BI Norwegian Business School - campus Oslo

GRA 19703

Master Thesis

Thesis Master of Science

Liquidity Frictions in Convertible Bond Arbitrage: Evidence from the US

Navn: Mads Arnø Bartok, Erik Tesli Haugen

Start: 15.01.2021 09.00

Finish: 01.07.2021 12.00

Liquidity Frictions in Convertible Bond Arbitrage: Evidence from the US

Master Thesis

by

Mads Bartok and Erik Tesli Haugen

MSc in Business with Major in Finance

Supervised by Thomas K. Poulsen

Oslo, July 1, 2021

ABSTRACT

We study Over-The-Counter (OTC) market frictions in the convertible bond arbitrage strategy. using noise and intermediary risk factors, in the US. We analyze two hedge fund indices, the convertible arbitrage indices of Credit Suisse (CSFB) and Hedge Fund Research (HFRI), alongside a simulated convertible arbitrage portfolio based on historical data. Using multiple regression models, we find that the strategy has negative exposure towards noise risk and positive exposure towards intermediary risk. Our results are robust to including standard risk factors. We conclude that noise and intermediary risk factors explain part of convertible arbitrage returns in the US.

Acknowledgements

We would like to express our deepest gratitude to our thesis supervisor, Assistant Professor Thomas K. Poulsen, from the Department of Finance at BI Norwegian Business School. He has provided us with valuable guidance, interesting insights, and constructive feedback. His contribution has been highly appreciated.

Furthermore, we would like to express our gratitude to Jun Pan, Professor of Finance at Shanghai Jiao Tong University, for providing us with an updated version of the noise measure dataset.

Table of contents

1.0 Introduction

Convertible bonds are fixed-income debt securities issued by companies. This type of bond yields interest payments, in addition to the opportunity to convert the bond into equity. For this reason, convertible bonds are usually referred to as a corporate bond with a built-in call option on the issuer company's equity (N. Calamos, 2003). The conversion feature makes these securities more complex and difficult to value correctly. They are often issued at prices below their model-implied prices.

Corporate finance theory leans towards a multitude of reasons for firms to issue convertible debt. On one hand, issuing convertible bonds may mitigate some financial costs that would not be possible with common debt or equity. On the other hand, the demand side from investors and hedge funds may drive up the price. This leads to cheaper access to capital for the issuer (Dutordoir et al., 2014). As opposed to equities and regular bonds, convertible bonds can be issued in a short time. The time of issuance can take as little as one day via an underwriting process, which makes them beneficial for highly illiquid firms (Pedersen, 2015).

Convertible bonds have existed since the 1800 century and have historically been a popular source of financing for growth companies, due to their low yield compared to other debt sources. Since then, the convertible bond market has developed vastly and created a range of different convertible securities, such as contingent convertible bonds and bonds with different built-in warrants (N. Calamos, 2003). As of December 2019, the convertible bond market was valued at 336 billion USD. The US dominates the market with a 63.2% market share, which constitutes 212 billion USD (J. P. Calamos, 2020). The market has historically been dominated by hedge funds. Brown et al. (2012), referenced in Dutordoir et al. (2014), find that around 75% of newly issued convertible bonds are purchased by convertible arbitrage hedge funds. The bonds trade in Over-The-Counter (OTC) markets and bond prices reflect financial frictions. Due to the poor liquidity, these bonds might be underpriced for long periods before being corrected (Mitchell et al., 2007).

1.1 Arbitrage strategy

The mispricing of convertible bonds has led to the opportunity of the convertible bond arbitrage strategy (convertible arbitrage). Arbitrageurs seek to benefit from systematic underpricing between a convertible bond and its model-implied value. The arbitrageur usually buys underpriced convertible bonds and takes offsetting positions in other assets, attempting to offset any risk. This is usually done by combining a long position in the convertible bond and a short position in the underlying stock or other offsetting assets (Mitchell et al., 2007). The offsetting positions are adjusted over time and, theoretically, result in a riskless abnormal return for the arbitrageur. Convertible arbitrage has historically been a popular strategy, especially among hedge funds being able to apply high leverage to increase the strategy's return.

When arbitrageurs perform this strategy, an appropriate hedge ratio is needed to determine the relative quantity between the two assets. This ratio is determined by the sensitivity of the price of a convertible bond to changes in the price of the stock, commonly known as delta. The delta will change whenever the stock price changes, and therefore the arbitrageurs must continuously adjust their positions in order to be delta-hedged (N. Calamos, 2003).

Occasionally, arbitrageurs reverse the strategy by shorting the convertible bond and buying the underlying stock. However, this is rarely the case because convertible bonds historically have been underpriced. Furthermore, less liquid assets, such as convertible bonds, usually have higher short lending fees reducing the return potential (Pedersen, 2015). Arbitrageurs would also face lending fees when shorting the stock, but these are significantly lower than the lending fees for bonds. Pedersen, (2015) states that "for about 90% of the stocks in the United States, the loan fee is small, typically around 0.10–0.20% annualized".

1.2 Risk factors

Previous literature finds systematic exposure to asset-based risk factors. However, our thesis will focus on the strategy's return in light of two more recent market-based risk factors, noise measure (noise factor) and intermediary capital risk factor (intermediary factor). The noise factor reflects illiquidity by exploiting the connection between arbitrage capital in the market and observed pricing error in US Treasury bonds (Hu et al., 2013). Hu et al. state that "the shortage of arbitrage capital allows yields to deviate more freely from the curve, resulting in more noise in prices".

Changes in the noise factor have a significant impact on hedge fund returns. Due to the strong liquidity and presence of credit in the US Treasury market, the noise factor provides a good proxy for the overall market liquidity. Furthermore, the noise factor tends to increase sharply during periods of financial distress (Hu et al., 2013). We argue that these properties of the noise factor will capture the main risk exposures of convertible arbitrage, since the strategy historically has shown bad performance during financial crises and is highly sensitive to market liquidity (Mitchell et al., 2007).

The intermediary risk factor reflects a proxy for intermediaries' marginal value of wealth. The economic intuition is that assets paying off in bad times are preferred, while assets paying off in good times must offer higher expected returns. He et al. find that an extension of CAPM including the intermediary risk factor successfully explains return differences across a variety of asset classes. They use intermediary risk to price multiple OTC assets, such as CDS, swaps and derivatives, but they do not investigate convertible bonds. This means that financial intermediaries have a central role in pricing of OTC-traded securities, especially in illiquid and complex markets (He et al., 2017). As both frictions are present in the convertible bond market, we investigate whether the intermediary risk has an effect on convertible bond prices.

1.3 Research question

To summarize, the noise factor captures illiquidity in a new way for the US Treasury bond market. Due to the importance of this market, illiquidity will often spill over to other markets (Hu et al., 2013). Furthermore, since convertible bonds are traded over the counter, intermediaries play a strong role in the efficiencies of these markets. We therefore hypothesize whether the noise- and the intermediary risk factor can capture the illiquidity and market inefficiency of the convertible bond market. In this thesis we will examine the following research question:

"Do noise and intermediary risk factors explain convertible bond arbitrage returns in the US?"

We analyze the performance of two convertible arbitrage hedge fund indices using the noise and intermediary risk factors. Since hedge funds report their own performance, this can lead to multiple sources of bias (Pedersen, 2015). Therefore, our analysis also includes multiple simulated arbitrage portfolios using historical data, in order to work around hedge fund reporting bias. Our approach will focus on firms in the United States, which have issued about 50% or more of the convertible bonds globally in the last two decades (J. P. Calamos, 2020). By this delimitation, our research will not be affected by currencies and other international factors. Our sample period is from June 2002 to September 2020, due to the availability in TRACE.

The opportunity to contribute to the empirical application of modern factor theory led to our motivation for writing this thesis. We want to take a new look at the convertible arbitrage and emphasize the pricing implications of frictions in OTC markets. Our thesis is important as it provides a better understanding of which risk factors drive the convertible arbitrage returns. Academics with research focus within fixed income securities, and especially factor theory and hedge fund performance, can benefit from our findings by an improved understanding of modern factors' impact on convertible bond prices. Furthermore, hedge fund managers and other investors can benefit from our findings in order to more efficiently evaluate funds performing this strategy. Finally, our thesis also helps policy makers better understand the relevant risk-factors in the convertible bond market.

2.0 Literature Review

In this section, we present relevant literature for our research. The section is split into four parts: fundamentals of arbitrage theory, risk factor theory, our new proposed risk factors, and research within convertible arbitrage.

2.1 Arbitrage theory

The foundation of our research topic is the financial concept of arbitrage. The common textbook arbitrage requires no capital, involves no risk, and generates positive returns.

Ross (1976) pioneered the Arbitrage Pricing Theory (APT), which later has become the modern factor theory. APT assumes that markets are efficient, and that all returns are compensation for a set of risk factors investors are exposed to by holding the asset. These risk factors are systematic and cannot be diversified away. Therefore, in efficient markets investors will require compensation for risk exposure. APT further assumes that portfolios can be adjusted to eliminate idiosyncratic risk. This leaves the portfolio with only a set of systematic risk factors driving the returns (Roll & Ross, 1980).

In the absence of arbitrage, all excess returns must be compensation for exposure to systematic risk factors. Otherwise, there is an opportunity to create a riskless portfolio with positive returns and zero net investment (Lehmann & Modest, 1988). Shleifer & Vishny (1997) point out the difference between arbitrage in textbooks and reality. They highlight the fact that most arbitrages require capital, and typically involve risk. Furthermore, they find that there is a possibility of arbitrage becoming ineffective in extreme events when prices do not reflect the fundamentals.

Chen et al. (1986) develop a framework to analyze different systematic risk factors that drive stock returns. They analyze the effect of macroeconomic factors on stock returns with multiple significant factors. Sharpe (1992) uses risk factors to analyze the performance and risk exposure of funds. Fung & Hsieh (1997) further develop a framework to analyze the hedge fund industry using portfolios of hedge funds as a linear combination of synthetic hedge fund strategies. All the above-mentioned authors find that returns are driven by systematic risk factors. Their findings are vitally important for benchmarking and performance evaluation, and our research will be of similar importance within convertible bonds.

2.2 Risk factors

Duarte et al. (2007) investigate the risk factors of different fixed income arbitrage strategies by constructing monthly return indices. This includes swap spread, yield curve, mortgage, volatility, and capital structure (or credit) arbitrage. They conclude that fixed income arbitrage mostly generates positively skewed excess returns, which contradicts the common wisdom that arbitrage mostly generates small positive returns and experiences infrequent heavy losses. Furthermore, while most of the strategies attempt to remain market neutral, they still exhibit exposure to both equity- and bond risk factors.

Ammann et al. (2010) examine the risk factors of US mutual funds that primarily invest in convertible bonds. They find evidence that returns are driven by equity factors using the Carhart four-factor model, as well as bond factors such as default-, high yield- and term structure risk. They disprove that implied volatility from the built-in call option is compensated for.

Capocci & Hübner (2004) investigate hedge fund performance using various combinations of Carhart, Fama and French, and Agarwal and Naik models, in addition to a new factor reflecting hedge funds investing in emerging bond markets. Their research is based on hedge fund data from HFR- and MAR database from 1984 to 2000. They find that convertible arbitrage hedge funds show positive exposure towards Fama three-factors and default risk, while negative exposure towards government bond index. The estimated alpha for these funds is statistically significant and positive, indicating an arbitrage profit from the strategy. They find low market betas for convertible arbitrage funds between 0.05 and 0.08 in their models, when using a value-weighted portfolio of NYSE, Amex, and Nasdaq as benchmark. They do not take illiquidity into account in their models. In terms of financial crises, the authors only consider the Asian crisis in their sample period, where convertible bond arbitrage was unaffected. Long-Term Capital Management's large unwinding in 1998 caused a major loss in the convertible bond market that is not covered by the authors (Asness et al., 2009). In our study, we use more recent data. Our analysis covers two major crises, the financial crisis in 2008 and the corona crisis in 2020, both having strong effects on the corporate- and convertible bond market. We also use more recent methodology in our analysis, by including lagged variables to better capture total factor exposure (Getmansky et al., 2004).

2.3 New risk factors

Hu et al. (2013) construct the noise factor based on the implied yield curve of bonds from CRSP Daily Treasury database. The factor is obtained by aggregating deviations of market yields to model yields across all bonds. They find that this measure of illiquidity spikes up during market crises, which suggests that the measure captures market-wide liquidity risk. In addition, they find that the measure can help explain cross-sectional variation in hedge fund returns and currency carry trade strategies. We consider the former to be highly relevant for our research in order to explain the convertible arbitrage returns.

While Hu et al. (2013) construct the noise factor using Treasury bond yields, Goldberg & Nozawa (2021) construct a similar noise factor using corporate bond yields. Their factor is computed using weekly bond prices gathered from the Merrill Lynch U.S. Corporate Master database from 2002 to 2016. The use of noise builds on the research of Fontaine and Garcia (2012) and Hu et al. (2013), both studying noise in Treasury bonds and assuming it is driven by liquidity supply by dealers. Goldberg and Nozawa (2021) investigate the noise factor together with the quantity of liquidity provided in order to distinguish between an increase in noise due to reduced liquidity supply or increased liquidity demand among investors. They find complementary results as Hu et al. (2013). However, due to the importance of the US Treasury bond market and the effect of illiquidity spillover to other markets, we will mainly focus on the noise factor from Hu et al. (2013) in our research.

