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INTEREST RATES SENSITIVITY ARBITRAGE – THEORY AND PRACTICAL ASSESMENT FOR FINANCIAL MARKET TRADING

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Abstract. *Purpose* – Nowadays popular algorithmic trading uses many strategies which are algoritmizable and promise profitability. This research assess if it is possible successfully use interest rates sensitivity arbitrage in bond portfolio (also known as convexity arbitrage) in financial praxis. This arbitrage is sparsely described in literature and an assessment about its practical success is missing.

Research methodology – Methodology steps: mathematical definition of given arbitrage; construction of sufficient portfolio; backtesting on USD zero-coupon curves. Portfolio of two bonds is constructed (theoretically and practically) to have the same Macaulay duration and price, but a different convexity at certain YTM point. Therefore, being long the first bond while shorting the second (of higher convexity) would result in a market-directional bet for parallel zero-coupon yield curve shifts.

Findings – To construct practically the portfolio which is sufficient for the convexity arbitrage could be unrealistic on markets with low liquidity; the presumptions necessary to practically succeed are not fulfilled enough to ensure the arbitrage is profitable.

Research limitations – The backtesting is limited to USD market, testing other markets is recommended, but different result is not expected.

Practical implications – The research helps practitioners considering this strategy for its implementation to algorithmic trading.

Originality/Value – New important results for financial practitioners; states that practical and profitable utilization of convexity arbitrage is unrealizable and save costs during implementation of the strategy.

Keywords: convexity arbitrage, interest rate sensitivity, Macaulay duration, convexity, bond portfolio.

JEL Classification: G1, G10, G12, G14.

Introduction

Interest rates sensitivity arbitrage in bond portfolio is also known as convexity arbitrage and it has already been mentioned in financial literature (Questa, 1999), but an assessment of its practical implementation and possible practical success of this speculative technique is missing.

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Let's use the term "convexity arbitrage" in the following text.

The main contribution of this financial engineering research is to answer the question if convexity arbitrage is suitable for financial praxis? In this research we try to construct (theoretically and also practically) the portfolio which is sufficient for this type of arbitrage and moreover we do backtesting of such speculative approach using real liquid financial market – development of USD interest rate zero-coupon curves. The backtesting is needful to assess if the presumptions necessary for successful functionality are practically fulfilled enough to ensure that convexity arbitrage is profitable strategy for financial praxis. To clarify the aim of the study we explicitly formulate 2 hypotheses. Hypothesis 1: It is possible practically construct the portfolio sufficient for convexity arbitrage. Hypothesis 2: Convexity arbitrage strategy, using sufficient portfolio, provides positive payoffs (in average) in financial practice.

Briefly, in the other words: The purpose of this study is to asses, if practical utilization of convexity arbitrage is possible, and what kind of results we may expect.

We also provide in the text certain examples for better explanation of the strategy for financial practitioners. The research also trails the aim to be thinking provoking.

This research is a typical financial engineering one as it fulfils the definition: "Financial engineering is a multidisciplinary field involving financial theory, methods of engineering, tools of mathematics and the practice of programming".

Convexity arbitrage belongs to statistical arbitrages and from our point of view it should be defined as the arbitrage between two interest rates sensitive prices, where the first price is a market price and the second one is a certain price which we expect in the future based on certain statistical calculations. It provides a positive expected excess return and an acceptably small potential loss. In the literature review we go back to the development of statistical arbitrage concept.

1. Literature review

The concept of arbitrage is one of the fundamentals in financial literature and has already been used in classical analysis of market efficiency (Fama, 1969; Ross, 1976), whereby arbitrage opportunities were quickly exploited by speculators. However, pure arbitrage (defined as profit taking using two different market prices of an asset at one time) opportunities are unlikely to exist in a real trading environment (Shleifer & Vishny, 1997; Alsayed & McGroarty, 2014).

