Trending Fast and Slow

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KEY FINDINGS

- The performance of a time-series momentum strategy is determined by both its responsiveness and the market volatility regime. A slow time-series momentum strategy tends to outperform a fast time-series momentum strategy when market volatility is low, and vice versa.
- A decision tree gives a simple and insightful way to determine the threshold in characterizing the market volatility regime, with minor judgment required from an investor.
- Relative performance between slow and fast time-series momentum strategies in different volatility regimes can be attributed mainly to market-timing alpha.

ABSTRACT

This article develops a methodology to combine fast and slow time-series momentum signals using machine learning techniques based on market volatility. Starting with the US equity market, the authors find that the performance of a time-series momentum strategy is determined by both its responsiveness and the market volatility regime, among other factors. A decision tree gives a simple and insightful way to determine the threshold in characterizing low- and high-volatility regimes. A slow time-series momentum strategy tends to outperform a fast time-series momentum strategy when market volatility is low. The opposite tends to occur when volatility is high. This pattern of relative performance can be attributed to market-timing alpha and exists in most global equity markets, including both developed and emerging markets.

In both theory and practice, it has been documented that direct hedging of tail risks can cause a meaningful performance drag in the long term. As a result, investors have been searching for relatively inexpensive tail risk diversifying strategies, even though they are generally understood not to be tail risk hedges. Trend-following strategies based on time-series momentum (TSM) are believed to be able to capture both up and down trends in the price of the underlying asset and therefore can deliver a performance profile with a relatively symmetric payoff when the future price volatility of the underlying asset is sufficient; see Moskowitz, Ooi, and Pedersen (2012), Asvanunt, Nielsen, and Villalon (2015), and Hurst, Ooi, and Pedersen (2017) for examples. Because of their perceived diversification benefits for traditional asset classes, TSM strategies are often included in alternative risk premiums together with other nonmarket factors, such as value, carry, and momentum, in the investment industry.

TSM strategies are based on the assumption that past returns have some degree of predictive power on future returns. Typically, a strategy is implemented by taking long positions on securities in uptrend phases (positive sign of past return) and short positions on securities in downtrend phases (negative sign of past return). TSM is pervasive: The academic literature documents that asset returns measured over the recent past are positively correlated with future returns. The efficacy of TSM strategies has been supported across multiple time periods, in many markets, and in numerous assets. For instance, Moskowitz, Ooi, and Pedersen (2012) found substantial profitability for 12-month TSM strategies and documented return predictability evidence across lookback horizons from 1 to 12 months. By their nature, strategies based on slower signals tend to better capture long-term trends and exhibit better historical risk–return profiles than strategies based on faster signals.

However, as found by Garg et al. (2021), TSM strategies can suffer from turning points in market direction, manifesting as a reversal in trend from uptrend to downtrend or vice versa. At and after turning points, TSM strategies tend to take undesirable positions because they rely on observations of realized returns.[1] Strategies based on slower signals, such as the 12-month TSM, take more time to turn and therefore can be more greatly affected by these turning points. Their higher embedded asset betas, as discussed by Lee (2021), can also become a negative contributor to their performance during market downturns. On the other hand, strategies based on faster signals, such as one-month returns, are more reactive and suffer less from turning points. However, because of their greater responsiveness, faster signals can be the most susceptible to false turning points and, as a consequence, may suffer from excessive turnover and weaker performance.

One way to potentially reduce the losses endured by strategies based on slow signals during market turbulence (which often correspond to turning points) is to use volatility managed portfolios (VOM), a concept well supported by academic literature. For instance, Moreira and Muir (2017) claimed that “Managed portfolios that take less risk when volatility is high produce large alphas, increase Sharpe ratios, and produce large utility gains for mean-variance investors.” The general idea behind these strategies is to scale the position size by the inverse of the previous realized variance (or volatility), reducing exposure when variance was recently high and vice versa. The potential to improve risk-adjusted return by use of VOM strategies is based on the assumption that variance is highly forecastable at short horizons and that variance forecasts are only weakly related to future returns at these horizons. Harvey et al. (2018) and Plessis and Hallerbach (2016) presented similar methods, helping to reduce risk when times are uncertain and increase exposure during quiet times.

With respect to the momentum signal speed, TSM strategies face a key trade-off: Follow the slow signal and risk incurring a Type II error (failing to react to a turning point), or follow the fast signal and risk incurring a Type I error (reacting to noise when a turning point has not occurred). An effective combination of signals from two speeds can take advantage of different market cycles and reduce exposure to the downside associated with turning points.

We take a different approach to risk management of TSM strategies compared to that used for VOM and static intermediate speeds strategies. Indeed, these latter two techniques seem to adopt a similar risk management approach. For instance, VOM reduces the capital allocation to risky assets when volatility is high by scaling the position by the inverse of volatility. On the other hand, fast and slow signals disagree during turning points, which often correspond to market events. As a result, a static strategy based on an equally weighted position of fast and slow signals will

[1] Moreover, cross-sectional momentum also suffers in periods of uncertainty when market direction is unclear. As highlighted by Daniel and Moskowitz (2016), momentum crashes occur in panic states following market declines and when market volatility is high and are contemporaneous with market rebounds.

most likely offset exposure (take less risk) during periods of high volatility. In our approach, instead of hedging our exposure during times of high uncertainty, we take active positions to try to extract value from these periods to improve market-timing efficiency. Our approach, therefore, is also different from factor timing, which Baltas and Ivanova (2019) identified as particularly important for low Sharpe ratio strategies.

The layout of the article is as follows. In the first section, we start by defining simple fast and slow momentum signals and explore the relationship between the speed of the TSM signal and market volatility using an easily interpretable tool from supervised machine learning: a decision tree classifier. In the next section, our volatility-based TSM strategy is applied to a broader asset universe. We show additional steps to improve the robustness of volatility-regime detection and present the empirical results across international equity markets.

MOMENTUM SPEED WITH MARKET REGIME

In this section, we first define simple fast and slow momentum signals and then assess the relationship between the TSM signal speed and market volatility from an empirical perspective.

Definition of Momentum

We follow the literature (e.g., Moskowitz, Ooi, and Pedersen 2012; Garg et al. 2021; Lee 2021) in defining the TSM. Given month t, for trailing N-month return $r_{t-N,t} \geq 0$, we will long one unit of underlying asset for the next period. Otherwise, we will short one unit. This can be expressed as

$$w_{t,N} = \begin{cases} 1 & \text{if } r_{t-N,t} \geq 0 \\ -1 & \text{if } r_{t-N,t} < 0 \end{cases} \tag{1}$$

where we choose $N = 1$ for fast momentum and $N = 12$ for slow momentum, denoted as fast and slow, respectively. They can provide the most distinct information given our less than one-year lookback horizons. Because we want to focus on the direction of asset price movement, we do not take into account the magnitude of trailing N-month returns. The return of momentum for the next month is $r_{N,t+1} = w_{t,N} r_{t+1}$, where r_{t+1} is the return of the underlying asset from month t to $t + 1$.

