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Does Trend Following *Still* Work on Stocks?

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Abstract

This paper revisits and extends the results presented in 2005 by Wilcox and Crittenden [1] in a white paper titled *Does Trend Following Work on Stocks?* Leveraging a survivorship-bias-free dataset of all liquid U.S. stocks from 1950 through October 2024, we examine more than 66,000 simulated long-only trend trades. Our results confirm a highly skewed profit distribution, with less than 7% of trades driving the cumulative profitability. These core statistics hold up out-of-sample (2005–2024), maintaining strong returns despite a modest decline in average trade profitability following the original publication. In the second part of this study, we backtest a long-only trend-following portfolio specifically aimed at capturing outlier returns in individual stocks. While the theoretical portfolio exhibits exceptional gross-of-fees performance from 1991 until 2024 (e.g., a CAGR of 15.02% and an annualized alpha of 6.19%), its extensive daily turnover poses a significant challenge once transaction costs are considered. Examining net-of-fee performance across various asset under management (AUM) levels, we find that the base trend-following approach is not viable for smaller portfolios (AUM less than $1M) due to the dampening effect of trading costs. However, by incorporating a Turnover Control algorithm, we substantially mitigate these transaction cost burdens, rendering the strategy attractive across all tested portfolio sizes even after fees.

Keywords: *Trading Systems, Algo Trading, Momentum, Trend-Following, Stock Investing*

1 Introduction

Markets are never wrong,
opinions often are.
– Jesse Livermore

Academic literature and industry research have extensively documented the tendency for prices to exhibit momentum. In simple terms, when prices are moving upward, they are likely to continue rising, and the same holds true for declining prices. Numerous examples exist of traders who have successfully exploited this pattern, particularly in futures markets (Covel [2]). This trading style, known as *Trend-Following*, underpins a multi-billion dollar industry[1] focused on entering the early stages of a trend and riding it as long as possible. In the stock market, momentum has been studied and applied mainly from a cross-sectional perspective (Jegadeesh [3], Gray [4]), where the best-performing stocks tend to continue outperforming, while the worst-performing stocks often deliver subpar returns relative to others. However, fewer studies have explored pure trend-following systems applied to stocks.

The primary goal of this paper is to extend and update the results presented in the 2005 white paper by Wilcox and Crittenden [1], where the authors examined the efficacy of a long-only trend-following strategy in the U.S. market for generating meaningful returns for investors and speculators. That study utilized a survivorship-bias-free database of all liquid stocks traded in U.S. markets from 1980 to 2004.

In the first part of this paper, we extend this database to include data from January 1950 until October 2024. Using the same methodology proposed by Wilcox and Crittenden, we examine the key properties of the return distribution for all simulated trades in our backtest engine. We also present the time-varying profitability of the trend-following

[1] BarclayHedge estimates that assets under management (AUM) reached $340 billion as of Q3 2024. See link: `https://www.barclayhedge.com/solutions/assets-under-management/cta-assets-under-management/`

approach to determine if the method remained robust out-of-sample (2005-2024). To aid readers in understanding how positions are opened, managed, and closed, we provide several examples of historical trades, including some from the past two years.

In the second part of this paper, we propose a simplified yet effective trading strategy derived from the principles discussed earlier. We begin by evaluating a theoretical portfolio that excludes transaction costs (i.e. commissions, slippage, and borrowing expenses) and allows for trading in fractional shares to achieve precise allocations. After incorporating transaction costs, however, the high daily turnover implied by the baseline model necessitates the introduction of a turnover control mechanism to manage the trend-portfolio more efficiently and significantly reduce the impact of costs assosiated to small rebalancements. Moreover, since commissions and market impact can vary significantly with different levels of assets under management, we conduct multiple backtests using various initial capital assumptions.

2 Database

The database consists of 31,000 common stocks traded in NYSE, AMEX and Nasdaq from 1950 until August 2024. To avoid any bias coming from the database, we make sure to include all delisted stocks (approximately 24,000) and to properly account for dividends, splits and other corporate actions. The data for these stocks were sourced from Norgate Database.[2]

3 Statistical Investigation

3.1 The Universe

Before detailing the entry and exit criteria, it is essential to define the daily filtering rules for excluding stocks that lack sufficient liquidity or are priced too low to produce reliable historical results. A stock qualifies for trading eligibility if, at the close of day t, it meets the following conditions:

[2]Norgate Data is a provider of historical end-of-day stock market data with survivorship bias-free databases, which include delisted and merged securities. For details, see `https://norgatedata.com/`.

- Closing price above \$10
- Average dollar volume over the last 42 trading days above \$1,000,000

The minimum dollar volume threshold is adjusted over time using a decay rate aligned with inflation, as measured by the Consumer Price Index (CPI)[3]. For example, the minimum average dollar volume threshold would have been approximately \$80,000 in 1951, \$300,000 in 1980, and \$600,000 in 2005.

The minimum price threshold is applied to the unadjusted closing price (i.e., the closing price not adjusted for dividends or splits). If a stock in the portfolio no longer meets these criteria, it is retained until reaching the stop-loss threshold. These filters serve as necessary conditions for establishing long positions.

In Figure 1 we plot the time evolution of the number of stocks eligible for trading.

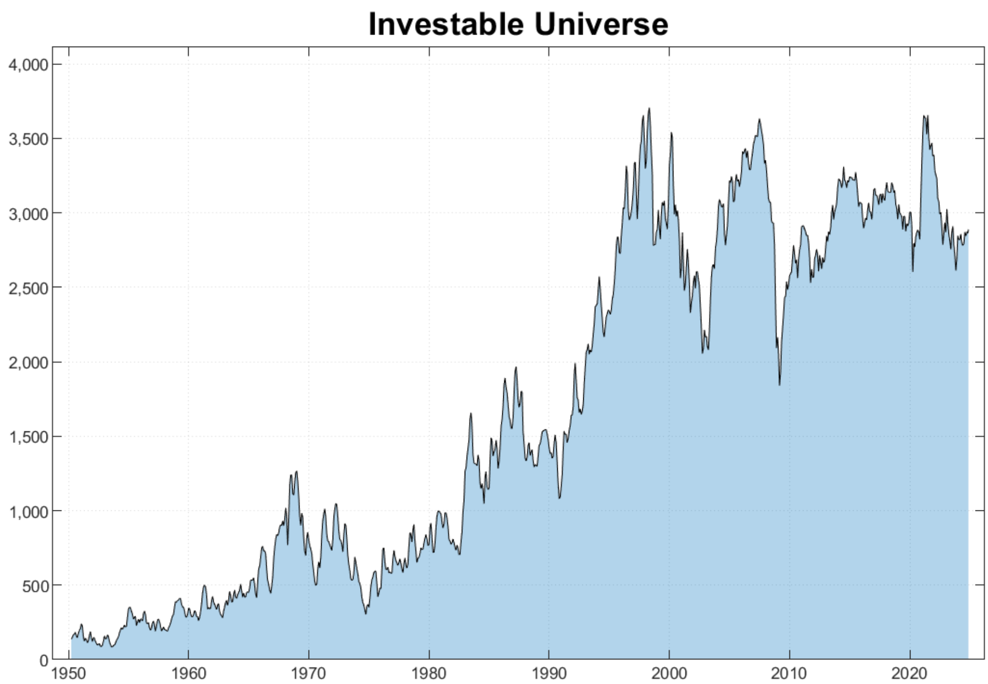


Figure 1: Time evolution of the number of stocks eligible for trading. The universe was filtered by applying the conditions outlined in Section 3.1

[3]https://fred.stlouisfed.org/series/CPIAUCSL

3.2 The Rules

Entry. There are several methods for identifying whether a stock is trending upward. Common techniques include measuring price momentum (e.g., returns over the past n days), using price channels (such as Donchian Channels), or combining price with volatility metrics (like Keltner or Bollinger Bands). In this research, following the methodology of Wilcox and Crittenden [1], we use an all-time high breakout as the trend signal. This method offers several advantages: first, it removes ambiguity—a stock reaching an all-time high is, by any standard, in an uptrend. Second, this extreme filter enhances selectivity, reducing portfolio holdings to a manageable number of stocks.

If, at the close of day t, a stock meets the price and liquidity filters, and its closing price equals or exceeds the highest adjusted close (considering splits and dividends) in its history, then a buy order is placed at the open on day $t + 1$.

Exit. As a general principle, a trend position should be exited once the price experiences a significant adverse move that effectively invalidates the existence of a prior trend. It is crucial to distinguish between random price fluctuations and moves carrying meaningful information. A widely-used indicator among systematic and technical trend traders is the Average True Range (ATR)[4], which estimates the maximum distance a stock's price is expected to travel from one day's closure to the close of the next business day. By using the ATR to set stop-loss levels, we thus account for the fact that stocks have different level of volatility.

We implement a trailing stop designed to adapt dynamically as the trade progresses. At the close of day t, the trailing stop level is calculated using the 42-day ATR as follows:

[4]The Average True Range (ATR) is a technical analysis indicator used to measure market volatility. It was introduced by [5] in his book, *New Concepts in Technical Trading Systems*. The ATR calculates the average range between the highest and lowest prices over a given number of past trading sessions. This range includes the comparison of the current high to the previous close, the current low to the previous close, and the current high to the current low. The ATR does not indicate price direction but rather the degree of price volatility. High ATR values indicate high volatility, suggesting wider price ranges and potentially greater risk or opportunity for traders. Conversely, low ATR values suggest low market volatility, indicating tighter price ranges.

$$\text{Trailing Stop}_t = \text{ATH}_t \times \left(1 - \frac{\text{ATR}_t}{\text{Close}_t}\right)^{10},$$

where ATH_t is the all-time high price achieved by the stock up to day t, and ATR_t is the 42-day Average True Range at day t.

This trailing stop is updated daily but never lowered, thereby ensuring that the protective threshold ratchets upward as the stock's price trends higher. If, at the close of day t, the stock's price falls below this stop level, a sell order is executed at the open on day $t + 1$. Although a stop corresponding to approximately 10 ATRs may appear wide, it is deliberately designed to accommodate the natural volatility of the asset and prevent premature exits. This approach prioritizes capturing longer-term trends rather than exiting positions during short-term pullbacks.

3.3 Commission and Slippage

A transaction cost of 0.50% per round turn is deducted from each trade to account for estimated commissions and slippage.[5] While this level of commission may appear high by 2024 standards, we believe it serves as a reasonable proxy for the average transaction costs incurred throughout the entire sample period.

3.4 Examples

The charts exhibited in Figure 2, 3, 4 and 5 display historical examples of how trend positions would have been initiated, managed, and exited. These cases also include some well-known stocks that, only a few months after the exit signals were triggered, were delisted due to reasons such as accounting misconduct or bankruptcy. Quite remarkably, despite the dramatic drop, the trend-following approach would have yielded profitable trades in all these stocks (in Lehman, only the last trade resulted in a small loss).

[5] De Groot, Huij, and Zhou [6] analyzed data from a major global broker, indicating costs between 5 and 25 basis points (bps) for the 500 largest US stocks (with an average of 10.9 bps). Novy-Marx and Velikov [7] focused on bid-ask spreads, finding round-trip costs of 40 to 70 bps for the largest US stocks. Additionally, Frazzini, Israel, and Moskowitz [8] estimated transaction costs at 15–16 bps in global developed markets , while Israel, Moskowitz, Ross, and Serban [9] reported average costs of 6.4 bps in the US. Taken together, 25 bps represents a reasonable, conservative assumption for average trading costs, assuming the trades are not disproportionately large.

