is uncorrelated with liquidity changes in the underlying equity.

***$H_{1,1}$* (Liquidity):** Convertible bond arbitrage activity is correlated with liquidity changes in the underlying equity.

If convertible bond arbitrageurs lack superior knowledge regarding the value of the underlying equity, their involvement in the stock market can be seen as liquidity improving, by increasing the available share supply to buyers. Conversely, if they do have private information, the costs related to adverse selection may rise, which potentially reduces liquidity. These costs may arise as other market participants may be reluctant to trade due to the perceived information asymmetry (i.e. they believe hedge funds have superior information). However, I do not anticipate finding evidence for the later reasoning, as arbitrageurs generally aim to exploit underpricing in bonds and not in equity. This is because the strategy usually hinges on technical mismatches in pricing of the convertible bonds rather than on superior or non-public information about the underlying stock. Arbitrageurs generally focus on the underpricing of convertible bonds because of their unique characteristics. Convertible bonds, being hybrid instruments, have more complex pricing dynamics compared to (common) stocks. The bond market is less liquid, primarily dominated by institutional investors, and their prices are influenced by the credit risk of the issuer and prevailing interest rates. This complexity often leads to greater pricing inefficiencies, which generally provides greater substantial arbitrage opportunities.

Furthermore, the relationship between convertible bond arbitrage and price efficiency is investigated. A similar research as previously mentioned (analyze short levels around issuance) is conducted, but now various price efficiency measures are examined. Consequently, the second hypothesis is formulated:

***$H_{0,2}$* (Efficiency):** Convertible bond arbitrage activity is uncorrelated with price efficiency changes in the underlying equity.

***$H_{1,2}$* (Efficiency):** Convertible bond arbitrage activity is correlated with price efficiency changes in the underlying equity.

As explained, I expect hedge funds to be uninformed investors in regard to the short selling of the stocks. If this is the case, it is expected that hedge funds employing convertible bond arbitrage strategies will not affect price efficiency. This is because their trading actions would not lead to price movements that better reflect the true underlying value of the securities, if they do not hold superior knowledge.

In detecting the arbitrage, I expect to find that the amount of short selling will be highest around the date of the issuance. This is because arbitrage hedge funds often hedge their positions (i.e. short selling) immediately upon going long in the convertible bonds.

For the analysis on liquidity and price efficiency, various proxies are examined. For liquidity, I examine the following measures: turnover (log turnover), number of trades (log number of trades), dollar volume (log dollar volume), an illiquidity measure following Amihud (2002)[3], dollar spread, and percentage spread. For stock price efficiency the variance ratio (Lo & McKinlay, 1988) and the daily autocorrelation of returns are examined. The variance ratio measures the efficiency of stock prices by comparing their variances across different time frequencies. Smaller deviations from a ratio of 1 indicate higher market efficiency, suggesting that prices reflect all available information more accurately. Autocorrelation can help identify whether returns are trending or mean-reverting over time. Positive autocorrelation, where high returns are likely to follow high returns (and low returns follow low returns), suggests momentum or trend-following behavior. Negative autocorrelation, where high returns tend to follow low returns and vice versa, indicates mean-reversion. A market in which prices fully reflect all available information, should exhibit little to no autocorrelation in returns. As stated, it is not expected to find a strong relationship between convertible bond arbitrage and price efficiency measures. Therefore, after issuance, I do not expect to find any notable changes in these measures. Together with these price efficiency measures, several other stock characteristics are examined: returns, standard deviations of returns, idiosyncratic volatility (Bris et al. 2004), (adjusted) R-squared values, and Betas. The idiosyncratic volatility, R-squares and Betas are derived from a regression of daily stock data over the value-weighted market excess return. All definitions can be found in the explanatory variables section (Appendix A). In addition, an analysis of long-run returns is conducted to gauge further price-efficiency effects.

Finally, I will contribute to the field by testing for investor sentiment as discussed in Section 2.3. More specifically, I control for investor sentiment in my regressions. The index used for this analysis is the Baker and Wurgler (2006) sentiment index. Section 3, the data section, will provide a detailed explanation of the characteristics and functionality of this index. Section 4, the methodology section, will provide an explanation on how this index is incorporated in my research. The third and last hypothesis of my paper is as follows:

***$H_{0,3}$* (Investor sentiment):** The influence of convertible bond arbitrage on liquidity and price efficiency measures is not directly related to investor sentiment.

***$H_{1,3}$* (Investor sentiment):** The influence of convertible bond arbitrage on liquidity and price efficiency measures is directly related to investor sentiment.

It is, on the one hand, expected that investor sentiment will not significantly alter the results. Although it is recognized that sentiment can significantly influence market quality, as discussed in Section 1, hedge funds are expected to show less sensitivity to general investor sentiment due to their sophistication. Consequently, their ability to affect market liquidity and price efficiency can be expected to remain consistent. On the other hand, as outlined in Section 2, Chau, Deesomsak and Koutmos (2016) argue that investor sentiment-driven traders can contribute to enhanced market quality and liquidity. Therefore, it will be interesting to explore the inclusion of investor sentiment in the analysis to see how it might relate to convertible bond arbitrage, liquidity and price efficiency. In the introduction, it is also mentioned that shorting behavior of hedge funds may contribute to negative investor sentiment in the market. To check the relevance of the investor sentiment proxy (i.e. that it is not influenced by the hedge fund itself, a reversed causality issue) in this research, an additional analysis is made.

CHAPTER 3 Data and Sample selection

To test my initial hypotheses regarding the impact of convertible bond arbitrage on liquidity and price efficiency, I begin by acquiring a sample of convertible bond issues with relevant information about the underlying equity. This sample will then be integrated with short volume and underlying stock data, to facilitate the research process. This approach and data collection will be described in the first two sub-sections of this chapter. Section 3.3 will present summary statistics for the firms in my sample after merging the convertible bond, shorting, and stock data. This data is needed for the first two hypotheses (liquidity and price efficiency). Finally, in Section 3.4, the investor sentiment data is introduced and discussed, which is crucial for testing my third hypothesis.

3.1 Convertible bond issues

For the initial sample of this research, I obtain data from all convertible debt issues that are either a public placement or a private placement under SEC Rule 144a[3], by U.S. publicly traded firms from May 2009 - June 2023. I have selected this time frame to be as recent as possible, focusing on the period following the study of Choi, Getmansky, and Tookes (2007). As will be explained in Section 3.2, my data on short sales starts in 2009, thus the period from 2009 to 2023 is the most recent and novel timeframe for this study. I retrieve the issue dates and other relevant information from the Mergent Fixed Income Database (Mergent FISD).

I exclude convertible bonds that were issued in another currency than the USD, and observations that showed that the issuer is a Canadian entity issuing the bond in USD. Furthermore, I remove issues of which their primary listing is not an U.S. stock exchange[4]. Next, I exclude issues that have missing data on offering prices or other relevant metrics such as number of securities issued, volume, shares of the underlying equity outstanding, or tickers. This data on specific metrics is important for two reasons. First, I need clear summary statistics for my study to compare periods of the issuers before and after detection of convertible bond arbitrage. Second, I need information on the underlying securities, such as tickers, to merge the dataset with short-selling data. This is elaborated upon later in the paper. Lastly, I remove issues of financial firms (SIC codes 6000-6799) and utility companies (SIC codes 4900-4999). This is standard practice, as financial firms and utility companies are subject to regulations that impose constraints on their use of debt. These regulations can affect their financing strategies, making their convertible bond offerings less comparable to those from other industries. This regulatory environment might skew my dataset, which can introduce potential biases. These implementations leave me with 1213 observations of convertible bond issues for my data sample.

However, a notable issue with this dataset is that some convertible bonds appear in multiple issues in the sample. These bonds are initially privately placed under Rule 144a and later on offered to the

[3]Rule 144a is a regulation that enables purchasers of securities in a private placement to resell their securities to institutional buyers under certain conditions [4]A number of convertible bond issues in the sample showed that the bonds could be converted in equity on the TSXV (Toronto Stock Exchange).

public market under an SEC filing. Mergent FISD records these as separate issues, despite being the same bond. Following Grundy and Verwijmeren (2018), I retain only the initial issue by removing duplicates - duplicates are removed by filtering for issues with the same maturity date and issuer name. To ensure accuracy, I cross-check the maturity dates with the company-specific CUSIP. This process leaves me with 309 convertible bond issues.

3.2 Short sale and daily stock data

Choi et al. (2009) use monthly short interest data to identify arbitrageur activity in the stock market, acknowledging its limitations due to its monthly availability, which may not fully capture short-sale transactions. They address this gap by analyzing Reg-SHO[5] pilot data from one year (2005-2006), to see if their monthly data results are accurate in capturing short selling near the issuance. With addressing this gap, the study of Choi et al. (2009) illustrates that daily short volume data precisely tracks volumes during issuance and arbitrage hedging periods. Therefore, I obtain daily short volume data from FINRA. Regulation SHO made it possible for sources like FINRA (launched in 2009) to publish daily short-sale volume files. This regulation offers daily volume data for 1) off-exchange trades in listed stocks and 2) trades in non-exchange-listed securities[6]. Transactions reported to its Trade Reporting Facilities (TRFs), which are systems used to report transactions in equity that occur outside of formal exchanges (OTC), provide the main source of this data. Also, there could be data reported to an Alternative Display Facility (ADF) or Over-the-Counter Reporting Facility (ORF). These are both alternative systems developed by FINRA for quoting and trading of securities[7]. These facilities all report data outside regular exchanges. Given that this volume accounts for about a third of all trades, it should provide a reliable proxy for the market.

However, a noteworthy issue with this dataset is that this data from the TRFs is stored individually on the website. For example, short volume data might be available for stocks listed on both the NASDAQ TRF Chicago and the NYSE, but this data has not yet been consolidated into a single dataset. Therefore, the data must first be aggregated to have sufficient observations. I will explain shortly how I did this[8]. On FINRA, daily short volume files can be found in text files[9]. I modified the dates in the URL via a web scraper to retrieve historical data. Then, I modified the URL for the various exchanges. For example, looking at the URL in the footnote, one could see ‘’CNMSshvol’’, which represents the FINRA Consolidated NMS exchange. Changing this gives data on another exchange, the NASDAQ TRF Chicago (‘’FNQCshvol’’)[10] for example. After gathering all the data, I initially was left with around 66 million observations. Once I consolidated these based on their stock symbol, the count was reduced to approximately 2 million observations. After merging this with the

[5]Regulation SHO is a set of rules from the Securities and Exchange Commission (SEC) that regulates short sale practices. It was implemented in the U.S. in 2005, just one year before the Choi et al. (2007) sample ended. The regulation mainly focusses on ‘’locate’’ and ‘’close-out’’ requirements that are intended to prohibit ‘’naked short selling’’, i.e. shorting without borrowing securities or securing that ability first. [6]Non-exchange-listed or over-the-counter (OTC) equities refer to stocks that are traded through a broker-dealer network rather than on a centralized exchange such as the New York Stock Exchange (NYSE) or NASDAQ. [7]See Appendix. [8]I thank our alumni Leon van den Broek for helping me with this process. [9]TXT files in the form of a website URL: https://cdn.finra.org/equity/regsho/daily/CNMSshvol20240426.txt [10]For all exchanges see https://www.finra.org/finra-data/browse-catalog/short-sale-volume-data/daily-short-sale-volume-files

Mergent FISD data, my sample concludes 306 observations, as all issues had an observation in the shorting data. This is not surprising, considering I received 2 million observations of daily short data.

My shorting data has, compared to previous research (Choi et al., 2007), two apparent advantages. The first one is, as explained earlier, that daily short data has more accuracy in capturing convertible bond arbitrage around issue dates than monthly short data. Daily data gives insights in detecting rapid trading movements, as hedge funds might adjust their portfolios frequently. The second one entails the fact that earlier research exploited short interest data, whereas my study uses shorting volume data. Short-interest data shows the short positions that market players held on one or two distinct days each month at a certain point in time. This can lead to a misleading image of market dynamics and hedge fund behavior: if a fund shorts a significant number of shares but covers them before the reporting date, this activity will typically not appear in the short interest data. Volume data will capture the short selling behavior, even when the stocks are bought back. Especially on a daily basis, I can now capture the hedge fund trading activities much more effectively. In this way, rapid trading strategies will not go unnoticed.

I retrieve daily stock data, data on the three month U.S. treasury bill (proxy for the risk-free rate) and data on the S&P 500 (market return benchmark) from the Center for Research in Security Prices (CRSP) database. This data is needed to analyze firm specific variables, construct liquidity and price efficiency measures and examine long-run returns regressions. I lose another 3 observations, as I require non-missing data in the specific time-frame. I am aware that my filtering approach translates into a significant loss in data, but in this way I retain a highly accurate dataset. Considering the limited sample sizes in the literature, it is reasonable to assume the research still possesses statistical power. Table 1 summarizes my data filtering approach for the final sample of 306 observations.

Table (1) Data filtering table for the convertible bond issues. The table shows all filtering criteria and the number of observations left after applying the criteria, starting from the initial sample *Issues May 2009 -2023*. *Other currency than USD* is the removal of issues in another currency than the U.S. dollar. *Exchange outside U.S.* is the removal of issues of which the primary listing is not an U.S. stock exchange. *Missing data* is the removal of issues with missing data. *Financial firms and utility companies* is the removal of financial firms and utility companies. *Duplicates* is the removal of duplicates as defined by Grundy and Verwijmeren (2018).

Data / filtering criterium	Number of observations left
Issues May 2009 – June 2023	407,189
Other currency than USD	378,801
Exchange outside U.S.	378,752
Missing data	115,735
Financial firms and utility companies	1,213
Duplicates	309
Merge with CRSP daily stock data	306

3.3 Firm and issue characteristics

Table 2 provides summary statistics of the firms of my sample, prior to issuance. The table includes market capitalization; the exchange (NASDAQ, NYSE or NYSE_ARCA); issue size; issue size over market cap; short volume and short volume over shares outstanding. The exchange is included as Hirshleifer, Teoh, and Yu (2011) contend that constraints on short arbitrage differ across exchanges. The two variables *SV_%Issue* and *SV_%Shrout* are also included. *SV_%Shrout* is the change in short volume (number of shares) divided by total shares outstanding. *SV_%Issue* is the dollar value change in short volume divided by issue size[11]. These variables are highly important for my research, as they are my proxy's for convertible bond arbitrage. Section 4 will elaborate upon the calculation of these measures.