He et al. (2017) construct an intermediary capital ratio as a new risk factor capturing the change in wealth and shocks in the financial intermediary sector. They use an extended CAPM-model which includes exposure to intermediary capital risk. The data consists of historical lists of primary dealers from NY Fed’s website and their traded companies from CRSP/Compustat or Datastream. They find that assets’ exposure to changes in the capital ratio of primary dealers explain variation in expected excess returns across asset classes. All asset classes exhibit a positive risk premium from intermediary risk. This is relevant due to the structure of OTC markets where convertible bonds are traded. These markets are decentralized without a central exchange or broker. Instead, dealers act as market-makers by quoting their bid- and ask-prices, and thereby providing liquidity. This means that the liquidity in the convertible bond market is partly determined by dealers' capital and ability to act as market-makers, which affect convertible bond prices through liquidity premiums. Therefore, we will investigate the risk factor of He et al. (2017) in our research.

2.4 Convertible arbitrage

Similar to our approach, the paper of Hutchinson & Gallagher (2010) examines the simulation of a convertible arbitrage strategy in order to determine any risk factors. Their results show significant exposure to a multitude of equity factors, as well as default- and term structure risk. Liquidity and volatility factors were found to be non-significant in any model. The liquidity risk factor is non-significant when using both Eckbo and Norli’s (2005) and Pastor and Stambaugh’s (2003) liquidity extensions for the Carhart four-factor model. Their replicated portfolio is based on a sample period from 1990 to 2002. The paper also examines convertible arbitrage hedge fund indices during the financial crisis in 2008, finding evidence of negative abnormal returns.

Agarwal et al. (2011) construct an issue-size-weighted buy-and-hedge strategy consisting of holding convertible bonds until maturity or the end of the sample period, while dynamically hedging equity risk. They run a regression over a 30-day rolling window when estimating the hedge ratio, which differs from our approach of calculating end-of-month hedge ratios. Their model also includes assumptions on transaction costs, as opposed to our model. Further, the article explores how the strategy is affected by the supply of convertible bonds. Their data consists of daily US-denominated convertible bonds provided by Albourne Partners in London with a sample period from 1993 to 2003. They find that both their computed buy-and-hedge- and buy-and-hold strategy explain large portions of the variation in return among hedge funds performing convertible arbitrage. In addition, they find that supply conditions are an essential factor affecting these returns.

Choi et al. (2009) measure the changes in equity short interest activity near convertible bond issuance and investigate whether convertible arbitrage activity improves market liquidity and the efficiency of equity prices. The article uses a variety of proxies for liquidity and efficiency in their empirical analysis. Their initial sample includes all convertible bond issues by publicly traded firms in the US from July 1993 to May 2006. They find improved liquidity following convertible bond issuance, and that the improvement is systematically related to their proxy for convertible arbitrage activity. They do not find evidence of a systematic relationship between convertible arbitrage activity and stock return volatility and efficiency. However, they find evidence of average changes in volatility measures near bond issuance.

There is a common consensus among research papers that convertible bond arbitrage is compensation for risk factors. However, we find some conflicting results as risk factors and their estimated impact vary in previous literature. Which equity factors generate the returns seems to be consistent across previous literature, but their relative impact varies. There are some variations in bond factors, but default- and term structure risk are commonly used. However, Amman et al. (2010) find that high yield exposure can replace term structure risk. Some models attempt to capture the volatility exposure of the strategy. Hutchinson and Gallagher (2010) find no relationship between convertible arbitrage hedge funds and the Volatility Index. Amman et al. (2010) find the same for long-only convertible funds. They expand the analysis by including options as factors, but find no significant results. None of the above-mentioned research papers use risk factors to investigate the impact of OTC market frictions. Some authors use proxies to capture liquidity risk, but find poor estimates. The noise factor is a far more advanced estimate for liquidity opposed to previously available factors. This is due to the aggregated properties when constructing the noise factor on the entire yield curve, rather than parts of it (Hu et al. 2013). Using this new factor, we will attempt to capture the illiquidity of the convertible arbitrage better than the articles mentioned above.

Convertible bonds have been an interesting topic for researchers for a long time. A large portion of the literature focuses on pricing models or hedge funds using convertible bond-based strategies. Our research will mainly contribute to the second portion of the literature, by including noise and intermediary risk factors, and investigate whether they can explain the returns of convertible arbitrage in recent times. We find no research using the similar approach, but previous research provides us with a broad foundation for our analysis. Additionally, there are few research papers focusing on the strategy's market frictions and performance in times of financial distress (Agarwal et al., 2011; Capocci & Hübner, 2004; Hutchinson & Gallagher, 2010).

3.0 Data

Now that we have presented the relevant literature, we present the data used in our model and how this data is handled.

3.1 Model data

We use the TRACE daily bond trades as our main dataset. This dataset covers more than 99% of bonds traded in the US that meet the FINRA reporting criterions

(FINRA, n.d.). We use the time series period available to us, starting in July 2002, and ending in September 2020. The dataset includes bond prices, trading dates, volumes, coupon rate, coupon type, maturity date and CUSIP identifiers. The TRACE dataset contains multiple biases in their reporting and must be cleaned. We use a script written by Qingyi (Freda) Song Drechsler (2017) to clean the dataset for cancelations, corrections, reversals and double countings. This gives a dataset with a total of 2.5 million trades, across 2550 unique bonds.

3.2 Cleaning

We do not have access to the TRACE dataset for linking bonds and stocks. Therefore, we use Eikon Refinitiv as a secondary source of data for the remaining bond variables, including coupon frequency, bond type, issue date, maturity status, conversion ratio, asset status, event date, conversion start and end date, underlying asset Eikon ID and parent ID. In addition, Eikon provides us with bond issuer's daily stock prices from January 2000 to December 2020 and market capitalizations from January 2002 to December 2020. The stock prices are retrieved from two years before our sample period starts in order to estimate volatility.

The bonds' CUSIP ID reported in TRACE are used as an identifier for the bonds in Eikon. Bonds not found in both datasets are excluded. We remove any bond that has a different issuer than the underlying company. These bonds are usually a different type of structured debt instruments, issued by large financial institutions, that have different properties than standard convertible bonds (Huerga & Rodríguez-Monroy, 2019). Other adjustments to the main dataset are listed below:

- Remove bonds where the issuer's stock or the bond itself is denominated in non-USD or unknown currencies to avoid currency hedging.
- Remove bonds with negative time to maturity.
- Remove transactions with volume less than 25000, as we consider these positions too small for institutional investors.
- Remove bonds that have maturity status other than matured, issued, called, defaulted, or converted.
- Remove bonds with coupon types other than zero or fixed.

- Adjust all data to end-of-month date format.
- Replace missing dividends with 0, assuming no dividend payout if data is not available.
- Remove bonds with less than three months to maturity.

After cleaning the dataset, we are left with 602 unique convertible bonds. We find some bonds to be traded after their reported event date in Eikon. We set a new event date for these bonds to be one month after their last observed trade date. As mentioned earlier, TRACE is susceptible to misquoting of bond prices. We remove transactions outside the interval of 0.5 to 99.5 percentile of prices in order to decrease the impact from these.

We present summary statistics of our final bond sample. Table 1 gives an overview of the mean statistics, including price reported in TRACE, transaction volume, trade observations per bond, annual coupon rate and time from issue until maturity. In appendix 1, we provide similar tables for median and standard deviation of the sample.

Sample period	**# Bonds**	**# Issued bonds**	**Price ($)**	**Volume ($M)**	**# Trades per bond**	**Coupon rate (%)**	**Time to maturity (year)**
			Mean				
All	602	595	110.44	0.73	2777.38	2.91	8.76
2002-2005	18	32	107.59	2.20	2469.10	3.01	20.92
2006-2010	88	48	102.10	1.05	6499.42	3.11	20.75
2011-2015	225	234	108.99	0.70	3726.79	3.08	7.22
2016-2020	522	267	112.55	0.66	1548.13	2.74	6.21

Table 1: Summary statistics of sample.

3.3 Risk-free rate

We use the overnight index swap for the US (OISUS) as a proxy for the risk-free rate. Due to the liquidity and safety attributes of Treasury bonds, often referred to as Treasury convenience yield, we consider Treasury bonds to be too low as a proxy for the risk-free rate. We follow Hull and White and use the OISUS-rate as risk-free rate for this purpose (Hull & White, 2012). The data for the OISUS yield curve (1M-30Y) is gathered from WRDS, and we fill in with data from Bloomberg wherever WRDS have missing data.

3.4 Risk factors

We use Fama-French's website[1] to retrieve the equity factors Small Minus Big (SMB) and High Minus Low (HML). From AQR's website[2], we retrieve the Momentum (MOM) factor and AQR's version of the High Minus Low (HML_AQR) factor. For the rest of this thesis, we only use AQR's version of the HML factor, as it performs better in our statistical models.

Since the default- and term structure risk factors are not publicly available, we reconstruct these factors using Ilmanen's methodology (Ilmanen, 1996), based on Fama-French (1993). For the default (DEF) factor, we use the return difference between long-term corporate bonds and long-term Treasuries. The term structure (TERM) factor is constructed as long-term Treasuries minus short-term Treasuries. We use Bloomberg Barclays US Treasury 10+ year total return index as long-term Treasuries, Bloomberg Barclays US Treasury 1-3 year total return index as short-term Treasuries and Bloomberg Barclays US Corporate 10+ year total return as long-term corporate bonds. All these indices are retrieved from Bloomberg (Bloomberg L.P., n.d.).

[1] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[2] https://www.aqr.com/Insights/Datasets

We retrieve the noise and the intermediary risk factors from the authors' webpages[3]. The first dataset includes daily observations of the noise factor from January 1987 to December 2020. We construct a monthly noise factor as the first difference of the total noise each month (Hu et al., 2013). The second dataset includes monthly observations of four intermediary-related factors from January 1970 to December 2020. We only use the risk factor produced as the monthly change in capital ratio for dealers (He et al., 2017).

The two convertible arbitrage hedge fund indices, CSFB and HFRI, as well as the Russell 3000 index are retrieved from Bloomberg. Similar to Hutchinson & Gallagher (2010), we use the Russell 3000 index as our market factor. Russell 3000 is an equal-weighted index consisting of the 3000 largest US traded stocks based on market capitalizations (Bloomberg L.P., n.d.). 90.7% of convertible bonds are issued by companies that are B-rated, lower or unrated (J. P. Calamos, 2020). Russell 3000 represents the broad US economy and companies with lower ratings than the companies represented in S&P 500 and Dow Jones.

3.5 Hedge fund data

Preqin is a data provider for alternative asset classes and covers fund performance data on 24000 funds. It collects data on hedge funds, as well as other types of alternative funds (Preqin, n.d.). We retrieve data on monthly return for 49 convertible arbitrage hedge funds operating in North America.

3.6 Hedge fund bias

Hedge funds are not obligated to report their returns to others than their investors. They choose freely to report their returns to the public, and usually do so to promote their own performance. This leads to multiple sources of bias in hedge fund databases. Firstly, when hedge funds start reporting their returns, they can also report past returns. This leads to "backfill bias", as hedge funds with strong historical

[3] Noise risk factor: http://en.saif.sjtu.edu.cn/junpan/
Intermediary risk factor: https://voices.uchicago.edu/zhiguohe/data-and-empirical-patterns/intermediary-capital-ratio-and-risk-factor/

performance are more likely to start reporting their returns. Secondly, hedge funds can stop reporting their performance for periods of time or entirely. This leads to "survivorship bias" if hedge funds stop reporting during times they underperform (Pedersen, 2015).

Lastly, when hedge funds invest in illiquid assets, their reported returns are subject to "smoothing bias". Due to the infrequent trading, prices may be stale for long periods of time, and returns may therefore be based on stale prices. Occasionally, hedge funds use estimated prices when valuing their positions, resulting in smoother returns. These effects result in underestimating the true volatility and correlation for funds invested in illiquid assets (Ang, 2014; Getmansky et al., 2004).

4.0 Methodology

After having presented the data for our research, we will now present the construction of the simulated portfolio and the assumptions used in our model.

4.1 Assumptions

Volume-weighted prices

Convertible arbitrageurs usually take large positions in convertible bonds (N. Calamos, 2003). The convertible bond market is relatively illiquid, and prices quoted for small transactions are not necessarily achievable for large scale investors. Therefore, we use volume-weighted prices for all our computations to account for this aspect.

Risk-free rate

Our model includes linear spline interpolation of the risk-free rate using the nearest interest rate on both sides of the yield curve. In cases of extrapolation, we assume a flat yield curve.

Default probability

We assume a constant default probability of 0.58% for all companies, since a large portion of the bonds are non-rated. This is the historical default probability for BB rated bonds from S&P Global (2021).

Stock price volatility

We assume constant volatility for stock returns. The volatility is estimated based on the monthly standard deviation estimated over the full sample period. This is done in order to reduce the impact of small samples for some stocks, which would result in inconsistent volatility estimates.

4.2 Bond prices

The reported bond quotes in TRACE are reported on a clean-price basis, which is common practice in the US (J. Chen, 2021). We use monthly periodic data for our model and linear spline interpolation to find the approximate price for the end of each month. Then, we finalize our bond valuation by adding the accrued interest to the spline interpolated clean price. If there is a missing bond trade when spline interpolating, we use only the nearest observation. All bond quotes used in our calculations refer to the actual price at which bonds are traded, and we do not take bid-ask spreads into account.

4.3 Black–Scholes model

The bond holder receives new shares when converting into equity. This means that the convertible bond includes a warrant on the company's equity, which leads to a dilution of the company's shares when exercised. The conversion into a predetermined number of shares is possible at certain times during the lifetime of the convertible bond, usually at the bondholder's discretion (N. Calamos, 2003). Research papers often refer to this warrant as a call option for simplification. We will also do this in our research.

