Volatility Timing under Low-Volatility Strategy

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KEY FINDINGS

- The return profile of the volatility decile portfolio is time-varying. Its slope contains vital information on market condition—high-volatility portfolio outperforms low-volatility portfolio during good market condition, but underperforms during bad market condition. Since market regime and asset price behaviors are persistent, the slope parameter can be used to time volatility exposure.
- Holding the low-volatility portfolio benefits from the higher risk-adjusted return during general market condition. However, when the slope parameter is positive and statistically significant, it is optimal to hold the high-volatility portfolio for the subsequent period. This will ride on the higher return of high-volatility portfolio during strong growth periods. This leads to higher return and increased volatility, but both Sortini ratio and Information ratio exhibit statistically significant improvement.
- Stocks in the low-volatility portfolio are less correlated than stocks in the high-volatility portfolio. The outperformance of the volatility timing strategy formulated in this article can be attributed to holding a concentrated growth portfolio during good market conditions, and holding a diversified portfolio during bad market conditions, thus connecting the literature on low-volatility portfolio with studies on correlation structure and diversification.

ABSTRACT

The authors show that the slope of the volatility decile portfolio's return profile contains valuable information that can be used to time volatility under different market conditions in the United States. During good (bad) market conditions, the high- (low-) volatility portfolio produces the highest return. The authors proceed to devise a volatility timing strategy based on statistical tests on the slope of the volatility decile portfolio's return profile. Volatility timing is achieved by being aggressive during strong growth periods and conservative during market downturns. Superior performance is obtained, with an additional return of 4.1% observed in the volatility timing strategy, resulting in a fivefold improvement on accumulated wealth, along with statistically significant improvement in the Sortini ratio and the information ratio. The authors also demonstrate that stocks in the high-volatility portfolio are more strongly correlated compared to stocks in the low-volatility portfolio. Hence, the profitability of the volatility timing strategy can be attributed to successfully holding a diversified portfolio during bear markets and holding a concentrated growth portfolio during bull markets.

Low volatility has been established for some time as one of the winning factors in smart beta investing. Holding low-volatility stocks can provide superior risk-adjusted returns compared to holding high-volatility stocks, which is widely known to generate poor returns over time. The benefit of holding a low-volatility portfolio can be attributed to the compounding effect—a more stable return coupled with lower volatility enhances the long-term risk-adjusted performance in investment.

The fact that low-risk stocks have higher expected returns is an interesting anomaly in the field of finance. It is also a persistent anomaly—research has shown that US stocks with high volatility earned abnormally low returns over the 1963–2000 period. Blitz and van Vliet (2007) showed that this anomaly also extends to all equity markets in the world.

Most asset pricing models postulate a positive relationship between a stock portfolio's expected returns and volatility. If high-volatility stocks do indeed lead to higher returns over time, one would expect low-volatility stocks to generate lower returns over time. However, Black, Jensen, and Scholes (1972) and Haugen and Heins (1975) were among the first to show that high-volatility (or high-beta) stocks have lower returns than equilibrium suggests. On the contrary, low-volatility (or low-beta) stocks earn higher returns than conventionally expected. In short, the authors reported a strong negative relationship between return and volatility in both stock and bond markets. Since then, a long string of financial research has modeled stock return volatilities as being negatively correlated with stock returns (see, e.g., Cox and Ross 1976). A number of empirical analyses have also shown a significant negative relationship between expected returns and volatilities, lending support to claims that stock returns are negatively correlated with stock volatilities (see Li et al. 2005).

Our objective in this work is to analyze the performance of the low-volatility strategy under different market conditions in the United States and then augment its performance by volatility timing. Although a low-volatility portfolio generates higher risk-adjusted returns relative to a high-volatility portfolio when aggregated across multiple decades, we show that their relative performance varies depending on market conditions. Using a generic definition of *market condition*, our analysis confirms the intuition that during good market conditions, a high-volatility portfolio produces the highest return, whereas during bad market conditions, a low-volatility portfolio exhibits the least negative return.

Based on this insight, we proceed to devise an ex ante volatility timing strategy that switches between holding low- and high-volatility portfolios based on statistical tests on the return difference between these two portfolios. Superior performance is obtained, with a 4.1% increment observed in annualized return compared to the low-volatility portfolio, and the Sharpe ratio improved from 0.621 to 0.719. Notably, the Sortino ratio improved from 1.184 to 1.549, and the information ratio of the timing strategy is 0.107. Both figures are statistically significant at the 1% level. This is achieved via successful ex ante volatility timing—by being aggressive in holding a high-volatility portfolio during strong growth periods to ride the rising trend and being conservative in holding a low-volatility portfolio during market downturns to avert significant drawdown.

Correlation analysis is also performed to investigate the role of diversification in our strategy. We found that regardless of market conditions, stocks in the high-volatility portfolio are more strongly correlated compared with stocks in the low-volatility portfolio. In other words, the profitability of the volatility timing strategy can be attributed to successfully holding a diversified portfolio during bear markets and holding a concentrated growth portfolio during bull markets. This fits consistently within the framework and empirical studies of market correlation structure and its impact on diversification (see Chua, Kritzman, and Page 2009). Thus, our results connect two separate strands of research in the portfolio management space.

LOW-VOLATILITY STRATEGIES

Contrary to basic finance principles, high-beta and high-volatility stocks have long underperformed low-beta and low-volatility stocks in more than 40 years of US data (see Baker, Bradley, and Wurgler 2011). A number of portfolio strategies have been developed to exploit this negative relationship between volatility and return. These include the minimum variance portfolio, the low-volatility portfolio, the maximum diversification portfolio, the bet-against-beta (BAB) portfolio, and the volatility-managed portfolio.

