EKONOMICKÉ ROZHĽADY – ECONOMIC REVIEW, 2026, 55(1), 1 – 28
https://doi.org/10.53465/ER.2644-7185.2026.1.1-28

BEATING THE MARKET WITH LEVERAGED ETFS IN DCA WITH USE OF MAXIMUM DRAWDOWN AND MOVING AVERAGE

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Abstract: *Time and compound interest are among the key factors influencing long-term investment success. In growing financial markets, a passive investment strategy based on long-term asset holding without frequent capital reallocation has proven effective. In practice, however, many investors lack sufficient initial capital, leading them to use a regular investment strategy known as dollar-cost averaging (DCA). This strategy allows for the gradual accumulation of an investment position and reduces the investor's sensitivity to short-term price fluctuations. In the article, we present an alternative that extends the DCA strategy. Our work shows that, with sufficient decline, it is appropriate to allocate investment funds to an instrument that tracks the same asset but with embedded financial leverage. In the long term, our Maxdrawdown-Moving average DCA strategy benefits from market declines, and investors do not need to set aside capital to take advantage of them.*

Keywords: *DCA, leverage, ETF, investing, drawdown*

JEL Classification: G11, G12, G14

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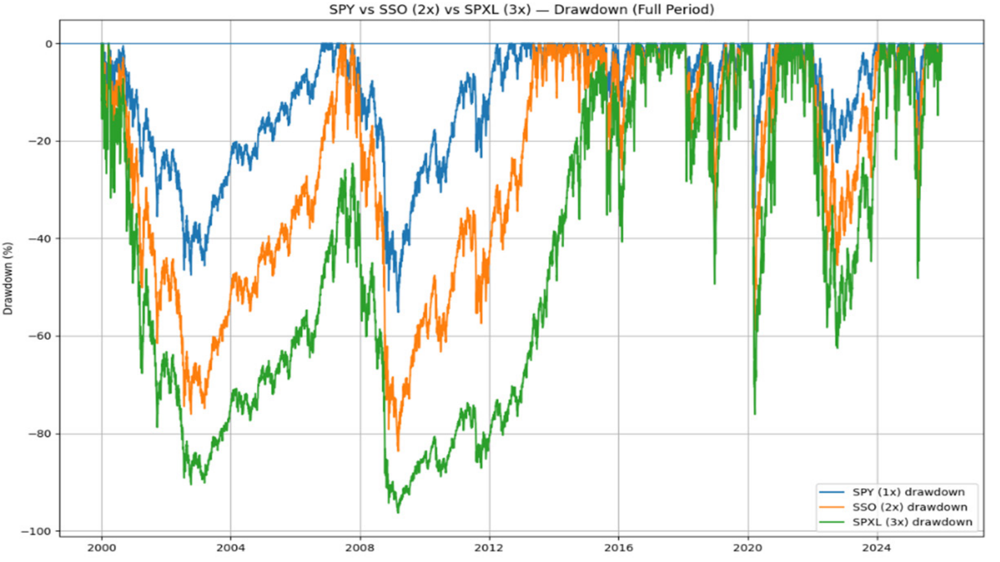
https://doi.org/10.53465/ER.2644-7185.2026.1.1-28

1 Introduction

Investing is always associated with risk, especially when investing in stocks. From a theoretical perspective, long-term equity investing is often discussed in the context of market efficiency and the historical growth of broad market indices such as the S&P 500. In the long term, it is usually true that the longer an investor has invested, the greater the profit can be. If we take one of the most widely followed equity indices, the S&P 500 (Standard & Poor's 500), over the past 40 years, in long-term investing, we do not find a fifteen-year period in which an investor invested and, after 15 years, would have been at a loss. If we look at ten-year periods, such cases are mainly observed for investments beginning in 1997-2001. However, investors who want to capitalize on this index's returns cannot invest directly in it, since it is only a statistical indicator of market performance. For investment purposes, it is necessary to use financial instruments that track the composition of this index, for example, exchange-traded funds (ETFs). There are many providers, such as BlackRock, Invesco, and BNP Paribas, that create ETFs that invest in the same underlying assets. It is therefore up to the investor to choose among funds based on preferences and costs, usually expressed by the Total Expense Ratio (TER). One of these funds is, for example, the SPDR S&P 500 ETF (SPY) from the American bank State Street. In addition to ETFs that directly replicate the index's composition, there are also products that carry embedded leverage. Most often, these products offer double leverage (double exposure), such as ProShares Ultra S&P500 (SSO), but triple-leveraged ETFs also exist, for example, Direxion Daily S&P 500 Bull 3X Shares (SPXL). Embedded leverage amplifies the ETF's price movements relative to the underlying index. The basic idea is that if the index rises, the leveraged ETF should rise faster, and if the index falls, the leveraged ETF should fall faster. However, due to the daily rebalancing mechanism, leveraged ETFs are subject to compounding effects. In volatile markets, this may lead to performance deviations from the expected simple multiple of the underlying index, a phenomenon often referred to as volatility drag. Therefore, when held for a longer period, the cumulative performance may differ significantly from a simple multiple of the index return. It is not true that if the index falls by 50%, a 2x-leveraged ETF will necessarily reach zero. The same applies to 3x leveraged ETFs. In a long-term uptrend, it might seem appropriate to allocate all funds to leveraged ETFs. However, these instruments have several pitfalls, especially in declining or highly volatile markets, as losses are amplified. Figure 1 shows the maximum drawdown (MDD), which indicates the largest peak-to-trough decline in investment value over the observed period. The figure shows that during the 2008 financial crisis, the maximum drawdown of the leveraged ETF exceeded 90%, while the standard ETF experienced approximately half that decline.

Figure 1: Maximum Drawdown 2000-2025



Source: own processing

Although leveraged ETFs are frequently analyzed in the context of short-term trading strategies, less attention has been devoted to systematic long-term allocation approaches that combine regular investing with risk-management indicators. This creates space for further empirical examination of whether dynamic allocation between leveraged and unleveraged exposure can improve overall portfolio characteristics. To limit losses, this work uses regular investing with DCA (Dollar Cost Averaging), which averages the purchase price over time and reduces the impact of investing a large amount at market peaks. In combination with DCA, the simple moving average (SMA) and maximum drawdown (MDD) indicators are used to determine whether to invest in an unleveraged product (SPY) or in a leveraged product in a given month. The aim of this paper is to evaluate whether such a rule-based allocation approach can improve risk-adjusted performance while reducing extreme drawdowns compared to standard buy-and-hold strategies.