Exhibits 1 and 2 show slow and fast momentum signals from January 2000 to December 2020, defined earlier based on the S&P 500 Index (ticker: SPX Index) data from Bloomberg. Fast momentum represents the speed of adaptation to market changes, and slow reflects the market's long-term movement. During this 21-year period, fast and slow share the same sign about 63.5% of the time. When signals conflict, investors would face a dilemma in choosing which signal to follow or may even choose to stay neutral. A more efficient way of choosing fast or slow could potentially improve performance.

Exhibit 3 and 4 show slow and fast momentum signal performance alongside S&P 500 Index returns. Both signals generate positive returns, reflecting the existence of momentum in the index. Inspection of Exhibit 3 suggests that the performance of the fast and slow signals was not always synchronized; therefore, there may be performance benefits from combining fast and slow signals.

EXHIBIT 1

Slow Momentum Signal of S&P 500 from January 2000 to December 2020

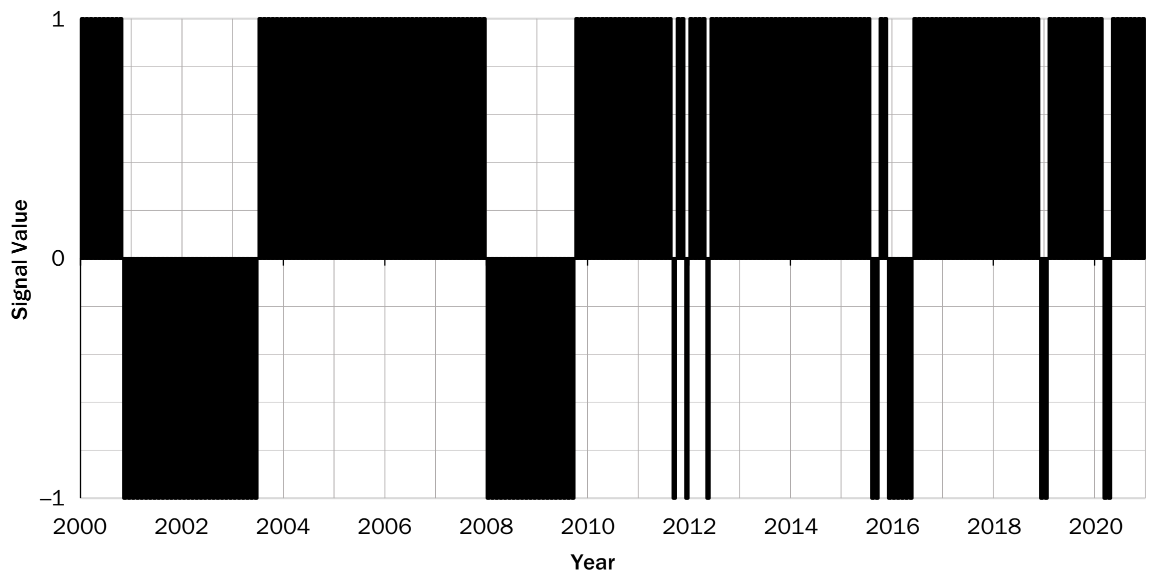
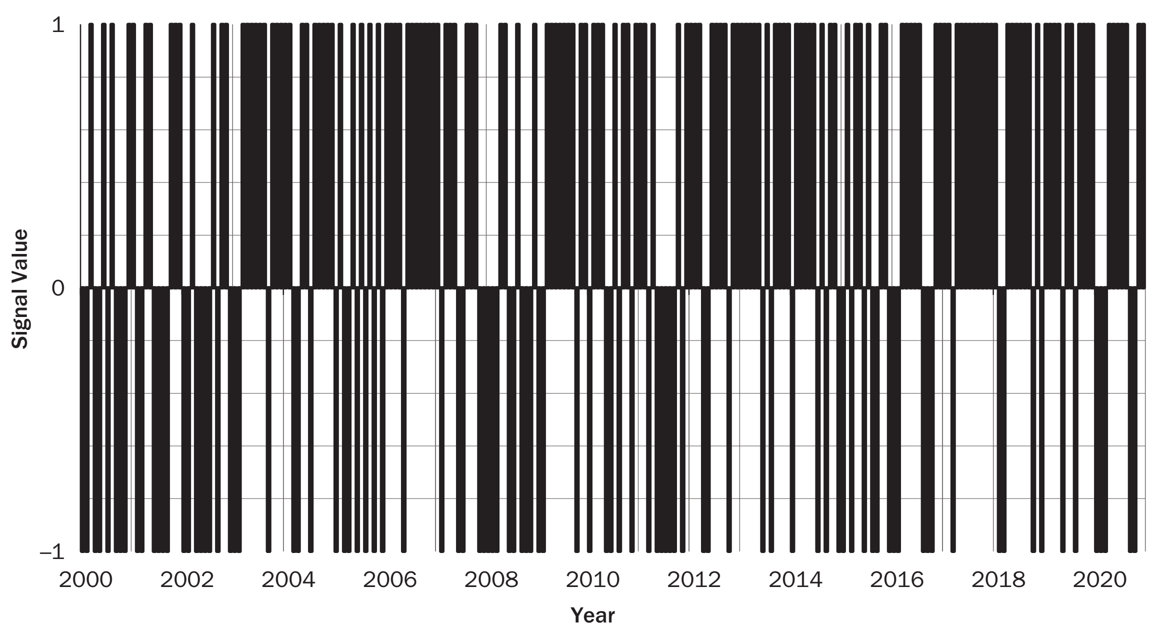


EXHIBIT 2

Fast Momentum Signal of S&P 500 from January 2000 to December 2020



Momentum under Different Volatility Regimes

When markets are relatively stable, it seems that investors are operating out of Newton's first law of motion (inertia), and slow signals seem to be best adapted to capture the trend of the markets. Strategies based on slower signals benefit from this long-term perspective and historically have added more value than faster signals. However, it is difficult to imagine that investment behavior will stay the same during periods of high market turbulence. When markets are volatile, investors can be driven