The minimum variance portfolio by Clarke, de Silva, and Thorley (2006) uses the full covariance matrix, coupled with an optimization algorithm, to demonstrate that minimum variance portfolios of the 1,000 largest US stocks over the 1968–2005 period can achieve a volatility reduction of about 25% while delivering average returns comparable to or even higher than the market portfolio.

The low-volatility portfolio by Blitz and van Vliet (2007) and Baker and Haugen (2012) uses only the diagonal of the historical covariance matrix. They found that portfolios of stocks with the lowest historical volatility are associated with Sharpe ratio improvements and statistically significant improvement in alpha. Robustness tests clearly indicate the existence of a volatility effect: Low-volatility stocks exhibit significantly higher risk-adjusted returns than the market portfolio, whereas high-volatility stocks significantly underperform on a risk-adjusted basis.

The maximum diversification portfolio by Choueifaty and Coignard (2008) uses an objective function that maximizes the ratio of weighted-average asset volatilities to portfolio volatility. Like minimum variance, maximum diversification portfolios equalize each asset's marginal contributions, given a small change in the asset's weight. The authors showed that the resulting maximum diversification portfolios have higher Sharpe ratios than the market-capitalization-weighted indexes and exhibit both lower volatilities and higher returns in the long run.

In addition to using historical volatility, standard asset pricing models also use beta, which measures the asset's covariance with the market, along with its idiosyncratic volatility, to construct low-volatility strategies. With their BAB portfolio, Frazzini and Pedersen (2014) argued that because constrained investors bid up high-beta assets, high beta is consequently associated with low alpha. A BAB factor, which is long leveraged low-beta assets and short high-beta assets, produces significant positive risk-adjusted returns.

Clearly, ranking stocks on their historical volatility is related to ranking stocks on their historical capital asset pricing model (CAPM) betas. Ang et al. (2006) showed that, in addition to beta, stocks with low idiosyncratic volatility significantly outperform stocks with high idiosyncratic volatility. In a subsequent study, Ang et al. (2009) expanded their research, applied their method to a global market, and arrived at the same conclusion: Stocks with high idiosyncratic volatility—calculated as the variance of the residuals in a Fama–French regression—have bad performance, whereas stocks with low idiosyncratic volatility perform well.[1]

More recently, Moreira and Muir (2017) developed this strategy further in the form of volatility-managed portfolios. They constructed portfolios that scale monthly returns by the inverse of their previous month's realized variance, decreasing risk exposure when variance was high recently and vice versa. They called these portfolios *volatility-managed portfolios*.[2] They provided evidence that volatility-managed portfolios that take less risk when volatility is high produce large alphas, have increased Sharpe ratios, and produce large utility gains for mean–variance investors.

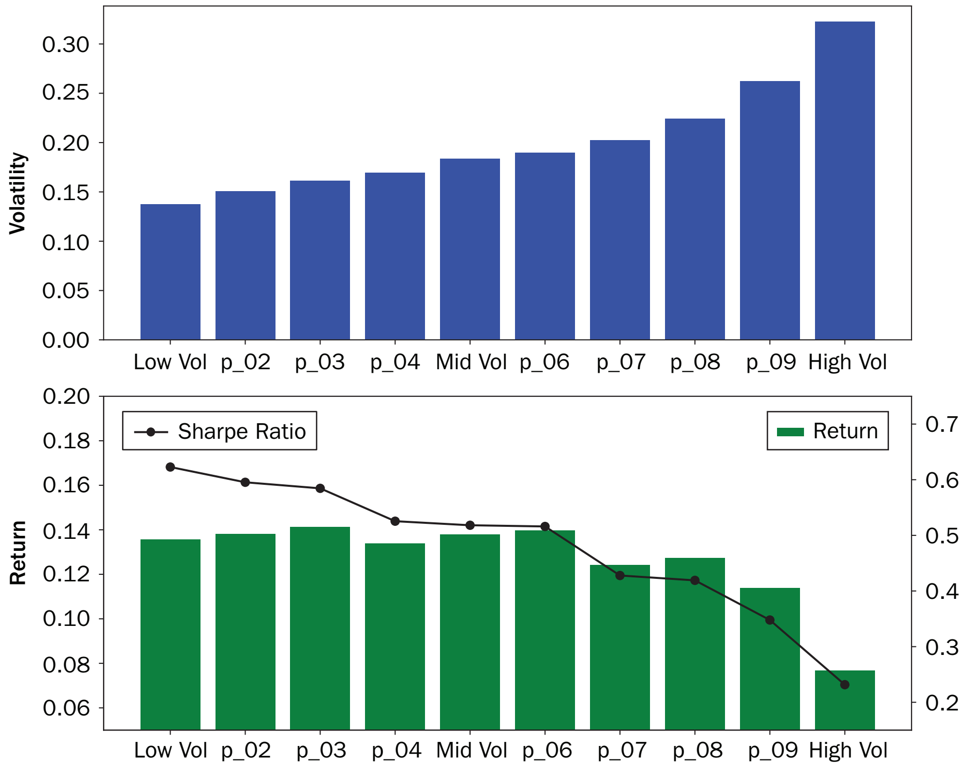
In this work, we begin by extending the low-volatility portfolio analysis to include the recent period of data. We focus on the US equity market; daily stock return

[1] Fu (2009) used an EGARCH model to estimate expected idiosyncratic volatility and sort stocks into decile portfolios. His results showed no evidence of a low-volatility anomaly. Quite the opposite, the high-volatility portfolio clearly outperformed the low-volatility portfolio.

[2] This is different from the risk parity approach, which ignores information about expected returns and covariances. Volatility-managed approaches only increase or decrease overall risk exposure based on total volatility.

EXHIBIT 1

Volatility and Return of Decile Volatility Portfolios



data are obtained from the Center for Research in Security Prices (CRSP). Our US equity data include all available common stocks on CRSP between January 1963 and December 2016. The Fama–French factor data are downloaded from Kenneth R. French's website. Other US firm-level data are obtained from COMPUSTAT.

