The Volatility Index: A Hedging Tool or an Object of Speculation?

Askar Koshoev
College of Business, Chung Yuan Christian University,
Taoyuan City, Taiwan.

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ABSTRACT

The volatility index, VIX, measures market expectations of one-month forward volatility. Ideally, VIX should possess a property for hedging equity portfolios against unexpected volatility. However, the nature of the index may be sentimental, as suggested by its other name, the 'fear gauge,' which questions its rationality and reliability. If the VIX has a reliable property to forecast actual one-month volatility, it may be a valuable addition to equity portfolios. On the contrary, if the VIX is not consistently related to the realized volatility but represents mostly sentiments, it should be used for speculative reasons instead of hedging. This study concluded that VIX has some forecasting power by conducting a comprehensive examination, including analysis of correlations, Granger causalities, and ARMA-GJR-GARCH model regressions. However, its instability and dependence on market conditions make it an unreliable benchmark for tradable hedging assets.

Keywords: VIX; Implied volatility; Fear gauge; GJR-GARCH; Leverage effect; Investor Sentiments.

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1 INTRODUCTION

When the market calamity was caused by the global pandemic in 2020, multiple professional analysts made various, sometimes contradictory, predictions of the future development of the stock market and the economy. However, they were worried about elevated volatility levels measured by the volatility index, or simply VIX estimated and published by the Chicago Board Options Exchange (CBOE). The Google search engine detected that the search term "VIX" was at an all-time high in March 2020 and became one of the most discussed topics. Unlike in the past, when sudden shocks caused calamity in the markets, the possibility of a global pandemic was rising daily, hinting to market participants with a prospect of an event that would trigger a volatility surge. Could they prepare and take appropriate actions to minimize the negative impact?

Investors can mitigate potential drawdowns by liquidating long positions or offsetting short positions. These strategies can originate significant costs ranging from opportunity loss to the inability to maintain short positions and reversing in inappropriate moments. Large, sophisticated, usually institutional investors can hedge their positions through various derivative instruments tailored to manage those risks. Most individual investors do not possess proper expertise or access to those over-the-counter derivatives. However, they can hedge their portfolios using exchange-traded equivalents. An investor should

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identify a suitable derivative to generate income when the market moves undesirably to implement this strategy successfully. The accurate identification of underlying is among many other essential factors determining proper derivatives for hedging purposes. Moreover, since the volatility of the US market may display spillover effects internationally (Chen and Gankhuyag, 2022), the usefulness of such a tool may be found favorable across the globe.

Only two decades ago, the volatility index was considered an innovative asset that allowed investors to predict short volatility and eventually mitigate portfolio fluctuations. VIX carries investors' opinions on one-month forward volatility, implied volatility embedded into the volatility index. Frequently VIX is addressed as the indicator of investors' concerns or the "fear gauge." Such words as fear, optimism, and pessimism may refer to sentimental or irrational investing principles. According to a vast literature on behavioral finance, an irrational investment may lead to suboptimal decision-making as the market tends to overreact to new information. As a result, the market may move in the opposite expected direction, resulting in losses by investors who make irrational decisions. On the contrary, if an investor considers all available information and the estimates suggest a high probability of a market decline in the following month, acting on this conclusion should be considered rational.

Among many questions concerning VIX and its potential to serve as a benchmark of future volatility, the primary motivation of this study is to find an answer to whether VIX is a "fear gauge" or a justified predictor of future volatility spikes. The former has a more sentimental or irrational interpretation. At the same time, the latter implies that VIX may serve as a fair predictor of future volatility and that the very investors who price call and put options on the stock index are driven mainly through rational conclusions rather than sentiments. To test whether VIX is driven by "fear" or rationally estimated probabilities, this study examines VIX's capacity to predict a one-month forward S&P 500. If the implied volatility embedded into VIX and a one-month forward realized volatility has a significant relationship, VIX is undeservedly referred to as the "fear gauge." On the other hand, the opposite will verify the label of VIX and signal that the volatility index carries mostly sentimental information with low predictive power over future conditions on the stock market.

This study offers a few contributions to the existing literature in portfolio management and behavioral finance. Firstly, it broadens the coverage period and comprises more events and phases of economic cycles than preceding research. Most existing literature covers short periods from the relatively recent inception of tradable volatility instruments in the mid-2000s until the banking crisis of 2008. In addition, the early instruments that made VIX tradable belong to derivative markets, which are not accessible to usual investors. Popular exchange-traded products with large trading volumes, such as VXX or VXZ, were introduced only after the crisis. The study sample covers all major and minor events with slumps and surges in the past 30 years, including the Asian financial crisis, the internet bubble, the banking crisis, the European debt crisis, and the beginning stage of the market uncertainty caused by the Covid-19 pandemic. Another contribution is the comprehensive approach implemented in this study.

The remaining article is designed as follows. Findings of the related studies are provided in Section 2. Section 3 demonstrates the methodology that has been employed in this

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study. The outcomes and discussion are situated in Section 4. Finally, section 5 concludes the findings of this study.

2 LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Compared to traditional asset classes such as equities, fixed-income securities, and commodities, literature on VIX and its tradable derivatives is still relatively novel and considerably homogeneous. Historical facts of the index development and classification of derivatives on the index are extensively described by Alexander *et al.* (2015).

Earlier research articles suggest that VIX derivatives are valuable assets for diversification purposes. A negative correlation of VIX with broad market equity indices makes it one of the asset classes suitable for diversifying equity portfolios, especially in times of market calamity (Bekaert and Wu, 2000). Alexander *et al.* (2016) point out that portfolios with VIX components significantly outperformed the S&P 500 long-only portfolios during the financial crisis of 2008. VIX had secured positive returns for the portfolios when the S&P 500 index plummeted, but it has also significantly improved the Sharpe ratio, shifting the efficient frontier upward. The advantage of VIX as a diversification tool that creates a serious hedge against market volatility suggests that every investor holding equities in their portfolios should take a long position in this innovative asset. The problem is that VIX is not available for trading, while its derivatives possess significant deficiencies, which makes them less attractive from a long-term investing perspective.