EXHIBIT 3

Slow and Fast Momentum and Market Performance from January 2000 to December 2020

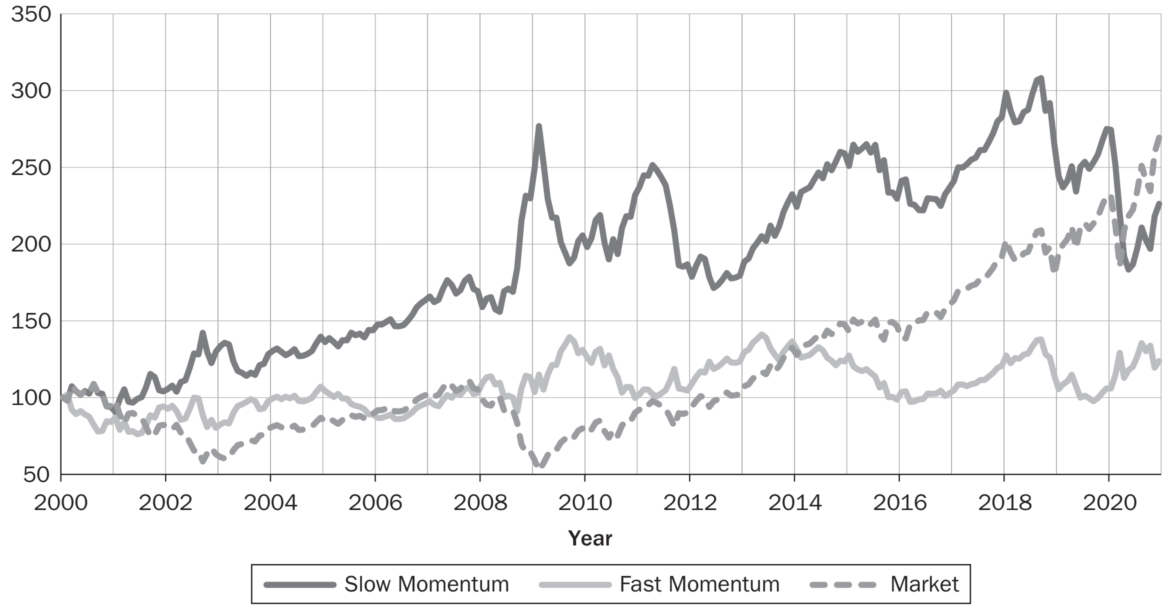


EXHIBIT 4

Performance Statistics of Slow Momentum, Fast Momentum, and Market from January 2000 to December 2020

	Slow Momentum	Fast Momentum	Market
Annualized return	3.98%	1.03%	4.85%
Annualized volatility	15.20%	15.25%	15.17%
Sharpe ratio	0.26	0.07	0.32
Max drawdown	–40.5%	–31.1%	–52.6%
Hit rate	57.9%	56.3%	61.9%

NOTE: Based on futures contract returns, backtests show excess returns of strategies.

SOURCE: S&P 500 first generic futures (ticker: SP1 Index) from Bloomberg.

by fear and uncertainty, likely spurring more frequent trading behavior for different reasons. Based on perceived new information, some investors may trade to protect their portfolio, whereas others may trade to take advantage of newly created buying/selling opportunities. It is likely that investors tend to focus on short-term market events during periods of high volatility. Therefore, we hypothesize that faster momentum signals are better adapted and have better predictive power over slower signals during these periods.

To test our hypothesis, we use a decision tree, a supervised learning technique, to determine the optimal switching mechanism between fast and slow trend signals in different volatility regimes. We define our training target as the prevailing strategy to adopt in the next period given currently volatility when slow and fast disagree on what positions to take. At time *t*, the prevailing strategy to adopt is fast if we have $r_{Fast,t+1} \geq r_{Slow,t+1}$, where 1 denotes 100% investment in fast and 0 indicates that slow is the optimal signal to adopt. This can be expressed as

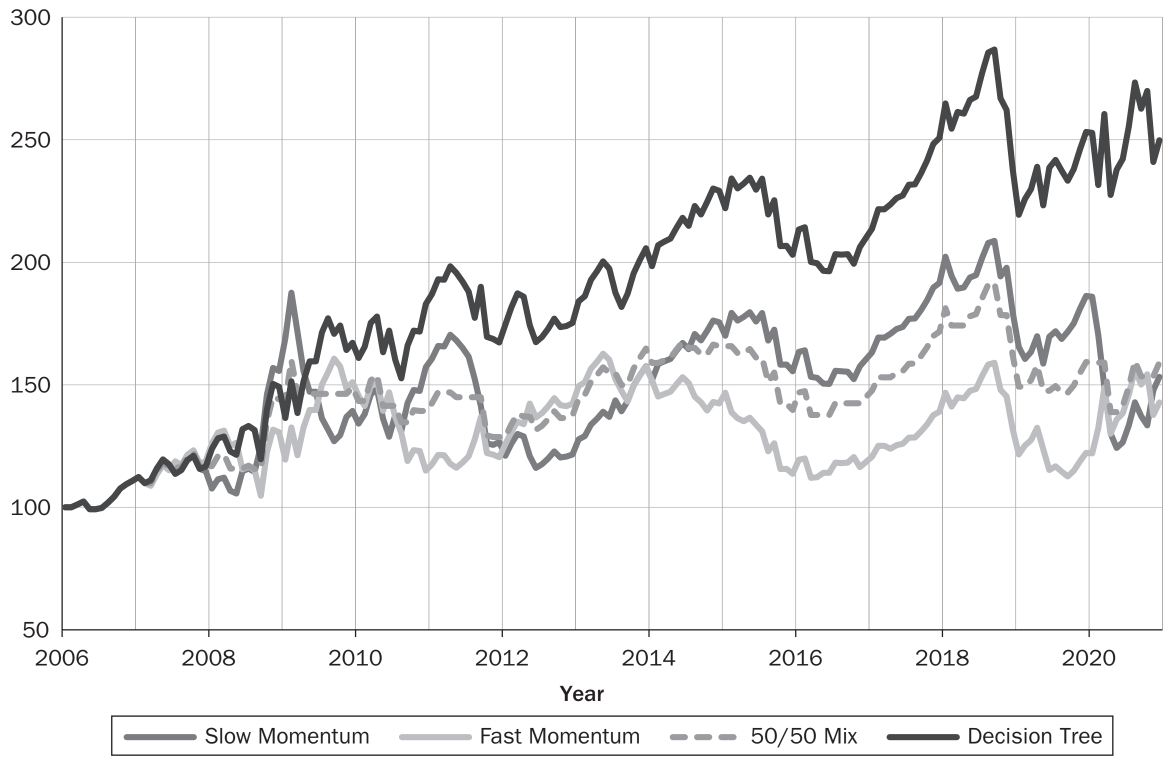
$$bet_{Fast,t} = \begin{cases} 1 & r_{Fast,t+1} \geq r_{Slow,t+1} \\ 0 & r_{Fast,t+1} < r_{Slow,t+1} \end{cases} \; ; \; bet_{Slow,t} = 1 - bet_{Fast,t} \tag{2}$$

where we equally weight fast and slow if they agree.

We calculate rolling one-month S&P 500 volatility using daily returns from January 1971 and then split the sample into a 35-year training and validation period (ended in December 2005) and a 15-year test period (ended in December 2020). We use a decision tree model with a hyperparameter of maximum depth equal to three and train

EXHIBIT 5

Decision Tree Volatility Model Out-of-Sample Strategy Performance and Comparison from January 2006 to December 2020



it only using periods when fast and slow disagree. Further inspection of the resulting tree highlights one particularly valuable node at the threshold volatility of 17%. In a nutshell, the tree shows that fast can outperform slow when one-month S&P 500 Index volatility is above this volatility threshold, and slow will be a better choice otherwise.