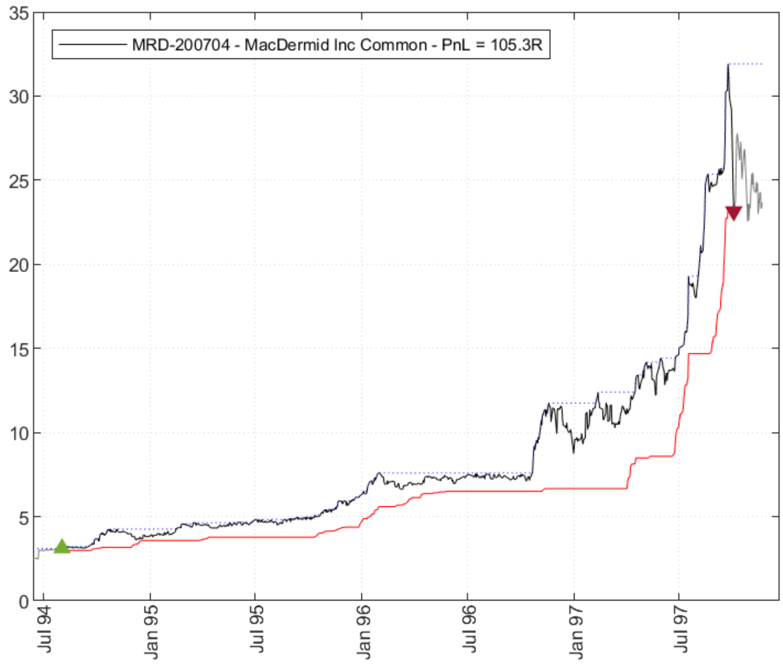
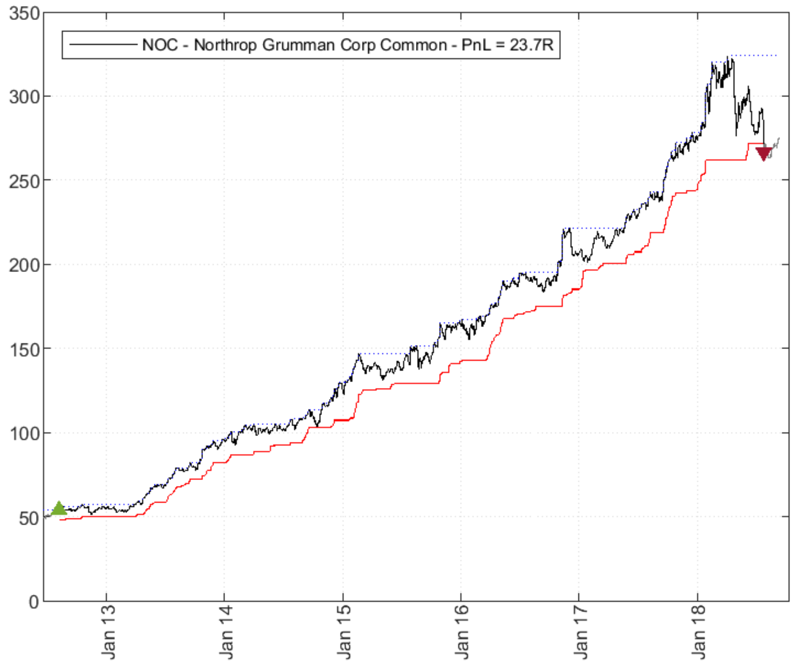


Figure 2: The blue dotted lines indicate the price levels corresponding to the stocks' all-time highs, red lines represent the trailing stop-loss levels. Green and red arrows indicate system entries and exits respectively.



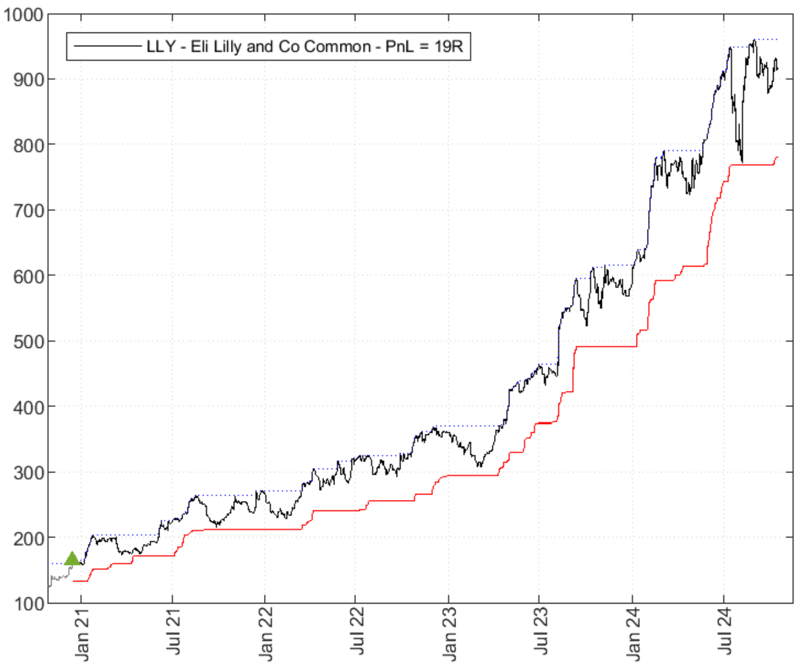


Figure 3: The blue dotted lines indicate the price levels corresponding to the stocks' all-time highs, red lines represent the trailing stop-loss levels. Green and red arrows indicate system entries and exits respectively.

Figure 4: The blue dotted lines indicate the price levels corresponding to the stocks' all-time highs, red lines represent the trailing stop-loss levels. Green and red arrows indicate system entries and exits respectively.

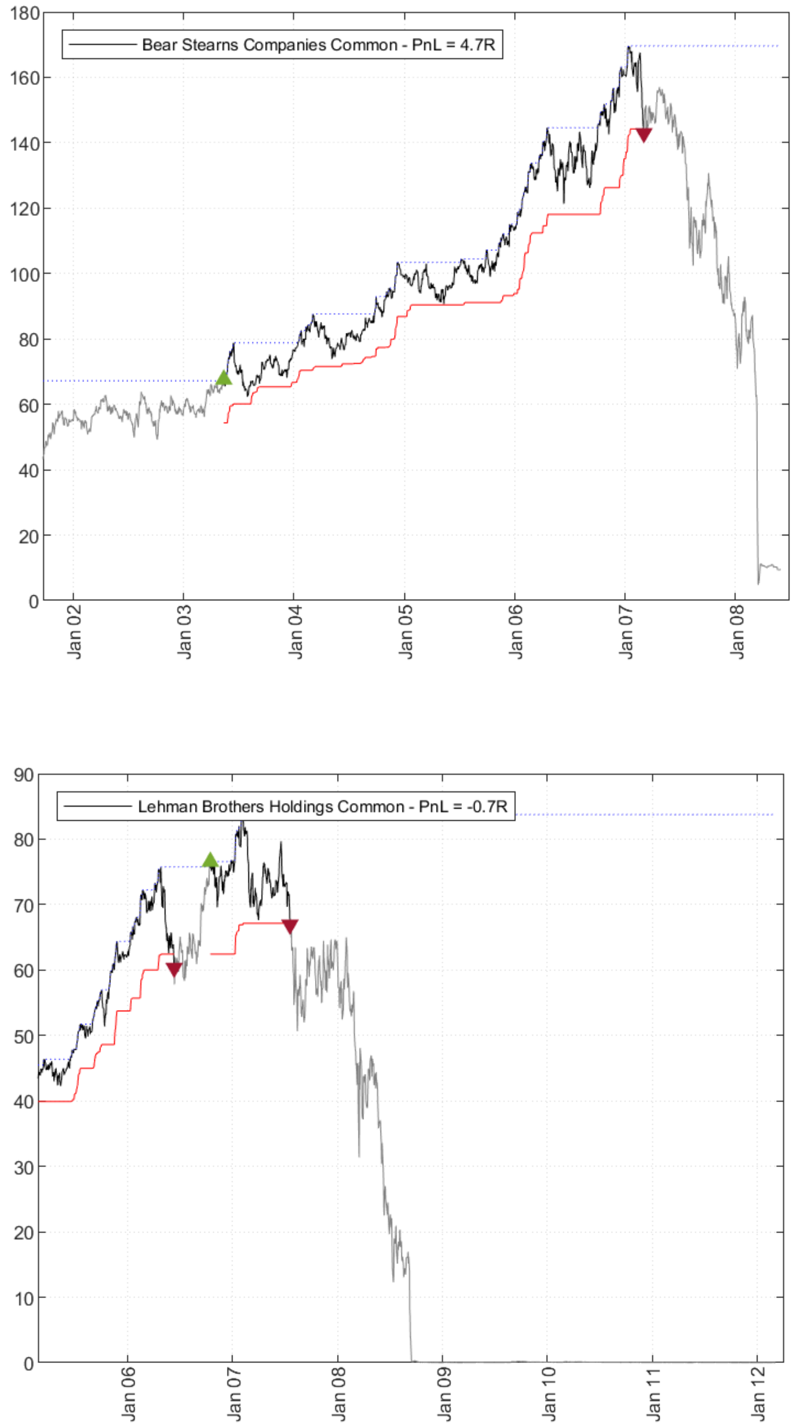


Figure 5: The blue dotted lines indicate the price levels corresponding to the stocks' all-time highs, red lines represent the trailing stop-loss levels. Green and red arrows indicate system entries and exits respectively.

3.5 Results

In this section, we evaluate the efficacy of this trend-following approach over the past 75 years by examining key summary statistics from approximately 66,000 trades. Additionally, we compare profitability before and after the publication of Wilcox white paper [1].

In line with industry standards and to account for the heterogeneity of stock volatility, we normalize each PnL by the initial risk. Rather than analyzing the PnL relative to the entry price, we express it in risk units, calculated as:

$$\mathrm{PnL}_R = \frac{\mathrm{ExitPrice} - \mathrm{EntryPrice}}{\mathrm{EntryPrice} - \mathrm{StopLoss}} \tag{1}$$

where StopLoss is the first stop-loss used when the trade is initiated. The denominator represents the maximum risk at the inception of the trade - the risk unit.

To illustrate, consider two stocks (Stock A and Stock B), each with an entry signal at \$100. For Stock A, the initial stop is set at \$80, while for Stock B, the stop is placed at \$98. After a few months, both trades close with a profit of \$10, exiting at \$110. On the surface, these outcomes appear identical; however, they fail to account for the difference in risk exposure. For Stock A, the \$10 gain amounts to only 50% of the initial risk (\$20, from \$100 to \$80), whereas for Stock B, the same \$10 gain represents an impressive 500% of its initial risk (\$2, from \$100 to \$98). Finally, in risk units, Stock A made 0.2R, while Stock B made 5R.

The distribution of trade PnL_R, as shown in Figure 6, highlights a clear positive skew in the results, which is a common feature of trend-following strategies. While many trades cluster around small losses and moderate gains, there is a distinct right tail representing the relatively few trades that generate outsized returns. These large winning trades are essential to the overall profitability, compensating for the more frequent smaller losses.

