**The Relationship between VIX and Technical Indicator:**

**The Analysis of Shared-Frailty Model**

**Abstract**

This paper uses a shared-frailty model concerning the recurrence of spell time for the Volatility Index (VIX). Ten futures VIXs have been selected. The article examines the impacts of the top five market technical indicators, including the Moving Average Convergence–Divergence (MACD), Relative Strength Index (RSI), Triple Exponential Average (TRIX), Historical Volatility (HV), and Vertical Horizontal Filter (VHF). On the spell time of upward, downward, and overall trends, our findings supported the hypothesis that investors can better understand the pattern and trend of volatility risk by impacting the relevant technical index on various futures VIXs. We looked at the extent to which technical indicators have an effect on the volatility index. In the Weibull distribution, the upward trend data has the most significant values. The positive values provided by MACD and TRIX imply a strong positive relationship with VIX and a longer survival time. The results also show that the greater the value of historical volatility, the more risky trading investments are. As a result, the possibility of VIX in the trading pattern has a shorter time because the selling signals are coming out.

**Keywords: VIX Index, Technical Indicator, Shared-frailty Model**

**Introduction**

The Volatility Index (VIX) has introduced by the Chicago Board Options Exchange (CBOE) in 1993. It has gained in popularity as a proxy for risk related to the standard deviation of returns used by Markowitz (1952) and implied volatility. (Black and Scholes, 1973; Merton, 1973) Based on the out-of-the-money puts and calls, CBOE calculates the formula of the VIX to track the volatility of the S&P 500.

From an investor perspective, volatility provides useful information for examining the market environment and is associated with investment opportunities. The widespread use of VIX is due to its link with a negative impact on the performance of shares dealing with hedging risk and vice versa. The implementation of volatility investing helps investors speculate on ascending and descending directions.

Fernandes, Medeiros and Scharth (2007) found that implicit volatility was not related to the price structure of options. Andreas and Alexander (2013) found that jump-diffusion models are suitable for measuring the dynamics of the return volatility for the VIX. Jubinski and Lipton (2013) analyzed the relationships between implied volatility and returns on gold, silver, and oil commodities. However, Leung and Ward (2019) summarized the weak relationship between various VIX futures and spot movements. Clemens (2016) highlighted the different results of the VIX, which overestimated volatility in regular time and reflects the underestimated volatility at crash time. It has shown that VIX is not suitable for managing risk. As a result, investors need an advanced and reliable risk measure rather than the current VIX measure.

There is a vast body of literature, concentrating on technical analysis for evaluating investors' valuable investment decisions, such as Dempster, and Payne, Romahi, and Thompson (2001), Chi, Peng, Wu, and Yu (2003), and Atsalakis and Valavanis (2009). It is widely recognized that the relevant factors for the technical analysis are trading volume and stock price, which play a strategic role in forecasting price fluctuations and examining the timing of transactions. However, technical analysis of stock forecasting is limited by the expression of personal experience or preference, resulting in poor signal purchase or sale decisions.

Wong, Du, and Chong (2005), Chong and Ng (2008), and Muruganandan (2020) showed that technical analysis could provide a trading signal for stock market entry and exit, especially for Relative Strength Index (RSI) and Exponential Moving Average (EMA), Dual MA, Triple MA, the Moving Average Convergence–Divergence (MACD), and Triple Exponential Average (TRIX). The performance of these technical indicators outperformed the buy-and-hold approach in terms of returns.

Despite numerous attempts to examine the implied volatility and the VIX for measuring the negative impact on stock performance, the spell time of upward and downward trends of the VIX has received little attention. The influence of technical indicators based on investor preference to react to the duration of the VIX spell is still uncertain. Thus, the motivation of this study is to use a shared-frailty model concerning the reoccurrence of spell time for upward and downward trends of ten VIX. This study also focuses on the determinants of the technical indicators that affect the recurrence of the two motions of the spell duration. The results demonstrate that the higher the value of historical volatility, the riskier the trading investment. As a result, the possibility of VIX in the trading pattern involved a shorter period due to the sell signals. The highest log-likelihood value would be used to characterize the best-fitting distribution. (Cleves et al., 2008). We observed that the average uptrend of the VIX likelihood value found a much higher value in the Weibull distribution than the average value of the exponential distribution. The Weibull distribution is best suited to the data for the rising VIX Index. While for the rest of the data sample in a downward trend and overall trend in VIX index, we found the log-Normal and Log-logistic distributions are the best-fitting models for the data sample, respectively.

