Risk and Uncertainty in Style Rotation

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**Abstract**

This article examines the effectiveness of the VIX index as a leading indicator of style returns. The study also introduces the concept of ambiguity (uncertainty) as an indicator of returns to value, as measured by the CBOE “volatility of volatility” (VVIX) index. We analyze returns from highly liquid ETFs to demonstrate that strategies based solely on the VIX index experience positive returns to value only for holding periods greater than twenty days. However, when our proxy for ambiguity is included in the analysis, a short-term significant negative return to value from the VIX index is present that switches to a positive influence at the twenty day return horizon. We show that short-term uncertainty leads to positive short-term returns to value, but as this uncertainty is resolved in the marketplace, its effect becomes negative and volatility (risk) becomes the main driver of returns to value.

**1. Introduction**

The effectiveness of the VIX index as a leading indicator of style returns is examined by Copeland and Copeland (1999), who find that increases in the VIX Index lead to the outperformance of value-based portfolios relative to growth-based portfolios. Boscaljon et. al. (2011) find that these effects have diminished over time and are more recently only observable over longer return horizon periods. The theoretical underpinnings of both of these papers postulate that investors gravitate towards “value” in times of expected market turbulence (increased risk). This supposition is first proposed by Merton (1980) and French et. al. (1987), who suggest a positive relationship between the market risk premium and expected future volatility that is related to the asymmetric volatility phenomenon. Hence, lower beta value stocks perform better as stock prices fall in the face of expected increases in future volatility. The converse applies to higher beta growth stocks.

 Numerous studies have shown that forward-looking implied volatility measures such as the VIX index provide predictive evidence regarding future realized volatility. These studies examine the implied volatility of options as an indicator of investor expectations regarding future equity volatility. The results of early studies are somewhat mixed but most recent studies confirm a generally positive relationship between implied volatility and future realized volatility.[[2]](#endnote-1) Sarwar (2005) finds a positive relation between implied volatility and options trading volume in S&P 500 Index options. Ammann et. al. (2009) find a positive relation between implied volatility and future realized volatility in single stock options. Christoffersen et. al. (2013) find a similar relation for the stocks in the Dow Jones Industrials Average. DeMiguel et. al. (2013) find that implied volatility is a useful factor to consider in the selection of efficient mean-variance portfolios, since single stock implied volatility is useful in forecasts of both future volatility and returns of S&P 500 component stocks on a daily and intraday basis. Similarly, Giot (2005) finds a positive relationship between the VIX Index and future stock returns, confirming the results of Copeland and Copeland (1999) and Boscaljon et. al. (2011) that are partially supported by the results in this article. An et. al. (2014) finds a positive relation among in increases in call implied volatilities and future stock returns, and additional evidence on this topic is provided by Bali et. al. (2015), and Brous et. al. (2009).

The literature regarding the use of the volatility measures to enhance asset allocation decisions is well documented in Boscaljon et. al. (2011), so the discussion here is limited to a few papers that directly relate to our results. Goldwhite (2009) demonstrates that the VIX index is a useful indicator for investors with different levels of risk aversion as he examines the relationships among volatility and the returns to value and growth stocks. Below et. al. (2009) find that active rebalancing outperforms a passive approach to style investing, although they caution that the most optimal timeframes for rebalancing schemes require further study, consistent with our results. Puttonen and Seppä (2006) further document the value added by an active approach to investing in value and growth stock indexes. While the present study is related to this prior research, our main contribution to the literature is the introduction of the additional concept of “uncertainty” (also known as “ambiguity”) into the analysis. We use the recently developed CBOE VVIX Index (the “volatility of volatility” index) as a proxy for uncertainty, or “unknown unknowns.” As noted in a CBOE (2012) white paper, the VVIX measures the expected volatility of the 30-day forward price of the CBOE Volatility Index (the VIX), and further details on the VVIX index can be found there. We use this measure as a proxy for uncertainty about the future distribution of returns in the mean-variance framework.

This concept is commonly known in the literature as “Knightian Uncertainty” based on Knight (1921), since he suggests a distinction between risk (volatility that can be measured using probabilities) and “unmeasurable uncertainty.” Expected utility theory posits that risk and risk aversion are the only parameters that determine expected returns, but Ellsberg (1961) provides empirical examples where an agent’s decisions in ambiguous states provide support for Knightian uncertainty. Ellsberg’s paradox shows that decision-makers prefer gambles with known probabilities over those with ambiguous probabilities. There remain considerable differences of opinion regarding the theoretical and empirical evidence on the relation between returns and ambiguity. Baltussen et. al. (2014) explore this issue relative to single stocks using a proxy for uncertainty that is similar to the VVIX index (“vol of vol” in single stocks) to find a negative relation between uncertainty and future single stock returns. Brenner and Izhakian (2012) find similar results for the SPDR S&P 500 ETF using intraday data. Aboura and Arisoy (2015) provide some theory supporting the idea that uncertainty is a significant part of the equity risk premium and should thus be related to expected returns. They also conduct an empirical study of returns and the VVIX index that supports the supposition that uncertainty generates positive contemporaneous returns to value on a daily basis, which is similar to one of the results of this paper. Our study sheds some light on the topic since we find that the relation between ambiguity and returns for our sample of ETFs is dependent on the time horizon examined, and may explain some of the conflicting theoretical and empirical evidence. The distinction between volatility and uncertainty is illustrated in Figure 1. Although the two measures are positively correlated (correlation coefficient of 0.39) and generally move together, that is not always the case. As shown in the graph, ambiguity increased significantly in 2014 without a concurrent increase in volatility.

