Efficiency in the fixed income ETF market

Niek Stevens[*]
MSc Thesis Finance
University of Tilburg [†]
Supervisor: dr. Jens Kværner

September 18, 2020

Abstract

The Covid-19 crisis had a great impact on fixed income markets. Beginning in early March 2020, yield spreads soared, dealers shifted from buying to selling, and liquidity seemingly evaporated. Fixed income ETFs traded substantially below net asset value as there were no natural buyers, resulting in the Federal Reserve stepping in and buying corporate bonds and fixed income ETFs. This paper reveals new trading strategies for alternative liquidity providers to step in during times of distress and appear as the natural buyer. It examines opportunities to set up spread trading strategies to profit from the discrepancies that can exist and it presents new ways to circumvent the non-tradability of the NAV by using a genetic algorithm. The paper provides new perspectives on the complex mechanics of arbitrage trading and it highlights the possibilities for alternative liquidity providers to create a more efficient fixed income ETF market.

Word count: 10,094

Key words: Exchange-traded funds, Arbitrage, Spread trading, Genetic algorithm

[*]Student number: 2047455, E-mail: g.h.stevens@tilburguniversity.edu
[†]Faculty of Economics and Management

1 Introduction

Exchange traded funds (ETFs) have become a popular investment product during the last decade. The first ETF was launched in 1993, but overall adoption has seen its widest success after the Global Financial Crisis (GFC) in 2008 (Crabb, 2018). The products have massively benefitted from the rise in popularity of passive investing and low-cost, diversified index fund management (Hill, 2016). Although ETFs were tracking equity indices at first, investors can nowadays buy ETFs that track many different asset classes. Historically, investors diversified their investments mainly into equities and fixed income products (Ziemba, 2013). Therefore, it should not come as a surprise that ETFs are increasingly tracking fixed income benchmarks. This, however, poses a lot of challenges as the underlying baskets of fixed income ETFs are discontinuously liquid. Bonds are mainly traded over-the-counter (OTC) and, subsequently, do not show as much transparency as equities that are traded on an exchange. This leads to poorer price discovery and greater premiums and discounts between the ETF and its underlying net asset value (NAV), especially during times of distress (Madhavan et al., 2018).

Although there is an emerging base of literature on the mechanics of ETFs and their adoption in portfolios, most of the literature has focused on ETFs that track equity indices and their relative performance to active investment management (Rompotis, 2009). Recently, there has been an increased interest in the underlying mechanics of fixed income ETFs. Especially after the COVID-19 period, when fixed income ETFs showed wide premiums and discounts, interest has evolved regarding discrepancies that can exist in this market. Nevertheless, it remains relatively unexplored how efficiency in terms of pricing could be improved. Therefore, this paper seeks to fill this gap and contribute to the existing literature by developing new ways for alternative liquidity providers to arbitrage premiums and discounts in the fixed income ETF market. The contribution of the study is two fold. Firstly, it investigates the price discovery process and the spreads that can exist between the fixed income ETF and its NAV. Secondly, it shows how alternative liquidity providers can circumvent the non-tradability of the NAV and trade the spread with sophisticated arbitrage strategies.

During the Covid-19 period, dislocations in terms of pricing in the fixed income ETF market were evident as the Federal Reserve had to step in as dealer of last resort. These dislocations were also evident during the GFC and its aftermath as revealed by Tucker and Laipply (2013). This paper builds on the authors's examination and complements their research by quantifying the inefficiencies during the latest period of market distress but differs in that it examines a broader data set of fixed income ETFs to investigate differences between segments of the fixed income market. I run the same procedure as the authors to quantify the discrepancies in the form of a spread trading strategy and optimize it for practical usage. Tucker and Laipply (2013) argued that while possibilities for spread arbitrage existed, this was complicated due to the non-tradability of the underlying NAV. The current study shows that alternative liquidity providers can circumvent this non-tradability with the help of a genetic algorithm developed by Andriosopoulos et al. (2013). The developed strategy replicates the movement of the underlying

NAV with a basket of five other fixed income ETFs that can subsequently be implemented in the original spread trading strategy.

In addition, this paper shows that there is still evidence of the presence of substantial deviations that can occur between fixed income ETFs and their underlying value. Especially in times of distress substantial discrepancies can arise in certain segments of the fixed income ETF market. For example, trading different high yield ETFs during the period of May 2019 – May 2020, when COVID-19 had a great impact on the fixed income market, would have allowed one to obtain returns close to 20% per ETF if the NAV could be traded. This study shows that especially ETFs with discontinuously liquid underlying constituents could be made more efficient using the developed spread trading strategy. I find that these segments of the fixed income ETF market are more opaque and less transparent. These discrepancies can be even greater for ETFs that are smaller in terms of assets under management. Moreover, the ETF shows explanatory power for the underlying market. As the ETF is traded on a liquid exchange, it absorbs new information faster than in the underlying OTC market and, hence, it gives an implication of where the underlying market is heading.

To circumvent the non-tradability of the NAV, I use a genetic algorithm to replicate the NAV with a basket of five other fixed income ETFs. This allows for an arbitrage strategy between the fixed income ETF and its replicated NAV. This paper applies the strategy to two high yield ETFs and shows that alternative liquidity providers could implement the strategy to profit from the dislocations that can exist. It provides new perspectives on the complex mechanics of arbitrage trading within the fixed income ETF market by introducing new ways to create more efficiency in terms of pricing.

Additional sections cover the following: Section 2 discusses previous research and section 3 provides an overview of fixed income ETFs and genetic algorithms. Section 4 discusses the development of the hypotheses of the paper. Section 5 outlines the methodologies applied to conduct the empirical research. Section 6 gives a description of the data. The results are presented and interpreted in section 7. Section 8 concludes.

2 Literature review

While it is commonly expected that APs, through the inventory mechanism, keep the deviation between the ETF and its NAV in place, discrepancies occur regularly (Petajisto, 2017; Tucker and Laipply, 2010). Especially for fixed income ETFs the deviations can take longer to dissipate. Fulkerson et al. (2013) find that premiums and discounts can sometimes persist for as long as 30 days. This phenomenon can be partly explained by the fact that NAV pricing for bonds is based on bid prices. As long as the bid-ask spread on the ETF is smaller than that of the underlying basket, a premium for the fixed income ETF exists. If an ETF has a liquid underlying basket there is a narrower spread and, consequently, a lower premium or discount. One of the biggest issues in arbitraging away premiums and discounts in the fixed income market is that the underlying bonds are mostly traded OTC. Spreads in OTC markets tend to be quite wide and thus the OTC market can be opaque and discontinuously liquid (Bessembinder and Maxwell, 2008). This creates poor price discovery, especially in periods of increased volatility. There has been strong growth and wider adoption of fixed income ETFs as they provide a solution to this lack of transparency and liquidity. If investors have certain liquidity requirements, ETFs provide an excellent opportunity to get fixed income exposure while maintaining access to broad market liquidity. As ETFs are traded on an exchange where liquidity and volumes are higher, they give good inferences as to where the underlying assets are heading. Tse and Martinez (2007) find that International iShares ETFs exhibit a one to one correspondence with their underlying, indicating that ETF prices reflect all fundamental information from their underlying assets. This is particularly interesting in times of higher volatility. Madhavan et al. (2018) note that in times of higher volatility ETFs tend to trade with large discounts to NAV. Interestingly, this indicates efficient pricing and not illiquidity. The discrepancies that regularly exist between the ETF and its NAV tend to converge back to a normal range. Tucker and Laipply (2013) asserted that a fixed income ETF and its NAV are cointegrated, which provides for possibilities in terms of potential arbitrage profits. While normally arbitrage is done by APs, other market participants tend to step in as liquidity providers when there are abnormal deviations in terms of the spread between the ETF and its NAV. Fulkerson et al. (2017) note that a typical bond ETF has 32 AP agreements, whereas most ETFs only show three to five active APs. As the underlying basket of bonds brings a lot of challenges for arbitrage in terms of liquidity, large deviations tend to persist in times of distress. This presents opportunities for alternative liquidity providers to step in and set up arbitrage trading strategies.

