Trading with a Tailwind

Identifying Repeatable Kinetic Windows in Equity Prices

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Photo courtesy of Daher-Socata

Abstract

Tailwinds are powerful forces that people have been harnessing to their advantage since the first sailing ships were used by the Ancient Egyptians to transit the Nile. The benefits of having the wind at your back are instinctually obvious. But do similar forces exist in the financial markets? This paper will empirically show that predefined seasonal periods, called "Kinetic Windows", both exist in U.S. equity markets, and provide outperformance over the broader market that is statistically and economically significant.

Introduction

5,000 years after the Ancient Egyptians invented the sailing ship, tailwinds continue to be a force that materially impacts our civilization's ability to move from point A to point B. Flying westward at high altitude, airliners often battle jet streams, powerful wind currents that can blow at more than 100 miles per hour[1]. Flying home, those same jet streams provide powerful tail winds that increase an aircraft's speed over the ground.

The question this paper aims to answer is whether similar tailwinds exist in the financial markets.

It is important to note that this concept is similar to the idea of seasonality, however, for the purposes of this paper, the two are treated as distinct (if complementary) forces. There has been considerable attention paid to seasonal price patterns, particularly in the technical analysis community, however, the very nature of market seasonality makes it difficult to test with statistical rigor. Because of this, most seasonality work is anecdotal at best, and it is very likely that many of the older, well-known seasonal phenomena that traders have focused on have been arbitraged away at this point[2]. While past research has found that seasonal forces exist[3], that research was limited to monthly returns. This author believes that the artificial constraint of calendar months masks some of the seasonality present in individual securities in the Jegadeesh study.

This paper will provide background on how seasonal market forces combine with trend to identify "Kinetic Windows" — timeframes where a stock is statistically predisposed to outperform. This author's research shows that buying during Kinetic Windows over the decade ending December 31, 2016 would have produced statistically significant outperformance over the S&P 500 of 1.118%, on average per window, with an average window timeframe of 74.6 days.

Further, the author will show that intuitive filtering metrics can be used to increase the likelihood of a profitable trade to 88.2% between January 1, 2006 and December 31, 2016. These filters increase the outperformance versus the S&P 500 to 11.076%, with an average window timeframe of 89.9 days. When applied to a trading system, this approach to trading with a tailwind generates substantial outperformance over a passive buy-and-hold approach.

Background: First Principles

Because of some of the challenges of working with seasonal price data, it is necessary to begin by identifying some "first principles" — that is, axioms that will act as a starting point for identifying Kinetic Windows.

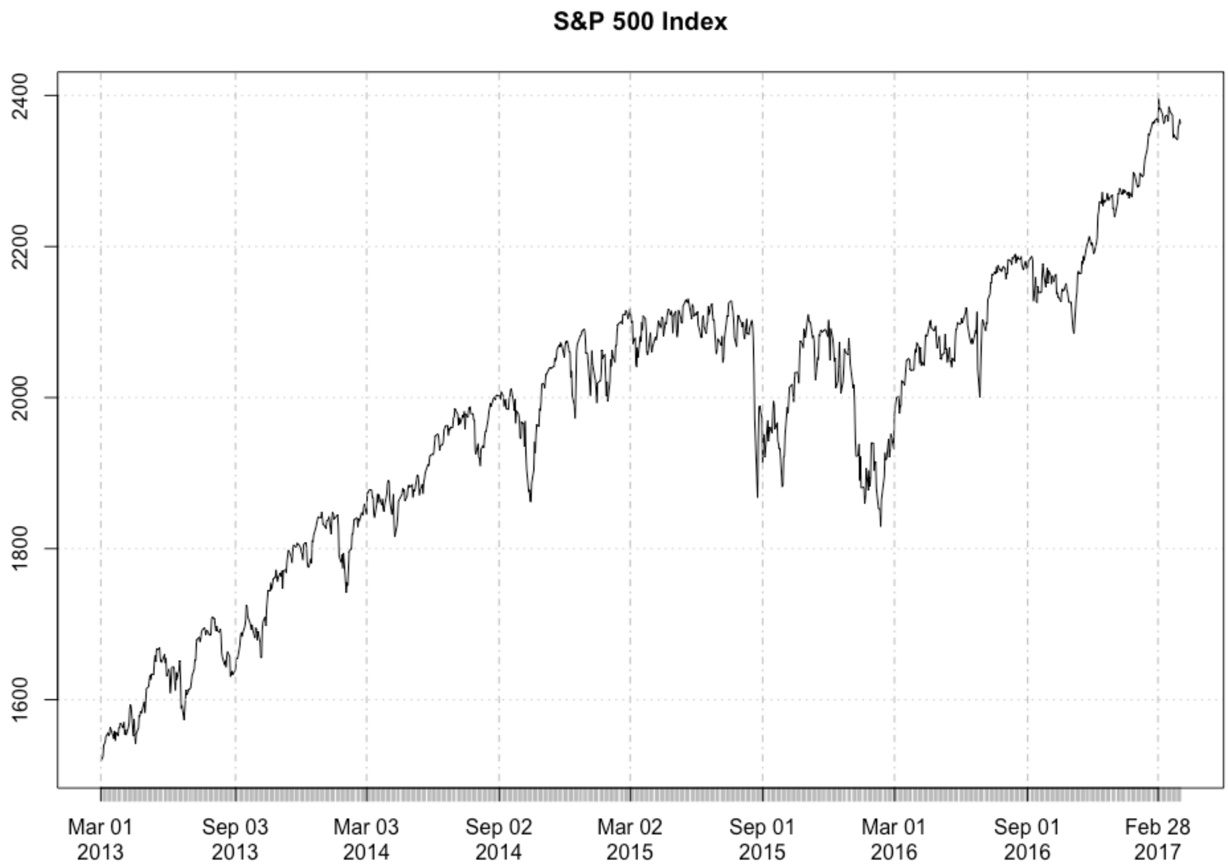

Figure 1.: A price chart of the S&P 500.

The S&P 500 price chart in Figure 1 is a standard line chart produced using closing prices for the S&P 500 index. While this type of chart is familiar to most investors, the exact same raw price data used to construct Figure 1 can also be used to generate a time series decomposition. Time series decomposition is a statistical method that is used to estimate non-linear relationships in data.

While this statistical procedure is used in applications such as estimating monthly aircraft miles flown for policy analysis, or forecasting future carbon dioxide production[4], it also has parallels with the first principles we'll apply to the financial markets in this paper.

Figure 2 applies a statistical time series decomposition to the raw price data of the S&P 500 from Figure 1.