On an out-of-sample basis, this volatility threshold model generates strong performance compared to either individual strategy as well as the simple, static combination of the two, as shown in Exhibits 5 and 6, respectively. The model successfully avoids catastrophic drawdown during the most volatile period. Although the 50/50 mix of slow and fast also does relatively well in preventing drawdowns, it is inactive with a neutral position 30% of the time.

Source of the Outperformance

To examine the source of the superior performance of the decision tree model, we follow the alpha and beta determinants decomposition from Garg et al. (2021). Covariance between the momentum strategy return $r_{N,t+1}$, where $N = 1$ for fast and $N = 12$ for slow, and the market return r_{t+1} can be used to present static and dynamic elements. By definition

$$Cov[r_{N,t+1}, r_{t+1}] = E[w_{t,N}]Var[r_{t+1}] + Cov[w_{t,N}, r_{t+1}]E[r_{t+1}] + Cov[w_{t,N}, (r_{t+1} - E[r_{t+1}])^2]$$

The market beta can be decomposed as follows:

$$Beta[r_{N,t+1}] = E[w_{t,N}] + \frac{Cov[w_{t,N}, r_{t+1}]}{Var[r_{t+1}]}E[r_{t+1}] + \frac{Cov[w_{t,N}, (r_{t+1} - E[r_{t+1}])^2]}{Var[r_{t+1}]} \quad (6)$$

EXHIBIT 6

Performance Statistics of Decision Tree Volatility Model Out-of-Sample Strategy Performance and Comparison from January 2006 to December 2020

	Slow Momentum	Fast Momentum	50/50 Mix	Decision Tree
Annualized return	2.90%	2.42%	3.16%	6.84%
Annualized volatility	15.31%	15.32%	11.69%	15.19%
Sharpe ratio	0.19	0.16	0.27	0.45
Max drawdown	–40.5%	–31.1%	–27.6%	–23.5%
Hit rate	60.3%	59.8%	65.0%	63.1%

where the three parts in the equation are static, market timing, and volatility timing beta, respectively. Alpha can be derived from this equation as

$$Alpha[r_{N,t+1}] = Cov[w_{t,N}, r_{t+1}]\left(1 - \frac{E[r_{t+1}]^2}{Var[r_{t+1}]}\right) - \frac{Cov[w_{t,N}, (r_{t+1} - E[r_{t+1}])^2]}{Var[r_{t+1}]} E[r_{t+1}]$$

where $E[r_{t+1}]^2 \approx 0$. Therefore, we have

$$Alpha[r_{N,t+1}] = Cov[w_{t,N}, r_{t+1}] - \frac{Cov[w_{t,N}, (r_{t+1} - E[r_{t+1}])^2]}{Var[r_{t+1}]} E[r_{t+1}] \tag{7}$$

where the first term is market timing alpha and the second term is volatility timing alpha.

At time t, fast and slow take positions $w_{Fast\ t,N}$ and $w_{Slow\ t,N}$, respectively. Their next period return, $r_{Fast\ N,t+1}$ and $r_{Slow\ N,t+1}$, will be attributed to the regime detected at time t. Classified in the same way as return, $Alpha[r_{N,t+1}]$ and $Beta[r_{N,t+1}]$ can be expressed as

$$Beta[r_{N,t+1}] = \begin{cases} Beta_{High}[r_{N,t+1}] & \mathbb{P}(\sigma_t \in High) \geq \mathbb{P}(\sigma_t \in Low) \\ Beta_{Low}[r_{N,t+1}] & \mathbb{P}(\sigma_t \in High) \leq \mathbb{P}(\sigma_t \in Low) \end{cases} \tag{8}$$

$$Alpha[r_{N,t+1}] = \begin{cases} Alpha_{High}[r_{N,t+1}] & \mathbb{P}(\sigma_t \in High) \geq \mathbb{P}(\sigma_t \in Low) \\ Alpha_{Low}[r_{N,t+1}] & \mathbb{P}(\sigma_t \in High) \leq \mathbb{P}(\sigma_t \in Low) \end{cases} \tag{9}$$

Results in Exhibits 7 and 8 suggest that the most distinct contribution to alpha comes from market timing. Slow has much higher market timing alpha than fast in low-volatility regimes, whereas fast has much higher market timing alpha than slow in high-volatility regimes. The results confirm that the slow signal does predict market movement better in low-volatility regimes, whereas fast signal performs better in high-volatility regimes. Both fast and slow deliver positive volatility timing alphas regardless of regime. However, fast delivers much higher volatility timing alpha during low-volatility regimes. Although the alpha between slow and fast momentum is not statistically significant in either the low- or high-volatility regime, we still believe that this relationship provides valuable investment insights.

Exhibits 9 and 10 show the alpha and beta decomposition of the slow, fast, 50/50 mix, and decision tree strategies we show in Exhibit 5, as well as that of the buy-and-hold, long-only position of the S&P 500 Index. The SPX volatility-based decision tree strategy achieves its outperformance in two ways: First, it has relatively neutral