Standard convertible bonds can be converted into equity at any time during the lifetime of the bond, functioning as an American call option. In our model, we treat the convertible feature as a European call option. We consider the European option to best fit our model since our strategy only exercises at maturity or the last available date for exercising. This is consistent with the results of Merton (1973) and similar to the buy-and-hold strategy used by Ammann et al. (2010). We acknowledge the weakness of this assumption, since early option exercise can be optimal when investors face frictions (Jensen & Pedersen, 2016). However, this assumption enables us to value the convertible feature using the standard Black-Scholes model. The convertible bond is priced as a straight corporate bond plus a call option on the firm's stock (N. Calamos, 2003). We modify the formula to include dividend yield from the equity.

$$\mathrm{Call_t}^{4} = S_t e^{-q_t \Delta t} \mathrm{N}(d_1) - IV_t e^{-R_{f_t} \Delta t} \mathrm{N}(d_2)$$

Where S_t is the current stock price at time t. IV_t is the remaining investment value computed as the discounted cash flows of the bond floor. This represents the sunk cost of the remaining debt claim the bond holder must give up when converting into equity. R_{f_t} is the monthly risk-free rate from time t to the bond's maturity, T. σ is the constant forward-looking volatility. $\Delta \mathrm{t}$ is the time to the option's maturity. $\mathrm{N()}$ is the CDF of the standard normal distribution and *e* is Euler's constant. q_t is the continuous dividend yield, computed as:

$$q_t = \frac{\ln\left(1 + \frac{D}{S_t}\right)}{12}$$

Where *D* is the annual dividend and S_t is the nearest stock price.

4.4 Delta hedging

The delta of convertible bonds is the measure of the change in bond price with respect to the change in the underlying stock price. By holding a short position in the underlying stock, the arbitrageur can create a delta neutral position where the total

[4] $d_1 = \frac{\ln\left(\frac{S_t}{IV_t}\right) + \left(R_{f_t} + \frac{\sigma^2}{2}\right)\Delta t}{\sigma\sqrt{\Delta \mathrm{t}}}$

$d_2 = d_1 - \sigma\sqrt{\Delta \mathrm{t}}$

value of the positions is unaffected by changes in the underlying stock price. The convertible bond delta can be estimated at any point in time, and changes throughout the bond's lifetime. In theory, the delta hedge should be continuously updated to perfectly hedge the positions. However, this would result in large transaction costs. Convertible arbitrage hedge funds therefore update their short position on a timestep basis (N. Calamos, 2003). In our model, we estimate and rebalance the short positions on a monthly frequency.

We estimate the convertible bond delta as the derivative with respect to the stock price, using the modified Calamos (2003) valuation model. The conversion ratio indicates the number of shares received for each converted bond. The appropriate number of shares to short is the delta multiplied by the conversion ratio. The hedge ratio is calculated as the following:

$$\Lambda_{\mathrm{t}} = \lambda \frac{\partial \mathrm{Call}_{\mathrm{t}}}{\partial S_t} = \lambda e^{-q_t \Delta t} \mathrm{N}(d_1)$$

Where Λ_t is the number of shares to short and λ is the conversion ratio of the bond.

For bonds where the available conversion period ends before maturity, the hedge ratio will be set to 0 in the period the bondholder is unable to convert. This means that the bond position is unhedged after the conversion period ends, given that the bond is not converted at this point in time. However, a bond with available conversion period starting after bond issuance, but still lasts until maturity, will have the same value as a normal convertible bond and be hedged as usual. This is due to our assumption that the arbitrageur will only convert at the last available point in time. Some bonds may have more complex conversion rules, such as stock price range- or periodic constraints. These restrictions are not taken into account in our model.

4.5 Maturity

We create a variable for the final payoff from each bond and use EIKON to identify the maturity type. For each type of maturity, we create a final payoff method as listed in table 2.

Type	Indicator	Result
Matured	MAT	Final payment is the face value plus accrued interest.
Issued	ISS	The bond is still actively traded, no final payoff yet.
Called	CLD	The bond has been called for its redemption value. Final payoff is redemption value.
Defaulted	DEF	The bond has defaulted, and final payoff is 0.
Converted	EXC	The bond has been converted into stocks, and then instantly sold. Final payoff equals stock price multiplied by conversion ratio.

Table 2: Maturity payoff for bonds.

When a bond is about to be called, the issuer can still exercise their conversion claim (N. Calamos, 2003). Bonds that are nearing the end of the available conversion period or about to be called, will have a payoff equal to the maximum of the redemption value and the conversion value of the bond. The bondholder can exercise immediately and liquidate their position in the market. For bonds where the convertible feature expires before maturity, we calculate the maximum payoff at this date.

4.6 Portfolio returns

We compute the monthly return of a position as the following:

$$r_{i,t}^{p} = \frac{P_{i,t}^{CB} - P_{i,t-1}^{CB} + C_{i,t} - \Delta_{\mathrm{i,t}}\left(P_{i,t}^{S} - P_{i,t-1}^{S} + D_{i,t} + R_{t-1}^{S} P_{i,t-1}^{S}\right)}{P_{i,t-1}^{CB} + \Delta_{\mathrm{i,t}} P_{i,t-1}^{S}}$$

Where $P_{i,t}^{CB}$ and $P_{i,t}^{S}$ is the price of convertible bond and stock for firm i at the end of month t. $C_{i,t}$ is the monthly accrued interest and $D_{i,t}$ is the monthly dividend for the shorted stock. R_{t-1}^{S} is the short interest rate in the previous month.

Convertible arbitrage portfolios are usually highly leveraged. Khan (2002), referenced by Hutchinson & Gallagher, (2010) estimates the average position to have a leverage of 2.5 to 3.5 times equity. In our model we add a leverage of 1 times equity, indicating an equal split between debt and equity. We assume leverage is available at the one-year risk-free rate, with monthly interest payments. The leverage is added in order to obtain estimated returns of our replicated portfolio closer to the returns of the HFRI and CSFB indices.

4.7 Portfolio construction

We construct a total of five portfolios: three main convertible arbitrage portfolios using our simulated positions, and two additional portfolios for a style analysis. The main convertible arbitrage portfolio is constructed as an equal-weighted portfolio, where the arbitrageur invests in every convertible bond available in the market. The other portfolios are weighted by market capitalization. One of them invests in 50 convertible bonds issued by the largest firms in our sample, while the other one invests in 50 convertible bonds issued by the smallest firms. We use an equal weighting for all portfolio allocations, as this is less affected by varying market capitalizations. Furthermore, we have one portfolio consisting only of the convertible bond positions, and another consisting only of the equity positions. For simplicity, we change the short equity positions into long positions.

5.0 Empirical Methodology

We will now present our six main regression models, as well as other statistical methodologies applied in our analysis. All statistical models are estimated using Ordinary Least Squares (OLS). Since our data is highly heteroscedastic and autoregressive, we use Newey-West robust standard errors and coefficient estimates for all our models (Newey & West, 1987). Unless otherwise stated, all statistical significances are computed using Student's t-distribution with normal degrees of freedom. We first estimate the models without noise (NOISE) and intermediary (INT) risk factors, then with the factors estimated separately, and finally in a joint model including both factors.

5.1 Factor regression

Convertible arbitrage is a market neutral strategy, characterized by low, negatively skewed returns with no systematic risk exposure (N. Calamos, 2003). The theoretical arbitrage strategy should therefore be presented by the following model:

$$R_t{}^P - R_{f_t} = \alpha + \epsilon_t$$

Where R_t^P is the return on the strategy, R_{f_t} is the risk-free rate represented by OISUS, α is the estimate of the abnormal return generated and ϵ_t is the idiosyncratic risk. We first test the theoretical arbitrage regression, with returns only being affected by the arbitrage profit and no systematic risk factors. The null hypothesis states there are no abnormal returns.

$$H_0: \alpha \ = \ 0$$

The alternative hypothesis states there are abnormal returns:

$$H_1: \alpha \ \neq \ 0$$

5.2 Factor models

Factor theory states systematic risk factors determine the asset's risk premium. Since these cannot be diversified away, the excess return on an asset is based on its dependence with a set of risk factors (Ang, 2014). We expand the model to include systematic risk factors. If the excess return of the strategy is compensated by some risk factor, this would be captured by the beta estimate, and further affect the alpha estimate. This can be expressed as the following:

$$R_t{}^P - R_{f_t} = \alpha + \beta_1 F_1 + \beta_2 F_2 + \beta_3 F_3 + \ldots + \epsilon_t$$

Where β_i is the estimated risk exposure towards factor F_i. The null hypothesis states there is no exposure from factor i on the strategy's excess return:

$$H_0: \beta_i \ = \ 0$$

The alternative hypothesis states that factor i has an effect on the strategy's excess return:

$$H_1: \beta_i \ \neq \ 0$$

The second model we estimate is a CAPM model, with market excess return as the only risk factor, represented by excess return of Russell 3000 (MKT) over the risk-free rate. In our third model, we extend to a Fama-French three-factor model by including size (SMB) and book-to-market (HML_AQR) factors. In our fourth model we estimate the common bond factors proposed by Fama (1986) with default (DEF) and term structure (TERM) factors. We also run a combined model of Fama-French three-factor model, including the bond factors, proposed by Capocci & Hübner (2004). Our sixth model is the Carhart (1997) four-factor model, which includes the momentum (MOM) factor.

5.2.1 Breuch-Godfrey test for autocorrelation

Hedge funds are known to have downward biased exposure towards risk factors and contain highly serially correlated data (Hutchinson & Gallagher, 2010). The test is done by performing an auxiliary regression on the model's residuals, with lags and no intercept to estimate systematic trends in the residuals (Brooks, 2019). We perform a Breuch-Godfrey test on our estimated models with ten lags. The auxiliary model can be expressed as the following:

$$\epsilon_t = \rho_1\epsilon_{t-1} + \rho_2\epsilon_{t-2} + \ldots + \rho_{10}\epsilon_{t-10} + v_t$$

The null hypothesis states there are no autocorrelation in the residuals:

$$H_0: \rho_1 = 0, \rho_2 = 0 \ldots \rho_{10} = 0$$

The alternative hypothesis states that at least one of the residuals is autocorrelated:

$$H_0: \rho_1 \neq 0 \; or \; \rho_2 \neq 0 \ldots or \; \rho_{10} \neq 0$$

The statistical significance is determined by a Chi-square distribution and has the following test statistic:

$$(T - r)R^2$$

Where T is the number of observations, r is the number of lags tested and R^2 is the R-squared of the related model being tested.

5.2.2 Jarque-Bera test for normality

The Jarque-Bera test is a goodness-of-fit test for skewness and kurtosis relative to the normal distribution (Brooks, 2019). We use the Jarque-Bera test to examine whether the OLS normally distributed residuals assumption holds and whether portfolio returns are normally distributed. The test statistic is conducted as the following:

$$W = \frac{t}{6}\left(b_1{}^2 + \frac{(b_2 - 3)^2}{4}\right)$$

Where b_1 and b_2 are the skewness and kurtosis of the dataset and t is the number of observations. The test statistic follows the Chi-square distribution with two degrees of freedom. The null hypothesis states that the distribution has no skewness or kurtosis:

$$H_0: b_1 \ = \ 0 \text{ and } b_2 \ = \ 0$$

The alternative hypothesis states that the skewness and kurtosis are jointly different from zero:

$$H_1: b_1 \ \neq \ 0 \text{ and } b_2 \ \neq \ 0$$

5.3 Getmansky

We use a model proposed by Getmansky et al. (2004) to regress hedge fund excess return upon contemporaneous and lagged factors. This model reduces the impact from smoothed returns and underestimates correlations that would otherwise be present using OLS on illiquid assets. The total exposure to a factor is estimated as the sum of all lagged coefficients to this factor. We present the following model:

$$R_t{}^P - R_{f_t} = \alpha + \beta_1 F_{1,t} + \beta_2 F_{1,t-1} + \beta_3 F_{1,t-2} + \ldots + \epsilon_t$$

The null hypothesis states that the strategy has no exposure to both a risk factor and its lags:

$$H_0: \beta_1 \ = \ 0 \text{ and } \beta_2 \ = \ 0 \text{ and } \beta_3 \ = \ 0$$

The alternative hypothesis states that the strategy has jointly exposure to the contemporaneous risk factor and its lags:

$$H_1: \beta_1 \ \neq \ 0 \text{ and } \beta_2 \ \neq \ 0 \text{ and } \beta_3 \ \neq \ 0$$

The statistical significance is given by a joint F-test using a restricted model which excludes the risk factor and the lags being tested.

5.4 Fama-MacBeth

We use the Fama-MacBeth two-step regression model to estimate the factor premium from our two proposed risk factors. In the first step, we estimate the market exposure for each hedge fund using multiple regression models, including market-, noise- and intermediary risk factor. Hedge funds are sorted into ten portfolios based on their market risk exposure, where portfolio 10 consists of the five hedge funds with the highest market betas. The first step of the Fama-Macbeth model is to estimate the factor betas for each portfolio using a 60-months rolling window (Fama & MacBeth, 1973).

$$R_{i,t}{}^{P} - R_{f_t} = \alpha + \beta_{i,1}F_1 + \beta_{i,2}F_2 + \beta_{i,3}F_3 + \ldots + \epsilon_t$$

The second step is to estimate the market price of risk using the betas for the last estimated period. We regress the following model for each period:

$$R_t{}^{P} = \gamma_0 + \gamma_1\beta_{t-1}{}^{F1} + \gamma_2\beta_{t-1}{}^{F2} + \ldots + \epsilon_t$$

Where R_t^P is a vector of portfolio returns in period t and $\beta_{t-1}^{F_i}$ is a vector of the estimated exposure to risk i of all portfolios in period $t-1$. We test the significance of our estimated premiums using a t-test, with the following null hypothesis:

$$H_0: \gamma_i = 0 \,\forall i$$

The alternative hypotheses state that the risk-free rate is positive and that risk i has a premium in the market:

$$H_1: \gamma_0 > 0$$

$$H_2: \gamma_i \neq 0$$

We use two sets of risk factors. Firstly, we include market risk, and secondly, we include default- and term structure risk. We use these factors as these are the most impactful variables from our previous models and therefore likely to be compensated.

