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The Relationship between VIX and Technical Indicator: The Analysis of Shared-Frailty Model

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Abstract

This article uses a shared-fragility model for the recurrent spell length for the volatility index (VIX). Ten future VIXs have been chosen. 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 examined how technical indicators affect 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 greater the risk to commercial investments. As a result, the possibility of VIX in the trading pattern has a shorter time because the selling signals are coming out.

JEL classification numbers: G15.
Keywords: VIX Index, Technical Indicator, Shared-frailty Model.

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1. Introduction

The Volatility Index (VIX) has introduced by the Chicago Board Options Exchange (CBOE) in 1993. It has become increasingly popular as a risk indicator for 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 valuable insight into the marketplace environment and is associated with investment opportunities. Implementing volatility investments helps investors speculate on up and down directions. The widespread use of VIX is due to its association with a negative impact on the performance of stocks facing hedging risk and vice versa.

Fernandes, Medeiros, and Scharth (2007) found that implied volatility was not related to the price structure of options. Kaeck and Alexander (2013) found that jump-diffusion models are appropriate for measuring yield volatility dynamics for VIX. Jubinski and Lipton (2013) analyzed the relationships between implied volatility and gold, silver, and oil commodity returns. However, Leung and Ward (2019) summarized the weak relationship between various VIX futures and spot movements. Clemens (2016) pointed to different VIX results, which overestimate volatility in normal times and reflect underestimated volatility in times of crisis. It has proven that VIX is not appropriate for risk management. Therefore, investors need an advanced robust risk measure rather than the current VIX measure.

There is a large body of literature focusing on technical analysis to evaluate valuable investment decisions by investors, such as Dempster et al. (2001), Chi et al. (2003), and Atsalakis and Valavanis (2009). It is widely recognized that the relevant factors for 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 restricted by expressing personal experience or preference, resulting in poor signal buying or selling decisions.

Wong et al. (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 metrics surpassed that of the buy-and-hold approach in terms of performance.

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 yet to receive much attention. The influence of technical indicators based on investor preference to respond to the duration of the VIX rate is still unclear. Thus, the motivation of this study is to use a shared frailty model concerning the recurrence of spell time for upward and downward trends of ten VIX. This study also examines the determinants of technical indicators that influence the recurrence of both movements of spell duration. The results show that the greater the historical volatility value, 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 noted that the average upward trend of the VIX likelihood value was much higher in the Weibull distribution than the average value of the exponential distribution. The Weibull distribution is best suited to the data of the rising VIX Index. While for the rest of the data sample in a downward trend and overall trend in the VIX index, we found the Log-Normal and Log-logistic distributions are the best-fitting models for the data sample, respectively.

The observed survival times for the four abovementioned variables are parallel and close. There is no difference between a longer and shorter mean survival time for a rising trend of VIX in MACD, TRIX, VHF, and HV. Thus, MACD, TRIX, VHF, and HV have a slightly positive survival time in an ascending pattern. Aside from TRIX, this research has shown significant positive impacts on the investing behavior of traders in most cases.

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

2. Literature Review

The role of technical analysis and trading strategy based on optimizing investment decisions has been studied closely 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 September 2003, the CBOE released two indices for market volatility. First, the VXO reflected the implied volatility in the hypothetical S&P 100 index option at 30 calendar days. 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 et al. (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) looked at a collection of dynamic and static VIX futures portfolios and their usefulness in tracking VIX. They develop each portfolio using optimization approaches and assess its tracking efficiency from analytical and theoretical perspectives. The results showed that the static portfolios in different VIX futures contracts do not closely track the VIX index. Similarly, futures VIX is not responding fast enough to VIX spot movements.