There is no difference between a longer and shorter average survival time for an upward trend in VIX in MACD, TRIX, VHF and HV. The observed survival times for all four variables above are parallel and close. This means that MACD, TRIX, VHF and HV have a slightly positive survival time in an ascending pattern. Apart from TRIX, this research has shown considerable positive effects on the investment behaviour of traders in most cases.

The rest of the paper is structured as follows. Section II describes the literature review. Section III presents the relevant variables of technical indicators, data, and the hypothesis. This section also offers a shared-frailty model concerning the recurrence of spell time. Section IV shows the empirical results. Section V reveals the conclusions.

**Literature Review**

The role of technical analysis and trading strategy based on optimizing investment decisions has been studied with great attention in academic and professional groups. Since 1993, the Chicago Board Options Exchange (CBOE) has measured the volatility index (VIX) to calculate investor perceptions of the near-term volatility of stock option price indexes. In fact, as of September 2003, the CBOE published two market volatility indices. First, the VXO reflected the implied volatility of the hypothetical 30-calendar-day S&P 100 implied index option. The second VIX was based on the portfolio values of the 30-calendar-day S&P 500 call and put options. Constructing a volatility index from option prices has emerged since 1973. Fernandes, Medeiros, and Scharth (2007) estimated the VIX and found that the implied volatility can be a model-free estimator regardless of any formal option pricing structure. Leung and Ward (2019) studied a collection of dynamic and static portfolios of VIX futures and their usefulness in monitoring the VIX. They draw up each portfolio using optimization approaches and assess its monitoring efficiency from analytical and theoretical outlooks. The findings have shown that static portfolios of various VIX futures do not closely follow the VIX index. Likewise, VIX futures do not respond rapidly enough to VIX spot movements.

Jubinski and Lipton (2013) discussed how implied volatility and the current stock market index affected future returns on gold, silver, and oil commodities. The estimation of the implied volatility was the VIX index, and the measurement of contemporaneous volatility used aggregated intra-day S&P 500 index returns. They found that gold and silver potential returns responded to increased implied volatility but not actual fluctuations. Oil has a statistically adverse reaction to implied volatility and a slightly negative response to recent volatility. These results have been exacerbated after recessionary cycles and robust after controlling the dollar index.

Andreas and Alexander (2013) discussed the potential of many distinct one- and two-factor jump-diffusion models to identify the dynamics of the return volatility VIX for the period between 1990 and 2010. They found that the unaffiliated one-factor models outperform their affinity, and modeling the log index is better than explicitly modeling the VIX level.

Technical analyses usually focus on technical indicators. The traders have been widely used to define the knowledge for analyzing trends, patterns, and strengths to foresee the path of price changes and measure the timing to sell or buy. By using 60-year data of the London stock exchange Index (FT30), Chong and Ng (2008) found that returns related to both the Moving Average Convergence–Divergence (MACD) and Relative Strength Index (RSI) can be generated and is superior to the buy-and-hold approach. Wong, Du, and Chong (2005) analyzed the profitability of three big stock exchanges - Shanghai, Hong Kong, and Taiwan and used technical analysis indicators signaling stock market entry and exit. Moving Average (MA), Exponential MA, Dual MA, Triple MA, MACD, and Triple Exponential Average (TRIX) for long and short-term strategies were reviewed. Results suggested that MA family trading signals to all three markets produce significant positive returns that exceed the buy-and-hold approach.

Muruganandan (2020) explores the economic sustainability of the technical analysis, such as RSI and MACD, in the Indian context. By gathering the historical data period from February 2000 to May 2018 from the Bombay Stock Exchange Index, the selected data is further subdivided into Bull and Bear markets. Results revealed that the relative strength index rules failed to get positive returns even before transaction costs. However, a signal rule of sell for moving average exchange trading rules regarding MACD has outperformed the unconditional average return mean.

Chen and Do Thi (2017) used the parametric shared-frailty survival model and discovered the probability of inflation recurrence time among countries. The findings highlight several contributions; firstly, the industrial manufacturing index is the main factor in the inflation period's recurrence time. Other determinants also influence the inflation time, such as inventory return, actual exchange rate, GDP per capita, government spending, money, and reserves. A nation that wishes to keep inflation stable should consider these variables impact when fiscal and monetary policies are mixed.