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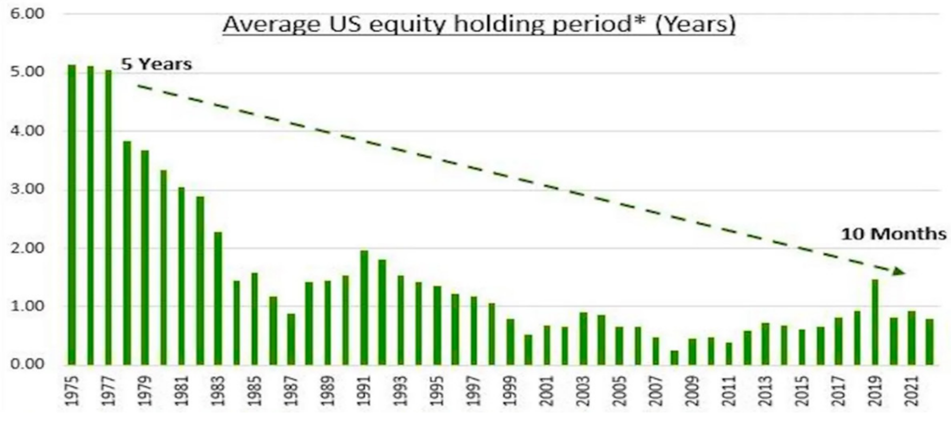
2 Literature Review

This paper uses the Simple Moving Average and Maximum Drawdown as two tools that determine whether an investor will buy a leveraged product targeting the S&P 500 index. The Simple Moving Average (SMA) is a widely used tool for interpreting market direction. It often serves as a threshold level from which many investors react, thereby representing support or resistance for an asset's value. This tool was also used to analyze investment in financial markets during the COVID-19 pandemic, supporting decisions on whether to sell or buy securities in the S&P 500 index (Licona-Luque et al., 2023). However, stocks are not the only area that can be analysed using the SMA. The moving average is widely used for assets such as bonds, commodities, and cryptocurrencies. Bitcoin was analysed using this tool in 2022. The authors focused on predicting the price of Bitcoin, a decentralized digital currency operating without the control of a central authority. Due to the high volatility of this asset, they proposed using algorithms to improve prediction accuracy. The study compares the Simple Moving Average and Radial Basis Function Neural Network methods (Yudono et al., 2022).

There are many modifications of the Moving Average. The most basic and widely used is the Simple Moving Average (SMA), which is the arithmetic average of an asset's closing prices. The Exponential Moving Average (EMA) assigns greater weight to more recent prices, thereby reacting more quickly to changes in trend than the SMA. This method is especially popular in short-term trading (Sukma & Namahoot, 2024). The Weighted Moving Average (WMA) assigns predefined linear weights to prices, with newer prices given greater importance. It has a smaller lag than the SMA (Dongrey, 2022). Among other modifications, the Smoothed Moving Average (SMMA) is also used. It effectively smooths price fluctuations, is less sensitive to short-term movements, and is well-suited for tracking longer, more stable trends. In addition to Moving Averages, another fundamental analytical tool is Drawdown, which measures market declines from a peak to a subsequent trough. Drawdown not only assesses volatility but also focuses on realized losses. As with Moving Averages, several modifications exist depending on the method of use. Maximum Drawdown (MDD) represents the largest recorded decrease in portfolio value from peak to trough over the entire monitored period. It is one of the most widely used risk indicators and is applied in this paper as well. A disadvantage of MDD is that it captures only the single worst decline and ignores smaller drawdowns (Battistelli, 2024). Conditional Drawdown-at-Risk (CDaR) measures the average value of the worst drawdowns at a selected confidence level. This method extends MDD and provides a more comprehensive view of downside risk. It has been applied to various investment assets, including cryptocurrencies (Zarezade et al., 2024). Another measure is Average Drawdown (ADD), which expresses the average size of all recorded drawdowns within a given period. Unlike MDD, ADD considers multiple declines rather than focusing solely on the most extreme event (Chekhlov et al., 2005). In addition to these measures, the Ulcer Index evaluates the depth and duration of drawdowns and is often associated with the psychological stress investors experience (Alireza, 2024). Using these tools, this paper determines whether it is appropriate to invest in a leveraged ETF in a given period. Leveraged exchange-traded funds (LETFs) amplify market movements through embedded financial leverage. Numerous studies analyse financial leverage and the market impact of LETFs. In The Market Impact of Leveraged ETFs: A Survey of the Literature, Lenkey (2024) provides an overview of research examining whether the daily rebalancing of leveraged and inverse ETFs affects end-of-day market conditions. Although theoretical concerns exist about potential price pressure effects, empirical evidence does not strongly support them. The compounding mechanism and path dependency of leveraged ETFs have been formally analysed in academic literature. Cheng and Madhavan (2009) demonstrate that the daily reset feature may lead to significant deviations from the expected leverage multiple over longer holding periods. Similarly, Avellaneda and Zhang (2010) provide a stochastic framework to explain the volatility decay observed in leveraged exchange-traded funds. These findings highlight that the long-term performance of leveraged ETFs depends not only on the final index return but also on the volatility and return path of the underlying asset. These leveraged products may enhance returns during sustained market growth. However, in periods of high volatility, prolonged declines, or sideways markets, holding leveraged ETFs for multiple years may result in performance deterioration due to daily leverage resets and the ETF's Total Expense Ratio (TER) (Rautio, 2024). In addition to market volatility, TER significantly affects fund performance. Over the long term, a higher TER for otherwise identical products may materially reduce total returns (Audita, 2023). The debate between lump-sum investing (LSI) and dollar-cost averaging (DCA) has been widely examined in academic and practitioner literature. Payne and Bredthauer (2014) analyse the performance of LSI and DCA strategies while considering different risk-adjustment methods and implementation timing. Their findings indicate that the relative attractiveness of each strategy depends on the investment horizon, the duration of DCA implementation, and the selected risk-adjustment approach. Lu, Hoang, and Wong (2021) further compare DCA and lump-sum strategies using both the Sharpe ratio and an Economic Performance Measure (EPM), concluding that DCA may outperform lump-sum investing in volatile and longer-term scenarios. Practitioner evidence provided by Shtekhman, Tasopoulos, and Wimmer (2012) suggests that lump-sum investing historically outperformed DCA approximately two-thirds of the time across several developed markets. However, they also emphasize that DCA may reduce perceived downside risk and psychological regret associated with investing a lump sum immediately before a market downturn. An essential factor in designing an investment strategy is the investment horizon. Several sources indicate that the time investors allocate to investment assets has decreased. Historically, asset holdings were measured in years, whereas today they are often measured in months. According to Fidelity, the average holding period for US equity funds is approximately 27 months for advisory accounts and 20 months for retail accounts. For international funds, the average was 25 months and 20 months for advisory and retail accounts (Saacks, 2017). Other studies indicate a shorter investment horizon of 15-17 months (Tucker, 2018). If investors focus on individual stocks rather than funds, the holding period may decline to approximately 10 months, as shown in Figure 2 (Desjardins, 2019).

Figure 2: Maximum Drawdown 2000-2025



Source: World Federation of Stock Exchanges WFE, International Monetary Fund IMF.

When comparing alternative investment strategies, it is insufficient to evaluate differences in Sharpe ratios solely descriptively. The statistical significance of differences in risk-adjusted performance should be formally tested. The author proposes a refined methodology for evaluating Sharpe ratios, improving the earlier Jobson–Korkie framework and addressing small-sample properties. This approach provides a basis for determining whether observed differences in Sharpe ratios reflect genuine performance differences or are driven by sampling variation (Memmel, 2003). In addition, the issue of performance persistence has been widely discussed in asset management research. The author examines persistence in mutual fund performance and highlights that observed outperformance may not necessarily reflect managerial skill, but rather exposure to systematic risk factors or random variation (Carhart, 1997). These findings underline the importance of verifying whether superior performance remains stable across different periods and market environments.

3 Methodology and Methods of Research

In this section, we discuss the potential advantages of regular investing when using leveraged products. We then explain the principles of drawdown and moving average, focusing on their application in leveraged products.