Jubinski and Lipton (2013) discussed how implicit volatility and the current stock index had impacted future returns of gold, silver, and oil commodities. The implied volatility estimate was the VIX Index, and the contemporary volatility measure used the aggregated intraday returns of the S&P 500 Index. They found that potential gold and silver returns responded to increased implicit volatility but not actual fluctuations. Oil has a statistically unfavorable reaction to implicit volatility and a slightly adverse reaction to recent volatility. These results have been exacerbated after recessionary cycles and robust after controlling the dollar index. Kaeck 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 refer to technical indicators. 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 et al. (2005) analyzed the profitability of three major exchanges - Shanghai, Hong Kong, and Taiwan, and used technical analysis indicators to indicate the inflow and outflow of equity markets. Moving Average (MA), Exponential MA, Dual MA, Triple MA, MACD, and Triple Exponential Average (TRIX) for long- and short-term strategies were examined. The 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 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. The results showed that the relative strength index rules did not achieve positive returns even before transaction costs. However, a sell signal rule for the moving average foreign exchange trading rules for MACD surpassed the unconditional average return.

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 affect the period of inflation, such as inventory returns, real exchange rates, GDP per capita, government expenditures, money, and reserves. A country wishing to keep inflation steady should take account of these variables when fiscal and monetary policies are mixed.

Shim et al. (2015) revealed the impact of weather on the unstable emerging stock market. 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 when developing trade 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 stock market developments with consistent results.

3. Data

This research examines the stability and variability time period and separates an index under multiple inception periods. The statistical data from this study consists of panel data series of 10 forward VIX indices. The information is covered based on different inception dates from the yahoo finance website. The market indicators, The Moving Average Convergence–Divergence (MACD), Relative Strength Index (RSI), Triple Exponential Average (TRIX), Historical volatility (HV), and Vertical Horizontal Filter (VHF) measure the predictability of spell time, and both stability and variability in high and low during the inception period. This paper estimates the number of days that VIX index patterns stayed from the bottom to the peak for an upward trend and the peak to the bottom for a downward trend.

The RSI is a technical measure determining the relation between overbought and oversold financial stocks. Chong and Ng (2008) used market measurement indicators such as RSI value, which should be between 0 and 100. Where the value is greater than 70, a stock is deemed unsustainable. If the value is less than 30, it is regarded as over-bought. When the RSI value exceeds 50, it represents a bull signal. On the other hand, security is treated as bearable when the RSI value is less than 50. The RSI is an indicator commonly used in market valuation specified as:

$$\boldsymbol{RSI_t(n)} = \frac{\sum_{i=0}^{n-1}(\boldsymbol{P_{t-i}} - \boldsymbol{P_{t-i-1}})\boldsymbol{I}\{\boldsymbol{P_{t-i}} > \boldsymbol{P_{t-i-1}}\}}{\sum_{i=0}^{n-1}|\boldsymbol{P_{t-i}} - \boldsymbol{P_{t-i-1}}|} \times \mathbf{100}, \tag{1}$$

where RSI_t is a relative Strength Index at time t. P_t represents the index value at time t, while n denotes the numbers of the *RSI* period.

The 14-day RSI will be considered for 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 of buy, sell and hold.

The 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:

$$\boldsymbol{EMA_t} = \left[\frac{2}{n} \times (P_t - EMA_{t-1})\right] + EMA_{t-1}, \tag{2}$$

where EMA_t 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 purchase signal is enabled when the MACD hits the zero line from the bottom. A sell signal is launched when the MACD goes through the zero line from the top. 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 is derived 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 runs 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. The standard criteria, generally 9-12 periods for each EMA, can be used or calculated based on a specific scenario (Fishbein, 2002). TRIX can be utilized as a trend predictor and oscillator. If a VIX is trending upwards, this indicates a positive signal. While the trend decreases from zero, it points to a negative sign. The trend is neutral when TRIX prices are up to 0 (middle).

Wang and Kim (2018) showed that different investors preferred different metrics to maximize the performance of different stocks. This search also utilizes a historical volatility indicator as a guide for weight. For this purpose, the validity and consistency of the MACD will be greatly enhanced.