Multiple researchers claim that VIX, especially its ETPs, is not straightforward. Some deceptions maybe not be so apparent for unsophisticated investors. These studies have concluded that, although specifics of these ETPs give a possibility for profitable short-term trading strategies (Bordonado *et al.* 2017) as well as for the short-term hedge in the times surrounding severe market fluctuations (Alexander *et al.*, 2016), these products are not appropriate for the diversification on the long-term because of continues value erosion, the so-called “Contango trap” (Alexander & Korovilas, 2013; Alexander *et al.*, 2016; Whaley, 2013). Bordonado *et al.* (2017) elaborate that the costs inflicted by continuously rolling these futures contracts create a downside push making them a burden for portfolios during market stability. Alexander *et al.* (2016) assert that VIX-related instruments provide diversification benefits only during crisis periods. At other times, traditional portfolios of equity and bonds are better off without volatility instruments.

Similarly, Bordonado *et al.* (2017) recommend that buying VXX would be justified only in times of backwardation, which occurs less frequently than contango, making it unsuitable for long-term asset allocation decisions but profitable for short-term trading strategies. Alexander *et al.* (2015) have estimated that in five years, from its inception in 2009 to 2014, VXX’s value has declined by more than 90% and continued its negative trend. Whaley (2013) analyzed a broad spectrum of short-term VIX-related products and discovered significant losses by investors holding these volatility-linked products. Interestingly, even those investors who kept the short position in those products had negative returns in the long run. In their study, Bordonado *et al.* (2017) support Whaley’s assertion by taking a hypothetical long position on VXX in January 2009 and holding it to April 2014; the position would cost 99.5% of the investments.

The constant value erosion in times of absence of extreme volatility and tracking error exhibited by VIX ETPs make their use debatable. The studies on the comovements of

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VIX and VIX ETPs investigate their reaction to the news and have established a non-linear relationship depending on the data frequency. The ultra-short-term intraday samples showed close to zero correlations (Frijns *et al.*, 2016), while daily samples indicated high correlations (Basta & Molnar, 2019; Zhang *et al.*, 2010). Basta & Molnar (2019) analyzed monthly data and revealed that VIX outpaces VXX. Although this fact could create a trading opportunity, in their further analysis, they have established that VIX cannot serve as a reliable predictor of VXX.

While the abovementioned may shy out investors from using VIX ETPs for diversification purposes, few research studies suggest that not all VIX ETPs are the same, and the term structure of these ETPs may play a key role in their value erosion properties in times when a market is in contango. ETPs that hold short-term contracts on VIX roll them more frequently and, as a result, bear more costs than their longer-term alternatives. Hill (2013) demonstrates that VIX's mid-term futures are suitable for diversification in the long term. Guobuzaite & Martellini (2012) confirm it using a sample of European markets. Furthermore, the short-term hedge that VIX ETPs may offer is possibly what most investors need. Dew-Becker *et al.* (2017) found that an average investor is mainly concerned with a hedge against short-term shocks, not fluctuations in the distant future.

As the volatility of stock returns is considered to reflect risk, return volatility is one of the significant factors in the investment decision process. One of the approaches to forecast volatility is by extracting implied volatility (IV) from options spreads that reflect market expectations about future volatilities. Multiple researchers using various methodologies yielded inconclusive outcomes about IV and volatility predictions. Becker *et al.* (2007) suggest that VIX does not contain incremental information to improve the model's predictive power for volatility forecasting. Two years later, Becker *et al.* (2009) adjusted their model and came to an opposite conclusion. Finally, Qiao *et al.* (2019) assert that they could improve volatility predictions of the Chinese CSI 300 stock index by analysis of iVX, a local alternative to VIX.

Similarly, Pan *et al.* (2019), employing the GARCH model, found that VIX can predict stock volatility both in-sample and out-of-sample. On the other hand, Bekaert and Hoerova (2014) assert that the relationship between IV in VIX and realized volatilities is not straightforward because VIX embeds a risk premium and, for that reason, cannot be treated as an unbiased predictor of future realized volatility. Therefore, they attempted to forecast the monthly realized variance of the S&P 500 by segregating the risk-neutral expected stock market variance into two constituents: variance premium and conditional variance. They find that the variance premium better predicts stock returns, while the conditional variance has higher predictive power for financial instability.

By following the suggestion of Becker *et al.* (2007), as well as considering other studies and their findings mentioned above, the following hypothesis was formed:

Because stock returns cannot be forecasted with high precision and it is unfeasible to time a market calamity precisely, its beginning and ending points, VIX can only gauge current sentiments, and it has no consistent predictive power over a one-month realized volatility.

In other words, it is presumed that IV embedded in VIX has primarily sentimental character. However, similar to other sentiments on the market, it may be driven by the momentum of prevailing the moment market sentiments and cannot last long.

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3 DATA SOURCE AND METHODOLOGY

VIX itself is an index and, therefore, cannot be directly traded. However, it can be used as an underlying asset for various financial derivatives, offering exposure to the volatility index. While over-the-counter derivative instruments such as swaps and forwards can be tailored with specific properties demanded by the parties, they are used mainly by sophisticated investors who have sufficient expertise, high trading volumes, and access to the network of dealers who can serve as a counterparty. For those investors who do not possess these capacities, exchange-traded products are available, including exchange-traded funds (ETFs) and exchange-traded notes (ETNs). Both of these categories are somewhat similar in their application to investors. They represent financial derivative portfolios, including exchange-traded futures and options intended to offer exposure to the VIX with a specific time horizon. These exchange-traded products (ETPs) significantly broaden an investable universe for various investors who do not have direct access to the abovementioned derivatives.

Although ETFs and ETNs may serve for hedging and speculation purposes, they have one major limitation—their values erode in the long term. The reason why these instruments cannot serve as traditional buy-and-hold assets is the process of their formation and operation. They are formed by purchasing financial derivatives, such as futures or options on the VIX index with various lengths, depending on the strategy of a particular ETF or ETN, and rolling them over from period to period. This fact causes the value of the assets to erode with time. Moreover, the erosion process is magnified if the ETFs or ETNs use leverage to extend the exposure to VIX returns.

