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Optimal Momentum

# A Century of Profitable Industry Trends

*2025 Charles H. Dow Award Winner*

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**Abstract**

This paper evaluates the profitability of an industry-based long-only trend-following portfolio. Utilizing 48 industry portfolios from 1926 to 2024, our analysis explores the model's profitability over a century, highlighting its adaptability and effectiveness across diverse market epochs. We assess the overall profitability of the model and examine the distribution of long-term returns and associated risks. Our analysis includes the impact of individual industry contributions on overall portfolio performance, focusing on the frequency and average profitability of trades at both the portfolio and industry levels. The Timing Industry strategy achieves an average annual return of 18.2% with an annual volatility of 12.6%, resulting in a Sharpe Ratio of 1.39, compared to the US equity market's 9.7% return, 17.1% volatility, and 0.63 Sharpe Ratio. The model's outperformance is underscored by an annualized alpha of 10.9%, with the timing strategy reducing drawdown by almost 60% compared to a passive long exposure. Further investigations reveal the active strategy's ability to fully participate during market upswings while significantly limiting exposure during downturns. In the final section, we introduce 31 sector ETFs provided by State Street Global Advisors and backtest the same trading methodology over the last 20 years. The ETFs successfully replicate the model's exposure and returns. We also assess the impact of commissions and slippage, demonstrating that the active timing strategy remains largely profitable even with high trading costs.

***Keywords:*** *Momentum, Trend-Following, Dual Momentum, Industry Rotation, Algo Trading*

# 1 Introduction

Over the past 30 years, hundreds of research papers have documented momentum's pervasive and significant presence across asset classes, industries, and time frames. Momentum is often referred to as the tendency for asset prices to maintain the same trajectory as in the most recent period. Momentum is categorized into two types: time-series momentum and cross-sectional momentum.

In finance jargon, cross-sectional momentum refers to the tendency of an asset that was stronger than a benchmark (or other assets) to continue being stronger. Conversely, a relatively weak asset tends to remain weaker in the months ahead. In cross-sectional momentum, the magnitude of the stock move itself does not matter; what matters is the relative move versus a benchmark or a group of other stocks. Cross-sectional strategies are sometimes implemented in a long-short fashion, where the best-performing stocks are bought while simultaneously selling the worst-performing stocks.

On the other hand, time-series momentum refers to the tendency of an asset to move in the same direction as it did in the last period. The exposure of each asset strictly depends on its own price history, and no comparison with other assets is considered when deciding the exposure bias. Consequently, time-series momentum portfolios may have a time-varying exposure, sometimes with most of the portfolio constituents being long while others being fully short. Time-series momentum strategies are also referred to as trend-following strategies and constitute one of the hedge fund industry's most long-lived and highly capitalized sectors.

In the first decade of the 21st century, a blend of time series and cross-sectional momentum was introduced. These approaches, usually called Rotation Strategy or Dual Momentum, typically involve creating a portfolio that is always exposed to the strongest assets, conditional on these assets being in an uptrend (Antonacci, 2014). When implemented in equity markets, this approach allows investors to never bet against the positive long-term equity risk premium while trying to be exposed to the strongest stocks dynamically.

Given that industry momentum is the central topic of this paper, we provide a brief review of the key papers on this subject. One of the first studies of industry momentum was by Bohan (1981); the author showed that the best and worst-performing S&P 100 industry groups tend to continue performing that way.

Moskowitz and Grinblatt (1999) conducted another early study of industry rotational investing. The authors show that industry momentum is stronger than individual stock momentum over 6—to 12-month horizons, providing a significant basis for future research in this area.

Faber (2010) employed Kenneth French's monthly dataset for 10 industries from 1926 to 2010 to investigate a rotational strategy that dynamically takes exposure only to the strongest sectors. Faber suggests a long-only implementation, combined with a trend filter to move the portfolio to cash during market declines, showing an adaptive approach to long-only momentum investing.

Andreu et al. (2013) utilize Kenneth French's monthly data for 10 industries to test the profitability of a cross-sectional momentum portfolio across various momentum formation periods and holding horizons. This research later incorporates nine sector ETFs from State Street to analyze the profitability of cross-sectional momentum strategies.

Grobys and Kolari (2020) leverage the Kenneth French monthly database to construct a long-short quintile portfolio using 48 industries. The study demonstrates significant returns for the long-short strategy, emphasizing the efficacy of momentum strategies at the industry level.

Li et al. (2019) extend this analysis to a broader dataset using all ETFs listed in the CRSP database to create a long-short portfolio based on the best and worst deciles. This study confirms the profitability of momentum strategies with a large and diverse set of ETFs.

Vanstone et al. (2021) focus on the profitability of cross-sectional momentum strategies using nine sector ETFs from State Street. This study highlights momentum strategies' continued relevance and profitability when applied to sector ETFs.

Despite the numerous studies on the subject, we have never found an academic paper investigating the profitability of long-only trend-following systems in U.S. industries. Moreover, most of the studies mentioned earlier are conducted using monthly databases, while many trend-following programs are calibrated and traded daily.

This paper provides a useful bridge linking academic rigor with real-market trading habits in the trend-following space. Using a daily dataset of 48 US industry portfolios, we investigate the profitability of a long-only trend-following momentum strategy over 100 years.

In the last section of the paper, we replicate the long-only timing program using 31 sector ETFs provided by State Street and study the sensitivity of results by applying different trading costs and rebalancing approaches.

## 2 Database

For the paper's first section, we construct the industry database from Kenneth French's online data library[1]. The industry portfolios are built using the 4-digit SIC industry classification codes assigned to each stock traded on the NYSE, AMEX, and NASDAQ. Each portfolio is rebalanced annually, with stocks weighted based on their market capitalization on the rebalancing date. Our database includes daily total returns for 48 industries from July 1926 to March 2024.

We also rely on Kenneth French's online database for the time series of daily total returns of the market[2] and the 1-month Treasury bill rate.

The daily data for the 31 sector ETFs are obtained from Yahoo Finance and cover the

[1] The Kenneth French's online data is available for free from his website.

[2] The market is a market-capitalization-weighted index and includes all CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ with share code 10 or 11.

period from January 2005 to March 2024. Section 6 provides more details about the ETFs' database constituents.

# 3 Model Description

The primary goal of the model described in this paper is to identify a set of rules that allows a speculator to create a portfolio well-positioned to capture long-term upward trends as soon as there is sufficient evidence that a particular industry is experiencing demand pressure. Conversely, when the demand pressure diminishes or its trend becomes less evident, the strategy should liquidate the exposure to the industry and invest the resulting cash into 1-month Treasury bills. As is the case for all rules-based strategies, the Timing Industry portfolio described in this paper is built upon three main building blocks:

1. Entry Criteria
2. Sizing and Position Management
3. Exit Criteria

The trend-following model described in this paper utilizies certain technical analysis indicators and sizing methodologies commonly employed by market professionals. As we did not rely on ex-post optimization, the choice of indicators and parameters may seem sub-optimal for many readers. Therefore, we encourage readers to tweak the base model to fit their subjective utility preferences.

## 3.1 Entry Criteria

For each industry, we compute two well-known technical indicators that have been used by successful traders over the last century to capture market trends: Keltner Channels and Donchian Channels. Unlike other indicators such as Simple Moving Averages or Exponential Moving Averages, these indicators include a *Noise Region*, allowing prices to oscillate without requiring position adjustments. Both indicators consist of an upper band and a lower band. When an asset's price trades above the upper band, it typically signals strength; when it trades below the lower band, it signals weakness.

Let us briefly introduce each indicator and the basic math behind them.

**Keltner Channels**

Keltner Channels are a technical indicator traders use to assess financial asset volatility and potential price trends of financial assets. Developed by Chester W. Keltner in the 1960s, this tool consists of three lines: a central moving average line and two outer lines positioned above and below the moving average, creating a channel. The outer lines are typically set a fixed percentage away from the central line based on the asset's Average True Range (ATR)[3], which measures daily volatility.

Chester W. Keltner (1960), an early pioneer in the field of technical analysis, introduced the concept in his book *How To Make Money in Commodities*. Initially, Keltner's method used a 10-day moving average of the daily price (an average of the high, low, and close prices) as the central line. The channel width was determined by adding and subtracting the 10-day exponential moving average of the high-low price range. In modern applications, the channel width is defined by the ATR. Traders use Keltner Channels to identify potential breakout points and the start of potential trends. Mathematically, we can express the boundaries of the Keltner Channel of stock $j$ on day $t$ as:

$$\text{KeltnerUp}_{t,j}(n,k) = \text{EMA}(\text{Price}, n) + k \times \text{ATR}(n) \tag{1}$$

$$\text{KeltnerDown}_{t,j}(n,k) = \text{EMA}(\text{Price}, n) - k \times \text{ATR}(n) \tag{2}$$

Given our industry database consists only of closing prices, we cannot properly compute the ATR. We thus investigated using OHLC over the last 20 years and compared the

[3]The Average True Range (ATR) is a technical analysis indicator used to measure market volatility. It was introduced by Wilder (1978) 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, typically 14 days. 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.

20-day ATR with the 20-day rolling average of the daily price changes. We noticed that the ratio between ATR and this rolling average is quite stable over time and its long-term average is around 1.4. We thus adapted the Keltner Channels as follow:

$$\text{KeltnerUp}_{t,j}(n,k) = \text{EMA}(\text{Price}, n) + 1.4 \times k \times \frac{1}{n}\sum_{i=0}^{n-1} |\Delta\text{Price}_{t-i,j}| \tag{3}$$

$$\text{KeltnerDown}_{t,j}(n,k) = \text{EMA}(\text{Price}, n) - 1.4 \times k \times \frac{1}{n}\sum_{i=0}^{n-1} |\Delta\text{Price}_{t-i,j}| \tag{4}$$

For the upper band of the Keltner Channels we use a lookback period of $n = 20$ days and $k = 2$, while for the lower band, we use a longer lookback period of $n = 40$ days and $k = 2$. This creates an economic bias towards long exposure, as the longer lookback period for the lower band allows for a wider range before signaling a sell, thereby favoring holding long positions during periods of moderate pullbacks.

**Donchian Channels**

Developed by Richard Donchian, a pioneer in managed futures and commodities trading, Donchian channels are used by traders to identify market trends and volatility. They consist of three lines: the upper band, lower band, and the middle band, which is the average of the two. The upper and lower bands are based on the highest high and lowest low of a specified period, typically 20 days.

Donchian Channels help traders identify potential breakout points and trend reversals. When the price moves above the upper band, it indicates a bullish breakout, while a move below the lower band indicates a bearish breakout. This tool is particularly useful for trend-following strategies, helping traders to enter and exit positions based on the identified trends. The width of the area between the upper and lower lines of the Donchian Channel indicates the asset's volatility. A wider channel suggests high volatility, larger price swings, and significant potential for price fluctuations. In contrast, a narrower channel signifies lower volatility, indicating that the asset may be more stable or consolidating its previous gains or losses.

Richard Donchian introduced these channels as part of his broader contributions to technical analysis and managed futures. His work laid the foundation for many modern trading strategies, emphasizing systematic and disciplined approaches to trading. A famous example of Donchian Channel application was the experiment conducted by Richard Dennis and William Eckhardt in the 1980s, where they trained a group of novice traders, known as the *Turtle Traders*, to use Donchian Channels and other trend-following principles. The *Turtles* demonstrated that substantial profits could be achieved with a systematically, validating Donchian's methodologies. Mathematically, we express the Donchian Channel's boundaries as:

$$\text{DonchianUp}_{t,j}(n) = \max\left\{\text{Price}_{t,j}, \text{Price}_{t-1,j}, \ldots, \text{Price}_{t-n+1,j}\right\} \tag{5}$$

$$\text{DonchianDown}_{t,j}(n) = \min\left\{\text{Price}_{t,j}, \text{Price}_{t-1,j}, \ldots, \text{Price}_{t-n+1,j}\right\} \tag{6}$$

We utilize a lookback period of 20 days for the upper band of the Donchian Channels and 40 days for the lower band.

We design the Timing Industry portfolio to open a long position as soon as one of the two indicators signals price strength. Specifically, we establish a long exposure when an industry's closing price exceeds the upper band of at least one of these indicators. Mathematically, we combine the upper bands of the Keltner and Donchian Channels to form a *Upper Band* defines as

$$\text{UpperBand}_{t,j} = \min\Big(\text{DonchianUp}_{t,j}(20), \text{KeltnerUp}_{t,j}(20,2)\Big) \tag{7}$$

As soon as $\text{Price}_{t,j} >= \text{UpperBand}_{t-1,j}$ the strategy initiates a long position. Given the positive long-term equity risk premium, we allow the strategy to take only long positions.

## 3.2 Sizing and Position Management

Another key ingredient of a systematic trading program is the sizing methodology. There are numerous approaches to positioning in quantitative trading, some of which use very sophisticated statistical methods, including the study of correlation across portfolio constituents. Even though some of these highly complex methods may improve the profitability and stability of the trading program, we believe that relying on more intuitive and practical methods is more appropriate for the purposes of this paper.