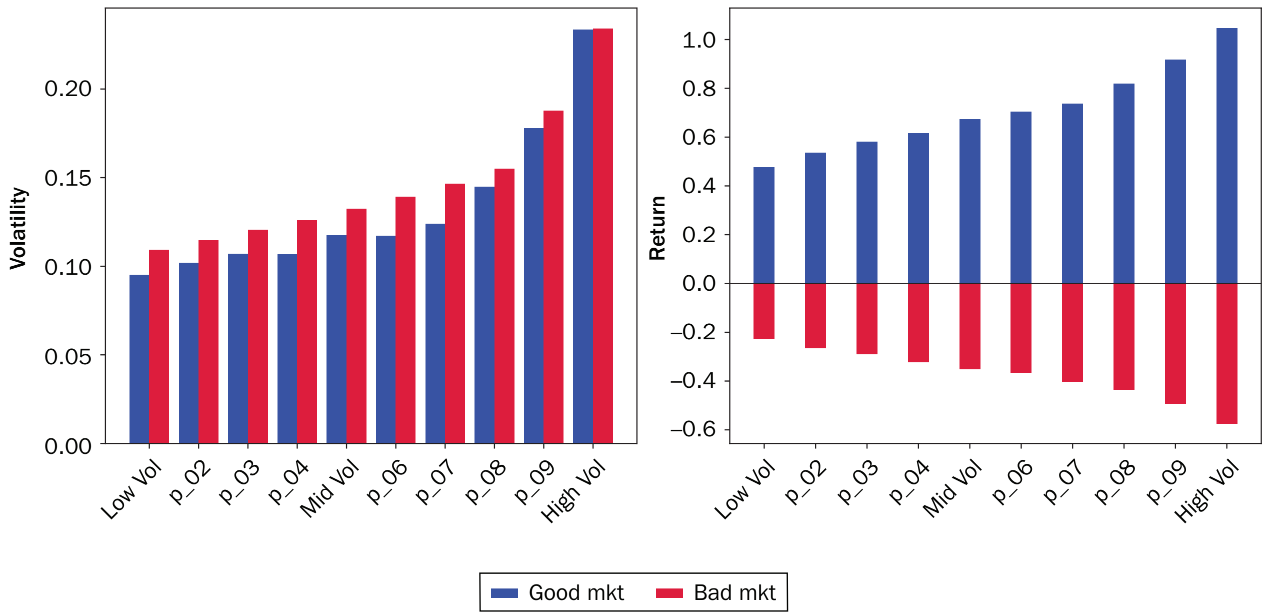
To construct a low-volatility portfolio, we first rank stocks by their market capitalization. The top 1,000 stocks with the greatest market capitalization are selected to form the volatility decile portfolios at each period. For each month, we calculate the realized volatility of each stock using daily returns from the past six months and use this information to group the stocks into decile portfolios. The ex post portfolio annualized returns and volatilities, along with Sharpe ratios, are presented in Exhibit 1. The ex post portfolio volatilities (upper panel) increased monotonically across the decile portfolios, whereas the variation in returns is more muted (lower panel), although the highest-volatility portfolio clearly exhibits the smallest return. This results in a clear downward sloping trend in the risk-adjusted returns, as measured by Sharpe ratios, among the decile portfolios. This is fully consistent with the existing literature, in which the high-volatility portfolio underperforms, whereas the low-volatility portfolio outperforms, in risk-adjusted returns.

RISK AND RETURN PROFILES UNDER DIFFERENT MARKET CONDITIONS

We proceed to explore whether the characteristic of the low-volatility anomaly differs under different market conditions in the United States. It is natural to expect that under periods of strong growth, high-volatility stocks will outperform the low-volatility stocks and vice versa. Following Bessembinder (2018), we use Treasury bills as a benchmark to measure stock market performance: If the overall stock market return

EXHIBIT 2

Volatility and Return Profile under Different Market Conditions



outperforms the T-bill return, we classify the period as a good market condition, whereas the opposite is true for a bad market condition. In our dataset, there are a total of 612 monthly observations, of which 360 (59%) months are good and 252 (41%) months are bad.

Exhibit 2 plots the volatilities (left panel) and return (right panel) of the volatility decile portfolio under good and bad market conditions. The portfolio volatilities under bad market conditions are higher than those under good market conditions, as one would expect. Nevertheless, under both good and bad market conditions, the volatility trend remains the same: increasing monotonically from the lowest to the highest volatility decile portfolios, differing only in their magnitude.

The same observation, however, cannot be made for the return trend under different market conditions. Clearly, all decile portfolios have better return performance under good market conditions compared to bad market conditions. However, under good market conditions, all portfolios experience positive returns, and the high-volatility portfolio has the highest return. Conversely, under bad market conditions, all portfolios experience negative returns, and the low-volatility portfolio performs best, with the smallest loss incurred. This results in opposite risk–return trends under different market conditions. Although it should not be surprising to see low-volatility stocks perform better during bad market regimes (and high-volatility stocks perform better during good market regimes), we note that if there is persistence in the market condition, this information can be used to time volatility exposure.