This study employs a range of available data at daily frequency, from January 2, 1990, to May 7, 2020, making the period lengths slightly exceed 30 years. Due to the value-eroding nature of these ETNs, the original VXX and VXZ got fully exhausted and delisted in January 2019. However, because these assets were popular and actively traded, they were shortly replaced by their successors with identical tickers and properties. In this study, the time series of these two generations were merged to represent one hypothetical ETN that was never retired. Time series data for the first-generation ETNs was collected in investing.com; for the second generation in finance.yahoo.com.

Before measuring volatility expectations by VIX, a couple of issues should be addressed. The first issue concerns VIX levels and signals that VIX sends. Should VIX values be treated as absolute or relative and compared with their historical values? For example, consider a hypothetical market where in the first year, the volatility index was averaged around the value of 10. The index rose to 15 the following year and has held ever since. Does it mean investors are constantly pessimistic about future volatility, or is it a new equilibrium? Another issue concerns the noise that daily data may carry. If one day, VIX is at 30 and another 25, and when it reaches 30 on the third day, does it mean that market participants, in general, are changing their forecasts daily, or the fluctuations of VIX are a result of noise that day-traders cause? To address these potential problems, the study uses deviations from fluctuating 'normal' value that derives from the following equation:

$$SVIX = VIX - VIXMA \tag{1}$$

where *SVIX* is an excess of *VIX* over the 200-day moving average, *VIXMA*.

ISSN: 2304-1013 (Online); 2304-1269 (CDROM); 2414-6722 (Print)

Table 1. The variables and their corresponding sources

Variable	Definition	Source	Frequency
VIX	CBOE volatility index®	The Chicago Board Options Exchange	Daily
S&P	Returns on the S&P 500® index	Yahoo! Finance	Daily
VXX	ETN tracking S&P 500® the VIX Short-Term Futures Index	Yahoo! Finance; Investing.com	Daily
VXZ	ETN tracking S&P 500® the VIX Mid-Term Futures Index	Yahoo! Finance; Investing.com	Daily
TBIL	Secondary Market Rate on 3-Month Treasury Bills	Federal Reserve Economic Data	Daily
UMP	Unemployment Rate	Federal Reserve Economic Data	Monthly
INF	Consumer Price Index	Federal Reserve Economic Data	Monthly
CCI	Consumer Confidence Index	University of Michigan	Monthly
BCI	Business Confidence Index	Organization for Economic Co-operation and Development	Monthly

Daily implies trading days only. Assuming a five-trading day week, or approximately 22 days a month.

A 200-day moving average, a popular range of moving averages employed by technical analysts, was chosen to serve as a benchmark for a normal range at a particular time, and deviation from which will signal unusual for that time volatility. For example, if VIX stays at the value of 10 for some time and then suddenly rises to 20, it should signal to market participants that an increase in volatility is on the horizon, and they should make appropriate preparations. On the other extreme, during a market calamity, when the average VIX stands at 35 and then suddenly drops to the same value of 20, this time, the signal is the opposite. If VIX suddenly descends in a period characterized as turbulent, it may signal that investors predict market stabilization. Vice versa, at the first sign of future calamity on the market, VIX should rise above the average range considered normal.

Table 2. Descriptive Statistics

	SP22	VIX	VIXMA	SVIX
Mean	0.764	19.22	19.15	0.065
Median	1.182	17.05	17.14	-0.885
Maximum	25.05	82.69	44.89	65.32
Minimum	-33.67	9.140	10.78	-20.90
Std. Dev.	4.592	8.155	6.233	6.165
Skewness	-0.899	2.313	1.270	2.738
Kurtosis	8.209	11.80	5.157	20.18
Observations	7437			

SP22 represents returns (%) on the index portfolio held for one month or 22-trading days, VIX is a raw series of CBOE volatility index, VIXMA is a 200-day moving average of VIX, and SVIX denotes volatility sentiments or forecasts over one-month forward volatility that is the difference of VIX and VIXMA.

3.1 Descriptive Statistics

The balanced sample contains daily observations for almost 30 years with 7647 observations. Table 2 demonstrates the descriptive statistics of the significant variables used in this study. It shows that the distribution of observations for all series is non-normal with large kurtosis values, implying leptokurtic distribution with fat tails and extreme values. In addition, the market return series is negatively skewed, meaning that the sample

ISSN: 2304-1013 (Online); 2304-1269 (CDROM); 2414-6722 (Print)

contains more observations with positive returns but lesser values than observations with negative returns. The opposite is true for the volatility series, implying that the sample includes extensive observations that can be observed during a market calamity.

It is essential to set the limits for this normality range to establish significant deviations from a subjective range of values considered 'normal.' For example, *VIX* reached its maximum of 82.69 on March 16, 2020; the minimum value was recorded on November 3, 2017. The mean and median for *VIX* series are 19.32 and 17.27, respectively. Although this is somewhat distant for the series values imply skewed distribution, further visual analysis of its histogram, shown in Figure 1, confirms that the series is bound at zero. At the same time, most of the observations range from 10 to 30.

A comparison of descriptive statistics for *VIX*, *VIXMA*, and *SVIX* and their histograms depicted in Figure 1 concludes that *SVIX* can help interpret market signals of future volatility. In contrast to *VIX*, readings of the *SVIX* are more straightforward. When the values of *SVIX* are positive, it signals an expected rise in volatility and vice versa for negative values. The distribution of *VIX* demonstrated in Figure 1 suggests that *VIX* tends to decline slowly but rapidly surges in times of turbulence.