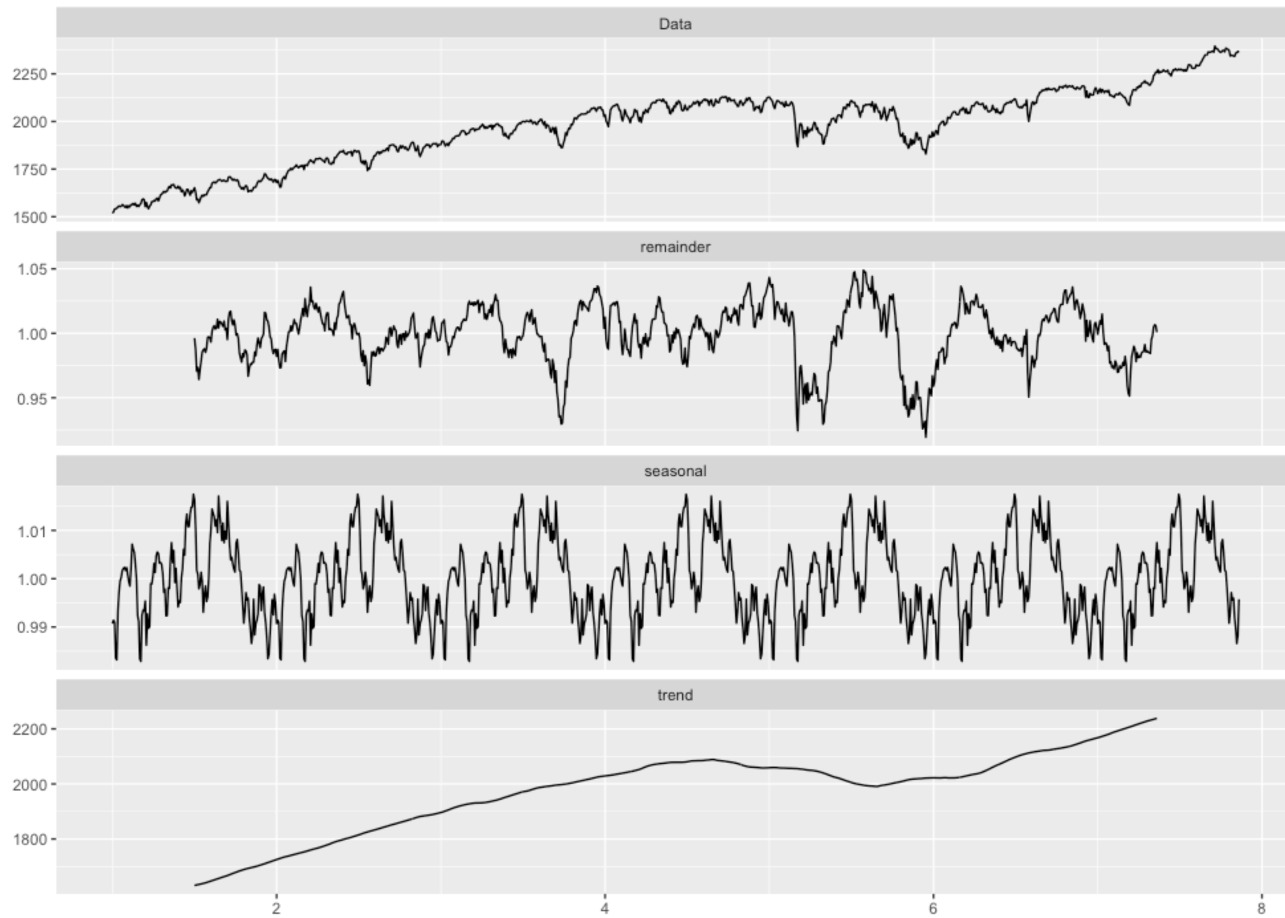

Figure 2.: Time series decomposition of S&P 500 raw price data from Figure 1.

The top panel shows the original price data found in Figure 1. The fourth panel shows the primary trend of the S&P 500 during the timeframe depicted. The third panel shows a repeating seasonal component of the price series — it's important to note that while the recurring seasonal component isn't visible to the naked eye, it is extracted from the S&P chart above. Finally, the second panel depicts the remainder, better described as "noise".

It's important to note that this paper defines "noise" differently than most academic financial research. For instance, while the efficient market hypothesis pejoratively describes "noise traders" as those who make investment decisions without the use of fundamental data, suggesting that they cannot influence prices in an efficient market, research has shown that these types of market participants can and do influence asset prices[5].

Instead, for the purposes of this paper and contrary to the aforementioned definition, "noise" is defined as event-driven price shocks that are not predictable by a statistical model. Examples of noise events include earnings, FDA letters for pharmaceutical companies, product news, terror attacks, etc. This author posits that market noise is unpredictable, and therefore should be ignored for trading purposes. It is important to note that this is starkly opposed to the approach taken by most market participants, who spend the vast majority of their research efforts and resources trying to predict what we've termed as unpredictable noise.