Shim et al. (2015) revealed how the weather impacted the leading emerging stock market's instability. When examining historical volatility and model-free implied volatility, the weather effect is better captured by historical volatility than implied volatility. Moreover, several researchers have used machine-learning technology over the last ten years to forecast price value increases or changes, such as the genetic algorithm (GA), the neural networks (NNs), and the support vector model (SVM). Allen and Karjalainen (1999) applied GA to producing trading rules. Phua et al. (2003) and Chen and Diaz (2021) used neural networks to evaluate financial forecasts and observed that they surpassed linear models. Huang et al. (2005) used SVM to forecast the stock market's movement and received consistent results.

**Data**

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where *RSIt* is a relative Strength Index at time t. *Pt* represents the value of the index at time t, while n denotes the numbers of RSI period. 14-day RSI will be studied in this research. A widespread length utilized by traders. I{.} stands for an indicator function expressing one for true and zero otherwise in the bracket. Welles (1978), Henderson (2002), and Rosillo et al. (2013) revealed the steps that can generate the strategy for buy, sell and hold.

MACD is designed to detect pattern changes based on a historical moving average of the index's closing value. It is determined based on the longer exponential moving average and the shorter exponential moving average. The concept of the EMA is:

where *EMAt* stands for the Exponential moving average at time t. n represents the total number of period length EMA. This article focuses on the 12- and 26-day EMAs reflecting short and long periods. (Murphy, 1999) A buy signal is activated when the MACD hits the zero line from below. When the MACD passes through the zero line from above, a sell signal is started. In addition, the nine-day simple moving average of the MACD is used as a signal period to generate the buying and selling of indicators. (Brock et al.; 1992)

The TRIX (Triple exponential moving average) results from the EMA. It is described as the EMA percentage change rate based on the original EMA of the underlying price. TRIX is an unconstrained oscillator that ranges along the zero line. The shortest interpretation is that a zero crossing to the upside shows the buying signal, and a zero-crossing to the downside is said to be a sell signal. Standard criteria, usually 9 to 12 periods for each EMA, can be used or calculated based on a particular scenario. (Donn, 2002) TRIX can be used both as a trend-following predictor and as an oscillator. If the trend of a VIX index is going upward, it means a positive signal. While the trend shows a downside from zero, it indicates a negative sign. If the TRIX prices go along 0 (middle), the trend is neutral.

Wang and Kim (2018) showed that different investors preferred different parameters to maximize returns on various stocks. This research also uses a historical volatility indicator as a guide for weight. For this purpose, the validity and consistency of the MACD are expected to be highly improved.

The Vertical Horizontal Filter is an indicator used to measure the strength of a price trend in technical analysis. The Vertical Horizontal Filter helps to distinguish patterns that are weak and strong. We also include this indicator in our study to measure the VIX market trend and the pattern. The VHF was first introduced in an article published in a Futures Magazine by White (1991). Table 1 presents the application characteristic used in the data set, and we have created different dummy variables for further analysis. The explanation of dummy variables is based on the information available in the literature.

**Hypothesis**

The following hypothesis was formed to test whether the relationship between independent and dependent variables is positive or negative returns of buy or sell signals differing from the unconditional average return. These hypotheses are based on the discussion available in the literature, as shown in Table 2. The Moving Average Convergence–Divergence (MACD), Relative Strength Index (RSI), Triple Exponential Average (TRIX), Historical volatility (HV), and Vertical Horizontal Filter (VHF) are the key market indicators.

RSI is a trading stock market indicator that measures the increasing price in a stock index. It is a technical measurement used to determine the overbought and oversold relationship. Chong and Ng (2008), González et al. (2011), Henderson (2002), and Rosillo et al. (2013) claimed that RSI increased in stock return easily to attract more investment from traders in a short period. Thus, the continuing rise in RSI helps to obtain a longer likelihood of survival time and positively impacts returns on the upward trend of the VIX. While continuing to enhance RSI indicates buying signals, it will quickly restore to a stable level after crises during a downward trend. We prospect a shorter survival time and a negative impact on the spell time of the VIX.