Table (2) Summary statistics of firm and issue characteristics. This table presents the summary statistics of my sample of convertible bond issues between May 2009 and June 2023. *MarketCap* is the equity market capitalization of the issuing firm. *NYSE*, *NASDAQ* and *NYSE_ARCA* are dummy variables indicating the exchange of where the equity of the issuing firm is listed. *Daily Dollar Volume* is the average daily volume of the stock. *Beta* is the coefficient of the regression of daily stock excess returns on the CRSP value-weighted market excess return. *Issue Size* is the offering size of the convertible bond issue (face value times offering price). *ShortVolume* is the shorted equity relative to the total volume. *SV_%Issue* is the dollar value change (current day and previous day) in short volume divided by issue size. *SV_%Shrout* is the change (current day and previous day) in short volume divided by total shares outstanding.

	Mean	Median	Std.Dev
MarketCap ($ million)	7,229	1,436	21,271
NYSE	0.465	0.000	0.499
NASDAQ	0.493	0.000	0.500
NYSE_ARCA	0.038	0.000	0.178
Daily Dollar Volume ($ million)	32.066	8.939	97.906
Beta	1.567	1.397	0.673
Issue Size ($ million)	298.448	200.000	383.247
IssueSize/MarketCap (in %)	16.649	12.484	23.660
Short Volume (in million shares)	538.741	111.342	2138.876
Short Volume/Shares Outstanding (in %)	2.971	1.324	8.022
SV %ISSUE	0.064	-0.008	26.777
SV %SHROUT	0.003	-0.001	0.732

The average market capitalization of the issuing companies is 7.2 billion dollars, with a median of 1.4 billion dollars. This difference is significant and is stemming from several really large firms in my data set. The issue sizes of the firms make up a substantial portion of market capitalization, with a mean (median) of 16.6% (12.4%). Our sample consists of 49.3% of NASDAQ and 46.5% of NYSE issuers with the remaining as NYSE_ARCA issuers. As NYSE_ARCA is a subsidiary from NYSE, the sample is about equally divided among the two exchanges. I also observe short selling in the stock with mean (median) of 2.9% (1.3%) prior to issuance. Appendix D, table 9 gives a more comprehensive summary of my dataset. The Appendix includes not only typical characteristics but

[11]The ''change'' here refers to the value of the current day minus the value of the previous day.

also the conversion premium and maturity, as Choi et al. (2009) suggest that arbitrageurs tend to favor stocks with lower conversion premia (as outlined in section 2.3). My sample indicates a mean and median conversion premium of 28%, which indicates a standard range for this measurement[12].

3.4 Investor sentiment

To incorporate investor sentiment in my research, monthly data of the investor sentiment index constructed by Baker and Wurgler (2006) is used in my regressions. This data is directly retrieved from the NYU stern finance department website from Jeffrey Wurgler[13]. This index originally was constructed from various components including the Closed-End Fund Discount, NYSE share turnover, the number of IPOs, average first-day returns of IPOs, the proportion of equity issues relative to total debt and equity issues, and the dividend premium (as described by Baker and Wurgler, 2006). In the most recent update, the index has been reduced to five components because the NYSE share turnover was removed (it has been determined that this indicator was no longer relevant in correlation with the other components). Given that each indicator might relate differently in timing to investor sentiment, the index is constructed using either the current or lagged values of each indicator, depending on which has the strongest correlation with the preliminary index. Ultimately, the index that I will use is SENTIMENT, defined as the first principal component within the correlation matrix of all the indicators. To interpret the results, I first need to define the SENTIMENT index interpretation. In the index, a positive z-score means that the proxy is above its historical average and suggests that investors are bullish, a negative z-score means that the proxy is below its historical average which indicates that investors are bearish. The index is standardized in my data (mean of zero, standard deviation of one), which helps in comparing values across time. Positive values of the index indicate higher-than-average sentiment, whereas negative values suggest lower-than-average sentiment.

[12]According to https://www.calamos.com/blogs/voices/yield-opportunities-in-convertible-bonds/ average conversion premia ranged from 25% to 40% in the past years (2021-2023).
[13]See https://pages.stern.nyu.edu/~jwurgler/

CHAPTER 4 Methodology

4.1 Event study

I use a simple event study framework as described by Brown and Warner (1985) to measure changes in liquidity and price efficiency pre- and post-convertible bond issuance. In this way, I can test for the first and second hypothesis on whether convertible bond arbitrage is correlated with these changes. In brief, an event study is a statistical technique used to assess the influence of a specific event on financial metrics (Brooks, 2019). In my research, the event is the issue of the convertible bond offerings. This event is significant, as it triggers changes in short volume, my proxy for convertible bond arbitrage. The financial metrics are the liquidity and price efficiency measures. The basic idea is to examine to what extent market liquidity and price efficiency are affected, that is, how these metrics change, in the presence of convertible bond arbitrage. To determine this, I first need to identify the activity of convertible bond arbitrageurs around the issuance. Subsequently, changes can be observed, where "changes" are defined as the mean differences between the post-issue and pre-issue periods of the price and liquidity measures as described in Section 2.4. The post-issue period refers to the six months following the issuance of a convertible bond starting one month after issuance, while the pre-issue period refers to the six months prior to the issuance ending one month before issuance. The rationale for selecting this time frame is detailed upon further in this section.

As explained in Section 2, I follow Choi, Getmansky and Tookes (2007), by constructing two measures to capture changes in short selling activity around the issuance to detect convertible bond arbitrage. These proxies have a lot of advantages, as explained in the Section 1 (direct measurement of positions of arbitrageurs in securities, avoidance of incomplete data from self-reported hedge fund databases and circumvention of hidden actual positions due to leverage use). However, I utilize volume data, as explained before. Volume data will capture the short selling behavior, even when the stocks are bought back. Especially on a daily basis, I can capture the hedge fund trading activities much more effectively. This leads to two measures utilized in my study:

- *SV_%Shrout*: the change in short volume (number of shares) divided by total shares outstanding. The change in short volume is the difference between short volume on the current day and short volume on the previous day.

- *SV_%Issue*: the dollar value change in short volume divided by issue size. Dollar value change is the difference in short volume on the current day and short volume on the previous day, times closing stock price on the issue date. Issue size is the face value of the convertible bond times its offer price.

Or, in mathematical forms:

$$SV\_\%Shrout = \frac{(ShortVolume_t - ShortVolume_{t-1})}{SharesOutstanding_{t-1}} \tag{1}$$

$$SV\_\%Issue = ((ShortVolume_t - ShortVolume_{t-1}) * CP_{ID})) \; / \; IS_{ID} \tag{2}$$

Where *SV_%Shrout* and *SV_%Issue* are defined as explained above, *ShortVolume* is the volume of stocks that have been shorted at date *t*, *SharesOutstanding* are the shares outstanding of the underlying equity at the issue date, CP_{ID} is the closing price at issue date and IS_{ID} is the issue size at issue date.

In my analysis, I primarily utilize the *SV_%Shrout* metric. This measure represents changes in short interest as a percentage of total shares outstanding, so it is directly linked to fluctuations in the underlying equity of the issuing firm. Although *SV_%Shrout* serves as my main analytic tool, I also include *SV_%Issue* for additional comparative insights. The latter is incorporated for two reasons. First, it should be noted that issue size matters: it is directly related to hedging activity, because a larger issuance requires more of the underlying equity to be shorted (if the delta is similar). Second, the incorporation of *SV_%Issue* allows me to verify whether both proxies exhibit similar patterns in the data, thereby enhancing the robustness of my findings. Figure 2 shows that both the *SV_%Issue* and *SV_%Shrout* measure show an increase in shorting volume around the convertible bond issuance (t=0). The mean (median) change around issuance is 25.9% (6.1%) for *SV_%Issue* and 1.2% (0.6%) for *SV_%Shrout*. As stated above, I use the increase *of SV_%Shrout* as my proxy for convertible bond arbitrage activity. Throughout the paper, this proxy is not referred to as the *unexpected* change in short volume, unlike some references in previous literature (see Section 2). It is more precise to name it the “change in short interest as a percentage of shares outstanding” rather than the “unexpected short interest”. This is because it does not inherently involve an element of surprise or deviation from a predicted level but measures the actual changes relative to the size of the issuing company.

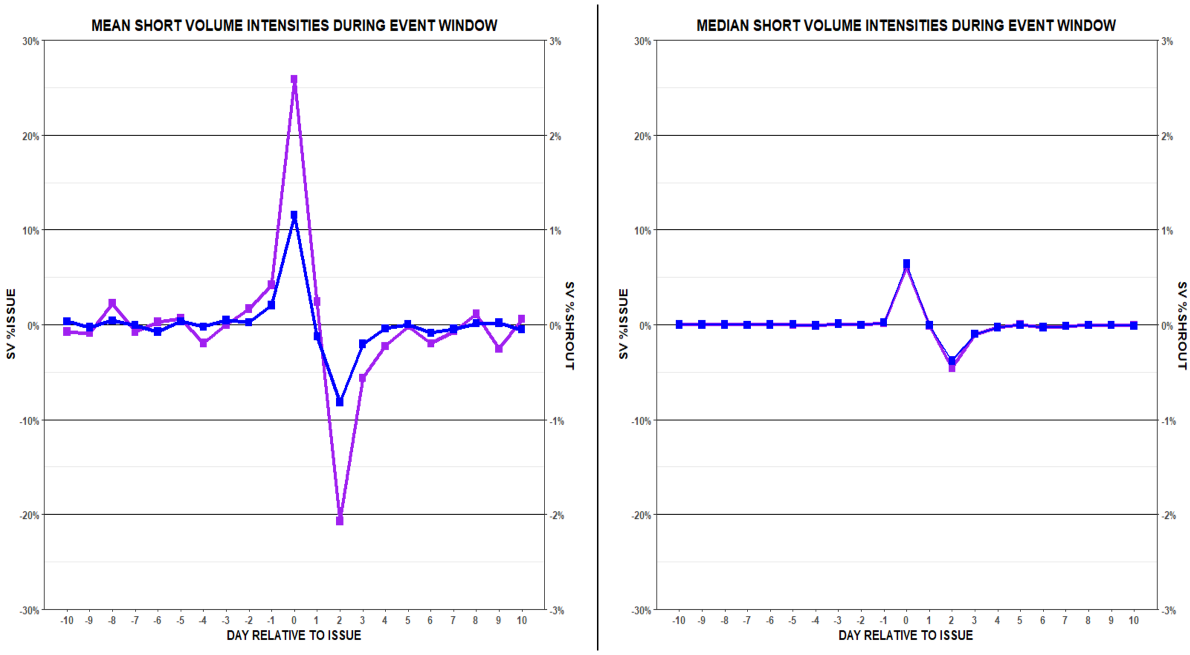

Figure (2) Mean and median shifts in short volume over the trading period from day -10 to day +10. *SV_%Issue* is the dollar value change in short volume divided by issue size (dollar value change is the difference in short volume on the current day and short volume on the previous day, times closing stock price on the issue date. Issue size is the face value of the convertible bond times its offer price). *SV_%Shrout* is the change in short volume (number of shares) divided by total shares outstanding (the change in short volume is the difference between short volume on the current day and short volume on the previous day). Appendix D figure 5 shows the range for the trading days -120, +120 days period.

For notable convenience, the -10, 10 trading days time frame is taken here. For the primary analysis of liquidity and price efficiency, a time period of six months, equivalent to 120 trading days, is utilized (following Choi, Getmansky and Tookes, 2007). The horizon starts six months prior to issuance, and ends six months following the issue. The whole graph for this time period can be seen in Appendix D, figure 5. The time-window of 6 months is relatively short. The research is conducted in this short period, to isolate the effects of convertible bond arbitrage. Convertible bonds have call provisions, and this callability could influence my results. According to Ingersoll (1977) and Asquith (1995) evidence has consistently shown us that firms tend to exercise these call options later than would be optimal. So, the presence of call provisions is likely to have minimal influence on my results over a six-month period, as bonds typically feature call protection periods that extend beyond six months. In this way, I can more confidently attribute changes in liquidity and pricing measures to convertible bond arbitrage rather than to factors related to early calls. The pre-issue period ends one month before and the post-issue period starts one month after issuance to avoid mechanical changes (Choi, Getmansky, Tookes, 2007): during the bond issuance period, there is often a significant increase in trading activity, which temporarily increases liquidity and causing abnormal price movements as traders adjust their positions. These fluctuations can distort our findings regarding the true long-term impact of convertible bond arbitrage on market liquidity and price efficiency.

What is notable in Figure 2, is the decrease in shorting volume right after issuance. This is a pattern which Choi, Getmansky and Tookes (2007) do not observe. However, it should be considered that I use daily short volume data and therefore might find more precise patterns. The decrease right after issuance can be attributed to the completion of the arbitrage setup. Once the convertible bond arbitrageurs have completed their initial setup, the urgency to continue shorting diminishes, which leads to a reduction in shorting volume. Furthermore, there is a possibility that stock prices decrease after bond issuance due to the perceived (future) dilution of shareholders. This decrease in stock prices might urge arbitrageurs to cover some of their short positions to remain delta-neutral (i.e. buying shares back, as explained in Section 1).

For my research, I will split the sample into four portfolios according to the variable *SV_%Shrout*. In this way, I can shed light on the type of issuers where convertible bond arbitrage is most pronounced. If the portfolios are divided according to the smallest (largest) change in short volume, it is possible to make issuer type related observations.

4.2 Regression and investor sentiment analysis

To control for factors other than the short-volume intensity and its effects on liquidity and pricing, a cross-sectional regression is incorporated in my research. In addition to examining the relationship between *SV_%Shrout* (independent factor) and liquidity and price efficiency (dependent factor), I control for several other factors.

First, I control for general firm-fixed effects: size, volatility and exchange type. Volatility is included in the model due to established relationships between volatility and liquidity in the literature. Spiegel and Wang (2005) note a strong correlation between the idiosyncratic volatility and liquidity effects, whereas Pastor and Stambaugh (2003) find a relationship between volatility and market illiquidity.

Second, I account for other stock characteristics, as outlined by Choi, Getmansky, and Tookes (2007). I include *the average stock price during the pre-issue period* and *the number of days between the pre-issue and post-issue periods*. The 6 months that conclude 1 month before issuance are known as the pre-issue period, while the 6 months that begin 1 month after issuance are known as the post-issue period. The average stock price during the pre-issue period serves as a proxy for liquidity, as price and liquidity are negatively correlated (Choi, Getmansky and Tookes, 2007). This is due to the fixed component in spreads, which is relatively lower for higher priced stocks (i.e. the fixed cost elements that contribute to the spread, like dealer fees or administrative costs, constitute a smaller relative proportion of the transaction for higher-priced stocks). With the inclusion of the average stock price during the pre-issue period the model anticipates greater potential for liquidity improvements in stocks that are less liquid initially. The number of days between the start of the pre-period and the end of the post-period is included to separate out the influence of holidays or other ‘’special’’ days where stock markets are closed. When there are no holidays or special days, this number is 200.