It is commonly accepted that statistical arbitrage (not the pure one) started with Nunzio Tartagliaho, in the mid-1980s, assembled a team of quantitative analysts at Morgan Stanley to uncover statistical mispricing in equity markets (Gatev et al., 2006). While the definition of pure arbitrage is clear, the definition of statistical arbitrage is more complicated. Common definition of arbitrage as a zero-cost (term "zero-cost" strategy means a trading or financial decision without any expense to execute; the zero-cost strategy costs a business or individual nothing while improving operations, making processes more efficient, or serving to reduce future expenses) trading strategy with positive expected payoff and no possibility of a loss is acceptable for pure arbitrage, but it is too strict for statistical arbitrage. Connor and Lasarte (2003) use the probability of certain loss in definition of statistical arbitrage as a zero-cost portfolio where the probability of a loss is very small but not exactly zero, or in other words, statistical arbitrage strategy is a relative value strategy with a positive expected excess return and an acceptably small potential loss. Hogan et al. (2004) provide an alternative definition of statistical arbitrage, which focuses on long horizon trading opportunities. Hogan's statistical arbitrage is a long-horizon trading opportunity that, at the limit, generates a risk-less profit. According to this definition, statistical arbitrage satisfies four conditions: It is a zero-cost, self-financing strategy; it has in the limit positive expected discounted payoff; probability of a loss is converging to zero; time averaged variance converging to zero if the probability of a loss does not become zero in finite time. The last condition is applied only when there exists a positive probability of losing money.

Saks and Maringer (2008) – statistical arbitrage accepts negative payoffs as long as the expected positive payoffs are high enough, and the probability of losses is small enough. Stefanini (2006) uses the expected value while states that statistical arbitrage seeks to capture imbalances in expected value of financial instruments, while trying to be market neutral. Focardi, Fabozzi, and Mitov (2016) focus on uncorrelated returns reporting that statistical arbitrage strategies aim to produce positive, low-volatility returns that are uncorrelated with market returns.

All the definitions mentioned above use profit/loss assessment, but the strategies itself could be based on different principles. In case of trading of pairs (one of the most popular strategy), we do simultaneous opening of long and short positions in each of two assets (portfolios) and utilization of mean reversion behavior of ratio of prices to be profitable (Gatarek et al., 2014; Alexander & Dimitriu, 2005; Nath, 2006). However, not all strategies need mean reversion but need a persistent positive spread-carry. Volatility arbitrage identifies relative value opportunities between volatilities. Swap spread plays a fixed spread versus a floating spread; mortgage arbitrage models the spread of mortgage-backed security over treasury. Capital structure arbitrage profits from the spread between various instruments of the same company. If spreads narrow, these strategies are less profitable and can turn into a loss. In addition, not all strategies are zero-cost. Among others statistical arbitrages, we should mention term structure models utilizing the spread between yields or future prices.

Other important research in the area of statistical arbitrage was done by Pole (2007), Montana (2009), Burgess (2000), Avellaneda and Lee (2008), Thomaidis et al. (2006), Zapart (2003), Hillier, Draper, and Faff (2006), Janda, Rausser, and Svarovska (2014), Cui, Qian, Taylor, and Zhu (2019). Technological developments in computational modelling have also facilitated the use of statistical arbitrage in high frequency trading and with the so-called machine learning methods, such as neural networks and genetic algorithms (Ortega & Khashanah, 2014; Brogaard et al., 2014; Chaboud et al., 2014; also Mahmoodzadeh et al., 2019). In more recent years, statistical arbitrage has seen renewed interest in emerging areas such as bitcoin Payne & Tresl, 2015; Brandvold et al., 2015; Lintilhac & Tourin, 2016), big data (McAfee et al., 2012; Lazer et al., 2014; Nardo et al., 2016) and factor investing (Maeso & Martellini, 2017). Algorithmic trading is now responsible for more than 70 percent of the trading volume in the US markets (Hendershott et al., 2011; Nuti et al., 2011). Birke and Pilz (2009) used non-arbitrage approach using convexity for their contribution to the field of financial options. More relevant literature, from our point of view, namely about convexity arbitrage is not available (in WOS, Scopus and other scientific databases), instead of Questa (1999).