**Table 1 Application Characteristics used in the study**

|  |  |  |
| --- | --- | --- |
| **Variables** | **Notations** | **Explanation** |
| Moving average convergence divergence | MACDP3 | A dummy variable for MACD characteristics, if MACDP3=1 is positive with >3. Otherwise, MACDP3 is 0 with <3. |
| MACDN3 | A dummy variable for MACD characteristics, if MACDN3=1 is negative with >-3. Otherwise, MACDN3 is 0 with <-3. |
| Relative Strength Index | RSIS50 | A dummy variable for RSI characteristics, if RSIS50=1 indicates selling signals or overbought with >50. Otherwise, RSIS50 is 0 with <50. |
| RSIW30 | A dummy variable for RSI characteristics, if RSIW30=1 indicates buying signals to wait for the price to settle and begin to rise higher with <30. Otherwise, RSIW30 is 0 with >30. |
| Triple Exponential Average | TrixP1 | A dummy variable for TRIX characteristics, if TrixP1=1 is positive with >0.1. Otherwise, TrixP1 is 0 to <0.1. |
| TrixP2 | A dummy variable for TRIX characteristics, if TrixP2=1 is positive with >0.2. Otherwise, TrixP2 is 0 with <0.2. |
| TrixN1 | A dummy variable for TRIX characteristics, if TrixN1=1 is negative with >-0.1. Otherwise, TrixN1 will be 0 if <-0.1. |
| TrixN2 | A dummy variable for TRIX characteristics, if TrixN2=1 is negative with >-0.2. Otherwise, TrixN2 will be 0 if <-0.2. |
| Vertical Horizontal Filter | Vthz55 | A dummy variable for VHF characteristics, if Vthz55=1 indicates prices related to the Vertical Horizontal Filter rises with >0.55. Otherwise, Vthz55 will be 0 if <0.55. |
| Vthz60 | A dummy variable for VHF characteristics, if Vthz60=1 indicates prices are connected with the Vertical Horizontal Filter rises with >0.6. Otherwise, Vthz60 will be 0 if <0.6. |
| Historical Volatility | Hist30 | A dummy variable for HV characteristics if Hist30=1. It indicates that prices are going up and down faster than normal, suggesting that something will change. There is an uncertainty situation if Hist30 >30. Otherwise, Hist30 will be 0 if <30. |
| Hist20 | A dummy variable for HV characteristics if Hist20=1. It indicates that prices are going up and down faster than normal. Again, uncertain situation if Hist20> 20. Otherwise, Hist20 will be 0 if <20. |

**Table 2. The list of variables that affect on VIX index**

|  |  |  |  |
| --- | --- | --- | --- |
| **Variable** | **Notation** | **Formula** | **Sign** |
| Moving average convergence divergence | MACD | (MACD) is calculated by subtracting the 26-period exponential moving average (EMA) from the 12-period EMA. | + |
| Relative Strength Index | RSI |  | **±** |
| Triple Exponential Average | TRIX | TRIX | + |
| Vertical Horizontal Filter | VHF | VHF = (HCP - LCP) / [Absolute value of SUM (Change, N)]  Where:  N - bar period selected by a user.  HCP - highest close price during N periods.  LCP - lowest close in N periods.  SUM (Change, N) - is the sum of absolute changes over n periods. | + |
| Historical Volatility | HV | It is calculated by the average deviation from the average price of a financial instrument over a specified time. | ­ |
| Note: The formulae are the refers to the Investopedia.com and https://www.marketvolume.com. | | | |

MACD plays a vital role in the stock market trading and designs to detect pattern changes based on a historical moving average of the index's closing value. Wang and Kim (2018) and Murphy (1999) showed that investors preferred different market trading indicators to maximize return on various stocks. If MACD hits the zero line from below, it is more likely to have a positive relationship and is more expected to increase survival time. While MACD value is going up, it represents a result of relatively strong buying signals. Since the volatility of a downward trend starts varies greatly, but diminishes, it is possible to recover in a short span of time to restore a stable position.

TRIX is another important stock market trading indicator. (Donn, 2002) TRIX incorporates pattern and momentum based on the formula composed of a triple continuously smoothed moving average rate. Therefore, we hypothesize that TRIX has strong momentum to resist greater volatility after the shock. It also affects the probability of long-term survival patterns in the selected upward period. If TRIX momentums increase continuously, it may decrease investors' fear of risk. On downward selected incepted period, it shows the selling signals. So, the possibility of shorter survival of time in the VIX pattern will happen.