6.0 Analysis

Now that we have presented the methodology, we provide the analysis by presenting our replicated portfolios and their performance against the hedge fund indices. Then, we go into detail on the results from our statistical tests. For our statistical analysis, estimates below the 5% significance level are marked with a star (*), while estimates below the 1% level are marked with two stars (**). Whenever we reference R-squared, we use the adjusted R-squared.

6.1 Portfolio characteristics

We present the performance for the two hedge fund indices and our main three replicated portfolios (REP, REP High and REP Low). Table 3 contains the mean, standard deviation, skewness, and kurtosis of excess returns, in addition to sharpe ratio and p-value of the Jarque-Bera test.

Statistic	**CSFB**	**HFRI**	**REP**	**REP High**	**REP Low**
Mean	0.25%	0.31%	0.05%	-0.03%	0.15%
Std	0.02%	0.02%	0.02%	0.03%	0.03%
Skewness	-2.59	-2.57	-0.75	-1.16	-0.62
Kurtosis	20.25	24.67	9.40	9.32	10.90
SR (annual)	0.45	0.51	0.07	-0.04	0.16
JB p-value	<0.01	<0.01	<0.01	<0.01	<0.01

Table 3: Statistics of portfolios.

The hedge fund indices show the same characteristics as suggested in the theory. The negative skewness indicates that most of the distribution is above the mean and the high kurtosis indicates more extreme observations than the normal distribution. This complements the theoretical background, where convertible arbitrage is supposed to generate low, positive returns during normal times and large losses during crises (Agarwal & Naik, 2004). Our replicated portfolios show the same characteristics, but they have higher skewness and lower kurtosis. Figure 1 shows the return distribution of our equal-weighted replicated portfolio. However, both indices and our replicated portfolios reject the Jarque-Bera normality test. We also note the higher volatility estimate in our portfolios, since the delta hedge is less sophisticated than the hedging strategies used by hedge funds.

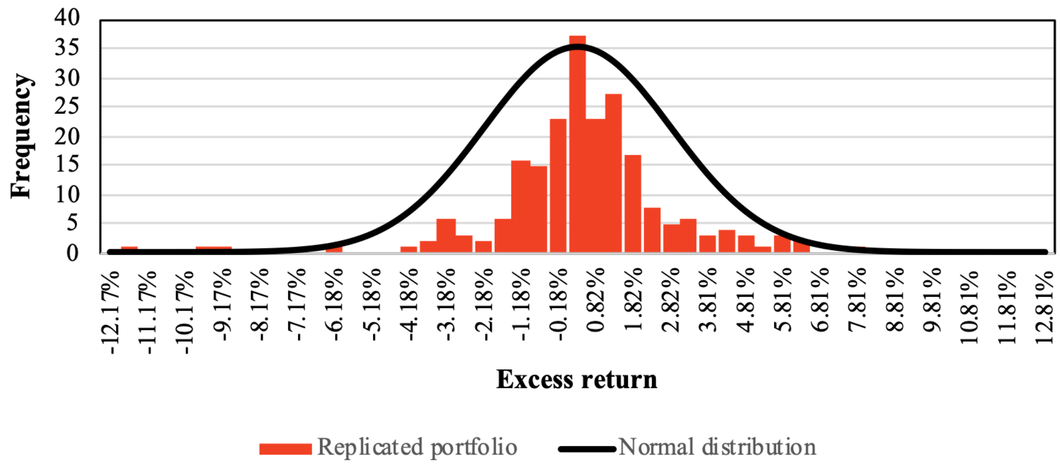

Figure 1: Monthly excess return distribution of our replicated portfolio.

We regress excess return of CSFB and HFRI upon the equal-weighted replicated portfolio. The results are provided in table 4. We report the estimated alpha, beta, tracking error and R-squared for both indices. The R-squared is 0.5 and 0.6 for the models, and both betas are statistically significant at the 1% level. HFRI fits better to our replicated portfolio, since they are both equally weighted, while CSFB is value-weighted (Bloomberg L.P., n.d.).

Portfolio	**Alpha**	**Beta**	**TE**	**R-squared**
CSFB	0.15%**	0.58**	0.01	0.51
HFRI	0.16%**	0.70**	0.01	0.60

Table 4: Regression results.

We argue that our equal-weighted portfolio provides a good fit as a benchmark and shows the same characteristics as the indices. The alphas of the hedge fund indices are also statistically significant, meaning hedge funds might add value compared to a passive replicated strategy. In figure 2, we present the cumulative return for our replicated portfolio and the indices.

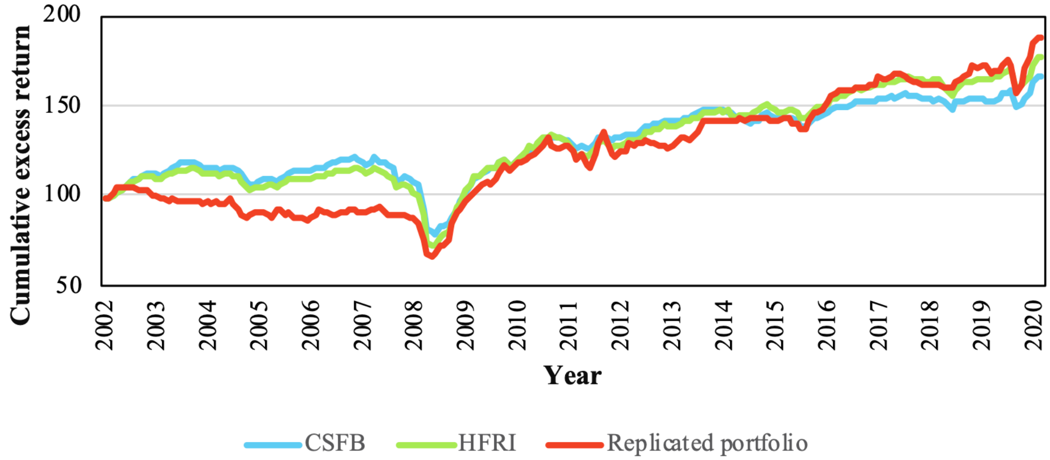

Figure 2: Monthly cumulative excess return of portfolios. All portfolios are adjusted to start at an index level of 100 in July 2002.

Figure 3 shows that our portfolio and the two indices generate less volatile returns than Russell 3000. However, the convertible arbitrage returns show a systematic exposure to the market, indicating that the strategy is not market neutral. Both our portfolio and the two indices crashed during the financial crisis in 2008 and the corona crisis in 2020. However, due to the simplified modeling of the short interest rate, our portfolio would perform worse in practice. The reason is that short positions become unavailable and short interest increases drastically in periods of financial distress, which is not accounted for in our model (Asness et al., 2009).

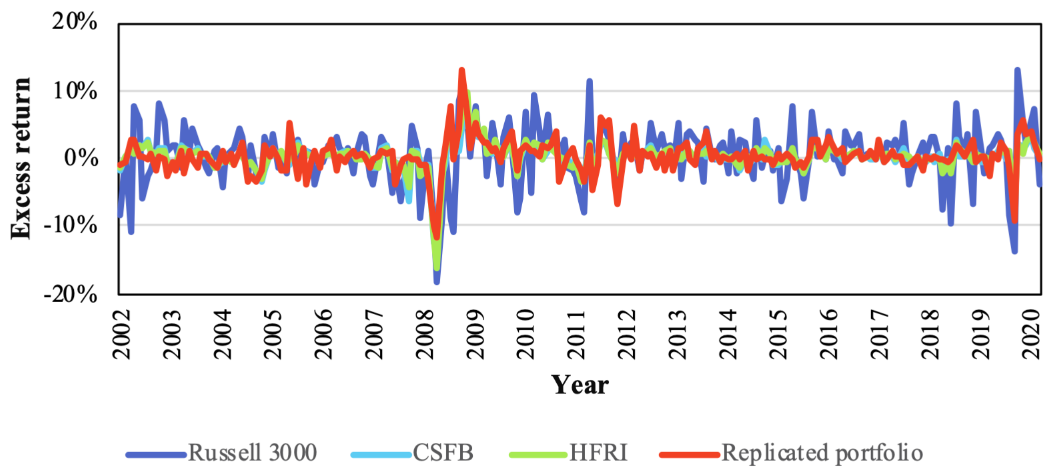

Figure 3: Monthly excess return of Russell 3000 and the portfolios.

Doing the same analysis for the value-weighted portfolios provides weaker results. These portfolios also show less similar characteristics to the hedge fund indices, compared to the equal-weighted portfolio. Furthermore, using a simple market capitalization approach results in few large positions, making the portfolio adversely concentrated. We use a percentile-based approach to work around this issue, where the strategies are equally invested in firms with the 50 largest or smallest market capitalizations. However, the value-weighted portfolio still shows more noisy characteristics. We therefore refrain from using the value-weighted portfolios further in our analysis.

6.2 Theoretical arbitrage returns

We estimate the theoretical arbitrage model where excess returns are unaffected by any systematic risk factors. In table 5, alpha and its p-value are reported, as well as Breuch-Godfrey- and Jarque-Bera p-value for the model. The portfolios generate a positive excess abnormal return. However, none of these are statistically significant when using robust standard errors and have both systematic and non-normal drift in the residuals. Only when using ordinary standard errors, HFRI's alpha is statistically significant at the 5% level, while the alphas of CSFB and the replicated portfolio are never significant. We find a significant degree of non-normality and a drift in the residuals. This indicates that the model has omitted variables, and that the strategy faces risk factors not captured by the simple arbitrage model.

Portfolio	**Alpha**	**P-value**	**BG P-value**	**JB P-value**
CSFB	0.25%	0.18	<0.01	<0.01
HFRI	0.31%	0.14	<0.01	<0.01
REP	0.18%	0.42	<0.01	<0.01

Table 5: Regression results, theoretically arbitrage model.

6.3 Factor models

We report the estimated regression models in appendix 2 for CSFB, HFRI and our equal-weighted portfolio. All portfolios have a positive market exposure with estimates in the range of 0.20-0.25. While convertible arbitrage has a low market exposure, we do not find it to be market neutral. Opposed to previous literature (Agarwal et al., 2011; Hutchinson & Gallagher, 2010), we find no significant exposure towards HML, SMB or MOM factors. Using a lagged version of the variables or replacing AQR's HML factor with Fama-French's version does not change the significance of these estimates. Overall, we find equity factors to provide little explanation for convertible arbitrage returns.

We find a strong exposure towards bond factors when including default- and term structure risk. The TERM factor is estimated to be between 0.5 and 0.57 for the indices, and around 0.6 for our replicated portfolio. All estimates are significant at the 1% level. Term structure risk captures the interest rate risk for holding bonds with a longer time to maturity. Convertible arbitrageurs can hedge the term structure risk by selling short bonds to offset the effect of interest rate changes (Fabozzi et al., 2008). Despite this fact, they still exhibit a positive exposure towards term structure risk.

The default risk is also significantly estimated for all models at the 5% level. Since convertible bonds are debt instruments until converted, the holder is exposed to the counterparty's default risk (Hutchinson & Gallagher, 2008). Most rated convertible bond issuers are rated below investment grade and thus tend to carry an overall higher default risk than other debt type instruments (J. P. Calamos, 2020). The short position in the underlying stock will offset some of the loss in the long bond position. Theoretically, the default risk exposure can be hedged by increasing the size of the short position beyond the implied delta hedge ratio (N. Calamos, 2003). Alternatively, credit default swaps can also be used to hedge the default risk. However, when including credit default swaps, Fabozzi et al. (2008) estimate lower average return and no significant improvement in a simulated study. While convertible arbitrage attempts to offer a riskless profit, it does show a positive loading of bond factors. The bond models have an R-squared of 0.5 and 0.57 for CSFB and HFRI, in comparison to the equity models, which have an R-squared of 0.28 and 0.36, respectively.

We find the noise exposure to be negative for all our models, with estimates between -0.04 and -0.06. The noise factor is statistically significant at the 1% level for all portfolios. This is consistent with the findings of Hu et al. (2013). When liquidity deteriorates, the noise increases and hedge funds with exposure towards liquidity will underperform. Mitchell et al. (2007) also consider the illiquidity of convertible bonds a major risk factor, since investors withdraw their capital when convertible hedge funds underperform, resulting in large price declines and selloffs.

We find a statistically significant exposure towards intermediary risk for both hedge fund indices. The estimated coefficients are 0.05 for CSFB and 0.06 for HFRI. Except for two instances, all estimates are significant at the 1% level and have an R-squared in the range of 0.3-0.4 for equity models, and 0.5-0.6 for bond models. Since convertible bonds are illiquid instruments and perform poorly during crises, they offer adverse hedging for intermediaries. They will therefore require a premium for holding convertible bonds (He et al., 2017). This is reflected in the positive intermediary risk exposure.

We estimate a model with noise and intermediary risk factors jointly. The estimated exposure towards noise risk is almost unaffected, however, we estimate lower exposure towards intermediary risk compared to previous models. The intermediary risk estimates are between 0.03 and 0.035 for both indices, and not statistically significant. Each model's R-squared increase by 0.01, compared to models including only noise factor, making the model offer little improvement. Both variables are proxies for illiquidity, however, they capture different inefficiencies in the market. These variables have a low and non-significant correlation with each other, indicating that multicollinearity is unlikely to be the cause of these results.