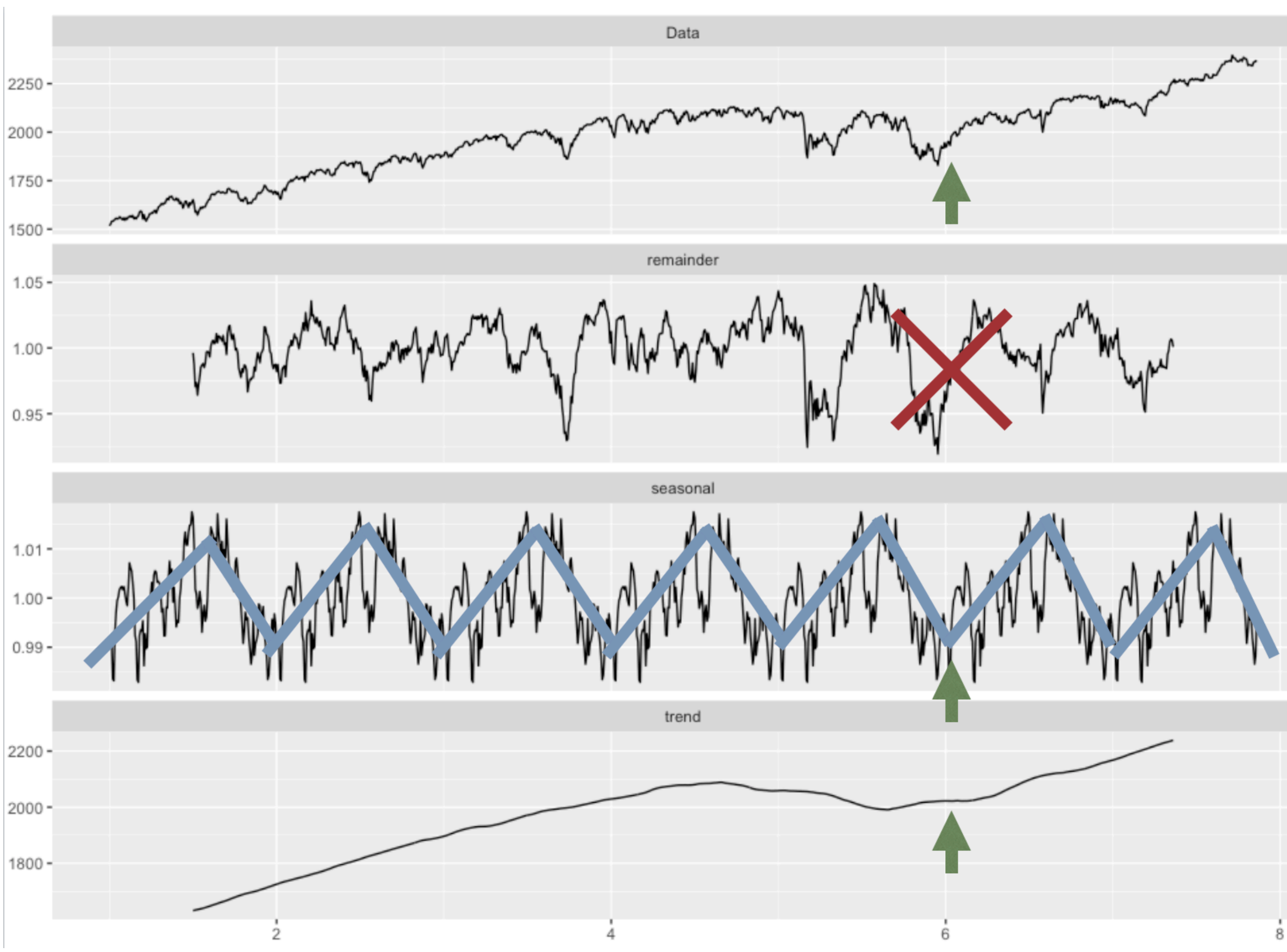

Figure 3.: Identifying the local minima in trend and seasonal factors signals the start of a Kinetic Window — and a buying opportunity in price.

On the other hand, the seasonal and trend components of Figure 2 are highly predictable. That seasonality is predictable is self-evident; by definition, seasonality is a characteristic of time series in which the data experiences a regular and predictable change. And significant research has shown that markets tend to trend[6]. Based on our decomposition model, we aim to buy securities whose seasonal and trend components reach a local minimum at the same time. These lows in seasonal and trend components are the beginning of our Kinetic Windows.

While statistical time-series decomposition provides an intuitive explanation of the statistical process behind our approach to finding market tailwinds, it's less effective in picking out the trend and seasonal factors (referred to as the Kinetic factor in this paper, going forward) in real-time. For that, we will construct a price composite based on multiple years of price data.

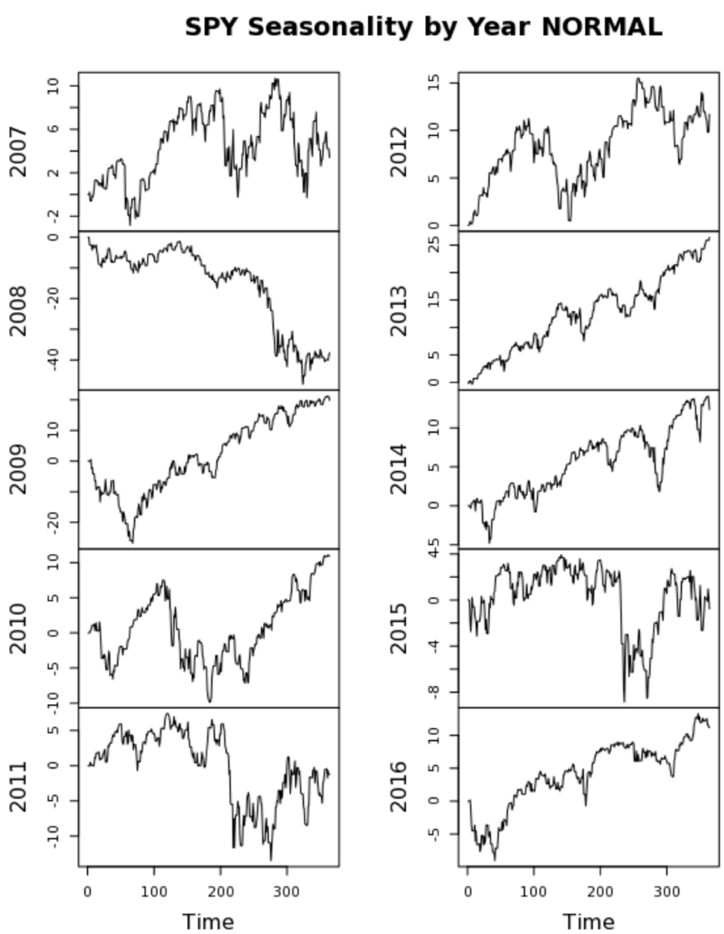

Figure 4.: S&P 500 price data by year (Z) is combined into a composite to identify Kinetic Windows.

Creating a Kinetic Composite

The idea of using a composite of price data to identify seasonal patterns isn't novel[7,8] — in fact, it is even commonly used outside of the financial realm[9]. What is unique, however is the specific calculation of the Kinetic Composite, as well as the notion that it is distinct from pure seasonality in a statistical sense. Because of the first principles concept that our price composite doesn't *just* reflect seasonality, we make no effort to remove the trend factor from the composite. Rather, the trend factor is an important component of the composite.

Simply put, the composite averages out the noise present in any single year's price data, as defined earlier.

While this paper won't delve into the specific construction of the Kinetic Composite, a simplified p-year seasonal price composite may be generalized to the following:

$$\frac{1}{p}\sum_{t=1}^{p} z_t,$$

$$\text{such that } z_t = (w_t \times \frac{x_{1t} - x_{1t}}{x_{1t}}, w_t \times \frac{x_{2t} - x_{1t}}{x_{1t}}, \ldots, w_t \times \frac{x_{nt} - x_{1t}}{x_{1t}}),$$

where z_t is a vector of normalized price values for year t, w is a weighting factor for that particular year's data, and x_{nt} is the nth price value for year t in a matrix $\mathrm{X}_{n \times t}$.