2. Methodology of empirical research

2.1. Theoretical background

The point is to construct a portfolio with the same yield and Macaulay duration of another portfolio, but with a higher convexity. Being long portfolio 1 while shorting portfolio 2 means that first portfolio should always outperform the second one whenever there is a change in yield to maturity (YTM) from the point of touch of Price/YTM curves. Example of such chart is in the Figure 1 where the point of touch is at $YTM = 3.5\%$.

Let us make an example of convexity arbitrage strategy to clearly explain its concept. We assume the ideal case when YTM develops for the portfolio 1 and the portfolio 2 in the same way (shifts of the same value and direction). Price/YTM chart of each of our two portfolios is in the Figure 1. Arbitrage portfolio consists of 2 portfolios:

- Portfolio 1 (thick line in the Figure 1) is represented by one typical coupon bond of 30 years to maturity; fixed coupon = 5.5; face value = 100.
- Portfolio 2 (thin line in the Figure 1) is represented by theoretical (artificial) bond defined by price formula: $P(YTM) = -23.2\ YTM + 217$.

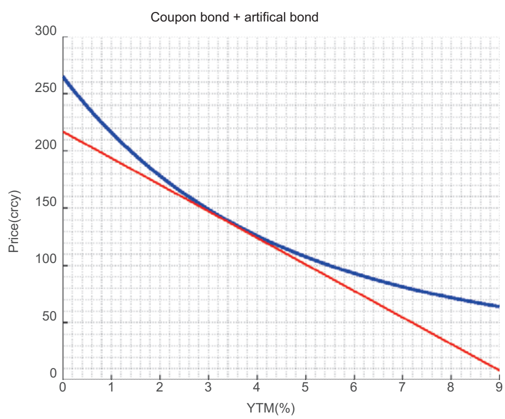


Figure 1. Situation for convexity arbitrage on 2 portfolios

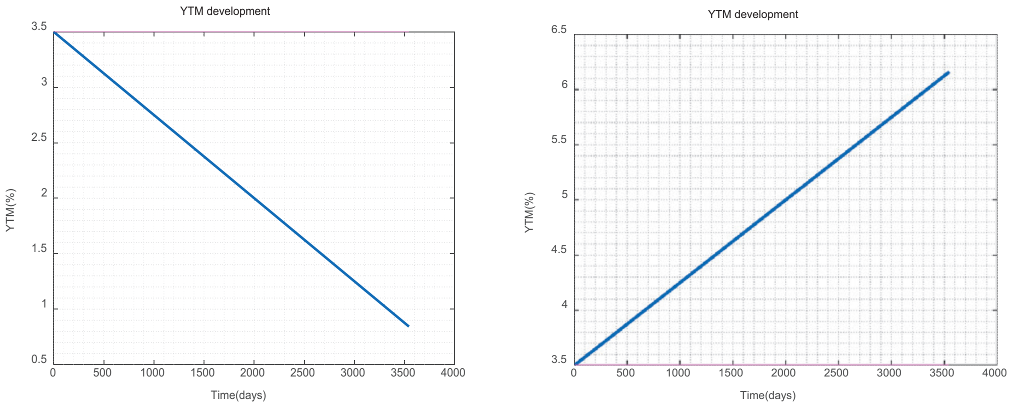
The values are certain amounts of currency, price at $YTM = 3.5\%$ is the same for portfolio 1 and portfolio 2. Let's denote this point as "point of touch".