We define $S(t)$ as the decile portfolio returns' slope at time t, which measures the difference in return between the high- and low-volatility portfolios; that is,

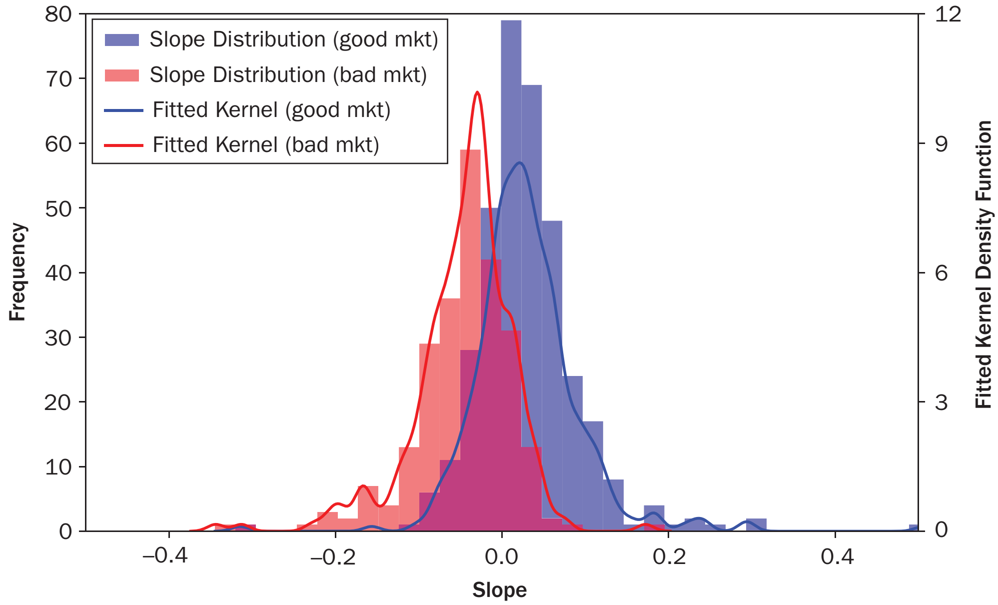
$$S(t) = r_{high-vol}(t) - r_{low-vol}(t)$$

where $r_{high\text{-}vol}$ and $r_{low\text{-}vol}$ are the returns of the high- and low-volatility portfolios for period t, respectively.

We first carry out a number of statistical analyses on the attributes of the slope parameters. We perform unit root tests, including both the augmented Dickey–Fuller test and the Phillips-Perron test, on the slope time series $S(t)$. Both tests consistently reject the unit root null hypothesis at less than the 1% significance level, suggesting

EXHIBIT 3

Slope Distribution of the Volatility Decile Portfolio's Return Profile



the time series is stationary. For robustness, we also perform the Kwiatkowski–Phillips–Schmidt–Shin stationarity test and obtain consistent results: The null hypothesis that the time series is stationary is accepted with a *p*-value of 94%.

Next, we move on to investigate the empirical distribution of the slope parameter *S*(*t*). Exhibit 3 plots the distribution of the slope parameter under good and bad market conditions. Both histograms and fitted kernel density estimates for the slope under the two market conditions are presented. The average slope is positive (negative) under good (bad) market conditions, with a mean of 3.03% under a good market condition and –4.54% under a bad market condition. The standard deviation of the two distributions is comparable at approximately 6%.

From the exhibit, it is clear that there is a certain degree of overlap in the slope distributions under the two market conditions in the center region. This implies that when the slope is not significantly different from 0, one cannot expect to use the slope parameter *S*(*t*) to determine the market condition. However, note that in the far right tail of the slope distribution under good market conditions, there is no overlap with the slope distribution under bad market conditions. The same observation applies to the far left tail of the slope distribution under bad market conditions. This suggests the possibility of using the slope parameter as a signal for volatility timing when its values deviate from 0 in a statistically significant manner. Our empirical analysis reveals that, conditional on the slope parameter being positive and statistically significant in a given period, there is a high empirical conditional probability that the slope parameter will remain positive for the following period as well. This should not be surprising—there is an extensive literature studying regime switches in the financial markets, and most transition probabilities in these studies indicated the presence of a certain level of persistence in the regime after a regime change. For instance, Ang and Timmermann (2012) pointed out that although the financial markets switch their regime abruptly, the changed behavior of asset prices generally persists for multiple periods after a switch. The goal of our work is not to apply regime-switching models to predict these sudden switches. Instead, we rely on a statistical test of the slope parameter to detect the regime in which significant high-volatility portfolio outperformance has occurred (i.e., when the slope parameter is positive and statistically significant) and use this as a signal to hold the high-volatility portfolio.

To summarize, given the established performance of low-volatility portfolios, our timing strategy aims to hold the low-volatility portfolio by default. When our statistical test indicates that the slope parameter is significantly positive for a given period, our timing strategy will then switch from holding the low-volatility portfolio to holding the high-volatility portfolio for the next period. The high-volatility portfolio will be held until its outperformance is no longer significant (i.e., when the slope parameter is no longer statistically significant). If there is persistence in asset price behavior subsequent to a regime change, as suggested by the literature, this strategy should be expected to generate excess return by benefiting from the higher return of the high-volatility portfolio during good market conditions and riding on the higher risk-adjusted performance of the low-volatility portfolio when there is no statistical evidence to indicate otherwise.