The developed strategy uses index tracking to circumvent the non-tradability of the NAV. Although a growing base of literature on index tracking is emerging, the field is relatively new (Karlow, 2013). This paper uses an evolutionary algorithm in the form of a genetic algorithm to create a more efficient fixed income ETF market. Genetic algorithms were initially developed by Holland (1975) in the field of physics and they have gained fast popularity in finance to their wide application in more complicated optimization problems. They are especially useful in index tracking as Andriosopoulos et al. (2013) show. The authors analyzed the successful performance of a GE in the application of tracking illiquid shipping indices with underlying constituents of the index itself. Moreover, one could even use other instruments such as ETFs that are not part of the underlying to track certain benchmarks (Roll and Srivastava, 2018). This raises opportunities to explore potential strategies to replicate other illiquid financial time series such as the NAV of a fixed income ETF.

3 The workings of fixed income ETFs and Genetic Algorithms

3.1 The mechanics of fixed income ETFs

Fixed income ETFs have been gaining fast popularity among market participants as they provide better liquidity and easier and more cost effective ways of investing. Historically, bonds have been integral to investment portfolios. They provide a reliable income stream, mitigate overall portfolio risk and generally provide a cushion for market distress. However, cost-efficient investing in individual bonds is hard to implement for individual investors and even for institutional investors it is difficult to obtain the required diversification by investing in individual bonds (Bao et al., 2011). In addition, the regulatory environment has impacted the fixed income market by reducing liquidity and disincentivizing market participants from trading bonds on a daily basis.[1] Hence, fixed income ETFs are increasingly adopted by investors as they exhibit more liquidity and are easier to trade.

Moreover, ETFs provide interesting characteristics for more advanced applications that individual securities are not able to offer. Market participants can write options on exchange traded funds, they allow for short selling and some of them are repackaged to gain exposure with a greater amount of leverage. Especially the possibility to short these instruments yields opportunities to set up spread trading strategies to exploit price discrepancies as this paper will display.

3.1.1 Characteristics of fixed income ETFs

Fixed income ETFs are traded in two markets – the primary market, the market in which shares are created and redeemed, and the secondary market, in which shares are traded on an exchange. The next part will give an overview of the primary and secondary market and it will continue with an outline of the underlying mechanics of the premiums and discounts that can exist.

The primary market

Authorized Participants (APs) create and redeem shares of ETFs (Antoniewicz and Heinrichs, 2014). This is an important process to keep the value of the ETF that is traded on the exchange in line with the underlying basket and this process differs from a traditional open-end mutual fund. Daily, ETF providers publish the underlying constituents and a list of bonds that can be delivered for the creation and redemption of shares. When there is strong demand on the buying side, the price of an ETF is bid-up in the market. An arbitrage opportunity will be created when the price of the ETF on the exchange is higher than the value of the underlying basket. At this point the role of APs kicks in. They can purchase the underlying basket, deliver

[1] After the GFC the Volcker rule had as a consequence that market makers reduced their non-treasury bond inventories e.g. in 2015 corporate bond inventories turned negative for the first time in history. This created a market with less liquidity and, subsequently, wider bid-ask spreads.

it to the provider in exchange for new ETF shares, and then sell the obtained shares in the market for a gain. This process works in the same way, but in the opposite direction, when there is strong selling pressure in the market. This market-driven inventory management mechanism prevents a consistent price divergence between the traded ETF and its NAV.

However, note that all the redemptions and creations are done at the NAV to ensure that the value of the shares that are passing into the fund, and those that are issued are equal and that there are no wealth transfers. In contrast, market participants that are buying or selling the ETF are trading at the market price of the fund. This differs from the classic mutual fund structure where market participants also buy and sell at the NAV of the fund. If an ETF uses an in-kind creation and redemption process each market participant incurs the transaction costs and this protects the existing shareholders.

The secondary market

The shares of an ETF are listed on an exchange which creates more transparency, liquidity and lower transaction costs. In contrast, the underlying securities are traded OTC where the trading process is more opaque. Trades are directly negotiated between different market participants while the rest of the market does not have detailed information about the characteristics of the trades.

The secondary market is the liquidity provider for the ETF. Most trades are done without the need for activating the inventory mechanism in the form of creating or redeeming shares in the underlying OTC market. As the pricing process on an exchange is more transparent bid-ask spreads tends to narrow.

The creation and redemption mechanism and subsequent ETF premiums and discounts

In the last few years, the discussion around fixed income ETF's premiums and discounts, where the price of an ETF on the exchange diverges from its NAV, has evolved (Hilliard, 2014). To better understand the underlying mechanics, it is important to know the different factors that play a pivotal role in the premium and discount discussion: the value of the underlying basket, the demand and supply mechanics in the secondary market, the cost of share creation, and the liquidity and volatility of the fixed income market in general.

The premium or discount for fixed income ETFs can be expressed as follows:

$$\textit{Premium or discount} = \textit{ETF price on the exchange - value of the underlying basket} \tag{1}$$

ETFs will always show some sort of premium or discount as transaction costs determine if market participants will enter the arbitrage trade. If the transactions costs are greater than the discount or premium, it will remain. A fixed income ETF will therefore most often trade at a premium to the bid-side of the NAV.

Following Tucker and Laipply (2010) the premium discount can be split up further per:

$$\textit{Premium or discount} = \textit{(creation cost * flow factor)} + \textit{execution risk adjustment} \quad (2)$$

Creation cost

The creation cost shows what it costs the market participants to acquire the underlying basket. The size of the cost is determined by the underlying liquidity and the level of transactions costs that have to be incurred. In times of market distress, a wider bid-ask spread can be observed and, hence, the creation cost increases.

Flow factor

The flow factor shows how the total amount of the creation cost that is already priced in and where the ETF bid-ask spread resides within the underlying basket bid-ask spread. It is a number between zero and one that shows the percentage of buys versus sales of the ETF relative to the available liquidity on the exchange. A value close to one indicates a high level of buys relative to the available liquidity, which may ensue in share creations. In such an instance, the price of the ETF in the market is close to the offer side of the underlying basket. A value near zero indicates the opposite.

Execution risk adjustment

The execution risk adjustment shows the execution and liquidity risk that APs (and alternative liquidity providers) face when they buy or sell underlying baskets to activate the creation and redemption mechanism. It is this specific risk adjustment that can reinforce the deviation from the underlying NAV with respect to the price of the ETF in the market. In volatile and distressed markets, liquidity decreases and it can be hard for APs to source the required underlying securities for creation or redemption for a given size of transaction. It shows the uncertainty around price discovery and the underlying strength of the market. As noted, bid prices are directly taken from offers in the market. This means that the obtained bid prices, and, consequently, the observed NAV pricing does not necessarily indicate underlying liquidity. This could result in the true liquidation value lying below the sourced bid prices. Subsequently, the discount between the ETF price and the underlying NAV could increase.

These factors determine the movement of premiums and discounts in the market. When, for example, the execution risk adjustment is high, APs will withhold trading the underlying securities. This will reinforce the discrepancy and will ultimately be offset as soon as market participants gain new confidence in the underlying strength of the market.

3.2 Index tracking with a Genetic Algorithm

Index tracking is used to replicate a targeted benchmark with other instruments as closely as possible (Frino et al., 2004). Generally, this is done with the whole underlying of the benchmark by buying all the constituents (*full replication*) or with a sample of the benchmark (*partial replication*). The former perfectly reproduces the target index but has some important drawbacks. First and foremost, by buying all the constituents one incurs high transactions costs. Furthermore, in the case of fixed income ETFs, it is hard to source all the underlying bonds. One not only incurs transaction costs but also wider bid-ask spreads. Additionally, the composition of an index changes frequently.

Due to all the imposed constraints, market participants ideally only want to use a subset of instruments. With partial replication, the transaction and management costs are minimised. However, using only a small number of instruments introduces a tracking error, the deviation of the targeted time series. Subsequently, the optimisation problem with a small number of instruments tries to minimize the tracking error.