Beyond the scope of this paper are the proprietary elements of constructing the X matrix and resulting Z matrix for the Kinetic Composite, in particular the methods for error handling and aligning calendar and trading days, normalization and scaling methods to account for heteroskedasticity of price returns, or the weighting of years.

That said, many different construction methods were tested to verify the robustness of this approach — all netted a degree of statistically significant outperformance over the broad market, suggesting that this approach, rather than the specific construction of the composite, is the driver of the broader results presented in this paper.

Data Sources

For the purposes of backtesting the strategies presented in this paper, price data was obtained from several sources. S&P 500 index data used in the preceding figures was obtained from the Bloomberg Professional service. Individual stock price data was obtained via the Quandl API using the Zacks Equity Prices database. This database was used due to its large universe of individual securities (more than 31,000 active and inactive tickers), and a high level of quality control.

Testing Methodology

The investment universe used for the backtests in this paper is comprised of the stocks in the S&P 500, less any securities that have fewer than 5 years of price history in the Zacks Equity Prices database at any point during the test. This ensures that any example trades have sufficient data to generate meaningful Kinetic Windows from the Kinetic Composite charts.

For the purposes of this paper, a 20 years of daily close price data was used to calculate Kinetic Composites in testing, except in cases where a security has fewer than 20 years of price history in our database. In these cases, we use the maximum number of years available. All results in this section use equal weighting of years (that is, $w = 1$ on the generalized composite equation on page 7).

One challenge of testing buy and sell signals generated by the Kinetic Composite is that the composite is comprised of the data from prior years' price action. For example, a strong upward price move in a security in 2015 would influence an upward move in the Kinetic Composite during that same timeframe, and make any testing on 2015 look unrealistically strong. This is an example of look-ahead bias. To remedy this, we generate a separate Kinetic Composite annually for each stock tested using data up to the final day of the year preceding the test year, and then test the Kinetic Windows projected for the test year.

Another challenge of testing Kinetic Windows is that they are, on average much shorter than a year. This makes comparisons versus a benchmark, such as the S&P 500, challenging. For instance, it's common practice to show the performance of a benchmark index during the same timeframe as each individual trade. However, because we're identifying tailwinds in individual stocks within the S&P 500, it stands to reason that the S&P 500 itself should perform better during these test periods than during non-Kinetic timeframes.

Likewise, it is inappropriate to annualize returns because of the relatively short timeframes that the Kinetic Windows represent — for example, while the S&P 500 declined 0.73% on a price basis during 2015, that number masks significant volatility during that calendar year, such as a 12.4% peak-to-trough drawdown between March 21, 2015 and August 25, 2015.

For a more appropriate benchmark, the author takes the number of calendar days of each Kinetic Window, and then simulates 1,000 random S&P 500 purchases of that same number of calendar days during the calendar year. This technique provides a more realistic benchmark for owning the S&P 500 for any n-day period during the year being tested, given an n-day Kinetic Window.

Validation

The first question that this paper aims to answer is: "Do Kinetic Windows provide a valuable trading signal?"

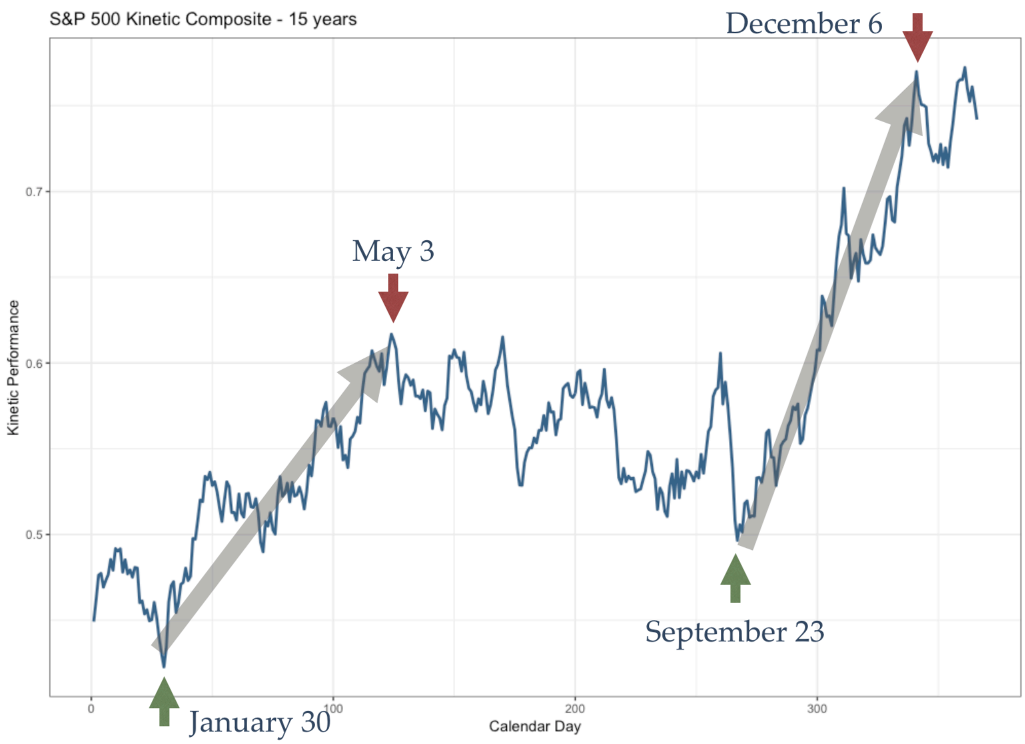

Figure 5.: The Kinetic Composite of the S&P 500, with two Kinetic Windows visually identified.

That is, do they really identify when a market is experiencing a tailwind?

Figure 5 shows Kinetic Composite for the S&P 500 for 2017. In grey, two Kinetic Windows are identified by visual inspection: the first, from January 30 through May 3, and the second, from September 23 through December 6. At a glance, the Kinetic Composite chart in figure 5 provides a visual clue as to when the S&P 500 is most likely to experience a tailwind. More importantly, these dates may generally look familiar to experienced market-watchers, as they correspond with the concept of "Sell in May and Go Away", an old market adage that's actually been shown to be true in out-of-sample testing[10].

Rather than visually identify Kinetic Windows visually for every individual security each year, this paper uses an algorithm to mechanically identify windows based on major turning points in the Kinetic Composite chart. For the purposes of this paper, these swings are identified using 40-day local maxima and minima on the Kinetic Composite.

A Kinetic Window is defined as the period from a 40-day local minimum on the Kinetic Composite chart to the ensuing 40-day local maximum. The test initiates a buy at the start of a Kinetic Window, and sells that position at the end of the window.