Historical Volatility (HV) is one of the technical analysis indicators that measures the dispersion of returns for a given security or market index over a given period. (Wang and Kim, 2018; and Chun et al., 2020) They suggested that the higher the HV value, the riskier the security. Therefore, we expect the probability of a shorter spell time for upward VIX in the trading pattern due to its selling signal accelerating the risks. Moreover, if the HV value increases, the buying signals will take a longer time to restore the downward VIX pattern's stable position.

White (1991) used a vertical horizontal filter (VHF) as an indicator to measure the strength of a stock price trend. The value of VHF may be used to denote the intensity of the pattern. Higher the value enhances the movement of the trend. Therefore, the likelihood of a longer spell time of upward VIX in our inception period pattern. Furthermore, if the VHF value goes up, it will attract investors' attention to strength buying signals when the crisis period declines. Therefore, it changes to the shorter spell of time of the downward trend in the selected inception pattern.

The association of independent variables with the dependent variable VIX index is shown in Table 2. For the analysis, the CBOE data of 10 VIX indexes collected from yahoo finance summarizes the variables VIX details, different inception dates, and recurrence time included in the data set are represented in Table 3.

**Methodology**

A latent multiplicative effect based on the hazard function is called frailty, associated with unit mean and variance considering spell-specific terms in Table 4. Gutierrez (2002) used frailty models connected with random effects for survival data, allowing for heterogeneity. As addressed in Gutierrez (2002) and Chen and Diaz (2014), a shared-frailty model is a random-effect model where the frailties are identical (or shared) between groups of subjects or spells. They are randomly spread across the groups. This method was developed to predict the timeline for life used to carry out

**Table 3. Data sample of VIX index and different inception dates**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **VIX index** | **Notation** | **Recurrence Times** | Inception dates | | |
| Upward trend:  Inception dates from bottom to peak | Downward trend:  Inception dates from peak to bottom | Overall trend:  Inception dates overall from bottom to bottom |
| **CBOE VIX VOLATILITY INDEX** | **^VVIX** | **6** | 7/16/2007 - 3/16/2020 | 8/13/2007 -4/20/2020 | 7/16/2007 - 4/20/2020 |
| **CBOE Volatility Index** | **^VIX** | **7** | 7/16/1990 - 3/16/2020 | 8/20/1990 - 4/27/2020 | 7/16/1990 - 4/27/2020 |
| **CBOE NASDAQ 100 Volatility** | **^VXN** | **4** | 3/25/2002 - 3/16/2020 | 7/22/2002 - 4/20/2020 | 3/25/2002 - 4/20/2020 |
| **CBOEO EX implied Volatility** | **^VXO** | **6** | 9/28/1987 - 3/16/2020 | 10/19/1987 - 4/20/2020 | 9/28/1987 - 4/20/2020 |
| **CBOE Gold Volatility Index** | **^GVZ** | **4** | 4/18/2010 - 3/8/2020 | 5/16/2010 - 4/12/20202 | 4/18/2010 - 4/12/2020 |
| **CBOE Crude Oil Volatility Index** | **^OVX** | **4** | 8/31/2008 - 3/15/2020 | 11/30/2008 - 4/12/2020 | 8/31/2008 - 4/12/2020 |
| **CBOE Euro currency Volatility index** | **^EVZ** | **4** | 8/17/2008 - 3/15/2020 | 10/26/2008 - 4/5/2020 | 8/17/2008 - 4/5/2020 |
| **CBOE Crude Oil Volatility Index (ETF)** | **^OVX** | **4** | 9/1/2008 - 3/16/2020 | 12/8/2008 - 4/13/2020 | 9/1/2008 - 4/13/2020 |
| **CBOE Russell 200 Volatility index** | **^RVX** | **3** | 4/12/2010 - 3/16/2020 | 5/17/2010 - 5/4/2020 | 4/12/2010 - 5/4/2020 - |
| **CBOE Silver Volatility Index (ETF)** | **^VXSLV** | **2** | 7/11/2011 - 3/16/2020 | 9/26/2011 - 4/20/2020 | 7/11/2011 - 4/20/2010 |

**Table 4. The distribution of survival and hazard function**

|  |  |  |  |
| --- | --- | --- | --- |
| **Distribution** | **Survival Function** | **Hazard Function** | **Shape** |
| Weibull |  |  | Monotonic  hazard rate |
| Exponential |  |  | Monotonic  hazard rate |
| Gompertz | exp | *p*exp | Monotonic hazard rate (exponential increase or decrease) |
| Log-Normal |  |  | Non-monotonic  hazard rate |
| Log-Logistic |  |  | Non-monotonic  hazard rate |

Note: Φ stands for the standard normal cumulative distribution.

death analysis techniques in health science and is now used in economics and the financial market.