The average return per trade is 0.50R, indicating that although many trades result in modest profits or losses, the strategy's ability to capture larger trends drives the positive

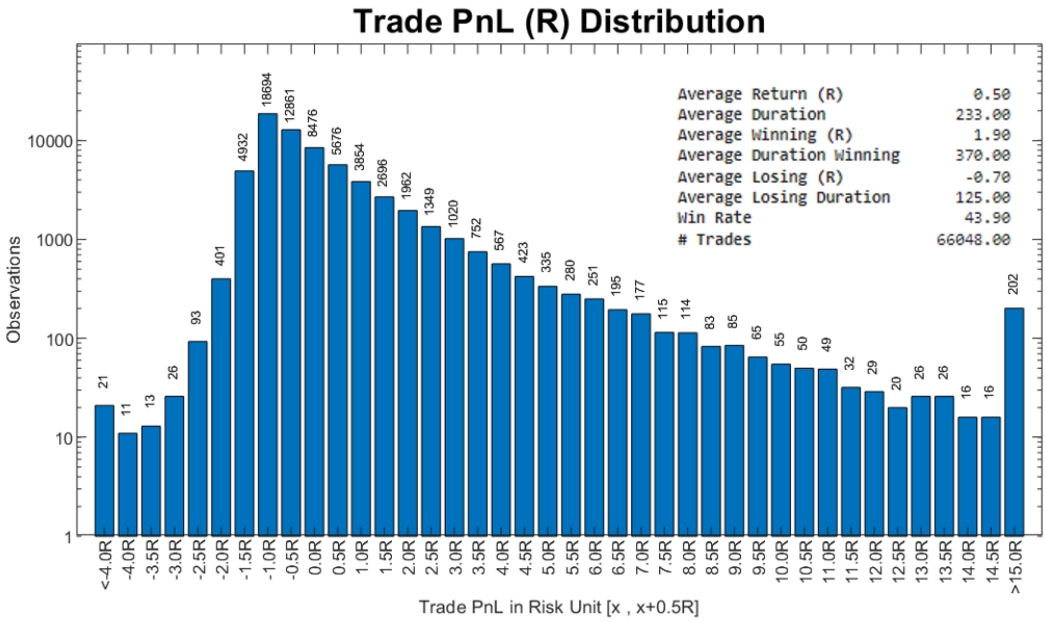


Figure 6: A bar chart that shows the PnL_R distribution of all the trades taken by the trend following system. PnL_R is expressed as a multiple of the initial risk taken as described in Equation 1

performance. Importantly, the average winning trade returns 1.90R, while the average loss is -0.70R, highlighting a favorable risk-reward asymmetry. This balance shows that losses are controlled while the winners are allowed to grow, which is a core principle of trend-following systems.

A Win Rate of 43.90% is consistent with what is typically observed in trend-following programs applied to futures markets. In such strategies, a hit ratio around this level is expected, as the overall profitability relies on capturing significant price movements in a select number of trades rather than achieving a high percentage of winning trades. The positive skewness in the return distribution offsets the moderate win rate, contributing to the strategy's overall success.

In addition, the chart reveals that the average duration of winning trades exceeds one year (370 days), which is beneficial from a tax perspective. Holding positions for over a year allows the strategy to avoid short-term capital gains taxes, thus improving after-tax returns. This long-term nature of the strategy is an advantage, as it reduces the tax burden and further supports the ability to capture extended trends in the market.

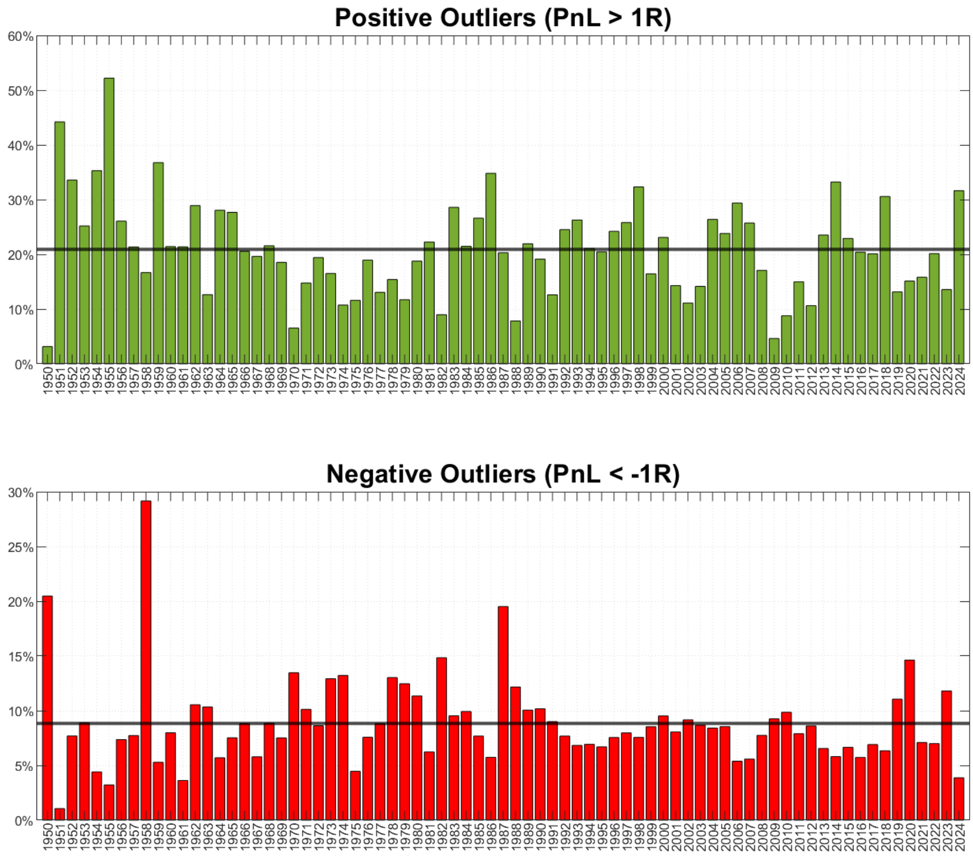


Figure 7: These bar charts illustrate the annual frequency of negative (red) and positive (green) outliers during the backtesting period. Outliers are defined as trades with PnL_R exceeding $1R$ in absolute value. The frequency is calculated as the ratio of outlier trades to the total number of trades executed each year. Black horizontal lines denote the mean outlier frequency across the entire period.

By studying the left tail, we noticed that 5,497 trades (8% of all trades) resulted in a loss that exceed the initial risk. This usually happens when stocks experienced negative overnight drops due to unexpected news. On the contrary, there are more than 14,800 trades (22% of all trades) that realized a profit that exceed the risk taken.

Figure 7 show how negative and positive outliers trades, as a percentage of total trades per year, would have been distributed over time. We notice a fairly stable presence of negative outliers with some occasional spikes usually in periods associated with famous sudden market crashes such as the Black Monday in 1987 and the Covid period in 2020.

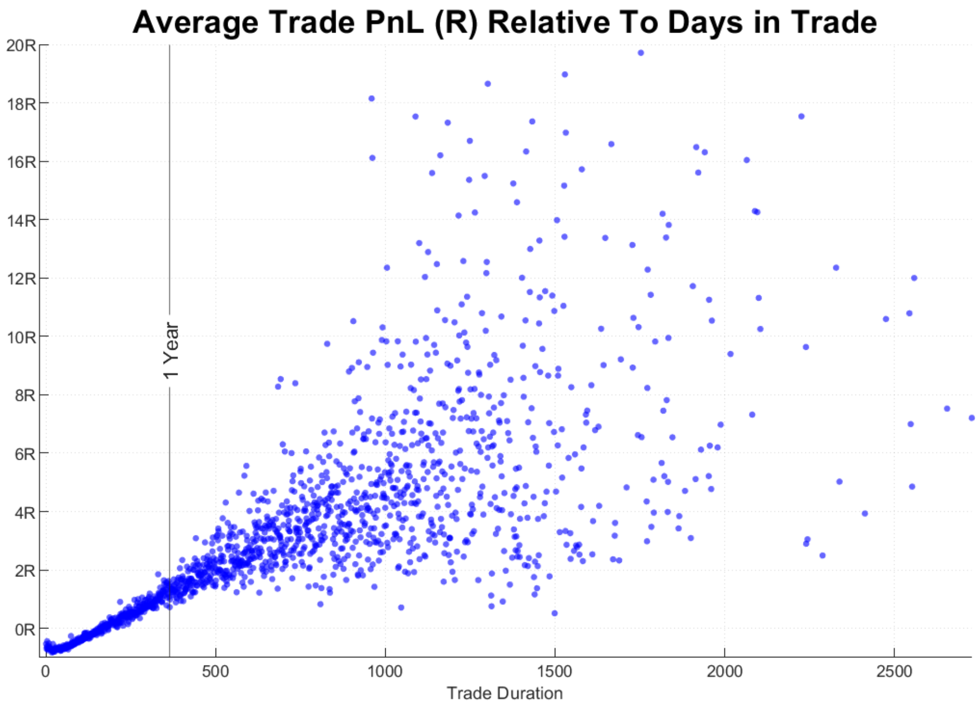


Figure 8: This scatter plot shows the relationship between the duration of trades (expressed in calendar days) and the average PnL_R (expressed as a multiple of the initial risk). All the dots that fall to the right side of the vertical line represent trades with a duration exceeding one calendar year.

In Figure 8 we illustrates the relationship between trade duration (in days) and the trade average PnL_R. There is a clear positive correlation between trade duration and PnL_R, as trades held for longer periods tend to produce higher returns. This trend-following strategy appears to benefit from extended holding periods, with trades held for 2 years often generating returns around 2R. Notably, shorter-term trades (< 1 year) cluster around lower PnL_R values, typically below 1R, suggesting that the strategy's performance improves significantly with time as long-term trends unfold. The chart emphasizes the importance of patience and holding positions over extended periods to maximize potential gains, which aligns with the overall trend-following philosophy of capturing large market moves.

We also studied the time-varying profitability over the years and compared the performance before and after the publication of Wilcox's paper. In Figure 9 we observe a slight decrease in average profitability post-publication, with the average PnL_R dropping from 0.39R in the pre-publication period to 0.31R afterward.

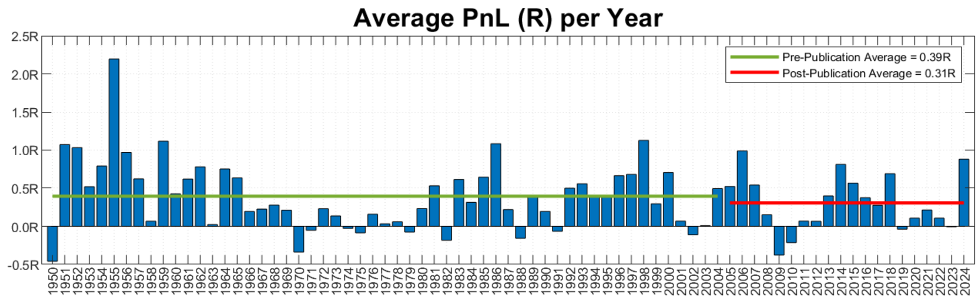


Figure 9: Each bar shows the average PnL_R (expressed as a multiple of the initial risk) for all the trades taken within a given year of our backtesting period. The green and red horizontal lines highlight the overall average PnL_R for pre-publication and post-publication years, respectively, i.e. before and after 2005, the year Wilcox and Crittenden published their white paper.