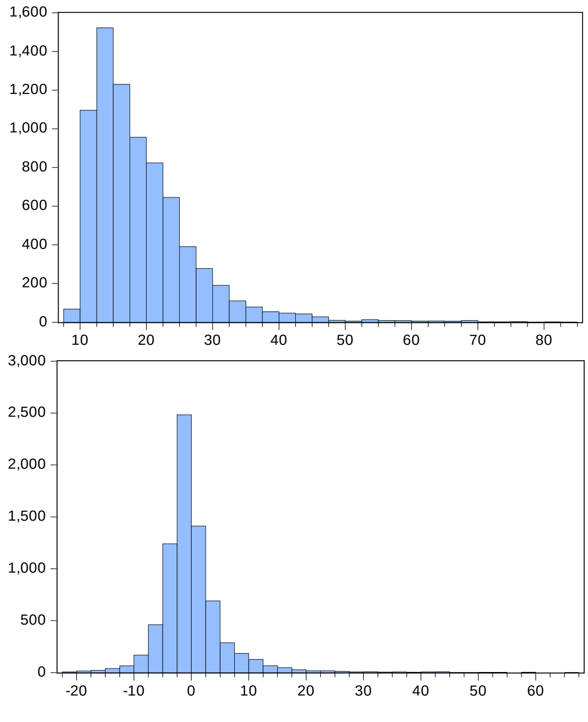

***FIGURE 1**. DISTRIBUTION OF VIX (LEFT) AND SVIX (RIGHT) OBSERVATIONS.*

Further analysis of the line graphs of these variables shown in Figure 2 suggests that *VIXMA* may be exposed to heteroscedasticity issues. Nevertheless, *SVIX*, similar to the *SP22*, displays signs of conditional heteroscedasticity, distinctive in 2008 and 2020.

ISSN: 2304-1013 (Online); 2304-1269 (CDROM); 2414-6722 (Print)

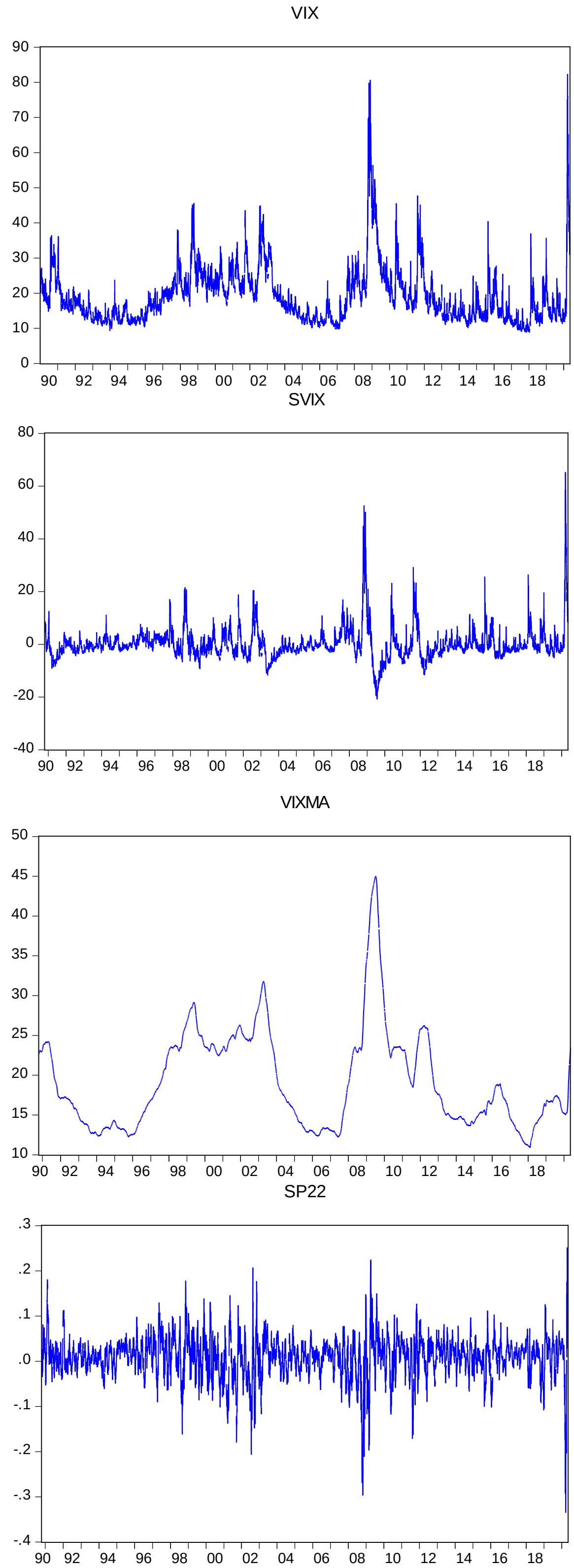

***FIGURE 2**. LINE GRAPHS FOR VIX (TOP LEFT), ITS 200-DAY MOVING AVERAGE (BOTTOM LEFT), THEIR DIFFERENCE (TOP RIGHT), AND RETURNS ON A MONTHLY PORTFOLIO OF THE S&P 500 INDEX (BOTTOM RIGHT).*

ISSN: 2304-1013 (Online); 2304-1269 (CDROM); 2414-6722 (Print)

3.2 Regression Model Specification

All variables were tested for the unit root by the augmented Dickey-Fuller test. The results confirm stationarity for all. The Breusch-Godfrey Lagrange multiplier (LM) test suggests a serial correlation. In this situation, the commonly employed model is an autoregressive moving average (ARMA) model that can solve the autocorrelation issue. The ARMA model was chosen with the AR and MA processes optimized according to the lowest Akaike information criterion. A further test for the effect of autoregressive conditional heteroscedasticity (ARCH effect) rejects the null hypothesis of the "No ARCH effect." This issue may arise due to the non-constant variance of the residual term, for example, in times of market turmoil when the residuals are expected to be elevated above normal levels. This issue can be solved by the generalized autoregressive conditional heteroscedasticity (GARCH) family of models.

The GJR-GARCH model by Glosten *et al.* (1993) extends the original GARCH model of Engle (1982) by allowing the conditional variance to depend upon the sign of the lagged innovations by adding a binary variable into the mean-variance equation that takes a value of one when the news is undesirable and zero otherwise. This additional component detects a volatility asymmetry, known as the leverage effect. When significant and negative, the coefficient of the binary variable signifies an asymmetric impact of bad and good news on the volatility index.