One method to solve the index tracking problem is by using a genetic algorithm (GA) (Gilli et al., 2019). The GA is a randomized search algorithm based on Darwin's method of natural selection. The general approach to set up a genetic algorithm is to maintain an artificial ecosystem. In this artificial ecosystem, an initial population of chromosomes exists. Each chromosome is a possible solution to the optimization problem. To test the quality of the solution a fitness value is implemented. With index tracking this fitness value is based on the tracking error. The goal is to find the chromosome with the highest fitness value by using mutation, crossover, and natural selection.

This process can be visualized as a search program that searches an entire search space for the optimal solution to a certain problem. To find the best solution, it tries all the different possibilities that could satisfy the imposed constraints on the problem. The GE goes over the search space with the use of new generations. Every generation should be an improvement until the best generation with a best possible solution is found. One imposes mutation in this process to cover all the regions of the space that is being searched to make sure that all possibilities are investigated. Crossover takes two 'parent' solutions to make a new 'child' solution. This is basically the following generation in the solution path. This process repeats itself until a perfect, or nearly perfect, solution is found.

4 Hypotheses development

The NAV and ETF are inherently related. As ETF pricing shows more liquidity and the underlying basket is traded OTC, it is paramount for market participants to know if the ETF shows the real underlying strength of the market in times of distress. If this would be the case, the ETF would reveal where the underlying market is heading. Moreover, from a liquidity point of view and to get a better understanding of the underlying mechanics of the fixed income ETF, it is crucial to understand this lead lag relationship. Hence, this leads to the following research question:

Q1: *Is it possible to elicit price discovery from fixed income ETFs for their underlying baskets?*

The next step will be investigating the inherent cointegrated relationship and look at possible spread trading strategies between both. Tucker and Laipply (2013) already found such possibilities in the form of discrepancies during the GFC and its aftermath, but this study will examine if these opportunities still exist. APs are trading through the inventory mechanism, but other market participants (e.g. hedge funds) could further help to provide liquidity in times of distress. Profitable spread trading strategies would allow market participants to help create more efficient markets. Therefore, this paper will continue with the following question:

Q2: *Can trading strategies be set up per discrepancies between bond ETF pricing and their underlying baskets?*

If it is possible to set up profitable trading strategies, the next step would be to look at possibilities to circumvent the fact that the NAV cannot be bought and sold in the market. The NAV is just a price estimation based on bid-prices in the market. Therefore, this paper will try to use a genetic algorithm to find a basket of ETFs that can replicate the NAV time series. Hence, this study ends with the following question:

Q3: *Can the NAV be replicated using other instruments that allow for continuous trading?*

If the NAV can be successfully replicated with other instruments this would open new possibilities to arbitrage large deviations between the ETF and its NAV. Subsequently, this would help to create more efficiency in the fixed income ETF market overall.

5 Methodology

Before looking at the price discovery process and potential trading strategies that can improve liquidity, it is a prerequisite to investigate the cointegrated relationship between the NAV and the pricing of the ETF on the exchange. I test for cointegration with widely adopted statistical procedures and employ the Engle-Granger cointegration test (Engle and Granger, 1987) by running a log-log regression on the NAV and ETF time series, capturing the residuals and running the Augmented Dickey fuller test on the residuals:

$$LN\left(NAV_t\right) = \alpha + \beta\left(LN\left(P_t\right)\right) + \varepsilon_t \tag{3}$$

Where $LN\left(NAV_t\right)$ is the natural log of the NAV, α is the intercept (a function of the premium and discount of the ETF), $LN\ (P_t)$ is the natural log of the price of the ETF, β is the cointegration coefficient, and ε is the error term.

If there happens to be a cointegrated relationship, it would hold that the spread between the two time series mean reverts over time with short-term deviations from its average. To further test for cointegration and a mean reverting process I conduct the Hurst Exponent test (Chan, 2013). The Hurst Exponent helps in providing a scalar that identifies whether a time series is mean reverting, random walking or trending. Random processes that contain an underlying trend have some degree of autocorrelation. When the autocorrelation has a long decay this kind of process is referred to as a long memory process. The decay of the autocorrelation in a long memory process is based on a power law:

$$p(k) = CK^{-a} \tag{4}$$

Where C is a constant and $p(k)$ is the autocorrelation function with lag k. The alpha in equation Eq. (4) is related to the Hurst exponent by:

$$H = 1 - \frac{\alpha}{2} \tag{5}$$

The Hurst Exponent has a value between zero and one, where a time series is mean reverting if $H < 0.5$, Geometric Brownian Motion if $H = 0.5$, and trending if $H > 0.5$. If a mean reverting process exists, it entails that it exhibits anti-persistent behaviour or negative autocorrelation. An increase in time step t_{i-1} to t_i will probably be followed by a decrease in time step t_i to t_{i+1}. The speed of a mean reverting process increases as the Hurst Exponent approaches zero.

Subsequently, after testing if the relationship between the NAV and ETF is mean reverting, I investigate if the NAV leads the ETF pricing or vice versa. This reveals explanatory power and gives an implication of where prices within markets are heading. To capture these effects, I run regressions of NAV returns on various lags of the ETF return and the other way around:

$$NAVreturn_t = \ \alpha + \sum_{i=0}^{n} \beta Preturn_{t-i} + \ \varepsilon_t \tag{6}$$

Where $NAVreturn_t$, is the NAV return at time t, α is the intercept (should be close to 0), $Preturn_{t-i}$ is the ETF price return at lag i, β is the return coefficient for lag I, ε is the error term.

This allows for observing the significance of the return coefficients and the decay in terms of significance and strength of leading and lagging relationships. Furthermore, it is important to see how fast the two time series converge. A potential fast convergence would allow market participants to trade faster in and out of the market. Therefore, the half-life, the time it takes for the spread to converge back to half its initial distance, of the mean reverting process is investigated by running a linear regression between the spread series and a lagged version of itself. The obtained Beta coefficient is then implemented into the Ornstein-Uhlenbeck process to estimate the half-life.[2] A short half-life would allow market participants to trade quicker in

[2]See (Chan, 2013) for a mathematical derivation.

and out of the market and this will be beneficial for the spread trading strategy. If dislocations between the ETF and the NAV would take over a year to converge, efficient spread trading would be complicated and opportunities to create efficiency would diminish.

To further investigate temporary dislocations between the ETF and its underlying basket, this paper conducts an evaluation on whether the fair value NAV returns and actual returns would give an implication of predictive power. An error-correction model (ECM) fits this purpose and is obtained from the financial time series. This is done by rearranging Eq.(3) to:

$$\varepsilon_t = LN\,(NAV_t) - \ \alpha - \ \beta(LN\,(P_t)) \tag{7}$$

Subsequently, the one period lagged error term of Eq.(7) will be captured and incorporated into:

$$NAVreturn_t = \ \delta_1 Preturn_t + \ \delta_2 \varepsilon_{t-1} + \ \mu_t \tag{8}$$

Where $NAVreturn_t$ is the NAV return, δ_1 is the return coefficient for the ETF, $Preturn_t$ is the ETF return, δ_2 is the coefficient for the lagged error term, ε_{t-1} is the one period lagged error term, μ is the residual. These forecasted errors can be used to compare with the actual performance of the time series.

After concluding that the ETF and the NAV are cointegrated a trading strategy can be set up to trade anomalous behavior in the spread between the ETF and the NAV. Trading signals must be set up regarding when to open and close positions (Caldeira and Moura, 2013). I start by calculating the spread between the NAV and the ETF as $\varepsilon_t = \ P_t^l - \ \gamma P_t^s$, where ε_t is the value of the spread at time t. Subsequently, I calculate a rolling based z-score based on a three-month trading window (63 days) with:[3]

$$Z\,(x_i) = \ \frac{x_i - \bar{x}_i}{s_i} \tag{9}$$

and the moving mean and standard deviation are based on:

$$\bar{x}_i = \ \frac{1}{w} \ \sum_{j=i-w}^{i-1} x_j \tag{10}$$

$$s_i = \ \sqrt{\frac{1}{w} \ \sum_{j=i-w}^{i-1} \ (x_j - \bar{x}_i)^2} \tag{11}$$

A three-month window is used as pricing information and economic factors take some time to be absorbed by the market and higher volatility affects the rolling z-score. In times of higher volatility there would be a higher mean and I want to make sure that the strategy only trades anomalous behavior on a consistent basis. Additionally, a rolling window prevents from having a look-ahead bias or look-back window that can be optimized to fit the data. The signal is

[3] A typical month has 21 trading days.

based on when the z-score is 2 standard deviations below or above its mean. The signals can be summarized as:

$$Buy\ if\ z_t < -2.00$$
$$Sell\ if\ z_t > 2.00$$
$$Close\ if\ z_t < 1.00$$
$$Close\ if\ z_t > -1.00$$

The strategy will be summarized in terms of losing and winning trades, Sharpe ratio etc.