YTM development (Figure 2) considers 2 separated cases described by formula (1) and (2):

$$YTM\ (t) = -t + 3; \tag{1}$$

$$YTM\ (t) = t + 3.5. \tag{2}$$

Inirially, it moves from $YTM = 3.5\%$ downward (Figure 2a) and then from this point upward (Figure 2b).



a) b)

Figure 2. Artificial development of YTM

In the Figure 3a, 3c we observe that in the case of downside movement of YTM from 3.5% (according to the Figure 2a), the profit which arises from the portfolio 1(thick line) is always higher than the loss on portfolio 2 (thin line). In the Figure 3a we observe cumulative profit and loss on portfolio 1 and portfolio 2. In the Figure 3c we see absolute value of both cumulative profits. We use absolute values for better visual comparison. And finally, the Figure 3e represents the sum of both cumulative P/L, which is of positive value. Analogically if YTM is moving from 3.5% upside (according to the Figure 2b), the profit arising from the portfolio 2 is always higher than the loss on portfolio 1. The subfigures 3b, 3d, 3f represent cumulative profit/loss on portfolio 1 and portfolio 2 (3b), absolute value of P/L (3d), for better comparison and finally cumulative P/L (3f) of the whole strategy.

We may formulate presumptions necessary for successful functionality of this strategy:

1. YTM performs shifts of the same value and the direction for both portfolios. In this case the convexity arbitrage could be considered to be risk-free and profitable strategy where we expect positive pay-off and zero loss.
2. If the opening of long and short positions is done at the point of touch and YTM keep moving downward or upward from YTM the cumulative P/L is always positive, irrespective the direction. If YTM moves away from the touch point the P/L increases. Analogically if YTM moves toward the touch point the P/L decreases.

The serious limitation of this strategy is that it will expose the investor to losses when there are nonparallel YTM shifts. The case of non-parallel shifts is quite common and for valuable assessment, if presumption of parallel YTM shifts (mentioned above) is fulfilled enough to ensure convexity arbitrage be profitable strategy in praxis, we have to make certain quantitative backtesting.