Modifying the original ARMA-GJR-GARCH(p,q) model to accommodate the regressors of interest, particularly the lagged term of VIX, the model can be expressed as follows:

$$SP22_t = c + \sum_{i=1}^{m} \varphi_i r_{t-i} + \sum_{j=1}^{n} \theta_j \varepsilon_{t-j} + \varepsilon_t \; ; \;\; \varepsilon_t | \psi_{t-1} \sim N(0, h_t) \qquad (2)$$

where $SP22_t$ is the series of returns on the portfolio of the S&P 500 index held for 22 trading days (1 month); φ_i is the parameter of the autoregressive component of order m; θ_j is parameters of the moving average component of order n; c is a constant; $\psi_{t-1}$is the set of all information up to time t; ε_t is a white noise disturbance term that follows the GARCH(p;q) process:

$$h_t^2 = \alpha_0 + \sum_{i=1}^{q} (a_i + \gamma_i D_{t-i}) \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j}^2 + \lambda SVIX_{t-22} \qquad (3)$$

where binary variable D_{t-i} takes the value of 1 if $\varepsilon_{t-i} < 0$ and 0 otherwise; γ_i is the coefficient of the D_{t-i}; when significant and positive, it signals that the leverage effect exists; $SVIX_{t-22}$is a one-month lag of the VIX index over its 200-day average; m and n orders of the ARMA, as well as p and q, the orders of the GJR-GARCH model, are non-negative integers. The exact specification of ARMA-GJR-GARCH models is defined by the Akaike information criteria (AIC) on the 3x3 grid, where the one with the lowest value is prioritized.

4 EMPIRICAL RESULTS AND DISCUSSION

As mentioned in Section 2, the study analyzes from multiple perspectives. Firstly, the correlation between VIX and other rational and sentimental factors is analyzed. It may give a general idea of whether *VIX* has substantial connections with the factors that affect the economy in general or those referred to as sentiments. In addition, Granger causality tests may expose cause-effect relationships between them. The step further involves identifying and analyzing *VIX* in extreme conditions during tranquility and turbulence.

ISSN: 2304-1013 (Online); 2304-1269 (CDROM); 2414-6722 (Print)

The final step comprises regression output analysis that involves returns on the market portfolio and the volatility index.

4.1 Correlations and Causality

The research begins examining *VIX* by establishing a linkage to various factors attributed to rational and sentimental factors. Table 3 demonstrates correlations of *VIX*, including its different lags, with multiple market indicators and returns on VIX ETPs.

The variables of interest are given in the first column, while each following column represents correlation coefficients of various lagged terms of *VIX*. These periods are chosen as *VIX* is expected to predict one-month forward volatility for which a 22-day lag was determined. The fifth column shows correlations of the current *VIX* with other variables. In contrast, the last three columns are expected to reveal connections lagged values of the variables with the forward *VIX*, signaling that they may be forming factors of *VIX*.

Table 3. Correlations of various VIX lags with the other factors

Variables	VIX_{t-22}	VIX_{t-10}	VIX_{t-5}	VIX_t	VIX_{t+5}	VIX_{t+10}	VIX_{t+22}
TBIL	-0.0443	-0.0416	-0.0371	-0.0325	-0.0246	-0.0238	-0.0172
UMP	-0.4841	-0.4935	-0.4996	-0.5048	-0.5084	-0.5117	-0.5201
INF	-0.1035	-0.0731	-0.0586	-0.0288	-0.0243	-0.0063	0.0025
CCI	0.4624	0.4469	0.4500	0.4528	0.4497	0.4487	0.4347
BCI	-0.2739	-0.2674	-0.2603	-0.2550	-0.2456	-0.2382	-0.2180
VXX	-0.0233	-0.0295	-0.0274	0.0798	0.0572	0.0519	0.0490
VXZ	-0.0219	0.0049	-0.0083	0.0645	0.0457	0.0486	0.0166

A set of macroeconomic factors comprises a proxy for the risk-free rate, unemployment, and inflation, denoted as *TBIL*, *UMP*, and *INF*, respectively. *TBIL* is a proxy for the “flight-to-safety” phenomenon when investors prefer to keep their funds in relatively safe assets such as the US Treasury bills in times of high uncertainty. *TBIL* measures yields on the 3-month US government securities. Negative correlation coefficients with the highest absolute values between *TBIL* and one-month-lagged *VIX* signal that VIX’s linkage to the flight-to-safety weakens over time. The inverse relation implies that the expectation of high fluctuations is correlated with the flight-to-safety phenomenon as the yields drop when demand for these instruments rises. *UMP* is anticipated to correlate with future uncertainty or volatility. For example, corporations would lay off employees in preparation for a recession or pause hiring until the market stabilizes.

On the other hand, if the concerns about future difficulties are a product of irrational sentiments, then the correlation may turn negative. A relatively strong negative correlation that gets even stronger with time requires further investigation a linkage between these two variables. Regression models that control for other essential factors that may distort a true relationship between these factors may shed more light. Another fundamental macroeconomic indicator, inflation (*INF*), shows a weakening connection with *VIX*. The results imply a negative correlation between price levels and implied stock volatility. As with the previous correlation pair, a connection between *VIX* and the inflation rate should be appropriately investigated before making any conclusions.

The following two variables, *CCI* and *BCI*, represent consumer sentiments of households and businesses, respectively. The University of Michigan estimates the former index by

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the Organization for Economic Co-operation and Development. As the correlation coefficients suggest, households have opposite opinions from the traders and investors regarding uncertainty in the market. Alternatively, *based on the industrial sector's production levels*, *BCI* involves professionals who do not share households' optimism about future perspectives despite high *VIX* levels and reduce their production volumes when expected volatility is high. At the same time, low expected volatility encourages them to expand their operations.

The final two rows of Table 3 demonstrate correlations with returns on the pair of the most popular tradable VIX-linked instruments. VXX is an ETN that offers exposure to VIX with the implied volatility of the S&P 500 over the following month. Similarly, the VXZ reflects the implied volatility over the following five months. These assets draw particular interest because of their nature. To maximize their returns, traders should acquire these ETNs before VIX rises. In other words, considering a stock market as a leading indicator, *VIX* is expected to predict the volatility of the S&P 500, while the ETNs should predict future *VIX*. Because all three series (*VIX*, *VXX*, and *VXZ*) are high-frequency series compared to the other factors in the list, the correlation coefficients of the lagged terms may not be as informative as their peers. However, the correlation rises as the periods coincide, aligning with expectations. Lower correlation coefficients with the lagged and future terms than the current term support this.