This study will employ the shared-frailty regression parameters. Despite the extensive theoretical and empirical literature on survival models, Pazarba¸ Sio ˘glu and Otker (1997) and Tudela (2004) show that academic evidence for survival analysis using shared-frailty models on the VIX index is still not found in the literature. Shared frailty models introduced by Clayton (1978) and Hougaard (2000) are used to answer the problems, such as how long the VIX index survival time recurs and how much and what factors impact at the VIX index spell duration recurrence time. This model is connected to the survival spans of repeated observations.

The survival model for the shared frailities across the VIXs is supposed to be correlated for each market indicator findings of the same group are defined as follows. , (1)

where  stands for for frailty which is assumed with a mean of one and a variance, , relating to unobserved observation for evaluating the specific effect.  represents the co-variate of the observation () connected with different indicators () at time t. Cleves et. al., (2004) expressed that if <1 or >1 revealed the reduction or rise in the hazard, there was a decrease or an increase risk related to the subject perpetually.

The following equation shows the relationship of the Hazard and survival function:

, (2)

where is based on the regular survival function. This paper uses the transforming hazard function to obtain the accelerated failure-time metric, which is a parameter of the positive hazard rate: , where and represent a positive scale and βx is the parameter.

To evaluate the distribution of parametric survival functions, this study applies () to follow the probability procedure of the shared-frailty model as:

, (3)

This paper utilizes the frailty for the ith group (Gi) for the likelihood of the unconditional shared-frailty model as follows.

, (4)

, (5) where the frailtyvariance measures the degree of heterogeneity, while g can be calculated by a gamma distribution based on the likelihood density. (Cleves et al., 2004)

The survival function connected with a gamma distribution can be shown as:

, (6)

where is the gamma function.

**Empirical Results**

Cleves et al. (2008) suggested two benchmarks to assess the best fitting model based on the greatest Log-likelihood value and the lowest Akaike Information Criterion (AIC). The findings of the parametric shared-frailty models for the VIX index are shown in Table 5. Among the five parametric shared-frailty models, the Exponential distribution is the best.

There are two variables, the MACD and TRIX are significant in the upward specification. Considering the measurement from down to peak, the negative impacts of MACD and TRIX probably indicate less survival time for futures VIX. When MACD value goes up, it is relatively a weak buying signal. Thus, it is possible to retain a short spell time in the selected upward period. We found the same results with less influence on overall and downwards specifications for VIX.

**Table 5. Test results of Parametric shared-frailty models for VIX index**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Variables | Upward | | Downward | | Overall | |
| MACD | -3.000 | **(0.038) \*\*** | -0.009 | **(0.000) \*\*\*** | -0.015 | **(0.000) \*\*\*** |
| TRIX | -0.228 | **(0.000) \*\*\*** | 0.159 | (0.356) | -0.015 | **(0.000) \*\*\*** |
| RSI | -0.002 | (0.674) | 0.007 | (0.645) | -0.012 | (0.200) |
| VHF | 0.010 | (0.927) | -0.320 | (0.682) | -0.145 | (0.449) |
| HV | 0.004 | (0.361) | -0.006 | (0.420) | 0.004 | (0.417) |
| Const | 4.183 | **(0.000) \*\*\*** | 4.715 | **(0.000) \*\*\*** | 5.895 | **(0.000) \*\*\*** |
| Log- Likelihood | -50.468 | | -56.766 | | -52.677 | |
| Distribution | Exponential | | Exponential | | Exponential | |

Note: \*, \*\*, and \*\*\* are significant for p-value at 10, 5, and 1%, respectively.

Table 6 explains the results of application characteristics. The highest log-likelihood value would be used to characterize the best-fitting distribution. For example, with a higher value, the Weibull distribution is the best fit for data for the upward specifications in the VIX index. For the rest of the data sample in the specifications of the downward and overall trend in the VIX index, we found the Log-Normal and Log-logistic distribution are the best-fitting models, respectively.