This serves the dual purpose of avoiding subjectivity in identifying windows on the chart, as well as enabling a much larger investment universe for the test. In total, this paper's validation examines 13,262 individual Kinetic Windows over a ten-year span.

The aggregate results of the backtest by year are displayed in Figure 6 and Table 1. In each year during the test period, average Kinetic Window performance beat average randomized S&P 500 returns of the same duration. Kinetic Windows outperformed by 1.118%, on average per window, with an average window timeframe of 74.6 days. That outperformance is significant ($p < .01$).

It is important to note that the backtest performed for this paper is nearly parameterless. That fact greatly reduces the chances that the outperformance exhibited by Kinetic Windows is due to overfitting market conditions that existed during the backtest period but may no longer be present in the market.

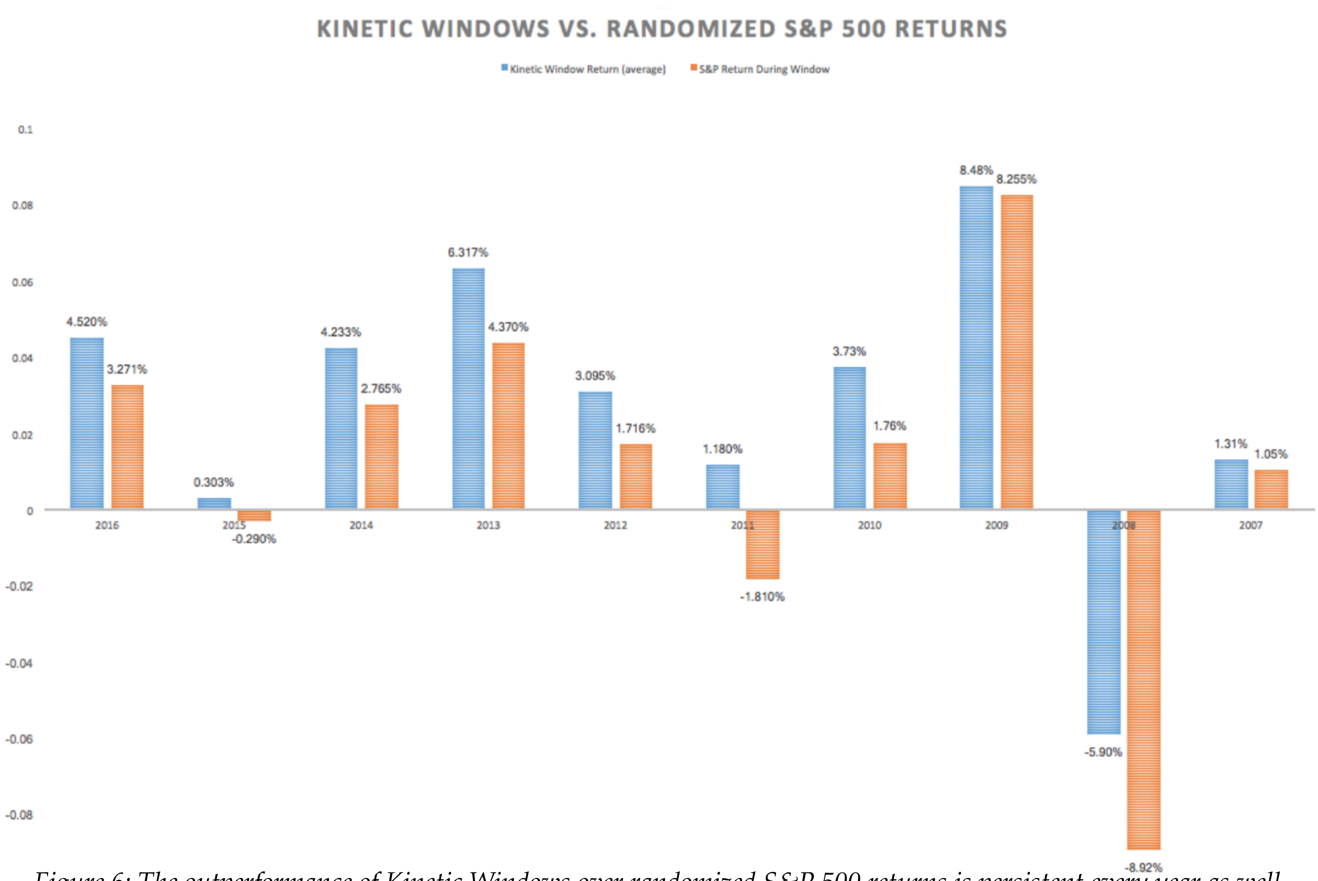

Figure 6: The outperformance of Kinetic Windows over randomized S&P 500 returns is persistent every year as well as statistically significant.

Kinetic Window Performance, 2007 - 2016

Backtest Year	Kinetic Window Return (mean)	Avg. Window Length	Kinetic (Annual)	Random S&P Perf.	Outperformance (Average)	S&P 500 FY	Percent Profitable
2016	4.52%	75.25	21.92%	3.27%	1.49%	9.54%	61.80%
2015	0.30%	75.49	1.46%	-0.29%	0.59%	-0.73%	52.10%
2014	4.23%	74.69	20.69%	2.77%	1.27%	11.39%	68.50%
2013	6.32%	74.00	31.16%	4.37%	0.73%	29.60%	76.30%
2012	3.10%	74.95	15.07%	1.72%	1.49%	13.41%	64.50%
2011	1.18%	76.15	5.66%	-1.81%	0.90%	-0.03%	56.00%
2010	3.73%	73.06	18.64%	1.76%	1.97%	12.78%	61.14%
2009	8.48%	73.26	42.26%	8.26%	0.23%	23.45%	68.56%
2008	-5.90%	75.68	-28.46%	-8.92%	3.01%	-38.49%	37.80%
2007	1.31%	73.96	6.47%	1.05%	0.26%	3.53%	52.57%

Table 1: Kinetic Windows outperformed randomized S&P 500 performance each year across a backtest of 13,262 individual Kinetic Windows between 2007 and 2016.

As an additional validation test, the investment universe was expanded for 2016 to 1,683 individual securities, comprised of every active security in the Zacks Equity Prices database with a market capitalization of $1 billion or more, as well as at least 10 years of price history. That test yielded 5,212 individual Kinetic Windows projected for 2016. The results were statistically indistinguishable from the much smaller S&P 500-only universe in 2016. That consistent Kinetic Window performance across different security characteristics indicates that Kinetic Windows are a robust signal.