Lastly, I control for the sentiment index of Baker and Wurgler (2006). As stated in Section 2 and 3, it is highly likely that the index correlates strongly with year or month fixed effects of the overall market. For example, significant economic or policy changes can affect IPO volume or first-day returns of IPOs, which are components of the sentiment index. This means that the sentiment index essentially serves as a substitute for (a part of) time-fixed effects within the market. Consequently, introducing time dummy variables in this context may not be practical. Nevertheless, as outlined in section 2.4, it is unlikely that this proxy captures all time-fixed effects. Therefore, to still correct for correlations across time periods and within industries, fixed effects are included. Each OLS regression in the analysis is clustered by time (years), industry (SIC codes) and their combination. This ensures that the statistical tests remain valid even when there are unobserved components within the clusters.

The ordinary least squares regression (OLS) model is then defined as follows:

$$\begin{aligned} \Delta Liquidity\ or\ \Delta Efficiency &= \alpha + \beta_1 SV_{\%Shrout} + \beta_2 \Delta MarketCap + \beta_3 \Delta Volatility + \beta_4 Pre \\ &- issue\ Price + \beta_5 NYSE + \beta_6 PrePost\ Days + \beta_7 SENTIMENT + \varepsilon\ , \\ &c(''SICCD'', ''Year'') \end{aligned} \tag{3}$$

Where $\Delta Liquidity\ or\ \Delta Efficiency$ represent the change in four of the six liquidity measures (turnover; number of trades; the AMIHUD factor; the dollar spread) or the two efficiency measures (the daily return first-order autocorrelation and the 5-day variance ratio). *SV_%Shrout* is the short volume intensity measure, as explained in Section 4.1. $\Delta MarketCap$ is the change in the (log) market capitalization of the issuing firm. This is calculated by multiplying the price of the stock with average daily shares outstanding. Δ*Volatility* is the change of the standard deviations of the returns, *Pre-issue Price* is the average (log) price during the pre-issue period, *NYSE* is a dummy variable that gives 1 if the firm is listed on the NYSE and 0 otherwise, *PrePost Days* is the number of days between the beginning and end of the whole period. *SENTIMENT* is the sentiment index factor of Baker and Wurgler (2006) as described in the Section 3. Since this dataset is based on monthly data, I aim to reflect the sentiment of the month in which the event (the issuance date) occurs. Therefore, I will use the sentiment variable without any lag. ε is an error term and $c(''SICCD'', ''Year'')$ is a clustering variable that determines whether the standard errors of the regression are clustered by *SICCD* (Standard Industrial Classification Codes), *Year* (year of the observation), or both.

CHAPTER 5 Results

In this Section, the main objective is to examine the relationship between variations in short volume around the time of issuance and characteristics of the equity market. I break the section down in various parts. In the first sub-section my sample size is divided in portfolios based on *SV_%Shrout*, my proxy for convertible bond arbitrage. Then price and liquidity measures are examined, as variables on its own. Furthermore, the changes in statistics for the pre- and post issue period are examined. In the second sub-section, I discuss the results from the changes in price and liquidity measures in conjunction with my control variables, including the investor sentiment proxy. In the last sections additional tests or robustness tests are conducted.

5.1 Univariate Analysis

In this sub-section, an univariate analysis on the influence of convertible bond arbitrage on liquidity and price-efficiency measures is conducted (investor sentiment is not yet considered). First, besides analyzing the whole sample, I divide the sample in four portfolios. Portfolio 1 corresponds to the smallest change in short volume around the issuance (*SV_%Shrout*) and Portfolio 4 to the largest. This is done to offer some insight into the types of issuers where the convertible bond arbitrage strategy is most prominently observed (Choi, Getmansky and Tookes, 2007). The summary statistics of the firms, prior to issuance and divided by *SV_%Shrout*, can be found in Table 3. Panel A shows the characteristics of the issuing firms and the convertible bonds. In this table, *NYSE_ARCA* is merged with *NYSE* observations. Panel B and panel C show the liquidity and return- and price efficiency measures, respectively. Panel A reveals the following observations. First, the significant positive value of P4-P1 for NASDAQ stocks indicates that there are more NASDAQ stocks in the largest portfolio than in the smallest. Thus, this means that NASDAQ stocks experience larger changes in *SV_%Shrout* following issuance, and for NYSE this is the other way around. However, the difference is not of significant size. Furthermore, the statistically significant observation of short volume over shares outstanding indicates that convertible bond arbitrage is greater in firms that already are highly shorted. This indicates that arbitrageurs select stocks based on their expectations of being able to short the stock. Turnover in Panel B indicates that shares in the largest *SV_%Shrout* portfolio are more liquid. In Panel C it can be observed that one of the measurements for price efficiency, namely the *Daily AR(1)*, has a very statistically significant value. The value is small, but this suggests that prices are efficient (as outlined in Section 2.5, markets in which prices fully reflect all available information, should exhibit little to no autocorrelation in returns). In conjunction with the insignificant results of the variance ratio, conclusions regarding the influence of convertible bond arbitrage on prices is ambiguous after the first results. This outcome does not fully align with my expectations, as hedge funs exploit the pricing inefficiencies between the convertible bond and the underlying stock, rather than relying on the general efficiency of the stock market.

Table (3) Univariate analysis of firm characteristics prior to issuance. Firms are divided into portfolios based on *SV_%Shrout. SV_%Shrout* is the proxy for convertible bond arbitrage and defined as the daily change in short volume (number of shares) divided by total shares outstanding. P1 corresponds to the smallest change in short volume and P4 to the largest. In panel A, *MarketCap* is the equity market capitalization of the issuing firm. *NYSE, NASDAQ* are dummy variables indicating the exchange of where the equity of the issuing firm is listed. Short Volume/Shares Outstanding is the average daily short volume relative to the outstanding shares. . *Conversion Ratio* is the number of shares that the convertible bond can be exchanged for. *Conversion Premium* is the amount by which the price of a convertible security exceeds the current market value of the stock. Both these ratios are winsorized, see Appendix B figure 4.
In panel B, *Turnover* is calculated as the average daily volume divided by shares outstanding. *Number of trades* is the average number of daily stock transactions on the firm's primary exchange. *Dollar volume* refers to the average daily dollar value of the stock traded. The *AMIHUD* illiquidity measure is the average ratio of the daily return to the dollar volume. *Dollar spread* is the time-weighted discrepancy between the bid and ask quote, expressed in dollars. *Percentage spread* is the time-weighted discrepancy between the bid and ask quote, expressed as a percentage of the bid-ask midpoint.
In panel C, *Return and Standard Deviation of Return* are the mean and the standard deviation of the daily stock return data. *Idiosyncratic Volatility* is the standard deviation of residuals from a regression of the daily stock data over the value-weighted market excess return. *R-squared* is the R-squared of the residuals of a regression of the daily stock data over the value-weighted market excess return. For both *Idiosyncratic Volatility* and *R-squared*, the market excess return is derived from the CRSP database. Beta is the coefficient estimate of this regression. *Daily AR (1)* is the daily return first-order autocorrelation. The *Variance Ratio (5)* is the 5-day variance ratio as described by Lo & McKinlay (1988).
The column P4-P1 shows the mean difference between portfolio 4 (largest *SV_%Shrout* change) minus portfolio 1 (smallest *SV_%Shrout* change). The first column shows the statistics for the whole sample. The last column shows the t-statistic of this difference. *, **, and *** indicate percentages of 10%, 5%, and 1%, respectively. The sample is from May 2009 until June 2023. Number of observations is 306.

Univariate Analysis Of Firm Characteristics Prior To Issuance,

divided in portfolios based on arbitrage activity

Panel A: Firm and convertible bond characteristics

	All	P1 (Smallest)	P2	P3	P4 (Largest)	P4-P1	t-stat
log MarketCap	14.364	14.269	14.440	14.583	14.165	-0.104	(-1.07)
NYSE	0.507	0.537	0.472	0.491	0.528	-0.009*	(2)
NASDAQ	0.493	0.463	0.528	0.509	0.472	0.009*	(-2)
Short Volume/Shares Outstanding (%)	2.971	2.620	1.533	2.244	5.493	2.872***	(3.23)
Conversion Ratio	51.312	57.296	46.831	42.675	58.340	1.044	(0.72)
Conversion Premium	26.939	27.066	28.035	25.557	27.092	0.025	(0.81)

Panel B: Liquidity measures

	All	P1 (Smallest)	P2	P3	P4 (Largest)	P4-P1	t-stat
log Turnover	-2.552	-2.466	-2.827	-2.621	-2.265	0.2*	(2.63)
log Number of Trades	6.199	6.261	5.959	6.132	6.470	0.209	(1.78)
log Dollar Volume	13.778	13.845	13.336	13.742	14.188	0.343	(0.28)
log AMIHUD	-10.419	-10.490	-10.009	-10.318	-10.853	-0.363	(-0.19)
Dollar Spread	0.034	0.026	0.028	0.046	0.036	0.01	(1.04)
Percentage Spread (%)	0.151	0.165	0.143	0.159	0.138	-0.027	(1.55)

Table (3) continued.

Panel C: Return and price efficiency measures

	All	P1 (Smallest)	P2	P3	P4 (Largest)	P4-P1	t-stat
Return (%)	0.200	0.193	0.161	0.308	0.139	-0.054*	(2)
Standard Deviation of Return (%)	3.619	3.741	2.994	3.473	4.266	0.525**	(2.64)
Idiosyncratic Volatility (%)	3.196	3.277	2.597	3.005	3.902	0.625**	(2.73)
R-Squared (%)	22.999	23.799	25.149	25.050	17.985	-5.814***	(-3.65)
Beta	1.567	1.650	1.411	1.531	1.671	0.021	(0.26)
Daily AR (1) (%)	0.002	0.002	0.002	0.002	0.002	-0.000***	(-3.41)
Variance Ratio (5)	0.966	0.951	1.009	0.944	0.962	0.011	(0.23)

I conduct a similar research but now look at changes in the liquidity and price efficiency measures. All changes are calculated by subtracting the mean of the pre-issue period from the mean of the post-issue period. Table 4 presents the results of the analysis of the impact of convertible bond arbitrage on liquidity and price efficiency in the stock market. What first is interesting, is that in both panels for some variables, the individual results in P4 and P1 are not statistically significant, yet their differential is significant. This can be explained by the fact that the difference between two means (P4 - P1) has its own standard error. It is possible for the standard error of the difference to be smaller than the individual standard errors, if P4 and P1 are positively correlated, leading to a significant result for P4-P1 even if P4 and P1 themselves are not significant.

The first null hypothesis is "*$H_{0,1}$ (Liquidity): Convertible bond arbitrage activity is uncorrelated with liquidity changes in the underlying equity*." I find evidence that convertible bond arbitrage increases liquidity, outlined in Panel A. I reject the null hypothesis *$H_{0,1}$ (Liquidity)* and conclude that convertible bond arbitrage is correlated with liquidity changes in the underlying equity. For the short volume over shares outstanding and the dollar spread, only statistical significant observation for the second portfolio (P2) are observed. This suggests that convertible bond arbitrage might increase the short interest of the underlying equity. As investors engaged in convertible bond arbitrage of course sell short the stock, it is expected that this explains the increase. However, as I do not find significant results for the other portfolios, there is too little evidence to draw harsh conclusions here. For turnover, significant increases in P2 and the differential P4-P1 indicate more trading activity due to convertible bond arbitrage, especially in larger *SV_%Shrout* portfolios. Furthermore, across the whole sample, there is a significant increase in the number of trades, indicating overall higher liquidity. Regarding the dollar volume variable we find strong evidence of increased liquidity. For the Amihud liquidity measures only negative observations are found, which indicates improved liquidity as well, but we do not find systematic variation across the sample. The findings on liquidity are consistent with previous literature (Choi, Getmansky and Tookes, 2007), namely that convertible bond arbitrage positively affects liquidity, but not all variables show systematic variation.

Table (4) Univariate Analysis of changes in firm characteristics. Firms are divided into portfolios based on *SV_%Shrout. SV_%Shrout* is the proxy for convertible bond arbitrage and defined as the daily change in short volume (number of shares) divided by total shares outstanding. P1 corresponds to the smallest change in short volume and P4 to the largest. *Short Volume/Shares Outstanding* is the average daily change in short volume divided by the number of shares outstanding of the previous day. *Turnover* is calculated as the average daily volume divided by shares outstanding. *Number of trades* is the average number of daily stock transactions on the firm's primary exchange. *Dollar volume* refers to the average daily dollar value of the stock traded. The *AMIHUD* illiquidity measure is the average ratio of the daily return to the dollar volume. *Dollar spread* is the time-weighted discrepancy between the bid and ask quote, expressed in dollars. *Percentage spread* is the time-weighted discrepancy between the bid and ask quote, expressed as a percentage of the bid-ask midpoint. *Return and Standard Deviation of Return* are the mean and the standard deviation of the daily stock return data. *Idiosyncratic Volatility* is the standard deviation of residuals from a regression of the daily stock data over the value-weighted market excess return. *R-squared* is the R-squared of the residuals of a regression of the daily stock data over the value-weighted market excess return. For both *Idiosyncratic Volatility* and *R-squared*, the market excess return is derived from the CRSP database. *Beta* is the coefficient estimate of this regression. *|Daily AR (1)|* is the absolute value of the daily return first-order autocorrelation of returns. The *|Variance Ratio (5)-1|* is the absolute value of the 5-day variance ratio as described by Lo & McKinlay (1988), as deviated from 1, where 1 would mean a random walk. The first column shows the statistics for the whole sample. The last column shows the t-statistic of this difference. *, **, and *** indicate percentages of 10%, 5%, and 1%, respectively. The sample is from May 2009 until June 2023. Number of observations is 306.