The additional contribution of the paper relates to the exponential growth and availability of high volume, easily traded exchange traded funds (ETFs) over the past decade. The availability of these products provides the opportunity to examine the relation of expected volatility and uncertainty to growth and value using similarly tradable instruments, as opposed to MSCI BARRA or S&P 500 value and growth portfolios that may be costly and or difficult to implement. Thus the use of ETF return time series’ allows for a more practical analysis of the data. Our initial results using the VIX index alone are consistent with Boscaljon et. al. (2011), finding insignificant short term effects that become positive returns to value at the twenty day return horizon.[[3]](#endnote-2) However, when we include the VVIX index in the analysis we find a short-term significant *negative* return to value from volatility (VIX) that switches to a positive influence at the same twenty day horizon. The VVIX index provides significant incremental information regarding the interaction of returns, volatility, and uncertainty since we find that short-term uncertainty (VVIX) leads to positive short-term returns to value. As this uncertainty is resolved in the marketplace over a period of about twenty days, however, its effect becomes negative while risk becomes the main driver of positive returns to value. Short term trading strategies of long-short ETF pairs based on extreme values of the VIX and VVIX indexes largely outperform strategies based on extreme values of the VIX index alone.

**2. Data sample and methodology**

The CBOE provides daily closing levels for the VVIX index beginning on June 1, 2006, so our sample data is collected from June 1, 2006 to December 31, 2014. All of the data is obtained from Bloomberg Professional® for the VIX index, the VVIX index, and six style-based ETFs that are listed in Table 1. As is evident in the table, each of these ETFs has been in existence for almost fifteen years, and they are all large, liquid instruments available to easily implement style-based trading strategies. They are also similar in terms of total net assets and trading volume (the average daily trading volume figures in the table are the most recent three-month average as of June 1, 2015). The one exception to this statement is IVW, the large-cap growth ETF that is quite a bit larger than the others.

Table 2 provides summary statistics for the data, where the figures for the volatility indices are closing daily levels and the ETF data are daily returns, hence the one observation difference in the sample size. Over our sample time period, each of the ETFs experiences similar returns, although standard deviations decline monotonically as market capitalization rises, as the larger capitalization stocks experience lower levels of volatility. A correlation matrix is provided in Table 3, and the first item of interest is the same positive relation between the VIX and VVIX that we observe in Figure 1, consistent with the results of Aboura and Arisoy (2015) . We also see the usual negative relation between the VIX index and contemporaneous returns, a result of the well-known asymmetric volatility phenomenon. Additionally, for all six of the ETFs, this negative relation is slightly larger for the VVIX, suggesting that it too may provide information regarding future payoffs to value and growth. Finally, with one exception, all of the correlations among ETF pairs are above 0.90, suggesting *ex ante* that it may be difficult to use volatility and or uncertainty information to forecast differential returns to style, as reported by Boscaljon et. al.(2011).

 Following their paper, our first approach to examine this data is to model several different future return windows as a function of changes in the VIX and VVIX indexes. Specifically, we estimate the following OLS equations:

where represents the relevant time period return (from *n* equals one to sixty days in discrete increments) for a long position in the value ETF *i* (e.g. IVE, the iShares S&P 500 Value ETF) and a short position in the growth ETF *j* (e.g. IVW, the iShares S&P 500 Growth ETF) for each of the three size-based ETF classifications. and represent daily changes in the levels of the VIX index and the VVIX index, respectively, on day 0. The first equation is similar to the specification of Copeland and Copeland (1999) for MSCI BARRA size and value indices, although they implement contemporaneous equations while ours are predictive as in Boscaljon et. al. (2011). The second equation adds daily changes in the VVIX index as a proxy for ambiguity to determine whether it possesses further explanatory power for future returns to value.

Since we find no significant relations among these indexes for the highly efficient and liquid ETFs in in our study, we also examine levels of these indices based on deviations from their seventy-five day moving averages, as suggested by the trading strategy results of Copeland and Copeland (1999) and Boscaljon et. al. (2011). Since both of these indexes are generally mean-reverting, these measures provide an indication of whether or not their levels are over- or under-“valued” relative to future returns to value. We estimate the following OLS equations:

In these specifications the percent deviations from the variables’ seventy-five day moving averages are represented by :

Based on the results of these equations, we follow Copeland and Copeland (1999) and Boscaljon et. al. (2011) to simulate trading strategies that capitalize on the results of these estimations by going long or short the appropriate value and growth ETFs based on the trading strategy suggested by these equations over various return horizons.

**3. Empirical Results**

The results of the estimation of Equation (1) that examine the returns to value from one-day changes in the VIX relative to the large-cap ETFs, in parallel to the earlier estimations of Copeland and Copeland (1999) and Boscaljon et. al. (2011), are presented in Panel A of Table 4. It is clear that the positive returns to value are no longer observable for these highly liquid and efficient liquid ETFs. None of the coefficients for returns to value from the VIX index are statistically significant, so it seems that the “returns to value” strategy presented in these previous papers are not profitable with these highly efficient ETFs.

Thus, in an attempt to further explore the returns to value from ambiguity, in Panel B we include the VVIX index as a potentially further explanatory independent variable in the estimations of Equation 2, where we find some indication of the potential returns to value from volatility in conjunction with ambiguity. The results for the five- to twenty-day returns to value are positive for changes in the VIX index (volatility) and negative for changes in the VVIX index (ambiguity). Thus over the very short term, investors are rewarded for investing in value stocks when volatility is high relative to its trailing moving average. However, the short-term returns to value from historical deviations in ambiguity, or uncertainty about the future return distribution, are negative, which is consistent with the recent empirical results of Brenner and Izhazian (2012) and Baltussen et. al. (2014). But these results are relatively weak since only six of eighteen coefficients are significant at the five or ten percent level, and do not provide strong impetus to examine trading strategies that may capitalize on these relationships. In unreported results, we also conduct the same analysis for the mid-cap and small-cap ETF pairs, with largely insignificant results. Although the direction of the coefficient signs are generally similar to the large-cap pair results in Table 4, only one of thirty-six coefficients is significant at the five percent level.