To circumvent the fact that the NAV cannot be traded, I follow the procedure used by Andriosopoulos et al. (2013) to set up a genetic algorithm and attempt to minimize the Root Mean Squared Error (RMSE).[4] I assume data on N ETFs and the pricing of the NAV over an time period [1,2,...,T]. The idea is to replicate the NAV time series as closely as possible for an out of sample period [T+1, T+Δ_t]. Subsequently, I define the tracking error as follows:

$$RMSE = \sqrt{\sum_{t=1}^{T} (r_t - R_t)^2 / T} \tag{12}$$

And the mean excess return is defined as follows:

$$ER = \sum_{t=1}^{T} (r_t - R_t)/T \tag{13}$$

Where r_t is the return of the tracking portfolio and R_t is the return of the NAV time series. The complete formulation to solve the index tracking problem can be expressed as:

Minimize
$$f = \lambda\ x\ RMSE\ - (1-\lambda)\ x\ ER \tag{14}$$

Subject to
$$\sum_{i=1}^{N} P_{it} x_i\ =\ C \tag{15}$$

$$z_i \varepsilon C\ \leqslant P_{it} X_i \leqslant z_i C\ \ \forall i = 1, \ldots, N \tag{16}$$

$$\sum_{i=1}^{N} z_i \leqslant K \tag{17}$$

$$x_i \geqslant 0, z_i \in \{0,1\}\ \ \forall i = 1, \ldots, N \tag{18}$$

[4] I also use the same parameters as Andriosopoulos et al. (2013) for the GE to obtain a good balance between the quality of results and the time it takes to find an optimal solution. Hence, I set the crossover arithmetic to 80%, the tournament size to four and the mutation rate at a 0.5% probability.

Where $0 \leqslant \lambda \leqslant 1$ outlines the tradeoff between excess return and the tracking error. When $\lambda = 1$ the algorithm has as its objective to minimize the tracking error and performs pure index tracking by replicating the target index as closely as possible. When $\lambda = 0$ the algorithm tries to improve the returns of the benchmark, its goal is to maximize the excess return. In this study, I set the λ to 1 to replicate as closely as possible the movement of the targeted NAV. Constraint (15) is the budgetary limitation and it makes sure that for every alternative tracking portfolio the same identical amount C is invested. As the algorithm is implemented with a real-valued solution scheme after normalization (to sum up to 1) the corresponding ETF weights are $(w_1, ..., w_N)$. Constraint (16) shows which ETFs are included in the tracking portfolio $z_i = 1$ and which are not $z_i = 0$. The variable ε puts a lower bound on the proportion of the capital invested in each ETF (in this study I set the parameter to 0.001). Constraint (17) gives a limit on the maximum number of ETFs that will be included in the portfolio that tracks the NAV. In this paper, I use a basket of at maximum 5 ETFs to limit transactions costs. Additionally, I let the algorithm rebalance monthly since Andriosopoulos et al. (2013) found that monthly rebalancing allows for the smallest tracking error.[5]

6 Data

The sample period of this study covers the period from January 2008 up to and including May 2020. Fixed income ETFs are relatively new instruments and not many ETFs are already in existence for more than 15 years. Therefore, I opted to go for the longest period as the data would allow and to use a basket of at minimum 10 ETFs. This period covers periods such as the GFC and the COVID-19 period that both greatly impacted fixed income markets. The required data points are daily ETF closing and NAV closing prices. The NAV of fixed income ETFs is normally determined daily as of the regularly scheduled close of business of the New York Stock Exchange ("NYSE") at 4:00 p.m. EST. The data used in this paper is derived from different sources. The ETF pricing data was obtained from Yahoo Finance, whereas the NAV pricing data was obtained from the different ETF providers. Every day, the ETF providers list the new NAV and keep historical records from the daily NAV since inception. I cleaned the data and removed certain data points from the data presented by the ETF providers as they sometimes included non-trading days. As the study's aim is to only show possibilities to create a more efficient market by setting up trading strategies, only actual trading days are useful for this study.

For the main tests a basket of 14 ETFs with good liquidity and sufficient size was used as these are the most commonly traded instruments by market participants. Only ETFs that have at least total assets of 1B USD were selected. Moreover, I selected ETFs that represent different segments of the fixed income market to investigate potential differences in efficiency. In table Table 1, the 14 ETFs used are listed.

[5] This will be 21 trading days.

Table 1

Major fixed income ETFs

Table 1 shows the basket of the 14 ETFs used in the study that are commonly used by market participants.

Ticker	Segment	Full Name	Total Assets$MM	Inception
AGG	Intermediate Multi-Sector	iShares Core U.S. Aggregate Bond ETF	$72,786.95	Sep 22, 2003
BLV	Long-term	Vanguard Long-Term Bond ETF	$4,736.26	Apr 10, 2007
BND	Intermediate Multi-Sector	Vanguard Total Bond Market ETF	$51,596.18	Apr 10, 2007
BSV	Total Bond Market	Vanguard Short-Term Bond ETF	$22,044.16	Apr 10, 2007
EMB	Emerging Markets	iShares J.P. Morgan USD Emerging Markets Bond ETF	$16,082.93	Dec 17, 2007
HYG	High Yield	iShares iBoxx $ High Yield Corporate Bond ETF	$17,695.21	Apr 11, 2007
JNK	High Yield	SPDR Barclays High Yield Bond ETF	$10,052.19	Nov 28, 2007
LQD	Intermediate Investment Grade	iShares iBoxx $ Investment Grade Corporate Bond ETF	$35,618.15	Jul 26, 2002
MBB	Mortgage backed securities	iShares MBS Bond ETF	$23,299.80	Mar 16, 2007
MUB	Intermediate Municipal	iShares National AMT-Free Muni Bond ETF	$16,202.55	Sep 07, 2007
PCY	Emerging Markets	Invesco Emerging Markets Sovereign Debt ETF	$3,582.55	Oct 11, 2007
SHM	Short Municipal	SPDR Barclays Short Term Municipal Bond	$3,874.91	Oct 10, 2007
TLT	Long U.S. Treasury	iShares 20+ Year Treasury Bond ETF	$19,166.76	Jul 26, 2002
USIG	Investment Grade	iShares Broad USD Investment Grade Corporate Bond ETF	$4,127.84	Jan 11, 2007

As markets with more opaque underlyings show less liquidity during times of distress, ten high yield ETFs were gathered to investigate the discrepancies that can occur. The data covers the period 5-29-2019 until 5-29-2020. Table 2 shows the ten high yield ETFs used to investigate the bigger discrepancies that exist in this market.

Table 2

High yield ETFs

Table 2 shows the basket of ten high yields ETFs used.

Ticker	Segment	Full Name	Total Assets$MM	Inception
ANGL	High yield	VanEck Vectors Fallen Angel High Yield Bond ETF	$2,164.77	Apr 10, 2012
BKLN	High yield	Invesco Senior Loan ETF	$4,079.97	Mar 03, 2011
HYG	High yield	iShares iBoxx $ High Yield Corporate Bond ETF	$17,695.21	Apr 11, 2007
HYLB	High yield	Xtrackers USD High Yield Corporate Bond ETF	$4,820.69	Dec 07, 2016
HYLS	High yield	First Trust Tactical High Yield ETF	$1,717.81	Feb 27, 2013
JNK	High yield	SPDR Barclays High Yield Bond ETF	$10,052.19	Nov 28, 2007
SHYG	High yield	iShares 0-5 Year High Yield Corporate Bond ETF	$4,292.63	Oct 15, 2013
SJNK	High yield	SPDR Barclays Capital Short Term High Yield Bond ETF	$3,188.01	Mar 15, 2012
SRLN	High yield	SPDR Blackstone/ GSO Senior Loan ETF	$1,456.78	Apr 03, 2013
USHY	High yield	iShares Broad USD High Yield Corporate Bond ETF	$5,296.74	Oct 25, 2017

Additionally, this paper contributes to the existing literature by looking at the differences in terms of pricing for bigger and smaller sized fixed income ETFs in terms of assets under management. Therefore, I gathered ten ETFs across different segments that have a small amount of assets under management for the same period as the high yield sample. Table 3 shows the list of ETFs used.