The data covered in the upward specification has significant values in the Weibull distribution. When MACDN3, TRIXP1, and TRIXP2 are relatively high, the expected positive values indicate more likely to increase survival time. The results are consistent with the hypothesis. When a weak MACD value is reversely going up, it shows continued strong buying signals. Thus, it is possible to retain a long spell time in a stable position and long-term survival pattern in the selected upward period. It decreases investor fear about the risk and encourages investing in VIX indexes. The results confirm that TRIX with a positive sign indicates a buy signal when it lies above the zero line, while a sell signal when it goes below the zero line is associated with TRIX for a negative sign.

**Table 6**. **Parametric shared-frailty models for the likelihood of spell time VIX index**

|  |  |  |  |
| --- | --- | --- | --- |
| **Variables** | **Upward** | **Downward** | **Overall** |
| TrixP1 | **0.717**  **(0.001) \*\*\*** | 0.197  (0.728) | **1.937**  **(0.012) \*\*** |
| TrixP2 | **0.788**  **(0.000) \*\*\*** | 0.425  (0.236) | -0.167  (0.244) |
| TrixN1 | 0.335  (0.185) | **1.586**  **(0.002) \*\*\*** | **1.251**  **(0.000) \*\*\*** |
| TrixN2 | **-0.790**  **(0.001) \*\*\*** | -0.859  (0.145) | **-2.116**  **(0.000) \*\*\*** |
| RSIW30 | **-0.622**  **(0.030) \*\*** | -0.083  (0.959) | -**1.244**  **(0.000) \*\*\*** |
| RSIS50 | **-0.658**  **(0.001) \*\*\*** | 0.450  (0.389) | **-0.470**  **(0.000) \*\*\*** |
| Vthz55 | 0.283  (0.149) | -0.976  (0.389) | **0.378**  **(0.018) \*\*** |
| Vthz60 | -0.363  (0.260) | **0.986**  **(0.047) \*\*** | **-0.464**  **(0.000)** \*\*\* |
| Hist20 | **-0.322**  **(0001) \*\*\*** | -0.013  (0.970) | .510  (0.428) |
| Hist30 | 0.073  (0.730) | -.102  (0.785) | .168  (0.802) |
| MACDP3 | **-0.617**  **(0.000) \*\*\*** | -0.573  (0.623) | **-.5697**  **(0.003) \*\*\*** |
| MACDN3 | **1.050**  **(0.000) \*\*\*** | -0.131  (0.617) | **1.887**  **(0.005) \*\*\*** |
| Const | **3.819**  **(0.000) \*\*\*** | **4.430**  **(0.000) \*\*\*** | **3.611**  **(0.000) \*\*\*** |
| Log-Likelihood | -26.114 | -43.822 | -27.538 |
| **Distribution** | **Weibull** | **Log Normal** | **Log logistic** |

Note: \*, \*\*, and \*\*\* are significant for p-value at 10, 5, and 1%, respectively.

A significant, but negative result in Historical Volatility (Hist20) also matches the hypotheses. The findings support the claim of (Wang and Kim, 2018 and Chun et al., 2020) that the security with an increase in HV value will be riskier. Therefore, it may probably have a shorter spell time for upward VIX, reflecting its selling signals for accelerating the risks. The empirical results also support the findings of Van et al. (2011) that the relationship between Historical volatility and stock return is negative.

A negative with significant results of RSIW30 and RSIS50 indicates the shorter impact on survival time. When the RSI indicator exceeds the set threshold, the continuous rise of the buying signal will help ease investor panic. The selling signal will make the sellers sell the stock early, allowing the upward trend of VIX to hit a peak point earlier. These results are consistent and confirm the hypotheses of this study.

Based on White (1991), if weak TRIX momentums decrease, it reflects more survival time due to increased risk. It needs more time to release the panic and for the downward trend. For the downward trend of VIX, we found two significant positive values for TrixN1 and Vthz60.

The significant positive for the Vthz60 value indicates the pattern's intensity. The greater the value, the greater the movement of the trend. The inception period pattern is more likely to have a longer spell time of VIX. If the value of Vthz60 rises, it will draw investors' attention to ending strong buying indications. As a result, it shifts to a long time with a negative trend in a downward pattern of extended risks. These findings are linked and steady with the study hypotheses.