3.1 Total Expense Ratio

The total expense ratio is a basic indicator of a fund's cost (Maciuskas, 2011). TER is regulated within the framework of European regulations, primarily through MiFID II (Markets in Financial Instruments Directive), as well as UCITS (Undertakings for collective investment in transferable securities) and PRIIPs (Packaged retail investment and insurance products). TER simply represents the cost of the fund's existence and operation. The term TER includes the ongoing costs of the fund, such as portfolio management, administration, and fund operations or custody, as well as legal services and audit. For ETFs, portfolio revaluation is also included in the TER. Fees determined by brokers, such as transaction (purchase and sale) fees, spreads, or investor taxes, are not included in the TER because they vary by broker. TER is calculated by the fund issuer, and the fund regularly deducts an aliquot of the fee daily. The value is thus regularly discounted by the appropriate amount, based on the overall TER, and this discounted value is also interpreted in the asset price on the chart. If the ETF tracks an index and has the same composition as the

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index, the ETF's return will always be discounted by the fees in the TER. Since the TER for SPY is included in the price (0.03%), it is necessary to account for the additional TER of leveraged products (SSO and SPXL). This value above the TER for SPY will be determined as an extra annual TER in the mathematical form:

$$\Delta TER = \max(0, TER_{FUND} - TER_{SPY}) \quad (1)$$

Where, ΔTER represents the extra annual TER above the unleveraged fund, TER_{FUND} is TER for chosen leveraged fund, TER_{SPY} is TER for non-leveraged fund.

3.2 Dollar Cost Averaging

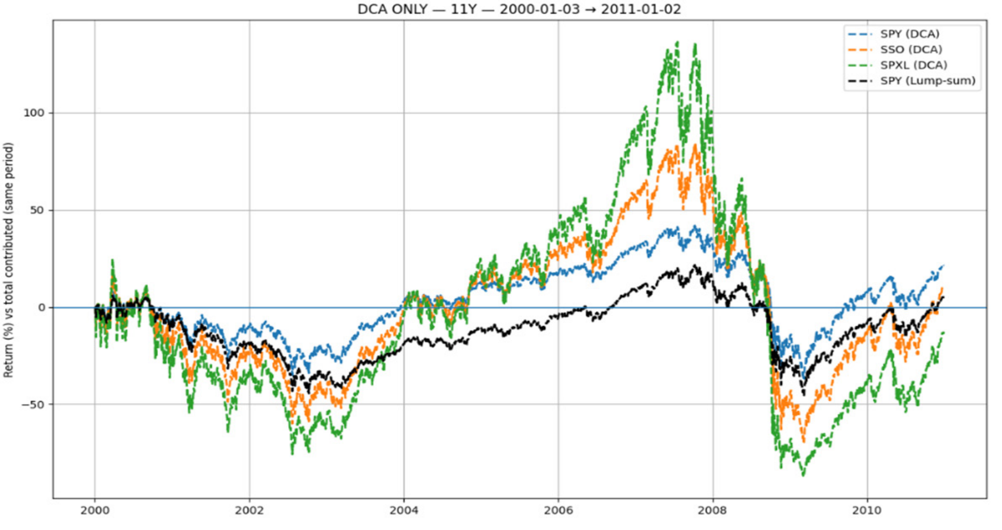
When investing, there are two purchasing approaches: one-time and regular. A one-time investment has major drawbacks if the market entry is made at the peak. There is a risk of a slump and a long recovery, which could lead to negative returns for several years. If an investor had made a one-time investment in April 2000, he would have had a positive return for a few months in 2006, and then only from 2011 onward. In the case of leveraged products, as shown in Figure 2, their decline is amplified. Leveraged products invest mostly in derivatives, thus maintaining increased exposure to ordinary ETFs. At the end of each day, the fund is rebalanced. The amount of derivative exposure is adjusted to match the required multiple of the fund's current value. If we invested in an ETF with twice the exposure, it could reach zero value only if the unleveraged product fell by 50% in one day. If the fund does not fall by half its value in a single day, the double-leveraged product is rebalanced the next day. In this way, the leveraged product can survive a long-term decline in the unleveraged asset below 50%. A great example is the COVID-19 pandemic in 2020. We can see this gradual market decline of up to 96% on a triple-leveraged ETF in Figure 3. The mathematical model for calculating leveraged products is as follows:

$$V_n = V_0 \cdot \prod_{i=1}^{n} (1 + L \cdot r_i) \quad (2)$$

Where V_n is value of leveraged product in day n, V_0 is initial value of ETF, L is leverage (where SSO represents L = 2, with SPXL is L = 3), r_i is daily percentage change of the index on day *i*.

Since leveraged ETFs such as SSO and SPXL were launched after the beginning of the analyzed sample period, their historical performance prior to inception is reconstructed synthetically using the daily leveraged return formula presented in equation (2). This approach assumes perfect daily rebalancing and does not account for potential tracking error, financing costs, liquidity constraints, swap spreads, or structural changes in derivative markets. As a result, the back-calculated performance may differ from the actual, real-time performance that would have been observed. The synthetic series, therefore, represents a theoretical approximation and may introduce upward or downward bias. This limitation is explicitly acknowledged when interpreting long-term results.

Figure 3: Drawdown of investments (SPXL by 96% in 2008)



Source: own processing.

The downside of leveraged products is their higher cost. The TER for SSO is 0.89% and the TER for SPXL is 0.97%, which, compared to the annual cost of 0.03% for unleveraged SPY, represents a significant cost disadvantage. The second biggest negative is that these ETFs take longer to recover from market losses. If SPY falls by -10%, SSO will fall by approximately -20%. For SPY, it takes a +11.1% return to return to its initial value, but for SSO, it takes a +25% return. This problem is partially solved by using regular DCA (Dollar cost averaging) investing. If an investor buys monthly, purchases occur during both growth and decline periods, which allows the strategy to benefit particularly

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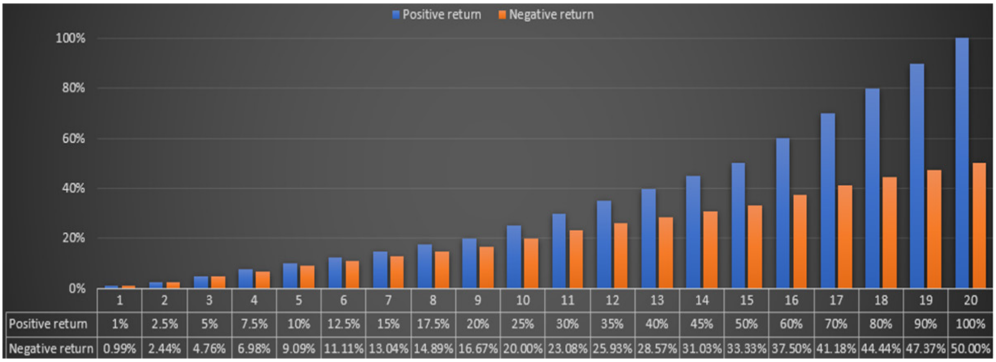
from lower prices during downturns. If we focus on the regular investment approach in 2006 and 2012, where the one-time investment in Figure 3 (black curve) turned positive, we even see excess returns for the 2x leveraged SSO ETF, and the longer the market grows, the more the 3x leveraged ETF profits. Appropriate timing of leveraged exposure may lead to excess return compared to a regular ETF. For this reason, in our work, we will consider using both SSO and SPXL during market declines for regular investment. In the case of poor timing of market entry, the decline in leveraged products can be illustrated very well in Figure 1, in the period from 2022 to 2023 or in 2008, where a one-time investment in SSO and SPXL resulted in losses approximately two to three times larger than the unleveraged ETF.

3.3 Market Analysis Tools

There are many ways to analyze the market. Maximum Drawdown is a basic tool and represents a decline from a maximum value. It is a standard risk metric that measures the decline in a portfolio or asset's value from its peak over a given period. Unlike volatility, MDD captures a decline directly from its highest value. It is important to note that negative returns carry more weight than positive returns, and a higher percentage of appreciation is required to return to the original value. For example, let's say we have 1000 €. After the first year, we earn +20% (+200€), bringing our total to 1200€. In the second year, our investment fell by 16.67% (-200€), bringing it to 1000€. From this, we see that a negative percentage has more power than a positive one. We show the consequences of the drawdowns in Figure 4.