Given the inconclusive nature of these results, we undertake a potentially deeper and more sophisticated analysis of the data as we examine deviations from each variable’s seventy-five moving average (as suggested by the trading strategies of Copeland and Copeland (1999)) to determine whether or not investors may observe deviations from their mean-reverting levels to construct potentially profitable trading strategies. The results of the estimations of Equations (3) and (4) for large cap stocks are presented in Table 5. In Panel A, the results indicate that the initial results of Copeland and Copeland (1999) that are attenuated in Boscaljon et. al. (2011) for MSCI BARRA portfolios are still present for value and growth ETFs. They observe these effects for periods of thirty days and longer, while we report similar results for the ETFs over twenty day and greater forecast periods. There is still a positive return to value in high volatility environments over return horizons of twenty days or longer, although the results are insignificant over shorter time frames, consistent with their results. In addition, the explanatory power of these models increases with the time horizon, as measured by the VIX coefficient t-statistics and the monotonically increasing values of R-squared. For instance a one percent increase in the deviation in the VIX index from its moving average leads to a return of 1.19 percent over the next thirty days, but the same percentage increase in the VIX leads to a 3.45 percent increase over the following sixty days. Thus it seems the initial results of a positive return to value indicated by the VIX index originally documented in Copeland and Copeland (1999) and confirmed over longer time frames by Boscaljon et. al. (2011) is still present for the heavily traded ETFs that we examine.

However, the most important results of our study are contained in Panel B of Table 5. Here we find the initial results of Copeland and Copeland (1999) that are attenuated in Boscaljon et. al. (2011) for MSCI BARRA portfolios are still present for value and growth ETFs, . Further insight is provided when we include VVIX as an explanatory variable to proxy for ambiguity that enhances the results. The results are illuminating since over the very short-term (time horizons of 10 days or less), the returns to value from the VIX index are actually significantly *negative* while the returns to ambiguity are *positive* and statistically significant at the one percent level, with just one exception. Once again the coefficient values increase with the length of the return horizon, and the adjusted R-squared values are all greater for the specification that includes both independent variables such that the VVIX index provides additional explanatory power.

Over the longer term (greater than twenty days), this ambiguity is resolved in the marketplace and the returns to value from ambiguity become negative as in earlier studies (e.g. Brenner and Izhakian (2012) and Baltussen et. al. (2014)). Conversely, the returns to volatility become positive over longer time frames, confirming a positive relationship between risk and expected returns from value that is consistent with the finance literature. As with the VIX-only results, the absolute coefficient values increase with the time horizon for both VIX and VVIX such that the returns to value are significantly higher over longer time frames. Finally, it is notable that all of the coefficients for the VIX index are greater than their counterparts in Panel A that only includes the VIX index. Thus the return to value provided by increases in the VIX index increases in the presence of the VVIX, our proxy for ambiguity.

These results provide an indication that the time frame over which the relationship between the return to value and volatility is important, an issue not addressed by previous studies. In the short term, the asymmetric volatility phenomenon seems to dominate as recent volatility leads to negative returns to value, while higher levels of ambiguity are rewarded with higher future returns to value in the short term. Thus investors seem to be ambiguity-seeking in the short-term since short-term returns to value are positively related to this variable, consistent with Abdellaoui, et. al. (2005), and Shyti (2013). However, over longer time frames, the returns to ambiguity are negative, consistent the recent empirical evidence of Aboura and Arisoy (2015), Baltussen et. al. (2014), and Brenner and Izhazian (2012). Thus it seems that the theoretical research on this topic needs to be reconciled with the empirical evidence, and that the relations among returns, style, volatility, and uncertainty may require further examination over various time horizons in order to be understood properly.

Similar results obtain for both the mid-cap and small-cap ETF results that are detailed in Tables 6 and 7, although the values of the coefficients, the t-statistics, and the R-squared values are generally smaller than in Table 5. The results for the mid-cap ETFs are especially weak in Panel A of Table 6 since the positive return to value from the VIX index is only significant at the sixty day time horizon, and then only at the ten percent level. In Panel B, there are some similar results to those in Table 5 for the large cap ETFs, but the results are less consistent. The results for the small-cap ETFs in Table 7 indicate slightly stronger relationships in Panel A since the positive relation between the VIX and returns to value is significant for all horizons of ten days or greater. The results that include the VVIX index in Panel B are stronger than those for the mid-cap ETFs, but still not as consistent as those for the large-cap ETFs. It seems that the effects of volatility and ambiguity are most effectively impounded into future stock returns for large cap stocks during our sample period. However, the return to value results indicated by the VIX and VVIX indices are clearly still a present factor during the time period under study for all of these ETFs.

In order to examine the potential economic value of trading strategies based on these results, in Table 8 we present the results of mechanical trading strategies suggested by Table 5 for the most liquid, large-cap ETFs over five different return horizons from one to sixty days. Following Boscaljon et. al. (2011), we calculate the seventy-five day moving average of the VIX index and examine four “triggers” that generate trading signals based on deviations from this moving average. These triggers are set at levels from ten to forty percent above and below the moving average, and are evaluated over each of the respective time frames. As suggested by the results in Panel A of Table 5 for periods of ten days or less, a positive deviation indicates the purchase of the value ETF and short sale of the growth ETF, and vice versa. In Panel A of Table 8, we present the results of trading strategies based solely on changes in the VIX index that are similar to those of Boscaljon et. al. (2011), using only changes in the VIX index as a trading indicator. Consistent with their paper, the results are mixed, with most positive outcomes occurring only for the highest level of deviations from the 75-day moving average of the VIX index (+/- 0.4). These results demonstrate that trading strategies based only on the VIX index experience positive returns to value based on levels of the VIX index only for large deviations from historical averages. Additionally, over short time frames and for low deviations from the moving average, there is actually a positive return to growth that has not been previously reported. For example, the one day horizon ten- and twenty-percent deviations lead to negative cumulative returns to value (or positive returns to growth) of 19.84 and 15.14 percent, respectively.

However, in Panel B of Table 8, we present the results of strategies that utilize both the levels of VIX and VVIX to provide somewhat different trading strategy results. As suggested by Panel B of Table 5, for strategies over periods of ten days or less, a trading trigger is only generated when the VIX is both significantly divergent from its 75-day moving average (at the trigger points) and the VVIX is also above or below its 75-day moving average in the opposite direction, given the inverse relationship of the indexes to returns to value. As shown in the Panel B, the long/short cumulative returns to this strategy are almost uniformly positive over all forecast horizons, with a significant reduction in the number of round trip transactions and the number of days in the market. The only exception is the thirty day horizon for deviations at the ten percent level, where the results are inconclusive since two of four of the strategies generate negative returns, and the average of the trading strategies is negative. But for the sixty-day time frame, all of the strategies that include consideration of the VVIX index provide superior returns and involve a very small number of round trip trades during our sample period. On average, at the sixty day forecast horizon, the long/short strategies that use both VIX and VVIX information result in an outperformance of 6.55 percent for a much smaller number of round trip transactions.