The genetic algorithm uses as an underlying basket five ETFs from Table 1. The genetic algorithm uses a training, validating and testing set and only the testing was used for the spread trading strategy. The total period covered by the genetic algorithm is from 1-2-2008 until 5-25-2020. Only the testing set was used for the actual trading strategy and covers 100 trading days. As the rolling z-score of 63 trading days does not allow for trading for the first 63 days, I used 63 days of the validation set to obtain the moving z-score to enter possible trading on day one of the testing set. This is justified, as the validation set should already perform close to its optimum.

Table 3
Smaller sized ETFs
Table 3 shows the basket of ten smaller sized ETFs used.

Ticker	Segment	Full Name	Total Assets$M	Inception
FHMI	Municipal	First Trust Municipal High Income ETF	$99,303.60	Nov 01, 2017
FSMB	Municipal	First Trust Short Duration Managed Municipal ETF	$48,201.30	Nov 01, 2018
HYDB	High yield	iShares Edge High Yield Defensive Bond ETF	$37,594.45	Jul 11, 2017
IBHC	High yield	iShares iBonds 2023 Term High Yield and Income ETF	$13,798.42	May 07, 2019
IBHE	High yield	iShares iBonds 2025 Term High Yield and Income ETF	$9,349.08	May 07, 2019
IIGV	Investment grade	Invesco Investment Grade Value ETF	$34,920.00	Jul 25, 2018
PBEE	Emerging markets	Invesco PureBetaSM FTSE Emerging Markets ETF	$2,252.27	Sep 22, 2017
PBND	Total bond market	Invesco PureBetaSM US Aggregate Bond ETF	$26,870.02	Sep 29, 2017
RNEM	Emerging markets	First Trust Emerging Markets Equity Select ETF	$8,472.00	Jun 20, 2017
SPHY	High yield	SPDR Portfolio High Yield Bond ETF	$102,176.90	Jun 18, 2012

7 Results

This section discusses the results of the study. Section 7.1 covers the initial tests necessary to set up a trading strategy. Section 7.2 looks at the price discovery process in times of distress. Section 7.3 looks at the ECM and its predictive power over time. Section 7.4 examines the possibilities to set up trading strategies and the results from arbitraging away premiums and discounts over time. Subsequently, Section 7.5 and Section 7.6 investigate the discrepancies that exist within the high yield market and in the market for smaller sized ETFs. Finally, Section 7.7 looks at the performance of a GE in the original spread trading strategy.

7.1 Cointegration and speed of adjustment

To test the hypotheses set it is paramount to make sure that the relationship between the ETF and the NAV is mean reverting and that the spread between the two converges relatively quickly. Table 4 reports the results of these tests. I find that all the ETFs exhibit a cointegrated relationship as the results are highly significant. Cointegration is a necessary feature of a spread trading strategy as the two time series have to mean revert over time around an average. The Engle-Granger test can be complemented with the Hurst exponent. All the fixed income ETFs used in the sample have a relatively small Hurst exponent, which indicates that the ETF price and the NAV mean revert over time. This makes sense from a logical point of view as the NAV is based on bid-prices of the underlying bonds they are inherently correlated to the pricing for the ETF on the exchange. Over time, however, the ETF and the NAV can diverge and for successful arbitrage trading strategies it is important to know how fast the two time series converge. The half-life estimation indicates that for the whole sample, on average, the spread converges in three days to half of its initial value. This is positive for arbitrage trading strategies as it would allow market participants to trade relatively fast in and out of the market.

Table 4

Cointegration and speed of adjustment

Table 4 reports the results of the Engle-Granger, Hurst exponent and Half-life tests. Statistical significance for the Engle-Granger test is based on the MacKinnon statistical values. Significance of the parameters are indicated as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Ticker	Engle-Granger		Hurst exponent	Half-life
	t-value	p-value	0<0.5<1	Days
AGG	-6.51***	0.00***	0.09	3
BLV	-6.82***	0.00***	0.02	2
BND	-5.43***	0.00***	0.01	3
BSV	-6.24***	0.00***	0.15	5
EMB	-8.63***	0.00***	0.05	3
HYG	-7.54***	0.00***	0.08	4
JNK	-6.11***	0.00***	0.05	2
LQD	-6.66***	0.00***	0.10	4
MBB	-6.73***	0.00***	0.04	1
MUB	-6.69***	0.00***	0.12	6
PCY	-5.87***	0.00***	0.13	3
SHM	-7.10***	0.00***	0.02	2
TLT	-11.66***	0.00***	0.01	1
USIG	-5.32***	0.00***	0.08	5

7.2 Price discovery process

Price discovery is most important in times of increased market volatility. As volatility kicks in, one would expect that the ETF gives a proper indication of where the underlying market is heading as it is traded on a liquid exchange. As the underlying bonds are traded OTC, pricing is more opaque and in general the market would move slower as there is less liquidity. Moreover, it could be that the prices that are in the market are not 'real' as it can happen that a bidder would hit the ask but was not be able to trade as the broker removes the offer. Therefore, it is crucial to investigate the explanatory power of the ETF in times of distress. Tucker and Laipply (2013) examined explanatory power of the ETF during the GFC and I ran the same procedure on the recent COVID-19 period (2/1/2020-5/29/2020) to test if this explanatory power still exists. I ran various regressions on the ETF and the lagged NAV time series and vice versa for different ETFs. The results are presented in Table 5. The results strongly suggest that the ETF has significant explanatory power as the average statistics of the NAV regressed on the ETF price are highly significant. The opposite procedure gives only a significant average statistic for the second lag. This makes sense to a certain extent as the NAV has some explanatory power as well. As soon as the underlying market value starts moving in the direction of the ETF, this can act as a confirmation of the predictive power of ETF pricing. There is a process of reflexivity that can accelerate the direction of the movement.

Table 5

Price discovery

Table 5 reports the results of various regressions of the ETF and the lagged NAV time series and vice versa for the period 2/1/2020-5/29/2020. Significance of the parameters are indicated as follows: * t>1.65 t<1.96 , ** t>1.96 t<2.58, *** t>2.58.

Ticker	NAV regressed on ETF price			ETF price regressed on NAV		
	1 day lag	2 day lag	3 day lag	1 day lag	2 day lag	3 day lag
AGG	4.72	-1.72	0.08	0.84	-1.08	-1.71
BLV	3.30	-2.21	-0.48	3.49	-0.88	-1.65
BND	4.40	-2.96	-0.41	1.35	-0.60	-2.15
BSV	1.85	0.47	2.84	2.62	0.78	-2.81
CWB	-0.99	4.29	0.54	-0.04	2.81	2.22
EMB	4.36	1.38	4.52	-0.76	2.04	0.06
HYG	3.33	3.55	2.36	0.23	3.35	-0.18
HYLB	3.68	3.58	2.15	0.39	3.60	0.10
JNK	4.41	3.59	2.53	0.82	3.43	-0.02
LQD	7.52	2.69	1.81	3.13	1.19	-2.35
MBB	3.98	-2.64	-5.58	2.06	-1.64	-2.81
MUB	8.52	3.92	0.44	2.41	-0.24	-3.11
PCY	3.89	1.64	4.64	-0.95	2.00	0.38
SHM	10.73	3.86	1.94	2.56	0.42	-2.50
SHYG	3.37	3.34	3.06	0.02	3.68	0.01
TLT	1.92	-2.85	-1.28	0.22	-4.50	-1.28
USIG	8.33	3.62	3.16	3.36	0.98	-1.97
Average ABS T-stats	4.66***	2.84***	2.22**	1.49	1.95*	1.49

7.3 Error correction model

This section covers the results of the ECM. The results are presented in Table 6. The ECM can be used to identify temporary dislocations between the ETF and the underlying NAV. A fair value for the NAV could be determined and compared to the actual changes. The model incorporates both long-term and short-term information. State Street's fixed income ETF JNK experienced big price dislocations during the second week of March 2020 (03-09-2020 03-13-2020). The ECM could give a fair estimation on what the underlying price movement should be. I used the parameters from the ECM to 'predict' the NAV return the following day in the second part of Table 6. The differences between the predicted and actual return varied widely. An error of -0.30% is relatively small but some of the errors went up to 2%. The remaining series showed similar movements. There are numerous plausible explanations for this. Ideally, the relationship changes are due to information convergence. However, in volatile periods, other factors play an important role as well: bid-offer spreads, liquidity in the underlying market and risk adjustment uncertainty (see section 3.1). These factors could obscure the information convergence. Although the ETF has explanatory power as to where the underlying market is heading, predicting actual daily returns is impractical.

