Technology Sector Influence on the VIX

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Abstract

In this paper, the relationship between the Chicago Board of Options Exchange Volatility Index (VIX) and two Electronically Traded Funds (ETFs) that encapsulate the technology sector will be examined. In order to determine if the technology ETFs are a viable predictor of the VIX, a Markov-switching model will be used where the two ETFs are used to predict the change in the VIX index. However, the VIX is largely state-specific, meaning that it can react differently depending on what kind of economy we are currently experiencing. The other factors that are known to predict the VIX, such as the unemployment rate, S&P 500 index, the federal funds rate, and consumer sentiment will also be used to predict the change in the VIX, and some will change depending on the state. More analysis should be done to determine if the model is truly accurate, or if the original proposed model is correct.

Introduction

The volatility index of the S&P 500 index (the VIX) is most infamously known as the 'fear index' mainly due to the index's ability to track economic uncertainty in the United States. However, how does that fear impact other sectors? The VIX index from the Chicago Board Options Exchange is a 30-day forward-looking volatility measure of the S&P 500 index option contracts. The index can also serve as a volatility expectation of the overall market sentiment. Volatility can have various adverse effects in a portfolio, causing many investors to use the VIX index to hedge their portfolio's risk. The VIX has an average level ranging from 15 to 20, but during calm or slow trading it can get as low as 10 or 15. Typically, during economic downturns, the VIX index will rise due to uncertainty of the market. When the COVID-19 pandemic hit the United States, it reached an all-time high of 82 (S&P Dow Jones Indices). During these same periods of instability, the S&P 500 will decrease since most stocks don't perform as well when there is instability. This causes the VIX and the S&P 500 to have an inverse relationship.

During economic uncertainty, demand for products that aren't necessary decreases since individuals do not have as much money to allocate towards discretionary spending. This would likely lead to companies investing less in sectors associated with non-essential services. One of those sectors is technology since it consumes a large amount of discretionary spending for both the company and consumer (Smales, 2017). Two years ago, many tech companies began laying people off to cut costs, which reveals their monetary struggles. From September 2022 to March 316,873 tech employees were laid-off (Saba, 2023). In order to see the effects of these large-scale events that affect the technology sector, we can examine the Electronically Traded Funds (ETFs) that monitor the technology sector. However, it is important to select funds that are representative of 2023, the entire technology sector. One of the most important aspects of this model is the market accuracy of the ETFs. If either doesn't have a good volume of traded stock, then the price they trade at would be irrelevant and not reliable market data. However, both funds have good volume levels, meaning that they accurately represent the fair value of the asset. The two ETFs that are the best representations of the technology sector and have the most volume traded are ROM and REW. Both funds encapsulate various tech-related stocks like semiconductors, software, hardware, etc., and the ROM ETF has almost 80,000 in average daily volume while REW has 18,000. <u>Therefore, what is the relationship between technology stocks and the VIX?</u>

In this paper, I will first discuss the properties of the chosen ETFs and the correlation of the ETFs to various market aspects. Then, I will explain how I constructed the model as well as the reasoning behind including certain variables. I will also walk through the results I obtained from my model. Finally, I will discuss the implications of this study.

Background

The two ETFs that I will be examining are REW and ROM. The companies packaged in these ETFs specialize in IT services, software, communications, technology, semiconductors, electronic equipment, and hardware. This provides a good indicator of the whole technology sector. The goal of the REW ETF is to return -2x the performance of the S&P 500 technology sector, and the ROM ETF returns 2x the S&P tech sector. Since the correlation between REW and tech stocks returns is negative, or the inverse, people primarily buy this when they believe the returns of the stocks will be negative. The reverse is true for the ROM ETF. The figures below display the relationship between the ETF and the VIX. In figure 1, we can see that REW has a positive correlation with VIX, but ROM has a negative correlation with VIX as shown in figure 2.

Figure 1: REW ETF vs. VIX

Data from Yahoo!finance

Figure 2: ROM ETF vs. VIX

Data from Yahoo!Finance

In these two figures shown above, it is clear that both funds track the changes in the VIX index accurately. This could make these ETFs good indicators for where the VIX trades and overall changes in the index.

One of the unique characteristics of the VIX is mean reversion. This means that it has the tendency to revert to approximately 15 or 20, which contributes to the mismatch between the manually calculated S&P volatility and VIX. However, this means that there is always pressure for the VIX to stay around that level unless there is a market influence that causes it to move. These influences will be discussed in the following section.