Moreover, most of the coefficients with the lagged terms are negative. However, they turn positive for the current and future terms. It may imply the sentimental component in their pricing. Although both correlation coefficients are positive, as expected, their values are much lower than one could expect from a derivative and its underlying. Correlation values of less than 10% imply that these instruments are far from perfect tracking tools and carry significant tracking errors.

Table 4. Pairwise Granger Causality Tests

Pair	Observations	F-Statistics	Prob.
VIX -> TBIL	5,954	14.01	0.000
TBIL -> VIX		3.743	0.002
VIX -> UMP	6,338	14.32	0.000
UMP -> VIX		3.798	0.002
VIX -> INF	6,333	6.015	0.000
INF -> VIX		1.216	0.299
VIX -> CCI	2,733	1.444	0.205
CCI -> VIX		1.024	0.402
VIX -> BCI	6,338	3.519	0.004
BCI -> VIX		3.089	0.009
VXX -> VIX	2,238	0.757	0.581
VIX -> VXX		2.723	0.019
VXZ -> VIX	2,202	0.264	0.933
VIX -> VXZ		0.673	0.644
VXZ -> VXX	2,202	0.140	0.983
VXX -> VXZ		248.8	0.000

"Granger cause" is replaced by "->."

Table 4 represents the output of the Granger causality test, including five lags. The test's null hypothesis is that "A" does not Granger cause "B." *TBIL*, *UMP*, and *BCI* are bidirectional, Granger causing *VIX* and being caused by it. *VIX* causes inflation but not the opposite. There is no causality between *CCI* and *VIX*. As anticipated, *VIX* causes

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returns on *VXX (at α=5%)*, while *VXX* does not cause *VIX*. Another interesting fact is that *VIX* does not cause *VXZ*, but *VXX* does, creating a chain of cause-effect relationships. Changes in *VIX* set the course for changes in *VXX*, which in turn causes changes in *VXZ*.

4.2 Tranquil and Turbulent Periods

Figure 3 depicts VIX and the S&P 500 indices trends from February 1, 1990, until May 7, 2020. The volatility index is ascribed to the left axis, while the stock index is to the right. The dashed lines represent high volatility threshold at the top and low volatility at the bottom. The pattern on the chart gives an impression that the “fear gauge” nickname is justified as the volatility spikes coincide with significant calamities in the market. Since 1995, the volatility has been rising hand in hand with market capitalization.

The most visually evident volatility surges occurred during the Asian debt crisis and the default of the Russian government in the late 90s, shortly followed by the collapse of the dot-com bubble, the global financial crisis in 2008, and the European debt crisis of the first half of the 10s. Although, after 2010, the consequences of subprime mortgage crises receded, several short-term spikes of volatility coincided with slumps in the equity index. Spikes that reached values of 45 have been observed at least six times, while the highest spikes of VIX that surpassed 80 were observed twice during the financial crisis of 2008 and the global pandemic in March of 2020. This chart reveals that *VIX* and S&P do not consistently offset each other. There were times when they moved in the same direction and times when they moved in opposite directions.

The sample was divided into ten quantiles to classify the extreme values of *VIX*. The first and tenth deciles are assumed to represent extreme market conditions delimited by the dashed line in Figure 3.

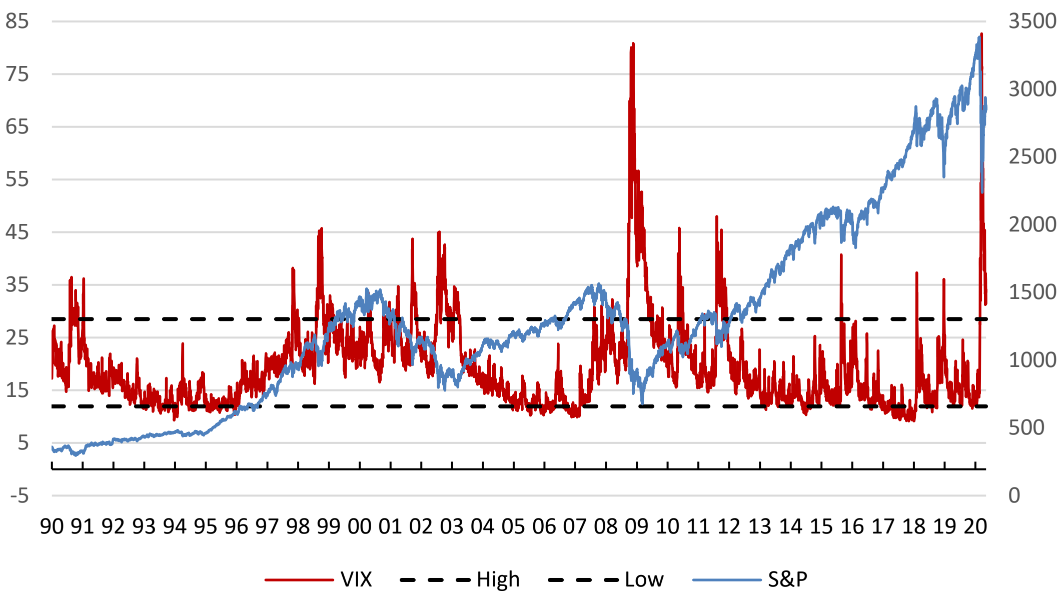

FIGURE 3*. VIX AND S&P 500*

Table 5 provides more information on the deciles and their corresponding distribution statistics. Besides mean, maximum, and minimum for each decile, the columns include average returns on the stock index and standard deviations. The statistics suggest that low volatility creates a favorable environment in the market with the highest returns, while

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high fluctuations result in the opposite. Interestingly, the middle deciles do not expressively follow this pattern. Standard deviations suggest that during tranquil periods there is a 95% probability that the daily returns on equities may fluctuate by 0.84% (=2*0.42%), while fluctuations during turbulent periods are as high as 5% (=2*2.51%) in each direction.