EXHIBIT 7

Alpha Decomposition of Low-Volatility Regime from January 2006 to December 2020

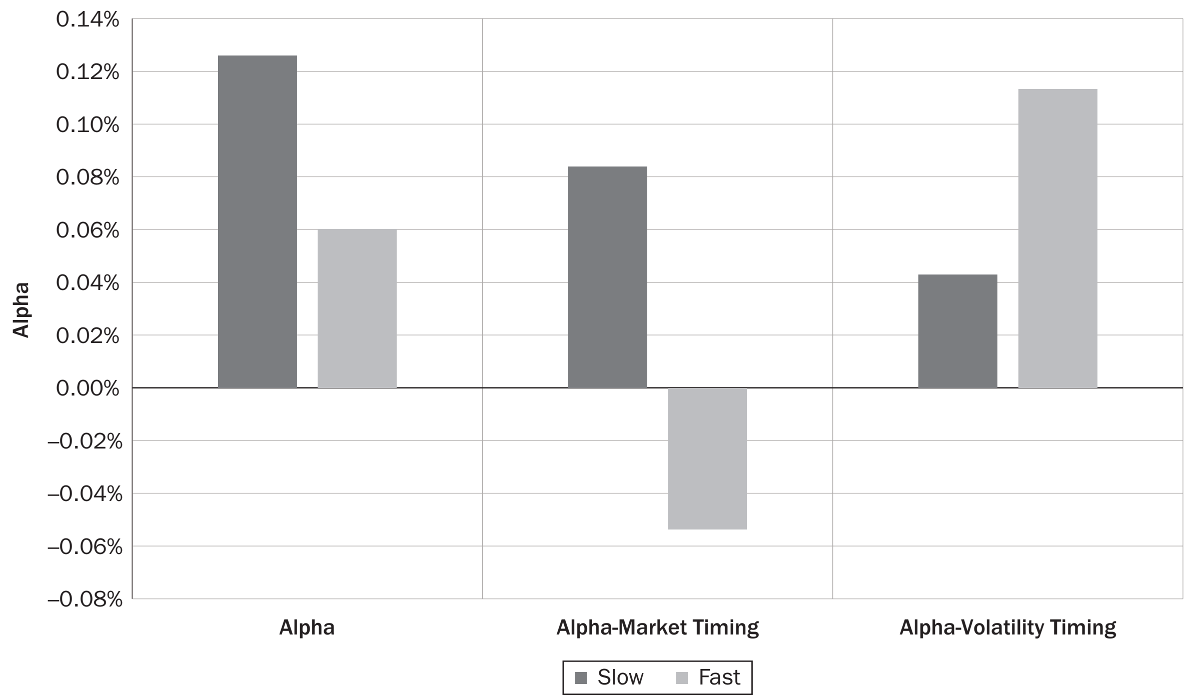


EXHIBIT 8

Alpha Decomposition of High-Volatility Regime from January 2006 to December 2020

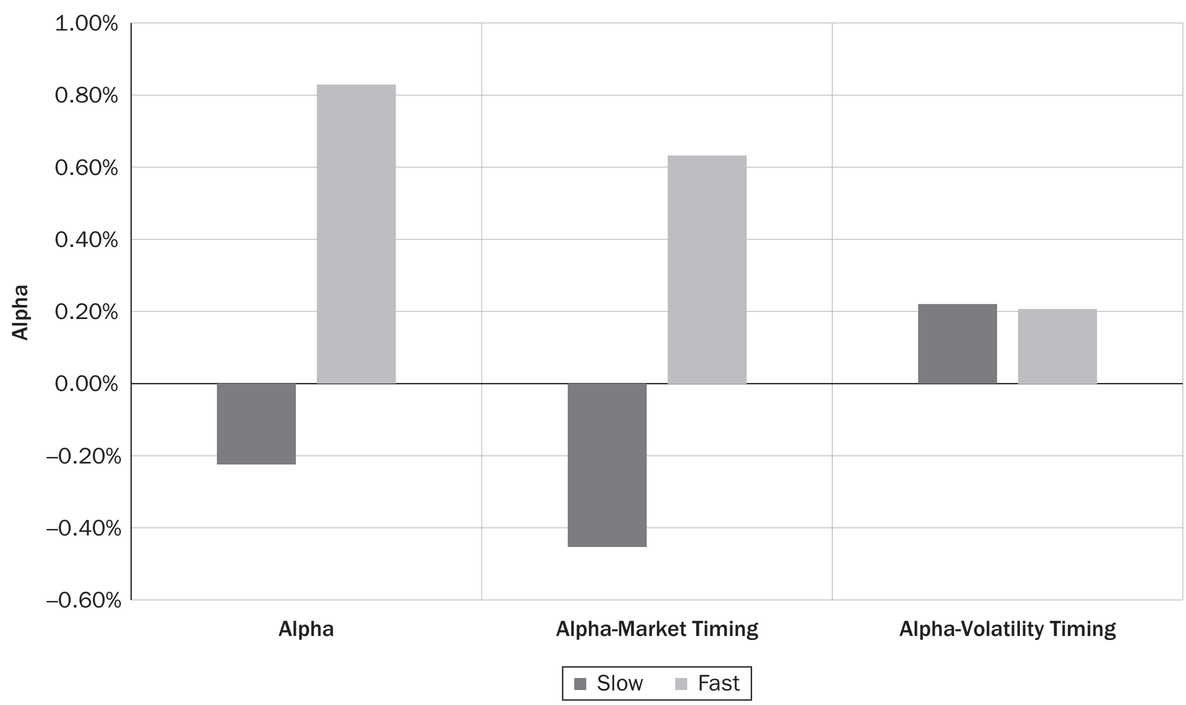
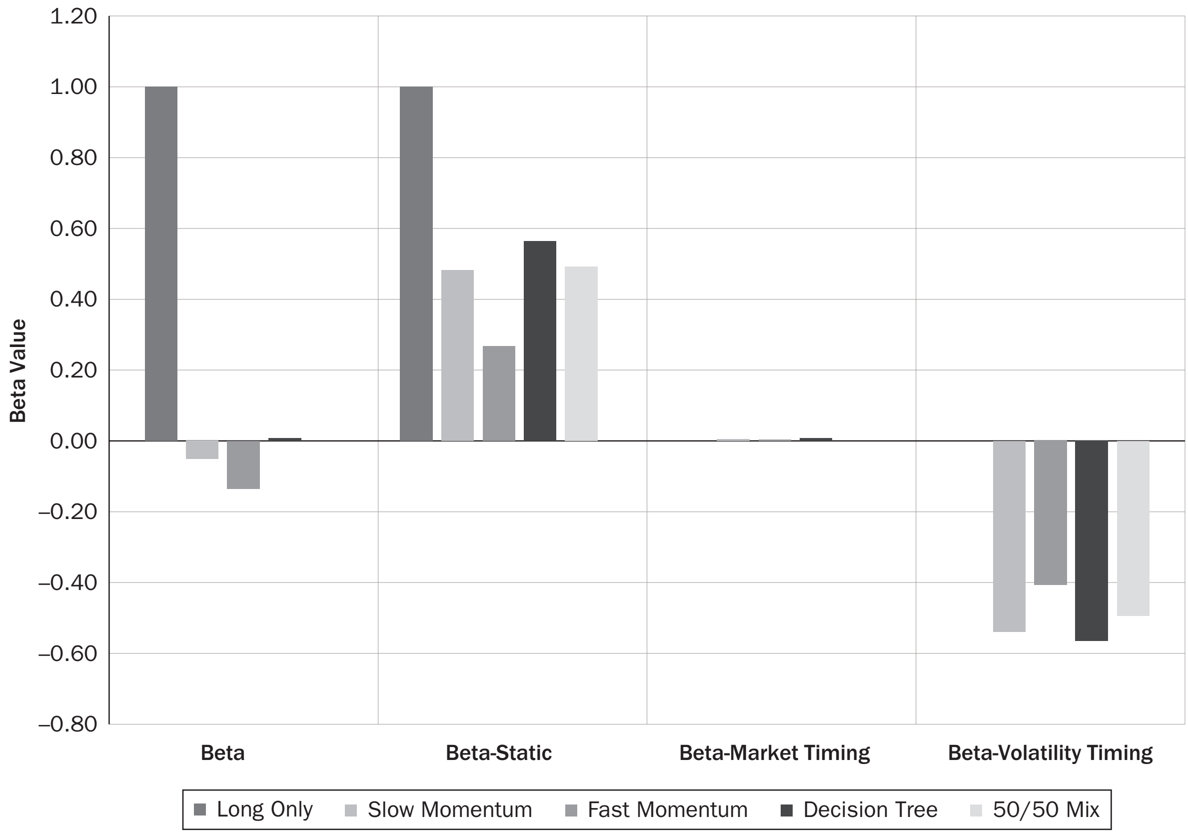


EXHIBIT 9

Beta Decomposition of Presented Strategies from January 2006 to December 2020



total beta exposure with the negative volatility-timing beta, which explains its lower drawdown; and second, its alpha comes from both market timing and volatility timing. In turn, it behaves smarter than the naïve 50/50 mix strategy.