Table 6
Error correction model

Table 6 reports the parameters of the ECM over the period 1-2-2008 up to and including 5-29-2020. The second part predicts the underlying NAV return of the JNK ETF for the second week of March 2020.

	α	β	SE	Adj. R^2
AGG	0.53	-0.15	0.01	0.53
BLV	0.91	-0.30	0.01	0.86
BND	0.62	-0.19	0.01	0.63
BSV	0.39	-0.05	0.01	0.38
EMB	0.46	-0.12	0.01	0.45
HYG	0.29	-0.17	0.01	0.43
JNK	0.39	-0.18	0.01	0.49
LQD	0.43	-0.19	0.01	0.49
MBB	0.75	-0.44	0.01	0.73
MUB	0.42	-0.12	0.01	0.49
PCY	0.23	-0.10	0.01	0.34
SHM	0.14	-0.11	0.01	0.21
TLT	0.93	-0.78	0.02	0.93
USIG	0.44	-0.18	0.01	0.46

Date	NAV	ETF	Predicted NAV return	Actual NAV return	Error
9/3/20	102.06	100.72	-1.83%	-3.43%	-1.60%
10/3/20	102.23	102.41	0.92%	0.17%	-0.75%
11/3/20	101.03	100.15	-0.88%	-1.18%	-0.30%
12/3/20	97.62	96.09	-1.43%	-3.37%	-1.94%
13/3/20	97.84	99.18	1.55%	0.22%	-1.33%

7.4 Spread trading strategy

This section covers the spread trading strategy results for the initial basket of 14 ETFs that are highly liquid and most commonly used by market participants. As the strategy is based on a rolling based z-score, the strategy enters trades as soon as the spread of the ETF and NAV is two standard deviations away from its average. For one, this gives opportunity to trade anomalous behavior and trade away dislocations in terms of premiums and discounts. Yet, potential profits also show the efficiency of the underlying market. If a lot of profit could be captured, it holds that there are more dislocations that could be traded away and this means that the market is less efficient in terms of pricing. Table 7 shows the results of the trading strategy for the period 2-1-2008 5-29-2020. This period captures different periods that included increased market volatility. For all 14 ETFs positive results could have been captured. Especially for the more opaque underlying markets e.g. high yield and emerging market ETFs there are more dislocations between the ETF pricing in the market and the underlying NAV. Over the whole period, the high yield ETF HYG would have delivered an annualized return of 10.22% after fees. If one would have invested 100 USD at the beginning of the period this would have accumulated into 334 USD.

Table 7

Spread trading

Table 7 reports the results of the spread trading strategy over the period 2-1-2008 5-29-2020. Where each abbreviation in the first row represents the ticker of that specific fixed income ETF. The spread trading results are presented with and without trading fees included (5bps). Additionally, annual returns for the NAV and the ETF are presented. However, these returns do not include distributions in the form of dividends. Total returns for an investor that did hold the ETF directly should therefore have been higher.

	AGG	BLV	BND	BSV	EMB	HYG	JNK	LQD	MBB	MUB	PCY	SHM	TLT	USIG
Spread trading strategy														
Annualized Return	2.08%	5.25%	2.05%	0.93%	7.35%	11.22%	11.34%	6.35%	1.89%	3.37%	11.29%	2.65%	7.31%	4.47%
Standard deviation	3.00%	2.79%	2.67%	1.61%	5.31%	6.74%	5.88%	4.73%	1.62%	3.24%	8.71%	3.02%	2.56%	4.81%
Sharpe ratio (Rf=0%)	0.69	1.88	0.77	0.58	1.38	1.66	1.93	1.34	1.17	1.04	1.30	0.88	2.86	0.93
Highest return	3.84%	4.58%	4.79%	2.76%	11.27%	12.11%	11.07%	9.62%	3.41%	3.42%	16.58%	6.28%	4.02%	7.96%
Lowest return	-6.33%	-2.30%	-4.44%	-2.88%	-3.75%	-5.30%	-4.07%	-2.81%	-2.82%	-5.19%	-6.78%	-3.62%	-0.78%	-8.41%
Spread trading strategy (trading fee 5bps)														
Annualized Return	1.15%	4.10%	0.99%	0.11%	6.36%	10.22%	10.24%	5.33%	0.92%	2.48%	10.36%	1.72%	6.17%	3.59%
Standard deviation	2.99%	2.77%	2.67%	1.62%	5.29%	6.71%	5.85%	4.70%	1.60%	3.24%	8.69%	3.00%	2.46%	4.80%
Sharpe ratio (Rf=0%)	0.39	1.48	0.37	0.07	1.20	1.52	1.75	1.13	0.57	0.77	1.19	0.57	2.51	0.75
Highest return	3.79%	4.53%	4.74%	2.71%	11.22%	12.06%	11.02%	9.57%	3.36%	3.37%	16.53%	6.23%	3.97%	7.91%
Lowest return	-6.38%	-2.35%	-4.49%	-2.93%	-3.80%	-5.35%	-4.12%	-2.86%	-2.87%	-5.24%	-6.83%	-3.67%	-0.83%	-8.46%
Annual Returns														
NAV	1.18%	2.84%	1.04%	0.57%	0.34%	-1.49%	-2.61%	1.80%	0.69%	1.01%	0.09%	0.74%	4.55%	1.33%
ETF	1.19%	2.86%	1.04%	0.57%	0.38%	-1.51%	-2.74%	1.78%	0.66%	0.96%	-0.11%	0.73%	4.54%	1.31%

The strategy incorporates a 5 basis points (bps) trading fee per trade to punish the results for costs that have to be made in terms of commission fees as well as slippage because of bid-ask spreads. After adjusting for fees double digit returns could be made in ETFs that have more opaque underlying markets. BSV covers the whole bond market and expresses strong efficiency in terms of ETF and NAV pricing. Only small profits could have been captured over the whole period, 0,93% and 0,11% after fees, which reveals an efficient ETF in terms of pricing. Fixed income ETFs that have more opaque constituents e.g. high yield and emerging markets exhibit less efficiency in terms of pricing.

7.5 Spread trading strategy for high yield ETFs

The previous section demonstrated that ETFs that cover more opaque underlying markets show a greater amount of dislocations over time. This is especially the case during distressed times when there is increased volatility. Therefore, I gathered a basket of ten high yield ETFs to further investigate the dislocations that happen in this market. The period covered for the strategy is the one year period 5-29-2019 5-29-2020 that includes the COVID-19 effects on the market. As can be seen in Table 8, the results further support that ETFs that cover opaque underlying markets reveal greater amounts of dislocations. For all the ETFs covered, double digit arbitrage returns could have been made over a one year period. Adjusting for fees and slippage, the average results are still close to or above 10% for a one year period.

Table 8

Spread trading for the high yield basket

Table 8 reports the results of the spread trading strategy over the period 5-29-2019 5-29-2020 for the basket of ten high yield ETFs. Where each abbreviation in the first row represents the ticker of that specific fixed income ETF. The spread trading results are presented with and without trading fees included (5bps). Additionally, annual returns for the NAV and the ETF are presented. However, these returns do not include distributions in the form of dividends. Total returns for an investor that did hold the ETF directly should therefore have been higher.