Table 5. Deciles of VIX and S&P

Ranges of VIX	Mean	Max	Min.	S&P(r)	S&P(σ)	Obs.
< 11.94	11.07	11.94	9.140	0.184	0.420	763
[11.94, 13.07)	12.47	13.01	11.95	0.129	0.479	759
[13.07, 14.30)	13.60	14.26	13.02	0.073	0.560	771
[14.30, 15.80)	15.00	15.75	14.27	0.114	0.693	766
[15.80, 17.29)	16.46	17.26	15.76	0.039	0.763	764
[17.29, 19.30)	18.21	19.25	17.27	0.047	0.870	765
[19.30, 20.70)	20.26	21.31	19.26	0.052	1.019	763
[20.70, 24.05)	22.62	24.11	21.32	0.039	1.121	767
[24.05, 28.50)	26.03	28.68	24.12	-0.119	1.371	763
>= 28.50	36.32	82.69	28.69	-0.219	2.511	766
All	**18.04**	**82.69**	**9.140**	**3.400**	**114.6**	**7647**

This table demonstrates the deciles of VIX. The first column specifies the cutoff values of VIX for each decile. The second, third, and fourth columns show mean, maximum, and minimum values VIX for each corresponding decile. For readability reasons, values for average daily returns on the S&P index – S&P(r), and their standard deviations – S&P(σ), are specified in percentage units. Finally, the last column states the number of observations classified under each decile.

Instances of implied market volatility within the range of normality comprise 80 percent or 6095 observations out of 7647. Periods of extremely low volatility add 789 observations, with the range of the *VIX* index from 9.14 to 11.9, while the periods of extremely elevated volatility comprise 763 observations with a range of 28.5 to 82.69. The longest streak of extremely high (low) volatility is 184 (193) trading days, which has been recorded for the period starting from September 15, 2008, to June 8, 2009 (April 24, 2017, to January 26, 2018). On average, streaks of high volatility remain for 62 days, and a streak of low volatility for 32 days. In the current research study, the index has a long unfinished streak of high volatility starting on February 24, 2020.

Table 6. Tranquil and Turbulent Periods.

Beginning Date	Ending Date	Extreme Conditions	Duration (in days)	VIX_{t-22}	σ^{VIX}_{t-22}	$SVIX_{t-22}$	σ^{SVIX}_{t-22}	S&P	$\sigma^{S\&P}$
12/13/93	02/03/94	Tranquility	38	12.511	1.818	-0.223	-0.151	0.094	0.420
06/13/05	08/03/05	Tranquility	37	12.585	1.329	-1.033	-1.317	0.105	0.535
11/17/05	01/17/06	Tranquility	40	12.741	1.636	-0.235	-0.764	0.104	0.539
10/04/06	02/26/07	Tranquility	98	11.271	0.822	-1.870	-2.014	0.086	0.454
04/24/17	01/26/18	Tranquility	193	10.959	1.486	-1.119	-1.360	0.105	0.433
10/27/97	11/26/97	Turbulence	23	21.788	2.354	1.027	0.875	0.069	2.175
08/10/98	10/29/98	Turbulence	58	30.559	7.997	7.112	7.836	0.014	2.002
09/06/01	11/12/01	Turbulence	44	28.671	7.067	3.825	2.964	-0.014	1.627
07/09/02	11/14/02	Turbulence	92	33.660	5.558	8.796	9.692	-0.061	2.185
01/24/03	03/25/03	Turbulence	42	29.210	3.450	-0.080	0.390	-0.022	1.588
09/15/08	06/08/09	Turbulence	184	45.267	13.65	12.30	8.901	-0.104	3.243
08/04/11	11/29/11	Turbulence	82	31.420	8.104	11.04	11.74	-0.041	2.184
02/27/20	05/07/20	Turbulence	50	38.568	21.91	21.92	22.45	-0.066	4.298

The first and second columns provide the beginning and end of extreme volatility periods. The third column defines the extreme condition. The number of days for each period is shown in the fourth column. Means and standard deviations

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for VIX, SVIX, and daily returns on the S&P 500 are provided in the consecutive columns. Returns on the S&P 500 and standard deviations are presented in percentages.

Table 6 lists the streaks of extreme volatility periods since VIX's inception. In this study, extreme volatility had to hold for at least one month to be considered a streak. They were combined when two or more days of non-extreme conditions separated two streaks. While a complete comparative analysis of means for these sub-samples is not definitive without further examination, a surface analysis may still provide some insight.

The upper section of the table, separated by a double line, lists periods of tranquility in chronological order. A look at the declining values of VIX predictions for tranquil periods may signal that the precision of predicting tranquil periods rises with time, but further analysis shows that the cause of lower means of VIX is the extension in the duration of these periods, which leads to greater stability on the market. The longer the streak lasts, the lower the VIX values get. As a result, the values for more recent periods are dragged down. All means of *SVIX* are negative, implying that VIX has some predictive power, but comparing standard deviations with returns on the S&P 500 does not draw a clear pattern. It may support the assumption that VIX is not consistent or normalized for the whole series but depends on the perception of normal value for a particular time.

A comparison of tranquil and turbulent periods reveals that prolonged turbulence is more likely than tranquility, with eight instances against five. However, on average, they are shorter in duration. The mean values of *VIX* at periods of turbulence have some connection to the duration of the streaks. On the contrary, *SVIX* values are diverse and follow no obvious pattern implying that *VIX* carries a significant portion of sentiments during market calamity and has a weak relationship with the returns' volatility provided in the last column.

It is noticeable that the duration of the extreme periods and the ranges of *VIX* and *SVIX* become more prolonged over time. It may be caused by a growing market capacity to withstand more extended periods without significant corrections or rising attention to stock trading and easing access to the market for individual participants who, compared to institutional investors, are assumed to rely more on sentiments.

Standard deviations of daily returns on the S&P 500 suggest that with 95% confidence, during tranquil periods, returns may fluctuate at one percent from their mean, and the most recent turbulent period brought daily fluctuation that led returns to deviate by as much as 8.5 percent from their mean.