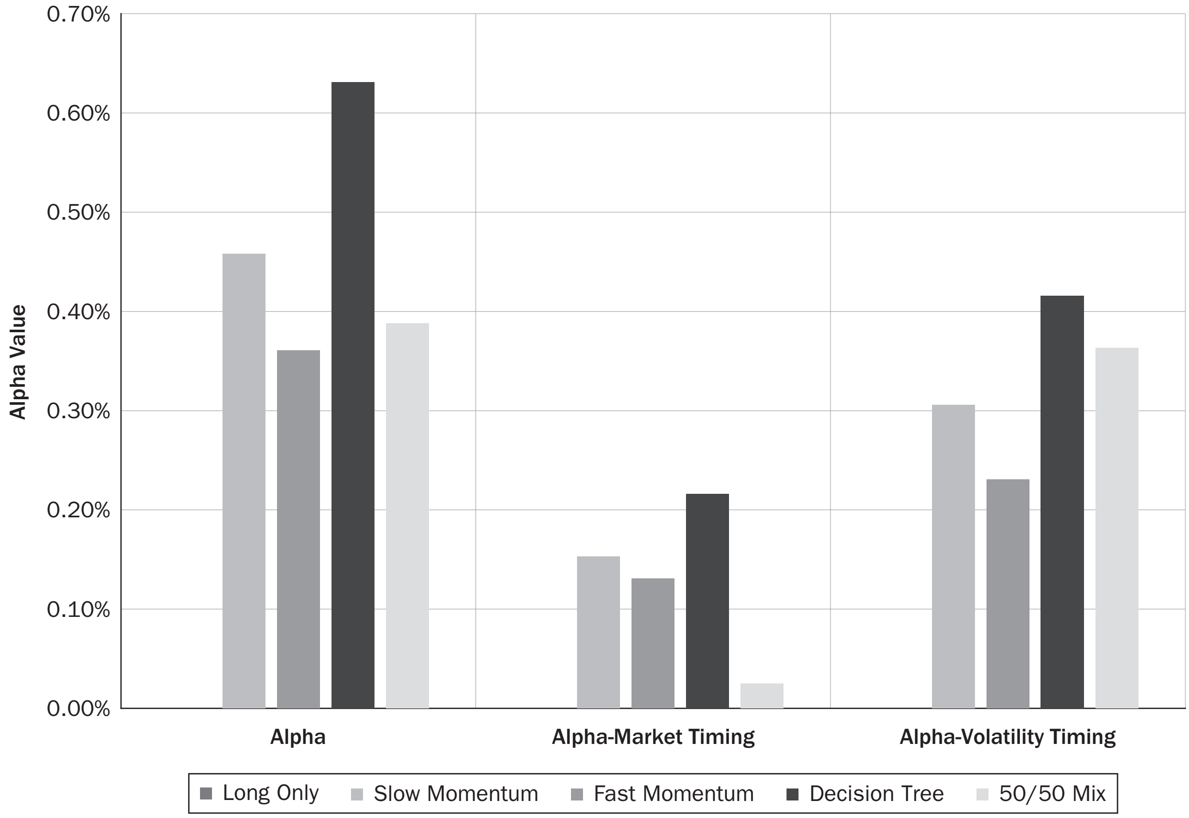
APPLICATION TO A BROADER EQUITY UNIVERSE

To further study the potential enhancement of momentum strategy performance through volatility-regimes identification, we use the volatility decision tree classifier. We calibrate it based on the rolling one-month volatility of the S&P 500 index to back test TSM strategies in each of the 20 equity indexes in our universe in the same manner we did for the S&P 500 index.[2] As reported by Baltas and Kosowski (2013) and Georgopoulou and Wang (2016), the performance of momentum strategies after the global financial crisis are affected by increasing correlations across markets and even assets. We believe that the S&P 500 index volatility can be a good volatility proxy for all other equity markets.

[2] All return data are the corresponding first generic futures from Bloomberg. The 12 developed market indexes include S&P/ASX 200 (XP1 Index), S&P/TSX (PT1 Index), CAC 40 (CF1 Index), DAX (GX1 Index), FTSE MIB (ST1 Index), TOPIX (TP1 Index), AEX (EO1 Index), IBEX (IB1 Index), OMX (QC1 Index), SMI (SM1 Index), FTSE 100 (Z 1 Index), and S&P 500 (SP1 Index). The six emerging market indexes are Hang Seng (HI1 Index), IBOVESPA (BZ1 Index), CSI 300 (IFB1 Index), FTSE/JSE Top 40 (AI1 Index), KOSPI 200 (KM1 Index), and TWSE (FT1 Index).

EXHIBIT 10

Alpha Decomposition of Presented Strategies from January 2006 to December 2020



Retraining the decision tree model, we use a larger dataset obtained by merging slow and fast strategy performance in different equity indexes with the corresponding one-month S&P 500 volatility. To improve its robustness, we use the well-established pruning technique and take a closer look at individual models going from seven nodes (corresponding to a hyperparameter of maximum depth equal to three) to one node. Exhibit 11 illustrates that high-complexity models are susceptible to data overfitting and therefore tend to be less accurate than models with low complexity. Decision tree models with one to three nodes deliver the top out-of-sample accuracy and the narrowest gap between in- and out-of-sample accuracy.

Nodes defined by the decision tree can work as the boundary line between categories. This serves two functions. First, it highlights the optimal decision (i.e., investing in slow or fast) under different volatility regimes. Second, given the same slow or fast momentum signals, it provides different confidence levels for each decision under a particular volatility regime by building nodes to extract clusters with high confidence. Often, because of the general structure of the volatility feature, this can be achieved by isolating a few time periods with extremely high volatility. However, in our setting, only the first function of the node benefits us owing to the binary bet we make: slow or fast. In other words, we are not interested in having several clusters at different confidence levels in high-volatility regimes to follow fast, for instance. Instead, our goal is to detect the most valuable node, which is the one that separates the most sample data and is less extremely data driven.

Exhibit 12 shows the threshold from the first three nodes and highlights the most valuable node when we retrain the tree on an expanding window from 1996 to 2005.