Univariate Analysis Of Changes In Firm Characteristics,

divided in portfolios based on arbitrage activity

Panel A: Changes in Liquidity						
	All	P1	P2	P3	P4	P4-P1
Short Volume/Shares Outstanding (in %)	0.358	-0.424	0.584*	0.376	0.912	1.337
log Turnover	0.111	0.044	0.164**	0.043	0.183	0.142*
log Number of Trades	0.189***	0.109	0.206**	0.119	0.316	0.221**
log Dollar Volume	0.184**	0.031	0.248***	0.199*	0.259*	0.227***
log AMIHUD	-0.20***	-0.080	-0.310***	-0.218***	-0.227	-0.114
Dollar Spread	0.005	0.003	0.000*	0.002	0.015	0.012
Percentage Spread (in %)	0.006	-0.001	0.012	0.040	-0.023	-0.022
Panel B: Changes in Return and Price-efficiency Measures						
	All	P1	P2	P3	P4	P4-P1
Return (%)	-0.198**	-0.224	-0.073	-0.135	-0.3585**	-0.134
Standard Deviation of Return (%)	-0.314***	-0.487*	0.041	-0.103	-0.703*	-0.216
Idiosyncratic Volatility (%)	-0.281**	-0.423*	0.106	-0.102	-0.702**	-0.278
R-Squared (%)	-0.339	0.117	-1.761	-1.093	1.370	1.253
Beta	-0.026	-0.054	-0.109	-0.094**	0.153	0.208
|Daily AR(1) (%)|	-0.001***	-0.001***	-0.002***	-0.001***	-0.002***	0.000
|Variance Ratio (5) -1| (%)	-2.156	-0.396	-3.381	2.289	-7.169**	-6.772*

The second null hypothesis is "*$H_{0,2}$ (Efficiency): Convertible bond arbitrage activity is uncorrelated with price efficiency changes in the underlying equity*." In Panel B, I observe significant variations in the price efficiency measures, which does not align with my expectations nor with prior literature. However, I do not immediately reject the null hypothesis *$H_{0,2}$ (Efficiency)* and conclude that arbitrage activity influences price efficiency. There are several reasons for this decision. First, when examining the variance ratio, I find significant systematic variation across the *SI_%Shrout* portfolios. However, for the daily autocorrelation of returns, I do not find systematic variation across different segments (P4-P1). Significant results were only evident across all portfolios isolated. This implies that while each portfolio individually shows significant autocorrelation, the difference between the highest and lowest portfolios is not large enough to be statistically significant. Secondly, I should also note that the variance ratio only shows a significant result for systematic variation at the 10% level. As one out of two price efficiency measures (only the variance ratio) shows a significant results for systematic variation at the 10% level, drawing harsh conclusions would be premature. Therefore, after the univariate analysis, the conclusion on *$H_{0,2}$ (Efficiency)* remains ambiguous.

However, as I am the first, to my knowledge, to find a relationship between convertible bond arbitrage and price efficiency, it is interesting to consider potential explanations for this phenomenon. There are several potential reasons why I find results that somewhat contradict the existing literature (Choi, Getmansky and Tookes 2007). First, my data sample and period is novel. Market conditions, regulatory changes, or macroeconomic factors unique to my period could impact the results. Other unique sample characteristics (i.e. more volatile firms) could also influence the results. Secondly, technological advances between the time of previous work and mine could also be of influence. To account for these potential factors, additional research will be performed later in this paper. Thirdly, and maybe most interesting, is that some results would indicate that hedge funds engaging in convertible bond arbitrage are informed investors. This contradicts my expectations, since hedge funds typically employ short sales to hedge their positions, rather than to exploit informational advantages. Theoretically, if these sophisticated have private knowledge and the short selling I have identified is due to an informational advantage, price efficiency should indeed increase. This would contradict the existing literature (Choi, Getmansky, Tookes 2007). I should consider that there is a possibility that convertible bond arbitrage and informational short selling (for example, in relation to other trading strategies) take place at the same time.

Lastly I find, in line with previous research, an average decline in the variance of total returns as well as idiosyncratic component of returns after the issuing of convertible bonds. Nevertheless, I find no indication that the average decline is systematically correlated with short selling activity: the value of P4-P1 is not significant. In other words, we can not conclude that convertible bond arbitrage is the real cause of the declines. It is possible that the results found in table 2 and 3 are due to other factors than convertible bond arbitrage activity. Therefore a multivariate analysis is considered in the next sub-section.

5.2 Multivariate Analysis

In order to account for other factors than the short-volume intensity (i.e. convertible bond arbitrage activity), the regression analysis as outlined in Section 4.2 is conducted. Applying equation (3) across different measures of liquidity and price efficiency results in six distinct main regressions. Furthermore, by clustering based on both time and industry, as stated previously, the total number of different (sub-) regressions increases to 24. In the regressions, the dependent variables are the different liquidity and price efficiency factors. Table 5 shows the results of my multivariate analysis. Panel A, B, C, D, E, F and G show the changes in Turnover, Number of Trades, the Amihud factor, the Dollar Spread, the daily Autocorrelation of Returns and the Variance Ratio, respectively. A number of observations can be made. In the following three paragraphs, I will discuss the results relating to liquidity, price efficiency, and sentiment factors, respectively, and draw conclusions about the hypotheses based on these findings.

First, it is observed that the proxy for convertible bond arbitrage, *SV_%Shrout*, is showing a positive and significant relationship for two of the four liquidity measures throughout all sub-regressions (*Δ Turnover* and *Δ Number of Trades*). For *Δ Dollar Spread* we find a significant negative relationship, which indicates higher liquidity as well (narrowing of the dollar spread (the difference between the bid and ask prices)) generally indicates an improvement in liquidity. This is because a smaller spread suggests that the bid and ask prices are closer to each other, which makes more buyers and sellers agreeing on the price, making it easier to trade. These findings are in line with the literature (Choi, Getmansky and Tookes 2007) and there is enough evidence to reject my first null hypothesis "*$H_{0,1}$ (Liquidity): Convertible bond arbitrage activity is uncorrelated with liquidity changes in the underlying equity*."

Second, one of the two price-efficiency measures (*Δ |Autocorrelation 1|*) is significantly related to the convertible bond arbitrage proxy, i.e. short-selling volume around the issuance. The mangnitude of *Δ |Autocorrelation 1|* in the multivariate analysis is small (1.6%), which indicates price efficiency. This finding contradicts the literature (Choi Getmansky, Tookes 2007) and differs from my prediction as stated in the second null hypothesis ''*$H_{0,2}$ (Efficiency): Convertible bond arbitrage activity is uncorrelated with price efficiency changes in the underlying equity*.'' Although I have identified some significant findings in both the univariate and multivariate analyses concerning the impact of convertible bond arbitrage on price efficiency, it is still premature to draw harsh conclusions: the results did not exhibit consistent patterns across the univariate analysis. However, based on these analyses, I may conclude that there is at least some relationship present. In an attempt to find possible explanations to find more evidence or possible explanations for this observed relationship, extra tests in the form of long-run returns are conducted, as outlined in Section 5.3.

Third, the significant positive relationships between the *SENTIMENT* factor and both *Δ Turnover* and *Δ Number of Trades*, alongside the significant negative relationships between the *SENTIMENT* factor and both *Δ AMIHUD* and *Δ Dollar Spread*, indicate that higher (positive) sentiment enhances liquidity. This is in line with the literature on investor sentiment and liquidity (Liu, Wu and Zhou, 2023; Liu, 2015). There is no relation found between the *SENTIMENT* factor and price efficiency, which differs from the existing literature (Li, 2011; Tetlock, 2007; Chau, Deesomsak and Koutmos, 2016). The inclusion of the COVID-19 period in my sample did not result in higher price efficiency, despite higher returns as described by Bai and Duan (2023). It can be concluded that the results on *SV_%Shrout* and *SENTIMENT* suggest that both contribute to predicting liquidity. While *SV_%Shrout* captures specific arbitrage opportunities, *SENTIMENT* reflects the broader market environment that may enhance or support the trading volume associated with those opportunities. The significance of the convertible bond arbitrage proxy across all model specifications, even when the sentiment factor is included as a control variable, indicates that it remains a robust predictor of liquidity. These results and robustness suggests that convertible bond arbitrage independently drives trading activity, but its impact might be further enhanced or amplified by positive market sentiment. I conclude that the main results of the influence of convertible bond arbitrage on liquidity and price efficiency are not significantly changed by the inclusion of investor sentiment. There is enough evidence to accept the third null hypothesis *"$H_{0,3}$ (Investor sentiment): The influence of convertible bond arbitrage on liquidity and price efficiency measures is not directly related to investor sentiment."*

Furthermore, although it is not of primary interest for my main analysis, some other remarks can be made. It can be observed that liquidity increases with volatility (three of the four liquidity measures show a significant positive relationship). Between price-efficiency and volatility, a negative significant relationship can be observed. The pre-issue price demonstrates significant relationships across the liquidity measure panels, although the magnitude of these relationships is quite small and practically negligible. The number of days between the start of the pre-period and the end of the post-period (to control for holidays), is positively related to one of the two price efficiency measures, but of small size. The F-statistics and R^2 of the models overall indicate predictive power as a whole, except for model (1) of *Δ Turnover* and all the models for the *Δ |Variance Ratio 5-1|*. However, for these non-predictive models, we still can interpret the independent variables individually in their relationship with the dependent variable (liquidity or price efficiency). Lastly, there is in general a significant increase in explanatory power when controlling for industry and time clusters (more significant outcomes). This suggests that there were intra-industry and intra-time correlations that were not accounted for in the unclustered model. These more significant outcomes correspond to the F-statistics and degrees of freedom found for regressions (2), (3) and (4) for all panels. The lower degrees of freedom in the model when clustered, are due to the usage of the number of clusters rather than individual observations to adjust standard errors. This accounts for similarities within each cluster. Most regressions show much higher (and therefore more significant) F-statistics, which points out that the industry and time clustering captured structural patterns across the data.

Table (5) Multivariate Analysis of the relationship between liquidity, price efficiency measures, short-volume intensity and other predictors. The analysis comprises of six main Ordinary Least Squares (OLS) regressions with 4 sub-regressions each, as defined in equation (3). The dependent variables are given with every panel. The sub-regressions vary as described in the details provided below for each regression (*Industry Cluster* and *Time Cluster*). Furthermore, R^2, *adjusted* R^2, the *Residuals of the Standard Errors* of the regressions and the *F-statistics* are given. For all panels, *SV_%Shrout* is the proxy for convertible bond arbitrage and defined as the daily change in short volume (number of shares) divided by total shares outstanding. *ΔMarketCap* is the change in the (log) market capitalization of the issuing firm, calculated by multiplying the closing price of the stock with average daily shares outstanding. *ΔVolatility* is the change of the standard deviations of the returns, *Pre-issue Price* is the average (log) price during the pre-issue period, *NYSE* is a dummy variable that gives 1 if the firm is listed on the NYSE and 0 otherwise. *Pre Post Days* is the number of days between the start of the pre-period and the end of the post-period. *SENTIMENT* is the sentiment index factor as described by Baker and Wurgler (2006). *Constant* represents the regression intercept. *Δ Turnover, Δ Number of Trades, Δ AMIHUD* and *Δ Dollar Spread* are the changes of the (log) measures, calculated as the mean in the post-period compared to the pre-period. *Turnover* is the average daily volume divided by shares outstanding. *Number of trades* is the average number of daily stock transactions on the firm's primary exchange. The *AMIHUD* illiquidity measure is the average ratio of the daily return to the dollar volume. *Dollar spread* is the time-weighted discrepancy between the bid and ask quote, expressed in dollars. *Δ |Autocorrelation (1)|* and *Δ |Variance Ratio (5)|* are the changes of the measures *Daily |AR (1)|* and *|Variance Ratio (5)-1|*, respectively and expressed in percentages. *Daily AR (1)* is the daily return first-order autocorrelation. The *|Variance Ratio (5)-1|* is the absolute value of the 5-day variance ratio as described by Lo & McKinlay (1988), as deviated from 1, where 1 would mean a random walk. T-statistics are given within brackets. Standard errors are clustered standard errors. When adjusting for clustering, the assumption of independent errors no longer holds and no residual standard errors are given. *, **, and *** indicate percentages of 10%, 5%, and 1%, respectively. The sample is from May 2009 until June 2023. Number of observations is 306.

Multivariate Analysis, Ordinary Least Squares (OLS) Regressions

Panel A: Dependent variable 'Δ Turnover'

	Δ Turnover (1)	Δ Turnover (2)	Δ Turnover (3)	Δ Turnover (4)
SV_%Shrout	5.104*	4.202*	4.202**	4.202***
	(2.752)	(2.515)	(1.931)	(1.450)
ΔMarketCap (100 million)	−0.003	−0.004	−0.004	−0.004
	(0.001)	(0.004)	(0.005)	(0.005)
ΔVolatility	0.008**	0.008**	0.008***	0.008***
	(0.004)	(0.003)	(0.003)	(0.002)
Pre-issue Price x100	0.000	0.000	0.000***	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
NYSE	0.010	0.004	0.004	0.004
	(0.052)	(0.007)	(0.008)	(0.007)
Pre Post Days x1000	−0.004	−0.003	−0.003	−0.003
	(0.004)	(0.003)	(0.004)	(0.004)
SENTIMENT	−0.006	0.005	0.005	0.005**

	Δ Turnover (1)	Δ Turnover (2)	Δ Turnover (3)	Δ Turnover (4)
	(0.011)	(0.008)	(0.004)	(0.002)
Constant	1.247	1.056	1.056	1.056
	(1.468)	(1.167)	(1.288)	(1.359)
Industry Cluster	No	Yes	No	Yes
Time Cluster	No	No	Yes	Yes
Observations	306	306	306	306
R^2	0.495	0.184	0.184	0.184
Adjusted R^2	0.044	0.125	0.125	0.125
Residual Std. Error	0.045 (df =256)			
F-statistic	1.099 (df = 49;256)	8.312*** (df = 7;42)	16.185*** (df = 7;12)	4.449** (df = 7;75)

Panel B: Dependent variable 'Δ Number of Trades (million shares)'

	Δ Trades (1)	Δ Trades (2)	Δ Trades (3)	Δ Trades (4)
SV_%Shrout	1.601***	1.153**	1.153**	1.153**
	(0.246)	(0.443)	(0.557)	(0.486)
ΔMarketCap (100 million)	−0.002*	−0.002***	−0.002***	−0.002***
	(0.001)	(0.000)	(0.001)	(0.000)
ΔVolatility	0.001**	0.0005**	0.0005*	0.0005*
	(0.003)	(0.002)	(0.003)	(0.003)
Pre-issue Price x100	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
NYSE	0.003	0.001**	0.001	0.001**
	(0.005)	(0.001)	(0.001)	(0.001)
Pre Post Days x1000	0.003	−0.004	−0.004	−0.004
	(0.004)	(0.002)	(0.002)	(0.002)
SENTIMENT	0.003**	0.002***	0.002	0.002***
	(0.001)	(0.001)	(0.002)	(0.001)
Constant	−0.105	0.015	0.015	0.015
	(0.131)	(0.061)	(0.065)	(0.064)
Industry Cluster	No	Yes	No	Yes
Time Cluster	No	No	Yes	Yes
Observations	306	306	306	306
R^2	0.623	0.438	0.438	0.438
Adjusted R^2	0.287	0.398	0.398	0.398
Residual Std. Error	0.004 (df = 55)			
F-statistic	1.853** (df = 49; 55)	7.201*** (df = 7;42)	11.146***(df = 7;12)	4.383*** (df = 7;12)

Table (5) continued.