6.4 Getmansky

We redo our factor models with one and two lags. The coefficients are reported as the sum of the estimated coefficients towards a factor and standard errors are estimated with Newey-West robust standard errors (Newey & West, 1987). The estimated models are reported in appendix 3.

Complementary with the theory, the use of one lag increases the estimated exposure towards most factors. For the models including noise factor, we estimate a higher market- and noise exposure for HFRI in comparison to the unlagged model. We also find a positive, significant exposure towards SMB in the Carhart model and Fama equity- and bond model. These models provide a better fit than previously estimated, with the highest observed R-squared of 0.66 for CSFB and 0.77 for HFRI. We find less prominent results in our analysis of CSFB. The market exposure increases to 0.17, however we find no significant exposure to equity factors in any of the models. The estimated exposure towards default- and term structure risk decreases to 0.15 and 0.42, respectively. When combined with term structure risk, we obtain weaker estimates for market risk, occasionally, with no statistical significance. We find the multicollinearity between market risk and term structure risk to be persistent. Lastly, we find significant positive alphas for the hedge fund indices. This implies that the indices have risk-adjusted abnormal returns.

6.5 Breusch-Godfrey test

As discussed in previous sections, hedge fund returns in illiquid assets are subject to smoothing, making estimated exposure using OLS downward biased. We use the Breusch-Godfrey test to analyze if there are any trends in the residuals for our models. We reject the null hypothesis of no systematic trend in the residuals for both hedge fund indices at p-value less than 0.01. Our replicated portfolio does not reject the null hypothesis, with a minimum p-value of 0.06. Most of the systematic trend comes from the first lag. In all the Breusch-Godfrey tests, this parameter is positively estimated and significant at the 5% level. The average value is 0.3 and 0.4 for CSFB and HFRI, respectively. We therefore consider the Getmansky model a possible solution to better estimate the risk exposure.

When redoing the Breuch-Godfrey test on the lagged models, none of the models for the convertible arbitrage indices can reject the null hypothesis of no systematic trend in the residuals. Therefore, we consider the one-lagged model to best capture the smoothing process. Increasing the lag length to two lags offers little to no improvement over the one-lagged model. In the two-lagged model, the new estimated standard error also increases substantially, resulting in poor estimates and low significance for our models.

6.6 Fama-MacBeth

Thus far, we have estimated a significant exposure towards noise- and intermediary risk. In this section of the thesis, we estimate if these risk factors are priced in the market using the Fama-MacBeth two-step regression model to estimate their market premiums. The results are provided in table 6 and 7:

Coefficient	**Estimate**	**T-stat**	**P-value**
Rf	<0.01**	3.52	<0.01
MKT	<0.01	1.31	0.19
NOISE	-0.08*	-2.72	0.01

Table 6: Fama-MacBeth results, including MKT and NOISE.

Coefficient	**Estimate**	**T-stat**	**P-value**
Rf	0.01**	4.39	<0.01
MKT	0.01	1.50	0.14
INT	-0.03	-1.74	0.08

Table 7: Fama-MacBeth results, including MKT and INT.

For the first model, the alpha is significant and positively estimated, indicating that the model sufficiently estimates the risk-free rate. The estimated risk premium for the noise factor is statistically significant and negatively estimated. As the factor exposure towards both noise and the risk premium are negatively estimated, this has a positive impact on convertible arbitrage hedge fund returns. The arbitrage therefore harvests a positive risk premium from noise risk exposure. These results are complimentary of what Hu et al. (2013) find in their paper. We find the estimated market price of noise risk to be -0.077.

Since convertible arbitrage has high exposure towards bond factors, we include these factors in a second Fama-MacBeth framework to reduce the potential impact of omitted variables in our model. Appendix 4 shows the correlation matrix for all risk factors. We exclude market risk, due to the strong multicollinearity with term structure risk. This makes the noise factor higher estimated and more significant. However, the risk-free rate is no longer significant, and none of the other variables included, TERM and DEF, are significant either. The results are provided in table 8 and 9.

Coefficient	**Estimate**	**T-stat**	**P-value**
Rf	<0.01	1.73	0.09
DEF	0.01	0.41	0.68
TERM	0.01	1.49	0.14
NOISE	-0.01*	-2.74	0.01

Table 8: Fama-MacBeth results, including DEF, TERM and NOISE.

Coefficient	**Estimate**	**T-stat**	**P-value**
Rf	<0.01	0.73	0.47
DEF	0.01	0.72	0.47
TERM	<0.01	0.05	0.96
INT	0.03	0.58	0.56

Table 9: Fama-MacBeth results, including DEF, TERM and INT.

6.7 Time-varying exposure

Hutchinson & Gallagher (2008) argue the changing delta is an important driver for the convertible arbitrage returns. When market returns are weak, the delta will decrease, resulting in a higher exposure towards bond factors. When market returns are strong, the delta will increase, resulting in higher exposure towards equity factors. The authors consider convertible arbitrage a hybrid strategy with non-linear exposure. Correcting for this non-linear exposure removes any abnormal returns.

Figure 4: Percentage bonds in portfolio through time. The financial crisis in 2008 and the corona crisis in 2020 are shaded in grey.

Since the delta varies over time, the ratio between bond and equity in the portfolio is time-varying. A linear regression framework with risk factors does not capture the time-varying asset changes since factors have different exposure between assets. We perform a stylized analysis by decomposing the replicated portfolio into two separate equity- and bond-only portfolios. The results are reported in appendix 5.

The short equity is changed to a long equity portfolio for simplicity. In our equity-only portfolio, we regress Fama French three-factor model and Carhart four-factor model. The three-factor model shows a significant positive exposure towards SMB and HML. When including MOM, the HML factor becomes insignificant, and MOM is significant with a negative coefficient. Both models have a high R-squared of 0.88 and 0.89, respectively. The Carhart four-factor model provides the best fit for the equity portfolio. In models including bond factors, TERM is significant at the 1% level, while DEF, NOISE and INT become insignificant.

We find market risk, size, and momentum to be the main risk factors for the decomposed equity part of the strategy. The equity-only portfolio shows a high exposure towards the SMB factor, which indicates that the convertible arbitrage holds both short equity- and long debt positions in firms with small-firm characteristics. We find this to be consistent with the literature, since convertible bonds have been a popular source of financing among smaller firms.

Hutchinson & Gallagher (2010) use an alternative approach to analyze the time-varying risk exposure. They split their sample period into sub samples based on the market performance. They construct three sub samples, where the market returns are above, below, or in between one standard deviation from the mean return. When doing so, the abnormal return from the strategy disappears.

We use the same approach in a model with one lag, including bond factors, noise, and intermediary factors. The results are provided in appendix 6. Consistent with their findings, we observe a high exposure towards bond factors during periods of low market returns. The default and term structure factors are positively estimated and significant at the 1% level. These estimates decrease during normal market conditions while the market exposure increases. Similar to Hutchinson & Gallagher, we find both indices to have a negative alpha during well performing market conditions. During bad and normal conditions, we estimate CSFB to have an alpha of 0, while HFRI has a positive estimated alpha during bad market conditions only.

The estimated noise exposure increases both during high and low market conditions, compared to normal conditions. However, we do not find it to be statistically significant. Using the intermediary risk factor, we find statistically significant results for both normal and high market conditions. The estimated exposure seems to be higher during well performing market conditions. We find this to be complementary with the theory, as financial intermediaries' capital ratio is strongly procyclical (He et al., 2017).

7.0 Discussion

In this section we discuss other market frictions present in the convertible bond market and other alternative factors that can explain convertible arbitrage.

7.1 OTC frictions

Since convertible arbitrage returns are related to noise risk, liquidity frictions explain part of the underpricing of convertible bonds. Convertible bonds are often traded infrequently and sensitive to capital invested. Investors redeem their capital when convertible arbitrage is underperforming, causing selling pressure, and declining prices (Mitchell et al., 2007). Convertible arbitrage shows a positive exposure towards intermediary risk. When financial intermediaries are poorly capitalized, the value of liquidity increases. This usually occurs during periods of financial distress, resulting in a procyclical exposure (He et al., 2017).

7.1.1 Inventory risk

Investors attempting to buy or sell assets do not necessarily have the same timing. Intermediaries supply liquidity in OTC markets and solve the order imbalances by acting as market makers. However, this exposes the intermediaries to inventory risk, as they are subject to price risk on their positions (Bessembinder et al., 2020).

7.1.2 Search-and-bargaining

To mitigate the cost of search frictions, dealers use their network to find trade partners. Dealers with more valuable networks, also known as central dealers, can choose their counterparties more freely, opposed to other dealers. Dealers with more connected networks can also offer lower spreads for their bonds, implying lower costs from search friction (Bessembinder et al., 2020). In the model of Henderson & Tookes (2012), they find evidence that repeated transactions with the same dealers have lower fees for the counterparties. Recent literature also analyzes intermediary chains, since bonds move within intermediaries' networks through multiple dealers, before reaching the clients' portfolio. Long chains of intermediaries are associated with smaller yield spreads, indicating a larger and more efficient intermediary sector (Friewald & Nagler, 2019).

7.1.3 Asymmetric information

Since issuer-specific information has an impact on the value of bonds, market participants with better access to information have an advantage, resulting in asymmetric information. However, fixed income securities tend to be less sensitive to new information than equities. Microstructure theory argues that dealers in the fixed income market should charge a lower fee, since they are less exposed to information- and inventory risk. However, this is not found in empirical research, and asymmetric information is found to be a little impactful fraction in the bond market (Bessembinder et al., 2020; Friewald & Nagler, 2019).

7.2 Size effect on market frictions

Previous literature finds transaction size to be an important factor of transaction cost across bonds. Due to the opaque and decentralized structure of the bond market, less sophisticated investors are at a disadvantage. Dealers with more valuable networks will prioritize investors with larger transactions, forcing investors with smaller transactions to find dealers with less valuable networks. This makes large investors able to execute trades faster, with lower average bid-ask spreads and more investment opportunities available, opposed to smaller investors (Bessembinder et al., 2020).

On the contrary, Feldhütter (2010) finds large transactions to be more negatively affected by selling pressure than small transactions. During periods of low selling pressure, investors executing large transactions can sell assets for higher prices compared to small investors. However, large investors accept selling at lower prices in periods of high pressure. Similar to the noise factor, the selling pressure increases in periods of financial distress. Hence, a portfolio of only large transactions should have a higher exposure to the noise factor.

We investigate these relationships further by simulating two additional portfolios, limited to either small or large transactions only, based on TRACE reported transaction sizes. Transactions with volume lower or equal to 100 000 are considered small, and transactions with volume above that are considered large. We redo our regression models for these two new portfolios. The coefficients are provided in table 10. Complementary with the theory, we find evidence that the large portfolio has a higher and more significant exposure to the noise factor. However, investigating if there are any significant changes in intermediary risk between the portfolios provides no evidence, as the estimates are not statistically significant.

Coefficient	**NOISE**		**INT**	
Model	**Large**	**Small**	**Large**	**Small**
2	-0.08**	-0.07**	0.07	0.08
3	-0.07**	-0.06**	0.06	0.08
4	-0.06**	-0.05**	0.04	0.03
5	-0.05**	-0.05**	0.03	0.04
6	-0.06**	-0.06**	0.05	0.07

Table 10: Regression results, separated by transaction size.

7.3 Assets under management factor

Altas (2005) referenced by Fabozzi et al. (2008) notes that 75% of daily convertible bond transactions are made by hedge funds. Mitchell et al. (2007) find similar results in their estimates. A concern for these hedge funds is the risk of investors withdrawing their capital, forcing convertible bonds to be liquidated at low prices. This may force other hedge funds to do the same, leading to a downward spiral and resulting in huge losses (Mitchell et al., 2007). There is a common consensus in the convertible arbitrage literature that hedge fund liquidity affects the convertible bond prices and thereby convertible arbitrage returns. It has previously been estimated that hedge funds account for most of the demand for new convertible bond issues and transactions (Hutchinson & Gallagher, 2008). Hedge funds holding more assets under management invest more aggressively, which pushes the price of convertible bonds and reduces the returns from the arbitrage strategy (Ding et al., 2009).

Based on this, we include the hedge funds' assets under management (AUM) as a risk factor in our models. We create this factor as the logarithm of the total hedge funds' AUM, using hedge funds with more than 10 million USD in AUM. Regressing this provides a statistically significant negative exposure to this factor. When hedge funds have more capital to invest, the demand for convertible bonds increases, pushing prices and reducing the return on the strategy. This is complementary with evidence of this relationship from previous literature (Agarwal et al., 2011).

8.0 Robustness analysis

We control for robustness in our model and regression results. For our model robustness we analyze the effect of changing some of our main assumptions previously taken. We also test the robustness of our regression results by replacing some main variables.

8.1 Model robustness

In our first robustness test, we change the use of spline interpolated bond prices for trades and maturity payoff. Both are constructed non-empirically, which could result in modeling bias. Our alternative method uses the nearest observed bond price for bond trades and liquidates all bonds at the last observed bond price. Figure 5 shows a comparison between the original and alternative method.