EXHIBIT 11

Prediction Accuracy vs. Complexity for Test and Training Periods from 1971 to 2006

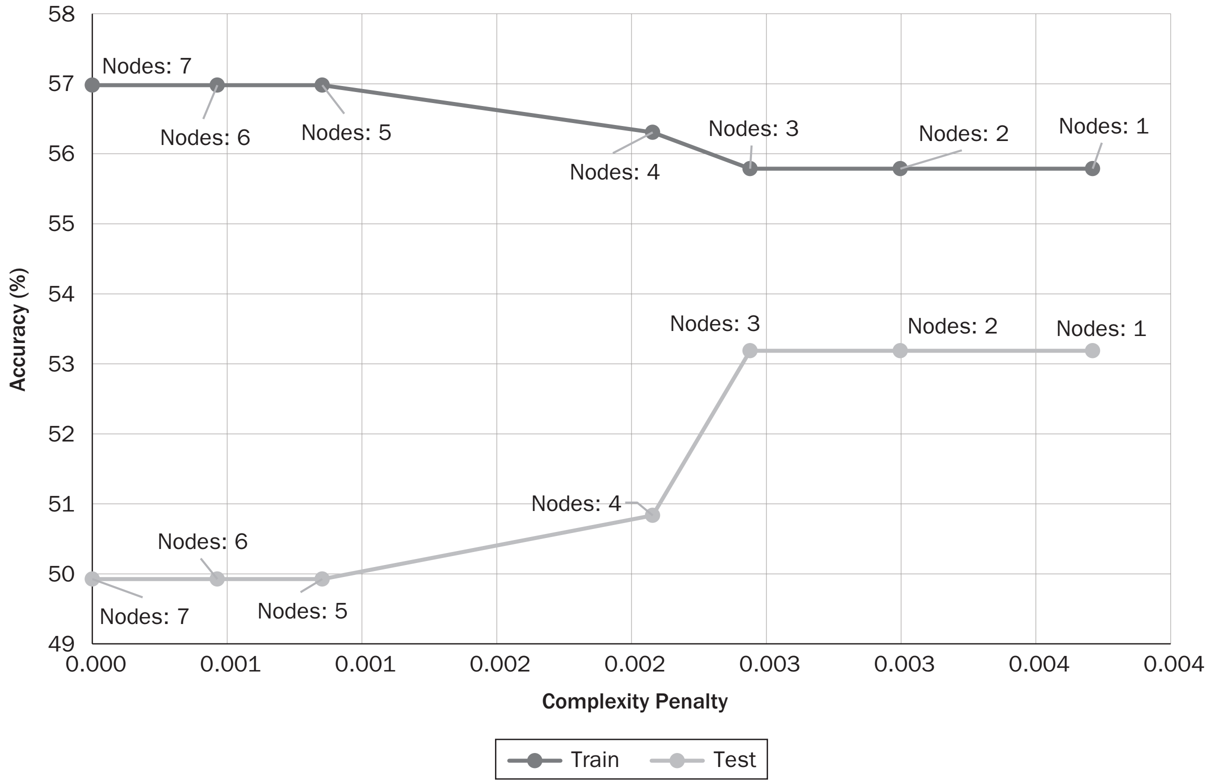


EXHIBIT 12

Threshold from the First Three Nodes Based on Training Period from 1971 January to Various Years

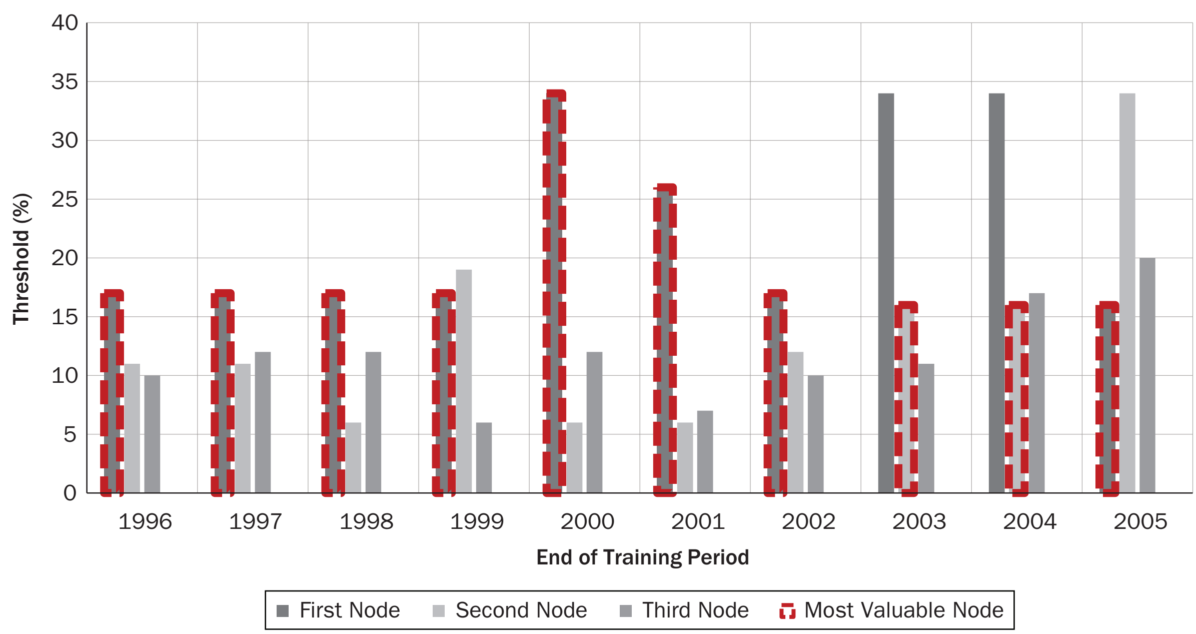
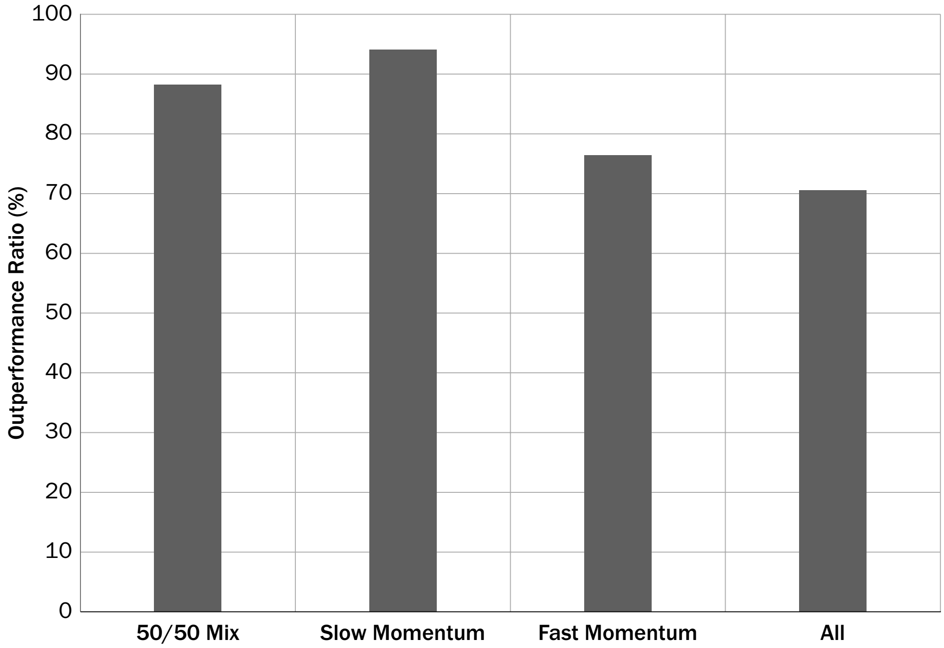