Figure 4: Maximum Drawdowns vs Returns at Initial Value



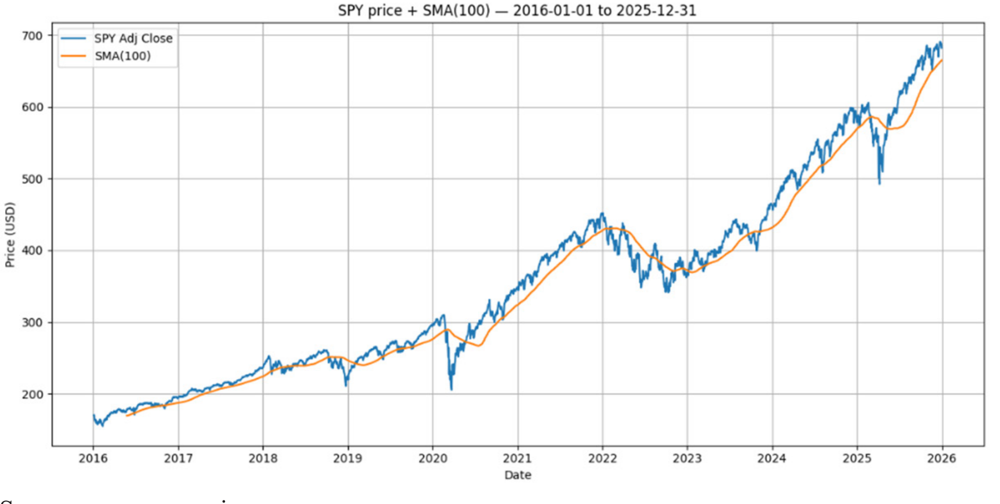
Source: own processing.

The second basic tool is the Simple Moving Average, used for financial time-series analysis. The aim of the SMA is to smooth short-term price movements, thereby providing a more stable estimate of a financial asset's price development. The SMA is mainly used to identify market trends and manage risk exposure. Mathematically, we can express the SMA as follows:

$$SMA_t^{(N)} = \frac{1}{N}\sum_{i=0}^{N-1} P_{t-i} \tag{3}$$

Where P_t represents price at time t, N is the size of the smoothing window in time t. Each observation has the same weight, which means that the SMA is a linear filter. In Figure 5, SMA(100) represents the average of the 100 most recent closing prices. In this case, the construction uses an ETF tracking the Standard & Poor's 500 index (SPY).

Figure 5: Simple Moving Average 100 – 10 Year Period



Source: own processing.

In investing, the SMA is often used as a market indicator, and we interpret it as a dynamic support and resistance level. These levels are created based on the historical price consensus to which the market repeatedly returns. If the value of an asset is less than the SMA at the same point, then this is a downward trend. We speak of an upward trend if the value exceeds the SMA. When comparing statistics, we will also present the CAGR, Sharpe Ratio, Sortino Ratio, Calmar Ratio, and CVaR indicators. CAGR (Compound

Annual Growth Rate) is the average annual return of an asset, representing the compound interest rate over the entire period. The Sharpe Ratio measures the return above the risk-free rate per unit of total volatility (Sharpe, 1966). In addition to reporting the Sharpe ratio for each strategy, a formal statistical comparison of Sharpe ratios is conducted to assess whether differences in risk-adjusted performance are statistically significant. The testing framework follows the refinement proposed by Memmel (2003), which improves the small-sample properties of the original Jobson–Korkie test. This approach allows us to evaluate whether the observed differences between the dynamic strategy and benchmark portfolios (SPY DCA, SPY lump-sum, and leveraged DCA strategies) are statistically distinguishable from zero. The Sortino Ratio measures return relative to negative volatility (Sortino, 1994). The Calmar Ratio compares CAGR with MDD (Young, 1991). CVaR is a risk indicator that measures the average loss across the worst percentage of cases (e.g., 5%) (Rockafellar & Uryasev, 2000).

3.4 Economic Rationale and Parameter Selection

The parameter values used in this study are guided by both empirical convention and economic reasoning. The SMA window of 100 trading days is an intermediate-term trend indicator commonly used in technical analysis and risk management. It is sufficiently long to filter out short-term market noise while remaining responsive to regime changes. The 10% drawdown threshold is selected as a moderate market correction level. In equity markets, declines of 5–10% are commonly interpreted as minor corrections, while drawdowns exceeding 20% are typically associated with bear markets. The selected threshold, therefore, aims to capture periods of elevated downside risk without requiring extreme market stress. The combination of a trend filter (SMA) and a drawdown condition (MDD threshold) aims to reduce exposure to leveraged products during unstable or downward-trending regimes while allowing increased exposure during recoveries. The second trend filter, SMA(200), is used as a longer-horizon regime indicator, commonly interpreted as a boundary between long-term uptrends and downtrends. Compared to SMA(100), it reacts more slowly but reduces whipsaw signals in choppy markets and is therefore used for the higher-leverage allocation. The 20% drawdown threshold is selected to represent a deep correction/bear-market regime, which justifies allocating new contributions to a 3x leveraged exposure only under more severe market stress. The 30% threshold is treated as a crash regime, where the drawdown signal dominates the trend filter, because the objective is to concentrate purchases during extreme dislocations rather than wait for confirmation from a lagging moving average.

4 MDD-SMA DCA model

Regular investing may seem like a successful strategy at first glance. It is difficult to find a rule that would consistently outperform the market in the long term, for example, through systematic redemptions after a predefined profit or purchases after market declines. With regularity, investors can average out market fluctuations and buy both in times of decline and in times of market growth, thereby reducing portfolio volatility. From a return perspective, however, this strategy does not achieve the maximum possible return because it invests equal amounts during both growth and decline periods, which can be considered a drawback of regular investing. The same applies to risk reduction (drawdowns), which we address in this article using MDD and SMA. One possible approach to outperforming an unleveraged ETF is to increase monthly investments when the market is not at its peak or is in decline, so that a larger volume of the investment asset can be purchased at a lower price. This also reduces the risk compared to pure investment in a leveraged product, as the investor does not expose the monthly investment to double losses if the market reaches its maximum. Without leveraged products, the investor's cash flow may be a constraint, preventing additional purchases in months when the market is down and preventing the investor from profiting from the market decline. If the investor were to wait for this decline, he would not have the opportunity to profit from the market's regular growth again and would lose income. Our strategy is focused on investing in three assets: SPY, SSO, and SPXL.