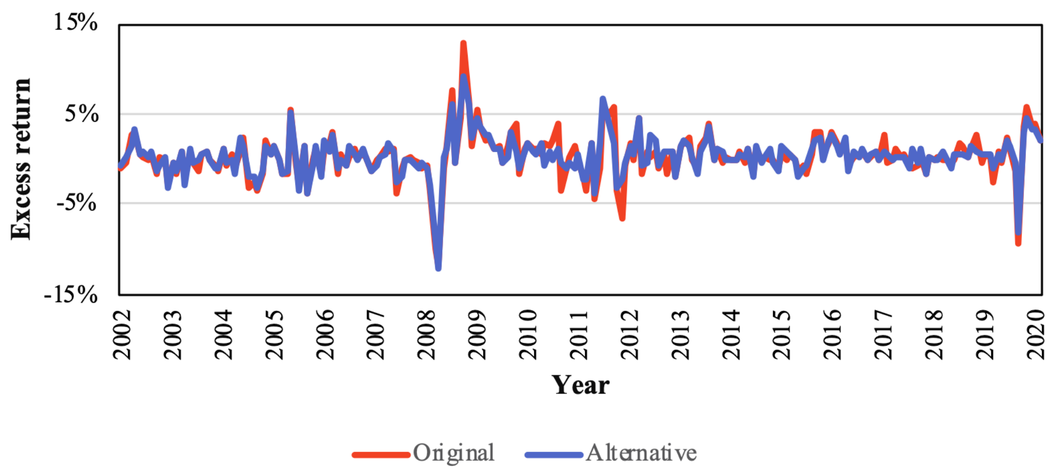

Figure 5: Excess return of the portfolio for the original and alternative use of bond price calculation and maturity payoff.

The portfolios track each other closely. Hence, the change in these assumptions have little impact on the overall performance of the strategy. The results in our statistical tests do not change either. This indicates that our spline interpolated bond prices provide fair estimates.

8.2 Constant volatility estimate

In this section, we investigate our volatility assumptions. Firstly, our model's volatility estimates are based on the full stock price data, resulting in a look-ahead bias. We address this problem by estimating the volatility by only using data available at each point in time. Secondly, we have assumed constant volatility for our model. There is a common consensus in financial literature that stock price volatility is time-varying. We fit a GARCH(1,1) model to estimate the stock return volatility for each month, using the full sample of returns available. In figure 6, we plot the bond ratio for the different methods.

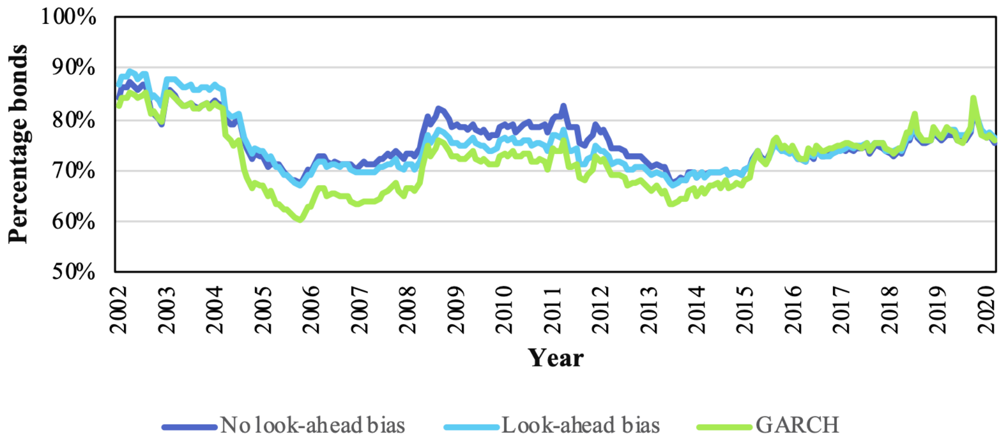

Figure 6: Percentage bond ratio in portfolio using different volatility estimates.

The change in the volatility estimate only affects the hedge ratio for the convertible bonds. Since the volatility estimates now are time-varying, the delta changes more frequently between periods compared to using constant volatility. This would result in overall higher transaction costs for the strategy, as the arbitrageur would need to readjust the portfolio more often. However, transaction costs are not present in our model, making us unable to observe this relationship. In terms of statistical significance, this does not change our results in an impactful way.

8.3 Replacement variables

We use alternative variables for market- and noise risk to test if the relationship found will hold with alternative measures. Russell 3000 is replaced with Fama-French market risk factor (Mkt_rf). We modify the Fama-French market factor by subtracting the same risk-free rate as used for the rest of the thesis. Furthermore, we replace the noise factor with Goldberg and Nozama's (2021) corporate noise factor. Since both are estimated using similar methodologies, we consider this to be a good replacement variable. Noise in the corporate bond market should also have a close connection to the pricing of convertible bonds, despite the spillover effect from the noise in the Treasury market. As of writing this thesis, we have data from 2002 until 2016 for this factor, and therefore perform this analysis on a smaller sample. The estimated models with one lag are reported in appendix 7.

8.4 Multicollinearity

The inclusion of default- and term structure risk causes the estimated market risk to decrease significantly. The new risk exposure is much lower compared to equity models, and the estimate is no longer statistically significant. We argue that this could be caused by multicollinearity in the model and investigate this by regressing market risk upon default- and term structure risk. The results are provided in table 11. We find market risk to be strongly multicollinear with term structure risk, resulting in a biased estimate for our model.

Coefficient	**Estimate**	**SE**	**T-stat**	**P-value**
(Intercept)	<0.01*	<0.01	2.02	0.04
DEF	0.11	0.09	1.23	0.22
TERM	1.17**	0.12	9.86	<0.01

Table 11: Regression results.

8.5 Extended Fama-MacBeth analysis

We perform a robust extended version of the Fama-MacBeth model. This is done by including a squared term for risk factors and a control variable for omitted risk factors, estimated using the estimated residual variance from the first step's regression. The extended model is provided below:

$$R_t{}^P = \gamma_0 + \gamma_1\beta_{t-1}^{F_1} + \gamma_2(\beta_{t-1}^{F_1})^2 + \ldots + \gamma_3 s_t + v_t$$

Where s_t is the variance in residuals from the first step's regression. This is used as a proxy for systematic effect from non-beta risk. The framework can test two additional conditions of the model:

Hypothesis 1; the relationship between the factors and the assets are linear:

$$H_0: \gamma_2 = 0$$

$$H_1: \gamma_2 \neq 0$$

Hypothesis 2; there is no systematic effect form non-beta risk:

$$H_0: \gamma_3 = 0$$

$$H_1: \gamma_3 \neq 0$$

We consider our results of the Fama-MacBeth models to be weak. While the noise factor is statistically significant, we find it susceptible to changes in the models. We also point out that none of the other factors have a significant factor price in the market. Therefore, we use a robust model to investigate these findings. We only perform this analysis on the noise-based model, as this is the only one providing statistically significant results in the first test. The estimates are provided in table 12:

Coefficient	**Estimate**	**T-stat**	**P-value**
Rf	<0.01	0.64	0.52
MKT	0.01	0.65	0.51
NOISE	-0.03	-0.20	0.84
MKT^2	-0.02	-0.63	0.53
$NOISE^2$	14.73	0.84	0.40
s	-9.40*	-2.02	0.05

Table 12: Fama-MacBeth results, extended analysis.

We note that the estimate for the risk-free rate is no longer significant, in addition to the estimated factor premiums. The only significant variable is the omitted risk premium exposure, s. There is a systematic explanatory effect in the residuals of the model, indicating that our factor model fits poorly to the risk exposure. The model for TERM and DEF shows similar results. These findings provide evidence of the limitations in our analysis.

8.5.1 Lagged factors

We have not taken lagged factors into consideration in this model. To control for the exclusion of lagged variables, we estimate a model with noise- and lagged noise factor as the only factors. The results are provided in table 13.

Coefficient	**Estimate**	**T-stat**	**P-value**
Rf	0.01*	2.52	0.01
NOISE_t	-0.15*	-2.36	0.02
NOISE_{t-1}	-0.01	-0.09	0.93

Table 13: Fama-MacBeth results, including NOISE and lagged NOISE.

The estimated market premium is only significant for the unlagged noise factor. The estimated premium of this factor is -0.15, while the lagged estimate is non-significant with a lower value of -0.01. We therefore argue that lagged variables provide little explanatory power in the model. The estimate is easily affected by inclusion of other variables and has overall weak significance.

9.0 Conclusion

We find that noise and intermediary risk factors explain convertible arbitrage returns in the US. Our results show a negative exposure towards noise risk and a positive exposure towards intermediary risk. The noise increases as the illiquidity increases, resulting in lower strategy performance. The positive intermediary risk exposure confirms that the strategy underperforms when intermediaries are poorly capitalized. We find that convertible bonds have a positive exposure to the market, and intermediaries will therefore require a premium for holding this asset. Our findings for both factors show that the value of liquidity increases during periods of financial distress, hence, the strategy's performance has a procyclical exposure towards liquidity. Our results provide evidence that frictions in the OTC markets have an impact on the convertible arbitrage performance. The noise- and intermediary risk factor contribute to capture the illiquidity and market inefficiency of the convertible bond market. Finally, we find that the two hedge fund indices have no abnormal risk-adjusted return in our decomposition analysis.

He et al. (2017) find all asset classes to exhibit a positive risk premium from intermediary risk, and Hu et al. (2013) find that the noise factor can contribute to the explanation of cross-sectional variation in hedge fund returns. Our findings are in line with their empirical evidence and complement the literature by further investigating the convertible arbitrage using both hedge fund indices and a simulated portfolio. However, we find low to no systematic exposure towards HML, SMB or MOM factors, contradicting previous literature (Agarwal et al., 2011; Hutchinson & Gallagher, 2010).

9.1 Further research

For future research it would be interesting to extend our simulation methodology by including bid-ask spreads. The relationship between bid-ask spreads, noise- and intermediary risk remain largely unexplored. As mentioned in our discussion, there are several frictions present in the convertible bond market, which we have not investigated in our thesis. We urge further research to investigate how this market friction affects the convertible arbitrage returns.

Furthermore, there is an interesting dynamic of callable convertible bonds. Since these bonds still can be converted after the call notice, issuers can "force" bond holders to convert their bonds at certain periods of time. In our dataset, we found multiple occasions of issuers sending call notice even if the redemption value was higher than the current conversion value. This contradicts the assumption that bond issuers only will call bonds when the bond price is higher than the redemption value. We urge researchers to investigate this from bond issuers' perspective.

Appendix

Appendix 1: Additional summary statistics, including median and standard deviation.

Sample period	# Bonds	# Issued bonds	Price ($)	Volume ($M)	# Trades per bond	Coupon rate (%)	Time to maturity (year)
			Median				
All	602	595	102.61	1.00	1148.00	2.50	5.00
2002-2005	18	32	104.19	2.00	728.00	2.88	20.00
2006-2010	88	48	101.00	1.00	2415.50	3.13	20.00
2011-2015	225	234	103.55	8.95	2362.00	2.75	5.00
2016-2020	522	267	102.38	1.00	869.00	2.25	5.00

Sample period	# Bonds	# Issued bonds	Price ($)	Volume ($M)	# Trades per bond	Coupon rate (%)	Time to maturity (year)
			Standard deviation				
All	602	595	35.76	0.79	4009.00	1.87	7.40
2002-2005	18	32	23.97	2.39	4321.61	1.50	4.02
2006-2010	88	48	29.05	2.37	7784.78	1.35	8.86
2011-2015	225	234	26.85	2.93	3945.46	1.89	5.47
2016-2020	522	267	28.17	2.62	2068.89	1.97	4.60

Appendix 2: Regression results, including estimated coefficients, R-squared and Breusch-Godfrey p-value of the residuals.

CSFB					
Model	**2**	**3**	**4**	**5**	**6**
Alpha	0.13%	0.14%	0.15%	0.15%	0.15%
MKT	0.2331**	0.2140**	0.0484	0.0558	0.2085**
SMB		0.0118		-0.0010	0.0250
HML_AQR		0.0411		-0.0359	-0.0158
DEF			0.1471*	0.1486*	
TERM			0.5152**	0.5336**	
MOM					-0.0556
R-squared	0.2812	0.2805	0.5021	0.5012	0.2830
BG	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001

HFRI					
Model	**2**	**3**	**4**	**5**	**6**
Alpha	0.17%	0.17%	0.18%	0.17%	0.19%
MKT	0.2910**	0.2655**	0.0958*	0.1001*	0.2591**
SMB		0.0203		0.0096	0.0359
HML_AQR		0.0520		-0.0288	-0.0150
DEF			0.1715*	0.1737*	
TERM			0.5523**	0.5658**	
MOM					-0.0656
R-squared	0.3607	0.3630	0.5690	0.5669	0.3670
BG	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001

REP					
Model	**2**	**3**	**4**	**5**	**6**
Alpha	-0.18%	-0.15%	-0.14%	-0.13%	-0.12%
MKT	0.2269**	0.2029**	0.0143	0.0293	0.1953**
SMB		-0.1519*		-0.1692**	-0.1250
HML_AQR		0.1485*		0.0651	0.0125
DEF			0.1731**	0.1553*	
TERM			0.5871**	0.5731**	
MOM					-0.1309
R-squared	0.1768	0.2231	0.3779	0.4016	0.2409
BG	0.0542	0.0205	0.0500	0.0683	0.0372

CSFB - including NOISE					
Model	**2**	**3**	**4**	**5**	**6**
Alpha	0.14%	0.14%	0.14%	0.13%	0.14%
MKT	0.1788**	0.1713**	0.0428*	0.0507*	0.1711**
SMB		0.0193		0.0122	0.0200
HML_AQR		0.0085		-0.0488	0.0057
DEF			0.1468**	0.1502**	
TERM			0.4202**	0.4426**	
MOM					-0.0028
NOISE	-0.0573**	-0.0571**	-0.0476**	-0.0481**	-0.0570**
R-squared	0.5108	0.5073	0.6518	0.6549	0.5051
BG	<0.0001	<0.0001	0.0056	0.0235	<0.0001