However, this decrease in average profit is partially offset by an increase in the opportunity set, as evidenced by the average total return per year exhibited in Figure 10, which actually increased after publication. While the profitability per trade has declined slightly, the broader application of the strategy across a larger set of market opportunities has allowed the strategy to continue generating returns, albeit at a slightly reduced rate.

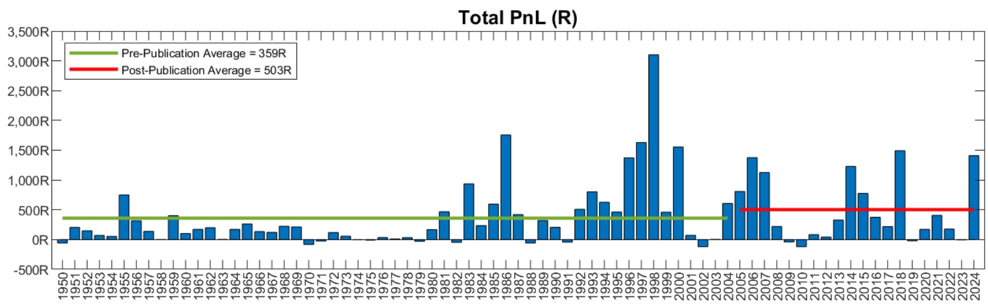


Figure 10: Each bar shows the cumulative PnL_R (expressed as a multiple of the initial risk) for all the trades taken within a given year of our backtesting period. The green and red horizontal lines highlight the overall average cumulative PnL_R for pre-publication and post-publication years, respectively, i.e. before and after 2005, the year Wilcox and Crittenden published their white paper.

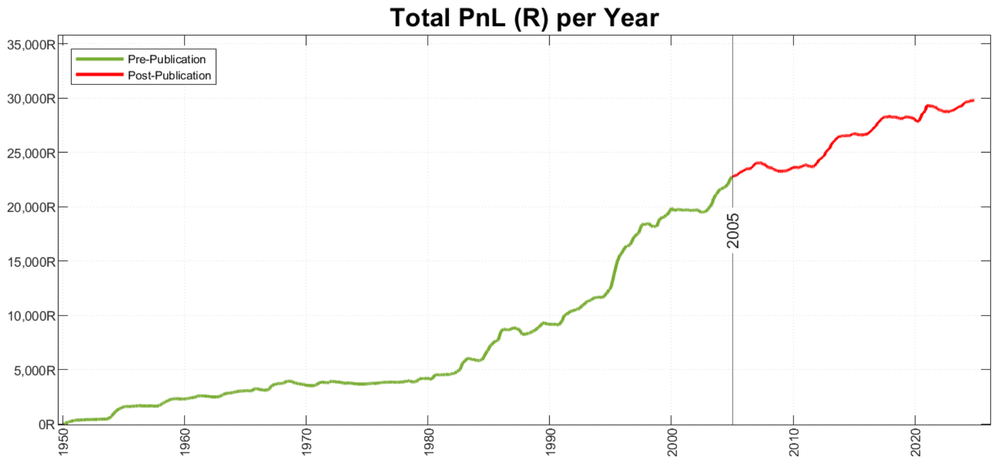


Figure 11: This figure illustrates the evolution of cumulative PnL_R from 1950 through 2024. The green line shows returns generated prior to Wilcox and Crittenden's (2005) publication, while the red line represents returns accumulated thereafter.

Figure 11 illustrates the long-term profitability of the trend-following strategy over the past several decades. The green line, representing the pre-publication period, shows consistent growth, with some periods of accelerated gains, particularly in the late 1990s and early 2000s. Following the publication of Wilcox's paper (marked by the vertical line), the cumulative PnL_R continues to rise, albeit at a slightly slower rate. Despite this, the strategy remains profitable, with the total PnL_R steadily increasing post-publication.

Another way to capture the positive asymmetry of trade profitability is to plot the cumulative sum of all trades' PnL_R, sorting them in ascending order from the smallest to the largest. Figure 12 illustrates this point. The orange curve, which orders the trades by size, highlights that 56% of the trades resulted in losses. The middle section, approximately 37% of trades, managed to recover these losses, essentially breaking even. However, the most striking observation is that less than 7% of the trades were responsible for generating all of the strategy's profits.

This positive skew is crucial to the overall success of the trend-following approach. The few highly profitable trades, shown by the sharp rise in the final section of the orange curve, more than compensated for the larger number of losing trades. The blue line, which plots the cumulative PnL_R ordered by entry date, shows the steady and consistent growth of the strategy over time, despite the high proportion of losing trades. This highlights

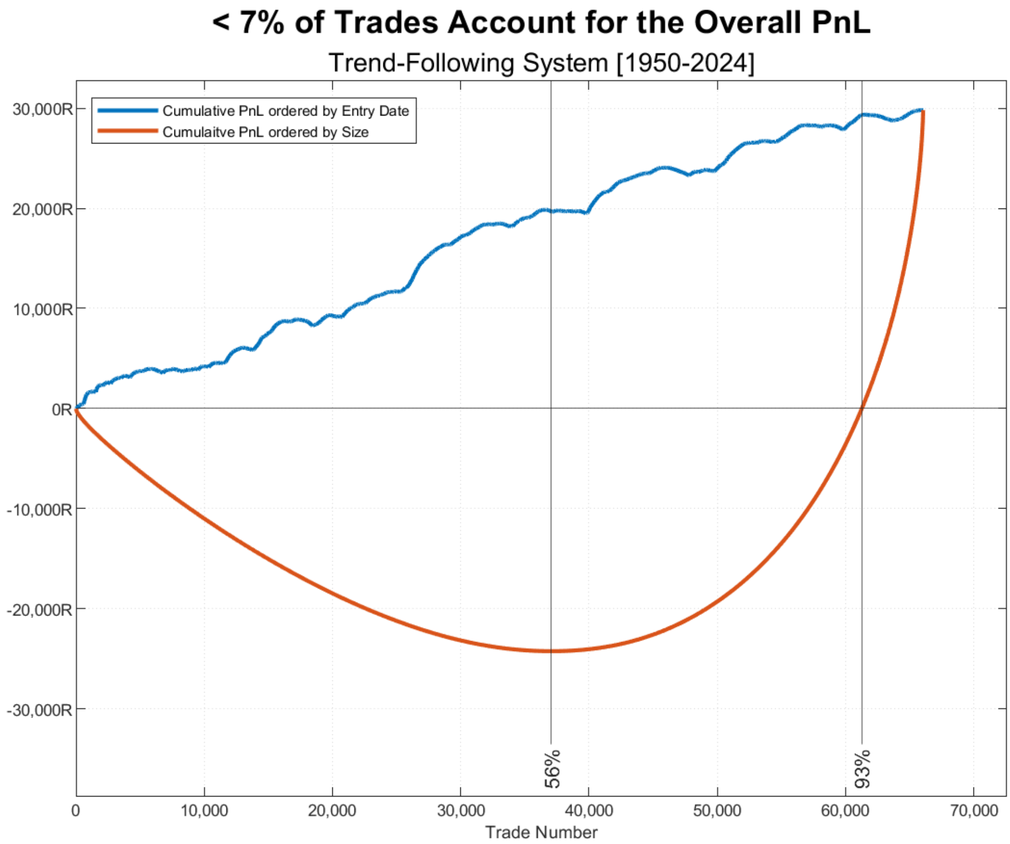


Figure 12: The blue line represents the cumulative realized PnL_R, expressed as a multiple of the initial risk, for all trades executed during the backtesting period in chronological order. In contrast, the orange line depicts the cumulative PnL_R for the same trades, but ordered from the largest loss to the largest gain.

the core principle of trend-following: while the majority of trades may be unremarkable or even unprofitable, the small number of significant winners drives the long-term profitability of the strategy.

4 A Trend-Following Portfolio

As discussed in previous sections, our results support the hypothesis that there may be significant value in investigating long-only trend-following strategies in U.S. stocks. The goal of this section is to introduce and thoroughly backtest a tradable strategy from 1991 until 2024 built upon the same principles and investment philosophy underlying the statistical tests conducted on all U.S. stocks from 1950 to 2024.

The key principle of this portfolio is to ensure that it captures all liquid long-term outliers within the investable universe and rides their upward trends as long as possible. Below, we outline the filters and methodology used to define the investable universe and manage the portfolio.

4.1 Investable Universe

At the close of day t, new potential long positions must meet the following criteria:

- **Index Membership:** The stock is part of the Russell 3000 index.
- **Price Threshold:** The stock price exceeds \$10.
- **Liquidity Threshold:** The 42-day average dollar volume exceeds \$1 million (back-adjusted for inflation using the CPI index[6]).

4.2 Entry Rules

At the end of each trading day, all stocks within the investable universe that achieve a new all-time high (ATH) but are not yet part of the portfolio will form the buy list for the next day's open.

4.3 Position Sizing

Position sizing is determined based on the stock's recent volatility to ensure that each holding contributes equally to the overall portfolio's volatility. The annualized volatility

[6] https://fred.stlouisfed.org/series/CPIAUCSL

target is set at 30%. The weight for stock i in the portfolio, calculated at the close of day t (though traded at the open of day $t+1$), is:

$$\widetilde{w}_{t,i} = \frac{30\%}{\sigma_{t,i}} \times \frac{1}{N_{holdings,t}}$$

where $N_{holdings,t}$ is the number of stocks with positive weights based on the signals update at the closure of day t and $\sigma_{t,i}$ is the 42-days annualized volatility of stock i.

To prevent excessive concentration, especially during bear markets when most stocks might hit stop-loss levels, the formula is adjusted as follows:

$$\widetilde{w}_{t,i} = \frac{30\%}{\sigma_{t,i}} \times \frac{1}{\max(200, N_{holdings,t})}$$

This adjustment ensures that the denominator of the second part of the equation does not drop below 200. Additionally, portfolio leverage is capped at 200% to comply with U.S. brokerage limits. If the ideal portfolio exposure exceeds this threshold, all weights are scaled proportionally:

$$w_{t,i} = \widetilde{w}_{t,i} \times \max\left(1, \frac{2}{\widetilde{W}_t}\right)$$

where $\widetilde{W}_t$ is the sum of all ideal portfolio weights before scaling (i.e. $\widetilde{W}_t = \sum_i \widetilde{w}_{t,i}$).

For example, if the ideal portfolio exposure totals 300%, an initial weight of 0.30% in Stock A would be adjusted to:

$$0.30\% \times \frac{2}{3} = 0.20\%$$

Similarly, all ideal weights will be adjusted by the same correction factor, $\frac{2}{3}$, making the final portfolio leverage equal to 2.

4.4 Trade Execution

Once the position sizes are computed, market-on-open orders are sent for each stock in the buy list for the next trading day. In line with trend-following principles, a trailing stop-loss is applied, the first day set at:

$$\text{Stop}_t = \text{ATH}_t \times \left(1 - \frac{\text{ATR}_t}{\text{Close}_t}\right)^{10}.$$

where ATH_t represents the All-Time High, and ATR_t is the 42-day Average True Range (ATR), both computed at the end of day t.

4.5 Managing Positions

Unfortunately, when managing a long-only trend-following portfolio on all U.S. stocks, it is not sufficient to define how to enter and exit a position; the most challenging and complex part is related to how positions are managed and adjusted throughout the life of each trade.