Trading Strategy Creation

While the previous section provided empirical evidence that Kinetic Windows are a valid trading signal that adds alpha over the S&P 500, there are some limitations to using them in isolation. For instance, using the pared-down S&P 500 investment universe to search for signals required entering 1,290 individual trades in 2016. While such a large number of transactions might be feasible in an institutional setting, it's not economically viable for retail investors or smaller funds.

Part of the reason for that high number of transactions is that there's no effort made to filter the Kinetic Windows generated in the prior section. For instance, we include those windows that have historically not produced large returns. Returning to our first principles established in the first section of this paper, we can assume that not all Kinetic Windows will work equally well each year — some filtering is required to identify the strongest market tailwinds.

Interestingly, the vast majority of filtering mechanisms are completely ineffective at identifying Kinetic Windows that produce larger returns in year $p+1$ — that is, the test year.

Our system automatically generates and stores a series of statistics for each Kinetic Window observed in a given calendar year. These statistics include average returns during the backtest period, calendar days of the window, worst drawdown, maximum gain, win rate during the backtest period, maximum adverse and favorable excursions, linear slope of the Kinetic Composite during the window, standard deviation of window returns during the backtest period, and many more. Despite this large array of descriptive data that would seem to be instructive as to the quality of a specific Kinetic Window, testing revealed that all of these factors had a near-zero correlation with future returns.

Despite that apparent setback, once again, our first principles provide an intuitive filtering mechanism for Kinetic Windows: the stock's year-to-date correlation with its Kinetic Composite.

If our Kinetic Composite is our roadmap for a stock's likely price behavior over the course of a calendar year, then how closely that stock correlates with its Kinetic Composite in the current calendar year is likely to be an important guide to how that stock behaves during its Kinetic Windows.

As Figure 7 shows, this assumption proved to be correct. A stock with a positive correlation with its Kinetic Composite vector in the timeframe leading up to its Kinetic Window is more likely to produce a profitable result than one with a zero or negative correlation.

(Note: As one might expect, there are a large number of Kinetic Windows with zero correlation to their current year's price action. While these are included in Figure 7, their distribution in return space is relatively uniform, and as we would expect, have no predictive value over the following window's returns.)

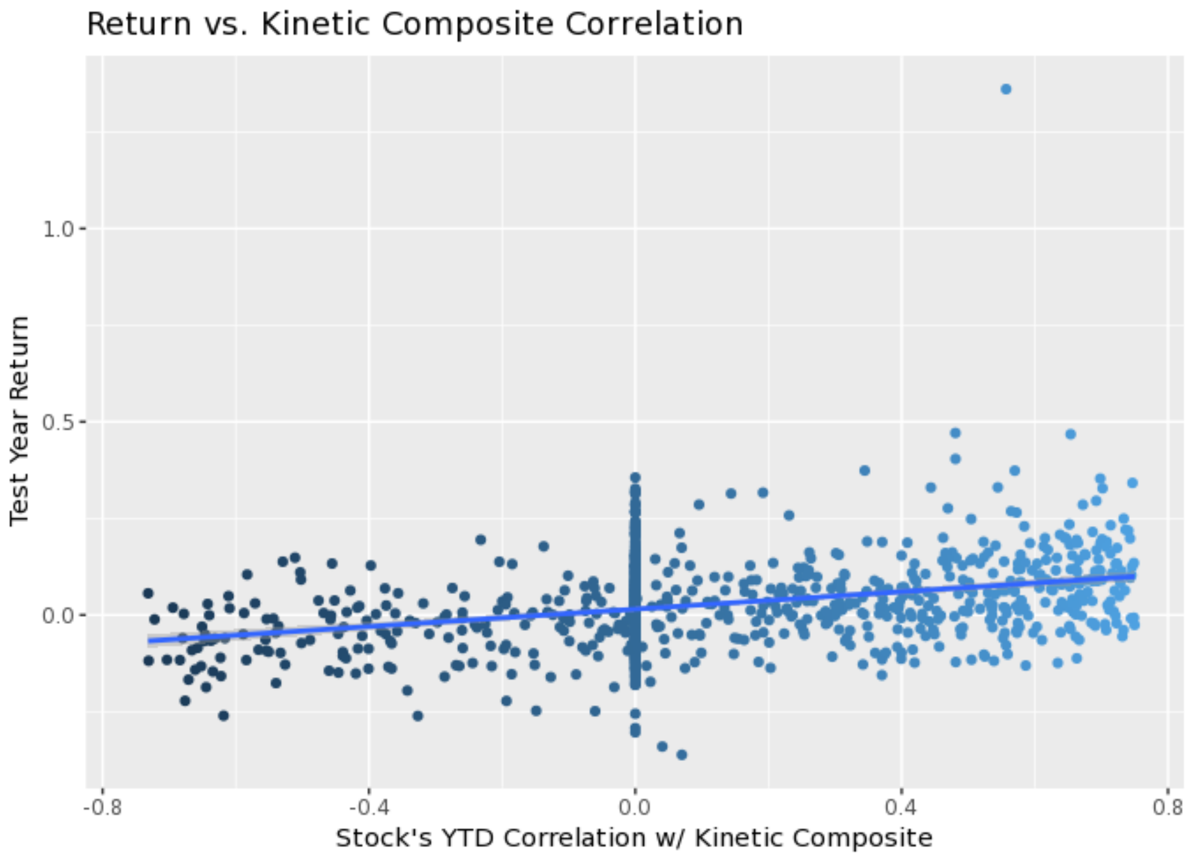

Figure 7: 2016 scatterplot of a stock's year-to-date correlation with its Kinetic Composite versus its ensuing test year return during its Kinetic Windows.

To avoid overfitting factors, correlation testing was done in 2016 only, with out-of-sample testing performed in all prior years. The results of this filter are significant. Using positive correlation alone, the average return during a Kinetic Window increases to 9.03%, outperformance of 7.29% (per window per year) during the period starting on January 2, 2006 and ending on December 31, 2016. Additionally, the average win rate during the entire test period increases to 80%.

Using only positive correlation as a filtering method, the average winner increases to 13.46%, while the average loser decreases to 7.17%. Expectancy is positive and significant each year, and outperformance over the benchmark is statistically significant ($p < .01$) with 1,187 trades during the 11-year span of the backtest.

While throwing out any Kinetic Windows with a zero or negative correlation does remove a large number of ultimately profitable trades, the immense level of predictability as well as large remaining universe of qualifying trades make it a tradeoff easily worth accepting.

Despite the performance of this approach, we can further filter our trade universe by looking at trailing 3-month returns leading up to the start of the Kinetic Window. As with positive correlation between a stock's price and Kinetic Composite, there exists a positive and meaningful relationship between negative trailing 3-month returns and the subsequent profitability of the Kinetic Window, suggesting mean reversion is taking place.