Similarly to the sizing methodology proposed by Basso (2023) and inspired by legendary trend-following trader Larry Hite (2019), we size each position such that all traded instruments contribute equally to the portfolio's overall volatility. We limit the overall exposure to 200% to meet maximum leverage constraints. Clearly, if an asset is not in an uptrend, the exposure to that asset will be zero.

Let's explain the logic and mathematical formula behind the volatility scaling approach, assuming that the Timing Industry portfolio can trade N assets.

### Volatility Target

The target volatility at portfolio level coming from a single industry exposure has to be equal to $\frac{1.5\%}{N}$. As a consequence, the sizing of each industry exposure is inversely proportional to its recent volatility. Mathematically, the weight of asset $j$ at the closure of day $t$ is equal to

$$w_{j,t}^{vt} = \frac{\frac{1.5\%}{N}}{\sigma_{j,t}} \tag{8}$$

where $\sigma_{j,t}$ is the 14-day volatility of the returns of asset $j$ computed on day $t$.

**Example:** A strategy has 10 assets. The target volatility at the portfolio level is 1.5%. The target volatility for each asset is 0.15% ($\frac{1.5\%}{10}$). If an asset $j$ has a volatility of 3% per day, the optimal weight based on the Volatility Target method is

$$w_{j,t}^{vt} = \frac{\frac{1.5\%}{N}}{\sigma_{j,t}} = \frac{0.15\%}{3\%} = 5\% \tag{9}$$

**Max Leverage**

The leverage of the overall portfolio cannot exceed 200% of the equity (or AUM). In mathematical terms, $\sum_{j=1}^{N} w_{j,t} \leq 200\%$.

**Optimal Sizing**

The optimal weight of asset $j$ at day $t$'s closure can be computed using the volatility target approach as in Equation 9. If $\sum_{j=1}^{N} w_{j,t}^{vt} = \text{Exposure} \geq 200\%$, the positions are rescaled to meet max leverage constraints as

$$w_{j,t}^{*} = \frac{w_{j,t}^{vt}}{\text{Exposure}} \times 200\% \tag{10}$$

Each position is rebalanced daily and given the new optimal weight computed at the end of the day.

### 3.2.1 Exit Criteria

As mentioned above, each position has its own stop loss level. The stop loss represents the price level that invalidates the existence of an upward trend. To remain consistent with the indicators deployed to identify the start of a new uptrend, we use the lower bands of Keltner Channels and Donchian Channels to close out the long-trend trades.

To be conservative and cut positions quickly, the Lower Band of the Timing strategy is defined as

$$\text{LowerBand}_{t,j} = \max\Big(\text{DonchianDown}_{t,j}(40), \text{KeltnerDown}_{t,j}(40,2)\Big) \tag{11}$$

Moreover, in line with trend-following habits, we never allow the trailing stop to be updated downward. In practice, the prevailing Trailing Stop used in day $t+1$ is the maximum between the Trailing Stop used in day $t$ and the Lower Band computed at the end of day $t+1$.

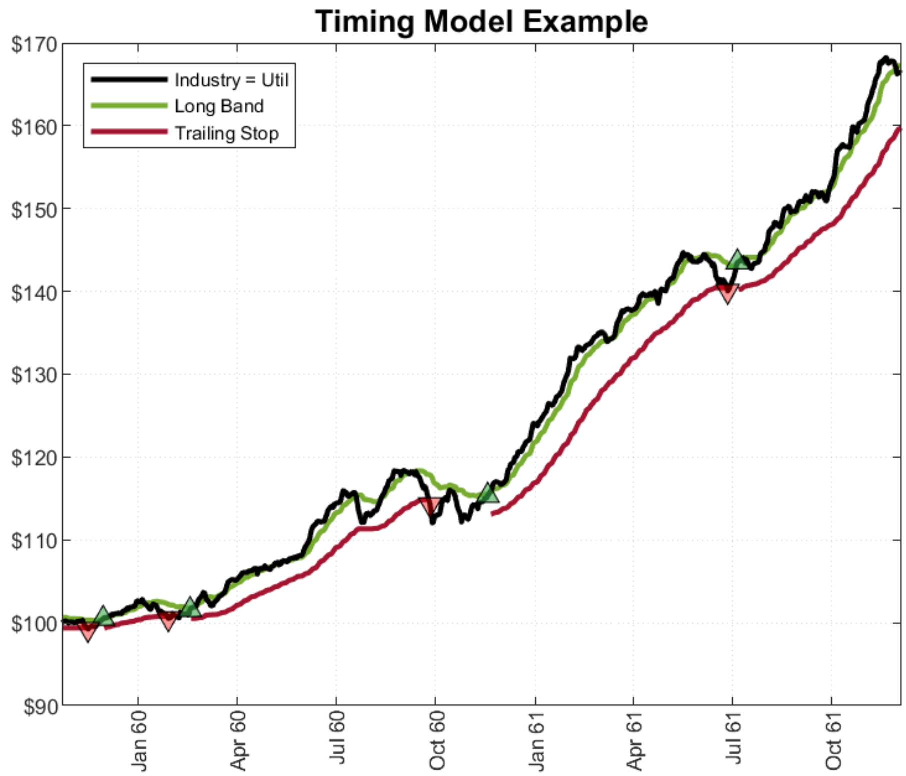


**Figure 1: Timing Model Example**. This figure illustrates the application of the trend-following model to the Utilities sector between October 1959 and November 1961. The black line represents the daily closing price, the green line indicates the LongBand of the model, and the red line represents the trailing stop, which is activated only when the portfolio has a long exposure in the sector. The triangles denote the trades: an upward green triangle marks the establishment of a long position, while a downward red triangle indicates the days when a position is stopped out.

$$\text{LongTrailingStop}_{t+1,j} = \max\Big(\text{LongTrailingStop}_{t,j}, \text{LowerBand}_{t,j}\Big) \tag{12}$$

### 3.3 Graphical Example

In Figure 1, we provide an example of how the Long Band and the Trailing Stop of the Timing Strategy would appear over a two-year window. The black line represents the closing price for the Utility sector. The green line represents the Upper Band of the Timing strategy, while the red line, active only when a long position is in place, represents the trailing stop loss. A new long position is initiated when the black line moves above the green line. New long exposures are marked with green up triangles on the chart. Each position is maintained if the closing price does not cross the red line, representing the long Trailing Stop. As clearly depicted on the chart, the trailing stop never moves downward and remains active until the stop is hit. In this example, after two initial stop losses were hit, a strong uptrend emerged in March 1960, and the timing strategy initiated a long position in the Utility sector. In October 1960, after a move of 20%, the price started a sharp decline, and the stop loss was hit. A few months later, the trend was reestablished, and the active strategy reentered long, participating in a strong uptrend.

# 4 Empirical Results

We backtested the Timing Industry portfolio over the last 100 years, specifically from 1926 to 2024. While we recognize that transaction costs can significantly impact active trading strategies, we chose not to include these costs in this section of the paper. Estimating such costs accurately is particularly challenging for the early part of the backtest due to the different market microstructure. In the paper's final section, we introduce the use of ETFs and thoroughly consider the impact of transaction costs. Given the dynamic nature of our portfolio, during periods when industry trends are absent, the portfolio may predominantly consist of cash. We assume that the available cash is invested in 1-month Treasury bills. Conversely, when the portfolio uses leverage to meet risk management objectives, we assume that the borrowing cost equals the 1-month Treasury rate.

Figure 2 graphically compares the equity trajectory of a passive investment in the market with that of the Timing Industry portfolio. A passive $1 investment in the market in 1926 would have grown to approximately $16,000 by 2024. In contrast, the same $1 invested in a dynamic, long-only Timing Industry portfolio would have grown to over $25 million. Moreover, the equity trajectory of the active portfolio appears much more stable, with infrequent and less significant drawdowns. A passive market exposure would have experienced dramatic drops that in some periods eroded more than 80% of the equity, with prolonged recovery periods, making it difficult for Buy&Hold investors to endure.

Table 1 reports the performance statistics of the active timing portfolio and the passive market portfolio. This table quantitatively confirms the qualitative analysis conducted

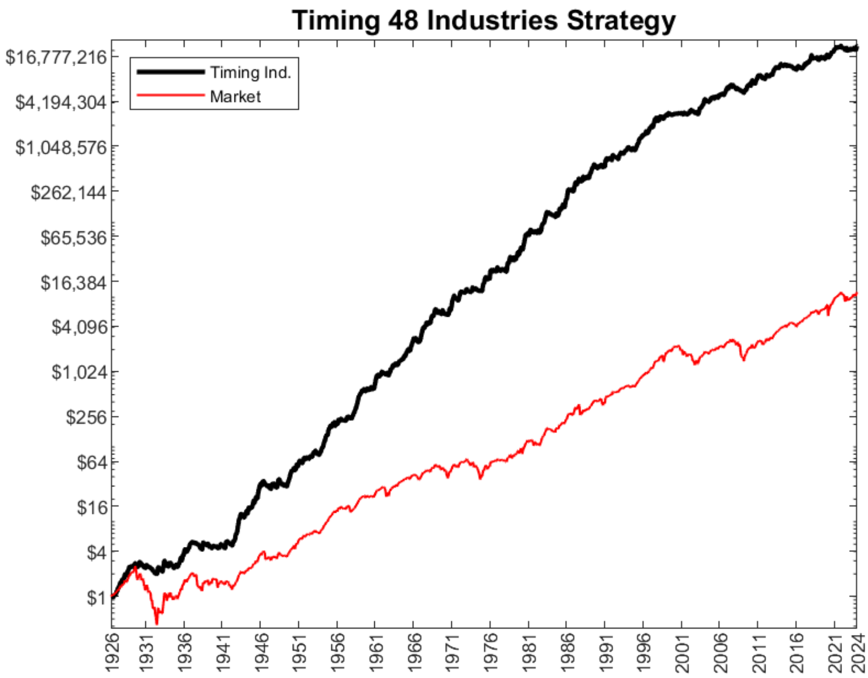


**Figure 2: Performance of the Last 100 Years**. This figure shows the equity evolution over the past 100 years of a $1 investment in the Timing Industry portfolio (black line) compared to a passive market position (red line). The Timing Industry portfolio takes exposure to 48 industries and is rebalanced daily based on new optimal weights. The market portfolio includes all stocks traded on the NYSE, Nasdaq, and AMEX, using a market capitalization weighting scheme. This backtest does not account for commissions and slippage. The data is sourced from the Kenneth French website, covering the period from July 1926 to March 2024.

in the previous paragraph. Over the last century, the active timing portfolio would have appreciated by an average of 18.2% per year with an annualized volatility of 12.6%, achieving a Sharpe Ratio of 1.39. During the same period, the market's average annualized return was 9.7% with a volatility of 17.1% and a Sharpe Ratio of 0.63. The maximum drawdown for the market was 84%, almost triple what was experienced by the Timing Industry portfolio (33%).

The daily skewness for the Timing portfolio is more negative compared to the market portfolio. However, when skewness is calculated monthly and yearly, it becomes significantly positive and more pronounced than market skewness. We speculate that this pattern arises because prices tend to move higher smoothly, while the end of uptrends often involves sudden and sharp reversals. These reversals can wipe out the profits from recent trading days but do not significantly affect the profits accumulated over longer periods.

**Table 1: Performance Statistics**. This table presents key summary statistics for the Timing Industry portfolio and the passive Market portfolio. IRR stands for the Internal Rate of Return, representing the 1-year geometric average return. MDD indicates the Maximum Drawdown. Alpha and Beta are the regression coefficients from the regression described in Equation 13. The t-statistics are calculated using Newey and West (1987) standard errors. The backtests do not include commissions and slippage. The data is sourced from the Kenneth French website, covering the period from July 1926 to March 2024.

| **Strategy** | **Timing Ind.** | **Market** |
|---|---|---|
| # Assets | 48 | 1 |
| IRR | 18.2% | 9.7% |
| Volatility | 12.6% | 17.1% |
| Sharpe Ratio | 1.39 | 0.63 |
| Sortino | 1.66 | 0.78 |
| Hit Ratio (daily) | 59% | 55% |
| Hit Ratio (monthly) | 56% | 63% |
| Hit Ratio (yearly) | 82% | 76% |
| Skewness (daily) | -0.9 | -0.2 |
| Skewness (monthly) | 0.7 | 0.1 |
| Skewness (yearly) | 1.1 | -0.5 |
| MDD | 33% | 84% |
| Alpha | 10.9% | |
| Alpha t.stat | 11.3 | |
| Beta | 0.5 | |
| Beta t.stat | 135 | |
| Worst Return | -12.0% | -17.4% |
| Worst Day | 26-Sep-1955 | 19-Oct-1987 |
| Best Return | 5.4% | 15.8% |
| Best Day | 07-Nov-1940 | 15-Mar-1933 |

To further assess the outperformance of the Timing Industry portfolio we run a regression between the excess daily return of the timing strategy (indicated as $\widetilde{Ret}_{\text{Timing},t}$) and those of the passive market exposure (indicated as $\widetilde{Ret}_{\text{Market},t}$)[4]. Given the long-only nature of the active timing strategy, we expect the *Beta* ($\beta$) to be positive. The intercept of the regression, usually called *Alpha* ($\alpha$) in financial jargon, indicates the return in excess of those attributed to a mere passive exposure in the market. Mathematically, the formula for the regression is

$$\widetilde{Ret}_{\text{Timing},t} = \alpha + \beta \times \widetilde{Ret}_{\text{Market},t} + \epsilon_t. \tag{13}$$

[4]In line with academic standard, we use daily returns in excess of the return obtained by a same-dollar exposure in a risk-free asset.