ADDING VOLATILITY TIMING TO THE LOW-VOLATILITY STRATEGY

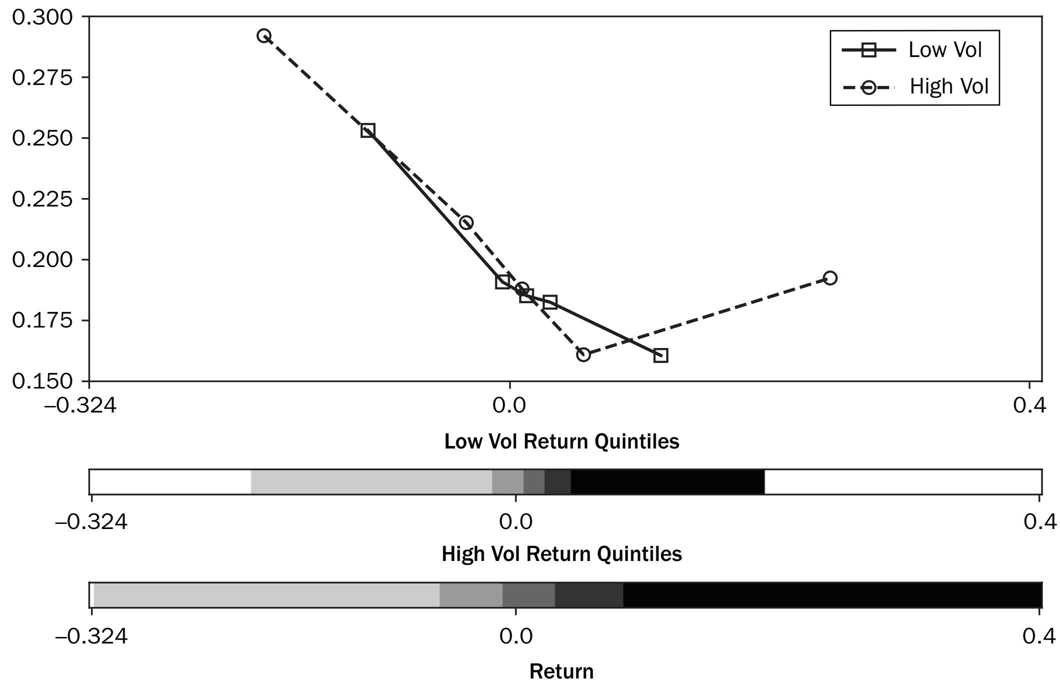
Blitz and van Vliet (2007) showed that the low-volatility portfolio exhibits a marginal improvement in return, accompanied by a sizable reduction in volatility. This results in a significant improvement in risk-adjusted returns. Holding a low-volatility portfolio not only reduces volatility exposure, it also allows exposure to other sources of return by tilting away from the market portfolio, leading to a higher degree of diversification. Nevertheless, in the context of portfolio optimization, diversification during a bull market is not necessarily a desirable characteristic. Investors prefer unification on the upside but diversification on the downside. However, Chua, Kritzman, and Page (2009) demonstrated empirically that observed correlations are higher during market downturns but lower when the market is good. In other words, diversification works well during good times (when it dampens returns) yet suffers a significant drop in efficiency during down markets (when it is desirable). Conventional approaches to portfolio construction generally ignore this correlation asymmetry, which might inadvertently cause static portfolios to be unnecessarily diversified when the market is experiencing strong growth and to be concentrated during market downturns.

If the main benefit of holding a low-volatility portfolio stems from diversification, but naively following it will subject investments to underperformance during good markets (see Chow, Hsu, and Li 2014), it would be beneficial to incorporate a timing strategy to improve the performance of low-volatility portfolios. Research by Fleming, Kirby, and Ostdiek (2001) on the benefit of market timing demonstrated that efficient timing strategies can potentially outperform static portfolios. In the context of our study, the purpose of adding a timing strategy is to allow one to optimally hold a portfolio in which assets returns are more diversified on the downside but more concentrated on the upside.

Our portfolio correlation analysis shows that the low- and high-volatility portfolios have the required correlation attributes that are suitable for the volatility timing strategy. Exhibit 4 illustrates the differences in portfolio correlation between the low- and high-volatility portfolios. The two horizontal bars at the bottom of the correlation plots illustrate the return quintile for the respective volatility portfolios. Different return quintiles are represented using different shades in the plots. Naturally, the range and size of the return quintile in the high-volatility portfolio are expected to be greater than those in the low-volatility portfolio.

EXHIBIT 4

Correlation of Low- and High-Volatility Portfolios



The portfolio correlation $\bar{\rho}$ is calculated using daily return data and is defined as

$$\bar{\rho} = \frac{2\sum_{i=1}^{N}\sum_{j>i}^{N} w_i w_j \rho_{ij}}{1-\sum_{i=1}^{N} w_i^2}$$