HFRI - including NOISE					
Model	**2**	**3**	**4**	**5**	**6**
Alpha	0.18%	0.18%	0.17%	0.16%	0.18%
MKT	0.2318**	0.2192**	0.0895**	0.0945**	0.2186**
SMB		0.0285		0.0241	0.0304
HML_AQR		0.0166		-0.0429	0.0083
DEF			0.1712**	0.1755**	
TERM			0.4478**	0.4657**	
MOM					-0.0083
NOISE	-0.0624**	-0.0620**	-0.0523**	-0.0528**	-0.0618**
R-squared	0.5845	0.5829	0.7180	0.7196	0.5811
BG	0.0012	0.0009	0.0133	0.0244	0.0009

REP - including NOISE					
Model	**2**	**3**	**4**	**5**	**6**
Alpha	-0.16%	-0.14%	-0.14%	-0.13%	-0.12%
MKT	0.1744**	0.1632**	0.0055	0.0213	0.1607**
SMB		-0.1471*		-0.1598**	-0.1316*
HML_AQR		0.1205**		0.0543	0.0421
DEF			0.1735**	0.1568**	
TERM			0.5140**	0.5066**	
MOM					-0.0768
NOISE	-0.0494**	-0.0467**	-0.0376**	-0.0364**	-0.0444**
R-squared	0.2943	0.3275	0.4417	0.4619	0.3315
BG	0.0731	0.0185	0.1317	0.1504	0.0288

CSFB - including INT					
Model	**2**	**3**	**4**	**5**	**6**
Alpha	0.13%	0.13%	0.14%	0.14%	0.15%
MKT	0.2307**	0.2175**	0.0539	0.0639	0.2117**
SMB		-0.0100		-0.0169	0.0040
HML_AQR		0.0383		-0.0361	-0.0234
DEF			0.1627*	0.1630*	
TERM			0.5040**	0.5241**	
MOM					-0.0603
INT	0.0552**	0.0546**	0.0481**	0.0492**	0.0551**
R-squared	0.3159	0.3138	0.5271	0.5273	0.3177
BG	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001

HFRI - including INT					
Model	**2**	**3**	**4**	**5**	**6**
Alpha	0.16%	0.17%	0.16%	0.16%	0.19%
MKT	0.2884**	0.2696**	0.1023**	0.1095*	0.2628**
SMB		-0.0040		-0.0087	0.0125
HML_AQR		0.0489		-0.0289	-0.0238
DEF			0.1892**	0.1899**	
TERM			0.5392**	0.5547**	
MOM					-0.0711
INT	0.0615*	0.0604*	0.0550**	0.0557**	0.0608*
R-squared	0.3969	0.3972	0.5966	0.5951	0.4024
BG	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001

REP - including INT					
Model	**2**	**3**	**4**	**5**	**6**
Alpha	-0.17%	-0.15%	-0.14%	-0.13%	-0.12%
MKT	0.2248**	0.2043**	0.0167	0.0333	0.1966**
SMB		-0.1619**		-0.1749**	-0.1350*
HML_AQR		0.1454*		0.0641	0.0077
DEF			0.1804**	0.1633*	
TERM			0.5818**	0.5680**	
MOM					-0.1325
INT	0.0319	0.0332	0.0213	0.0252	0.0341
R-squared	0.1812	0.2283	0.3785	0.4038	0.2467
BG	0.0709	0.0230	0.0679	0.0849	0.0479

CSFB - including NOISE and INT					
Model	**2**	**3**	**4**	**5**	**6**
Alpha	0.14%	0.14%	0.13%	0.13%	0.14%
MKT	0.1799**	0.1752**	0.0466*	0.0561*	0.1746**
SMB		0.0068		0.0016	0.0086
HML_AQR		0.0083		-0.0483	0.0002
DEF			0.1566**	0.1590**	
TERM			0.4172**	0.4406**	
MOM					-0.0080
NOISE	-0.0549**	-0.0548**	-0.0455**	-0.0459**	-0.0545**
INT	0.0303	0.0298	0.0302*	0.0306*	0.0299
R-squared	0.5200	0.5160	0.6608	0.6641	0.5139
BG	<0.0001	<0.0001	0.0006	0.0321	<0.0001

HFRI - including NOISE and INT					
Model	**2**	**3**	**4**	**5**	**6**
Alpha	0.17%	0.17%	0.16%	0.15%	0.18%
MKT	0.2331**	0.2237**	0.0942**	0.1009**	0.2226**
SMB		0.0142		0.0116	0.0175
HML_AQR		0.0164		-0.0423	0.0017
DEF			0.1825**	0.1855**	
TERM			0.4439**	0.4632**	
MOM					-0.0146
NOISE	-0.0597**	-0.0594**	-0.0499**	-0.0503**	-0.0590**
INT	0.0344	0.0334	0.0355*	0.0353*	0.0337
R-squared	0.5951	0.5926	0.7290	0.7303	0.5910
BG	<0.0001	<0.0001	0.0265	0.0546	<0.0001

REP - including NOISE and INT					
Model	**2**	**3**	**4**	**5**	**6**
Alpha	-0.15%	-0.14%	-0.14%	-0.13%	-0.12%
MKT	0.1745**	0.1644**	0.0063	0.0231	0.1621**
SMB		-0.1507**		-0.1624**	-0.1354*
HML_AQR		0.1199**		0.0541	0.0395
DEF			0.1756**	0.1602**	
TERM			0.5132**	0.5057**	
MOM					-0.0787
NOISE	-0.0487**	-0.0458**	-0.0371**	-0.0357**	-0.0433**
INT	0.0088	0.0119	0.0063	0.0105	0.0137
R-squared	0.2916	0.3255	0.4394	0.4602	0.3298
BG	0.0773	0.0186	0.1432	0.1598	0.0299

Appendix 3: Lagged models.

CSFB - including NOISE					
Model	**2**	**3**	**4**	**5**	**6**
Alpha	0.14%	0.21%**	0.20%**	0.21%**	0.21%**
MKT	0.2499**	0.2008**	0.0569*	0.0466	0.1967**
SMB		0.0209		0.0178	0.0222
HML_AQR		0.0982**		0.0361	0.1159*
DEF			0.1811**	0.1889**	
TERM			0.4970**	0.4974**	
MOM					0.0160
NOISE	-0.0519**	-0.0438**	-0.0334**	-0.0309**	-0.0450**
R-squared	0.5314	0.5576	0.6912	0.6994	0.5532
BG	0.9218	0.9235	0.6687	0.5932	0.9116

HFRI - including NOISE					
Model	**2**	**3**	**4**	**5**	**6**
Alpha	0.14%	0.22%*	0.19%*	0.21%**	0.23%*
MKT	0.3106**	0.2463**	0.1316**	0.1092**	0.2448**
SMB		0.0752		0.0736*	0.0804*
HML_AQR		0.0911**		0.0329	0.0702
DEF			0.1696**	0.1797**	
TERM			0.4630**	0.4486**	
MOM					-0.0236
NOISE	-0.0768**	-0.0693**	-0.0595**	-0.0579**	-0.0669**
R-squared	0.6676	0.6862	0.7654	0.7682	0.6845
BG	0.6820	0.6882	0.3663	0.2870	0.6558

REP - including NOISE					
Model	**2**	**3**	**4**	**5**	**6**
Alpha	-0.12%	-0.04%	-0.02%	-0.01%	-0.03%
MKT	0.3058**	0.2582**	0.0767	0.068	0.2662**
SMB		-0.0415		-0.0480	-0.0304
HML_AQR		0.1581**		0.0829	0.0685
DEF			0.1743*	0.1871*	
TERM			0.5367**	0.5671**	
MOM					-0.0910
NOISE	-0.0743**	-0.0612**	-0.0531**	-0.0457**	-0.0530**
R-squared	0.3910	0.4387	0.4796	0.5106	0.4348
BG	0.0409	0.0129	0.0421	0.0438	0.0200

CSFB - including INT					
Model	**2**	**3**	**4**	**5**	**6**
Alpha	0.22%*	0.29%**	0.25%**	0.26%**	0.27%**
MKT	0.2425**	0.1941**	0.0434	0.0327	0.2095**
SMB		-0.0087		-0.0053	0.0049
HML_AQR		0.1468**		0.0652	0.0441
DEF			0.1977**	0.2007**	
TERM			0.5304**	0.5190**	
MOM					-0.0978*
INT	0.0744	0.0596*	0.0407	0.0410	0.0556*
R-squared	0.4478	0.5143	0.6498	0.6724	0.5246
BG	0.5469	0.7699	0.4092	0.3156	0.6589

HFRI - including INT					
Model	**2**	**3**	**4**	**5**	**6**
Alpha	0.30%	0.38%*	0.33%*	0.35%*	0.34%**
MKT	0.2626**	0.2056**	0.0567	0.0404	0.2348**
SMB		0.0334		0.0390	0.0584
HML_AQR		0.1513**		0.0654	-0.0412
DEF			0.2029**	0.2092**	
TERM			0.5393**	0.5218**	
MOM					-0.1829**
INT	0.1124*	0.0923**	0.0802**	0.0769**	0.0851**
R-squared	0.5362	0.5816	0.6825	0.6927	0.6173
BG	0.3801	0.5114	0.1143	0.1195	0.4583

REP - including INT					
Model	**2**	**3**	**4**	**5**	**6**
Alpha	0.03%	0.13%	0.11%	0.12%	0.09%
MKT	0.2810*	0.2019	0.0081	-0.0146	0.2349
SMB		-0.0740		-0.0698	-0.0480
HML_AQR		0.2108**		0.1023	0.0074
DEF			0.2238**	0.2363**	
TERM			0.6326**	0.6573**	
MOM					-0.1900*
INT	0.0601	0.0636	0.0289	0.0383	0.0585
R-squared	0.2841	0.3830	0.4306	0.4859	0.3991
BG	0.0943	0.0288	0.1006	0.1376	0.0683

CSFB - including NOISE and INT					
Model	**2**	**3**	**4**	**5**	**6**
Alpha	0.13%	0.19%**	0.18%*	0.19%**	0.19%**
MKT	0.2367**	0.2015**	0.0660*	0.0523	0.2013**
SMB		0.0222		0.0227	0.0244
HML_AQR		0.0917**		0.0310	0.0859
DEF			0.1799**	0.1912**	
TERM			0.4651**	0.4655**	
MOM					-0.0075
NOISE	-0.0496**	-0.0427**	-0.0338**	-0.0313**	-0.0420**
INT	0.0532*	0.0478*	0.0308	0.0371*	0.0468*
R-squared	0.5601	0.5873	0.6995	0.7102	0.5817
BG	0.6980	0.8034	0.4866	0.4020	0.8048

HFRI - including NOISE and INT					
Model	**2**	**3**	**4**	**5**	**6**
Alpha	0.16%	0.21%*	0.19%*	0.20%**	0.22%*
MKT	0.2618**	0.2213**	0.1074**	0.0860*	0.2255**
SMB		0.0742		0.0810**	0.0799*
HML_AQR		0.0678		0.0045	0.0298
DEF			0.1796**	0.1980**	
TERM			0.4045**	0.4074**	
MOM					-0.0416
NOISE	-0.0721**	-0.0670**	-0.0581**	-0.0577**	-0.0633**
INT	0.0790**	0.0740**	0.0672**	0.0746**	0.0724**
R-squared	0.6989	0.7133	0.7818	0.7868	0.7116
BG	0.6807	0.6505	0.3343	0.2521	0.6212

REP - including NOISE and INT					
Model	**2**	**3**	**4**	**5**	**6**
Alpha	-0.09%	-0.02%	0.01%	0.01%	-0.01%
MKT	0.2625**	0.2136*	0.0372	0.0158	0.2256*
SMB		-0.0442		-0.0445	-0.0343
HML_AQR		0.1293*		0.0493	0.0489
DEF			0.1896**	0.2154**	
TERM			0.5374**	0.5769**	
MOM					-0.0834
NOISE	-0.0709**	-0.0589**	-0.0506**	-0.0440**	-0.0516**
INT	0.0305	0.0465	0.0118	0.0329	0.0465
R-squared	0.3871	0.4369	0.4777	0.5129	0.4320
BG	0.0528	0.0189	0.0456	0.0565	0.0290

Appendix 4: Factor correlation matrix.

Factor	**MKT**	**SMB**	**HML_ AQR**	**DEF**	**TERM**	**MOM**	**NOISE**	**INT**	**Mkt_rf**	**CORP NOISE**
MKT	1.00									
SMB	0.40	1.00								
HML_ AQR	0.45	0.29	1.00							
DEF	-0.28	-0.25	-0.15	1.00						
TERM	0.63	0.32	0.43	-0.50	1.00					
MOM	-0.38	-0.16	-0.84	0.14	-0.38	1.00				
NOISE	-0.20	0.00	-0.11	0.16	0.03	-0.22	1.00			
INT	0.10	0.17	0.21	-0.13	-0.19	0.16	-0.12	1.00		
Mkt_rf	>0.99	0.38	0.45	-0.29	0.66	-0.38	-0.22	0.08	1.00	
CORP NOISE	-0.16	-0.07	-0.06	-0.01	0.14	-0.06	-0.02	-0.12	-0.15	1.00

Appendix 5: Decomposition analysis, lagged models.

Bond-only portfolio					
Model	**2**	**3**	**4**	**5**	**6**
Alpha	0.18%	0.32%**	0.25%	0.29%*	0.29%**
MKT	0.5754**	0.4564**	0.3779**	0.3238**	0.4763**
SMB		0.1781**		0.1825**	0.2026**
HML_AQR		0.1296**		0.0523	-0.0799
DEF			0.1366	0.1714*	
TERM			0.4305**	0.4215**	
MOM					-0.1874**
R-squared	0.6997	0.7341	0.7568	0.7757	0.7508
BG	0.1952	0.2515	0.0788	0.1200	0.2874

Equity-only portfolio					
Model	**2**	**3**	**4**	**5**	**6**
Alpha	0.02%	0.34%	0.15%	0.31%	0.28%*
MKT	1.3854**	1.1147**	1.2749**	1.0981**	1.1595**
SMB		0.5446**		0.5489**	0.5846**
HML_AQR		0.2106**		0.1939*	-0.1865
DEF			-0.0464	0.0658	
TERM			0.1210	0.0949	
MOM					-0.3506**
R-squared	0.8186	0.8757	0.8218	0.8735	0.8887
BG	0.5894	0.1662	0.5404	0.2183	0.2769

Appendix 6: Hutchinson & Gallagher's alternative approach, lagged models.