In fact, every day, we need to ensure that trailing stops are updated, position sizing is adjusted due to changes in stock volatility, and new long positions are accommodated by freeing liquidity as needed. Managing positions involves:

1. **Updating Trailing Stops:** Stop-loss levels are only adjusted upward, following the rule:

$$\text{Stop Loss}_t = \max\left(\text{Stop Loss}_{t-1}\ ,\ \text{ATH}_t \times \left(1 - \frac{\text{ATR}_t}{\text{Close}_t}\right)^{10}\right).$$

2. **Exiting Positions:** If a stock's closing price falls below its stop-loss, the position is unwound at the following day's open.[7]

3. **Recomputing Weights:** Due to changes in holdings and stock volatility, ideal portfolio weights are recalculated at the close of each day following the procedure explained in Section 4.3. This ensures liquidity is freed for new long positions or adjusted for existing holdings.

[7] The stop-loss mechanism in this strategy doesn't rely on placing hard stop orders with the broker that automatically trigger intraday when a certain price is reached. Instead, it works more like a *soft-stop* checked at the end of each trading day. If, at the close, the stock's price has dropped below the stop-loss threshold, it signals the need to exit that position. The actual exit happens the next day, at the market's opening price, ensuring there is time to review and act on the stop-loss breach systematically rather than reactively.

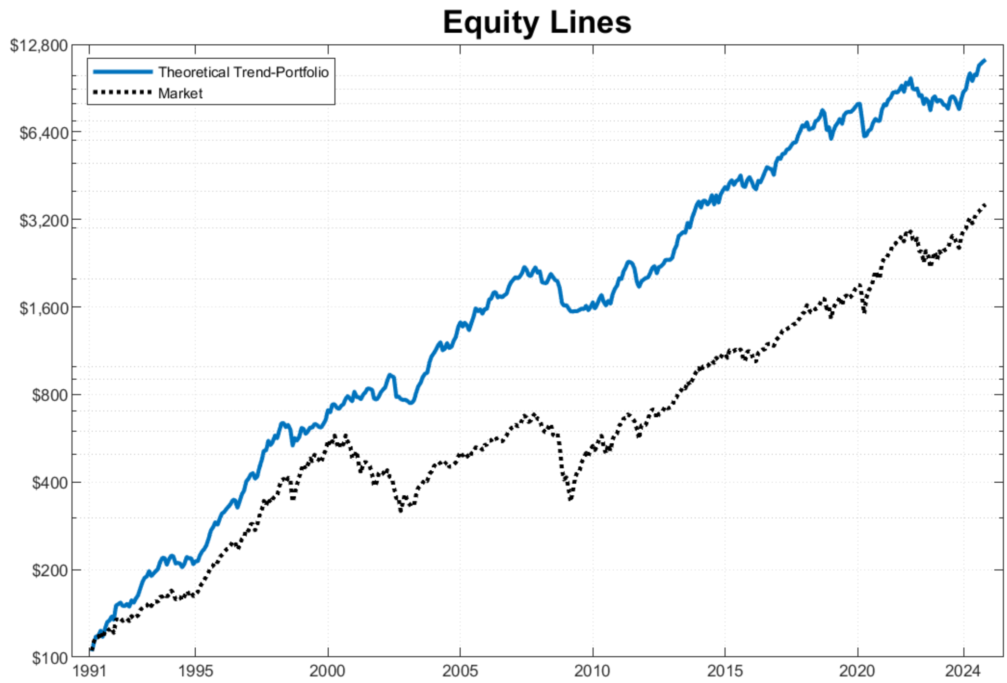


Figure 13: A comparison between the Theoretical Trend Portfolio (blue line) and a market capitalization-weighted index of all US stocks (black line). *Theoretical* refers to the fact that this version of the strategy does not account for transaction costs, slippage, or interest, and it also allows for trading of fractional shares.

4.6 Results

The initial backtest does not account for transaction costs, slippage, or interest, and it also allows for fractional share positions to ensure precise alignment with the intended portfolio weights. The goal in this part of the research is to create a theoretical trend-following portfolio that would serve as the basis for conducting further robustness checks in the later part of the paper.

The backtest spans from January 1991 to October 2024. Figure 13 compares the equity curve of the theoretical trend-following strategy (shown in blue) to that of the market (represented by a dashed black line), a market capitalization-weighted index of all US stocks[8]. Both portfolios assume continuous reinvestment of dividends.

Over the full testing period, the trend-following strategy achieves a compound annual

[8]The daily return of the market is sourced from Kenneth R. French's website: `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`

Table 1: Monthly and annual returns in % of the Theoretical Trend Portfolio compared to the market from 1991 to 2024.

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Yearly	Mkt
1991	4.8	7.0	5.1	0.4	4.3	-4.7	6.7	5.2	1.3	3.2	-2.5	12.0	**50.6**	**34.9**
1992	1.1	1.3	-2.6	0.0	1.5	-2.1	5.1	-1.9	3.5	2.5	5.8	5.3	**20.7**	**9.7**
1993	3.2	0.9	4.4	-3.9	1.7	2.2	1.8	5.9	3.1	0.0	-5.2	4.5	**19.5**	**11.1**
1994	2.9	-0.7	-5.5	0.6	-0.5	-3.0	2.5	5.8	-1.0	0.1	-4.8	2.6	**-1.5**	**-0.1**
1995	-0.2	4.7	3.2	1.9	3.3	5.4	6.5	2.7	3.9	-2.0	5.1	3.9	**45.7**	**36.7**
1996	1.4	2.3	1.9	2.4	3.2	-0.4	-5.7	5.3	5.6	3.0	7.4	2.4	**32.0**	**21.2**
1997	3.4	1.0	-4.3	1.6	7.4	5.9	8.2	-0.3	8.2	-3.4	2.5	5.3	**40.7**	**31.1**
1998	-2.2	6.3	6.0	0.0	-3.1	1.8	-3.8	-11.7	6.1	-2.0	2.9	7.3	**6.1**	**24.2**
1999	-0.7	-3.8	2.1	3.2	-0.4	3.1	-0.7	-1.8	-0.3	2.8	3.4	7.9	**15.2**	**25.6**
2000	-1.7	6.4	0.1	-2.5	-1.1	2.4	1.4	4.4	2.2	-2.2	-1.9	7.9	**15.7**	**-11.9**
2001	-4.1	-0.2	-1.4	3.7	1.9	3.0	-0.3	-0.8	-6.8	-0.6	2.2	3.8	**-0.3**	**-11.2**
2002	2.1	1.7	5.4	4.8	-1.2	-1.0	-14.3	0.4	-2.1	-0.6	0.1	-0.9	**-6.7**	**-21.2**
2003	-1.6	0.0	2.2	5.9	5.5	2.7	4.7	2.6	0.6	8.5	4.9	2.8	**45.9**	**31.7**
2004	2.9	3.4	2.4	-6.1	1.1	4.8	-4.0	1.2	4.9	2.9	8.3	3.9	**27.8**	**11.9**
2005	-3.5	3.3	-2.1	-3.7	5.9	5.0	6.9	-2.3	1.5	-3.5	4.1	-0.4	**10.8**	**6.0**
2006	8.0	0.6	4.9	0.7	-4.3	1.1	-1.0	1.9	0.9	6.0	3.6	1.8	**26.2**	**15.4**
2007	2.3	-1.2	1.5	2.8	4.9	-1.9	-4.6	-0.6	4.0	3.2	-4.2	1.2	**7.0**	**5.8**
2008	-8.3	-0.5	-0.3	3.7	3.9	-2.5	-2.3	-0.8	-5.5	-10.9	-2.1	0.3	**-23.6**	**-36.6**
2009	-2.5	-2.2	-0.2	0.2	0.0	1.0	1.0	-0.4	2.7	-3.5	2.6	3.7	**2.3**	**28.3**
2010	-4.8	2.8	5.0	3.0	-5.1	-3.0	3.8	-2.3	7.6	4.4	2.7	6.1	**21.0**	**17.5**
2011	-0.6	6.2	3.2	4.6	-0.2	-1.4	-3.8	-10.0	-3.8	4.3	1.5	1.2	**0.1**	**0.5**
2012	0.5	3.4	4.3	1.4	-5.5	5.0	0.9	1.8	3.2	0.0	0.0	1.7	**17.5**	**16.2**
2013	6.8	3.3	7.5	1.6	1.6	-0.6	8.2	-3.7	7.9	5.0	5.1	3.2	**56.1**	**35.1**
2014	-4.7	5.4	0.2	-3.0	2.2	5.4	-7.1	7.5	-5.6	6.9	3.0	2.9	**12.2**	**11.7**
2015	-1.9	5.1	2.4	-3.7	3.0	1.2	3.5	-8.0	-0.8	5.5	2.5	-3.4	**4.4**	**0.1**
2016	-4.3	-1.9	7.1	-1.3	4.1	4.3	3.9	-1.0	-0.7	-4.4	10.1	4.1	**20.7**	**13.5**
2017	-0.9	4.1	0.1	3.2	0.9	2.6	2.3	0.0	5.5	4.0	4.5	-1.2	**27.7**	**22.5**
2018	3.6	-5.7	0.9	0.6	5.6	0.7	2.8	5.4	-2.4	-12.5	2.4	-9.0	**-9.1**	**-5.1**
2019	6.3	4.2	2.3	3.4	-3.9	7.2	2.3	0.3	0.0	1.7	2.3	2.3	**31.7**	**30.4**
2020	0.3	-10.9	-13.3	0.8	3.8	1.1	5.2	3.2	-1.4	-0.3	9.3	4.6	**-0.1**	**24.1**
2021	-1.0	4.5	1.7	4.0	0.6	-0.5	2.2	3.5	-4.9	7.8	-1.7	5.3	**22.8**	**23.5**
2022	-8.1	-0.5	0.8	-5.9	0.8	-6.9	4.5	-2.3	-6.8	10.0	1.5	-4.2	**-17.0**	**-20.2**
2023	1.5	-0.9	-3.0	-0.2	-2.9	8.6	1.8	-1.6	-4.4	-4.1	8.2	5.8	**8.1**	**26.5**
2024	2.0	8.1	5.1	-5.9	5.3	-0.6	8.1	1.6	1.8	1.3			**29.2**	**22.5**

growth rate of approximately 15%, substantially outpacing the comparable market index whose CAGR was 11.18%. Accompanying this strong growth is an enhanced risk-adjusted return profile, as reflected in a Sharpe ratio of 0.85 that clearly surpasses that of the broad market (0.54). Moreover, while the market suffered a maximum drawdown of nearly 55% during the Great Financial Crisis, the trend-following strategy's largest drawdown remained contained at about 32%. Finally, when viewed in the context of standard performance benchmarks, the strategy demonstrates a statistically significant annualized alpha of 6.19% (p-value of 0.05%), further underscoring its capacity to deliver outperformance over the long run.

Table 1 presents the portfolio's monthly returns from 1991 to October 2024, alongside the annual realized returns of both the strategy and the market.