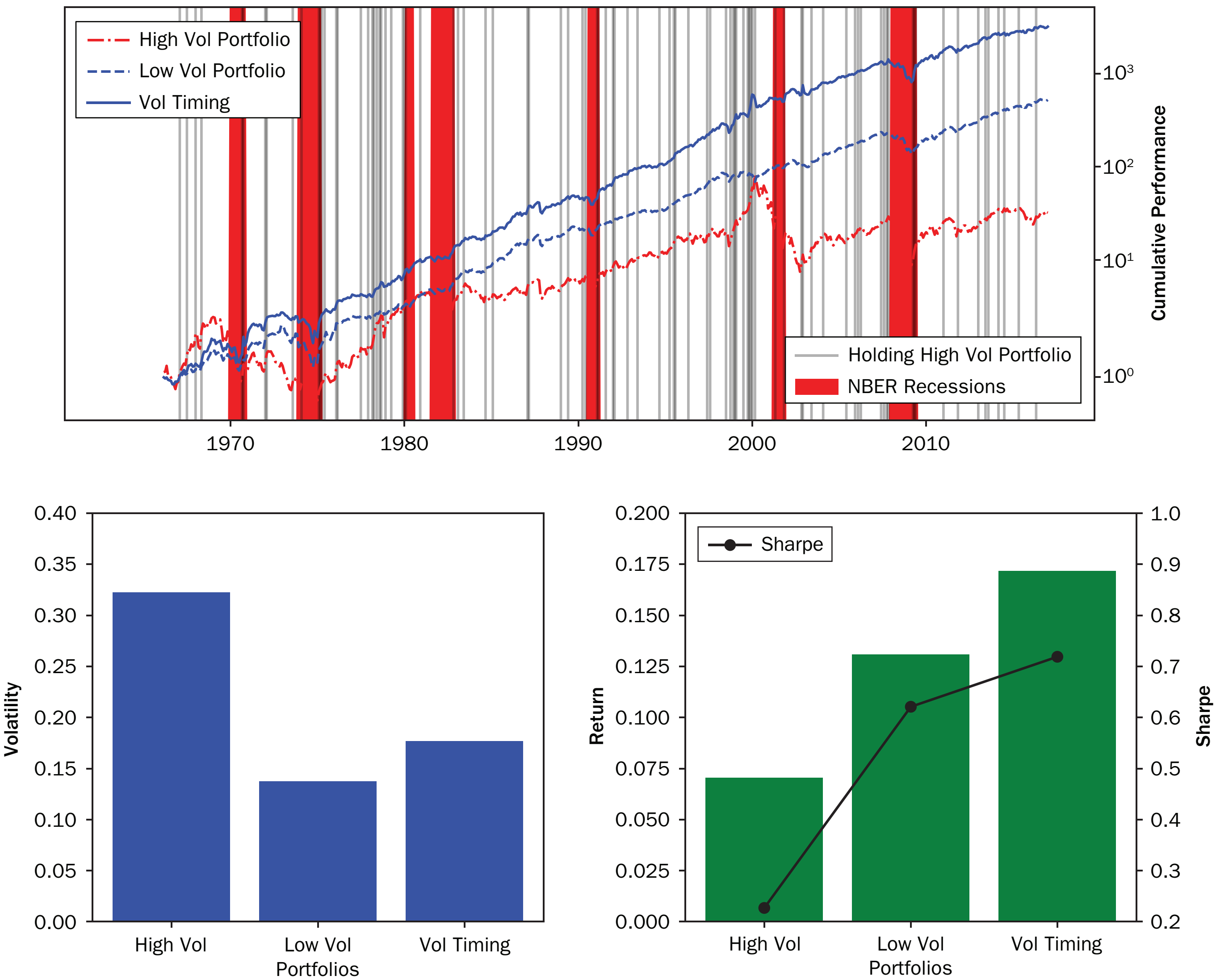
where ρ_{ij} is the pairwise correlation between stock i and j, and w_i and w_j are their allocations in the portfolio, respectively.[3] The portfolio correlation is calculated for each month and then aggregated according to the return quintile. In Exhibit 4, the correlation is higher (lower) in both volatility portfolios when returns are negative (positive). This is consistent with the correlation asymmetry characteristics reported in the literature. The portfolio correlation of the low-volatility portfolio decreases monotonically across the return quintiles and is lower than the portfolio correlation of the high-volatility portfolio, on average. On the other hand, the portfolio correlation of the high-volatility portfolio is lowest in the middle quintile and higher in both the first and last quintiles.

Here we formulate a volatility timing strategy that uses the ex ante slope parameter as a signal to switch between holding a low- or high-volatility portfolio. The main goal of our volatility timing strategy is to hold the high-volatility portfolio for the next period if and only if the slope parameter is significantly positive in the current period (i.e., the high-volatility portfolio significantly outperforms the low-volatility portfolio). The rest of the time, we will hold the low-volatility portfolio because it has higher risk-adjusted returns, on average. This strategy allows one to benefit from strong growth with the high-volatility portfolio during good market conditions and brace for

[3] We also use the alternative definition $\bar{\rho} = \frac{\sigma_P^2 - \sum_{i=1}^{N} w_i^2\sigma_i^2}{2\sum_{i=1}^{N}\sum_{j>i}^{N} w_i w_j \sigma_i \sigma_j}$ in our analysis and obtain consistent results.

EXHIBIT 5

Performance and Wealth Plots of the Volatility Timing Strategy



bad market conditions with the low-volatility portfolio via the diversification effects it offers.

Our volatility timing strategy performs a statistical test on the slope parameter every period. The null hypothesis is that the volatility decile portfolio's return profile is downward sloping because the aggregated return profile takes this shape (see Exhibit 1). Hence, the default is to hold the low-volatility portfolio. However, whenever the slope is found to be positive and statistically significant for a given period, we reject the null hypothesis, accept the alternative hypothesis, and hold the high-volatility portfolio for the next period. Given the empirical conditional probability of persistence in market conditions, this strategy can be expected to exhibit a statistical advantage in volatility timing.

We use *t*-statistics with a moving-window sample period size of $n = 12$ and a significance level of $\alpha = 0.2\%$ to carry out the hypothesis testing. A small α value is chosen deliberately because we are testing for outliers—unequivocally good market

EXHIBIT 6
Performance Measures of Volatility Timing Strategy

Panel A: Empirical Performance Measures of the Volatility Timing Strategy

	Correct Switches	Wrong Switches	Total Switches
Percentage	59.3%	40.7%	Low-/High-vol split: 85%/15%
Return Out Performance	+6.8%	–4.2%	

Panel B: Performance and Risk Measures of the Various Volatility Portfolios

	Low Volatility	High Volatility	Volatility Timing
Return	13.1%	7.0%	17.2%
Volatility	13.8%	32.2%	17.7%
Sharpe ratio	0.621	0.227	0.719
Max Drawdown	41.7%	90.9%	43.0%
SQRT (Semi variance)	7.6%	18.5%	8.5%
Sortino ratio	1.184	0.415	1.549
Information ratio	Benchmark	–0.012	0.107

conditions in which the overlap between the good and bad markets' slope distribution in Exhibit 3 is minimized.

Based on the formulation outline discussed earlier, the volatility timing strategy ends up holding the low- (high-) volatility portfolio 85% (15%) of the time. The wealth and portfolio statistics of the volatility timing strategy for the low- and high-volatility portfolios are presented in Exhibit 5. From the cumulative wealth plot, it is evident that the volatility timing strategy has a wealth process similar in characteristics to the low-volatility portfolio because the low-volatility portfolio was held for the majority of the time. Nevertheless, the volatility timing strategy is able to capture periods of strong market growth, resulting in a fivefold increment in terminal wealth. Compared to the low-volatility portfolio, the timing strategy, which holds the high-volatility portfolio at selected times, leads to an increase in the annualized return of the volatility timing strategy from 13.1% to 17.2% compared to the low-volatility portfolio (Panel C). This 4.1% increment in return is accompanied by an increase in risk from 13.8% to 17.7% (Panel B), resulting in a marginally improved Sharpe ratio from 0.621 to 0.719.