Table 1 reports the annualized *Alpha* ($\alpha$) and *Beta* ($\beta$) of the regression; over the last 100 years, the outperformance of the active timing strategy stands at 10.9% per year while the beta versus the market is 0.47[5].

The timing strategy may vary its risky exposure substantially throughout the backtest period, alternating between periods of *Risk-On* and *Risk-Off*, depending on the overall market trajectory. Therefore, we are interested in studying the degree of participation during strong up trending markets and how this participation changes during market decline phases. We conduct a more sophisticated regression where we regress the yearly return of the timing portfolio against positive-only yearly market returns and negative only yearly market returns. The beta coefficient for the positive-only yearly market returns indicates the degree of participation during up trending markets, while the beta coefficient for the negative-only yearly market returns indicates the participation of the timing strategy during market declines. We run the following regression:

$$Ret_{\text{Timing},t} = \alpha + \beta_{\text{up}} \times Ret^{+}_{\text{Market},t} + \beta_{\text{down}} \times Ret^{-}_{\text{Market},t} + \epsilon_t \tag{14}$$

where $Ret^{+}_{\text{Market},t}$ takes a value of 0 when the yearly return is negative, while $Ret^{-}_{\text{Market},t}$ takes a value of 0 for all the years with a positive market return.

Results are exhibited in Figure 3 and clearly indicate that the Timing Strategy has higher participation during positive market phases while significantly limiting the decline during market downturns. Impressively, the beta during positive market years exceeds 1, while it reduces to 0.31 during negative market years. The worst yearly loss for the Timing Strategy is approximately -15%, a great achievement if compared to the magnitude of the worst yearly returns for the market.

[5] We also conducted the classic Fama and French three-factor model regression using daily returns of the market (in excess of the risk-free rate), the size long-short portfolio (SMB), and the value long-short portfolio (HML). The regression coefficients and t-statistics (in brackets) are as follows: $\alpha_{\text{yearly}} = 10.6\%$ *(11.1)*, $\beta_{\text{MKT}} = 0.48$ *(20.1)*, $\beta_{\text{SMB}} = 0.2$ *(22.7)*, $\beta_{\text{HML}} = 0.01$ *(2.4)*

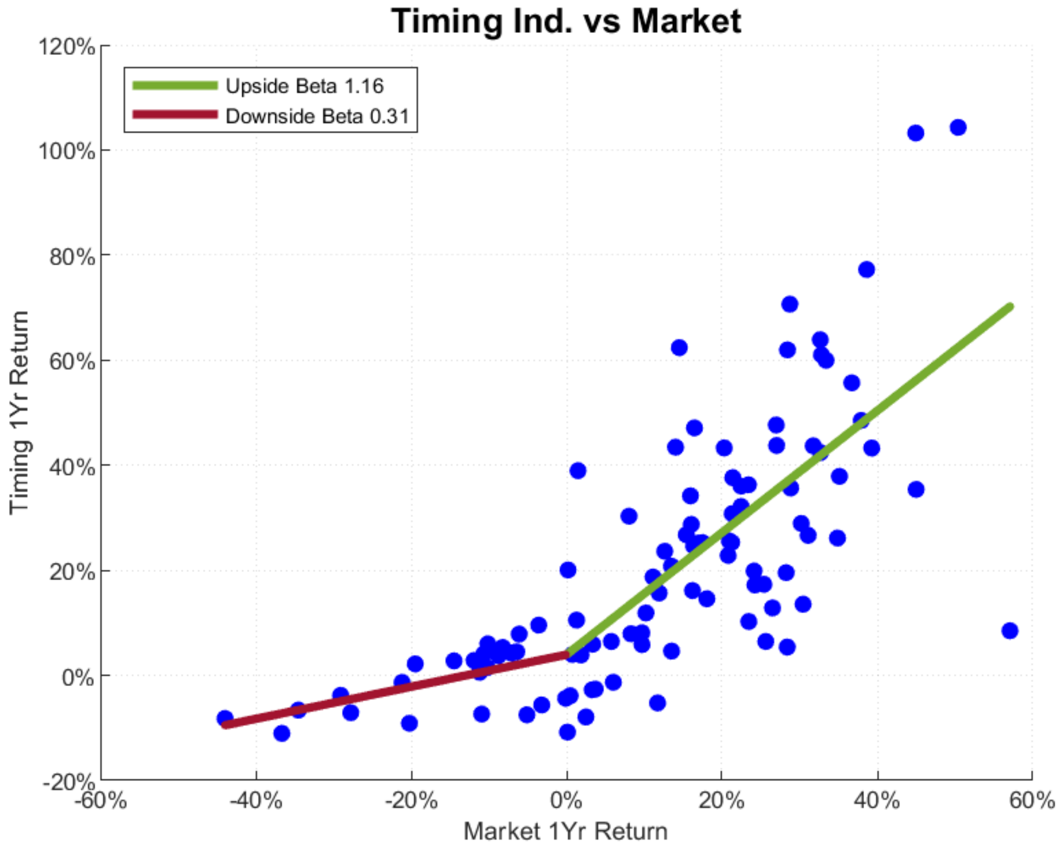


**Figure 3: Upside vs Downside Participation**. This figure plots the yearly return of the Timing Industry portfolio (y-axis) against the yearly return of the passive market portfolio (x-axis) using blue dots. The green line represents the linear fitted relationship between market returns and strategy returns during positive market years. The red line represents the fitted relationship during negative market years. The slope coefficients, reported in the legend, are obtained from the regression presented in Equation 14.

As described in previous sections, an entry signal is triggered as soon as the closing price exceeds the lower upper band among the Keltner and Donchian indicators. Conversely, a position is closed as soon as the price crosses below the lower band among the same indicators[6]. Analyzing all the entry and exit trades, we find that 69% of the longs are initiated due to a cross of the upper band of the Donchian Channel, while 31% are initiated due to the Keltner indicator. Most of the trades (85%) are stopped out after a cross below the lower band of the Keltner Channel.

Regarding position sizing, we estimate that approximately 99.5% of the traded positions are sized using the Volatility Target approach, while only on 0.5% of days the positions

[6]To be more precise, a position is closed once price crosses the Trailing Stop which is the maximum between previous day's stop and the lowest bands among both technical indicators.

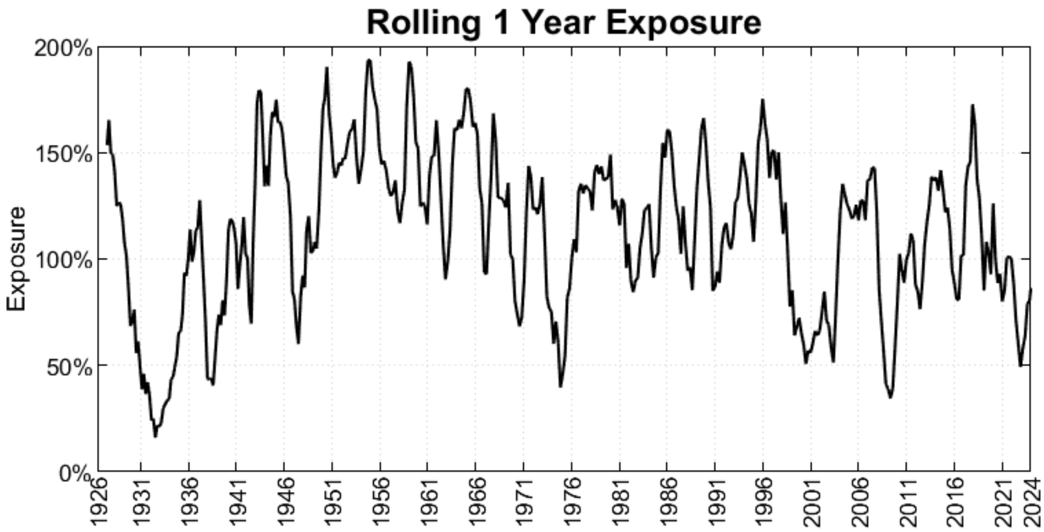


**Figure 4: Time-Varying Exposure**. This figure plots the 1-year rolling average of the notional exposure of the Timing Industry portfolio. The backtests do not include commissions and slippage. The data is sourced from the Kenneth French website, covering the period from July 1926 to March 2024.

are sized due to leverage constraints.

Figure 4 shows the rolling 1-year exposure of the Timing Industry portfolio. The exposure varies from a low of 18% in 1933 to a high of 195% in 1955. Exposure increases in strong market environments and decreases during market weakness. Therefore, this strategy raises portfolio Beta under favorable market conditions and lowers portfolio Beta in bear market environments.

## 4.1 Portfolio Profitability by Decades

Figure 5 shows the returns per year of the Timing Industry strategy and the yearly Sharpe Ratios. From a graphical perspective, the profitability of the dynamic, active strategy decreased over the last 30 years. We also notice an increase in the number of negative years. This negative stance may be either due to weaker market trends or the presence of higher noise within trends that may cause long positions to be stopped out just before the previous upward trend is re-established. We leave this topic for a future investigation. Table 2 reports the monthly returns over the full backtest period.

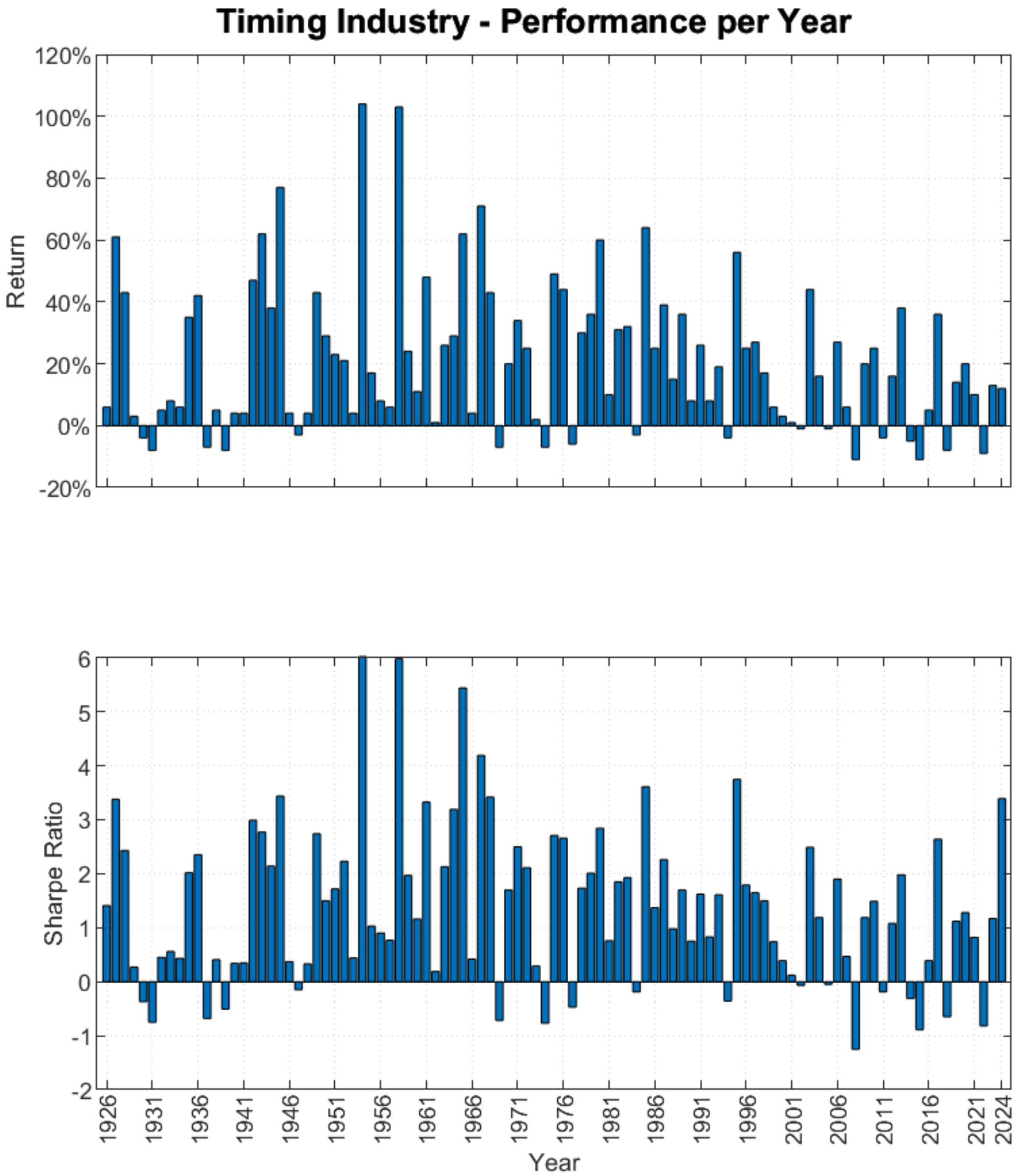


**Figure 5: Yearly Performance Analysis**. The top chart displays the yearly return of the Timing Industry portfolio, while the bottom chart plots the yearly Sharpe Ratio computed using the daily returns of the Timing Industry strategy. The backtests do not include commissions and slippage. The data is sourced from the Kenneth French website, covering the period from July 1926 to March 2024.