Panel C: Dependent variable 'Δ AMIHUD'

	Δ AMIHUD (1)	Δ AMIHUD (2)	Δ AMIHUD (3)	Δ AMIHUD (4)
SV_%Shrout	−0.516	−0.223	−0.223	−0.223
	(0.436)	(0.246)	(0.232)	(0.273)
ΔMarketCap (100 million)	−0.000	−0.001	−0.001	−0.001
	(0.002)	(0.001)	(0.001)	(0.001)
ΔVolatility	−0.001	−0.001**	−0.001**	−0.001**
	(0.001)	(0.003)	(0.003)	(0.003)
Pre-issue Price x100	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
NYSE	−0.002	−0.001	−0.001	−0.001
	(0.003)	(0.001)	(0.001)	(0.001)
Pre Post Days x1000	0.001	−0.001	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)
SENTIMENT	−0.003	−0.004***	−0.004***	−0.004***
	(0.002)	(0.001)	(0.001)	(0.001)
Constant	−0.304	0.231	0.231	0.231
	(0.203)	(0.228)	(0.215)	(0.217)
Industry Cluster	No	Yes	No	Yes
Time Cluster	No	No	Yes	Yes
Observations	306	306	306	306
R^2	0.797	0.598	0.598	0.598
Adjusted R^2	0.612	0.584	0.584	0.584
Residual Std. Error	0.010 (df = 111)			
F-statistic	4.310***(df = 101; 111)	10.222*** (df = 7;94)	7.139*** (df = 7;13)	9.309*** (df = 7;160)

Table (5) continued.

Panel D: Dependent variable 'Δ Dollar Spread'

	Δ Spread (1)	Δ Spread (2)	Δ Spread (3)	Δ Spread (4)
SV_%Shrout	−3.126***	−1.157	−1.157	−1.157
	(0.972)	(0.929)	(1.116)	(1.223)
ΔMarketCap (100 million)	−0.003	−0.001	−0.001	−0.001
	(0.001)	(0.004)	(0.001)	(0.001)
ΔVolatility	−0.001	−0.001	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Pre-issue Price x100	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.00)	(0.000)	(0.000)
NYSE	−0.005	−0.003	−0.003	−0.003
	(0.006)	(0.004)	(0.003)	(0.003)
Pre Post Days x1000	0.001	−0.001**	−0.001***	−0.001**
	(0.001)	(0.001)	(0.0004)	(0.0004)
SENTIMENT	−0.010**	−0.016***	−0.016***	−0.016***
	(0.004)	(0.005)	(0.004)	(0.003)
Constant	−0.249	0.361**	0.361**	0.361**
	(0.454)	(0.176)	(0.144)	(0.146)
Industry Cluster	No	Yes	No	Yes
Time Cluster	No	No	Yes	Yes
Observations	306	306	306	306
R^2	0.924	0.843	0.843	0.843
Adjusted R^2	0.854	0.837	0.837	0.837
F-statistic	13.290*** (df = 101; 111)	2.188** (df = 7;94)	2.505* (df = 7;13)	2.189** (df = 7;160)

Table (5) continued.

Panel E: Dependent variable '∆ |Autocorrelation 1|'

	∆ AR (1) (1)	∆ AR (1) (2)	∆ AR (1) (3)	∆ AR (1) (4)
SV_%Shrout	0.017***	0.016***	0.016***	0.016***
	(0.005)	(0.006)	(0.005)	(0.005)
∆MarketCap (100 million)	−0.00000*	−0.00000	−0.00000	−0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
∆Volatility	−0.000	−0.000*	−0.000*	−0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Pre-issue Price x100	−0.00002	−0.00001	−0.00001	−0.00001
	(0.00003)	(0.00002)	(0.00001)	(0.00001)
NYSE	−0.00001	−0.00000	−0.00000	−0.00000
	(0.00001)	(0.00000)	(0.00000)	(0.00000)
Pre Post Days x1000	0.0001**	0.0001***	0.0001***	0.0001***
	(0.00002)	(0.00001)	(0.00002)	(0.00002)
SENTIMENT	0.001	−0.001	−0.001	−0.001
	(0.002)	(0.001)	(0.001)	(0.001)
Industry Cluster	No	Yes	No	Yes
Time Cluster	No	No	Yes	Yes
Observations	306	306	306	306
R^2	0.542	0.295	0.295	0.295
Adjusted R^2	0.133	0.271	0.271	0.271
Residual Std. Error	0.0001 (df =112)			
F-statistic	1.324* (df = 100; 112)	7.078*** (df = 7;94)	6.287***(df = 7;13)	5.961***(df = 7;160)

Table (5) continued.

Panel F: Dependent variable '∆ |Variance Ratio 5-1|'

	∆ VR (5) (1)	∆ VR (5) (2)	∆ VR (5) (3)	∆ VR (5) (4)
SV_%Shrout	−924.967	−554.631	−554.631	−554.631
	(835.582)	(345.825)	(499.987)	(393.886)
∆MarketCap (100 million)	0.009	−0.002	−0.002	−0.002
	(0.045)	(0.023)	(0.022)	(0.021)
∆Volatility	−0.0002	−0.0002***	−0.0002***	−0.0002***
	(0.0002)	(0.0001)	(0.00005)	(0.0001)
Pre-issue Price x100	−6.914	−1.452	−1.452	−1.452
	(5.432)	(2.453)	(2.037)	(1.951)
NYSE	−0.777	−0.263	−0.263	−0.263
	(1.123)	(0.505)	(0.395)	(0.379)
Pre Post Days x1000	1.021	0.824	0.824	0.824
	(3.839)	(2.293)	(1.537)	(1.702)
SENTIMENT	272.954	92.451	92.451	92.451
	(398.786)	(178.431)	(138.918)	(133.497)
Industry Cluster	No	Yes	No	Yes
Time Cluster	No	No	Yes	Yes
Observations	306	306	306	306
R^2	0.438	0.016	0.016	0.016
Adjusted R^2	-0.065	-0.017	-0.017	-0.017
Residual Std. Error	19.969 (df = 112)			
F-statistic	0.871 (df = 100;112)	1.18 (df = 7;94)	2.958** (df = 7;13)	1.127 (df = 7;160)

5.3 Long-run returns

Especially because my main (univariate and multivariate) analysis report some statistically significant results on the relationship between convertible bond arbitrage and price efficiency, it is interesting to conduct an additional test regarding long-run returns of the short sellers. In other words, I look whether the equity market positions of these short sellers are profitable for the arbitrageurs (i.e. hedge funds) in the long-run. If short sellers engaged in convertible bond arbitrage consistently make money, it might suggest that stock prices were initially inefficient, and over time, were corrected to reflect the true value of the stock – with the arbitrageurs contributing to this efficiency. Figure 3 shows the cumulative abnormal returns of the equity for the whole sample period. The abnormal returns are calculated using the residuals from a standard market model which uses the CAPM, with the S&P 500 as the market return benchmark. The S&P 500 is a widely recognized and relevant index for the U.S. market, making it a suitable benchmark for this analysis.

Figure (3) Cumulative abnormal returns of the equity in the whole sample period starting May 2009 until June 2023. The CAR (%) and the years are displayed on the y-axis and the x-axis, respectively. Number of observations is 306.

Throughout the sample period, the underlying stocks of the convertible bond issues performed well. This indicates that negative (short-term) returns around the issuance founded by previous literature (Duca, Dutordoir, Veld and Verwijmeren, 2012) are mainly related to hedging-related price pressure. I also observe that during the start of the COVID-19 period, the stocks of my sample underperformed compared to the overall market. To be more precise, as issuance dates vary for each convertible bond, I further conducted an analysis to see the holding period return from long stock positions after issuance. Table 6 shows the mean, median and standard deviation from holding periods of 6,12, 18 and 24 months.

Table (6) Cumulative abnormal returns of the equity of the firms issuing convertible bonds. Intervals are 6,12,18 and 24 months after the issue date. Number of observations is 306.

Cumulative Abnormal Stock Returns After Issuance					
	Issue date	+ 6 months	+ 12 months	+ 18 months	+ 24 months
Mean		5.18 %	5.02 %	4.80 %	4.53 %
Median		3.87 %	4.08 %	3.82 %	3.55 %
St.dev		14.04 %	14.10 %	14.45 %	14.61 %

What is puzzling, is that I find positive long-run returns after issuance. This is puzzling as Brophy et al. (2009) state that companies receiving financing from hedge funds, tend to significantly underperform in the long run. They outline several reasons for this phenomenon. First, hedge funds may target distressed firms. These firms might issue convertible bonds because they are constrained in raising capital through traditional means. Second, firms with pronounced information asymmetries might attract hedge fund investments, as hedge funds are better equipped to analyze these situations. However, the fact that I find positive returns in the equity does not necessarily imply that convertible bond arbitrage, and thus hedge fund financing, has caused this. Nor does it give evidence that short sellers at issuance make or lose (positive returns would mean losing money for short sellers) money from their equity market positions. Lastly, I observe that the cumulative returns decrease systematically over time, which indicates that there was a decline in the stock performance after the initial 6 months. To analyze whether the market exhibits a similar pattern (which would indicate broader market trends) and to see if short sellers make a profit from their stock holdings, a final other long-run return test is conducted. I compare the mean cumulative returns of long stock positions in the equity of my sample with the mean market return of the market model. Table 7 shows the results.

Table (7) Long-run returns from long stock positions after issuance. Intervals are 6,12,18 and 24 months after the issue date. Number of observations is 306.

Issuing Firm Long-run Returns					
Cumulative return	Issue date	+ 6 months	+ 12 months	+ 18 months	+ 24 months
Issuing Firm		5.18 %	5.02 %	4.80 %	4.53 %
Market		6.82 %	6.31 %	6.05 %	5.76 %
Difference		-1.64 %	-1.29 %	-1.25 %	-1.23 %
T-statistic		(0.55)	(0.36)	(0.15)	(0.69)

Consistent with Choi, Getmansky and Tookes (2007) we do not find evidence that arbitrageurs make a profit on their equity market positions. This is not consistent with the weakly significant systematic result of price-efficiency, when defined as the variance ratio, in my main analysis. My results show that there is no evidence that arbitrageurs yield abnormal profits from their short positions. This indicates the overall effectiveness and neutrality of the arbitrage activity in relation to equity positions: the strategy is designed, as described in Section 1, to maintain a neutral position rather than generating gains from changes in the stock price.

5.4 Robustness

5.4.1 Different time-windows

To see whether my results are dependent on methodological choices, I conduct additional robustness checks. I change the time-window of equation (3) from 120 trading days to 100, 80, 60, and 40 trading days. All timeframes still end 20 trading days prior to and start 20 days after issuance. Table 8 contains the replications of table 5. Replications for all panels are given. I only include the regressions controlling for the year and industry effects (sub-regression (4) in the multivariate analysis). Overall, changing the time window does not significantly alter the results of my main analysis. However, I must conclude that some observations show a weakened correlation, as not all results remain significant for all different time-frames (such as the 100 and 80 days trading time window for *SV_%Shrout* for panel A and panel B). These weakened relationships may be attributed to a decrease in sample size. What is further interesting is that *SV_%Shrout* shows a significant relationship with *ΔAMIHUD* over shorter time horizons, even though no such significant relationship was found in the main analysis. This could indicate that convertible bond arbitrage leads to immediate market reactions that influence liquidity. Arbitrageurs might concentrate their activities around the issuance date, leading to a more pronounced impact on liquidity in the (40-60 day) short term. Over longer periods, the impact might diffuse as the market adjusts and arbitrage activities stabilizes. Furthermore, I observe that for some time-frames *MarketCap* now has a statistically significant relationship with the *Δ |Variance Ratio 5-1|*, which was not the case in the main analysis. These findings are in line with Choi, Getmansky and Tookes (2007). Lastly, it is noteworthy that *SV_%Shrout* consistently predicts *Δ |Autocorrelation 1|*, a measure for price efficiency, across all time frames.

Table (8) Multivariate Analysis, clustered for industry and time fixed effects, with different time-windows. The results are from Ordinary Least Squares (OLS) regressions as defined in equation (3). Columns (1), (2), (3), and (4) report the periods starting and ending 100, 80, 60, and 40 trading days before and after the issuance, respectively, excluding the 20 days before and after issuance. For example: *Δ Turnover (100)* corresponds to the results of (-100, -20; 20, 100) timeframe and *Δ Turnover (80)* to the (-80;-20 20;80) timeframe. The table starts again in Column 5 for the new variable, which makes Column 5 the 100 days timeframe again. Variables are explained in Explanatory Variables (Appendix A). Clustering and number of observations remain consistent for all regressions and is indicated below the table. T-statistics are given within brackets. *, **, and *** indicate percentages of 10%, 5%, and 1%, respectively. The sample is from May 2009 until June 2023. Number of observations is 306.

Panel A: Dependent variable 'Δ Turnover' and 'Δ Number of Trades'

	Δ Turnover (100)	Δ Turnover (80)	Δ Turnover (60)	Δ Turnover (40)	Δ Number of Trades (100)	Δ Number of Trades (80)	Δ Number of Trades (60)	Δ Number of Trades (40)
SV_%Shrout	1.324*	-1.718	4.713*	10.066***	0.023	−1.288	1.736**	2.364***
	(2.545)	(3.124)	(2.601)	(3.512)	(0.790)	(1.201)	(0.705)	(0.385)
ΔMarketCap (100 million)	−0.003	−0.003	0.002	0.001	0.000	−0.003**	−0.001	-0.00004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ΔVolatility	0.007**	0.013***	0.015***	0.009***	0.001	0.003*	0.002*	0.001**
	(0.003)	(0.004)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.0005)
Pre-issue Price x100	0.000	−0.000*	−0.000***	−0.000**	0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
NYSE	−0.002	−0.002	−0.020***	−0.022	0.0002	−0.001	0.003***	0.004***
	(0.005)	(0.004)	(0.005)	(0.014)	(0.001)	(0.001)	(0.001)	(0.001)
Pre Post Days x1000	−0.003	−0.004	−0.004	−0.005***	0.002	0.003	0.003	0.002
	(0.004)	(0.004)	(0.004)	(0.001)	(0.003)	(0.003)	(0.001)	(0.005)
SENTIMENT	−0.003	−0.008	−0.013	−0.023	0.001**	0.001	−0.001	0.004*
	(0.006)	(0.010)	(0.012)	(0.019)	(0.001)	(0.001)	(0.001)	(0.002)
Constant	1.092	1.305	1.557	1.665***	−0.072	−0.119	−0.108	−0.060
	(1.427)	(1.412)	(1.258)	(0.417)	(0.116)	(0.112)	(0.182)	(0.160)

Industry Cluster: Yes
Time Cluster: Yes
Observations: 306

Table (8) continued.