	ANGL	BKLN	HYG	HYLB	HYLS	JNK	SHYG	SJNK	SRLN	USHY
Spread trading strategy										
Annualized Return	10.14%	11.70%	13.65%	18.58%	19.13%	18.32%	11.91%	10.36%	12.51%	18.68%
Standard deviation	10.30%	6.49%	4.61%	5.72%	5.83%	6.22%	5.41%	5.94%	7.80%	5.82%
Sharpe ratio (Rf=0%)	0.98	1.80	2.96	3.25	3.28	2.94	2.20	1.74	1.60	3.21
Highest return	5.28%	3.43%	2.41%	3.25%	3.53%	3.02%	2.53%	2.49%	3.50%	2.61%
Lowest return	-5.47%	-2.43%	-0.68%	-0.57%	-0.49%	-0.81%	-2.67%	-3.16%	-2.13%	-0.58%
Spread trading strategy (trading fee 5bps)										
Annualized Return	9.38%	10.82%	12.47%	16.89%	17.38%	17.15%	10.64%	9.22%	11.49%	16.81%
Standard deviation	10.29%	6.45%	4.57%	5.67%	5.74%	6.18%	5.42%	5.95%	7.77%	5.78%
Sharpe ratio (Rf=0%)	0.91	1.68	2.73	2.98	3.03	2.78	1.96	1.55	1.48	2.91
Highest return	5.23%	3.38%	2.36%	3.20%	3.48%	2.97%	2.48%	2.44%	3.45%	2.56%
Lowest return	-5.52%	-2.48%	-0.73%	-0.62%	-0.54%	-0.86%	-2.72%	-3.21%	-2.18%	-0.63%
Annual Returns										
NAV	-2.30%	-5.89%	-4.21%	-4.85%	-3.27%	-4.81%	-7.59%	-7.27%	-5.82%	-5.28%
ETF	-1.25%	-5.73%	-3.40%	-4.31%	-2.98%	-4.40%	-6.99%	-6.78%	-6.54%	-5.04%

7.6 Spread trading strategy for smaller sized ETFs

Table 9 shows the trading strategy for the one year period 5-29-2019 5-29-2020 using a basket of smaller sized ETFs. The results show dislocations of extremer size for less liquid fixed income ETFs. For example, over a one year period the IBHE ETF shows the possibility for arbitrage returns of 40%. This indicates an inefficient market in terms of pricing. Additionally, some other smaller sized ETFs show greater dislocations as well. Nevertheless, as in previous results, if the underlying market is transparent and efficient the dislocations are smaller in size. For example, the IIGV ETF, that covers the investment grade market, shows only smaller sized opportunities for arbitrage.

Table 9

Spread trading for the smaller sized ETF basket

Table 9 reports the results of the spread trading strategy over the period 5-29-2019 5-29-2020 for the basket of ten smaller sized fixed income ETFs. Where each abbreviation in the first row represents the ticker of that specific fixed income ETF. The spread trading results are presented with and without trading fees included (5bps). Additionally, annual returns for the NAV and the ETF are presented. However, these returns do not include distributions in the form of dividends. Total returns for an investor that did hold the ETF directly should therefore have been higher.

	FHMI	FSMB	HYDB	IBHC	IBHE	IIGV	PBEE	PBND	RNEM	SPHY
Spread trading strategy										
Annualized Return	10.73%	5.88%	8.42%	24.32%	40.60%	2.91%	22.44%	3.20%	38.43%	16.73%
Standard deviation	5.86%	2.62%	3.54%	7.93%	19.75%	9.52%	5.92%	1.57%	14.23%	6.03%
Sharpe ratio (Rf=0%)	1.83	2.24	2.38	3.07	2.06	0.31	3.79	2.04	2.70	2.78
Highest return	3.85%	2.06%	2.51%	4.50%	16.01%	5.28%	2.89%	0.92%	9.57%	3.20%
Lowest return	-2.02%	-0.19%	-0.31%	-0.51%	-2.45%	-6.19%	-0.15%	-0.39%	-0.12%	-1.05%
Spread trading strategy (trading fee 5bps)										
Annualized Return	9.69%	48.30%	7.62%	22.43%	39.15%	2.10%	21.12%	1.88%	37.14%	15.24%
Standard deviation	5.83%	2.56%	3.45%	7.85%	19.71%	9.51%	5.81%	1.53%	14.16%	5.95%
Sharpe ratio (Rf=0%)	1.66	1.89	2.21	2.86	1.99	0.22	3.63	1.22	2.62	2.56
Highest return	3.80%	2.01%	2.46%	4.45%	15.96%	5.23%	2.84%	0.87%	9.52%	3.15%
Lowest return	-2.07%	-0.24%	-0.36%	-0.56%	-2.50%	-6.24%	-0.20%	-0.44%	-0.17%	-1.10%
Annual Returns										
NAV	-5.42%	-0.10%	-3.90%	-7.34%	-5.03%	4.81%	-7.76%	7.12%	-17.68%	-5.73%
ETF	-5.92%	-0.26%	-4.29%	-7.14%	-5.04%	5.27%	-7.47%	7.60%	-18.43%	-5.05%

7.7 Spread trading using a genetic algorithm

The results from previous sections are promising for market participants who are able to trade in these markets. However, the biggest issue in capturing these potential profits is the fact that, as previously discussed, the NAV cannot be traded as a single instrument. The proposed GE offers opportunities to target the NAV time series with a basket of five other ETFs. Although this replication will never exactly replicate the movement of the NAV, results are promising. In practice, one would ideally source from a great amount of ETFs to replicate. In Table 10, I summarized the results using a GE to replicate the NAV time series of two high yield ETFs that showed potential to capture arbitrage profits in section 7.5. In the Appendix, the replication and return distribution plus the cointegration and speed of adjustment tests are presented. The strategy incorporates an additional 10bps trading fee per trade to account for the fact that more instruments must be bought and sold in the market. The last line in the table shows the results from section 7.4 using a trading fee of 5bps. Incorporating the newly obtained time series from the GE in the original trading strategy, plus adding an additional 10bps trading fee, would give opportunity to capture a part of the potential profit that could have been obtained if the NAV would have been tradable. The tracking errors are relatively small (0.06-0.07) but could be improved if the algorithm would source from a greater number of ETFs to find the perfect fit. The current strategy only uses the initial 14 ETFs to source from. Furthermore, large institutions could source some of the underlying bonds of ETFs to replicate the NAV time series from that specific ETF as they have broader access to the underlying market. This would further improve the tracking error and subsequently the trading results. Nevertheless, using replicating portfolio theory in spread trading strategies shows substantial possibilities to capture profits in the fixed income ETF market and make the market more efficient.

Table 10

Spread trading using a GE to replicate the NAV

Table ten reports the results of the spread trading strategy using a GE over the period 1-7-2020 5-29-2020. Both the NAV of the HYG and JNK ETF are replicated and a trading fee of 15bps is implemented.

	HYG	JNK
Basket of ETFs used		
1	BLV	BSV
2	CWB	CWB
3	EMB	EMB
4	JNK	HYG
5	SHM	SHM
RMSE	0.06	0.07
Spread trading strategy		
Return	4.28%	5.76%
Standard deviation	5.19%	2.88%
Sharpe ratio (Rf=0%)	0.82	2.00
Highest return	4.08%	1.96%
Lowest return	-1.72%	-1.05%
Spread trading strategy (trading fee 15bps)		
Return	3.35%	4.50%
Standard deviation	5.20%	2.92%
Sharpe ratio (Rf=0%)	0.64	1.54
Highest return	3.93%	1.81%
Lowest return	-1.87%	-1.20%
Tradable NAV (trading fee 5 bps)	10.12%	15.06%

8 Conclusion

This paper investigates the price discovery process and potential arbitrage trading strategies for fixed income ETFs. During times of increased volatility, liquidity tends to dry up in the underlying OTC market. This subsequently leads to increased premiums and discounts. However, as the ETF is traded on the exchange and shows more liquidity it gives good inferences of the strength of the underlying assets. Hence, fixed income ETFs have explanatory power as to where the underlying bond market is heading.