**Table 2: Monthly Returns**. This table presents the monthly returns of the Timing Industry portfolio from July 1926 to March 2024. The backtests do not include commissions and slippage. The data is sourced from the Kenneth French website.

| Year | Jan. | Feb. | Mar. | Apr. | May | Jun. | Jul. | Aug. | Sep. | Oct. | Nov. | Dec. | Yearly |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1926 | | | | | | | 0.2 | 1.5 | 0.3 | -3.5 | 3.6 | 3.7 | 5.9 |
| 1927 | -2 | 8.5 | 1.5 | 2.3 | 10.7 | -1.8 | 10.6 | 3.3 | 7.3 | -2.8 | 7.3 | 5.1 | 61.0 |
| 1928 | 0.2 | -2.6 | 11.2 | 6.9 | 3.9 | -5.2 | -0.5 | 10.8 | 3.5 | 3.8 | 12.2 | -5.7 | 43.3 |
| 1929 | 6.8 | -1.8 | -2.7 | 2.2 | -4.4 | 5.1 | 5 | 3.4 | -4.6 | -3 | 0.4 | -2.6 | 2.8 |
| 1930 | 4.8 | 4.1 | 6.2 | -2.2 | -2.6 | -2.9 | 0 | -2.9 | -5.8 | -0.1 | 0.1 | -1.7 | -3.8 |
| 1931 | 0.1 | 11.1 | -4.8 | -1.5 | -0.5 | 2.5 | -4.6 | -1.2 | -2.3 | -1.2 | -4.7 | -0.5 | -8.2 |
| 1932 | -2.7 | -1.1 | -4.7 | -0.2 | -0.4 | -1.2 | 10.8 | 15.1 | -1.3 | -3.7 | -3.5 | 0.1 | 5.3 |
| 1933 | 0.2 | -6.8 | -2.6 | 14.6 | 13.2 | 6.9 | -7.6 | 0.8 | -5.3 | -0.8 | -0.3 | -1.3 | 8.5 |
| 1934 | 11.3 | -1.3 | -0.8 | -2.8 | -1.7 | -0.6 | -3.4 | -1.6 | -3 | -0.2 | 11.4 | -0.2 | 5.9 |
| 1935 | -4.8 | -1.4 | -1.6 | 7 | 2.8 | 3.7 | 11.5 | -2.6 | 1.5 | 4.5 | 7.5 | 3.8 | 35.4 |
| 1936 | 8.4 | 4.8 | -0.8 | -4.8 | 1.9 | 1.9 | 8.6 | -0.3 | 2.6 | 7.7 | 6.9 | -0.3 | 42.4 |
| 1937 | 3 | 0.7 | -0.7 | -3.3 | 0 | -2 | 5.4 | -5.1 | -0.8 | -0.1 | -1 | -2.5 | -6.6 |
| 1938 | -4.2 | 0.7 | -6 | -2.2 | -1.3 | 15.5 | 6.6 | -3.4 | -2.8 | 3.8 | -2.6 | 2.9 | 5.4 |
| 1939 | -6.5 | 1.9 | -4.5 | -0.1 | 4.6 | -5.9 | 3.5 | -6.4 | 4.5 | 2.9 | -2.9 | 1.7 | -7.9 |
| 1940 | -2.7 | 1.2 | 1.3 | 0.1 | -5.3 | 0.4 | 4.7 | -2.1 | 4.1 | 4 | -0.2 | -1 | 4.3 |
| 1941 | -3.6 | -1.2 | -0.1 | -4.2 | -0.8 | 9.3 | 14.5 | -0.3 | -1.7 | -2.2 | -0.5 | -3.7 | 4.1 |
| 1942 | 0.2 | -2.1 | -1.6 | -2.1 | 3.3 | 4.2 | 6.9 | 2.9 | 5.5 | 12.5 | 2 | 8.5 | 47.1 |
| 1943 | 15.3 | 13 | 13.5 | 0.9 | 10.4 | 2.5 | -5.8 | -0.3 | 3.7 | -3.3 | -4.7 | 6.9 | 62.0 |
| 1944 | 4.9 | 0.3 | 4.8 | -4.6 | 8 | 13.6 | -2.8 | 3.5 | -3.9 | 0.2 | 2.2 | 7.7 | 37.6 |
| 1945 | 4.9 | 11.3 | -7.9 | 8.9 | 5.3 | 1 | -2.2 | 7.3 | 11.1 | 9.2 | 9.9 | 1.8 | 77.2 |
| 1946 | 9.3 | -6.4 | 4.3 | 9.6 | 5 | -8.7 | -1.3 | -4.4 | -0.2 | -2.6 | -1.9 | 3.7 | 4.5 |
| 1947 | -2.6 | -3 | -2.5 | -2.5 | -1.5 | 6.7 | 6.9 | -2.2 | -0.9 | 1.7 | -1.8 | -0.4 | -2.7 |
| 1948 | -4.1 | -1.2 | 6.3 | 5.9 | 14.6 | -2.8 | -4.2 | 0.3 | -4.8 | 4 | -8 | -0.2 | 3.9 |
| 1949 | -0.8 | -3.3 | 5.7 | -3.4 | -2.5 | -0.2 | 9.6 | 5 | 5.9 | 5.9 | 4.4 | 11.5 | 43.3 |
| 1950 | 4.4 | 2.9 | -0.5 | 4.1 | 6.3 | -8.5 | 1.2 | 4.4 | 11.7 | -1.8 | -0.3 | 3 | 28.9 |
| 1951 | 9.8 | 3.2 | -4.6 | 3.3 | -3.7 | -3.2 | 5.3 | 7.9 | 3.3 | -3.9 | 0.5 | 4.1 | 22.8 |
| 1952 | 2.2 | -3.4 | 3 | -4.7 | 2.4 | 6.1 | 2.7 | 0.4 | -2.4 | -1.2 | 10.4 | 4.5 | 20.8 |
| 1953 | 1.1 | -0.3 | -1.6 | -1.8 | -0.7 | -3 | 1.7 | -4.2 | 0 | 6 | 6.7 | 0.6 | 4.0 |
| 1954 | 9.6 | 2.6 | 5.9 | 6.5 | 6.4 | 4.2 | 11.2 | -3.2 | 6.5 | -1.8 | 15.6 | 11.7 | 104.3 |
| 1955 | -0.8 | 5.8 | -4.4 | 2.7 | 1.6 | 6.9 | 1.5 | -0.9 | -6.8 | -0.3 | 7.7 | 4 | 17.3 |
| 1956 | -4.9 | 4.3 | 10.2 | -1 | -4 | 2.4 | 5.9 | -3.1 | -2.2 | -1.5 | 0.3 | 2.2 | 7.9 |
| 1957 | -0.6 | -2.5 | 3 | 5.2 | 4.3 | -1 | 0.3 | -2.9 | -0.4 | 0 | 2.6 | -1.9 | 6.0 |
| 1958 | 8.3 | 0 | 6.7 | 5 | 5.3 | 5.6 | 8.3 | 5.6 | 8.7 | 6.8 | 6.3 | 6.6 | 103.2 |
| 1959 | 3.2 | 2.3 | 2.2 | 5.6 | 1.2 | -0.1 | 5.1 | -3.7 | -3.9 | 2.7 | 3.8 | 3.5 | 23.6 |
| 1960 | -6.1 | 1.9 | -2.5 | 0.1 | 5.7 | 4.1 | -3.4 | 3.5 | -6.5 | -0.6 | 6.1 | 9.1 | 10.5 |
| 1961 | 13.7 | 10.2 | 6.9 | -0.6 | 3.5 | -5.4 | 0.4 | 6.1 | -3.5 | 3.1 | 9.2 | -2.2 | 47.7 |
| 1962 | -2.7 | 0.4 | -2.1 | -2.3 | 0 | 0.2 | -0.1 | 4.1 | -6.8 | -0.1 | 11.3 | 0.5 | 1.5 |
| 1963 | 11.3 | -4 | 3.6 | 8.9 | 4.2 | -4 | -0.5 | 8.4 | -4 | 3 | -4.5 | 2.1 | 25.6 |
| 1964 | 3 | 4.2 | 3.9 | -0.3 | 1.7 | 0.8 | 4.6 | -2.6 | 6.7 | 2.7 | 1.3 | -0.1 | 28.7 |
| 1965 | 10.6 | 4 | -0.2 | 7.5 | -2.7 | -2.4 | 0.9 | 7.5 | 6 | 8.2 | 5.3 | 6 | 62.4 |
| 1966 | 5.8 | 1 | -3.7 | 2.5 | -5.8 | -2.7 | -1.4 | -0.6 | 0.2 | 2.5 | 5 | 1.5 | 3.8 |
| 1967 | 18.6 | 3.4 | 10.5 | 7.2 | -4.7 | 1.5 | 10.4 | -1.3 | 7.8 | -2.9 | -1 | 7.6 | 70.7 |
| 1968 | -2.4 | -2.3 | 0.4 | 13.7 | 7.9 | 2.9 | -2.8 | 1.7 | 10.6 | 1.4 | 12 | -4.6 | 43.4 |
| 1969 | -2.5 | -5.7 | 2.2 | 1.2 | -0.7 | -4.1 | 0 | 2.2 | -3 | 10.4 | -7.1 | 0.6 | -7.4 |
| 1970 | -4.3 | 3.2 | -2.4 | -3.4 | 0.6 | -0.8 | 2.6 | 4.7 | 9.6 | -4.4 | 2.8 | 11.6 | 20.1 |
| 1971 | 13.4 | 6.1 | 8.4 | 7.1 | -5.9 | -1 | -3.1 | 0.3 | -1.5 | -3.1 | 0.1 | 11 | 34.2 |
| 1972 | 7.9 | 7.4 | 1.6 | 1.7 | -1.4 | -2.2 | -0.4 | 2.3 | -2.7 | 0.9 | 9.3 | -0.9 | 25.2 |
| 1973 | -3.4 | -0.3 | -1.1 | -0.8 | -0.5 | -0.6 | 7.2 | -5.5 | 11.9 | -1.7 | -3.2 | 1.5 | 2.2 |
| 1974 | 0.2 | 1 | -3.1 | -0.9 | -0.4 | -2.5 | 0.5 | -1.2 | 0.6 | 3.4 | -3.6 | -1.2 | -7.1 |
| 1975 | 15.4 | 6.8 | 6.3 | 5 | 7.6 | 8.2 | -7.5 | -0.4 | -1.2 | 2.7 | 5 | -5.4 | 48.5 |
| 1976 | 24.1 | 3.8 | 1.4 | -3.7 | -1.3 | 5.7 | -1.6 | -1.1 | 1.2 | -3.9 | 2.4 | 13 | 43.8 |
| 1977 | -5.5 | -1.7 | -3 | -0.9 | -2 | 7.6 | -1.6 | -0.8 | -0.1 | -2.9 | 5.4 | 0.5 | -5.6 |
| 1978 | -7.4 | -2.2 | 7.6 | 16.5 | 6.7 | -1.7 | 10.2 | 9.8 | -3 | -4 | 0.1 | -2.9 | 30.3 |
| 1979 | 5.5 | -6.2 | 8.9 | 1 | -5.6 | 7.9 | 2.4 | 13.7 | -2.1 | -6.3 | 7.4 | 7.2 | 36.3 |
| 1980 | 7.5 | -4.4 | -1.9 | 2.6 | 10.5 | 6 | 18.4 | 4.1 | 3.9 | 0 | 8.4 | -4.8 | 60.0 |
| 1981 | -1.6 | 2.4 | 11.7 | 1.1 | 1.4 | -3.7 | -0.8 | -3.6 | 1 | 4.2 | 2.8 | -4.7 | 9.6 |
| 1982 | -2.3 | -1.1 | 0 | 6.3 | -5.7 | 0.7 | -1.6 | 8.1 | 1.2 | 17.1 | 6.4 | -0.1 | 30.8 |
| 1983 | 2.5 | 5.5 | 6.3 | 11.4 | 3 | 4.2 | -3.7 | 0 | 0.9 | -1.6 | 4 | -3.4 | 32.1 |
| 1984 | -2.3 | -0.7 | 1.4 | -0.7 | -4.7 | 1.2 | -2.5 | 10.9 | -2.3 | -2 | -2.3 | 2.3 | -2.6 |
| 1985 | 16.4 | 3 | -1.6 | -1.2 | 9 | 2.4 | 2.2 | -1.7 | -2.9 | 4 | 14.3 | 8.5 | 63.9 |
| 1986 | 2.5 | 16.3 | 10.8 | -2.1 | 5.3 | 0 | -5.5 | 5.3 | -6.9 | 4.8 | -2.1 | -3.8 | 24.7 |
| 1987 | 15.4 | 9.1 | 2.5 | -1.9 | -0.6 | 3.2 | 9.8 | 5.6 | -4.1 | -4.5 | 0 | 1 | 39.0 |
| 1988 | 0.8 | 8.7 | -0.4 | -0.3 | -1.2 | 7.3 | -3.5 | -2.2 | 4.9 | 1.4 | -4.1 | 3.4 | 14.6 |
| 1989 | 12.3 | -2.5 | 3.4 | 8.7 | 7.1 | -2.6 | 11.4 | 4.5 | -2.4 | -8.4 | 2 | -0.4 | 35.7 |
| 1990 | -5.3 | 0.7 | 4 | -4.1 | 10.4 | -1.7 | -2.2 | -2.2 | 0.2 | 0.3 | 4 | 4.5 | 7.9 |
| 1991 | 2.4 | 9.2 | 3.8 | -0.1 | 5.4 | -5.6 | 3.4 | -0.4 | -0.5 | 0.3 | -5.2 | 12.2 | 26.1 |
| 1992 | 1.8 | 2.4 | -3.2 | -1 | -0.6 | -2.2 | 2.6 | -5.2 | 1.3 | -0.1 | 9.2 | 3.7 | 8.1 |
| 1993 | 1.9 | 0.3 | 2 | -2.8 | 3 | -0.9 | 1.1 | 7.5 | -1.2 | 3.8 | -1.1 | 4.2 | 18.7 |
| 1994 | 6.8 | -3.1 | -4.2 | 0 | 0.1 | -5 | 1.1 | 9.1 | -3.6 | -1.7 | -3.8 | 0.7 | -4.4 |
| 1995 | 3.2 | 6.6 | 5.5 | 2.8 | 4.9 | 4.6 | 7.1 | 1.2 | 5.4 | -2.2 | 5.6 | 0.9 | 55.7 |
| 1996 | 1 | 2.8 | 2.3 | 2 | 5.1 | -1.8 | -4.1 | -0.2 | 8.8 | 0.5 | 11 | -3.5 | 25.3 |
| 1997 | 5.9 | 0.7 | -3.7 | 0.8 | 8.1 | 8.1 | 9.5 | -3.8 | 6.2 | -7.6 | 1.3 | 0 | 26.7 |
| 1998 | -2.5 | 8.4 | 8.3 | -0.5 | -2.4 | 0.3 | -3.2 | -1.7 | 0.5 | 3.4 | 4.5 | 1.7 | 17.2 |
| 1999 | 0.6 | -1.6 | 1.1 | 6.6 | -1.6 | 2.9 | -4.6 | -1.3 | -0.5 | 0.7 | -0.6 | 5 | 6.5 |
| 2000 | -2.4 | 0.7 | 3 | -1.6 | -0.7 | -1.3 | 0.1 | 3.7 | -2.1 | 0.4 | -0.5 | 3.8 | 2.8 |
| 2001 | -0.5 | -2.7 | -2.4 | 2.4 | 2.3 | -1.5 | -0.4 | -1.4 | -1.5 | -1.1 | 3.7 | 4.2 | 0.6 |
| 2002 | -1 | 2.1 | 5.1 | 1.1 | -0.7 | -2.4 | -1.1 | -0.7 | -3.2 | -0.9 | 3.5 | -2.9 | -1.3 |
| 2003 | -3.3 | -0.3 | -0.7 | 6.4 | 9.1 | 1.8 | 3.1 | 4 | -2.1 | 7.7 | 3.4 | 8.6 | 43.7 |
| 2004 | 2.6 | 3.2 | -2 | -2 | -1.3 | 3.9 | -6 | -0.1 | 2.4 | 0.5 | 7.8 | 6.5 | 15.7 |
| 2005 | -4.8 | 2.3 | -2.6 | -2.1 | 1.9 | 0.6 | 5.8 | -2.6 | 0.4 | -3 | 3.6 | -0.2 | -1.3 |
| 2006 | 5.4 | -0.3 | 4.2 | 1 | -2.4 | -0.1 | -1.4 | 3.1 | 2.4 | 6.9 | 3.9 | 1.7 | 26.8 |
| 2007 | 4.4 | -2.2 | -0.9 | 5.9 | 6.8 | -3.3 | -2.9 | -0.9 | 3.1 | 2.3 | -3.7 | -1.7 | 6.4 |
| 2008 | -3 | -1.7 | -2.1 | 1.1 | 2 | -3.8 | -1 | 0.9 | -4 | 0 | -0.5 | 0.6 | -11.0 |
| 2009 | -4.6 | -1.6 | 0.3 | 7.1 | 3.3 | -0.9 | 5.4 | 3.3 | 5.3 | -3.9 | 1.9 | 3.4 | 19.6 |
| 2010 | -2.4 | 0.7 | 9.1 | 5.6 | -5.1 | -2.3 | 0.8 | -3.3 | 5.7 | 5.2 | 1.9 | 8.3 | 25.3 |
| 2011 | 2.8 | 3.9 | -1.1 | 4.2 | -1.7 | -3 | -4 | -2 | -1.7 | 1.6 | -2.9 | 0.3 | -3.9 |
| 2012 | 5.4 | 6.1 | 3.6 | -4.2 | -3 | 1.4 | -1 | 1.7 | 5.9 | -1.5 | -1.1 | 2.5 | 16.1 |
| 2013 | 9.1 | 2.4 | 7.8 | -0.8 | 2 | -3 | 3 | -4.6 | 3.2 | 4.7 | 4.6 | 5 | 37.9 |
| 2014 | -6.3 | 1.5 | -0.7 | -1.6 | 2.3 | 5 | -4.5 | 2.7 | -3.6 | 0 | 4.8 | -4.2 | -5.2 |
| 2015 | -3.1 | 4.4 | -3 | -1.9 | 0.4 | -2.7 | 1.2 | -4.7 | -0.3 | 2.8 | -1.4 | -2.8 | -10.8 |
| 2016 | -1.6 | 0.7 | 7.8 | 2.2 | -0.3 | -3.8 | 1.9 | 0.4 | -4.4 | -1.6 | 3.6 | 0.3 | 4.6 |
| 2017 | 4.6 | 5.7 | 0.6 | 2.3 | 1.3 | 1.1 | 1.1 | -1.3 | 4.2 | 4.4 | 5.2 | 2.2 | 36.0 |
| 2018 | 9.5 | -7.3 | -4.3 | -1.4 | -0.1 | 0.5 | 3.5 | 1.6 | 0.1 | -4.8 | -0.6 | -3.5 | -7.5 |
| 2019 | 3.4 | 5.2 | -0.8 | 3.4 | -5.8 | 4 | 0.7 | -3.9 | -0.1 | -2.3 | 4.7 | 5 | 13.6 |
| 2020 | -1.4 | -2.9 | 0.2 | 1.7 | 3.4 | 0.1 | 5 | 6.3 | -2.9 | -2.5 | 6.2 | 6 | 19.9 |
| 2021 | -0.3 | 2.9 | 4.3 | 4.2 | 0.9 | -1.7 | 0.9 | 1.4 | -4.7 | 2.6 | -2.2 | 2 | 10.3 |
| 2022 | -3.9 | 0.3 | 1.2 | -3.8 | -0.6 | -3.4 | 4.5 | -3.6 | -1.6 | 2.1 | 4.3 | -4.4 | -9.1 |
| 2023 | 4.8 | -2.4 | -0.6 | 0 | -2.6 | 6 | 3.6 | -4.9 | -3.1 | -0.6 | 4.5 | 8.5 | 12.8 |
| 2024 | -0.8 | 5.3 | 7.2 | | | | | | | | | | 11.9 |