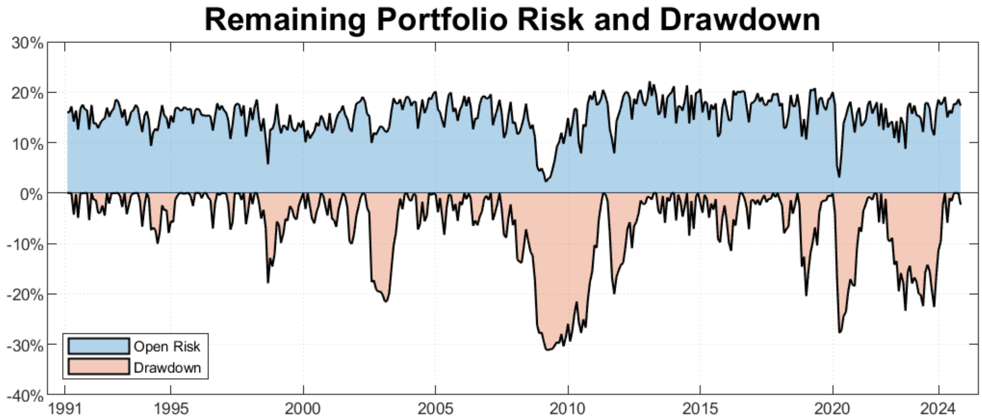


Figure 14: These two areas provide a visual representation of distinct risk metrics for the Theoretical Trend Portfolio. The blue area illustrates the open risk, defined as the percentage of NAV that would be lost if all positions simultaneously reached their stop-loss levels. The orange area, on the other hand, represents the realized drawdown of the strategy.

Figure 14 exhibits the time-varying underwater curve and the portfolio's open risk of the theoretical portfolio. Due to volatility-sizing mechanisms and stop losses that are a function of stock-specific volatility, the open risk (defined as the percentage of the AUM expected to be lost if all stops are hit on the same day) remains quite stable around 17%, with significant decreases during bear market phases when most stocks are stopped out and the portfolio is largely in cash.

Drawdowns may exceed open risk for two reasons:

1. **Compounding Losses:** Stocks being stopped out (partially realizing the open risk loss) create space for new stocks, which may also be stopped out, compounding previous realized losses.

2. **Upward Adjustment of Weights:** When many stocks are stopped out (partially realizing the open risk loss), but the portfolio still holds more than 200 stocks, the weighting procedure explained in 4.3 may imply that existing positions are adjusted upward, potentially increasing overall portfolio losses if these stocks are stopped out as well.

3. **Overnight Gap-Downs:** Drawdowns can exceed the predefined open risk due to overnight gap-downs, where stock prices open significantly below the stop-loss level, causing losses greater than the initial risk allocation for that position.

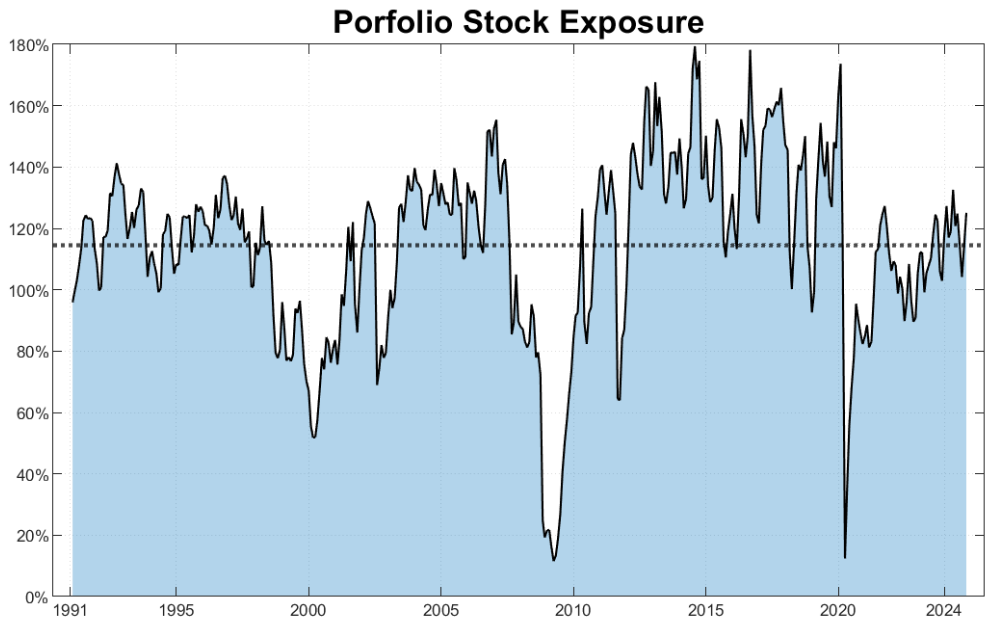


Figure 15: The stock exposure of the Theoretical Trend Portfolio throughout the backtesting period. Values exceeding 100% indicate that the portfolio is employing leverage. The dotted line represents the average portfolio exposure over the entire period.

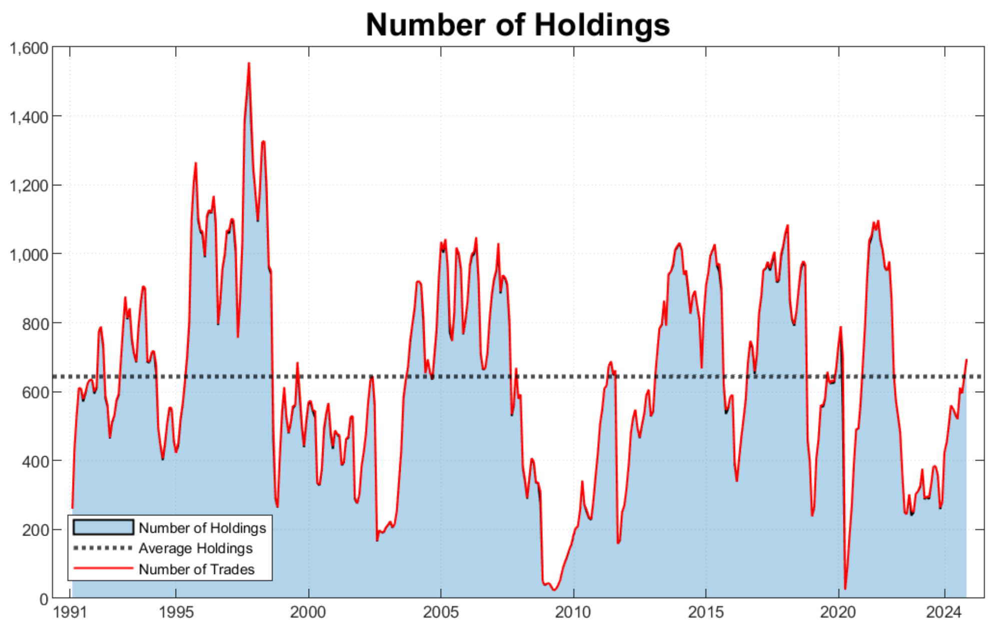


Figure 16: The blue area illustrates the number of open positions held by the Theoretical Trend Portfolio, with the black dotted line indicating the average number of open positions throughout the entire period. The red line represents the number of executed trades, including entries, exits, and rebalancing transactions.

Figures 15 and 16 show the stock exposure (i.e. portfolio leverage) and the number of holdings in the trend portfolio. As expected, stock exposure increases during bull market phases when the number of stocks making new highs rises, and stock volatility tends to decrease.

The red line in Figure 16 reveals that the daily number of trades, driven primarily by frequent small position rebalancements, is so high that it could pose significant challenges to implementing this portfolio in real-world scenarios, especially for less-capitalized trading accounts. This challenge arises from several factors. First, without an automatic order management system, it is nearly impossible to efficiently execute hundreds of trades per day. Additionally, making numerous small adjustments to the portfolio can become prohibitively expensive due to the cumulative impact of transaction costs and the minimum fees charged per transaction by brokers.

We also acknowledge that the profitability of this strategy is highly influenced by capital constraints. On one hand, less-capitalized trading accounts may struggle with minimum cost thresholds and position sizing, as some stocks might have share prices exceeding the optimal notional allocation suggested by the model. On the other hand, larger accounts may face significant challenges with market slippage when trading less liquid securities.

4.7 Accounting for Commission, Slippage, and Interest

We thus decided to conduct a further analysis on the profitability of this long-only trend-following model by including commission costs, slippage, and interest paid/earned on the portfolio cash.

The study is conducted on eight different portfolios, each with a different starting capital, ranging from \$100,000 to \$100 million. Given the upward trajectory of the theoretical trend model, the backtests are conducted assuming that at the beginning of each calendar year the AUM is reset to its original value. For example, if in 2010 the \$100 million portfolio earned \$50 million, we assume these profits are distributed to investors so that in January 2011 the AUM resets to its original \$100 million.

As previously mentioned, there are three sources of potential performance drag that we should take into consideration:

1. **Commission:** As per Interactive Brokers' tier pricing standard, we assume a commission of \$0.0035 per share with a minimum cost per transaction of \$0.35.[9] For sell transactions, we also account for SEC clearing fees and double the commission assumed for buy orders.

2. **Slippage:** We use the I-Star Market Impact model originally developed by Kissell and Malamut [10]. I-Star estimates slippage costs based on the size of the order, the overall daily market volume and the volatility of the stocks. Mathematically, slippage (in bps) is expressed as:

$$I^*_{bp} = a_1 \cdot \left(\frac{Q}{\text{ADV}}\right)^{a_2} \cdot \sigma^{a_3}$$

where Q is the number of shares to transact, ADV is the 30-day average daily volume, and σ is the 30-day price volatility of the stock. The parameters estimated by Kissell for the entire U.S. stock universe are $a_1 = 708$, $a_2 = 0.55$, and $a_3 = 0.71$. These parameter values are used in our backtesting engine.

[9]For more details on Interactive Brokers' tier pricing structure, visit: `https://www.interactivebrokers.com/en/pricing/commissions-home.php`

3. **Interest:** For interest earned on the remaining portfolio cash, we used risk-free returns as provided by the French database[10]. For borrowing costs, we double the risk-free rate and assume a minimum spread of at least 100 bps (annualized).

We include these costs in our backtesting procedure, along with the assumption that fractional shares cannot be traded.

The results of the new backtest are initially disappointing. Table 2 summarizes the key performance statistics for all tested portfolios. As anticipated, portfolios with limited AUM are the most adversely affected. For instance, the \$100,000 portfolio (*0.10M*) experiences a dramatic decline in CAGR, dropping from 15.02% in the theoretical scenario to just 2.45%, with alpha turning significantly negative at -4.63%. Additionally, the analysis reveals that risk-adjusted returns do not linearly improve with increasing AUM. For portfolios with very high AUM, the strategy's performance deteriorates further, likely due to heightened market impact.

Table 2: Summary statistics for the Trend-Following strategy across different AUM levels, incorporating transaction costs, slippage, and interest. The table includes metrics such as CAGR, Sharpe ratio, Sortino ratio, maximum drawdown (MDD), alpha, and beta. The bottom rows present the performance of the Theoretical Trend Portfolio and the market benchmark for comparison. Alphas in **bold** are statistically significant at the 2.5% level.