Most importantly, the average differences between the strategies that utilize VVIX information in addition to the VIX index are significantly greater than those that do not for all but one of the time horizons. For instance, the average long/short cumulative return to all of the strategies is 19.96 percent greater for strategies that include both triggers than for those that include only the VIX index for the one day holding period. So while we cannot suggest a particular trading strategy that is likely to perform well in the future, it seems clear that the use of VVIX information increases the likelihood of trading success over all but one of the time frames and trigger points. And while many of these strategies involve portfolios that are fully invested for only a small portion of our full sample period of 2,161 days (with a concurrent reduction in market exposure), they may be useful to multi-strategy investors and or hedge funds that have discretion to deploy excess capital (potentially with leverage) to a variety of tactical asset allocation strategies.

**4. Conclusion**

 We conclude that there are still returns to value in the evaluation of the VIX index that appear in the analysis of deviations from historical moving averages. These returns are incrementally larger when considering information from the VVIX index that provides a proxy for uncertainty that is currently under examination in the finance literature. The inclusion of the VVIX index in the analysis of the VIX effect on returns to value for easily traded ETFs is informative since it is straightforward and cost-effective to implement style-based trading strategies with these securities. While the returns to value are positive relative to increased levels of the VIX index over longer time frames, they are negative over shorter time frames. Returns to value from ambiguity, however, demonstrate opposite effects as they lead to positive returns in the short-term (ambiguity-seeking) and negative returns over longer time frames (ambiguity aversion). These results are consistent with much of the current literature that finds somewhat conflicting results depending on the time horizon being examined. Thus the time horizon considered is important to understanding the dynamics of the volatility and ambiguity relationships among volatility indices and their effect on future stock returns. The results provide further impetus to proceed in the examination of the future relationships among returns, ambiguity, and volatility, as well as their application to potential trading strategies.

**Figure 1 The volatility index (VIX) and the volatility of volatility index (VVIX)**

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Table 1 Exchange Traded Fund (ETF) descriptions, as of June 1, 2015

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| ETF | Symbol | Net Assets ($) | Average Daily Trading Volume ($) | Inception Date |
| iShares S&P Small-Cap 600 Value ETF | IJS | 3.46B | 10.86M | 07/24/00 |
| iShares S&P Small-Cap 600 Growth ETF | IJT | 3.32B | 21.45M | 07/24/00 |
| iShares S&P Mid-Cap 400 Value ETF | IJJ | 4.33B | 9.64M | 07/24/00 |
| iShares S&P Mid-Cap 400 Growth ETF | IJK | 5.63B | 24.61M | 07/24/00 |
| iShares S&P 500 Value ETF | IVE | 8.34B | 59.68M | 05/22/00 |
| iShares S&P 500 Growth ETF | IVW | 13.00B | 92.68M | 05/22/00 |

Table 2 Sample summary statistics for volatility indices and ETFs, daily data from June 1, 2006 to December 31, 2014

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Variable | Symbol | n | Mean | Std. Dev. | Skewness | Kurtosis | Min | Max |
| Volatility Index | VIX |  2,162  | 21.24 | 10.27 | 2.17 | 9.02 | 9.89 | 80.86 |
| Vol of Vol Index | VVIX |  2,162  | 85.79 | 12.95 | 0.79 | 4.21 | 36.14 | 145.12 |
| Small Value | IJS |  2,161  | 0.0004 | 0.0173 | -0.16 | 7.81 | -0.12 | 0.09 |
| Small Growth | IJT |  2,161  | 0.0004 | 0.0156 | -0.22 | 7.50 | -0.10 | 0.09 |
| Mid Value | IJJ |  2,161  | 0.0004 | 0.0157 | -0.18 | 10.37 | -0.11 | 0.11 |
| Mid Growth | IJK |  2,161  | 0.0004 | 0.0150 | -0.36 | 8.61 | -0.10 | 0.09 |
| Large Value | IVE |  2,161  | 0.0002 | 0.0142 | -0.15 | 10.83 | -0.09 | 0.11 |
| Large Growth | IVW |  2,161  | 0.0004 | 0.0127 | -0.10 | 12.30 | -0.09 | 0.11 |

Table 3 Correlation matrix of variables under study

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Variable / Style | Symbol | VIX | VVIX | SM VL | SM GR | MD VL | MD GR | LG VL | LG GR |
| Volatility Index | VIX | 1.0000 |  |  |  |  |  |  |  |
| Vol of Vol Index | VVIX | 0.3894 | 1.0000 |  |  |  |  |  |  |
| Small Value | IJS | -0.1182 | -0.1539 | 1.0000 |  |  |  |  |  |
| Small Growth | IJT | -0.1265 | -0.1576 | 0.9767 | 1.0000 |  |  |  |  |
| Mid Value | IJJ | -0.1253 | -0.1594 | 0.9653 | 0.959 | 1.0000 |  |  |  |
| Mid Growth | IJK | -0.1273 | -0.1635 | 0.9399 | 0.964 | 0.9688 | 1.0000 |  |  |
| Large Value | IVE | -0.1323 | -0.1565 | 0.9229 | 0.9078 | 0.9508 | 0.9174 | 1.0000 |  |
| Large Growth | IVW | -0.1275 | -0.1562 | 0.8995 | 0.9177 | 0.9345 | 0.9423 | 0.9473 | 1.0000 |

Table 4 Forecast returns of the large-cap value minus growth ETFs based on day 0 VIX and VVIX changes