## 4.2 Performance per Industry

Table 3 shows the performance statistics of the long-only trend-following model applied to each industry and provides useful information about the number of trades per year, the average duration (in days) per trade, and the average return per trade. Additionally, the same statistics are presented for the aggregate Timing Industry portfolio.

The three best industries for applying the trend-following model were Utilities, Building Materials, and Textiles, all achieving a Sharpe Ratio above 1. The worst-performing industries were Gold, Agriculture, and Toys; however, the resulting Sharpe Ratios for these industries were still largely positive, around 0.50. Overall, the average Sharpe Ratio at the industry level was approximately 0.80. When combining all the industry-level trend following strategies, the Sharpe ratio of the resulting portfolio increases to 1.39.

On average, the timing strategy executes 6.6 trades per year per sector with an average duration of 52.3 days. The expected return per trade is 5.8%, sufficient to remain profitable after accounting for transaction costs (more details are provided in Section 6.2). The combined portfolio averages 291 trades per year.

We also assess each industry's contribution to overall portfolio performance. For example, to study the contribution of the Utility industry to the aggregate portfolio, we compare the total return of the Timing Industry portfolio with the total return of a Timing Industry portfolio that excludes the Utility industry. In this example, we find that excluding Utility from the aggregate Timing Industry portfolio reduces the total return by almost 17%.

## 4.3 Industries, Timing and Sizing Performance Contributions

In this section, we evaluate which portion of the strategy's performance is attributable to industry portfolios, entry/exit criteria, and position sizing rules. To determine the contribution of each component, we construct the following portfolios:

1. **Equally Weighted Industry Portfolio**. Positions are rebalanced daily so that each industry receives an equal capital allocation of $\frac{1}{N}$.

**Table 3: Industry Performance Statistics**. This table reports the performance statistics of the Timing model applied to each of the 48 industries in the database. It includes the yearly geometric average return (IRR), yearly volatility (Vol), and yearly Sharpe Ratio. The table also shows the number of signals (entry and exit), the average number of signals per year, the average duration of a long position in days, and the average return per trade. The last column reports each sector's overall contribution in percentage terms on the profitability of the Timing Industry diversified portfolio, whose statistics are presented in the first row. The backtests do not include commissions and slippage. The data is sourced from the Kenneth French website, covering the period from July 1926 to March 2024.

| Industry | IRR (%) | Vol (%) | SR | Signals | Signals x Year | Avg.Dur. (days) | Avg.Ret. (%) | Contrib. (%) |
|---|---|---|---|---|---|---|---|---|
| **All Industries** | **18.2** | **12.6** | **1.39** | **29,687** | **291.0** | **52.3** | **5.8** | |
| Txtls | 21.7 | 18.9 | 1.13 | 585 | 5.7 | 56.1 | 9.6 | 13.6 |
| Util | 17.2 | 16.0 | 1.07 | 615 | 6.0 | 57.2 | 6.1 | 16.6 |
| BldMt | 20.0 | 18.7 | 1.07 | 613 | 6.0 | 56.0 | 7.7 | 6.7 |
| Mach | 19.5 | 18.7 | 1.04 | 629 | 6.2 | 54.6 | 7.2 | 6.7 |
| Rtail | 18.6 | 17.9 | 1.04 | 639 | 6.3 | 54.5 | 7.1 | 7.5 |
| Fin | 19.4 | 19.3 | 1.02 | 645 | 6.3 | 52.8 | 7.1 | 8.6 |
| Hlth | 20.3 | 20.6 | 1.00 | 343 | 6.3 | 50.8 | 7.8 | 6.4 |
| Banks | 18.2 | 19.0 | 0.98 | 639 | 6.3 | 54.1 | 6.8 | 5.3 |
| Food | 15.6 | 16.5 | 0.96 | 637 | 6.2 | 56.0 | 5.9 | 0.7 |
| Drugs | 17.4 | 18.7 | 0.95 | 627 | 6.1 | 56.6 | 6.6 | 4.6 |
| Comps | 18.4 | 20.1 | 0.94 | 625 | 6.1 | 54.5 | 7.8 | 8.1 |
| Clths | 16.4 | 18.2 | 0.92 | 648 | 6.4 | 51.8 | 6.0 | 2.5 |
| Rubbr | 17.3 | 20.3 | 0.89 | 581 | 6.0 | 56.7 | 7.1 | 2.8 |
| Insur | 16.6 | 19.5 | 0.89 | 633 | 6.2 | 54.8 | 6.5 | 5.0 |
| Smoke | 16.4 | 19.4 | 0.88 | 659 | 6.5 | 52.1 | 6.2 | 8.9 |
| Fun | 17.3 | 20.8 | 0.87 | 639 | 6.3 | 52.4 | 7.3 | 3.5 |
| Meals | 16.6 | 20.0 | 0.87 | 633 | 6.2 | 55.5 | 6.8 | 2.7 |
| FabPr | 16.8 | 20.4 | 0.86 | 371 | 6.1 | 51.8 | 5.8 | 1.8 |
| Whlsl | 15.4 | 19.1 | 0.85 | 651 | 6.4 | 51.6 | 6.0 | -3.4 |
| LabEq | 16.2 | 20.3 | 0.84 | 627 | 6.1 | 55.0 | 6.2 | 1.7 |
| Chips | 16.4 | 21.0 | 0.83 | 655 | 6.4 | 51.9 | 6.0 | 1.0 |
| Autos | 15.7 | 20.2 | 0.82 | 640 | 6.3 | 52.7 | 6.3 | -1.7 |
| RlEst | 15.4 | 19.8 | 0.82 | 633 | 6.2 | 51.2 | 6.1 | 0.4 |
| Chems | 14.6 | 18.9 | 0.82 | 663 | 6.5 | 52.3 | 5.2 | -2.4 |
| Other | 15.0 | 19.5 | 0.81 | 643 | 6.3 | 51.4 | 5.5 | -1.5 |
| Hshld | 14.3 | 18.7 | 0.81 | 623 | 6.1 | 56.7 | 5.6 | -2.9 |
| Mines | 15.0 | 19.8 | 0.80 | 683 | 6.7 | 47.9 | 5.3 | -1.5 |
| Books | 14.8 | 19.7 | 0.80 | 659 | 6.5 | 50.3 | 5.5 | -1.1 |
| Trans | 14.2 | 19.3 | 0.79 | 653 | 6.4 | 51.5 | 5.1 | -3.5 |
| Oil | 14.0 | 19.1 | 0.78 | 653 | 6.4 | 51.3 | 5.1 | -1.9 |
| Aero | 14.9 | 20.6 | 0.78 | 679 | 6.7 | 50.0 | 5.9 | -1.1 |
| Steel | 14.4 | 19.9 | 0.78 | 665 | 6.5 | 49.3 | 5.1 | -3.8 |
| Telcm | 12.6 | 17.3 | 0.77 | 619 | 6.1 | 57.0 | 4.9 | 0.4 |
| Guns | 14.9 | 21.3 | 0.76 | 391 | 6.4 | 53.0 | 5.2 | 0.8 |
| Soda | 14.4 | 20.9 | 0.75 | 379 | 6.2 | 55.4 | 5.0 | -0.4 |
| BusSv | 16.5 | 25.0 | 0.75 | 615 | 6.0 | 55.5 | 7.0 | 1.5 |
| Boxes | 13.6 | 19.7 | 0.74 | 661 | 6.5 | 52.6 | 5.0 | -4.3 |
| ElcEq | 13.6 | 20.3 | 0.73 | 657 | 6.4 | 52.2 | 5.3 | -5.6 |
| Beer | 12.9 | 19.9 | 0.71 | 663 | 6.5 | 52.9 | 4.7 | -5.6 |
| Ships | 13.0 | 20.1 | 0.71 | 661 | 6.5 | 49.9 | 4.4 | -6.7 |
| MedEq | 13.4 | 21.6 | 0.69 | 645 | 6.3 | 54.2 | 5.2 | -3.0 |
| Paper | 12.5 | 19.9 | 0.69 | 663 | 6.7 | 47.9 | 4.5 | -7.8 |
| Cnstr | 12.1 | 20.3 | 0.67 | 675 | 6.6 | 48.0 | 4.5 | -6.0 |
| PerSv | 12.3 | 20.9 | 0.66 | 659 | 6.5 | 49.0 | 4.8 | -5.9 |
| Coal | 10.6 | 20.1 | 0.60 | 688 | 6.7 | 46.5 | 3.7 | -8.4 |
| Toys | 10.3 | 20.7 | 0.58 | 677 | 6.6 | 47.5 | 3.9 | -9.8 |
| Agric | 9.8 | 20.7 | 0.56 | 691 | 6.8 | 48.7 | 3.5 | -9.0 |
| Gold | 6.8 | 20.0 | 0.43 | 455 | 7.5 | 39.6 | 2.1 | -6.8 |