AUM	**CAGR**	**Vol**	**Sharpe**	**Sortino**	**MDD**	**Alpha**	**Beta**
0.10M	2.45	12.83	0.06	0.08	39.79	**-4.63**	0.55
0.25M	4.76	14.00	0.23	0.29	39.31	-2.75	0.68
0.50M	6.87	14.48	0.36	0.46	38.99	-0.88	0.62
1M	9.01	14.75	0.49	0.64	36.54	0.91	0.64
5M	12.13	14.96	0.67	0.86	34.44	**3.73**	0.65
10M	12.53	15.00	0.70	0.91	34.29	**4.13**	0.65
50M	11.87	15.02	0.66	0.88	35.25	3.54	0.65
100M	10.97	15.03	0.65	0.87	36.23	2.72	0.65
Theoretical	15.02	14.93	0.85	1.11	31.75	**6.19**	0.66
Market	11.18	18.19	0.54	0.68	54.68	0.00	1.00

[10]https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

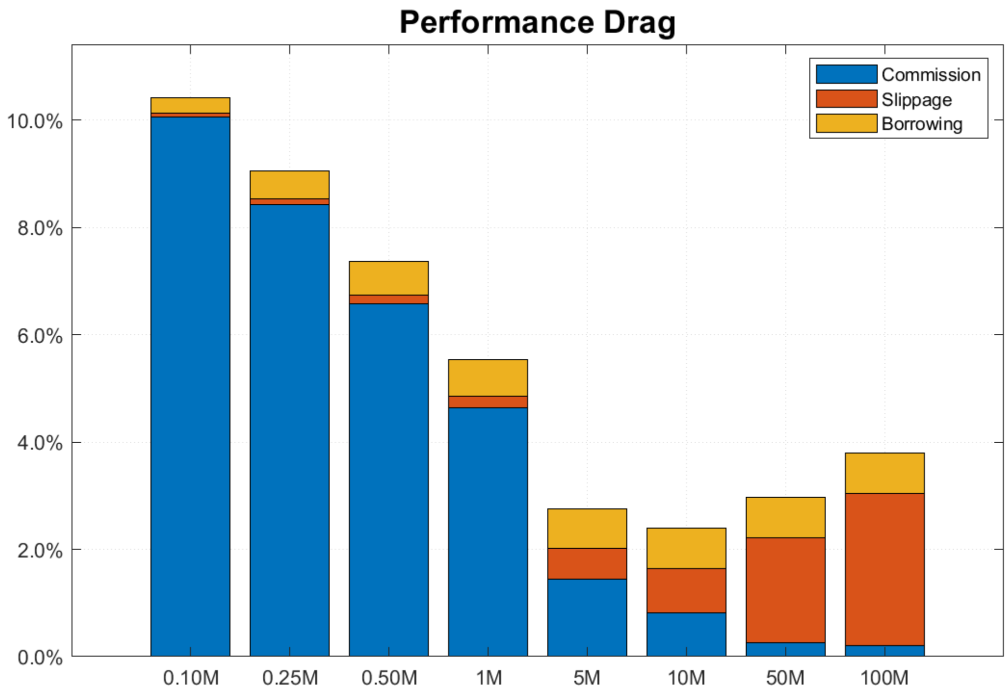


Figure 17: This vertical stacked bar chart illustrates the impact of realistic trading costs on eight trend-portfolios with varying AUM sizes (ranging from $0.10M$ to $100M$). The stacked bars represent the average yearly impact of commissions (blue), slippage (orange), and borrowing costs (yellow), expressed as a percentage of the portfolio's AUM.

To better understand the yearly performance drag caused by each cost component, Figure 17 presents a vertical stacked bar chart showing average yearly costs for each AUM size, split into commission, slippage, and borrowing cost. For the \$100,000 portfolio, yearly performance drag exceeds 10%, with commissions accounting for more than 95% of the total cost. As portfolio size increases, commission burden decreases, while slippage impacts rise to over 3% for the \$100 million portfolio. Based on these assumptions, the *sweet spot* for managing a trend-following portfolio on U.S. stocks appears to be around \$10 million, where the yearly drag due to cost is around 2.50% per year.

Figure 18 provides further visual confirmation of the significant impact of transaction costs, particularly on less-capitalized portfolios.

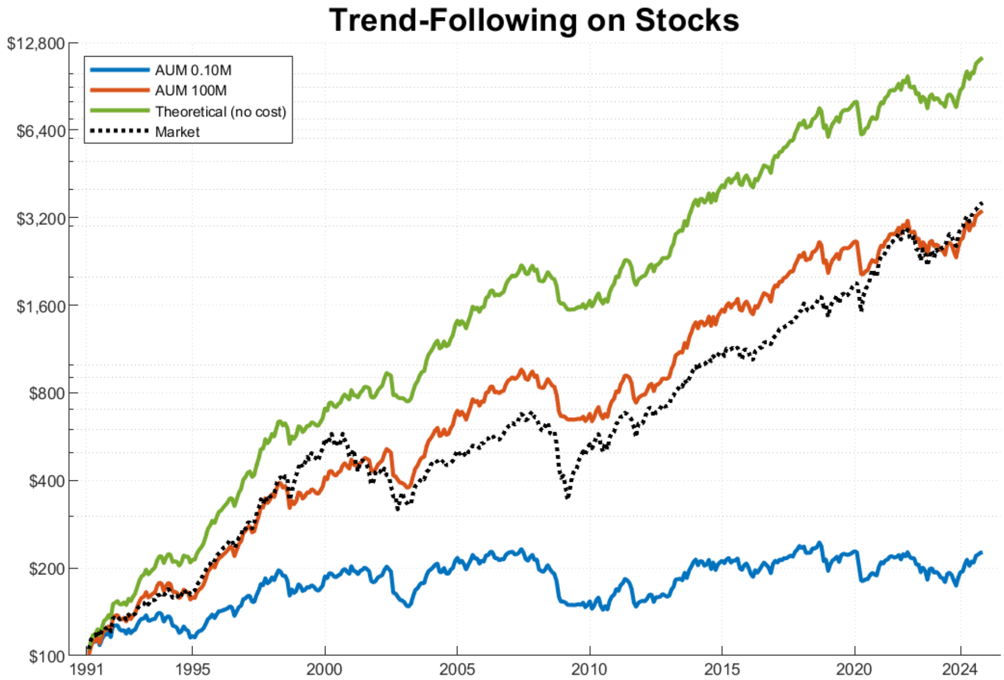


Figure 18: NAV comparison between the Theoretical Trend Portfolio (green line) and two historically accurate backtests with AUM sizes of 0.1M and 100M (AUM is artificially reset at the start of each year, while NAV remains unaffected). These portfolios incorporate realistic trading cost assumptions, as discussed in Section 4.7. The black dotted line represents a market capitalization-weighted index of all U.S. stocks.

4.8 Turnover Control Mechanism

The inclusion of transaction costs into the backtesting engine highlights a significant challenge: implementing a highly diversified trend-following strategy on U.S. stocks is likely feasible only for well-capitalized investors. This difficulty arises primarily from the high turnover associated with daily rebalancing in the trend model, where many trades contribute minimally to overall exposure but accumulate significant costs over time. Furthermore, most of these trades exhibit negative autocorrelation. Due to the inverse relationship between stock prices and volatility, combined with the short-term mean-reversion tendencies of stock prices, many rebalances are often reversed within a few days, resulting in unnecessary costs.

To address these inefficiencies and enhance the strategy's practical implementation, we introduced a Turnover Control mechanism. This framework is designed to optimize trading

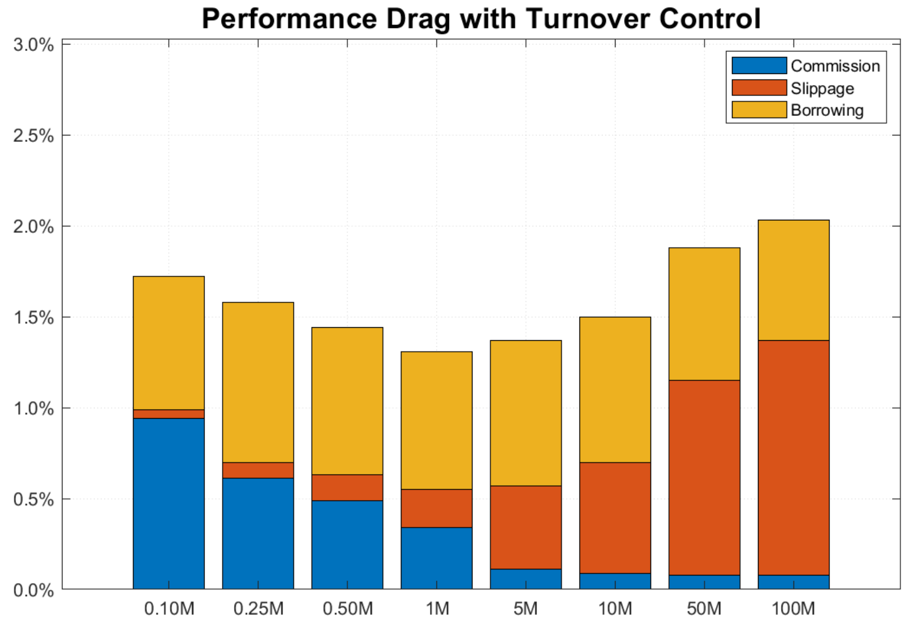


Figure 19: Vertical stacked bar chart illustrating the impact of realistic trading costs on eight trend-portfolios with varying AUM sizes (ranging from 0.10M to 100M) after applying the turnover control mechanism. The stacked bars represent the average yearly impact of commissions (blue), slippage (orange), and borrowing costs (yellow), expressed as a percentage of the portfolio's AUM.

activity by: (1) skipping trades where the required rebalancing adjustment falls below a defined threshold, (2) distributing trades over multiple days to mitigate the market impact of new positions or significant rebalances, and (3) avoiding rebalances when the expected commission costs exceed a preset threshold relative to the notional amount traded[11].

In Figure 19, we re-examine the yearly performance drag for each portfolio and find that the Turnover Control mechanism significantly improves cost management, enhancing efficiency and profitability in line with the theoretical trend portfolio. For example, the yearly drag due to commissions for the 0.10M portfolio decreased from approximately 10% (see Figure 17) to less than 1%. For larger portfolios, such as the 100M AUM portfolio, the benefit is also evident in a significant reduction in slippage—from 3% per year to 1.3% per year.

[11]For additional information about the Turnover Control mechanism, please contact us via email at carlo@concretumgroup.com.

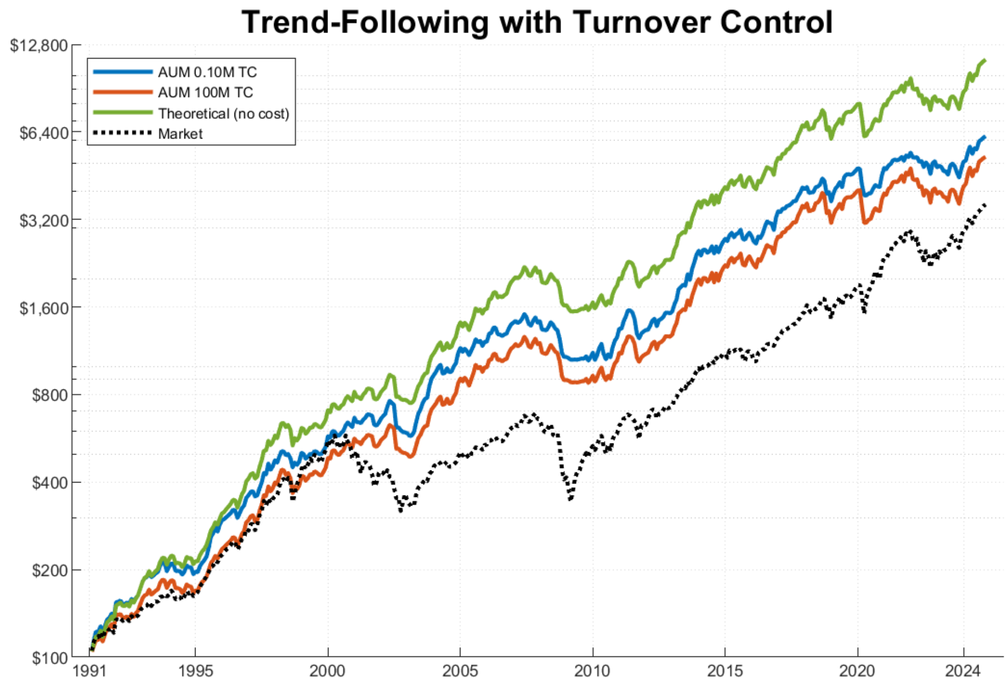


Figure 20: NAV comparison between the Theoretical Trend Portfolio (green line) and two historically accurate backtests with AUM sizes of $0.1M$ and $100M$. While AUM is artificially reset at the beginning of each year, NAV remains unaffected. These backtests account for realistic trading cost assumptions, as detailed in Section 4.7, and incorporate the turnover control mechanism described in Section 4.8. The black dotted line represents a market capitalization-weighted index of all U.S. stocks.