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Panel A: VIX only Return Forecast |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Forecast Days Ahead | 1 |   | 2 |   | 5 |   | 10 |   | 20 |   | 30 |   | 40 |   | 50 |   | 60 |   |
| VIX | 0.000 |  | 0.001 |  | 0.004 |  | 0.003 |  | 0.005 |  | -0.001 |  | 0.000 |  | 0.000 |  | 0.000 |  |
|  | (0.09) |   | (0.72) |   | (1.44) |  | (0.77) |   | (0.86) |   | (-0.14) |   | (-0.05) |   | (0.04) |   | (0.03) |   |
| Constant | 0.000 |  | 0.000 |  | -0.001 |  | -0.001 |  | -0.003 |  | -0.004 |  | -0.006 |  | -0.007 |  | -0.009 |  |
|  | (-1.36) |   | (-1.93) | \* | (-3.16) | \*\*\* | (-4.67) | \*\*\* | (-6.82) | \*\*\* | (-8.24) | \*\*\* | (-9.36) | \*\*\* | (-10.41) | \*\*\* | (-11.57) | \*\*\* |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Observations | 2,159 |  | 2,158 |  | 2,155 |  | 2,150 |  | 2,140 |  | 2,130 |  | 2,120 |  | 2,110 |  | 2,100 |  |
| R-squared | 0.00 |  | 0.00 |  | 0.00 |  | 0.00 |  | 0.00 |  | 0.00 |  | 0.00 |  | 0.00 |  | 0.00 |  |
| Adj. R-squared | 0.00 |   | 0.00 |   | 0.00 |   | 0.00 |   | 0.00 |   | 0.00 |   | 0.00 |   | 0.00 |   | 0.00 |   |
| t-statistics in parentheses, \*\*\* p<0.01, \*\* p<0.05, \* p<0.10 |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Panel B: VIX and VVIX Return Forecast |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Forecast Days Ahead | 1 |   | 2 |   | 5 |   | 10 |   | 20 |   | 30 |   | 40 |   | 50 |   | 60 |   |
| VIX | 0.001 |  | 0.004 |  | 0.009 |  | 0.010 |  | 0.013 |  | 0.009 |  | 0.008 |  | 0.003 |  | -0.003 |  |
|  | (0.47) |   | (1.37) |   | (2.17) | \*\* | (1.88) | \* | (1.75) | \* | (0.97) |   | (0.74) |   | (0.22) |   | (-0.20) |   |
| VVIX | -0.001 |  | -0.004 |  | -0.009 |  | -0.014 |  | -0.017 |  | -0.020 |  | -0.018 |  | -0.005 |  | 0.006 |  |
|  | (-0.61) |   | (-1.24) |   | (-1.65) | \* | (-1.97) | \*\* | (-1.66) | \* | (-1.62) |   | (-1.18) |   | (-0.28) |   | (0.34) |   |
| Constant | 0.000 |  | 0.000 |  | -0.001 |  | -0.001 |  | -0.003 |  | -0.004 |  | -0.006 |  | -0.007 |  | -0.009 |  |
|  | (-1.35) |   | (-1.92) | \* | (-3.15) | \*\*\* | (-4.65) | \*\*\* | (-6.81) | \*\*\* | (-8.24) | \*\*\* | (-9.35) | \*\*\* | (-10.4) | \*\*\* | (-11.57) | \*\*\* |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Observations | 2,159 |  | 2,158 |  | 2,155 |  | 2,150 |  | 2,140 |  | 2,130 |  | 2,120 |  | 2,110 |  | 2,100 |  |
| R-squared | 0.00 |  | 0.00 |  | 0.00 |  | 0.00 |  | 0.00 |  | 0.00 |  | 0.00 |  | 0.00 |  | 0.00 |  |
| Adj. R-squared | 0.00 |   | 0.00 |   | 0.00 |   | 0.00 |   | 0.00 |   | 0.00 |   | 0.00 |   | 0.00 |   | 0.00 |   |
| t-statistics in parentheses, \*\*\* p<0.01, \*\* p<0.05, \* p<0.10 |  |  |  |  |  |  |  |  |  |  |  |  |  |

Table 5 Forecast returns of the large-cap value minus growth ETFs based on levels of VIX and VVIX relative to their 75-day moving averages

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Panel A: VIX only Return Forecast |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Forecast Days Ahead (*n*) | 1 |   | 2 |   | 5 |   | 10 |   | 20 |   | 30 |   | 40 |   | 50 |   | 60 |   |
| VIX | -0.028 |  | -0.068 |  | -0.060 |  | 0.110 |  | 0.735 |  | 1.190 |  | 1.573 |  | 2.234 |  | 3.448 |  |
|  | (-0.65) |   | (-1.12) |   | (-0.64) |  | (0.86) |   | (4.14) | \*\*\* | (5.45) | \*\*\* | (6.13) | \*\*\* | (7.75) | \*\*\* | (11.07) | \*\*\* |
| Constant | 0.000 |  | 0.000 |  | -0.001 |  | -0.001 |  | -0.003 |  | -0.004 |  | -0.006 |  | -0.007 |  | -0.008 |  |
|  | (-1.37) |   | (-1.96) | \*\* | (-3.14) | \*\*\* | (-4.62) | \*\*\* | (-6.64) | \*\*\* | (-8.06) | \*\*\* | (-9.13) | \*\*\* | (-10.19) | \*\*\* | (-11.51) | \*\*\* |
| Observations | 2,161 |  | 2,160 |  | 2,157 |  | 2,152 |  | 2,142 |  | 2,132 |  | 2,122 |  | 2,112 |  | 2,102 |  |
| R-squared | 0.000 |  | 0.000 |  | 0.000 |  | 0.000 |  | 0.010 |  | 0.010 |  | 0.020 |  | 0.030 |  | 0.060 |  |
| Adj. R-squared | 0.000 |   | 0.000 |   | 0.000 |   | 0.000 |   | 0.010 |   | 0.010 |   | 0.020 |   | 0.030 |   | 0.050 |   |
| t-statistics in parentheses, \*\*\* p<0.01, \*\* p<0.05, \* p<0.10 |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Panel B: VIX and VVIX Return Forecast |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Forecast Days Ahead (*n*) | 1 |   | 2 |   | 5 |   | 10 |   | 20 |   | 30 |   | 40 |   | 50 |   | 60 |   |
| VIX | -0.120 |  | -0.244 |  | -0.409 |  | -0.345 |  | 0.644 |  | 1.801 |  | 2.946 |  | 4.133 |  | 5.491 |  |
|  | (-2.09) | \*\* | (-3.00) | \*\*\* | (-3.26) | \*\*\* | (-2.02) | \*\* | (2.70) | \*\*\* | (6.16) | \*\*\* | (8.64) | \*\*\* | (10.84) | \*\*\* | (13.51) | \*\*\* |
| VVIX | 0.244 |  | 0.467 |  | 0.927 |  | 1.210 |  | 0.242 |  | -1.640 |  | -3.691 |  | -5.120 |  | -5.611 |  |
|  | (2.40) | \*\* | (3.24) | \*\*\* | (4.17) | \*\*\* | (3.99) | \*\*\* | (0.57) |   | (-3.13) | \*\*\* | (-6.05) | \*\*\* | (-7.49) | \*\*\* | (-7.67) | \*\*\* |
| Constant | 0.000 |  | 0.000 |  | -0.001 |  | -0.001 |  | -0.003 |  | -0.004 |  | -0.006 |  | -0.007 |  | -0.008 |  |
|  | (-1.36) |   | (-1.95) | \* | (-3.14) | \*\*\* | (-4.63) | \*\*\* | (-6.64) | \*\*\* | (-8.07) | \*\*\* | (-9.22) | \*\*\* | (-10.3) | \*\*\* | (-11.60) | \*\*\* |
| Observations | 2,161 |  | 2,160 |  | 2,157 |  | 2,152 |  | 2,142 |  | 2,132 |  | 2,122 |  | 2,112 |  | 2,102 |  |
| R-squared | 0.000 |  | 0.010 |  | 0.010 |  | 0.010 |  | 0.010 |  | 0.020 |  | 0.030 |  | 0.050 |  | 0.080 |  |
| Adj. R-squared | 0.000 |   | 0.000 |   | 0.010 |   | 0.010 |   | 0.010 |   | 0.020 |   | 0.030 |   | 0.050 |   | 0.080 |   |
| t-statistics in parentheses, \*\*\* p<0.01, \*\* p<0.05, \* p<0.10 |  |  |  |  |  |  |  |  |  |  |  |  |  |