We found that nine variables have significant results for the overall specification, including MACDN3, TrixP1, TrixN1, and Vthz55. It indicates a higher likelihood of a positive relationship and a higher chance of increasing the survival time of VIX. A positive result for TRIX is a momentum indicator between -0.1 and +0.1 indicates the rising momentum, which may probably enlarge survival time to release the risks. We discovered most variables with the same results on overall and upwards specifications for VIX. These are associated with the positive effects of strong buying signals.

Figure 1 shows the survival spell time differences in the VIX upward, downward, and overall specifications concerning the effect of five variables such as MACD, TRIX, HV, VHF, and RSI, respectively. These observed survival times are parallel and close. In upward VIX, there is no difference in survival average spell time in MACD, TRIX, VHF,

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | MACD | TRIX | HV | VHF | RSI |
| y1 |  |  |  |  |  |
| y2 |  |  |  |  |  |
| y3 |  |  |  |  |  |

**Note:** MACD =1 if MACD >0 otherwise MACD=0 if MACD <0; TRIX=1 if TRIX >0 otherwise TRIS=0 if TRIX <0; HV=1 if HV >50 otherwise HV=0 if HV<50;

VHF=1 if VHF >50 otherwise VHF=0 if VHF <50; RSI=1 if RSI >50 otherwise RSI=0 if RSI <50.

**Figure 1. Upward (Y1), Downward (Y2), and Overall (Y3) Spell Time difference for VIX**

and HV. Given the survival rate, we discovered that the higher RSI (RSI >50) had a substantially shorter survival time in upward VIX.

In a downward trend, we found that the average TRIX has a big difference between positive Trix20 and negative Trix60 in survival spell time. As a result, there is a chance for positive Trix to narrow the VIX pattern for a shorter survival period. Therefore, investors attempt to sell their purchasing shares as soon as possible to protect their investment to avoid risk. We discovered no significant difference in spell time for MACD, VHF, RSI, and HV in the downward VIX. The observed survival times of all four variables are nearly identical.

The average HV and VHF significantly differed between high and low levels for survival spell duration in the overall specification. The low HV <50 and VHF >50 for the overall trend in the figure demonstrates a considerably short survival time, which has a significant impact on the trading behavior of investors. Investors want to sell their purchase shares as quickly as feasible to safeguard investment from the high hazard and risks. The observed survival times of all three variables, such as MACD, TRIX, and RSI, have a similar survival time. The survival time for upward VIX is much shorter than for downward VIX.

**Conclusion**

This study contributes to the study of a variety of the survival functions of VIX. In this research, the recurring periods of buying and selling signals and longer and shorter periods of volatility index are estimated using parametric shared-frailty models. We observed that the likelihood value of an upward trend in VIX has a much higher value in the Weibull distribution than in the exponential distribution.

The data covered in the upward specification has significant values in the Weibull distribution. When MACDN3, TRIXP1, and TRIXP2 are relatively high, the expected positive values indicate more likely to increase survival time. The study reveals that a negative with significant results of RSIW30 and RSIS50 indicates the shorter impact on survival time.

It reflects more survival time due to an increase in the risk. We have investigated the spell time recurrence on the VIX index and the impact of five technical indicators, including the Moving Average Convergence–Divergence (MACD), the Relative Strength Index (RSI), the Triple Exponential Average (TRIX), historical volatility (HV), and the Vertical Horizontal Filter (VHF) on it. We discovered most of the specifications with significant overall specification values, including MACDN3, TrixP1, TrixN1, and Vthz55. For the downward trend of VIX, we found two significant positive values for TrixN1 and Vthz60. It shows a probability of a greater potential of increasing VIX survival time.

The predicted positive values in MACD and TRIX imply a robust positive relationship with VIX and longer survival time. The results indicate that the greater the historical volatility value, the riskier the investment in trading. This study also displays the VIX survival spell time differences. In MACD, TRIX, VHF, and HV, we discovered no significant difference between longer and shorter surviving average spell time in an upward VIX pattern. The observed survival times of all four variables are nearly identical for the downward trend, except TRIX. The research found significant favorable effects on traders' investing behavior.

We have found that the average HV and VHF displayed a significant difference between positive and negative survival spell time in the overall specification, which substantially influences investor trading investment behavior in VIX.

The implication is to help investors, futures market traders, and funds with the right investing tool for decision making, future trade planning, and investment, minimizing the investment risk, knowing buying and selling signals, and their major effect on technical indicators.

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