Figure 20 illustrates the improvement in the net-of-cost NAV for the studied portfolios. Compared to Figure 18, the less-capitalized 0.10M portfolio now trades more efficiently, even surpassing the 100M portfolio in terms of total return. Notably, both net-of-cost portfolios align more closely with the theoretical curve, highlighting the significant impact of the Turnover Control mechanism in narrowing the gap between the tradable and theoretical performance.

Table 3 summarizes the improved performance statistics, showing more attractive and stable results across portfolios. Surprisingly, despite maintaining an average leverage of approximately 120% over the backtested period, the portfolio's average beta was significantly lower than 1, at 0.63. This low beta can be attributed to the nature of the market-cap-weighted index used as a benchmark, which is often dominated by a handful of highly capitalized stocks. In contrast, the trend-following portfolio distributes weights more evenly across its holdings, resulting in a lower correlation with the benchmark.

Table 3: Summary statistics for the Trend-Following strategy across different AUM levels after implementing the Turnover Control mechanism. The table includes metrics such as CAGR, Sharpe ratio, Sortino ratio, maximum drawdown (MDD), alpha, and beta. The bottom rows present the performance of the Theoretical Trend Portfolio and the market benchmark for comparison. Alphas in **bold** are statistically significant at the 2.5% level.

AUM	CAGR	Vol	Sharpe	Sortino	MDD	Alpha	Beta
0.10M TC	12.97	14.23	0.75	0.98	32.97	**4.94**	0.59
0.25M TC	13.49	15.12	0.75	0.98	33.98	**5.00**	0.65
0.50M TC	13.30	15.04	0.74	0.97	33.59	**4.83**	0.65
1M TC	13.40	14.92	0.75	0.98	32.91	**4.93**	0.64
5M TC	13.48	15.10	0.75	0.97	33.45	**4.86**	0.65
10M TC	13.38	15.12	0.74	0.97	33.33	**4.86**	0.65
50M TC	12.84	14.95	0.72	0.93	33.18	**4.47**	0.64
100M TC	12.43	14.72	0.70	0.91	32.30	**4.28**	0.64
Theoretical	15.02	14.93	0.85	1.11	31.75	**6.19**	0.66
Market	11.18	18.19	0.54	0.68	54.68	0.00	1.00

4.9 Stability of Alpha

As a final step, we investigated whether the strategy's alpha has significantly changed over time or remained stable. To perform a rigorous analysis and evaluate the efficiency of the trend portfolio, it is essential to use an appropriate benchmark that aligns with both the tradable universe and the weighting methodology employed by the trend program. For this purpose, we constructed an equally weighted index comprising all stocks that would have been included in the Russell 3000 on any given day within the dataset.

Using a well-diversified, equally weighted portfolio as the benchmark provides a better match to the key characteristics of the trend portfolio analyzed in this study. Specifically, the volatility sizing approach employed in the trend strategy results in a portfolio that resembles an equally weighted portfolio more closely than a market capitalization-weighted portfolio. The latter would be significantly skewed toward mega-cap stocks, thereby deviating from the balanced exposure intended in our trend portfolio.

Using the daily excess returns of the theoretical portfolio and those of the equally weighted benchmark, we ran the following regression:

$$\mathrm{Ret}_t^{\mathrm{theor}} - \mathrm{Ret}_t^{\mathrm{rf}} = \alpha + \beta \cdot \left(\mathrm{Ret}_t^{\mathrm{mkt}} - \mathrm{Ret}_t^{\mathrm{rf}}\right) + \epsilon_t,$$

where

- $\mathrm{Ret}_t^{\mathrm{theor}}$: daily return of the theoretical strategy,
- $\mathrm{Ret}_t^{\mathrm{rf}}$: daily risk-free rate,
- $\mathrm{Ret}_t^{\mathrm{mkt}}$: daily return of Russell 3000 Equally Weighted,
- α: regression intercept for the given year (representing the daily alpha),
- β: sensitivity of the strategy to market excess returns,
- ϵ_t: regression error term.

We then created a time series of the returns not captured by the market by simply adding the error terms ϵ_t to the daily alpha of the regression. This can be interpreted as the daily abnormal return of the strategy, whose stability also depends on the error terms. Finally, by computing the cumulative sum of this time series, we can assess how the abnormal return of the strategy has evolved over time.

The results, illustrated in Figure 21, show that the cumulative abnormal return of the theoretical trend model, though volatile, is on average trending upward. Periods of strong outperformance, such as the late 1990s and mid-2000s, demonstrate the strategy's effectiveness under favorable market conditions. Periods of lackluster performance are typically associated with post-crash environments, when the market begins to rebound while the trend portfolio remains largely in cash, unable to capitalize on the early stages of the new market cycle. This is evident during the recovery after the great financial crisis in 2009 and in 2020, when, after a sharp sell-off early in the year, the market strongly rebounded, catching the trend portfolio off guard as it had moved into cash.

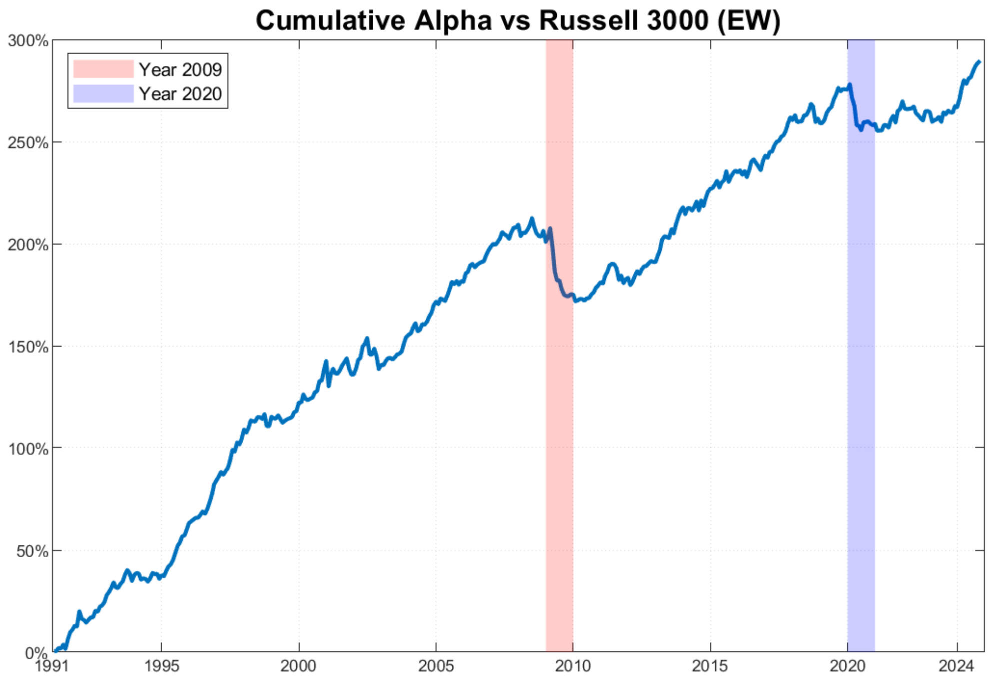


Figure 21: The chart represents the cumulative abnormal log returns of the Theoretical Trend Portfolio compared to an equally weighted Russell 3000 benchmark. Periods when the market rebounded significantly after large sell-offs are highlighted in red (2009) and blue (2020). These recovery periods are typically associated with lackluster returns for the trend portfolio, as it tends to remain largely in cash during the early stages of the rebound.

Notably, 2024 has been one of the best years for the trend portfolio, with an annual alpha exceeding 15%. This remarkable performance aligns with the significant dispersion observed in 2024 in the U.S. stock market, where only a portion of U.S. stocks drove substantial market gains. By focusing solely on positively trending stocks, the trend-following strategy effectively mitigated the performance drag from lagging stocks.

5 Conclusion

This study highlights the sustained potential of long-only trend-following strategies applied to U.S. equities, building on and extending the foundational research of Wilcox and Crittenden [1]. By analyzing over 75 years of data and more than 66,000 trades, the paper confirms the profitability of trend-following systems, driven by a small number of outsized winners that compensate for more frequent, smaller losses. The strategy's ability to thrive in various market conditions underscores its robustness, even in the face of evolving market dynamics.

In the second part of the paper, we developed and rigorously backtested a trading system inspired by the findings of the first section. This system incorporates principles such as capturing outlier returns through disciplined risk management and leveraging extended holding periods to maximize profitability. While the theoretical model demonstrates exceptional performance, with a compound annual growth rate (CAGR) of 15.02%, an annualized alpha of 6.19%, and a maximum drawdown of 31.75%, the practical implementation of this strategy is challenged by high turnover and transaction costs. These obstacles, particularly impactful for smaller portfolios, were addressed by introducing a Turnover Control mechanism, which significantly enhances cost-efficiency and ensures alignment with theoretical results.

Overall, the findings reinforce the value of trend-following strategies when applied systematically to individual stocks. While challenges such as transaction costs and real-world execution constraints exist, these can be mitigated through advanced portfolio management tecniques.

Author Biography

Cole Wilcox

Cole Wilcox is the Founder, Chief Executive Officer, and Chief Investment Officer of Longboard Asset Management, a boutique mutual fund manager specializing in alternative investment strategies. He has over 25 years of experience in hedge fund investment strategies and has guided Longboard in delivering systematic trading solutions to a global client base. Prior to founding Longboard in 2010, Cole served as Chief Investment Officer at Blackstar Funds, overseeing its global investment portfolio. He is recognized as a thought leader in the alternative investment industry and is a graduate of the Owner/President Management Program at Harvard Business School.

Carlo Zarattini

Originally from Italy, Carlo Zarattini currently resides in Lugano, Switzerland. After completing his mathematics degree in Padova, he pursued a dual master's in quantitative finance at Imperial College London and USI Lugano. He formerly served as a quantitative analyst at BlackRock, where he developed volatility and trend-following trading strategies. Carlo later established Concretum Research, assisting institutional clients with both high and medium-frequency quantitative strategies in stocks, futures, and options. Additionally, he founded R-Candles.com, the first backtester for discretionary technical traders.

Alberto Pagani

Based in Piacenza, Italy, Alberto Pagani holds a bachelor's degree in management engineering from the University of Parma. In 2020, he was included in the National Registry of Excellence by the Ministry of Education, University, and Research (MIUR), and in 2022 he received the Young Students Fund Award (MIUR), honoring high-achievers in STEM disciplines. As of 2024, he is pursuing a master's degree in supply chain management. Driven by a strong interest in finance and mathematics, his research focuses on quantitative investment strategies, particularly trend-following and volatility-based approaches.

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