Once again, this relationship was only examined for the 2016 calendar year in order to generate out-of-sample results in prior years and avoid the risks of overfitting. When this second filter is added to the positive correlation requirement established earlier in this section, the results are materially improved.

The average annual return during a Kinetic Window under this two-filter system increases to 12.8%, outperformance of 11.076% (per Kinetic Window, per year) during the 11-year test period. Additionally, the average win rate during the entire period increases to 88.2% during the entire test-period. Limiting the test to post-2008 to reduce outlier years increases the system's win rate to 93.5%.

(It is worth noting, however that both of the filtering methods presented in this section actually produce positive average Kinetic Window returns during the 2008 calendar year.)

Using this two-filter system, the average winner increases to 16.09%, while the average loser further decreases to 5.61%. It is important to note that the average loser statistic is affected somewhat by the fact that some years do not have enough losing trades to produce a statistically meaningful number. Once again, expectancy is positive and significant each year, and results are statistically significant ($p < .01$) with 476 trades during the 11-year span of the backtest.

A histogram of trade results for 2006 - 2016 is presented in Figure 9. A summary table of results is provided in Table 2. Returns approximately follow a normal distribution with positive skew and $\mu >> 0$.

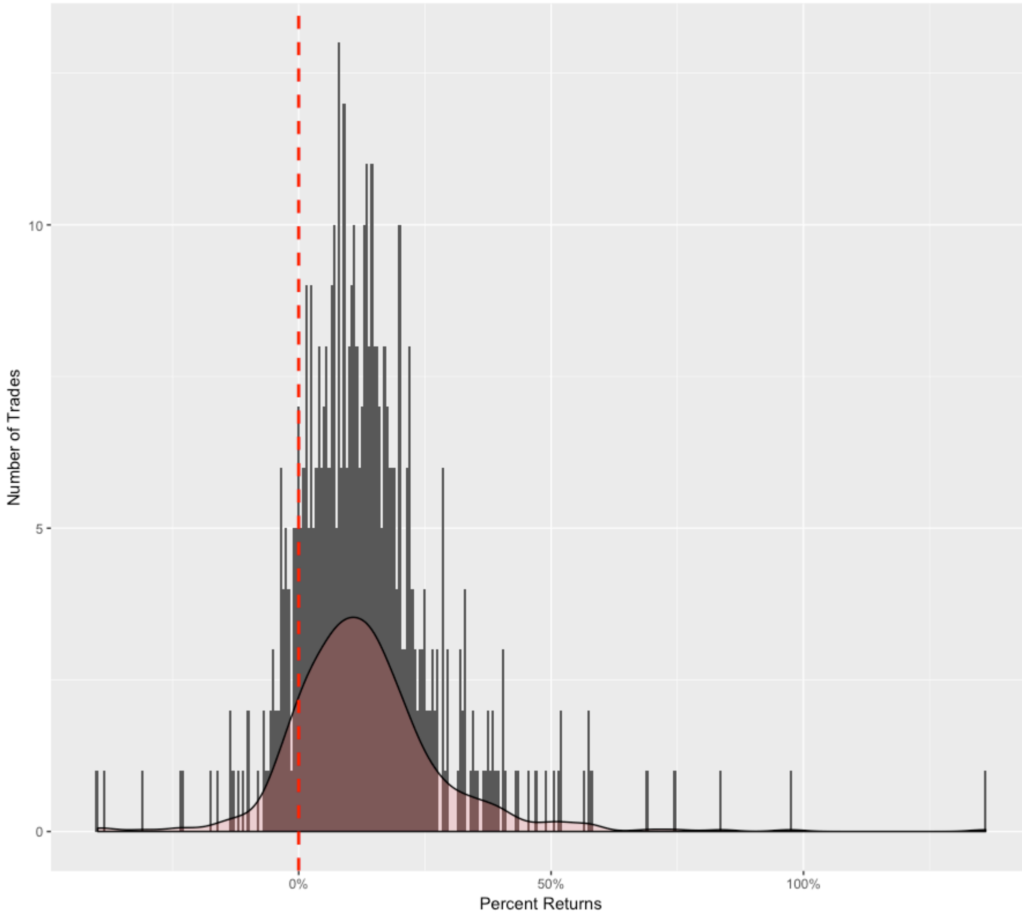

Figure 9: A histogram of trade results using the two-filter system presented in this section.

Kinetic Trading Strategy Performance, 2006 - 2016

Backtest Year	Kinetic Window Return (mean)	Avg. Window Length	Kinetic Return (Annual)	S&P Random Perf.	Outperformance (Average)	S&P 500 FY	Percent Profitable
2016	13.65%	104.0	47.901%	4.400%	9.248%	9.540%	86.6%
2015	11.08%	90.4	44.727%	0.09%	11.168%	-0.730%	95.0%
2014	10.49%	86.0	44.533%	2.96%	7.532%	11.390%	93.1%
2013	12.87%	85.9	54.678%	5.14%	7.731%	29.600%	95.5%
2012	7.17%	89.0	29.388%	1.82%	5.341%	13.410%	91.7%
2011	15.60%	88.0	64.693%	-1.52%	17.122%	-0.026%	96.4%
2010	18.26%	89.6	74.422%	2.56%	15.698%	12.780%	100%
2009	31.15%	89.6	126.919%	10.52%	20.632%	23.450%	89.5%
2008	3.78%	88.1	15.673%	-11.11%	14.889%	-38.490%	64.0%
2007	3.28%	91.3	13.108%	1.63%	1.649%	3.530%	67.0%
2006	13.50%	87.0	56.647%	2.67%	10.828%	13.620%	90.9%

Table 2: Annual results of the Kinetic Windows two-filter trading system.

Not surprisingly, the results of this system are substantial when dollars are applied to it. For the purposes of this paper, the author has used an overly-simplified trading strategy that assumes an investor is fully invested at all times during the test period, with any trading capital equally balanced between any open Kinetic Windows that meet the system criteria. During times when there are no open Kinetic Windows, the strategy is cash-only. No transaction costs are included in the performance chart shown in Figure 10, however the relatively small turnover of this strategy and exceptionally low transaction costs found at major discount brokers today make the effect of this negligible for the $10,000 account example shown.