2. **Equally Weighted + Timing Portfolio**. Whenever an industry is in an uptrend according to our timing signal, we allocate $\frac{1}{N}$ of the capital.

3. **Dynamic Sizing + Timing Portfolio (Max Leverage = 100%)**. This portfolio uses the formula in Equation 9, limiting the maximum leverage to 100% when computing the optimal weight in Equation 10.

4. **Dynamic Sizing + Timing Portfolio (Max Leverage = 200%)**. This is the portfolio presented in this paper.

Table 4 and Figure 6 clearly demonstrate that each component of the trading strategy contributes positively, both in terms of total return and risk-adjusted performance. The Sharpe ratio increases from 0.63 to 0.70 when shifting from a market portfolio to an equal-weight industry portfolio, likely due to the enhanced diversification across firms. While both portfolios are market capitalization-weighted, the industry-based strategy allocates equal dollar amounts across industries, reducing concentration in a few large-cap stocks.

**Table 4: Portfolio Statistics**. This table presents key summary statistics for the portfolios described in Section 4.3. IRR stands for the Internal Rate of Return, representing the 1-year geometric average return. MDD indicates the Maximum Drawdown. Alpha and Beta are the regression coefficients from the regression described in Equation 13. The backtests do not include commissions and slippage. The data is sourced from the Kenneth French website, covering the period from July 1926 to March 2024.

| **Strategy** | **Market** | **EW** | **EW + Timing** | **Sizing + Timing** | **Sizing + Timing** |
|---|---|---|---|---|---|
| Max.Leverage | 100% | 100% | 100% | 100% | 200% |
| IRR | 9.7% | 11.1% | 12.5% | 12.9% | 18.2% |
| Vol | 17.1% | 17.0% | 9.7% | 9.2% | 12.6% |
| SR | 0.63 | 0.70 | 1.26 | 1.37 | 1.39 |
| MDD | 84% | 83% | 41% | 32% | 33% |
| Alpha | | 1.5% | 6.1% | 6.7% | 10.9% |
| Beta | | 1.0 | 0.4 | 0.4 | 0.5 |
| Avg.Exposure | 100% | 100% | 65% | 77% | 112% |

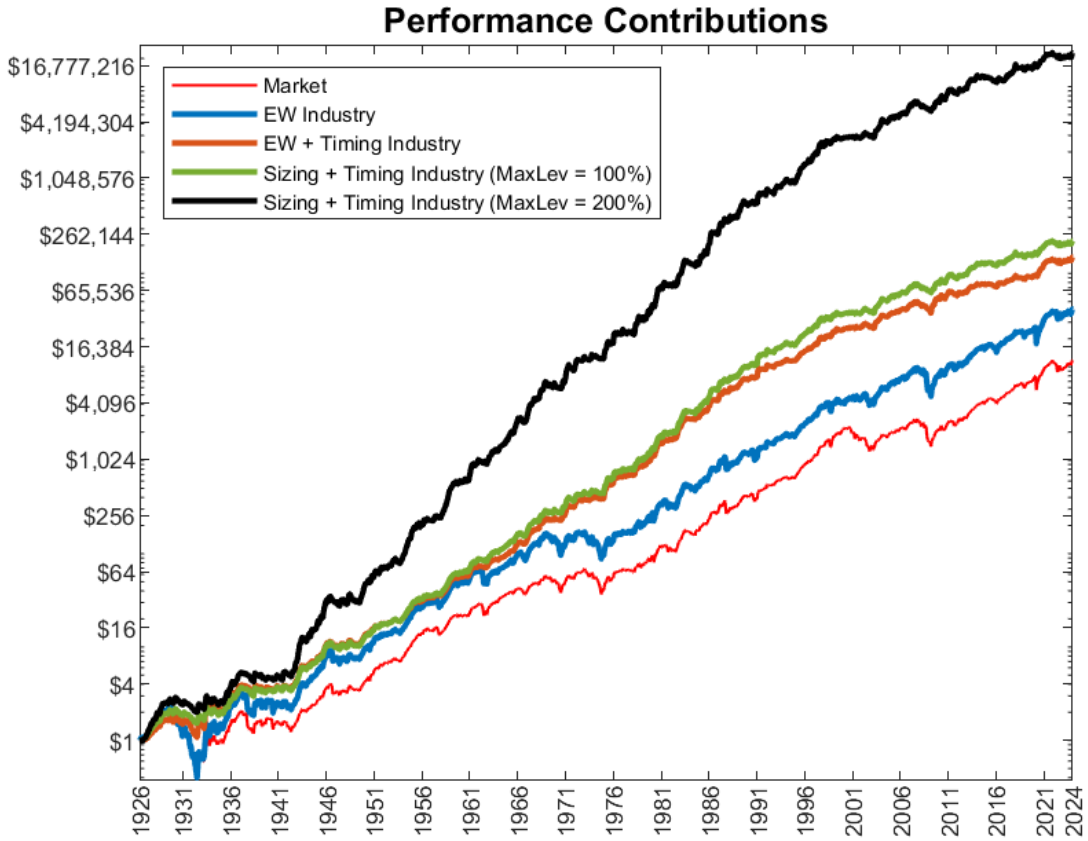


**Figure 6: Performance Contributions**. The top chart displays the equity curves for the portfolios described in Section 4.3. The backtests do not include commissions and slippage. The data is sourced from the Kenneth French website, covering the period from July 1926 to March 2024.

The most significant improvement occurs when timing rules are applied, with the Sharpe ratio jumping from 0.70 to 1.26, largely due to a substantial reduction in portfolio volatility and maximum drawdown (MDD is halved). Position sizing rules further enhance performance, though the impact is less pronounced. As expected, increasing leverage from 100% to 200% results in only a slight change in the Sharpe ratio.

In conclusion, this study indicates that the entry and exit criteria are the most critical factors in determining the profitability of the strategy presented in this paper.

# 5 Hedging Market Risk

The long-only trend following portfolio studied in this paper has an embedded hedging mechanism to avoid periods of market turbulence and drawdowns. In fact, when the overall market significantly turns south, we expect most of the stops to be hit, resulting in a portfolio mostly composed of cash invested in 1-month treasury bills. Nevertheless, some industries may be more resilient during market downturns, maintaining a long exposure.

We will look at offsetting any remaining beta risk during market declines by taking a short position in the market. The hedging portfolio is thus activated as soon as the closing price of the market index crosses below the Lower Band, defined mathematically as:

$$\text{LowerBand}_{t,mkt} = \max\Big(\text{DonchianDown}_{t,mkt}(40), \text{KeltnerDown}_{t,mkt}(40,2)\Big) \tag{15}$$

The hedge is removed as soon as either all industry positions are closed out or when the market price exceeds the trailing stop defined as:

$$\text{ShortTrailingStop}_{t+1,mkt} = \min\Big(\text{ShortTrailingStop}_{t,mkt}, \text{HigherBand}_{t,mkt}\Big) \tag{16}$$

where $\text{HigherBand}_{t,mkt}$ is defined as in Equation 7.

The amount of capital deployed in the short market position is calculated to ensure that the volatility from all long positions in the timing portfolio matches the volatility of the hedging portfolio. In practice, on a daily basis, we compare the 14-day volatility of the timing industry portfolio based on the current holdings with the 14-days volatility of the market and compute the resulting hedging ratio. For example, if the current portfolio's daily volatility is estimated to be 0.50% while the market's daily volatility is estimated to be 2% during the same period, the hedging portfolio would be short a gross notional equal to $\frac{0.50\%}{2\%} \times AUM = 25\% \times AUM$.

**Table 5: Performance Statistics**. This table presents key summary statistics for the Timing Industry portfolio, the Timing Industry + Hedge portfolio and the passive Market portfolio. IRR stands for the Internal Rate of Return, representing the 1-year geometric average return. MDD indicates the Maximum Drawdown. Alpha and Beta are the regression coefficients from the regression described in Equation 13. The t-statistics are calculated using Newey and West (1987) standard errors. The backtests do not include commissions and slippage. The data is sourced from the Kenneth French website, covering the period from July 1926 to March 2024.

| **Strategy** | **Timing Ind.** | **Timing Ind. + Hedge** | **Market** |
|---|---|---|---|
| # Assets | 48 | 48 | 1 |
| IRR | 18.2% | 17.7% | 9.7% |
| Volatility | 12.6% | 12.3% | 17.1% |
| Sharpe Ratio | 1.39 | 1.39 | 0.63 |
| Sortino | 1.66 | 1.61 | 0.78 |
| Skewness (monthly) | 0.7 | 0.8 | 0.1 |
| MDD | 33% | 28% | 84% |
| Alpha | 10.9% | 11.0% | |
| Beta | 0.47 | 0.39 | |
| Worst Return | -12.0% | -12.0% | -17.4% |
| Worst Day | 26-Sep-1955 | 26-Sep-1955 | 19-Oct-1987 |
| Best Return | 5.4% | 5.4% | 15.8% |
| Best Day | 07-Nov-1940 | 07-Nov-1940 | 15-Mar-1933 |
| Hedge Active (%) | - | 27.50% | - |

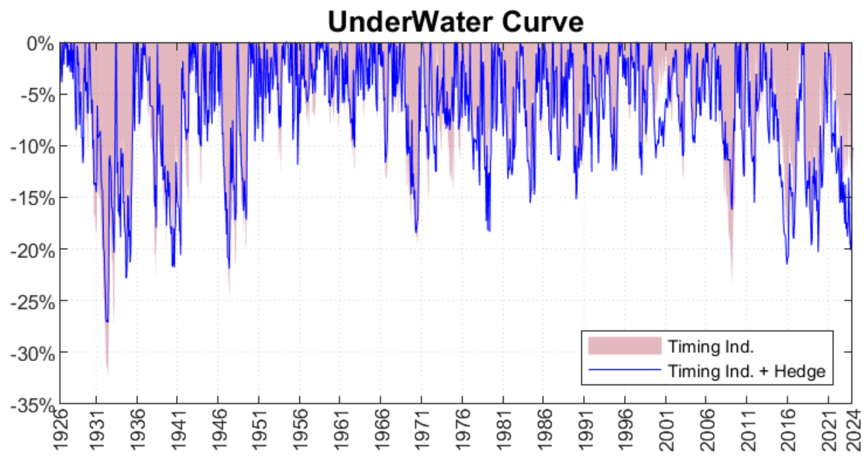


**Figure 7: Underwater Curve**. This figure shows the underwater curve for the Timing Industry portfolio (red area) and the Timing Industry + Hedge portfolio. The underwater curve illustrates the time-varying distance from preceding all-time highs. The backtests do not include commissions and slippage. The data is sourced from the Kenneth French website, covering the period from July 1926 to March 2024.