Panel B: : Dependent variable 'Δ AMIHUD' and 'Δ Dollar Spread'

	Δ AMIHUD (100)	Δ AMIHUD (80)	Δ AMIHUD (60)	Δ AMIHUD (40)	Δ Dollar Spread (100)	Δ Dollar Spread (80)	Δ Dollar Spread (60)	Δ Dollar Spread (40)
SV_%Shrout	−0.072	0.185	0.367*	0.497**	−1.124	−0.935	−0.649	−0.439
	(0.299)	(0.296)	(0.210)	(0.249)	(1.208)	(1.077)	(0.832)	(0.369)
ΔMarketCap (100 million)	−0.001	−0.000	0.000	0.003	−0.001	−0.05	−0.003	−0.001*
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.004)	(0.003)	(0.001)
ΔVolatility	−0.001*	−0.001	−0.001**	0.001	0.0001	−0.0001	0.0004	0.002*
	(0.003)	(0.001)	(0.003)	(0.001)	(0.004)	(0.005)	(0.001)	(0.001)
Pre-issue Price x100	0.000***	0.000 ***	0.000***	−0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
NYSE	−0.002	−0.003	−0.0004	−0.001	−0.002	−0.002	−0.001	0.001
	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Pre Post Days x1000	0.003	0.001**	0.002**	0.002**	−0.001***	−0.001**	−0.001*	−0.001
	(0.005)	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)	(0.004)	(0.004)
SENTIMENT	−0.004***	−0.003*	−0.001	0.002	−0.014***	−0.013***	−0.009***	−0.003*
	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
Constant	−0.096	−0.438**	−0.762**	−0.769**	0.391**	0.333**	0.255*	0.216
	(0.169)	(0.196)	(0.332)	(0.334)	(0.155)	(0.160)	(0.137)	(0.157)

Industry Cluster: Yes
Time Cluster: Yes
Observations: 306

Table (8) continued.

Panel C: Dependent variable 'Δ |Autocorrelation 1|' and 'Δ |Variance Ratio 5-1|'

	Δ AR (1) (100)	Δ AR (1) (80)	Δ AR (1) (60)	Δ AR (1) (40)	Δ VR (5) (100)	Δ VR (5) (80)	Δ VR (5) (60)	Δ VR (5) (40)
SV_%Shrout	0.015***	0.016***	0.015**	0.012***	−52.872	−73.017	−686.888	117.042
	(0.005)	(0.006)	(0.006)	(0.005)	(484.712)	(574.016)	(608.813)	(794.962)
ΔMarketCap (100 million)	−0.000	−0.000	−0.000	−0.000	−0.038**	−0.020	−0.009	−0.113***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.019)	(0.019)	(0.040)	(0.031)
ΔVolatility	−0.000*	−0.000*	−0.000	−0.000	−0.002***	−0.001	0.005	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.0001)	(0.0001)	(0.0001)	(0.000)
Pre-issue Price x100	−0.001	−0.000	−0.001	−0.001	−1.931	4.792***	1.420	−4.283
	(0.001)	(0.001)	(0.001)	(0.002)	(2.358)	(1.380)	(1.883)	(3.560)
NYSE	−0.000	−0.000	−0.000	−0.000	0.338	1.000	0.234	1.633**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.659)	(0.718)	(0.520)	(0.741)
Pre Post Days x1000	0.001***	0.001***	0.001***	0.005***	−0.808	2.963	−3.411	−1.628
	(0.002)	(0.002)	(0.002)	(0.002)	(2.330)	(2.969)	(2.496)	(2.279)
SENTIMENT	−0.001	−0.0004	−0.0002	−0.001	−118.255	−356.652	−84.572	−570.363
	(0.001)	(0.001)	(0.001)	(0.001)	(232.298)	(252.623)	(182.674)	(260.483)

Industry Cluster: Yes
Time Cluster: Yes
Observations: 306

5.4.2 Equities with and without options

As described in Section 1, there may be an upward bias in stock prices due to the incomplete reflection of negative information. This bias is especially evident in equities without (call or put) options. Figlewski and Webb (1993) find evidence that stocks with options attached have no constraints on shorting, which makes the upward bias disappear. To test for this, I plan to categorize my sample into two groups, stocks with call or put options attached, and stocks without. The sample of 306 final convertible bonds unfortunately includes no data where a (known) call option is attached to the stock. The number of observations with a put option attached to the stock is only 14, which makes the sample size too small to make observations. The only test that can be conducted are the issues where there is certainly no option attached to the stock. Table (9) gives a replication of Table (4) but now for the 292 issues where there is no option attached to the underlying stock of the issue. So, by removing the observations with options attached, it is expected that price efficiency decreases (as only stocks with the upward bias due to short selling restraints remain).

Overall, I find that using this smaller sample does not significantly alter the direction or strength of the found relationships in Table 4. However, although the removal of observations is small, I observe in Panel B that the systematic variation in the variance ratio, which was statistically significant in the main analysis, is not significant anymore. This could indicate that indeed price efficiency decreased due to the removal of stocks with options attached to it. This is in line with Figlewski and Webb (1993). Nonetheless, the removal is small as stated, so harsh conclusions may be premature.

Table (9) Univariate Analysis of changes in firm characteristics, for non-option stocks issues. Firms are divided into portfolios based on *SV_%Shrout*. *SV_%Shrout* is the proxy for convertible bond arbitrage and defined as the daily change in short volume (number of shares) divided by total shares outstanding. P1 corresponds to the smallest change in short volume and P4 to the largest. Variables are explained in Explanatory Variables (Appendix A). T-statistics are given within brackets. *, **, and *** indicate percentages of 10%, 5%, and 1%, respectively. The sample consists of only non-option stock issues and is from May 2009 until June 2023. Number of observations is 292.

Univariate Analysis of Firm Characteristics Changes in Non-Option Stocks Issues, divided in portfolios based on arbitrage activity

Panel A: Changes in Liquidity						
	All	P1	P2	P3	P4	P4-P1
Short Volume/Shares Outstanding (in %)	0.267	-0.533*	0.725*	0.322	0.974	1.542
log Turnover	0.074	0.039	0.188***	-0.000	0.223	0.198**
log Number of Trades	0.149***	0.104	0.233**	0.065	0.366	0.283***
log Dollar Volume	0.149**	-0.012	0.286***	0.166**	0.287*	0.269***
log AMIHUD	-0.211**	-0.047	-0.325***	-0.172***	-0.243	-0.189
Dollar Spread	0.001	0.003	0.000	0.003	0.016	0.013
Percentage Spread (in %)	0.0128	-0.010	0.002	0.042	-0.024	-0.011
Panel B: Changes in Return and Price-efficiency Measures						
	All	P1	P2	P3	P4	P4-P1
Return (%)	-0.199**	-0.205	-0.097	-0.132	-0.385**	-0.177
Standard Deviation of Return (%)	-0.340***	-0.512**	0.164	-0.129	-0.673*	-0.103
Idiosyncratic Volatility (%)	-0.315**	-0.472**	0.201	-0.117	-0.698*	-0.175
R-Squared (%)	0.085	0.983	-1.331	-1.349	2.109	1.083
Beta	-0.017	0.000	-0.092	-0.082*	0.187	0.199
|Daily AR(1) (%)|	-0.001***	-0.002***	-0.002***	-0.001***	-0.002***	0.0000
|Variance Ratio (5) -1| (%)	-2.377	-0.231	-2.782	-0.127	-6.331*	-5.874

5.4.3 Total shorting volume vs investor sentiment

In my third hypothesis *"$H_{0,3}$ (Investor sentiment): The influence of convertible bond arbitrage on liquidity and price efficiency measures is not directly related to investor sentiment"*, I expect (shorting) behavior of hedge funds to be unaffected by general investor sentiment. However, a potential reversed causality issue arises here. As explained in Section 1, it is assumable that shorting behavior of hedge funds contributes to negative investor sentiment in the market (i.e. investor sentiment may also be gauged by the extent of short selling in the market). High short interest levels indicate a bearish outlook, which should be incorporated in prices in efficient markets. There is also a connection between the volume of short sales associated with convertible bond arbitrage and the total market short volume, given that hedge funds – large investors with the capability to short many stocks without significant restrictions - play a substantial role in this activity. To (partially) check whether the sentiment factor analyzed in this study is influenced by the hedge fund itself, I compare the sentiment index data described by Baker and Wurgler (2006) with total market short interest data. The data on the short interest of the total U.S. market is given by NASDAQ. This comparison may allow us to see if certain trends are observable in the sentiment index that are also observed in the short interest for the total market.

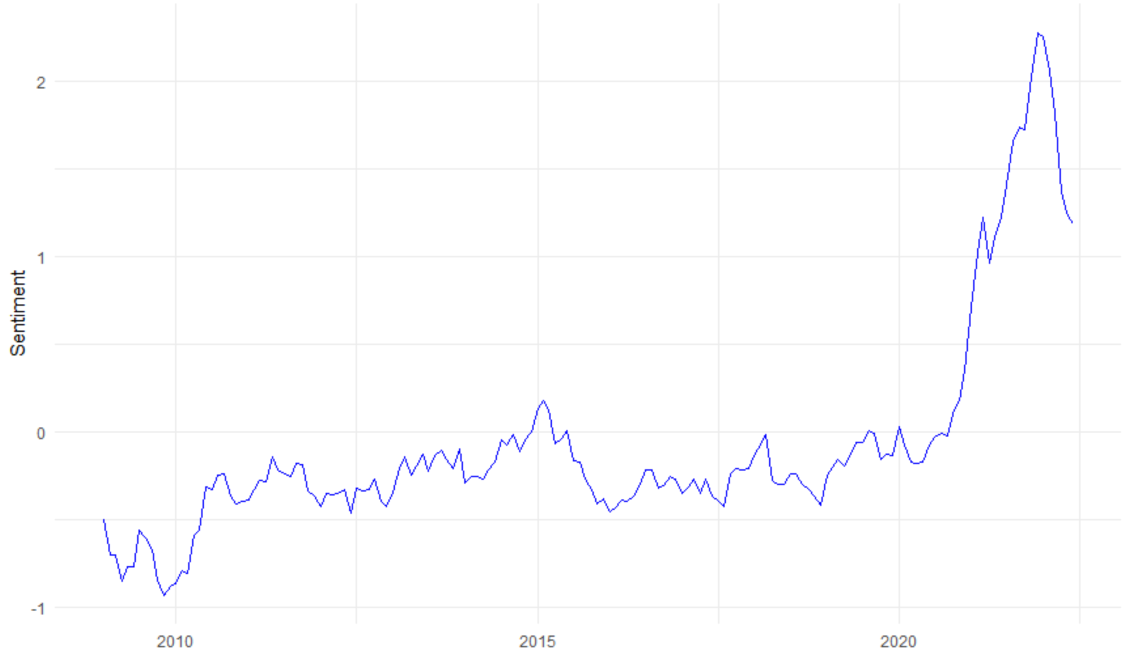

Figure (4) The Baker and Wurgler (2006) sentiment index over time. The sentiment factor (section 3.4) and the years are displayed on the y-axis and the x-axis, respectively. Positive values of the index indicate higher-than-average sentiment, whereas negative values suggest lower-than-average sentiment. Number of observations is 162.

To support the theory that shorting volume affects sentiment, as described above, it is expected for short interest to be high when sentiment is low, and vice versa. It is observed that investor sentiment is low during my sample period but rises significantly after 2020 (figure 4), right after COVID-19 lockdowns in the United States. What is interesting, is that at the same time, short interest in the total market dropped as well.

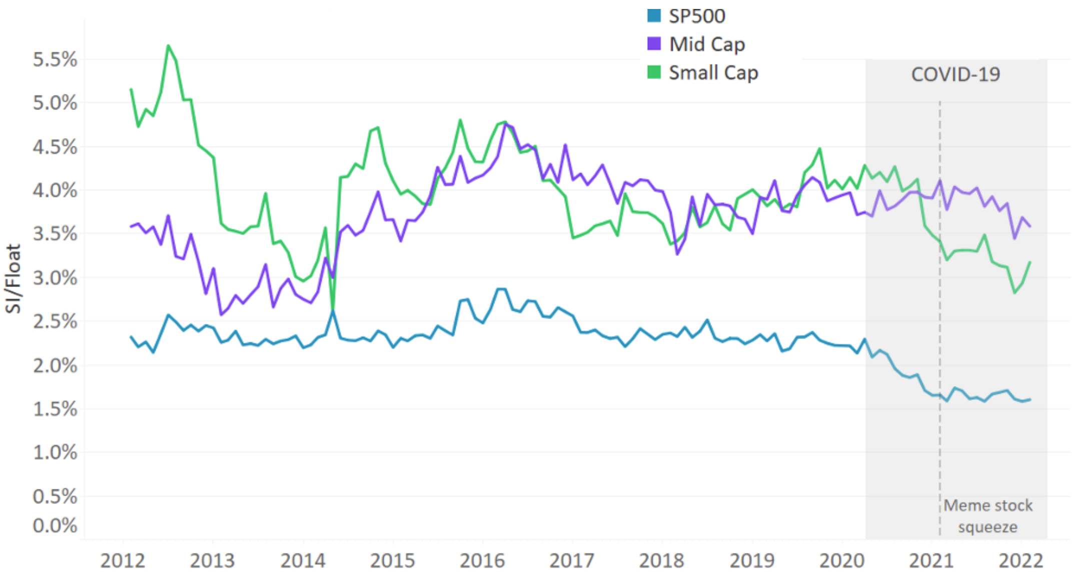

Figure (5) Median short interest levels over time. The short interest float in percentages and the years are displayed on the y-axis and the x-axis, respectively. Number of observations is unknown, source is the Nasdaq Economic Research Database[14]. The blue, purple and green line represent the short interest for the SP 500, Mid Cap Companies and Small Cap Companies, respectively.

However, as seen in figure (5), short interest dropped already starting from 2016 until 2020 whereas the sentiment does not show a consistent increase during that time-period. Additionally, the decline in short interest over recent years can also be attributed to the MEME stock squeeze[15], which has made large investors hesitant to engage in short selling. Therefore, it is highly likely that the investor sentiment index used in my research depends on factors other than shorting volume. This dependency enhances the robustness of its application in my study examining its impact on the relationship between convertible bond arbitrage, liquidity, and pricing.