4.1 Construction of CFD model for USA investors

To construct the investment model, we will use Python in the Jupyter notebook environment. To load the data, we used a library function to download daily closing prices for SPY from the Yahoo Finance website since 2000. Since leveraged products were only listed on the stock exchange since 2010, we had to calculate their prices according to equation (2) presented in subsection 3.1. We saved the loaded values along with the calculated ones and plotted them in a graph from January 1, 2000, to December 30, 2025. The input data,

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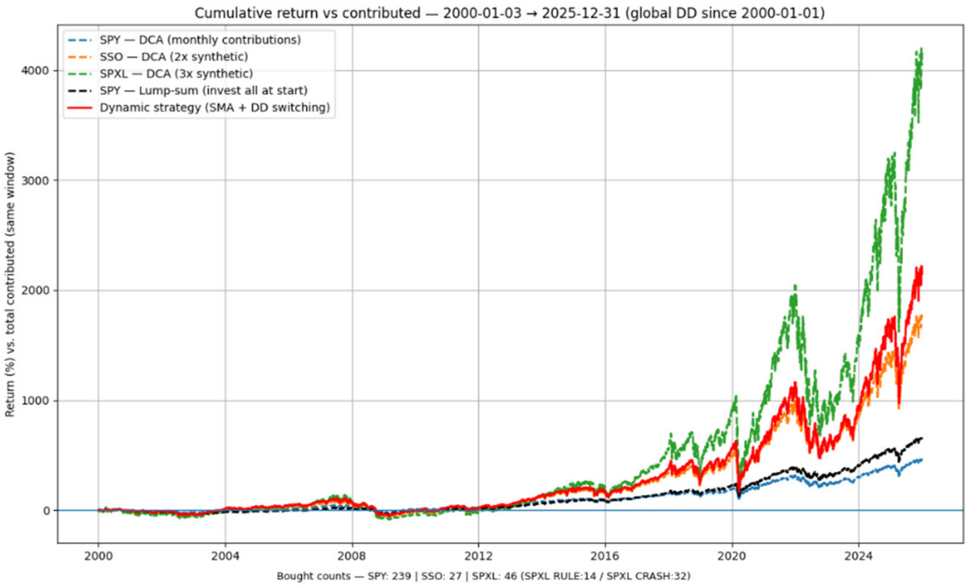
including TER costs, are shown in Figure 6.

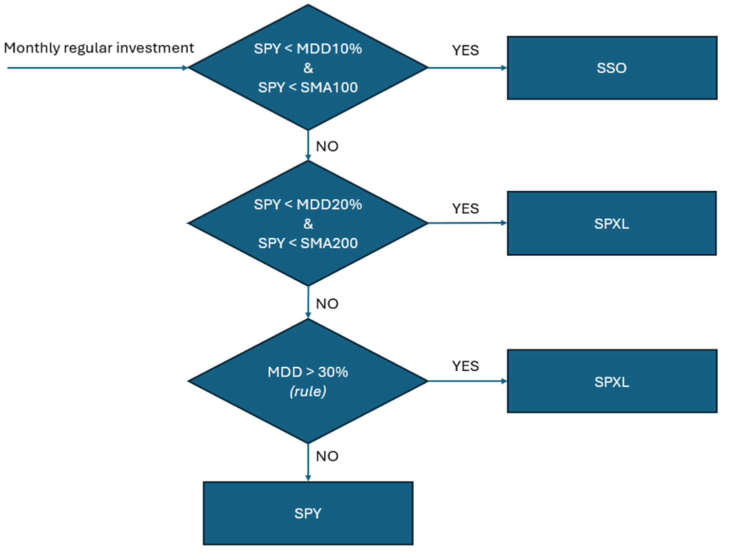
Figure 6: 25-year chart for SPY, SSO, SPXL & Our Strategy



Source: own processing.

The figure presents cumulative returns expressed as a percentage of total contributed capital. The DCA strategy assumes fixed monthly investments of $100, resulting in identical total contributions across all DCA-based portfolios. The lump-sum strategy invests the total equivalent DCA capital at the beginning of the observed period into SPY. The SSO and SPXL series represent synthetic daily-reset 2x and 3x leveraged paths derived from SPY returns, adjusted for incremental TER relative to SPY. The dynamic strategy allocates new monthly contributions according to SMA and global drawdown signals (since 2000) without portfolio rebalancing. After loading the data and calculating leveraged ETF values, we observe in Figure 6 that during sustained long-term market growth, leveraged ETFs achieve the highest cumulative returns despite their higher costs. However, since many investors do not maintain long-term investment horizons and are influenced by media coverage, it is necessary to consider the risk of short-term portfolio holdings and to avoid purchasing leveraged products at market highs. This will prevent extreme declines for positions purchased before the recession. The first allocation condition targets moderate drawdowns: when the global drawdown since the most recent peak reaches at least 10% and SPY is below SMA(100), the full monthly contribution is allocated to the 2x leveraged exposure (SSO). The second condition allocates the contribution to the 3x leveraged exposure (SPXL) when SPY is below SMA(200) and the drawdown is at least 20%. Finally, for drawdowns exceeding 30%, the strategy allocates to SPXL regardless of the moving-average filter, treating such events as crash regimes. The decision logic is shown in Figure 7.

Figure 7: Model Based on MDD and SMA



Source: own processing.

Based on Figure 7, we have created a strategy that regularly buys SPY and allocates funds to SSO or SPXL assets during market declines, depending on the extent of the decline. We apply our model based on investors' short investment horizons to 3-year and 10-year floating windows, with a monthly step-up. We add the 10-year window in case the investor decides to invest for a longer horizon. Table 1 lists the 5 worst 3-year periods for SPY returns. To cover multiple periods, we have predefined that the table must contain periods at least 1 year apart. It will not happen that all periods will be from the 2008 crisis, for example. The following tables are sorted by the SPY column.

Table 1: Worst 3-year Periods

Period	**SPY**	SOO	SPXL	**Strategy USA**
03.03.2006 – 02.03.2009	**-42,58 %**	-70,44 %	-84,99 %	**-52,20 %**

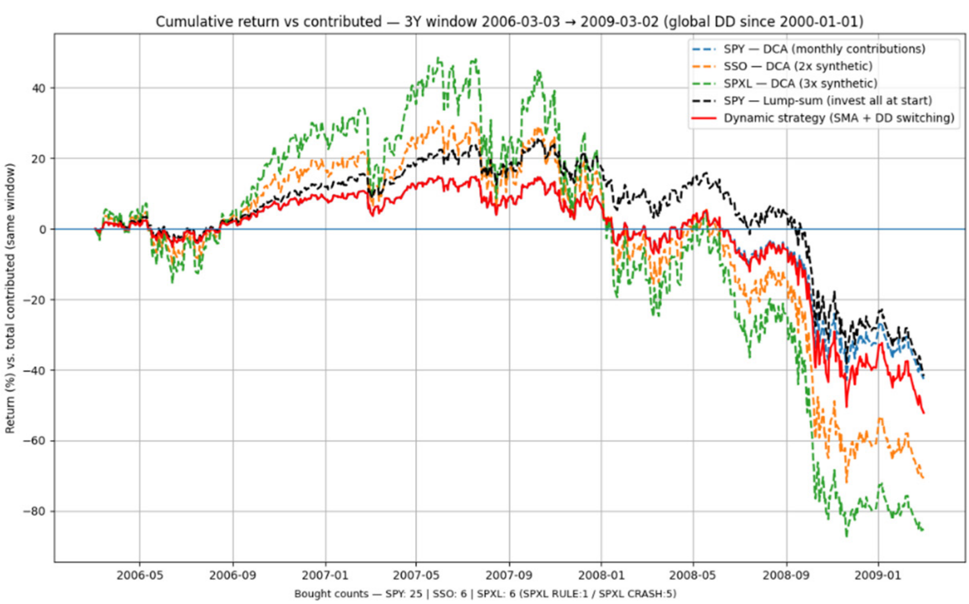
https://doi.org/10.53465/ER.2644-7185.2026.1.1-28

03.03.2000 – 02.03.2003	**-24,96 %**	-46,26 %	-62,23 %	**-41,96 %**
03.07.2007 – 02.07.2010	**-5,65 %**	-16,21 %	-26,16 %	**-5,85 %**
03.04.2017 – 02.04.2020	**-4,76 %**	-17,54 %	-35,68 %	**-4,84 %**
03.10.2019 – 02.10.2022	**-0,15 %**	-5,19 %	-15,46 %	**2,10 %**

Source: own processing.