Using the daily market return data provided by French, we study the performance statistics of the resulting Timing Industry + Hedge portfolio. Table 5 provides a summary of the main statistics. The hedging portfolio is active approximately 27% of the trading days, specifically on days when the market trend signal is negative and at least one industry is still long. Overall, adding the hedging portfolio results in a insignificant increase in the Sharpe Ratio. The most notable improvement was in the maximum drawdown, which decreased from 33% to 28%. The lack of a real significant advantage is also evident from Figure 7, where we plot the underwater curve of the Timing Industry portfolio and the Timing Industry + Hedge portfolio. Quite surprisingly, there are periods when the drawdowns experienced by the hedged version are even larger than those experienced by the unhedged version. Given the embedded hedging mechanism of the long-only trend following industry portfolio, we conclude that there is no significant advantage in adding the hedging component to the base timing portfolio.

# 6 Replicating Using ETFs

In previous sections, we documented that over the last century, a long-only timing industry portfolio would have significantly outperformed the market, with an annualized alpha of 10.9%. We also discovered that the timing strategy has a remarkable ability to fully participate during strong market upswings while drastically reducing downside participation by more than 60% during overall market negative years. Moreover, we concluded that adding a hedging component during market drops does not add significant value and may even worsen the drawdown in some instances.

The only concern came from an apparent deterioration of the overall efficacy of the strategy during the last 20 years. The lower-than-average profitability may be due to various reasons, including shallower-than-average industry trends, industry classification biases, changes in market dynamics, and potential trend-signal inefficiencies.

The goal of this section is to introduce a database of tradable sector-based ETFs and create a tradable Timing ETFs portfolio using the same methodology discussed earlier.

**Table 6: ETFs Details**. This table reports the ETFs used in Section 6 of this paper. It includes the ETF name, ticker, the date when the ETF became available in the paper's database, the 21-day average volume, and the 21-day dollar volume as of June 5, 2024. The data is sourced from Yahoo Finance.

| **Name** | **Ticker** | **From** | **Avg.Volume** | **Avg.$Volume** |
|---|---|---|---|---|
| Financial | XLF | Jan-2005 | 44,658,805 | $1,870,757,304.22 |
| Technology | XLK | Jan-2005 | 6,888,600 | $1,437,788,600.41 |
| Energy | XLE | Jan-2005 | 15,124,519 | $1,412,630,102.13 |
| Health Care | XLV | Jan-2005 | 7,960,557 | $1,175,853,949.02 |
| Industrial | XLI | Jan-2005 | 9,114,257 | $1,147,849,566.82 |
| Biotech | XBI | Feb-2006 | 11,990,348 | $1,138,003,936.43 |
| Utilities | XLU | Jan-2005 | 15,057,843 | $981,771,308.33 |
| Consumer Staples | XLP | Jan-2005 | 11,441,829 | $872,553,871.30 |
| Consumer Discretionary | XLY | Jan-2005 | 4,201,700 | $775,045,610.21 |
| Regional Banking | KRE | Jun-2006 | 14,387,938 | $719,684,670.11 |
| Materials | XLB | Jan-2005 | 5,671,171 | $525,377,317.68 |
| Communication Services | XLC | Jun-2018 | 5,946,476 | $486,362,293.06 |
| Retail | XRT | Jun-2006 | 5,888,495 | $461,422,490.45 |
| Oil & Gas Exploration & Production | XOP | Jun-2006 | 3,014,224 | $460,302,138.19 |
| Real Estate | XLRE | Oct-2015 | 7,067,933 | $277,628,412.71 |
| Homebuilders | XHB | Feb-2006 | 2,319,186 | $256,617,902.82 |
| Bank | KBE | Nov-2005 | 3,553,543 | $166,483,477.43 |
| Metals & Mining | XME | Jun-2006 | 2,601,643 | $154,953,852.14 |
| Insurance | KIE | Nov-2005 | 799,233 | $41,536,157.31 |
| Semiconductor | XSD | Feb-2006 | 50,129 | $11,593,234.93 |
| Aerospace & Defense | XAR | Sep-2011 | 72,052 | $10,106,066.56 |
| Oil & Gas Equipment & Services | XES | Jun-2006 | 104,205 | $9,664,991.67 |
| Capital Markets | KCE | Nov-2005 | 68,724 | $7,539,689.08 |
| Technology | XNTK | Jan-2005 | 18,700 | $3,416,489.94 |
| Health Care Equipment | XHE | Jan-2011 | 28,914 | $2,520,747.44 |
| Software & Services | XSW | Sep-2011 | 15,300 | $2,371,500.00 |
| Pharmaceuticals | XPH | Jun-2006 | 34,481 | $1,481,991.32 |
| Transportation | XTN | Jan-2011 | 10,162 | $852,787.03 |
| Health Care Services | XHS | Sep-2011 | 7,681 | $718,860.31 |
| Innovative Technology | XITK | Jan-2016 | 2,862 | $425,622.48 |
| Telecom | XTL | Jan-2011 | 2,548 | $188,804.05 |

To make the study more realistic, we also introduce commissions and slippage costs and assess different rebalancing techniques to mitigate the costs associated with insignificant and unnecessary rebalances.

To remain consistent with the model discussed earlier, we do not introduce the use of open, high, and low prices but compute the trading signals and position sizing using closing prices only.

Nowadays, numerous ETF providers offer investors exposure to various industries and sectors. We have found that State Street Global Advisors offers US investors a complete basket of ETFs that provides exposure to 31 US sectors and industries. Most of the ETFs were already available in 2005, with the most recent ETFs becoming available in early 2018. The full list of the ETFs used in this section is provided in Table 6, along with the average traded volume per day and the average dollar volume traded per day.

## 6.1 Performance Statistics

Figure 8 shows the equity lines for the Timing Industry portfolio, the Timing ETFs portfolio, and a passive long exposure in the S&P500. For the ETFs portfolio, we also include trading costs of $0.0035 per share[7]. It is evident that the Timing ETFs portfolio closely tracks the trajectory of the Timing portfolio using the French industry database. The small differences may be due to the inclusion of trading costs or less diversification; the French database consists of 48 industries, while the ETF dataset comprises only 31 instruments. During the period from 2005 to 2024, a passive market exposure yields higher total returns, but the overall trajectory is characterized by significant volatility and long drawdown periods.

Table 7 provides useful statistics to gauge each trading strategy's efficiency properly. The Sharpe Ratio of passive market exposure is 0.59, slightly below the Sharpe Ratio for the Timing ETFs portfolio (0.61). The maximum drawdown for the market is 55%, while the active Timing ETFs strategy limited the maximum losses to 24%. Moreover, the risk-adjusted outperformance of the Timing ETFs portfolio is confirmed by an annualized alpha of 2.7% per year. In line with the long-term backtest, the beta coefficient is 0.40, as the Timing ETFs strategy sometimes holds only a subset of all ETFs, thereby reducing market risk. Table 8 provides an overview of the monthly and yearly returns for the Timing ETFs strategy from January 2005 until March 2024.

[7]As of May 2024, the entry-level commission charged by Interactive Brokers is $0.0035 per share.

**Table 7: Performance Statistics**. This table presents key summary statistics for the Timing Industry portfolio, the Timing ETFs portfolio, and the passive Market portfolio. IRR represents for the Internal Rate of Return, representing the 1-year geometric average return. MDD indicates the Maximum Drawdown. Alpha and Beta are the regression coefficients from the regression described in Equation 13. The t-statistics are calculated using Newey and West (1987) standard errors. A transaction cost of $0.0035 per share is included for the Timing ETFs portfolio, . The data is sourced from the Kenneth French website and Yahoo Finance, covering the period from January 2005 to March 2024.

| **Strategy** | **Timing Industries** | **Timing ETFs** | **SPY** |
|---|---|---|---|
| Commission/Share | 0 | 0.0035 | 0 |
| # Assets | 48 | 31 | 1 |
| IRR | 9.1% | 7.7% | 10.0% |
| Vol | 13.5% | 13.7% | 19.2% |
| SR | 0.71 | 0.61 | 0.59 |
| Sortino | 0.87 | 0.74 | 0.72 |
| Hit Ratio (monthly) | 55% | 56% | 66% |
| Skewness (monthly) | 0.2 | 0.2 | -0.6 |
| MDD | 24% | 24% | 55% |
| Alpha | 4.0% | 2.7% | - |
| Beta | 0.4 | 0.4 | - |
| Worst Ret | -6.9% | -7.0% | -10.9% |
| Worst Day | 27-feb-2007 | 27-feb-2007 | 16-mar-2020 |
| Best Ret | 4.3% | 4.0% | 14.5% |
| Best Day | 02-Jan-2013 | 02-Jan-2013 | 13-Oct-2008 |

**Table 8: Monthly Returns**. This table presents the monthly returns of the Timing ETFs portfolio from January 2005 to March 2024. The backtest includes a transaction cost of $0.0035 per share. The data is sourced from Yahoo Finance.

| **Year** | **Jan.** | **Feb.** | **Mar.** | **Apr.** | **May** | **Jun.** | **Jul.** | **Aug.** | **Sep.** | **Oct.** | **Nov.** | **Dec.** | **Yearly** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2005 | 0.2 | 0.2 | -3.3 | -0.3 | 2.2 | -0.3 | 4.8 | -2.9 | -0.1 | -2.8 | 4.4 | 0.2 | 1.8 |
| 2006 | 2.9 | -0.5 | 0.5 | 2.3 | -3.4 | 0.6 | -0.4 | 2.5 | 2.8 | 5.5 | 2.3 | 0.1 | 16.1 |
| 2007 | 2.2 | -3.3 | 0.4 | 6.7 | 5.5 | -4.4 | -1.9 | -0.5 | 2.2 | 0.8 | -3.7 | -1.6 | 1.6 |
| 2008 | -3.8 | -0.9 | -1.4 | 1.0 | 2.6 | -2.9 | -0.8 | 0.9 | -2.0 | -0.5 | -1.4 | 0.3 | -8.7 |
| 2009 | -4.3 | -2.5 | 0.6 | 5.5 | 4.0 | -0.7 | 4.9 | 3.7 | 4.8 | -4.1 | 1.4 | 3.4 | 17.2 |
| 2010 | -1.8 | 0.5 | 7.8 | 4.9 | -5.2 | -2.6 | -1.0 | -3.7 | 4.8 | 4.7 | 2.1 | 8.5 | 19.6 |
| 2011 | 2.9 | 3.2 | -2.3 | 5.7 | -3.0 | -2.7 | -3.6 | -2.3 | -2.2 | 1.6 | -3.8 | 0.4 | -6.5 |
| 2012 | 4.8 | 7.1 | 2.4 | -2.5 | -4.0 | 0.8 | -1.2 | 2.5 | 6.7 | -2.0 | -1.8 | 1.9 | 15.0 |
| 2013 | 10.3 | 1.1 | 6.6 | -2.5 | 3.4 | -3.2 | 5.0 | -5.5 | 2.6 | 4.4 | 6.0 | 3.8 | 35.6 |
| 2014 | -4.8 | 1.8 | -0.1 | -1.0 | 1.7 | 6.3 | -5.1 | 2.6 | -4.6 | 1.0 | 4.2 | -2.0 | -0.8 |
| 2015 | -2.5 | 4.6 | -1.6 | -1.7 | 0.2 | -1.0 | 1.3 | -4.3 | -0.3 | 2.2 | 0.9 | -4.1 | -6.5 |
| 2016 | -1.3 | 0.5 | 6.6 | 2.0 | 0.2 | -4.4 | 2.7 | 0.3 | -1.9 | -2.3 | 7.0 | -0.6 | 8.5 |
| 2017 | 3.7 | 6.6 | -0.9 | 0.7 | 0.9 | 1.7 | 0.4 | -2.2 | 4.0 | 2.6 | 3.2 | 1.3 | 23.8 |
| 2018 | 10.2 | -8.4 | -3.2 | 0.0 | 1.9 | 0.6 | 1.3 | 3.0 | -2.0 | -5.2 | -0.4 | -2.6 | -5.7 |
| 2019 | 3.8 | 5.0 | -1.1 | 3.7 | -6.6 | 2.8 | 1.7 | -6.2 | -0.5 | -2.3 | 6.2 | 4.7 | 10.6 |
| 2020 | -1.2 | -2.3 | 0.1 | 2.2 | 3.6 | 0.8 | 3.8 | 5.4 | -4.7 | -2.9 | 6.6 | 6.6 | 18.7 |
| 2021 | 2.9 | 4.1 | 2.1 | 3.4 | 0.0 | 0.5 | -1.9 | 2.2 | -5.6 | 2.5 | -2.7 | 1.4 | 8.9 |
| 2022 | -3.9 | -0.2 | 1.8 | -4.4 | -0.1 | -3.4 | 3.6 | -2.5 | -1.4 | 1.7 | 2.7 | -5.1 | -11.0 |
| 2023 | 5.6 | -2.2 | -1.3 | -0.9 | -1.0 | 4.4 | 6.0 | -5.8 | -2.2 | -1.4 | 4.1 | 9.6 | 14.7 |
| 2024 | -2.0 | 5.0 | 5.4 | | | | | | | | | | 8.4 |