The VHF is an indicator used to measure the strength of a price trend in technical analysis. The VHF 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 in Futures Magazine by White (1991). Table 1 shows the application feature used in the dataset, and various dummy variables were created for further analysis. The explanation for the dummy variables is based on information from the literature.

4. 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 MACD, RSI, TRIX, HV, and VHF are the key market indicators.

The RSI is a stock market indicator that measures the rise in the price of a stock index and is a technical measure to determine the relationship between overbought and oversold. Chong and Ng (2008), González et al. (2011), Henderson (2002), and Rosillo et al. (2013) asserted that RSI quickly raised equity returns to attract more investment from traders over a short period. Thus, the continued rise in RSI helps achieve a higher likelihood of survival and positively impacts the upward trend of VIX. While continuing to improve the RSI indicates purchasing signals, it will quickly return to a stable level following crises during a downward trend. We expect a shorter survival time and a negative impact on the VIX's spell time.

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 uncertain 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 measured by deducting the 26-period exponential moving average (EMA) from the 12-period EMA.	+
Relative Strength Index	RSI	$\boldsymbol{RSI_t(n)} = \frac{\sum_{i=0}^{n-1}(P_{t-i} - P_{t-i-1})I\{P_{t-i} > P_{t-i-1}\}}{\sum_{i=0}^{n-1}\lvert P_{t-i} - P_{t-i-1}\rvert} \times \mathbf{100}$	±
Triple Exponential Average	TRIX	$\mathbf{TRIX}(\boldsymbol{i}) = \frac{EMA3_{(i)} - EMA3_{(i-1)}}{EMA3_{(i-1)}}$	+
Vertical Horizontal Filter	VHF	$\text{VHF} = \frac{(HCP - LCP)}{[Absolute\ value\ of\ SUM(Change, N)]}$ 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 (www.marketvolume.com)

MACD plays a vital role in the stock market trading and is designed to detect pattern changes based on a historical moving average of the index's closing value. Wang and Kim (2018) and Murphy (1999) have shown that investors prefer different market metrics to maximize returns for different securities. If MACD hits the bottom zero line, it is more likely to have a positive relationship and is more likely to increase survival time. As the MACD value increases, it represents the outcome of relatively strong buying signals. As the volatility of a downward trend begins to vary considerably but decreases, it is possible to recover quickly to return to a stable position.

TRIX is another major stock exchange indicator (Fishbein, 2002). TRIX incorporates pattern and momentum based on the formula composed of a triple continuously smoothed moving average rate. Therefore, we assume that TRIX has a strong momentum to withstand greater volatility after the crash. It also influences

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

the likelihood of long-term survival patterns over the selected upward period. On the downward selected incepted period, it shows the selling signals. If TRIX momentums increase on an ongoing basis, this could reduce investor fear of risk. So, the possibility of shorter time survival in the VIX pattern will happen.

Historical Volatility (HV) is one of the technical analysis indicators that measures the dispersion of returns based on market index (Wang and Kim, 2018; Chun et al., 2020). They suggested that the higher the HV value, the riskier the stock. 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 longer to restore the downward VIX pattern's stable position.

White (1991) used the VHF as an indicator to measure the strength of exchange rate developments. The value of VHF may be used to denote the intensity of the pattern. The higher the value, the more the pattern shifts. Therefore, the likelihood of a longer spell time of upward VIX in our inception period pattern. Furthermore, if the VHF value goes up, investors will be attracted 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 independent variables associated with the dependent variable of 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 which are represented in Table 3.

5. 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 assigned to groups. This method has been developed to predict the life expectancy of death analysis techniques in the health sciences 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, Pazarbaşioğlu and Ötker (1997) and Tudela (2004) show 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. It is related to the survival time of repeated observations.