In Table 1, it can be seen that, even though the strategy uses leveraged products, its performance in negative market periods approaches that of the unleveraged SPY, while at the same time showing fewer declines than the two- and three-times leveraged ETFs. For the period from 2007 to 2017, we see almost identical returns to SPY despite negative performance. In the latter period, the strategy even outperformed SPY, which was in the loss, and this strategy realized a profit of 2.10%. These results suggest that the strategy reduces risk relative to fully leveraged funds, as it invests in leveraged products only during periods of decline. In Figure 8, we show the course of the worst three-year period since 2006.

Figure 8: Worst SPY 3-year Return Periods



Source: own processing.

This strategy is primarily designed to profit from market declines in volatile markets, but it is also fully applicable for long-term investing. With DCA, regular purchases help reduce risk and smooth out market prices. If we focus on a longer 10-year period, we see that the worst three-year period from Table 1 begins as the fifth worst in the 10-year period, but with a positive return of +56%. The worst ten-year periods are shown in Table 2. In this table, we also see negative returns for SSO and SPXL since 2001, while SPY has a positive return, driven by market volatility. At the same time, as we can see, the period since 2006, during which SPY has higher returns than since 2010, does not imply a higher increase in the value of leveraged funds.

Table 2: Worst 10-year Periods

Period	**SPY**	SOO	SPXL	**Strategy USA**
03.07.2000 –02.07.2010	**-1,24 %**	-26,65 %	-52,49 %	**-17,01 %**
03.10.2001 – 02.10.2011	**10,64 %**	-8,21 %	-34,66 %	**8,47 %**
03.11.2002 – 02.11.2012	**34,65 %**	38,80 %	24,98 %	**52,40 %**
03.04.2010 – 02.04.2020	**55,53 %**	111,97 %	163,96 %	**66,77 %**
03.02.2006 – 02.02.2016	**56,12 %**	105,79 %	155,45 %	**126,23 %**

Source: own processing.

If we look at the overall performance of our strategy and the three ETFs in Figure 6, we can compare it with the double-leveraged SSO. In times of crisis, the strategy is less volatile and, in long-term continuous growth, less efficient than SSO. From an investor's perspective, this strategy represents a compromise between higher returns than SPY and lower risk than SSO.

4.2 Construction of CFD model for European investors

There is no option for European investors to directly invest in the above-mentioned leveraged products, as they are American ETFs. However, regulations allow investing in funds intended for European distribution, such as the Xtrackers S&P 500 2x Leverage Daily Swap UCITS ETF 1C (DBGP). This fund even has a TER lower than SSO's, at 0.6% p.a. European investors cannot yet use triple-leveraged ETFs, so we will adjust the calculation logic to consider only the first condition and the existence of a double-leveraged product. If we wanted to use SPY in combination with DBGP, we would run into a problem: SPY is traded in USD, while DBGP is traded in EUR. Therefore, there would be larger deviations due to the different currencies of the funds. In practice, we would replace SPY with other UCITS ETFs with

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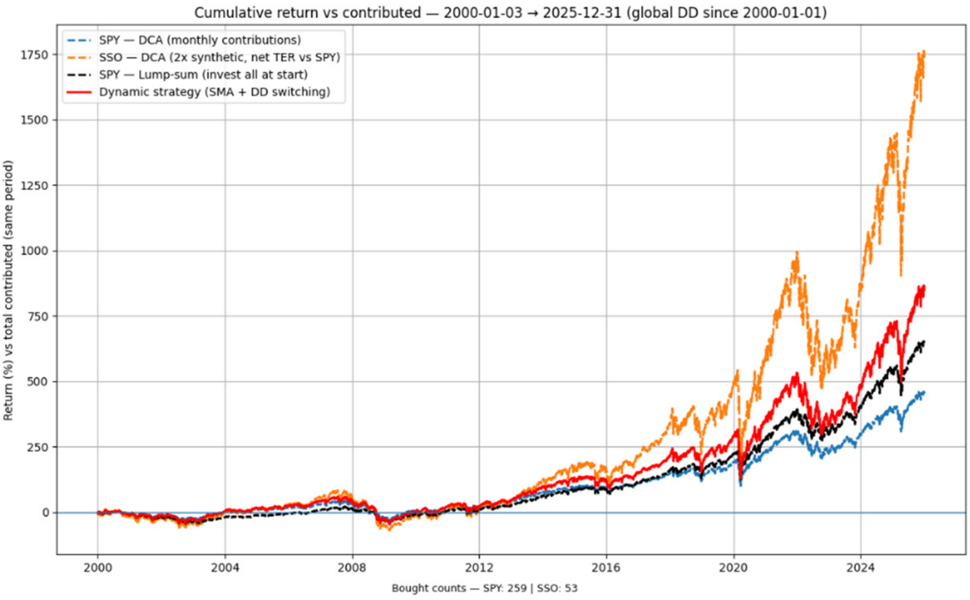
a low TER, and we would replace SSO with DBGP, however. In this case, however, we will consider substituting these European funds for the original SPY and SSO, which are closer in yield to the European alternatives (if we disregard the EURUSD exchange rate movement).

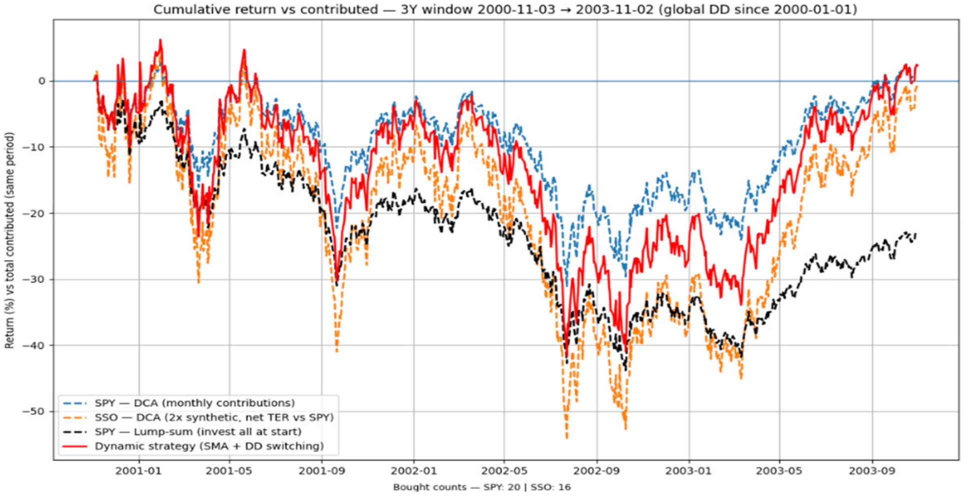
Figure 9: Model for EU Investors



Source: own processing.

As shown in Figure 9, the strategy does not achieve the high returns over a 25-year window that the American model using the three-times-leveraged SPXL does, which benefits from rising markets. If we focus on volatile markets with a decline followed by a rise, we see that the strategy delivers the highest return, even though the one-time investment is -25%, as shown in Figure 10.

Figure 10: High Volatility & Side Trend (3 years)



Source: own processing.

This strategy outperforms SPY in selected volatile periods and reduces exposure to fully leveraged products during downturns. It serves as a hedge against a prolonged recession, as the investor would be exposed to market downturns that would be amplified by 100% leveraged ETF exposure.