Literature Review

Since the VIX is taken from the 30-day forward-looking implied volatility of the S&P 500 options, it is likely that there is a correlation between the manually calculated index volatility and the VIX. To observe this correlation, we look at the 22-day volatility since there are 22 actual trading days within 30 calendar days. However, it was found that VIX is not a perfect linear predictor of the S&P implied volatility (Vodenska and William, 2013). This is due to other market considerations that aren't encapsulated simply in the formula of volatility such as the mean reversion property of the VIX discussed earlier. Since the S&P does not always accurately predict the VIX, other factors need to be considered to improve this prediction.

Other macroeconomic measures such as the unemployment rate are additional factors that can impact investor sentiment. This change in sentiment could bleed into the VIX, causing it to increase during uncertain times and decrease with more positive information. For example, if the unemployment rate is very high, volatility is expected to increase since people are less certain about the strength of the economy. These factors remain neutral during non-volatile market environments, but, during turbulent times (periods of high volatility), they are heavily correlated with the VIX level (Chomicz-Grabowska, 2020). The unemployment rate was found to be predictive of the VIX, therefore, the unemployment rate will be included in the model to account for investor sentiment. Another measure associated with market sentiment is the federal funds rate which is decided during the Federal Open Market Committee. This impacts the VIX since this change in interest rates affects banks, and investors typically associate drastic rate changes with an unstable market (Grieb, et al.). Another factor that considers market sentiment is the University of Michigan Consumer Sentiment Index which is a measure of confidence that Americans have for their current financial health and future investment prospects. Using the unemployment rate, the federal funds rate, and consumer sentiment data can help fill the gap in predicting the VIX.

These factors discussed above have already been established as accurate indicators of the VIX, so I will be adding the two tech ETFs to determine what relationship the VIX has with the technology sector.

Model

The proposed model is: $\ln(VIX_t) = \beta_0 - \beta_1(ROM_t) + \beta_2(REW_t) + \beta_3(Unemployment_t) + \beta_4(\ln(S\&P_t)) + \beta_5(FOMC_t) - \beta_6(Umich_t) + \varepsilon_t$

In this model, I am using six different variables to predict the change in value of the VIX index. If the VIX increases, that means that market volatility is increasing, and, if the VIX decreases, volatility is decreasing. The variable ROM_t is the value of the ROM ETF, and REW_t is the value of the REW ETF. Looking at Figure 2 discussed previously, you can see that the VIX and ROM seem to have a negative correlation. This is because as ROM increases, this means that the S&P is likely to increase as well. However, the S&P and VIX have an inverse relationship, therefore when ROM increases you can see that the VIX decreases. Therefore, the ROM_t will have a negative coefficient. The opposite is true for the REW ETF, meaning that an increase in the VIX will lead to an increase in the REW. Therefore, the REW_t variables will have a positive sign. The $unemployment_t$ variable will look at the unemployment rate in the US for a given month, which is found to have a positive correlation with the VIX index due to unemployment increasing during periods of economic uncertainty. The unemployment data from the St. Louis Federal is already a rate, so there is no alteration needed for this variable. The $S\&P_t$ variable will look at the natural log of the S&P 500 index. This is expected to have a positive coefficient since volatility (or large changes) in the S&P 500 will transfer to the VIX, leading to the natural log of the VIX to increase. The variable, $FOMC_t$, considers the Fed funds rate that is decided upon in the federal reserve meetings. This is expected to have a negative coefficient since a decreasing rate change is likely associated with increasing volatility in the market. For example, during COVID-19, the government decreased the federal funds rate to 0, and the VIX increased. The last variable, $Umich_t$, takes into account the consumer sentiment level for that month. A higher score means that people are more confident in the economy, and volatility normally decreases when people are more confident. Therefore, the variable will have a negative coefficient. While these signs are expected, they could change as a Markov-switching model will be used.

In the economy, investors typically consider the economic environment volatile or not volatile. To conduct this regression, I will be using Markov-switching to represent these two different states. The three state-specific variables will be the unemployment rate, FOMC, and the University of Michigan consumer sentiment data. This is because state-specific variables need to be indicative of the state. In this case, all three can show whether the economy is in a volatile or a non-volatile state.

Data and Results

The data for VIX index, S&P index, ROM, and REW ETFs closing value were all gathered on Yahoo Finance at https://finance.yahoo.com/. The FOMC and unemployment rate were both available on the FRED (https://fred.stlouisfed.org/) website. The data for consumer sentiment is from the University of Michigan (http://www.sca.isr.umich.edu/). The model explained above will take in monthly time series data, starting from when the ROM and REW ETFs started trading. Both ETFs began trading in February 2007, so the data will be collected from March 1st, 2007, to September 1st, 2023.