As the research now has two proxies that could serve for investor sentiment, as theoretically argued, I conduct a final test where the sentiment factor of Baker and Wurgler (2006) is replaced by the total shorting volume of the stock investigated to see if this alters the results. The variable *ΔShort Volume* captures the post versus pre-period change in short volume of the sample. In Table (10), it is observed that the direction or strength of the results do not significantly change much, when replacing the sentiment factor with the total shorting volume. The test is conducted on regressions clustered on time and industry, so all the regressions (4) in the main analysis. The outcomes confirm the validity of my original sentiment factor in the context of the model and implies that my results are robust.

[14]See https://www.nasdaq.com/articles/short-interest-in-decline

[15]The MEME stock squeeze refers to the rapid increase in stock prices of certain companies driven by retail investors and social media, particularly targeted to ‘’squeeze out’’ shorted stocks by institutional investors.

Table (10) Multivariate Analysis of the regressions with change in shorting volume. In this table, *ΔShort Volume* represents the mean change (post vs pre-period) in shorting volume of the stocks investigated. instead of the sentiment factor of Baker and Wurgler (2006). The regressions test the relationship between liquidity, price efficiency measures, short-volume intensity and other predictors**.** The analysis comprises of six main Ordinary Least Squares (OLS) regressions. Variables are explained in Explanatory Variables (Appendix A). T-statistics are given within brackets. *, **, and *** indicate percentages of 10%, 5%, and 1%, respectively. The sample consists of only non-option stock issues and is from May 2009 until June 2023. Number of observations is 306.

ΔShortVolume instead of SENTIMENT

Dependent Variable:	Δ Turnover	Δ Number of Trades	Δ AMIHUD	Δ Dollar Spread	Δ AR (1)	Δ VR (5)
SV_%Shrout	4.043**	0.889*	-0.350	-1.629	0.013*	-597.391
	(1.705)	(0.478)	(0.372)	(1.751)	(0.007)	(462.255)
ΔMarketCap (100 million)	-0.00003	-0.00002***	-0.00002*	-0.0001*	--0.00000	-0.001
	(0.0001)	(0.00001)	(0.00001)	(0.00005)	(0.00000)	(0.020)
ΔVolatility	0.007***	0.0004*	-0.001**	-0.001	-0.000**	-0.0002***
	(0.002)	(0.0003)	(0.0003)	(0.001)	(0.000)	(0.0001)
Pre-issue Price x100	0.00000**	0.00000	0.00000***	0.00001***	-0.00002	-1.595
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00001)	(1.931)
NYSE	0.002	0.0003	-0.001	-0.001	-0.00000	-0.279
	(0.006)	(001)	(0.001)	(0.003)	(0.00000)	(0.396)
Pre Post Days x1000	-0.003	0.0001	-0.001	-0.001	0.00000***	0.0004
	(0.004)	(0.0001)	(0.001)	(0.001)	(0.00000)	(0.001)
ΔShort Volume	0.00000	0.00000**	0.00000	0.00000	-0.0001	98.258
	(0.000001)	(0.00000)	(0.00000)	(0.00000)	(0.001)	(139.302)
Constant	1.041	-0.035	0.193	0.198	N.A	N.A.
	(1.238)	(0.040)	(0.246)	(0.241)	N.A.	N.A.

Industry Cluster: Yes
Time Cluster: Yes
Observations: 306

CHAPTER 6 Discussion

Within this Section, a few comments on the research and its limitations are made. First, I want to comment on why the results of my main analysis show less significant variables than the literature for systematic variation in liquidity and return measures. To find reasons for this I clustered the data sample based on industry and time and observed that this did not result in many clusters (mainly because of the SIC code 9999, which means non-classifiable). This means there is high variability within each cluster and fewer independent units to make a robust estimate. Because of the limited number of clusters, standard errors increase, which lowers t-values and increases p-values, making it harder to obtain significant results. Furthermore, since my research encompasses 306 final observations, I have to consider that there are approximately 77 observations per portfolio when the sample is divided into portfolios based on *SV_%Shrout*. Typically, this number may be too small to conduct reliable significance tests. Due to this, the differences between groups (portfolios) need to be very large to be statistically significant. However, previous research on convertible bond arbitrage also lacks significant sample sizes, and my data still demonstrates statistical power.

Furthermore, it is assumable that the control variables in the regression analysis might not reflect all variables influencing the relationship between convertible bond arbitrage and stock market effects. By controlling for firm, time and industry fixed effects, the research is robust, but it is assumable that there are still some variables omitted in the research that could be of influence. Omitted variables that could be of influence on the results could be special bond characteristics not taken into account (e.g. credit ratings), regulatory environments (e.g. differences per state) or corporate actions (e.g. stock splits or mergers and acquisitions). More research is needed to examine the role of these factors. Overall, the results also remain robust across different time windows, although the correlation sometimes weakens. A greater, more comprehensive dataset could possibly reduce this error.

CHAPTER 7 Conclusion

This research investigates the impact of convertible bond arbitrage on market liquidity and price efficiency, with an additional focus on investor sentiment. Convertible bond arbitrage involves exploiting pricing inefficiencies between convertible bonds and their underlying equities. Hedge funds typically buy undervalued convertible bonds while they simultaneously short sell the underlying stock. This strategy ensures that gains from one position offset losses in the other, theoretically neutralizing impact of market volatility. The funds aim to profit from a delta-neutral position. The post-COVID-19 surge in convertible debt issuance, coupled with increased hedge fund activity, underscores the relevance of this study - the paper attempts to fill the significant gap that has emerged in the existing literature, with a novel, more precise, dataset.

Below, I discuss the results of the hypotheses that collectively answer the research question:

“Are liquidity and price efficiency in markets affected by convertible bond arbitrage, and are these effects influenced by investor sentiment?”

The expectations driving this research were threefold. First, that convertible bond arbitrage would enhance market liquidity due to increased trading activity. The first hypothesis ‘’*$H_{0,1}$ (Liquidity): Convertible bond arbitrage activity is uncorrelated with liquidity changes in the underlying equity*’’ is rejected as the univariate (event-study) as well as the multivariate analysis (regression-study) both confirm enough evidence to conclude that market liquidity is enhanced by convertible bond arbitrage. Second, it was expected that convertible bond arbitrageurs, considering that they were uninformed investors, would not significantly affect price efficiency. The second hypothesis ’*$H_{0,2}$ (Efficiency): Convertible bond arbitrage activity is uncorrelated with price efficiency changes in the underlying equity*’’ is not rejected nor accepted, but the relationship is found as ambiguous. The main analysis reports significant effects of convertible bond arbitrage on price efficiency, but these results do not hold in additional long-run return research. This additional research indicates that hedge funds do not earn money from having superior information about the equities they short and therefore are no price predictors. Third, it was anticipated that investor sentiment would not influence the dynamics between convertible bond arbitrage and market effects. The third hypothesis *‘’$H_{0,3}$ (Investor sentiment): The influence of convertible bond arbitrage on liquidity and price efficiency measures is not directly related to investor sentiment’’* is accepted as the results of the multivariate analysis suggest that convertible bond arbitrage independent from sentiment drives liquidity and pricing effects. However, the study finds a positive relationship between high investor sentiment and liquidity measures, indicating that increased positive sentiment enhances and may amplify the effects of convertible bond arbitrage on liquidity.

Several additional analyses and robustness tests confirm the results or show methodological preciseness: Long-run returns analysis prohibit me from drawing firm conclusions about the effects of convertible bond arbitrage on price-efficiency. Changing the time-window or removing issues in the sample with option-attached stocks does not significantly alter the results. Comparing the exploited sentiment factor with the total shorting interest in the market confirms a robust approach.

The findings of the liquidity research is in line with previous literature (Choi et al., 2007, Choi et al., 2009), whereas the findings on pricing efficiency somewhat contradict the literature (Choi et al., 2007; Kumar et al. (1998); DeTemple and Jorion (1990)). The investor sentiment research is novel in this field, but the findings on its positive influence on liquidity are similar to existing literature (Tetlock, 2010; Chau, Deesomsak and Koutmos, 2016; Liu, Wu and Zhou, 2023; Bouteska, 2020).

In summary, this study advances the literature on convertible bond arbitrage by employing a comprehensive dataset, utilizing daily short-selling data for enhanced precision, and uniquely considering the role of investor sentiment. The findings highlight the complex interaction between arbitrage strategies and market dynamics. While liquidity effects are clear, the implications for price efficiency are more nuanced and require further investigation. The findings further show that convertible bond arbitrage can drive market dynamics independent of, but ostensibly amplified by, investor sentiment. The findings underscore the need for continuous exploration into the field of hedge funds and their impact on markets, and may have opened up the possibility of examining psychological factors in this relation.

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APPENDIX A Explanatory variables

- *MarketCap* is the equity market capitalization of the issuing firm. Calculated as ‘’The total number of securities/shares of the conversion commodity when the issue was first offered’’ * The market price of the conversion commodity when the issue was first offered. Data obtained from CRSP.
- *NYSE*, *NASDAQ* and *NYSE_ARCA* are dummy variables indicating the exchange of where the equity of the issuing firm is listed. Data obtained from Mergent FISD.
- *Daily Dollar Volume* is the average daily volume of the stock. Data obtained from CRSP.
- *Issue Size* is the offering size of the convertible bond issue (face value times offering price). Data obtained from Mergent FISD.
- *ShortVolume* is the shorted equity relative to the total volume. Data obtained from FINRA.
- *ShortVolume/Shares Outstanding* is calculated as ShortVolume/Shrout. Data obtained from FINRA and CRSP.
- *SV_%Shrout* is the change in short volume (number of shares) divided by total shares outstanding. The change in short volume is the difference between short volume on the current day and short volume on the previous day. $((\text{ShortVolume}_t – \text{ShortVolume}_{t-1}))/\text{Shares Outstanding}_{t-1})$
- *SV_%Issue* is the dollar value change in short volume divided by issue size. Dollar value change is the difference in short volume on the current day and short volume on the previous day, times closing stock price on the issue date. Issue size is the face value of the convertible bond times its offer price. $((\text{ShortVolume}_t – \text{ShortVolume}_{t-1})*\text{CP}_{ID}/\text{IS}_{ID}))$
- *Conversion Ratio* is the number of shares that the convertible bond can be exchanged for. Data obtained from Mergent FISD.
- *Conversion Premium* is the amount by which the price of a convertible security exceeds the current market value of the stock. Data obtained from Mergent FISD.
- *Turnover* is calculated as the average daily volume divided by shares outstanding. Calculated as NUMTRD (number of trades) / SHROUT. Data obtained from CRSP.
- *Number of trades* is the average number of daily stock transactions on the firm’s primary exchange. Calculated as NUMTRD (number of trades)*100. Data obtained from CRSP.
- *Dollar volume* refers to the average daily dollar value of the stock traded. Calculated as VOL*100000 (correction) per day. Data obtained from CRSP.
- *AMIHUD* illiquidity measure is the average ratio of the daily return to the dollar volume. Calculated as the absolute value(delta_PRC / `Daily Dollar Volume ($ million)`/1000) where PRC is price of the stock. Data obtained from CRSP.

- *Dollar spread* is the time-weighted discrepancy between the bid and ask quote, expressed in dollars. Calculated as ASK-BID. Data obtained from CRSP.
- *Percentage spread* is the time-weighted discrepancy between the bid and ask quote, expressed as a percentage of the bid-ask midpoint. Calculated as ((ASK-BID/ASK))*100 in %. . Data obtained from CRSP.
- *Return* is the mean of the daily stock data. Data obtained from CRSP.
- *Standard Deviation* of Return is the standard deviation of the daily stock data. Data obtained from CRSP.
- *Idiosyncratic Volatility* is the standard deviation of residuals from a regression of the daily stock data over the value-weighted market excess return. Data obtained from CRSP.
- *R-squared* is the R-squared of the residuals of a regression of the daily stock data over the value-weighted market excess return. Data obtained from CRSP.
- *Beta* is the coefficient estimate of the regression of the daily stock data over the value-weighted market excess return. Data obtained from CRSP.
- *Daily AR (1)* is the daily return first-order autocorrelation of returns. Calculated in a linear model for returns and returns of the previous day (%). Data obtained from CRSP.
- *The Variance Ratio (5)* is the 5-day variance ratio as described by Lo & McKinlay (1988). Calculated as (($Var(R_5)$)/($5*Var(R_1)$)) where R1 is the 1- and 5-period returns, respectively. Data obtained from CRSP.
- $\Delta MarketCap$ is the change in the (log) market capitalization of the issuing firm. Calculated by multiplying the price of the stock with average daily shares outstanding. Data from CRSP.
- Δ*Volatility* is the change of the standard deviations of the returns,
- *Pre-issue Price* is the average (log) price during the pre-issue.
- *PrePost Days* is the number of days between the beginning and end of the whole period
- *SENTIMENT* is the sentiment index factor of Baker and Wurgler (2006) as described in the Section 3.
- *Δ Turnover is* the change of the (log) average daily volume divided by shares outstanding. Change is the mean in the post-period compared to the pre-period.
- *Δ Number of Trades* is the change of the (log) average number of daily stock transactions on the firm's primary exchange. Change is the mean in the post-period compared to the pre-period.
- *Δ AMIHUD* is the change of the (log) average ratio of the daily return to the dollar volume. Change is the mean in the post-period compared to the pre-period.
- *Δ Dollar Spread* is the change of the (log) measures of the time-weighted discrepancy between the bid and ask quote, expressed in dollars. . Change is the mean in the post-period compared to the pre-period.
- *Δ |Autocorrelation (1)|* is the change of the measure *Daily |AR (1)|*, expressed in percentages.
- *Δ |Variance Ratio (5)| (1)|* is the change of the absolute value of the measure *The Variance Ratio (5),* expressed in percentages.

APPENDIX B Dynamic Hedging: Greeks

This appendix lays out the most common so called "Greeks" in the dynamic hedging field, **Delta**, **Gamma**, and **Vega**. These are all measures of sensitivity of the option price regarding another feature of the option. **Delta** is the primary tool in dynamic hedging, which involves adjusting the hedge ratio to maintain a delta-neutral position. Delta refers to the rate of change of the convertible bond's price with respect to the price of the underlying stock. When the stock price increases, the value of the conversion option within the bond might increase, making the convertible bond behave more like a stock. To maintain neutrality, more shares of the stock might be sold short. Conversely, if the stock price falls, the bond behaves more like a straight bond, and the short position in the stock is reduced. Because the delta of the convertible bond changes with the stock price and over time, the hedge must be continuously adjusted. This is why the hedging is termed "dynamic". **Gamma** represents the rate of change in Delta for each incremental (extra) move in the stock price. Gamma is the second derivative op the option value (with respect to the underlying stock price). So, it is the derivative of the Delta. **Vega** measures the sensitivity of the convertible bond to changes in volatility I the underlying stock of the. This factor also influences how the hedging positions need to be adjusted as market conditions change.