4.3 Robustness and Sensitivity Analysis

The results presented in the previous sections are based on a specific parameter configuration of the proposed MDD–SMA DCA model. However, any rule-based investment strategy may be sensitive to parameter choices. If the reported outperformance were driven solely by a single selected combination of inputs, the findings could reflect overfitting rather than a structurally robust investment mechanism. For this reason, a robustness and sensitivity analysis is conducted. The objective of this section is to evaluate whether the main conclusions remain valid under alternative parameter settings. Two key components of the model are varied: the length of the Simple Moving Average (SMA) used as a trend filter (50, 100, and 200 trading days), and the maximum drawdown (MDD) threshold required to activate leveraged exposure (10% and 20%). These parameters directly affect both the timing and the intensity of leveraged allocation. A shorter SMA reacts more quickly to price changes, while a longer SMA captures broader market trends and filters

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out short-term noise. Similarly, a lower drawdown threshold leads to earlier activation of leveraged exposure, whereas a higher threshold requires deeper market corrections before increasing risk. The sensitivity analysis is performed for the European version of the strategy (using 2× leveraged exposure). The table includes performance during the worst and best rolling SPY windows to assess how the strategy behaves under stressed and favorable market regimes. Table 3 shows that the qualitative behavior of the strategy remains consistent across parameter variations. All tested specifications preserve the model's central mechanism: leveraged exposure is activated selectively during market drawdowns, combined with a trend filter, which enhances medium- and long-term returns relative to a purely unleveraged allocation. However, the magnitude of returns and the associated risk metrics vary depending on the chosen parameter combination.

Table 3: Robustness analysis of Strategy for EU investors

	Strategy EU SMA50 / DD10	Strategy EU SMA50 / DD20	**Strategy EU SMA100 / DD10**	Strategy EU SMA100 / DD20	Strategy EU SMA200 / DD10	Strategy EU SMA200 / DD20
1Y return	25,72 %	24,41 %	**26,14 %**	24,82 %	26,77 %	25,42 %
3Y return	143,00 %	131,99 %	**146,71 %**	135,34 %	152,36 %	140,44 %
3Y CAGR	34,44 %	32,38 %	**35,12 %**	33,01 %	36,15 %	33,97 %
5Y return	155,19 %	144,83 %	**158,59 %**	147,94 %	163,79 %	152,68 %
5Y CAGR	20,61 %	19,61 %	**20,93 %**	19,91 %	21,41 %	20,37 %
10Y return	579,48 %	529,01 %	**596,66 %**	543,76 %	624,56 %	567,24 %
10Y CAGR	21,12 %	20,19 %	**21,42 %**	20,47 %	21,90 %	20,90 %
MDD	60,12 %	56,84 %	**60,58 %**	57,55 %	62,46 %	59,12 %
ADD	8,04 %	7,28 %	**8,07 %**	7,41 %	8,62 %	7,82 %
Sharpe ratio	0,99	1,00	**0,99**	1,00	0,98	1,00
Sortino ratio	1,81	1,90	**1,81**	1,89	1,75	1,89
Calmar ratio (10Y)	0,48	0,48	**0,48**	0,48	0,47	0,48
CVaR95 (daily)	-3,84 %	-3,58 %	**-3,85 %**	-3,62 %	-4,07 %	-3,62 %
Worst (SPY) 3Y period	-47,97 %	-44,74 %	**-50,10 %**	-45,27 %	-50,90 %	-45,27 %

Best (SPY) 3Y period	56,42 %	52,34 %	**59,44 %**	52,34 %	59,44 %	52,34 %
Worst (SPY) 10Y period	-7,92 %	-4,42 %	**-7,49 %**	-4,16 %	-8,95 %	-4,77 %
Best (SPY) 10Y period	142,42 %	141,29 %	**143,32 %**	141,29 %	143,32 %	141,29 %

Source: own processing.

When comparing drawdown thresholds, the DD10 variants generally produce higher returns than the DD20 variants. A lower threshold activates leveraged exposure earlier during market corrections, allowing the strategy to participate more aggressively in subsequent recoveries. For example, the SMA100/DD10 configuration delivers higher 3-year and 5-year returns than its DD20 counterpart. However, this comes at the cost of slightly higher maximum drawdown (MDD) and marginally worse tail-risk metrics. In contrast, DD20 acts as a more conservative filter, reducing leverage usage and therefore lowering both return potential and drawdown sensitivity. The effect of changing the SMA length is also economically intuitive. The SMA50 specification reacts more quickly to short-term price movements, which may lead to more frequent switching and potentially reduced exposure during early recovery phases. As a result, long-term returns under SMA50 are generally lower compared to SMA100 and SMA200. The SMA200 specification, on the other hand, produces the highest long-term return (notably the highest 10-year return and CAGR), indicating stronger participation in prolonged bull markets. However, this improvement is accompanied by higher drawdowns and weaker tail-risk metrics (higher MDD, ADD, and more negative CVaR95), suggesting increased exposure during volatile periods. Among the tested specifications, the SMA100/DD10 configuration (bolded in Table 3) is the most balanced and robust. It achieves the second-strongest performance across multiple return horizons (1Y, 3Y, 5Y, and competitive 10Y results) while maintaining risk-adjusted ratios (Sharpe and Sortino) comparable to those of other variants. Although the SMA200/DD10 specification achieves the absolute highest returns, it does so at the cost of noticeably higher drawdown and tail-risk exposure. Conversely, the more conservative DD20 variants reduce risk slightly, but sacrifice return potential across most horizons. Importantly, the robustness analysis confirms that the strategy's effectiveness is not dependent on a single narrowly optimized parameter setting. All reasonable SMA–DD combinations yield economically consistent results: a selectively leveraged

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allocation enhances return potential relative to pure SPY exposure, while the trade-off between aggressiveness and risk can be controlled by the chosen parameter pair. The SMA100/DD10 specification, therefore, serves as a central benchmark, offering a well-balanced compromise between performance enhancement and downside risk management.

5 Conclusions

There are many investment tools and approaches available for financial market analysis. It is never certain which is the best, but the right choice can improve an investor's portfolio returns. In this article, we analyzed the use of leveraged products focused on the S&P 500 index. If a purely leveraged product is chosen for a one-time investment, there is a high risk of bad timing, which can cause irreparable damage to the portfolio. The second obstacle for investors is that they may not have a large initial capital base and therefore prefer to invest regularly, on a monthly basis, using the DCA strategy. When creating a portfolio for regular investment, we used three assets: SPY, SSO, and SPXL. Leveraged products are used when markets decline, reducing the probability of buying them at maximum values (all-time highs) and limiting potential portfolio declines. In this paper, we analyzed two approaches that were aimed at both American and European investors. As shown in Table 4, the strategy's returns in negative scenarios are slightly lower than a pure SPY investment in some cases, but significantly better than those of fully leveraged strategies.

Table 4: Worst 3-year Periods

Period	**SPY**	SOO	SPXL	**Strategy USA**	**Strategy EU**
03.03.2006 – 02.03.2009	**-42,58 %**	-70,44 %	-84,99 %	**-52,20 %**	**-50,10 %**
03.03.2000 –02.03.2003	**-24,96 %**	-46,26 %	-62,23 %	**-41,96 %**	**-31,86 %**
03.07.2007 – 02.07.2010	**-5,65 %**	-16,21 %	-26,16 %	**-5,85 %**	**-8,13 %**
03.04.2017 – 02.04.2020	**-4,76 %**	-17,54 %	-35,68 %	**-4,84 %**	**-4,90 %**

03.10.2019 – 02.10.2022	**-0,15 %**	-5,19 %	-15,46 %	**2,10 %**	**0,76 %**

Source: own processing.

In Table 5, we show the top three-year periods in which excess returns are visible relative to the SPY strategy.