Table 4: The distribution of survival and hazard function

Distribution	Survival Function $S(t_{ij}\|x_{ij})$	Hazard Function $h(t_{ij}\|x_{ij})$	Shape
Weibull	$exp\left(-(\gamma t_{ij})\right)^{p}$	$\gamma p(\gamma t_{ij})^{p-1}$	Monotonic hazard rate
Exponential	$exp\,(-\gamma t_{ij})$	γ	Monotonic hazard rate
Gompertz	$exp\{(-p/\gamma)(e^{\gamma t} - 1)\}$	$pexp^{(\gamma t)}$	Monotonic hazard rate (exponential increase or decrease)
Log-Normal	$\Phi\left(-p.\,log(\gamma t_{ij})\right)$	ϕ/Φ	Non-monotonic hazard rate
Log-Logistic	$1/\left(1+(\gamma t_{ij})^{p}\right)$	$\gamma p(\gamma t_{ij})^{p-1}/\left(1+(\gamma t_{ij})^{p}\right)$	Non-monotonic hazard rate

Note: Φ stands for the standard normal cumulative distribution

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.

$$h(t_{ij}|x_{ij,}\alpha_i) = \alpha_i h(t_{ij}|x_{ij}), \quad (3)$$

where α_i stands for frailty which is assumed with a mean of one and a variance, θ, relating to unobserved observation for evaluating the specific effect. x_{ij} represents the co-variate of the observation $(j = 1, \dots \dots n,)$ connected with different indicators $(i = 1, \dots \dots G,)$ at time t. Cleves et al. (2008) expressed that if $\alpha_i < 0$ or $\alpha_i > 1$ revealed the reduction or rise in the hazard, there was a decrease or an increased risk related to the subject perpetually.

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

$$S(t_{ij}|x_{ij,}\alpha_i) = [S(t_{ij}|x_{ij})]^{\alpha_i}, \quad (4)$$

where $S(t_{ij}|x_{ij})$ 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: $lnt_{ij} = \alpha_{ij}w_{ij} + \beta_x x_{ij}$, where $\gamma = e^{-\beta_x}$ and $p = 1/\sigma_{ij}$ represent a positive scale and βx is the parameter.

This study applies (t_{0ij}, t_{ij}) to follow the probability procedure of the shared-frailty model for evaluating the distribution of parametric survival functions as:

$$L(t_{ij} \mid t_{0ij}, \alpha_i) = \left\{ \frac{S(t_{ij} \mid x_{ij})}{S(t_{0ij} \mid x_{ij})} \right\}^{\alpha_i} \{\alpha_i h(t_{ij} \mid x_{ij})\}^{c_{ij}} \quad (5)$$

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

$$L(G_i)=\int_0^{\infty}\alpha_i^{c_i}\prod_{j=1}^{n_i}\left[\left\{\frac{S(t_{ij}\mid x_{ij})}{S(t_{0ij}\mid x_{ij})}\right\}^{\alpha_i}\{h(t_{ij}\mid x_{ij})\}^{c_{ij}}\right]z(\alpha_i)d\alpha_i \tag{6}$$

$$S_{\theta}(t_{ij}\mid x_{ij})=\int_0^{\infty}\{S(t_{ij}\mid x_{ij})\}^{\alpha_i}\cdot z(\alpha_i)\cdot d\alpha_i \tag{7}$$

where the frailty $g(\alpha_i)$ variance measures the degree of heterogeneity, while a gamma distribution can calculate g based on the likelihood density (Cleves et al., 2008).

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

$$z(\alpha_i)=\frac{\alpha_i^{1/\theta-1}\cdot e^{-1/\theta}}{\Gamma(1/\theta)\cdot\theta^{1/\theta}} \tag{8}$$

where Γ is the gamma function.

6. 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.

Two variables, MACD and TRIX, are essential to the upward specification. Considering the measurement from down to peak, the negative impacts of MACD and TRIX indicate less survival time for futures VIX. As the MACD value increases, this is a relatively weak buy signal. As such, it is possible to maintain a short time in the selected uptrend. We found the same results with less influence on overall and downward 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 describes the results for the application features. The highest log-likelihood value would be used to characterize the best-fitting distribution. For example, with a higher value, the Weibull distribution best fits 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 show that they are more likely to increase survival time. The results are consistent with the hypothesis. When a weak MACD value is reversely increasing, it shows strong buying signals. Thus, keeping a long time in a stable position and a long-term survival model in the selected upward period is possible. It lessens investor fear of risk and encourages investment in VIX indices. 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.