EXHIBIT 13

Percentage of Equity Universe for Which Decision Tree–Based Strategy Outperforms Deterministic Strategies from February 2006 to December 2020



Some equity indexes may not be available historically; we omit them during the model construction phase. We note that the threshold of the first node can range from 16% to 34% because of the extremely high volatility threshold outliers during crisis periods, making them hard to implement in normal trading conditions. This variability is also observed for the second and third nodes. The results expose the instability of the decision tree, which makes it more appropriate as a proof-of-concept model than as a production model. Thus, under those cases, the most valuable node can be any of the three nodes we present. Investors can also benefit from more realistic thresholds in implementation. For example, although the 34% threshold undoubtedly marks a volatile market, its rare occurrence would make it a crisis signal at best.

At the end, we take into consideration all of these 10 years' most valuable nodes and use their median, 17%, as the final threshold in the following analyses. Note that this threshold can be extracted from the model during most cases, except for 2000 and 2001. We believe this number to be stable in the following period.

Exhibit 13 shows the percentage of the equity universe for which the decision tree–based strategy outperforms the 50/50 mix, slow, fast, and all combined strategies in terms of Sharpe ratio from February 2006 to January 2021.

We note that in 95% of the equity indexes in our universe (19 indexes from 20 available), decision tree–based models generate higher Sharpe ratios than the 50/50 mix of slow and fast. Moreover, in 70% of cases (14 indexes from 20 available), strategies based on decision trees are the best performing among the 50/50 mix, slow, and fast strategies.

Lastly, we examine equally weighted portfolios of strategies in the universe. For instance, the slow momentum portfolio is an equally weighted portfolio of individual slow strategies applied to different equity indexes in our universe. Exhibits 14 and 15 show the out-of-sample performance of these equally weighted portfolios.

Decision tree–based strategies provide the best risk–return profile compared to other deterministic and commonly used TSM strategies, delivering the highest

EXHIBIT 14

Out-of-Sample Strateys Performance of the Equally Weighted Equity Portfolio from January 2006 to December 2020

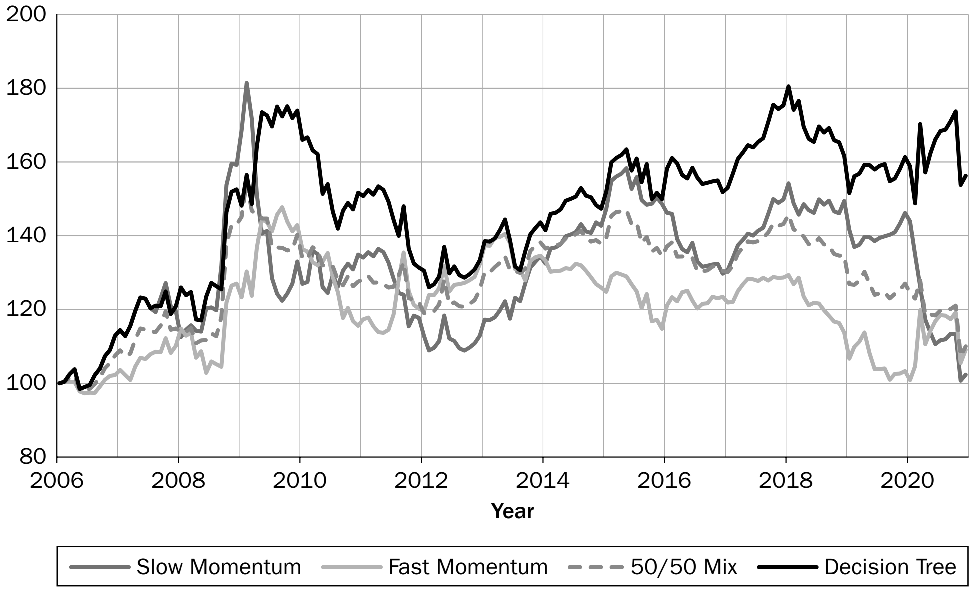


EXHIBIT 15

Performance Statistics of the Equally Weighted Equity Portfolio from January 2006 to December 2020

	Slow Momentum	Fast Momentum	50/50 Mix	Decision Tree
Annualized return	0.16%	0.58%	0.64%	3.04%
Annualized volatility	11.78%	11.31%	8.85%	11.67%
Sharpe ratio	0.01	0.05	0.07	0.26
Max drawdown	–44.5%	–31.8%	–30.7%	–28.0%
Hit rate	55.9%	52.0%	58.2%	58.1%

Sharpe ratio with the lowest maximum drawdown. Following the faster momentum signals during high-volatility regimes not only helps to catch meaningful and higher magnitude returns, it also helps to adapt faster to the market environment and, in consequence, reduce drawdowns.

Unlike the 50/50 mix strategy, which takes a zero position when slow and fast signals disagree, the decision tree–based strategy takes positions based on volatility regimes by actively choosing which signal, fast or slow, to follow. The enhanced strategy significantly improves the return and decreases the drawdown, taking risks similar to strategies based on slow or fast signals alone.

CONCLUSION

The disagreement between the uptrend or downtrend indications of the slow 12-month and the fast 1-month time-series momentum signals leaves the investor facing a dilemma in which signal to follow. The investor can run intermediate-speed strategies by blending slow and fast TSM strategies together. Indeed, such intermediate-speed strategies exhibit many advantages, including higher Sharpe ratios and less severe drawdowns. We instead resolve the dilemma by incorporating the information embedded in short-term volatility, also known as the fear gauge, to help us choose which signal to follow.

In this study, we leverage the simplicity and interpretability of a decision tree classifier to extract and understand the predictive properties of volatility for the signal speed problem faced by TSM investors. We document that when volatility is low, slow signals seem to be more effective in capturing the trend of the assets. However, in high-volatility regimes, investor behavior is catalyzed by fear and uncertainly, which forces investors to change their minds more frequently. Under these circumstances, a faster momentum signal is a better choice than a slower signal. Using a classic alpha and beta decomposition framework, we also identify the sources of outperformance as both market-timing and volatility-timing skills.

Finally, we apply the decision tree–based volatility-regime model to build a dynamic momentum strategy that varies its speed based on volatility regimes. We test this strategy in different equity markets and find consistent improvement compared to static strategies, delivering better out-of-sample risk-adjusted performance with less tail risk. However, decision tree classifiers can be unstable during certain periods; therefore, some judgment is necessary to preserve its interpretability and implementability.

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