The primary goal of dynamic hedging is to neutralize the risks associated with the equity component of the convertible bond. By doing so, traders aim to isolate and profit from the pure arbitrage opportunity, the mispricing of the bond relative to the stock, while minimizing exposure to broader market movements. Dynamic hedging is complex and requires a sophisticated understanding of derivatives and market dynamics, as well as real-time monitoring and adjustment capabilities. In the Black-Scholes framework, the Delta and Gamma for convertible bonds are derived from the derivative pricing equations, focusing on the embedded equity. The formula for Delta in a convertible bond context can be adapted from the European call option Delta formula of Black Scholes (Black & Scholes, 1973):

$$\Delta = e^{-qT} N(d_1)$$

where:

$N(d_1)$ is the cumulative normal distribution of d_1 an d_1 is given by:

$$d_1 = \frac{\ln\left(\frac{S}{K}\right) + \left(r - q + \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}}$$

Gamma is the derivative of Delta, and for European call options would then be:

$$\frac{\partial^2 C}{\partial S^2} = \Gamma = \frac{e^{-qT} N'(d_1)}{S\sigma\sqrt{T}}$$

where $N'(d_1)$ is the probability density function of the normal distribution at d_1. The Vega can also be arrived from the Black Scholes formula for European call options:

$$V = e^{-qT}\sqrt{T}\varphi(d_1)$$

For all formulas:

- C is the value of the option
- S is the current stock price
- K is the conversion price
- r is the risk-free rate
- q is the yield of the stock
- σ is the volatility of the stock
- T is the time to maturity of the convertible bond
- ϕ is the probability density function of the standard normal distribution
- d_1 is given as above in the Delta formula

To make the subject more tangible, I will outline a simple example. Consider a convertible with a delta of 0.5. This means that for every $1 increase in the price the stock, the price of the convertible bond is expected to increase by $0.50. If the gamma is 0.1, it means that for every $1 increase in the stock price, the delta of the bond will increase by 0.1. This means that the bond's price will become more (or less, at a negative gamma) sensitive to changes in the stock price as the stock price increases. For example, after an initial $1 increase in the stock price, if the delta increases to 0.6, the next $1 increase in the stock price would cause the bond's price to rise by $0.60. Lastly, the convertible bond has a vega, which measures the sensitivity of the bond's price to changes in the volatility of the underlying stock. For example, if the vega is 0.2, it suggests that a 1% increase in the volatility of the stock will lead to a $0.20 increase in the price of the convertible bond. This is because an increase in volatility makes the option to convert the bond more valuable, which in turn increases the overall price of the bond.

These formulas and overview provide a theoretical baseline for understanding how the price of a convertible bond relates to changes in the stock price. However, in practical terms, additional factors such as credit risk, covenants, and other terms specific to the bond issuance must also be considered.

APPENDIX C Market transparency reporting tools

TRFs (Trade Reporting Facilities), ADFs (Alternative Display Facility) and ORFs (OTC Reporting Facility) are key components in the U.S. securities landscape, particularly for the reporting of trade data for transparency and regulatory compliance in transactions outside the traditional exchanges. This appendix lays out the three systems that form the basis source of my shorting data in my research.

TRF (Trade Reporting Facilities)

The main purpose of a TRF is to maintain transparency and integrity in financial markets. This is done by trying to ensure that all trades, also those not executed on major exchanges, are reported and recorded. This helps in **market surveillance**, i.e. the monitoring of trading activities for potential manipulative practices. Furthermore, TRFs help **in price discovery**, which means that the reporting of trades helps in the determination of security prices, which in turn helps in ensuring fair market conditions. Lastly, it boosts **investor confidence**: transparency in trade reporting helps to build and maintain investor confidence in the markets.

ADF (Alternative Display Facility)

An ADF is a SEC-regulated electronic trading systems which provide opportunities (i.e. venues) for broker-dealers to post quotes, report trades, and compare trade reports for securities. It was developed by FINRA to facilitate the quoting and trading of stocks, primarily for stocks that are not listed on traditional exchanges. It is significant for **quoting and trading**. Although the ADF does not offer trading mechanisms like an exchange, it supports posting quotes and reporting trades. ADFs also serves as a facility for firms that choose not to participate directly in exchange environments but still need to meet regulatory trade reporting obligations (**regulatory compliance**). Lastly, ADFs mainly addresses over-the-counter (OTC) securities and stocks that are not actively traded on major national exchanges. This provides an **alternative** for market participants.

ORF (OTC Reporting Facility)

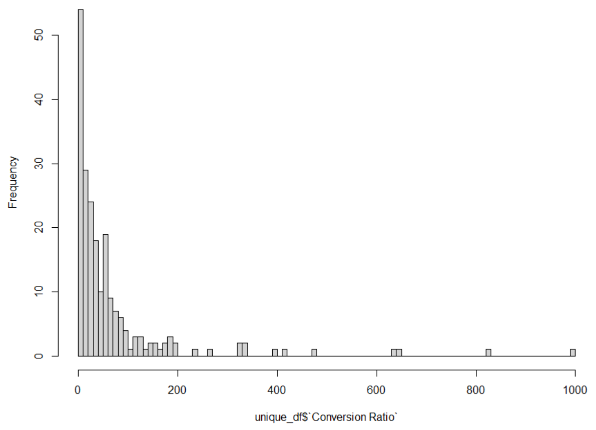
An ORF is also developed by FINRA for reporting of trade data for OTC transactions (see above). It plays a critical role in **trade reporting**. The ORF is used for reporting OTC trades in equity securities. This includes trades in non-exchange-listed securities, essentially covering stocks traded on platforms like OTC Markets. ORFs also provide a higher degree of **market transparency**. By collecting OTC trade information, the ORF enhances market transparency and helps maintain a fair and orderly market. Lastly, it benefits the **regulatory oversight**. It supports regulatory monitoring and compliance by ensuring that all relevant OTC trade data is captured and accessible.

So in essence, they have overlap in how they work: the key difference is that ORFs are solely applicable for OTC transactions and ARFs provide platforms for quoting and trading similar to an exchange, but for alternative exchanges. TRFs have the purpose to report for all securities outside the normal exchange.

APPENDIX D Extra figures and tables

Table (11) Comprehensive summary statistics of the data sample. *MarketCap* is the equity market capitalization of the issuing firm. *NYSE*, *NASDAQ* and *NYSE_ARCA* are dummy variables indicating the exchange of where the equity of the issuing firm is listed. *Issue Size* is the offering size of the convertible bond issue (face value times offering price). *Volume* is the total volume of the outstanding stock. *ShortVolume* is the shorted equity relative to the total volume. *SV_%Issue* is the dollar value change (current day and previous day) in short volume divided by issue size. *SV_%Shrout* is the change (current day and previous day) in short volume divided by total shares outstanding. *Conversion Ratio* is the number of shares that the convertible bond can be exchanged for. *Conversion Premium* is the amount by which the price of a convertible security exceeds the current market value of the stock. *Maturity* is the time-to-time length of time of when the financial obligation concerned with the convertible bond must be repaid in full.

Statistic	Mean	Std.Dev	Min	Q1	Median	Q3	Max	IQR	Skewness	Kurtosis
Market Cap (mln)	7,230	1,271	4,768	6,461	1,437	4,200	8,201	3,455	6.38	50.84
NYSE	0.46	0.50	0.00	0.00	0.00	1.00	1.00	1.00	0.14	-1.98
NASDAQ	0.49	0.50	0.00	0.00	0.00	1.00	1.00	1.00	0.03	-2.00
NYSE_ARCA	0.03	0.18	0.00	0.00	0.00	0.00	1.00	0.00	5.24	25.46
Issue Size (mln)	298.4	383.2	437.0	750.0	200.0	345.0	325.0	270.0	3.45	17.89
Issue Size / Market Cap	16.6	24.0	0.00	5.0	12.0	20.0	226	1.04	6.13	48.10
Volume (mln)	3,465	9,575	125.0	147.0	400.2	1,200	6,520	400.0	7.85	96.76
ShortVolume (mln)	594.8	2,063	7.0	46.09	129.2	374.1	1,173	328.1	16.08	585.56
Conversion Ratio	68.63	125.75	0.46	9.84	29.94	64.15	75.2	54.32	4.33	22.70
Conversion Premium (%, x100)	0.28	0.20	-0.76	0.20	0.28	0.35	1.69	0.15	1.39	16.05
Maturity (days)	2538	2108	886	1823	1839	2557	10975	734	2.99	8.3
SV_%ISSUE	0.064	0.37	-29.54	-0.01	-0.008	0.01	29.28	0.01	6.90	2228
SV_%SHROUT	0.003	0.01	-0.54	0.00	-0.001	0.00	0.57	0.00	5.46	2109



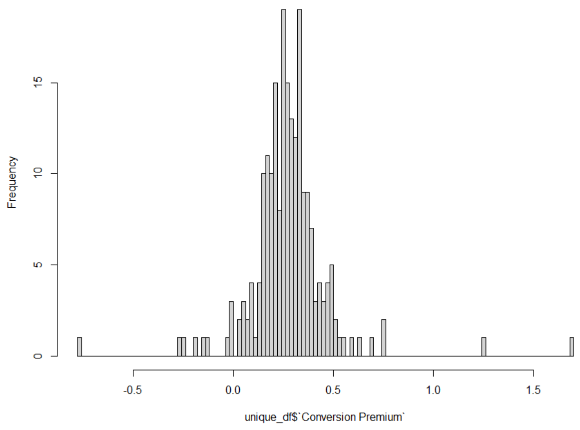


Figure (6) Conversion ratio and premium winsorizing. This figure shows the statistics before winsorizing, to show the distribution of the observations and the outliers. The left graph shows the conversion ratio on the x-axis, with the frequency of observations on the y-axis. The right graph shows the conversion premium on the x-axis, with the frequency of observations on the y-axis. The conversion ratio is winsorized at the 1.94% level on the right tail (those observations above 400). The conversion premium is winsorized at the 1% and 99% percentile (those observations below -0.3 and above 0.8).

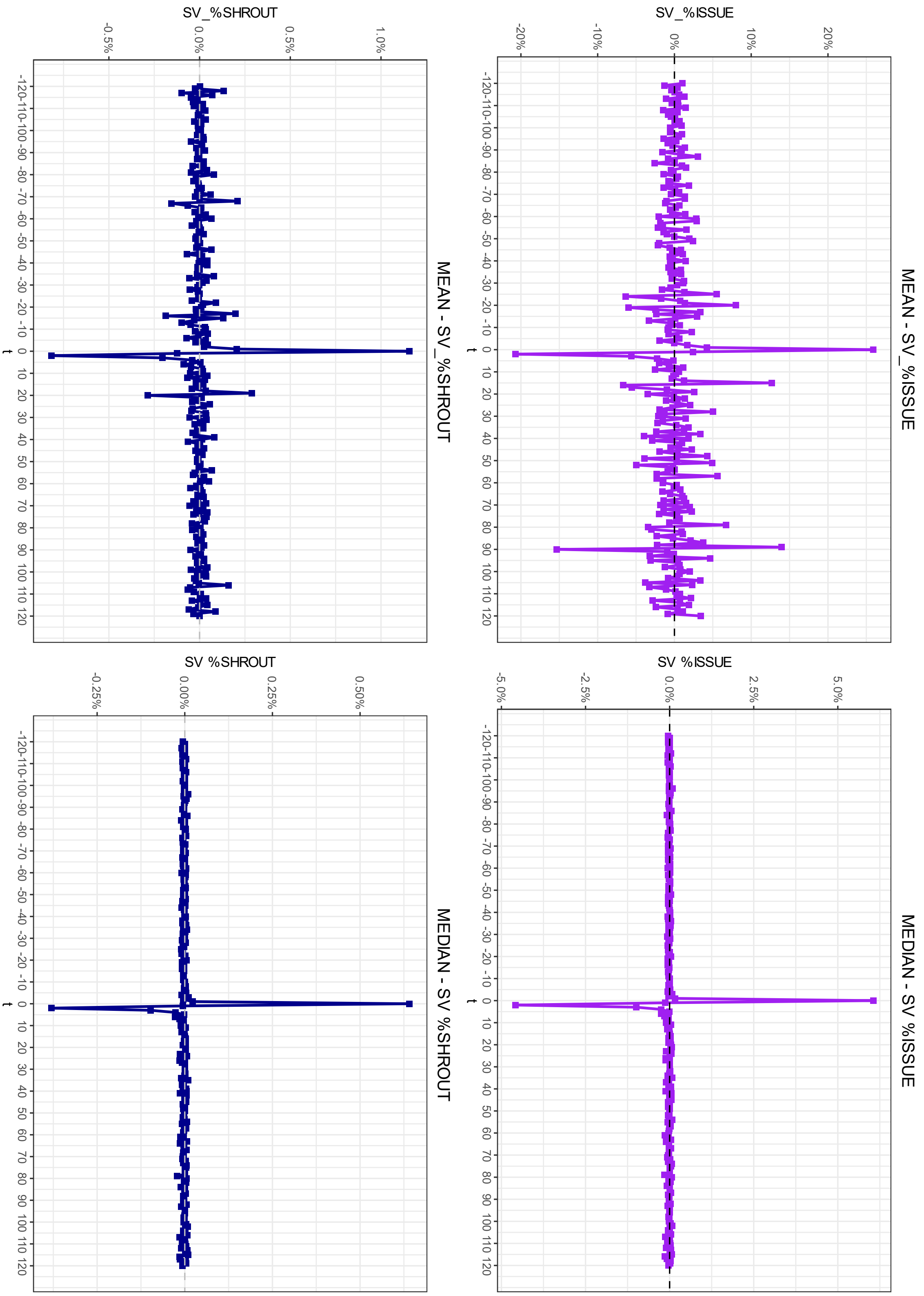


Figure (7) Mean and median shifts in short volume over the trading period from day -120 to day +120. *SV_%Issue* is the dollar value change in short volume divided by issue size (dollar value change is the difference in short volume on the current day and short volume on the previous day, times closing stock price on the issue date. Issue size is the face value of the convertible bond times its offer price). *SV_%Shrout* is the change in short volume (number of shares) divided by total shares outstanding (the change in short volume is the difference volume is the difference between short volume on the current day and short volume on the previous day).