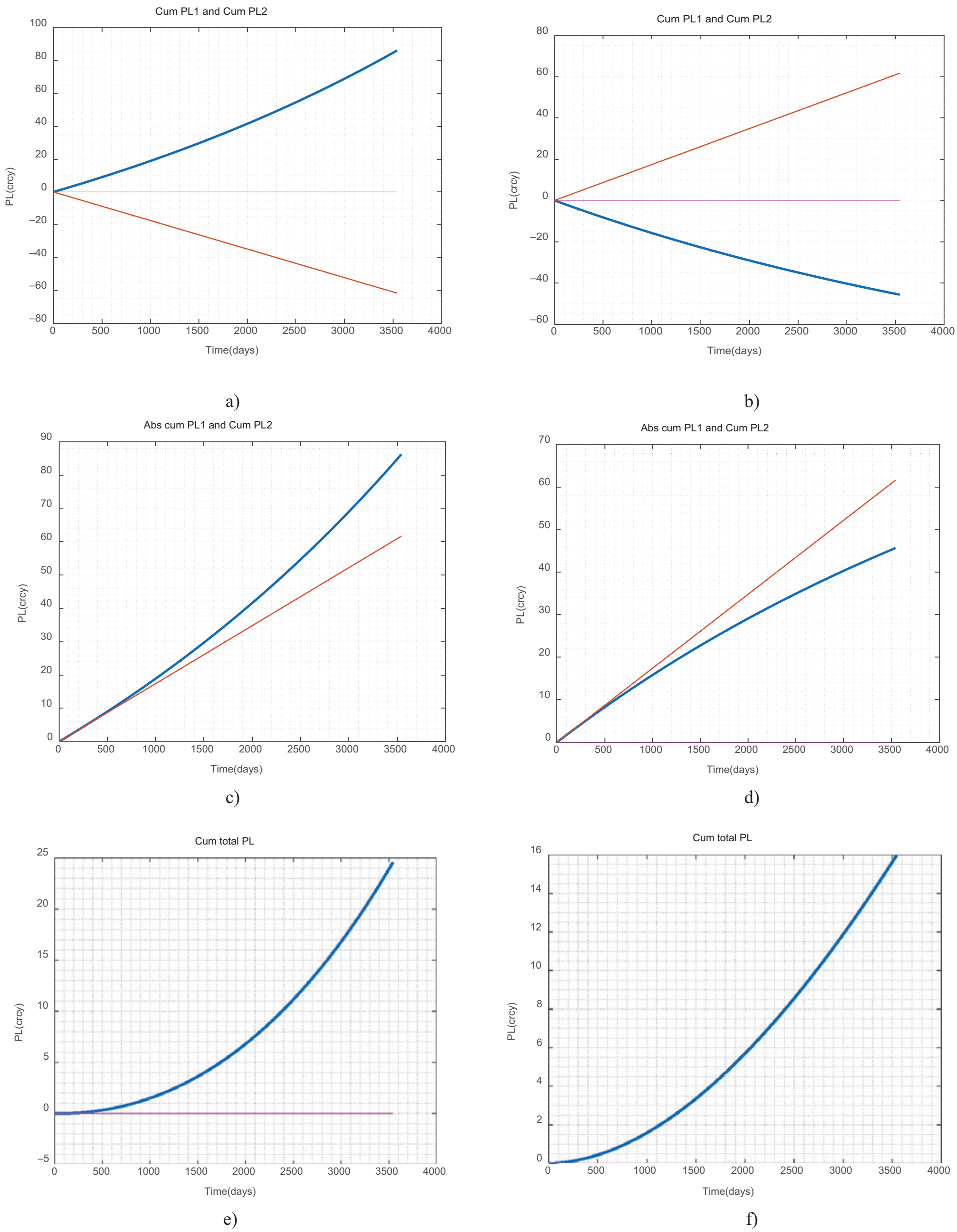


Figure 3. P/L development of convexity arbitrage portfolio

2.2. Methodological steps

Methodology could be divided into the following steps:

3. Mathematical definition of convexity arbitrage conditions for realization.
4. Construction of sufficient portfolio (theoretically and practically).
5. Backtesting on USD zero-coupon curves, backtesting is implemented in Matlab programming environment, data about zero-coupon curves are taken from Reuters (2001–2019, 4900 days), Figure 5.

We assume the bonds in the portfolio to be CMT (Constant Maturity Time) bonds.

Mathematical definition of convexity arbitrage situation:

$$P_1(YTM_A) = P_2(YTM_A); \tag{3}$$

$$P'_1(YTM_A) = P'_2(YTM_A); \tag{4}$$

$$convex_1 > convex_2, \tag{5}$$

where P_1 (YTM_A) is price of portfolio 1 at point A (point of touch) of YTM axis; P_2 (YTM_A) is price of portfolio 2 at point A of YTM axis, P'_1 and P'_2 are the first derivatives of portfolio 1 and portfolio 2 at point A of YTM axis; $convex_1$ and $convex_2$ is values of convexity of portfolio 1 and portfolio 2 at point A of YTM axis; A is the point on YTM axis of touching of P/YTM curves for portfolio 1 and 2 in the Figure 1.

Note that if the first derivatives have the same value at the same price and YTM, the values of Macaulay durations are the same as well.

3. Results

3.1. Construction of portfolio

The analytical solution of the set of Eqs (3), (4), and (5) deals with the equations of order higher than 5 in case of longer maturities, thus we have to deal with numerical solving. From the solutions we choose one, where the value of point of touch equals approximately the mean of YTM, which results from zero-coupon curves in the Figure 5, and we expect movements to both sides of this point: Such solution is the most appropriate for back-testing (according to Theoretical Background chapter).