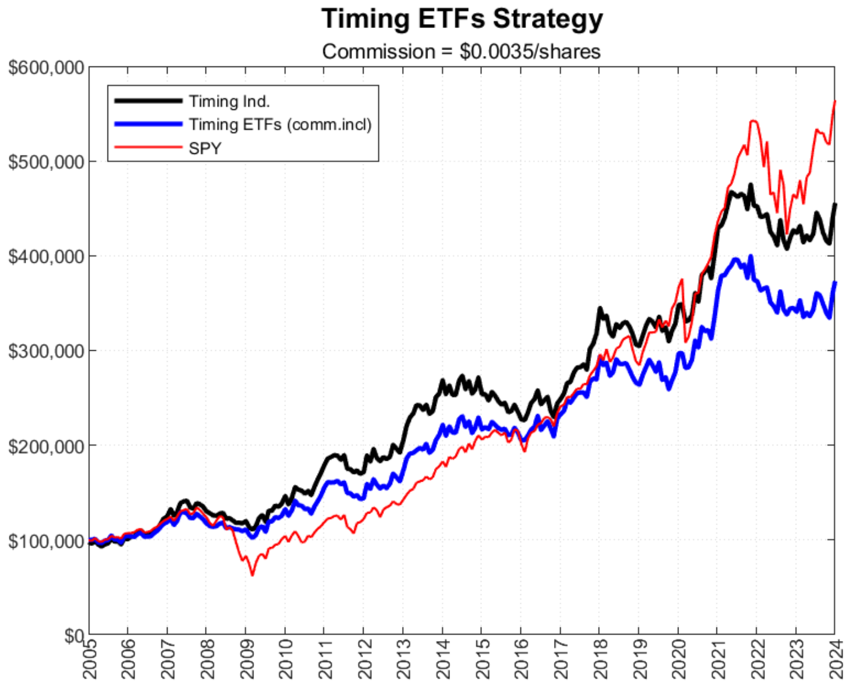


**Figure 8: Performance of the Last 20 Years**. This figure shows the equity evolution over the past 20 years of a $100,000 investment in the Timing 48 Industries portfolio (black line), the Timing ETFs portfolio (blue line), and the S&P 500 (red line). A transaction cost of $0.0035 per share is included for the Timing ETFs portfolio. The data is sourced from the Kenneth French website and Yahoo Finance, covering the period from January 2005 to March 2024.

## 6.2 The Impact of Transaction Costs

Commissions and slippage should be carefully considered when backtesting a quantitative trading strategy. Though the impact of commissions (and slippage) increases with trading frequency, even lower-frequency strategies, such as the one presented in this paper, may be significantly affected. Even if the signal does not change frequently, the adjustments required by the position management program may translate into numerous small daily rebalancing actions, which can create a long-term headwind for the active portfolio.

We thus introduce a *Rebalance Threshold* that indicates the minimum shares adjustment required to trigger a trade. For example, suppose the active portfolio is long 1,000 shares of ETF XLU and the *Rebalance Threshold* is set to 10%. At the end of day $t$, the signal is still long, but the sizing program suggests reducing the exposure to 970 shares due to an increase in XLU's daily volatility. In theory, the strategy should sell 30 shares of XLU to align with the new optimal share size. However, given that 30 shares on a long

1,000 shares position equates to an adjustment of 3%, which is lower than the *Rebalance Threshold* of 10%, no trades are actually executed. If at the end of day $t+1$ the optimal size moves to 850 shares, 15% lower than the current holding of 1,000 shares, the strategy will send the order and resize the position accordingly to the new optimal share size.

The higher the *Rebalance Threshold*, the lower the number of transactions and, consequently, the lower the commission costs (especially for small-sized portfolios). Conversely, a high *Rebalance Threshold* may result in substantial deviation from the results of the optimally sized portfolio.

Table 9 provides the main statistics for 35 different combinations of *Rebalance Threshold*s and trading costs. For comparison purposes, we also consider very high transaction costs that, although unrealistic, can help gauge how sensitive results are to different trading costs. In these backtests, we assume a starting capital of \$100,000 and a minimum cost per trade of \$0.35 (the minimum cost per trade is set to \$0 when we backtest the cost-free environment).

Introducing a *Rebalance Threshold* of just 5% reduces the number of trades by 65% (from 76,447 trades to 26,991 trades), translating into a saving approximately \$17,000 for \$0.0035 per share cost case. We also notice that the higher the *Rebalance Threshold*, the higher the total PnL. This benefit comes from reducing negligible trades that can accumulate significant transaction costs over the years. This is especially true when overall equity is limited, and we are often obliged to pay the minimum trading cost per trade of \$0.35. However, a closer analysis shows that profitability increases with the *Rebalance Threshold*, even when the trading costs are set to zero.

We believe that less frequent rebalancing reduces the drag caused by short-term mean reversion during medium-term trends. For example, consider a strategy that is long on an ETF in a strong uptrend with a daily volatility of 1%. If a moderate pullback occurs and the ETF's volatility increases to 2%, the volatility target sizing method would require halving the exposure. After a few days, the uptrend re-establishes, and new highs are reached. Unfortunately, because of the rebalancing at the pullback's low, the

**Table 9: Transaction Costs and Rebalance Threshold**. This table reports the performance statistics for the Timing ETFs portfolio under different scenarios of Transaction Cost per share and Rebalance Threshold. The Rebalance Threshold indicates the minimum percentage adjustment in shares required to trigger a trade. The data is sourced from Yahoo Finance, covering the period from January 2005 to March 2024.

| $AUM_0$ | Rebalance Threshold | Cost x Share | # Trades | IRR | Alpha | Total PnL | Total Cost Paid |
|---|---|---|---|---|---|---|---|
| $100,000 | 0% | | 76,447 | 7.9% | 2.9% | $328,397 | |
| $100,000 | 0% | $0.0035 | 75,679 | 7.0% | 2.1% | $269,187 | $27,797 |
| $100,000 | 0% | $0.0050 | 75,587 | 7.0% | 2.1% | $266,851 | $28,823 |
| $100,000 | 0% | $0.0100 | 75,540 | 6.9% | 1.9% | $257,435 | $32,889 |
| $100,000 | 0% | $0.0200 | 75,154 | 6.5% | 1.6% | $237,087 | $42,044 |
| $100,000 | 0% | $0.0500 | 74,031 | 5.4% | 0.6% | $174,207 | $69,101 |
| $100,000 | 0% | $0.1000 | 71,817 | 3.4% | -1.4% | $89,014 | $102,436 |
| $100,000 | 5% | | 26,991 | 7.9% | 2.9% | $332,645 | |
| $100,000 | 5% | $0.0035 | 26,998 | 7.6% | 2.7% | $310,343 | $10,913 |
| $100,000 | 5% | $0.0050 | 26,976 | 7.6% | 2.6% | $307,135 | $12,062 |
| $100,000 | 5% | $0.0100 | 26,974 | 7.4% | 2.5% | $297,444 | $16,549 |
| $100,000 | 5% | $0.0200 | 26,949 | 7.1% | 2.2% | $274,345 | $26,729 |
| $100,000 | 5% | $0.0500 | 27,016 | 6.0% | 1.2% | $208,316 | $56,052 |
| $100,000 | 5% | $0.1000 | 27,043 | 4.2% | -0.6% | $119,416 | $91,685 |
| $100,000 | 10% | | 15,251 | 7.9% | 3.0% | $333,928 | |
| $100,000 | 10% | $0.0035 | 15,230 | 7.7% | 2.8% | $318,343 | $6,852 |
| $100,000 | 10% | $0.0050 | 15,235 | 7.7% | 2.8% | $317,816 | $8,083 |
| $100,000 | 10% | $0.0100 | 15,211 | 7.6% | 2.6% | $305,723 | $12,802 |
| $100,000 | 10% | $0.0200 | 15,260 | 7.3% | 2.3% | $283,949 | $23,143 |
| $100,000 | 10% | $0.0500 | 15,253 | 6.2% | 1.3% | $219,348 | $51,202 |
| $100,000 | 10% | $0.1000 | 15,227 | 4.6% | -0.2% | $136,237 | $85,882 |
| $100,000 | 20% | | 8,494 | 7.9% | 2.9% | $334,508 | |
| $100,000 | 20% | $0.0035 | 8,480 | 7.8% | 2.8% | $324,536 | $4,628 |
| $100,000 | 20% | $0.0050 | 8,464 | 7.8% | 2.8% | $324,168 | $5,952 |
| $100,000 | 20% | $0.0100 | 8,498 | 7.6% | 2.6% | $310,282 | $10,841 |
| $100,000 | 20% | $0.0200 | 8,478 | 7.3% | 2.4% | $288,290 | $20,681 |
| $100,000 | 20% | $0.0500 | 8,498 | 6.4% | 1.5% | $232,026 | $46,924 |
| $100,000 | 20% | $0.1000 | 8,483 | 4.9% | 0.1% | $151,380 | $79,709 |
| $100,000 | 30% | | 6,252 | 8.1% | 3.0% | $343,423 | |
| $100,000 | 30% | $0.0035 | 6,255 | 8.0% | 2.9% | $335,294 | $3,977 |
| $100,000 | 30% | $0.0050 | 6,252 | 7.9% | 2.9% | $331,375 | $5,339 |
| $100,000 | 30% | $0.0100 | 6,263 | 7.7% | 2.7% | $319,468 | $10,160 |
| $100,000 | 30% | $0.0200 | 6,248 | 7.5% | 2.5% | $299,158 | $19,592 |
| $100,000 | 30% | $0.0500 | 6,253 | 6.7% | 1.7% | $244,704 | $44,867 |
| $100,000 | 30% | $0.1000 | 6,270 | 5.3% | 0.4% | $170,234 | $77,860 |

portfolio participates in the recovery phase with half the exposure it had during the decline, resulting in weaker performance compared to a strategy that did not adjust the position during the pullback.

# 7 Conclusion

Motivated by the lack of research on industry long-only trend-following systems, we use a daily database of 48 US industries to evaluate the profitability of a Timing Industry model over the last 100 years. We document strong profitability and remarkable resilience over the last century by exploiting trading techniques and risk management approaches suggested by trend-following veterans. A timing portfolio appreciates on average by 18.2% per year with an annual volatility of 12.6%, resulting in a Sharpe Ratio of 1.39. During the same period, the US equity market yields 9.7% per year with a volatility of 17.1% and a Sharpe Ratio of 0.63. The outperformance of the timing strategy is further confirmed by an alpha of 10.9% per annum. Remarkably, the timing strategy reduces the drawdown of a passive long exposure in the market by almost 60%; the active portfolio suffers a maximum loss of 33%, while a passive buy-and-hold exposure results in a maximum loss of 84% and a much longer recovery period.

We conduct further investigations to assess the active strategy's ability to participate during upside markets while limiting exposure during less favorable market environments. We find that during strong market years, the return of the active strategy has a beta of 1.16 versus the market, while during weak market periods, the beta decreases to 0.31.

In the last section of the paper, we introduce the use of 31 sector ETFs provided by State Street Global Advisors and backtest the same trading methodology over the last 20 years. We conclude that ETFs can replicate the exposure and returns of the model constructed on Kenneth French's industry database. Moreover, we assess the role of commissions and slippage on overall profitability and find that the active timing strategy remains profitable even after accounting for high levels of commissions. By using a simple rebalancing threshold, we propose a more efficient way to implement risk management rules.

This paper adds to the literature on tactical trading approaches using long-established channel breakout methods, showing results that outperform buy and hold over significantly long periods. Others include Lo et al. (2000), with popular charting patterns; Brock et al. (1992), with 89 years of moving averages and trading range breaks; Lempérière et al. (2014) with over 200 years of exponential moving averages, and Greyserman and Kaminski (2014), with simple rates of change since the beginnings of many major markets. We hope these results inspire academics and practitioners to explore trend-following and other tactical approaches further.

# Author Biography

**Carlo Zarattini**, originally from Italy, currently resides in Lugano, Switzerland. He holds a degree in mathematics from Padova and a dual master's in quantitative finance from Imperial College London and USI Lugano. Formerly a quantitative analyst at BlackRock, Carlo developed volatility and trend-following trading strategies. He later founded Concretum Group, a data-driven quant boutique that supports sophisticated investors and institutional clients in conducting quantitative investment research and uncovering trading opportunities across various markets and timeframes. Additionally, he established R-Candles.com, the first online backtesting platform for discretionary technical traders.

**Gary Antonacci**, has over 50 years of experience as an investment professional focusing on underexploited investment opportunities. His innovative research on momentum investing won the Founders Award for Advances in Active Investment Management, given annually by the National Association of Active Investment Managers (NAAIM). Gary wrote the popular book *Dual Momentum Investing: An Innovative Approach for Higher Returns with Lower Risk*. He introduced the investment world to dual momentum, which combines relative strength price momentum with trend-following absolute momentum. He is recognized as an authority on the practical applications of momentum investing. Gary received his MBA degree from the Harvard Business School.

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