Table 6 Forecast returns of the mid-cap value vs. growth ETFs based on levels of VIX and VVIX relative to their 75-day moving averages

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Panel A: VIX only Return Forecast |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Forecast Days Ahead (*n*) | 1 |   | 2 |   | 5 |   | 10 |   | 20 |   | 30 |   | 40 |   | 50 |   | 60 |   |
| VIX | 0.020 |  | 0.038 |  | 0.022 |  | -0.025 |  | -0.013 |  | -0.069 |  | -0.267 |  | -0.090 |  | 0.439 |  |
|  | (0.57) |   | (0.81) |   | (0.32) |  | (-0.26) |   | (-0.10) |   | (-0.42) |   | (-1.39) |   | (-0.42) |   | (1.84) | \* |
| Constant | 0.000 |  | 0.000 |  | 0.000 |  | -0.001 |  | -0.002 |  | -0.003 |  | -0.004 |  | -0.005 |  | -0.006 |  |
|  | (-0.96) |   | (-1.59) |   | (-2.90) | \*\*\* | (-4.34) | \*\*\* | (-6.01) | \*\*\* | (-7.49) | \*\*\* | (-8.75) | \*\*\* | (-9.97) | \*\*\* | (-11.13) | \*\*\* |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Observations | 2,161 |  | 2,160 |  | 2,157 |  | 2,152 |  | 2,142 |  | 2,132 |  | 2,122 |  | 2,112 |  | 2,102 |  |
| R-squared | 0.000 |  | 0.000 |  | 0.000 |  | 0.000 |  | 0.000 |  | 0.000 |  | 0.000 |  | 0.000 |  | 0.000 |  |
| Adj. R-squared | 0.000 |   | 0.000 |   | 0.000 |   | 0.000 |   | 0.000 |   | 0.000 |   | 0.000 |   | 0.000 |   | 0.000 |   |
| t-statistics in parentheses, \*\*\* p<0.01, \*\* p<0.05, \* p<0.10 |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Panel B: VIX and VVIX Return Forecast |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Forecast Days Ahead (*n*) | 1 |   | 2 |   | 5 |   | 10 |   | 20 |   | 30 |   | 40 |   | 50 |   | 60 |   |
| VIX | -0.019 |  | -0.042 |  | -0.146 |  | -0.264 |  | -0.193 |  | -0.079 |  | 0.119 |  | 0.570 |  | 1.379 |  |
|  | (-0.39) |   | (-0.67) |   | (-1.60) |   | (-2.11) | \*\* | (-1.08) |   | (-0.36) |   | (0.46) |   | (1.99) | \*\* | (4.37) | \*\*\* |
| VVIX | 0.104 |  | 0.213 |  | 0.446 |  | 0.638 |  | 0.482 |  | 0.025 |  | -1.036 |  | -1.778 |  | -2.580 |  |
|  | (1.22) |   | (1.90) | \* | (2.75) | \*\*\* | (2.86) | \*\*\* | (1.51) |   | (0.06) |   | (-2.26) | \*\* | (-3.45) | \*\*\* | (-4.55) | \*\*\* |
| Constant | 0.000 |  | 0.000 |  | 0.000 |  | -0.001 |  | -0.002 |  | -0.003 |  | -0.004 |  | -0.005 |  | -0.006 |  |
|  | (-0.96) |   | (-1.58) |   | (-2.90) | \*\*\* | (-4.34) | \*\*\* | (-6.01) | \*\*\* | (-7.49) | \*\*\* | (-8.76) | \*\*\* | (-9.99) | \*\*\* | (-11.14) | \*\*\* |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Observations | 2,161 |  | 2,160 |  | 2,157 |  | 2,152 |  | 2,142 |  | 2,132 |  | 2,122 |  | 2,112 |  | 2,102 |  |
| R-squared | 0.000 |  | 0.000 |  | 0.000 |  | 0.000 |  | 0.000 |  | 0.000 |  | 0.000 |  | 0.010 |  | 0.010 |  |
| Adj. R-squared | 0.000 |   | 0.000 |   | 0.000 |   | 0.000 |   | 0.000 |   | 0.000 |   | 0.000 |   | 0.000 |   | 0.010 |   |
| t-statistics in parentheses, \*\*\* p<0.01, \*\* p<0.05, \* p<0.10 |  |  |  |  |  |  |  |  |  |  |  |  |  |