A significant but negative result of historical volatility (Hist20) also aligns with assumptions. The findings support the claim of (Wang and Kim, 2018 and Chun et al., 2020) that security with an increase in HV value will be riskier. Therefore, it may 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 result with significant RSIW30 and RSIS50 results indicates less impact on survival time. When the RSI indicator exceeds the threshold, the increase in the buy signal will help ease investor panic. The sell signal will cause sellers to sell the stock early, allowing VIX's upward trend to peak earlier. These results are consistent and confirm the hypotheses.

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.

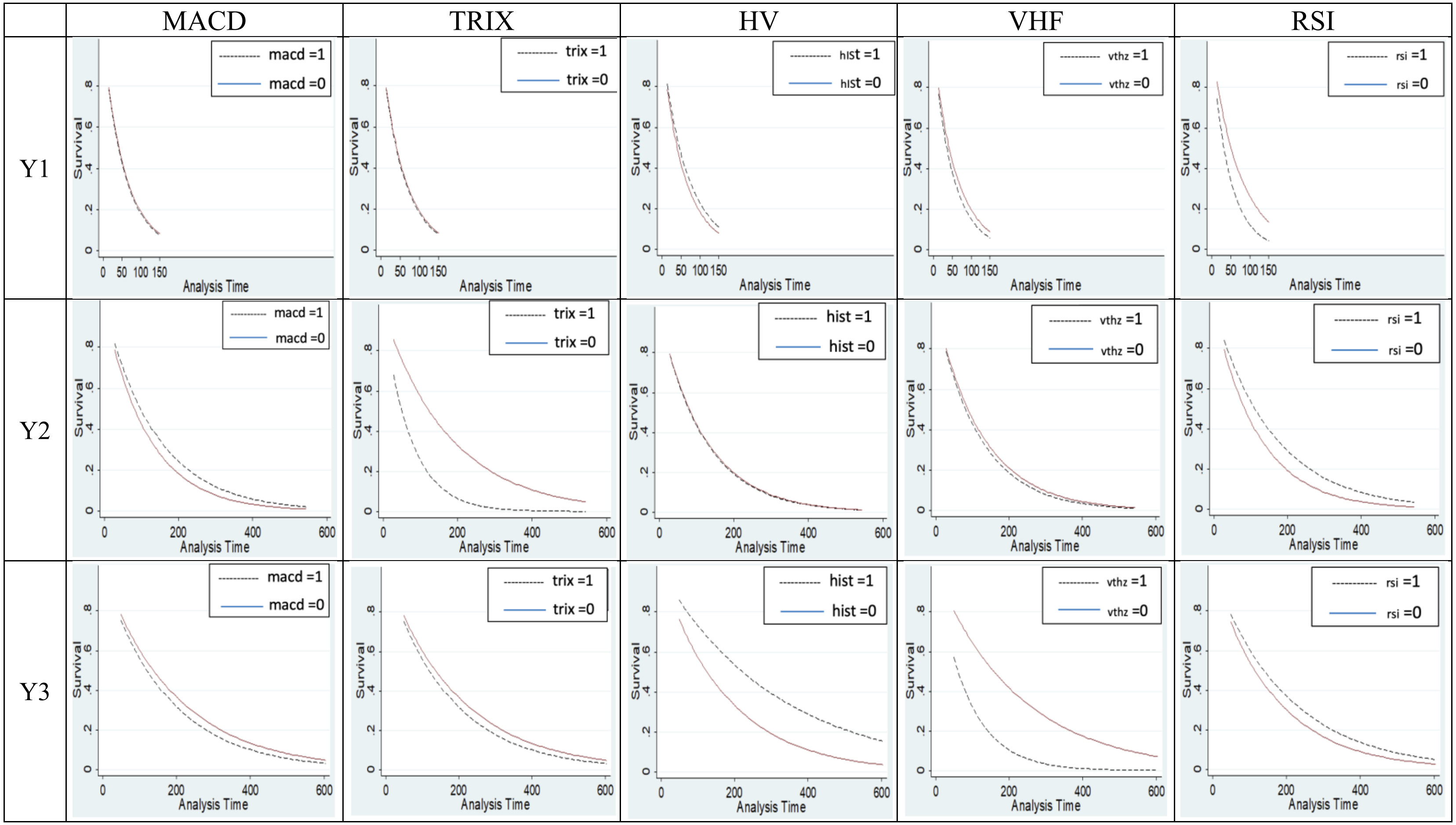

Figure 1: Upward (Y1), Downward (Y2), and Overall (Y3) spell time difference for VIX

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.

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. Two significant positive values were found for the VIX downtrend 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 initial period scheme will likely have a longer VIX spell duration. If the value of Vthz60 increases, this will alert investors to the end of strong buy indications. Therefore, it moves to a long period with a negative downward trend of prolonged risks. These findings are linked and steady with the study hypotheses. Therefore, it moves to a long period with a negative downward trend of prolonged 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. The results indicated a higher probability of a positive relationship and a higher probability of increasing VIX survival time. A positive TRIX result is an indicator of momentum between -0.1 and 0.1 indicates increasing momentum, which could likely increase survival time to release risks. We discovered most variables with the same results on overall and upwards specifications for VIX. These factors are related to 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: MACD, TRIX, HV, VHF, and RSI. These observed survival times are parallel and tight. In ascending VIX, there is no difference in the average survival time for the spell in MACD, TRIX, VHF, and HV. Given the survival rate, the higher RSI (>50) was found to have a much shorter survival time in the ascending VIX. In a decreasing trend, we found that the average TRIX shows a large difference between the positive Trix20 and the negative Trix60 in the survival spell time. As a result, there is a chance for positive TRIX to narrow the VIX pattern for a shorter survival period. Thus, investors try to sell their buying shares as soon as possible to protect their investment to avoid risk. We discovered no significant difference in spell duration for MACD, VHF, RSI, and HV in the descending VIX. The observed survival times of the four variables are virtually the same.