Solution used for the backtesting:

- Portfolio 1 is basically portfolio of two zero-coupon bonds:
  - l year maturity zero bond, price at 7% = 51.72; face value = 55.34
  - 30 years maturity bond, price at 7% = 48.28; face value = 367.49
- Portfolio 2 is zero-coupon bond: 15 years to maturity, price at 7% = 100; face value = 275.90.

The point of touch is at YTM = 7% and the value of both portfolios at this point is 100. As shown in the Figure 4, the portfolios are constructed in such a way as to have the same Macaulay duration but a different convexity. Therefore, being long the portfolio 1 (thick line in the Figure 4) while shorting the 15 years zero (thin line in the Figure 4) should result in profitable strategy under the presumptions mentioned above.

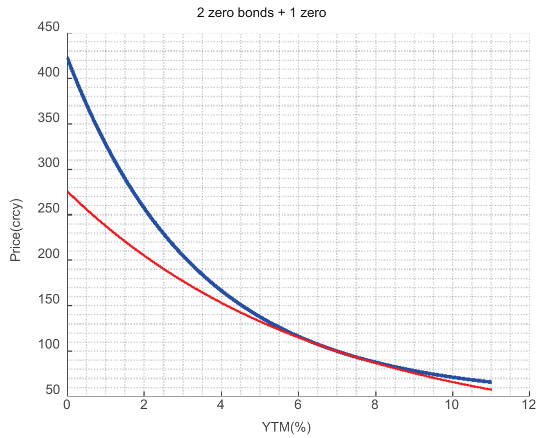


Figure 4. Portfolio of 2 bonds

3.2. Backtesting results

We use USD zero-coupon curve development (Figure 5) on daily basis to calculate the change of price of portfolio 1 and portfolio 2. Using the changes in prices, we evaluate P/L on the strategy.

Based on the results of the backtesting, in the Figure 6a, 6b, where we observe the development of P/L using convexity arbitrage strategy (portfolio 1-thick line, portfolio 2-thin line in the Figure 6a, P/L of the whole strategy in the Figure 6b) we may conclude that this arbitrage does not work well. It does not provide expected P/L development (described in the chapter Theoretical Background). Expected behavioral we do not observe during the backtesting even from the first point of view. The touch point in our portfolio is 7%, which

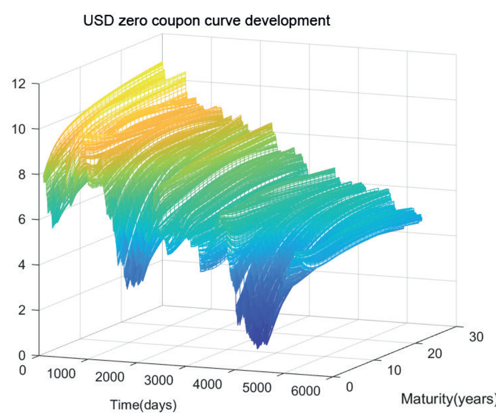


Figure 5. USD zero-coupon yield development, source: Reuters (2001–2019, 4900 days)

is approximately the mean value of YTM (using USD zero-coupon curves in the Figure 5). YTM (during the backtesting) decreases while time goes from 0 to the approx. 4900 days along the time axis, thus we expected initial drop-down below zero and then turnover at YTM = 7% following by upward movement towards zero, if the strategy works. In this case the expected shape of the development is in the Figure 7.