Table 7 Forecast returns of the small-cap value vs. growth ETFs based on levels of VIX and VVIX relative to their 75-day moving averages

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Panel A: VIX only Return Forecast |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Forecast Days Ahead (*n*) | 1 |   | 2 |   | 5 |   | 10 |   | 20 |   | 30 |   | 40 |   | 50 |   | 60 |   |
| VIX | 0.035 |  | 0.062 |  | 0.104 |  | 0.236 |  | 0.431 |  | 0.630 |  | 0.646 |  | 0.604 |  | 0.817 |  |
|  | (0.95) |   | (1.34) |   | (1.54) |  | (2.58) | \*\*\* | (3.29) | \*\*\* | (3.89) | \*\*\* | (3.37) | \*\*\* | (2.79) | \*\*\* | (3.41) | \*\*\* |
| Constant | 0.000 |  | 0.000 |  | 0.000 |  | -0.001 |  | -0.001 |  | -0.002 |  | -0.003 |  | -0.003 |  | -0.004 |  |
|  | (-0.50) |   | (-0.96) |   | (-1.82) | \* | (-2.83) | \*\*\* | (-4.01) | \*\*\* | (-5.01) | \*\*\* | (-5.87) | \*\*\* | (-6.86) | \*\*\* | (-8.00) | \*\*\* |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Observations | 2,161 |  | 2,160 |  | 2,157 |  | 2,152 |  | 2,142 |  | 2,132 |  | 2,122 |  | 2,112 |  | 2,102 |  |
| R-squared | 0.000 |  | 0.000 |  | 0.000 |  | 0.000 |  | 0.010 |  | 0.010 |  | 0.010 |  | 0.000 |  | 0.010 |  |
| Adj. R-squared | 0.000 |   | 0.000 |   | 0.000 |   | 0.000 |   | 0.000 |   | 0.010 |   | 0.000 |   | 0.000 |   | 0.010 |   |
| t-statistics in parentheses, \*\*\* p<0.01, \*\* p<0.05, \* p<0.10 |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Panel B: VIX and VVIX Return Forecast |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Forecast Days Ahead (*n*) | 1 |   | 2 |   | 5 |   | 10 |   | 20 |   | 30 |   | 40 |   | 50 |   | 60 |   |
| VIX | -0.052 |  | -0.088 |  | -0.196 |  | -0.196 |  | 0.059 |  | 0.405 |  | 0.753 |  | 1.013 |  | 1.557 |  |
|  | (-1.06) |   | (-1.41) |   | (-2.16) | \*\* | (-1.60) |   | (0.34) |   | (1.87) | \* | (2.93) | \*\*\* | (3.50) | \*\*\* | (4.92) | \*\*\* |
| VVIX | 0.228 |  | 0.398 |  | 0.795 |  | 1.149 |  | 0.997 |  | 0.605 |  | -0.285 |  | -1.102 |  | -2.032 |  |
|  | (2.64) | \*\*\* | (3.60) | \*\*\* | (4.96) | \*\*\* | (5.30) | \*\*\* | (3.18) | \*\*\* | (1.56) |   | (-0.62) |   | (-2.12) | \*\* | (-3.57) | \*\*\* |
| Constant | 0.000 |  | 0.000 |  | 0.000 |  | -0.001 |  | -0.001 |  | -0.002 |  | -0.003 |  | -0.003 |  | -0.004 |  |
|  | (-0.49) |   | (-0.95) |   | (-1.81) | \* | (-2.84) | \*\*\* | (-4.04) | \*\*\* | (-5.02) | \*\*\* | (-5.87) | \*\*\* | (-6.86) | \*\*\* | (-7.99) | \*\*\* |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Observations | 2,161 |  | 2,160 |  | 2,157 |  | 2,152 |  | 2,142 |  | 2,132 |  | 2,122 |  | 2,112 |  | 2,102 |  |
| R-squared | 0.000 |  | 0.010 |  | 0.010 |  | 0.020 |  | 0.010 |  | 0.010 |  | 0.010 |  | 0.010 |  | 0.010 |  |
| Adj. R-squared | 0.000 |   | 0.010 |   | 0.010 |   | 0.020 |   | 0.010 |   | 0.010 |   | 0.000 |   | 0.000 |   | 0.010 |   |
| t-statistics in parentheses, \*\*\* p<0.01, \*\* p<0.05, \* p<0.10 |  |  |  |  |  |  |  |  |  |  |  |  |  |

Table 8 Trading Strategies based on the returns to value based on deviations from their 75-day moving averages of the VIX, and VVIX indexes for large-cap ETFs.