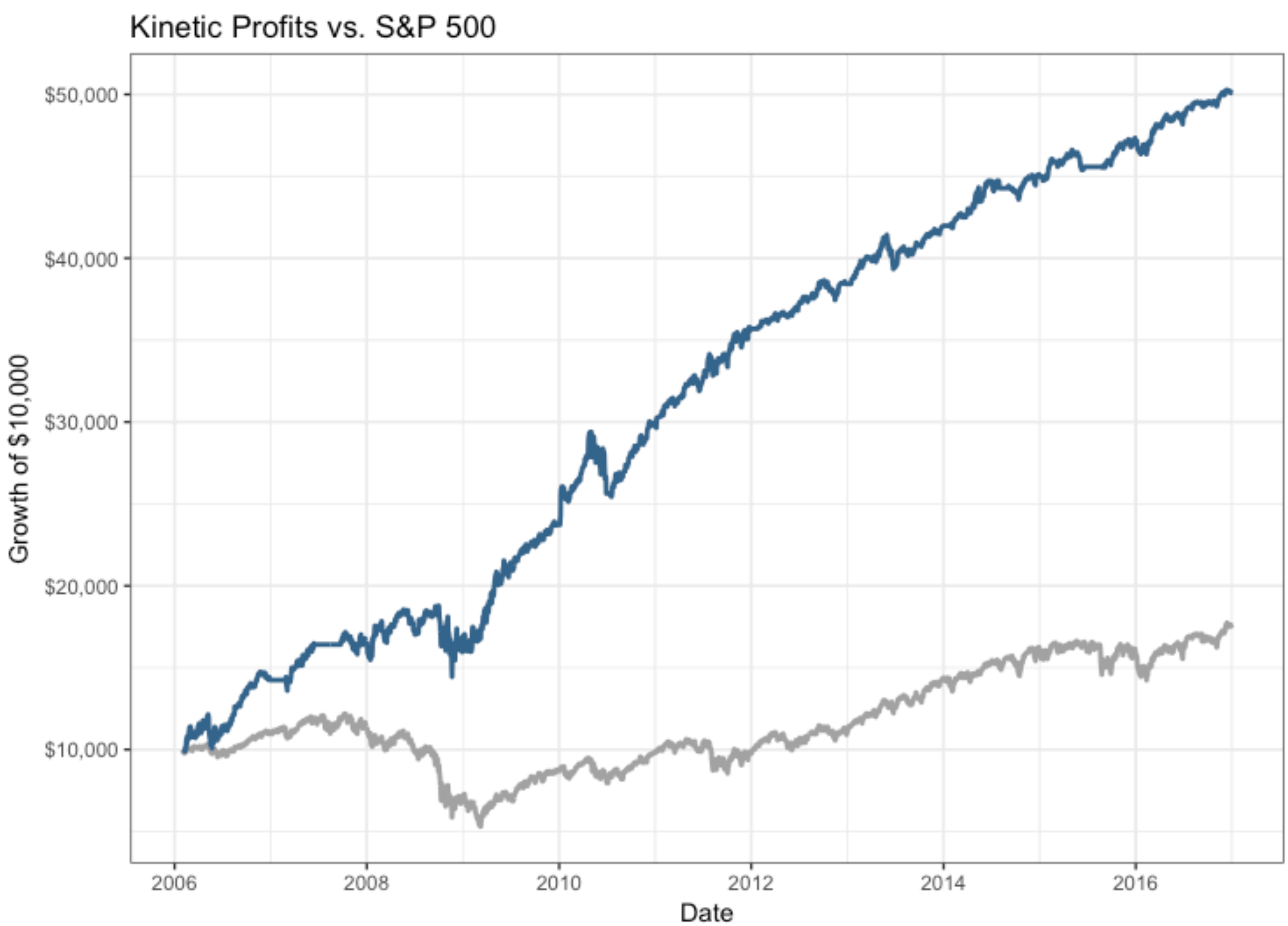

Figure 10: Growth of $10,000 invested in the two-filter Kinetic Windows strategy (blue line), versus $10,000 invested in the S&P 500.

In the example portfolio above, $10,000 invested in our two-filter Kinetic Windows strategy (blue line) would grow to $50,079.28 at the end of 2016, versus $17,410.23 for the S&P 500 during that same timeframe. It's important to note that the portfolio management strategy above is intentionally sub-optimal. For example, no stop losses or position sizing rules are used. As a result, Figure 10 shows a small loss in 2008 while the average Kinetic Window selected by our system that year was profitable — this is because the system was more allocated to unprofitable trades during the calendar year, despite profitable trades representing a majority of the Kinetic Windows in 2008.

This sub-optimal portfolio construction is intended to present a worst-case for the trading strategy presented in this section.

Conclusion

This paper provides evidence for the existence of discrete "Kinetic Windows", time periods that provide tailwind-like performance for U.S. equity prices.

The existence of seasonal periods that provide a higher likelihood of positive returns than other time periods has long been a part of investing lore, however empirical tests of such periods have been greatly limited in the past. Part of the reason for this lack of statistically meaningful research on seasonality is due to the technical and computational challenges of defining and then testing seasonal periods in traditional time-series price data. This author believes that the significant performance enhancement Kinetic Windows provide is also due to this challenge in acquiring and processing the data needed to compute Kinetic Windows in a systematic fashion.

Importantly, these aren't purely "seasonal" time periods. The trend component of the Kinetic Window offers an additional force we make no effort to remove from the price time-series.

These windows provide standalone trading profitability, but can also be used in concert with other technical and fundamental strategies to identify timeframes that could lead to larger profit opportunities in particular securities.

There's a measurable advantage in trading with a tailwind.

Appendix:
2017 Results and Further Research

Since originally conducting this research in early 2017, the author's firm has been managing a real-time model portfolio for subscribers based on a variation of the trading strategy presented in this paper.

As of early December 2017, the results of the stock-only Kinetic Window trades that have been closed are summarized below:

Year	Kinetic Window Return (mean)	Avg. Window Length	Kinetic Return (Annual)	S&P Random Perf.	Outperformance (Average)	S&P 500 FY	Percent Profitable
2017*	7.45%	95.5	28.475%	4.042%	3.408%	TBD	89%

These results are substantially in line with the results of the system testing presented in this paper.

Likewise, nearly a full year of real-world trading of this strategy has spawned some potential extensions of this approach to trading. Among these topics of further research are the idea of negative Kinetic Windows applied to short trading, ranking trading windows based on the robustness of Kinetic Composite charts over multiple timeframes, the use of unsupervised machine learning techniques to identify superior filters for successful Kinetic Windows, and the use of supervised machine learning techniques to predict the likely size of a profitable trade, among others.

*From 1/1/2017 to 12/7/2017. Only completed windows are included in this table, however closing all remaining trades as of this writing would result in nearly indistinguishable statistics.

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