Note that the muted improvement in the Sharpe ratio with respect to the low-volatility portfolio benchmark is expected because our volatility timing strategy strives to improve return by selectively holding the high-volatility portfolio, leading to an increment in both return and volatility. In other words, the volatility timing strategy is able to improve the performance of the low-volatility portfolio because it rides on the higher risk-adjusted return of the low-volatility portfolio but occasionally switches to hold the high-volatility portfolio when it significantly outperforms, as measured by the slope parameter; thus, the portfolio benefits from the upside while avoiding bad market periods. Consequently, the main improvement of the volatility timing strategy will only become apparent through asymmetric measures of performance and risk, which is evident in the statistics presented in Exhibit 6.

Exhibit 6, Panel A presents the empirical measures of the volatility timing strategy. Using the statistical significance of the ex ante slope parameter as a signal to switch to hold the high-volatility portfolio, we define the signal as true (correct switch) if the slope parameter remains positive in the next period after exhibiting statistical significance. On the other hand, the signal is defined as false (wrong switch) if the slope parameter abruptly turns negative in the next period after exhibiting statistical significance.

Our volatility timing strategy obtains an accuracy of 59.3%. In other words, whenever the slope parameter is significantly positive, there is a 59.3% chance that the high-volatility portfolio will outperform in the subsequent period as well. Consequently, it is optimal to switch from holding the low-volatility portfolio to holding the high-volatility portfolio whenever the slope parameter is significantly positive. Moreover, the mean return outperformance of the high-volatility portfolio relative to the low-volatility portfolio is +6.8% on these occasions when the signal is true (which leads to correct switches), compared to an underperformance of −4.2% when the signal is false (which leads to wrong switches), which occurs 40.7% of the time. In aggregate, over the period studied, the low-volatility portfolio is held 85% of the time, whereas high-volatility portfolio is held 15% of the time.

Exhibit 6, Panel B provides several performance and risk measures for the low-volatility portfolio, the high-volatility portfolio, and our volatility timing strategy. It is well known that, in aggregate, a low-volatility portfolio outperforms a high-volatility portfolio by generating higher return with lower risk, leading to a better risk-adjusted performance. Note, however, that our volatility timing strategy further enhances the return of the low-volatility portfolio from 13.1% to 17.2%. This increment in return is statistically significant at the 1% level. However, because the volatility timing strategy involves holding the high-volatility portfolio for certain periods, the volatility of the timing strategy inadvertently increases from 13.8% to 17.7% compared to the low-volatility portfolio benchmark. This results in a Sharpe ratio improvement from 0.621 to 0.719—although the improvement has a *t*-value of 1.004 and is therefore not statistically significant. Nevertheless, as alluded to earlier, the main advantage of the volatility timing strategy becomes apparent when considering asymmetric measures of performance and risk. For example, the maximum drawdown (semivariance) of the volatility timing strategy remains highly comparable to that of the low-volatility portfolio at 43% (8.5%), as opposed to the high-volatility portfolio, which has more than double the risk. Furthermore, both the Sortino ratio and information ratio demonstrate sizeable improvement and are statistically significant at the 1% level. These improvements clearly indicate that, riding on the higher risk-adjusted return of the low-volatility portfolio, the volatility timing strategy can further enhance returns by having a statistical advantage in holding the high-volatility portfolio at the right time, thus benefiting from the higher returns during periods of strong growth.

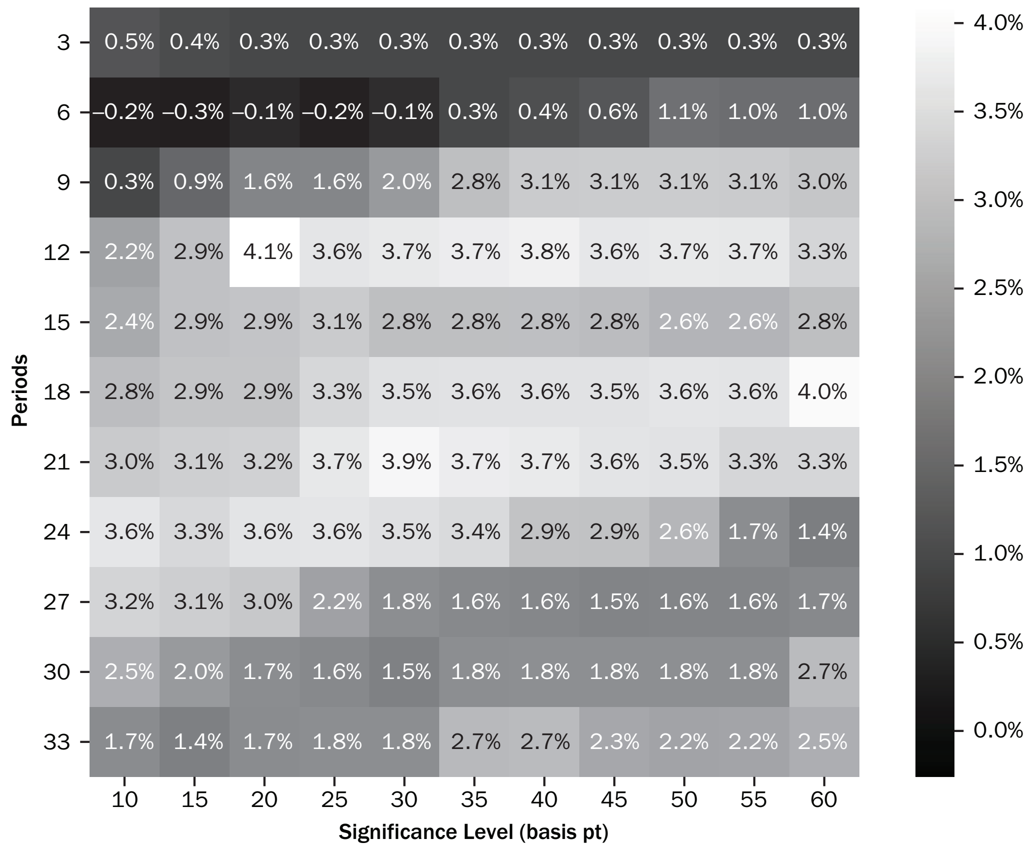
ROBUSTNESS TESTS AND FURTHER DISCUSSIONS