Additionally, the study shows that there can exist discrepancies in terms of pricing for fixed income ETFs. By setting up an arbitrage trading strategy based on spread trading between the ETF and the NAV, I show that some ETFs give opportunity to profitable arbitrage trading strategies. The fact that profitable arbitrage trading strategies can be obtained, indicates that the fixed income ETF market could be improved in terms of efficient pricing.

Moreover, the paper shows that fixed income ETFs that have opaque and less transparent underlying markets e.g. high yield and emerging market ETFs and fixed income ETFs that have a smaller amount of assets under management can show increased dislocations in terms of pricing during times of distress.

The biggest obstacle that prevents efficient pricing is the fact that the NAV of fixed income ETFs cannot be traded. This paper reveals that with replicating portfolio theory these complications can be overcome. The paper shows that alternative liquidity providers could use genetic algorithms to capture part of the potential arbitrage profits. These results could be further improved with more sophisticated algorithms. Moreover, large institutions should be able to source part of the underlying in order to replicate the NAV. This should further improve the possibilities to set up profitable arbitrage strategies and create a more efficient fixed income ETF market in the process.

Appendix A Cointegration and speed of adjustment plus GE replication

Table 11
Cointegration and speed of adjustment with replicated time series

Table 11 reports the results of the Engle-Granger, Hurst exponent and Half-life tests for the replicated NAV time series in the original spread trading strategy. Statistical significance for the Engle-Granger test is based on the MacKinnon statistical values. Significance of the parameters are indicated as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Ticker	Engle-Granger		Hurst exponent	Half-life
	t-value	p-value	0<0.5<1	Days
HYG	-4.31***	0.00***	0.04	4
JNK	-3.18**	0.02**	0.13	21

Figure 1
Return distribution HYG NAV and HYG replicated NAV

Figure 1 gives a visual interpretation of the HYG NAV and its replicated NAV time series.

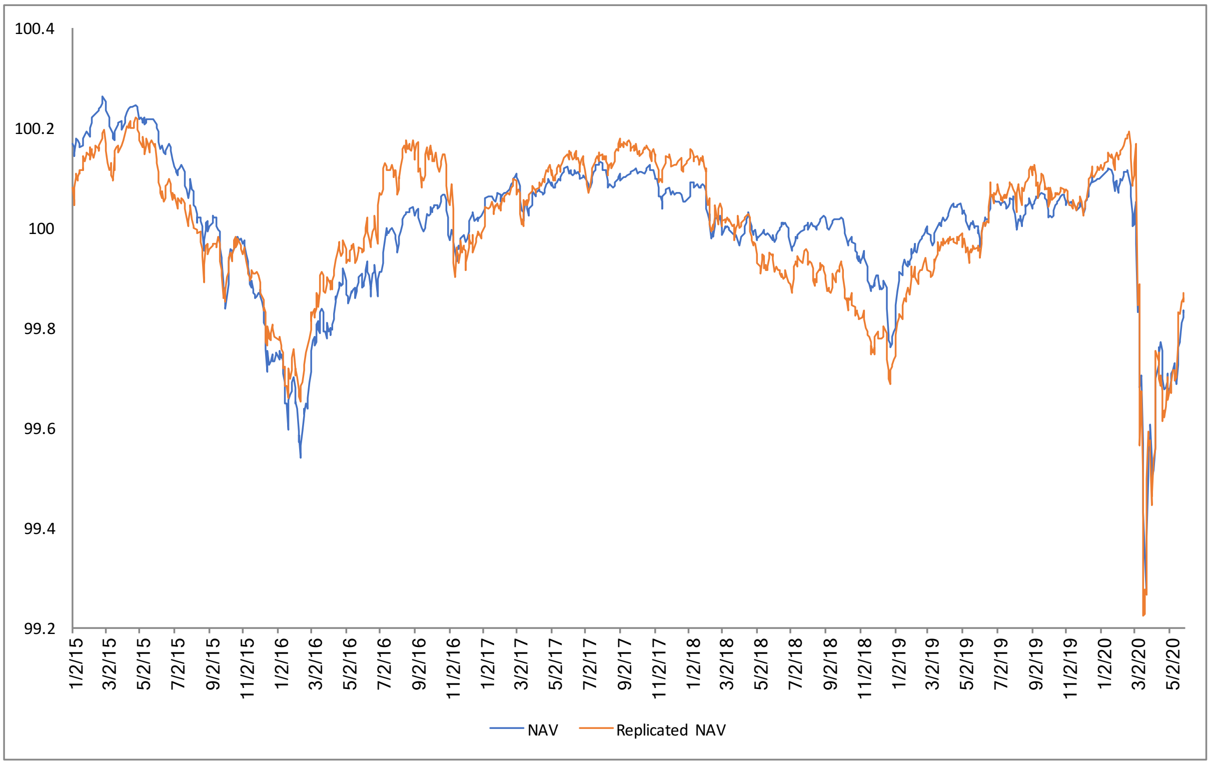
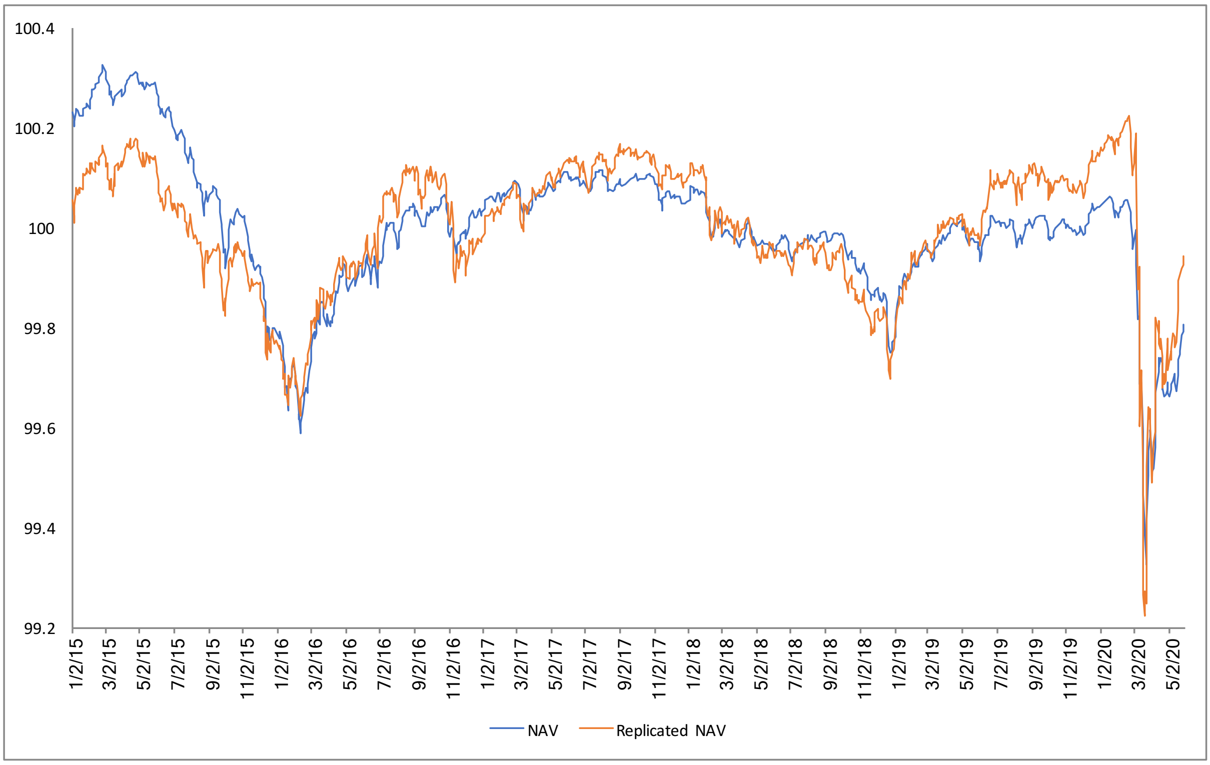


Figure 2

Return distribution JNK NAV and JNK replicated NAV

Figure 2 gives a visual interpretation of the JNK NAV and its replicated NAV time series.



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