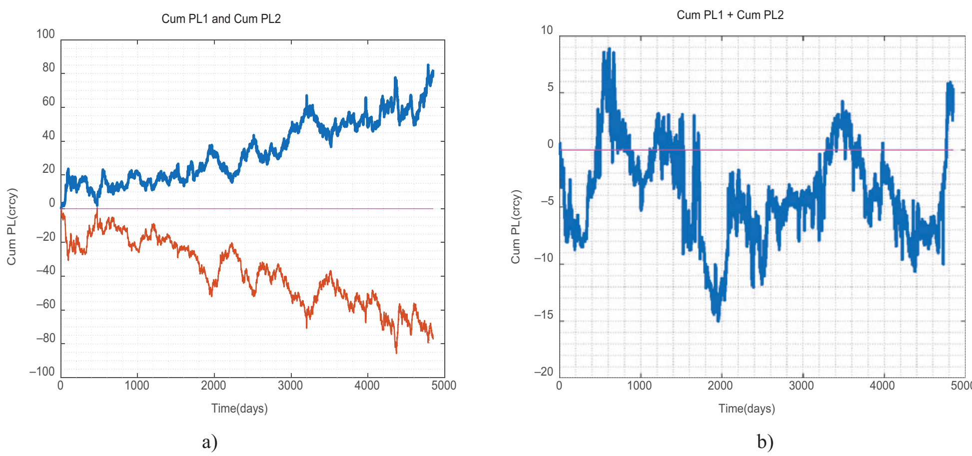


Figure 6. Cumulative PL on long portfolio 1 (thick line) and short portfolio 2 (thin line) in 6a, total PL in 6b

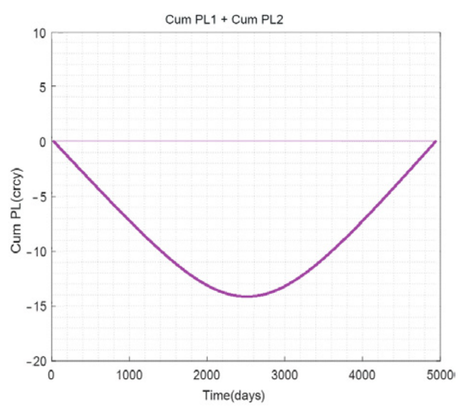


Figure 7. Expected P/L development in case the convexity arbitrage works

Scientific discussion and conclusions

In the context of the convexity arbitrage strategy, we have to deal with more serious troubles.

The initial problem is to theoretically suggest the portfolio of liquid assets which fulfill the Eqs (3), (4) and (5), as we deal with the set of equalities plus one inequality of higher orders; moreover its practical realization could be problematic mainly on illiquid markets because of difficulties to find required issues on the market. But theses troubles can be finally solved. We can conclude that hypothesis 1 is confirmed.

Based on the results of the backtesting of convexity arbitrage performance, we may conclude that this strategy does not work well as it does not provide expected P/L curve development. Means, the important presumption about parallel interest rates shifts; ideally of the same value and the same direction; is not fulfilled enough to ensure positive P/L in average. Arbitrage would work correctly in the case of bonds with the same maturity in portfolio, because of the parallel interest rates shifts in this case. But in the case that Macaulay durations must be the same and convexities differ, based on the requirements to the portfolio (Eqs (3), (4), (5)), the bonds must be of different maturities. Such statement results mathematically from the mentioned equations. Approximately in 25% of USD zero-coupon curve movements we empirically observe inverse shifts direction in comparison of short- and long-term maturities, means that approximately in 75% the YTM (YTM is calculated based on zero-coupon curve) should perform parallel movements. 75% should be sufficient to ensure positive payoff on average, but the other problem is the magnitude of the shifts.

As we find that there is minimally one case where convexity arbitrage does not work, using sufficient portfolio (USD interest rates market), we have to state that hypothesis 2 is rejected. Of course, it does not imply that the arbitrage does not work for all financial markets and cases.

The main limitation of the research is that the backtesting is limited to USD market, testing other markets is recommended. But we do not expect other results as the market functionality uses the same principles.

The research helps practitioners considering this strategy for implementation to algorithmic trading. We have to add that from the point of view of basic research it does not matter if the study concludes to the result which is practically profitable. Anyway, it can safe invested money during implementation process of the strategy which does not work.

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Disclosure statement

I do not have any competing financial, professional, or personal interests from other parties.

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