Table 1: Results of Markov Switching Regression

Variable	Coefficient	P-value
REW	0.0000744	0
ROM	-0.0034629	0.1475
ln(SPY)	0.5334495	0
umich – state 1	-0.0094	0
umich – state 2	0.0084	0.0275
fomc – state 1	-0.0370373	0.019
fomc – state 2	-0.6256	0
unemployment – state 1	0.0479443	0
unemployment – state 2	-0.0829	0.026
N = 189 AIC = 0.0003 HQIC = 0.1045 SBIC = 0.2576 Log Likelihood = 14.97		

In Table 1 you can see the variables, their respective coefficients, and p-values in each state. For *REW*, the coefficient is the same in both states since it is not a state-specific variable, meaning that it will have the same effect on the VIX regardless of the state it is in. This tells us that for every 1-point increase of the REW ETF, the VIX will increase by 0.007%. Earlier, it was predicted that *REW* would have a positive correlation since as the e the p-value is 0, we conclude that this variable is statistically significant.

The next variable, *ROM*, is also not state-specific and has 1 coefficient. This coefficient shows that for every 1-point increase in the ROM ETF, the VIX will decrease by 0.346%. This variable has a p-value of 0.1475, meaning that it is barely statistically significant at the 15% level, but not at the 10% level for a one-sided test. For the *ln(SPY)* variable, the model shows that for every 1% increase in the S&P index, the VIX will increase by 0.533% and is statistically significant. The variable *umich* is state-specific, and, in state 1, the coefficient shows that for every 1-point increase in consumer sentiment, the VIX will decrease by 0.937% and is statistically significant in the first state. In the second state, for every 1-point increase in the consumer sentiment index, the VIX will increase by 0.842%, and this is also statistically significant. The *FOMC* variable is state-specific as well, with the coefficient in the first state displaying that for every 1-point increase of the federal funds rate, the VIX will decrease by 37.034%. This is a large number since it is highly unlikely that a 1-point increase will occur since the FOMC typically will only change the rate by 0.25 percentage points at a time. This variable is also statistically significant. In state 2, a 1-point increase in the fed funds rate will cause a 62.554% decrease of the VIX. The p-value is 0, showing that *FOMC* is statistically significant in this state as well. The unemployment rate variable shows us that, in state 1, for every 1-point increase in the unemployment rate, the VIX will increase by 4.794%. This has a p-value of 0, showing it is statistically significant. In state 2, a 1-point increase in the unemployment rate would cause the VIX to go down 8.287%. The 1-sided p-value for this is 0.026, which is, again, statistically significant.

Conclusion

Using the results from the Markov-switching regression, it is observed that as stocks in the technology sector increase, the VIX typically decreases. In a macroeconomic sense, this means that tech stocks will perform better during a less volatile (more stable) economy. The reverse is true for decreasing returns in the technology sector. The two ETFs that were examined were taken from the technology sector of the S&P 500 index, meaning that, since the VIX and S&P are already strongly correlated, the ETFs and the VIX would likely be correlated as well. This model could also be applied to VIX-related products such as the futures contract VX or the pro-rated ETF UVXY. This model could be tested further by using other non-S&P related stocks to see if the effects are the same as what was concluded in this model.

While the variables in this model were all statistically significant at the 15% level, it would be interesting to see how the model would be impacted by adding other sectors and determining the effect those would have on the VIX. For example, what would change in the model if we added an ETF that covers the energy or a biotechnology sector. Additional research will need to be conducted to determine the theoretical effects of these ETFs on the economy, but this model is fairly versatile for determining the change in the volatility index since the foundations of the state changes and the largest indicators of the VIX are already included.

Adding different sectors could also lead to increased accuracy of the model since the VIX reacts to different sectors as well.

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Stata Tests

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. correlate rom rew unemployment_rate fomc lnspy umich
(obs=195)
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	rom	rew	unempl~e	fomc	lnspy	umich
rom	1.0000					
rew	-0.4429	1.0000				
unemployme~e	-0.3696	0.2777	1.0000			
fomc	0.0507	0.2317	-0.5377	1.0000		
lnspy	0.8379	-0.7401	-0.6054	0.1422	1.0000	
umich	-0.1276	-0.4328	-0.4153	0.0433	0.2591	1.0000

There is no evidence of multicollinearity.