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 significantly impacts investors' trading behavior. Investors want to sell their buying shares as quickly as possible to protect investments against high risks. The observed survival times for all three variables, such as MACD, TRIX, and RSI, have similar survival times. The survival time for upward VIX is much shorter than for downward VIX.

7. Conclusion

The present study contributes to the study of different VIX survival functions. In this research, recurrent periods of buy and sell signals and longer and shorter periods of volatility are estimated using parametric models of shared fragility. We found that the likely value of a rising trend in VIX is much higher in the Weibull distribution than in the exponential distribution.

The data covered in the upward specification has significant values in the Weibull distribution. Where MACDN3, TrixP1, and TrixP2 are relatively high, the expected positive values indicate they are more likely to increase survival time. The study reveals that a negative with significant RSIW30 and RSIS50 results show a shorter impact on survival time.

We have investigated the spell time recurrence on the VIX index and the impact of five technical indicators, including MACD, RSI, TRIX, HV, and VHF. We discovered most 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. The results reflect a longer lifespan as a result of increased risk. It shows a higher potential to increase the survival time of VIX.

Research has found significant positive impacts on the investment behavior of traders. The positive values anticipated in MACD and TRIX involve a robust positive relationship with VIX and a longer survival time. The results show that the higher the historical volatility value, the riskier it is to invest 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. Survival times for all four variables are virtually identical for the downward trend except for TRIX.

We have found that the average HV and VHF displayed a significant difference between positive and negative survival spell time in the overall specification, substantially influencing 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, minimize investment risk, and know buying and selling signals and their major effect on technical indicators.

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