Table 5: Best 3-year Periods

Period	**SPY**	SOO	SPXL	**Strategy USA**	**Strategy EU**
03.01.2019 – 02.01.2022	**47,67 %**	104,42 %	168,17 %	**63,28 %**	**59,44 %**
03.11.2022 – 02.11.2025	**40,77 %**	91,78 %	158,28 %	**40,77 %**	**48,25 %**
03.07.2011 – 02.07.2014	**36,75 %**	84,17 %	149,37 %	**43,48 %**	**48,35 %**
03.01.2018 – 02.01.2021	**32,56 %**	56,86 %	69,01 %	**39,86 %**	**37,15 %**
03.10.2021 – 02.10.2024	**31,11 %**	65,51 %	106,13 %	**45,81 %**	**42,80 %**

Source: own processing.

While the strategy is evaluated using historical market data, several real-world implementation factors may affect realized performance. Transaction costs such as brokerage commissions, bid–ask spreads, and potential slippage are not explicitly modeled. For European investors, additional considerations include currency risk arising from USD-denominated exposure and the potential use of derivatives or CFDs due to regulatory constraints. Moreover, leveraged ETFs involve daily rebalancing and derivative-based exposure, which may generate additional implicit financing costs not fully captured by TER alone. These factors may reduce the effective return achievable in practice and should be considered when interpreting empirical results.

The advantage of this strategy is the reduction in declines in continuously falling markets, and the excess returns in rising and volatile markets, compared to exposure in leveraged products and an unleveraged ETF. In general, the strategy can benefit from market declines and provide excess returns during

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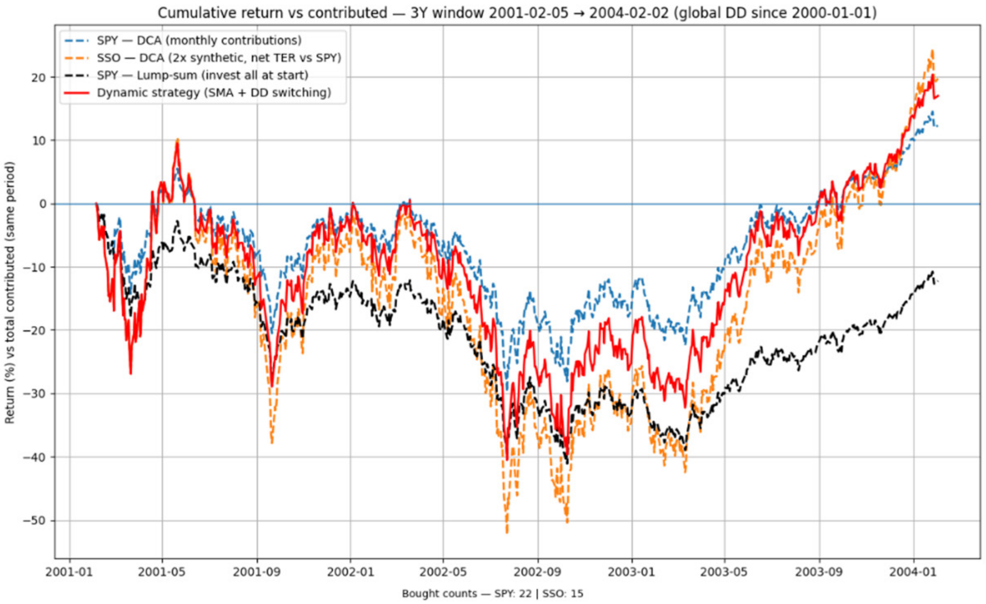
periods of volatility, as shown in Figure 11.

Figure 11: Side Trend (lowered risk, increased return)



Source: own processing.

The black curve in the graphs shows a one-time investment in an unleveraged product and we can see that DCA can significantly positively affect the value of an investor's portfolio if the timing of entry into the market is wrong. It should be noted, of course, that if the market were only falling, the strategy's leveraged component would partially offset the portfolio's return. If we focus on a 10-year period, we see that the strategy can significantly help the investor during periods of volatility and low returns, as shown in Table 6.

Table 6: Worst 10-year Periods

Period	**SPY**	SOO	SPXL	**Strategy USA**	**Strategy EU**
03.07.2000 – 02.07.2010	**-1,24 %**	-26,65 %	-52,49 %	**-17,01 %**	**-7,49 %**
03.10.2001 – 02.10.2011	**10,64 %**	-8,21 %	-34,66 %	**8,47 %**	**7,33 %**

03.11.2002 – 02.11.2012	**34,65 %**	38,80 %	24,98 %	**52,40 %**	**40,30 %**
03.04.2010 – 02.04.2020	**55,53 %**	111,97 %	163,96 %	**66,77 %**	**69,73 %**
03.02.2006 – 02.02.2016	**56,12 %**	105,79 %	155,45 %	**126,23 %**	**76,87 %**

Source: own processing.

For the period starting in 2002, the proposed strategy achieved the highest return among the analyzed solutions. If we look at 2001, we see that the strategy delivered a return almost as high as the unleveraged SPY, while the leveraged products were in the red. The strategy we proposed seems to be successful, especially in volatile periods with an increasing trend. Our strategy has the same return as the unleveraged SPY in the case of net growth without significant declines, since in this case, the leveraged products will not be bought. The overall statistics that take into account parameters such as MDD, ADD, returns in the period of 1 year, 3 years, 5 years, 10 years, Sharpe Ratio, Sortino ratio, Calmar ratio, and CVaR are shown in Table 7. We present these statistics only for the strategy applicable to European investors.

Table 7: Key metrics (as of December 2025 - from 2000)

	SPY	SSO	**Strategy EU**
1Y return	18,64 %	32,81 %	**26,14 %**
3Y return	91,52 %	218,95 %	**146,71 %**
3Y CAGR	24,19 %	47,20 %	**35,12 %**
5Y return	106,23 %	223,50 %	**158,59 %**
5Y CAGR	15,58 %	26,47 %	**20,93 %**
10Y return	367,33 %	1030,66 %	**596,66 %**
10Y CAGR	16,67 %	27,45 %	**21,42 %**
MDD	47,52 %	80,47 %	**60,58 %**
ADD	5,18 %	13,13 %	**8,07 %**
Sharpe ratio	1,01	0,91	**0,99**
Sortino ratio	2,17	1,44	**1,81**
Calmar ratio (10Y)	0,50	0,47	**0,48**
CVaR95 (daily)	-2,89 %	-5,80 %	**-3,85 %**

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Worst (SPY) 3Y period	-42,58 %	-70,74 %	**-45,27 %**
Best (SPY) 3Y period	47,67 %	104,42 %	**52,34 %**
Worst (SPY) 10Y period	-1,24 %	-26,65 %	**-4,77 %**
Best (SPY) 10Y period	139,89 %	398,88 %	**141,29 %**

Source: own processing.

From the above graphs and Table 7, it can be observed that the strategy achieves higher growth potential than SPY in selected medium- and long-term periods. This strategy reduces portfolio declines (MDD, ADD) compared to a fully leveraged ETF. The Sharpe ratio approaches 1, similar to the value for the unleveraged product and higher than the leveraged products' Sharpe ratios. It can therefore be stated that this strategy offers the opportunity to achieve excess returns through regular investment, at the cost of moderately increased risk due to leveraged exposure during market declines. Our work could be further developed by incorporating additional indicators, such as support and resistance levels, which often drive price action. We also see room for improvement in the possibility of considering macroeconomic factors such as inflation, GDP, or interest rate developments as potential extensions of this work

Acknowledgement

This work was supported by the Grant Agency of the Slovak Republic: VEGA 1/0285/24 The Impact of Inflation on Poverty and Social Exclusion in Slovakia and the EU

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