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Panel A: Large Caps VIX |  |  |  |  |  |  |  |  | Panel B: Large Caps with VVIX |  |  |  |  |  |  |  |  |
| Holding Period | Deviation of VIX from 75 day M.A. | Long/Short Cumulative Return | Daily Average Return (bps) | Daily Std. Dev. (bps) | "Sharpe Ratio" | Number of Days | Number of Round Trips | Avg. Days in Market |  | Holding Period | Deviation of VIX and VVIX from 75 day M.A. | Long/Short Cumulative Return | Daily Average Return (bps) | Daily Std. Dev. (bps) | "Sharpe Ratio" | Number of Days | Number of Round Trips | Avg. Days in Market | Difference | Average Difference |
| 1 |  +/- 0.1 | -19.84% | -1.82 | 1.12 | -1.63 | 1217 | 707 | 1.72 |  | 1 |  +/- 0.1 | 24.69% | 6.94 | 20.60 | 0.34 | 318 | 223 | 1.43 | 44.53% |  |
| 1 |  +/- 0.2 | -15.14% | -3.25 | 1.29 | -2.55 | 500 | 318 | 1.57 |  | 1 |  +/- 0.2 | 15.25% | 12.35 | 15.22 | 0.81 | 115 | 84 | 1.37 | 30.39% |  |
| 1 |  +/- 0.3 | -0.68% | -0.03 | 1.50 | -0.02 | 236 | 151 | 1.56 |  | 1 |  +/- 0.3 | 5.78% | 28.14 | 9.18 | 3.07 | 20 | 18 | 1.11 | 6.46% |  |
| 1 |  +/- 0.4 | 4.13% | 3.00 | 1.67 | 1.80 | 138 | 97 | 1.42 |  | 1 |  +/- 0.4 | 2.60% | 64.40 | 4.27 | 15.07 | 4 | 4 | 1.00 | -1.53% | 19.96% |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 5 |  +/- 0.1 | 16.19% | 1.15 | 1.10 | 1.03 | 1310 | 167 | 7.84 |  | 5 |  +/- 0.1 | 8.05% | 1.68 | 10.80 | 0.02 | 460 | 92 | 5.00 | -8.14% |  |
| 5 |  +/- 0.2 | -11.90% | -2.04 | 1.15 | -1.77 | 620 | 92 | 6.74 |  | 5 |  +/- 0.2 | 13.50% | 6.67 | 9.31 | 0.12 | 190 | 38 | 5.00 | 25.40% |  |
| 5 |  +/- 0.3 | 1.59% | 3.43 | 3.83 | 0.90 | 300 | 46 | 6.52 |  | 5 |  +/- 0.3 | 1.66% | 3.00 | 7.29 | 0.41 | 55 | 11 | 5.00 | 0.07% |  |
| 5 |  +/- 0.4 | 6.85% | 6.91 | 2.06 | 3.36 | 175 | 24 | 7.29 |  | 5 |  +/- 0.4 | 0.97% | 6.44 | 3.10 | 2.08 | 15 | 3 | 5.00 | -5.88% | 2.86% |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 10 |  +/- 0.1 | -5.32% | 0.34 | 0.98 | -0.35 | 1590 | 158 | 10.06 |  | 10 |  +/- 0.1 | 8.71% | 1.25 | 0.82 | 1.52 | 670 | 67 | 10.00 | 14.03% |  |
| 10 |  +/- 0.2 | -4.11% | -0.34 | 0.98 | -0.35 | 820 | 81 | 10.12 |  | 10 |  +/- 0.2 | 21.28% | 6.43 | 0.13 | 4.89 | 300 | 30 | 10.00 | 25.39% |  |
| 10 |  +/- 0.3 | 3.90% | 0.91 | 0.11 | 0.85 | 420 | 42 | 10.00 |  | 10 |  +/- 0.3 | 7.76% | 8.28 | 1.47 | 5.62 | 90 | 9 | 10.00 | 3.86% |  |
| 10 |  +/- 0.4 | 10.32% | 4.46 | 0.73 | 6.12 | 220 | 22 | 10.00 |  | 10 |  +/- 0.4 | 0.76% | 3.80 | 0.98 | 3.87 | 20 | 2 | 10.00 | -9.56% | 8.43% |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 30 |  +/- 0.1 | 3.90% | 0.21 | 1.05 | 0.19 | 1860 | 61 | 30.49 |  | 30 |  +/- 0.1 | -5.43% | -0.53 | 0.84 | -0.63 | 1050 | 35 | 30.00 | -9.33% |  |
| 30 |  +/- 0.2 | -1.00% | -0.07 | 1.03 | -0.07 | 1380 | 45 | 30.67 |  | 30 |  +/- 0.2 | 0.07% | -0.01 | 1.02 | 0.01 | 600 | 20 | 30.00 | 1.07% |  |
| 30 |  +/- 0.3 | -2.81% | -0.38 | 1.27 | -0.30 | 750 | 25 | 30.00 |  | 30 |  +/- 0.3 | 3.21% | 1.17 | 1.25 | 0.93 | 270 | 9 | 30.00 | 6.02% |  |
| 30 |  +/- 0.4 | 11.05% | 2.69 | 0.70 | 3.95 | 390 | 13 | 30.00 |  | 30 |  +/- 0.4 | 1.38% | 1.15 | 0.30 | 4.48 | 120 | 4 | 30.00 | -9.67% | -2.98% |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 60 |  +/- 0.1 | 3.95% | 2.00 | 8.70 | 0.22 | 1980 | 32 | 61.88 |  | 60 |  +/- 0.1 | 17.57% | 1.08 | 1.17 | 0.93 | 1500 | 25 | 60.00 | 13.62% |  |
| 60 |  +/- 0.2 | 0.08% | 0.00 | 0.72 | 0.01 | 1620 | 26 | 62.31 |  | 60 |  +/- 0.2 | 3.33% | 0.42 | 0.57 | 0.74 | 780 | 13 | 60.00 | 3.25% |  |
| 60 |  +/- 0.3 | -5.70% | -5.80 | 9.80 | -0.59 | 1020 | 17 | 60.00 |  | 60 |  +/- 0.3 | 0.77% | 0.21 | 0.67 | 0.32 | 360 | 6 | 60.00 | 6.47% |  |
| 60 |  +/- 0.4 | 7.35% | 1.19 | 0.40 | 3.05 | 597 | 9 | 66.33 |  | 60 |  +/- 0.4 | 10.19% | 8.09 | 2.20 | 3.63 | 120 | 2 | 60.00 | 2.84% | 6.55% |

**Notes**

1. \* Corresponding author. Tel +1 814 898 6326. Assistant Professor of Finance, Black School of Business, Penn State Erie – The Behrend College, 5101 Jordan Drive, Burke Center 281, Erie, PA 16563 tak25@psu.edu. [↑](#footnote-ref-1)
2. Canina and Figlewski (1993) demonstrate that implied volatility of the S&P 100 Index is a poor predictor of future realized volatility. Jiang and Tian (2005) examine the relation between past realized volatility and future realized volatility in S&P 500 Index options, finding it to be a more reliable indicator than implied volatility. Additionally, Chan et. al. (2009), find that historical volatility is not a reliable predictor of future implied volatility for S&P 500 index options. Chng and Gannon (2003) similar results on the Sydney Futures Exchange, and Bentes (2015) finds that GARCH forecasted volatility outperforms implied volatility as a forecasting device. [↑](#endnote-ref-1)
3. Boscaljon et. al. (2011) find largely insignificant results over shorter time frames, but do observe this negative relationship for small-cap portfolios in the near term. [↑](#endnote-ref-2)