The outperformance of the volatility timing strategy is due to its ability to indicate, statistically, the right time to load up on risk. The statistical test (with $n = 12$ and $\alpha = 0.2\%$) on the slope parameter signaled correctly that the high-volatility portfolio outperforms the low-volatility portfolio 59.3% of the time, and the mean return outperformance from making the portfolio switch is +6.8%. A wrong switch is registered when the ex post return of the high-volatility portfolio is less than that of the low-volatility portfolio (i.e., the slope parameter becomes negative in the following period). In this case, the average underperformance due to a wrong switch is −4.2%. This suggests that the volatility timing strategy is robust against switching error because the outperformance from good switches (true signal) is economically more significant than the underperformance from bad switches (false signal).

To determine the robustness of the volatility timing strategy, in this section, we investigate the sensitivity of the return outperformance with respect to the number of periods (n) and significant level (α) used in the statistical test. The heatmap in Exhibit 7 measures the return sensitivity of the volatility timing strategy with respect

EXHIBIT 7

Outperformance of the Volatility Timing Strategy with Respect to n (periods) and α (significance level)



to the periods (n) and significance level (α). Our analysis shows that the volatility timing strategy is robust to the selection of these parameters.

In Exhibit 7, the performance of the strategy is calculated with different combinations of n and α values used in the slope parameter statistical test. Recall that in the results reported in the previous section, the low-volatility portfolio return is 13.1%, whereas the volatility timing strategy has a return of 17.2%. Note that for the majority of combinations (lighter shades), returns remain above those of the low-volatility portfolio benchmark of 13.1%, indicating the robustness of the volatility timing strategy. Only when the number of periods (n) used in the statistical test is too low (top rows) or when the significance level (α) is too high (right columns) does the return outperformance vanish. This is intuitive because using a small n or a high α will result in frequent switching to hold the high-volatility portfolio, which will inevitably erode outperformance by holding the high-volatility portfolio at the wrong time during a market downturn. This robustness extends to the other performance measures reported in the previous section—the improvement observed in maximum drawdown, semivariance, Sortini ratio, and information ratio remains intact and robust to choices of the statistical test parameters.

Finally, we also compute the CAPM and Fama–French regressions using monthly return data to examine the sources of return in the portfolios. Exhibit 8 reports the alphas, betas, and adjusted R2 of the CAPM and Fama–French regressions for the low- and high-volatility portfolios and the volatility-timed strategy. The Newey and West robust t-statistics are also provided in parentheses. The values of beta in the volatility-timed portfolio lie between the values for the low- and high-volatility

EXHIBIT 8
CAPM and Fama–French Alphas

	Panel A: CAPM			Panel B: Fama–French				
Portfolio	**α (%)**	**β_{mkt}**	**R^2**	**α (%)**	**β_{mkt}**	**β_{SMB}**	**β_{HML}**	**R^2**
Vol Timing	0.618**	0.900**	0.634	0.522**	0.881**	0.228**	0.163*	0.655
	(5.108)	(24.789)		(4.223)	(24.460)	(2.795)	(2.090)	
Low Vol	0.328**	0.785**	0.796	0.204**	0.840**	–0.027	0.290**	0.838
	(4.219)	(33.809)		(2.870)	(33.833)	(–0.479)	(5.782)	
High Vol	–0.244	1.747*	0.717	–0.195	1.471**	1.041**	–0.372**	0.850
	(–1.217)	(30.314)		(–1.292)	(28.813)	(13.955)	(–4.849)	

NOTE: ** and * indicate significance at the 1% and 5% levels, respectively.

portfolios, suggesting that the volatility-timed strategy has the attributes of both the low- and high-volatility portfolios. This is expected because we are switching between the low- and high-volatility portfolios. However, the CAPM and Fama–French alpha of the volatility-timed strategy in both regressions is greater than that of the low- and high-volatility portfolios, suggesting that the volatility-timed strategy has an additional factor of return—the correct timing of risk loading—that is not present in the static low- and high-volatility portfolios.

CONCLUSIONS

We add to the low-volatility literature by developing a volatility timing framework that can be used to enhance the performance of a low-volatility portfolio in the US market. We show that the risk–return profile of the volatility decile portfolio differs under different market conditions, and this information can be harvested for volatility timing. When the market condition is good, the high-volatility portfolio outperforms, whereas during bad market conditions, a low-volatility portfolio is optimal. Our volatility timing strategy monitors the slope of the return profile for signals to switch between holding low- and high-volatility portfolios, with the objective of timely exposure to risk during good market conditions and holding the low-volatility portfolio during bad market conditions.

Portfolio correlation analyses show that high-volatility portfolios are more correlated compared to low-volatility portfolios. Our results thus connect research on low-volatility strategies with studies done on portfolio correlation and diversification, highlighting a feasible way to improve portfolio risk–return performance.

Follow-up work should investigate the transaction costs of incorporating volatility timing into low-volatility strategies. van Vliet (2018) demonstrated that a turnover level of around 30% is enough to create an effective low-volatility strategy. An in-depth comparison of the profitability of the volatility timing strategy, along with other related strategies such as momentum, in the presence of transaction cost will be of interest to investors. Nevertheless, our analyses reported in this article already reveal important insights into the behavior of the volatility decile portfolio's return profile and its statistical properties, demonstrating the feasibility of volatility timing using this information.

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