4.3 VIX and S&P 500 Volatility

This subsection proceeds with the regression analysis to further examine the relationship between VIX and realized volatility. The outcomes of the models are demonstrated in Table 7. The original mean equation regresses returns on S&P 500 (see equation 2). As a relationship between stock returns and VIX is out of the scope of this study, only the results of the mean-variance equation are shown.

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Table 7. Predictive Power of VIX and SVIX

Variables \ Models	1	2	3	4
ARMA	3;2	3;2	3;2	3;2
GARCH	2;3	2;3	2;3	2;3
Leverage effect (γ_i)	0.0822 (0.0000)	0.1144 (0.000)	0.0227 (0.2310)	0.0779 (0.0364)
$SVIX_{t-22}$	0.000000 (0.2697)		0.000003 (0.0000)	
$SVIX_{t-22}$*HV			0.000005 (0.0000)	
$SVIX_{t-22}$*LV			0.000015 (0.0000)	
VIX_{t-22}		0.000001 (0.0000)		0.000001 (0.0000)
VIX_{t-22}*HV				0.000015 (0.0000)
VIX_{t-22}*LV				-0.000002 (0.0000)
Adj. R^2	0.922	0.922	0.881	0.887
Observations	7, 425	7, 425	7,425	7,425
AIC	-6.243	-6.252	-5.792	-5.480
ARCH-LM	0.518	0.652	0.115	0.882

This table includes an output for the mean-variance equation of four ARMA-GJR-GARCH models. The first and second models consider only one-month-lagged terms of SVIX and VIX variables. Models 3 and 4 include binary variables for turbulent (HV) and tranquil periods (LV). Specifications of ARMA and GARCH orders are shown in the second and third rows. P-values are denoted in parentheses. In addition, the adjusted r-squared, the number of observations, and Akaike information criteria are provided. Results of the ARCH-LM tests, with p-values provided in the final row, confirm an absence of the ARCH effect for all models.

This model examines the effects of a one-month lag of *SVIX* or *VIX* on the realized volatility of the S&P 500. The first model results suggest that *SVIX* does not affect market volatility. The outcomes of the second model, however, are different. Although very slim, VIX has a significant association with realized volatility. This difference in significance leads to a conclusion that while *VIX* has a connection with forward volatility, VIX's short-term swings are driven by irrational or speculative sentiments. Rational investors should not extract information from the daily changes of *VIX* but rather look at the general level. Coefficient of the leverage term (γ_i) is significant and positive, which exposes the tendency to asymmetric volatility or overreaction to bad news.

Binary variables *LV* and *HV* are included in Models 3 and 4 to control for periods of tranquility and turbulence by taking a value of 1 if a period is characterized by extremely low or high volatility, respectively, and 0 otherwise. If significant, they affect predicting power of *SVIX* or *VIX* during these extreme periods by adding or reducing volatility. If insignificant, *SVIX* or *VIX* are insensitive to these extremes, and their predictive powers are steady despite these extreme conditions.

The regression outcome confirms that *SVIX* and *VIX* have different effects during tranquility or turmoil. Adding the interaction terms caused *SVIX* significance, although the goodness-of-fit has slightly declined from 92% to 88%. All positive and significant, three terms of interest in Model 3 provide some information about the effects under extreme conditions on *SVIX*. First, the coefficient for the tranquil periods is three times larger than for the turbulence period and five times larger than for the non-extreme periods. These distinctions may imply that awareness increases during these extreme periods, while it is maximum when the market seems calm and stable. Finally, the

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leverage effect term has an insignificant coefficient, meaning that this model cannot confirm the asymmetric volatility of the index returns.

The outcomes of Model 4 are relatively distinct from Model 3. The segregation of periods with extreme values seems not to benefit the forecasting capability of *VIX* under non-extreme conditions. Moreover, *VIX* has an inverse relationship with the forward volatility during market tranquility compared with other periods. It implies that *VIX* is driven by irrational sentiments that send contradictory signals to market participants in periods of stability. This dependence on the market conditions makes particular values of *VIX* unreliable for forecasting purposes in contrast to *SVIX*.

5 CONCLUSION

This study attempted to analyze the nature of the volatility index and its ability to consistently predict realized volatilities in the short-term future and therefore be a valuable instrument for hedging equity portfolios. On the contrary, it may serve only as a speculative instrument if the VIX is driven mainly by sentiments.

The study has examined the predictive power of the volatility index from various perspectives in a multistep analysis, which reveals substantial connections with such factors as unemployment consumer and business confidence indices. *VIX* is positively correlated with the *CCI* while inversely correlated with the *BCI*. Assuming consumers are prone to sentiments and biases compared to the industry sector suggests that the sentimental component prevails in *VIX*. Interestingly, exchange-traded products that should derive their values from VIX have unexpectedly low correlation coefficients, suggesting that these exchange-traded instruments do not share this property even if *VIX* could perfectly predict one-month forward volatility.

The Granger causality test results reveal that yields on T-bills, unemployment rate, and *BCI* have a bidirectional cause-effect relationship with *VIX*. Furthermore, *VIX* Granger causes *VXX* but not *VXZ*.

Regression analysis concludes that *VIX* has a connection with the forward volatility, but sentiments drive short-term swings of *VIX*. In other words, investors should not extract information from the daily changes of *VIX* but rather look at the general level of the index. Including the binary variables that represent periods of tranquility and turbulence provided more profound insight into the predictive property of *VIX* during those periods. *VIX* behaves differently when the market is stable and calm from market turmoil. *VIX* positively links to the one-month forward volatility when the market is exceptionally volatile. However, if the market is exceptionally stable, this link has a negative relationship, implying that the volatility index is primarily driven by irrational sentiments such as fear in those periods.

Overall, the outcomes suggest that the VIX has some properties for forecasting one-month forward volatility, and theoretically, it can provide diversification benefits to an equity portfolio. Nevertheless, a relatively fragile connection between the VIX and actual one-month forward volatility and its dependence on the market conditions make it an unreliable predictor. Moreover, the VIX itself is a non-tradable asset. At the same time, the most popular exchange-traded products, which are already burdened by the "contango trap" issue, are not expressively correlated with the index. One of the most popular tradable derivatives of the volatility index, *VXZ*, is not even Granger caused by the index.

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