CSFB						
Market state	**Alpha**	**MKT**	**DEF**	**TERM**	**NOISE**	**INT**
Low	0.00%	-0.1645	0.6280*	1.1381**	-0.0471**	0.0584
Medium	0.00%	0.0870	0.2018**	0.4867**	-0.0176*	0.0489**
High	-0.31%	-0.0186	0.0454	0.5249**	-0.0668**	0.0540

HFRI						
Market state	**Alpha**	**MKT**	**DEF**	**TERM**	**NOISE**	**INT**
Low	0.12%	-0.0637	0.6478*	1.1482**	-0.0153	-0.0953
Medium	0.00%	0.0482	0.1601**	0.5280**	-0.0354**	0.0457*
High	-0.18%	0.0215	0.1240	0.4882**	-0.0307**	0.0320

REP						
Market state	**Alpha**	**MKT**	**DEF**	**TERM**	**NOISE**	**INT**
Low	1.46%	0.0407	0.3738	0.9083**	-0.0155	-0.0005
Medium	-0.21%	0.0337	0.2188**	0.5113**	-0.0255*	0.0331
High	0.95%	-0.2419	0.0044	0.2372	-0.1127**	-0.1014

Appendix 7: Regression results with replacement variables, lagged models. MKT is replaced with Mkt_rf and NOISE is replaced with CORP NOISE.

CSFB					
Model	**2**	**3**	**4**	**5**	**6**
Alpha	0.27%*	0.32%**	0.27%**	0.28%**	0.33%**
Mkt_rf	0.2867**	0.1759**	0.0367	0.0240	0.1905**
SMB		-0.0078		-0.0093	0.0103
HML_AQR		0.1961**		0.0807**	0.0769
DEF			0.1971**	0.1784**	
TERM			0.6048**	0.5437**	
MOM					-0.0966*
CORP NOISE	-0.0279*	-0.0216	-0.0370**	-0.0299**	-0.0195
R-squared	0.3772	0.4843	0.6523	0.6543	0.4909
BG	0.4751	0.8962	0.7312	0.7931	0.7684

HFRI					
Model	**2**	**3**	**4**	**5**	**6**
Alpha	0.27%*	0.34%**	0.29%**	0.32%**	0.36%**
Mkt_rf	0.3815**	0.2110**	0.0962	0.0639	0.2461**
SMB		0.0496		0.0381	0.0814
HML_AQR		0.2635**		0.1473**	0.0259
DEF			0.1913**	0.1538**	
TERM			0.6671**	0.5146**	
MOM					-0.1915**
CORP NOISE	-0.0385**	-0.0348**	-0.0488**	-0.0450**	-0.0303**
R-squared	0.5015	0.6532	0.7199	0.7524	0.6942
BG	0.4739	0.5275	0.4160	0.5021	0.2805

REP					
Model	**2**	**3**	**4**	**5**	**6**
Alpha	0.31%*	0.38%*	0.28%*	0.31%*	0.4%**
Mkt_rf	0.2423**	0.1104	0.0177	0.0025	0.1471*
SMB		-0.0251		-0.0291	0.0127
HML_AQR		0.2636**		0.1378*	-0.0033
DEF			0.2340**	0.1994*	
TERM			0.5401**	0.4393**	
MOM					-0.2156**
CORP NOISE	-0.0641**	-0.0438**	-0.0783**	-0.0626**	-0.0388**
R-squared	0.3132	0.4227	0.4904	0.5073	0.4596
BG	0.1548	0.0699	0.0217	0.0101	0.3115

Bibliography

Agarwal, V., Fung, W. H., Loon, Y. C., & Naik, N. Y. (2011). Risk and return in convertible arbitrage: Evidence from the convertible bond market. *Journal of Empirical Finance*, *18*(2), 175–194. https://doi.org/10.1016/j.jempfin.2010.11.008

Agarwal, V., & Naik, N. Y. (2004). Risks and Portfolio Decisions Involving Hedge Funds. *Review of Financial Studies*, *17*(1), 63–98. https://doi.org/10.1093/rfs/hhg044

Ammann, M., Kind, A., & Seiz, R. (2010). What drives the performance of convertible-bond funds? *Journal of Banking & Finance*, *34*(11), 2600–2613. https://doi.org/10.1016/j.jbankfin.2010.04.016

Ang, A. (2014). *Asset management: A systematic approach to factor investing*. Oxford University Press.

Asness, C., Berger, A., & Palazzolo, C. (2009). *The Limits of Convertible Bond Arbitrage: Evidence from the Recent Crash*. AQR Capital Management, LLC.

Bessembinder, H., Spatt, C., & Venkataraman, K. (2020). A Survey of the Microstructure of Fixed-Income Markets. *Journal of Financial and Quantitative Analysis*, *55*(1), 1–45. https://doi.org/10.1017/S0022109019000231

Bloomberg L.P. (n.d). Retrieved March.10, 2021 from https://bba.bloomberg.net/

Brooks, C. (2019). *Introductory econometrics for finance* (Fourth edition). Cambridge University Press.

Calamos, J. P. (2020). *Convertible Securities*. https://www.calamos.com/insights/convertible-securities/

Calamos, N. (2003). *Convertible arbitrage: Insights and techniques for successful hedging*. John Wiley.

Capocci, D., & Hübner, G. (2004). Analysis of hedge fund performance. *Journal of Empirical Finance*, *11*(1), 55–89. https://doi.org/10.1016/j.jempfin.2002.12.002

Carhart, M. M. (1997). On Persistence in Mutual Fund Performance. *The Journal of Finance*, *52*(1), 57–82. https://doi.org/10.1111/j.1540-6261.1997.tb03808.x

Chen, J. (2021, mai 30). *Dirty Price*. Investopedia. https://www.investopedia.com/terms/d/dirtyprice.asp

Chen, N.-F., Roll, R., & Ross, S. A. (1986). Economic Forces and the Stock Market. *The Journal of Business*, *59*(3), 383. https://doi.org/10.1086/296344

Choi, D., Getmansky, M., & Tookes, H. (2009). Convertible bond arbitrage, liquidity externalities, and stock prices. *Journal of Financial Economics*, *91*(2), 227–251. https://doi.org/10.1016/j.jfineco.2008.02.008

Ding, B., Shawky, H. A., & Tian, J. (2009). Liquidity shocks, size and the relative performance of hedge fund strategies. *Journal of Banking & Finance*, *33*(5), 883–891. https://doi.org/10.1016/j.jbankfin.2008.10.003

Duarte, J., Longstaff, F. A., & Yu, F. (2007). Risk and Return in Fixed-Income Arbitrage: Nickels in Front of a Steamroller? *Review of Financial Studies*, *20*(3), 769–811. https://doi.org/10.1093/rfs/hhl026

Dutordoir, M., Lewis, C., Seward, J., & Veld, C. (2014). What we do and do not know about convertible bond financing. *Journal of Corporate Finance*, *24*, 3–20. https://doi.org/10.1016/j.jcorpfin.2013.10.009

Fabozzi, F. J., Liu, J., & Switzer, L. N. (2008). Market Efficiency and Returns from

Convertible Bond Hedging and Arbitrage Strategies. *The Journal of Alternative Investments*, *11*(3), 37–64. https://doi.org/10.3905/JAI.2009.11.3.037

Fama, E. F. (1986). Term premiums and default premiums in money markets. *Journal of Financial Economics*, *17*(1), 175–196. https://doi.org/10.1016/0304-405X(86)90010-3

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, *33*(1), 3–56. https://doi.org/10.1016/0304-405X(93)90023-5

Fama, E. F., & MacBeth, J. D. (1973). Risk, Return, and Equilibrium: Empirical Tests. *Journal of Political Economy*, *81*(3), 607–636. JSTOR.

Feldhütter, P. (2010). The Same Bond at Different Prices: Identifying Search Frictions and Selling Pressures. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1413672

FINRA (n.d.). *Trade Reporting and Compliance Engine (TRACE)*. *FINRA.org* https://www.finra.org/filing-reporting/trace

Friewald, N., & Nagler, F. (2019). Over-the-Counter Market Frictions and Yield Spread Changes. *The Journal of Finance*, *74*(6), 3217–3257. https://doi.org/10.1111/jofi.12827

Fung, W., & Hsieh, D. A. (1997). Empirical Characteristics of Dynamic Trading Strategies: The Case of Hedge Funds. *Review of Financial Studies*, *10*(2), 275–302. https://doi.org/10.1093/rfs/10.2.275

Getmansky, M., Lo, A. W., & Makarov, I. (2004). An econometric model of serial correlation and illiquidity in hedge fund returns. *Journal of Financial*

Economics, *74*(3), 529–609. https://doi.org/10.1016/j.jfineco.2004.04.001

Goldberg, J., & Nozawa, Y. (2021). Liquidity Supply in the Corporate Bond Market. *The Journal of Finance*, *76*(2), 755–796. https://doi.org/10.1111/jofi.12991

He, Z., Kelly, B., & Manela, A. (2017). Intermediary asset pricing: New evidence from many asset classes. *Journal of Financial Economics*, *126*(1), 1–35. https://doi.org/10.1016/j.jfineco.2017.08.002

Henderson, B. J., & Tookes, H. (2012). Do Investment Banks' Relationships with Investors Impact Pricing? The Case of Convertible Bond Issues. *Management Science*, *58*(12), 2272–2291. https://doi.org/10.1287/mnsc.1120.1553

Hu, G. X., Pan, J., & Wang, J. (2013). Noise as Information for Illiquidity. *The Journal of Finance*, *68*(6), 2341–2382. https://doi.org/10.1111/jofi.12083

Huerga, A., & Rodríguez-Monroy, C. (2019). Mandatory Convertible Bonds as an Efficient Method of Issuing Capital. I Á. Ortiz, C. Andrés Romano, R. Poler, & J.-P. García-Sabater (Red.), *Engineering Digital Transformation* (s. 59–66). Springer International Publishing. https://doi.org/10.1007/978-3-319-96005-0_8

Hull, J. C., & White, A. (2012). Libor vs. OIS: The Derivatives Discounting Dilemma. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2211800

Hutchinson, M. C., & Gallagher, L. A. (2008). Simulating convertible bond arbitrage portfolios. *Applied Financial Economics*, *18*(15), 1247–1262. https://doi.org/10.1080/09603100701604217

Hutchinson, M. C., & Gallagher, L. A. (2010). Convertible Bond Arbitrage: Risk and Return. *Journal of Business Finance & Accounting*, *37*(1–2), 206–241. https://doi.org/10.1111/j.1468-5957.2009.02178.x

Ilmanen, A. (1996). Does Duration Extensions Enhance Long-Term Expected Returns? *The Journal of Fixed Income*, *6*(2), 23–36. https://doi.org/10.3905/jfi.1996.408172

Jensen, M. V., & Pedersen, L. H. (2016). Early option exercise: Never say never. *Journal of Financial Economics*, *121*(2), 278–299. https://doi.org/10.1016/j.jfineco.2016.05.008

Lehmann, B. N., & Modest, D. M. (1988). The empirical foundations of the arbitrage pricing theory. *Journal of Financial Economics*, *21*(2), 213–254. https://doi.org/10.1016/0304-405X(88)90061-X

Merton, R. C. (1973). Theory of Rational Option Pricing. *The Bell Journal of Economics and Management Science*, *4*(1), 141. https://doi.org/10.2307/3003143

Mitchell, M., Pedersen, L. H., & Pulvino, T. (2007). Slow Moving Capital. *American Economic Review*, *97*(2), 215–220. https://doi.org/10.1257/aer.97.2.215

Newey, W. K., & West, K. D. (1987). A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica*, *55*(3), 703. https://doi.org/10.2307/1913610

Pedersen, L. H. (2015). *Efficiently inefficient: How smart money invests and market prices are determined*. Princeton University Press.

Preqin. (n.d). *Hedge Fund Database for Funds & Investors.* Retrived April.15, 2021 form https://www.preqin.com/data/hedge-funds

Qingyi (Freda) Song Drechsler. (2017). *Cleaning* [SAS Studios].

Roll, R., & Ross, S. A. (1980). An Empirical Investigation of the Arbitrage Pricing Theory. *The Journal of Finance*, *35*(5), 1073–1103.

https://doi.org/10.1111/j.1540-6261.1980.tb02197.x

Ross, S. A. (1976). The arbitrage theory of capital asset pricing. *Journal of Economic Theory*, *13*(3), 341–360. https://doi.org/10.1016/0022-0531(76)90046-6

Sharpe, W. F. (1992). Asset allocation: Management style and performance measurement. *The Journal of Portfolio Management*, *18*(2), 7–19. https://doi.org/10.3905/jpm.1992.409394

Shleifer, A., & Vishny, R. W. (1997). The Limits of Arbitrage. *The Journal of Finance*, *52*(1), 35–55. https://doi.org/10.1111/j.1540-6261.1997.tb03807.x

S&P Global. (2021, april 7). *Default, Transition, and Recovery: 2020 Annual Global Corporate Default And Rating Transition Study*. https://www.spglobal.com/ratings/en/research/articles/210407-default-transition-and-recovery-2020-annual-global-corporate-default-and-rating-transition-study-11900573