Dynamics of implied volatility surface and applications of implied volatility in different sectors

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Abstract: This paper aims to study the dynamics of implied volatility of Apple stock trading data. The dataset used in this paper is collected from an open source on Historical Option Data. The results examine knowledge of the implied volatility surface movement such as the level, skew, and smile effect. Besides, I also investigate the application of Black Scholes model on three different sectors that are Banking, Energy and Technology. In order to assess the results, I use root mean square error to conclude that Banking is the more consistent with Black Scholes formular. This paper examines a practical study about option price and implied volatility and its application in real financial markets.

Keywords: Implied volatility surface, Financial Analytics

1 Introduction

Derivatives are one powerful tool in financial markets that can benefit institutions and individuals' investment. It can be used to hedge risks or for speculation purposes. The Black Scholes model was first developed in 1973. This is one important theorical formular that was used to compute option price. The formula is then continue developed and can be applied to different option types (European option, American option etc.). Implied volatility is one important factor in Black Scholes that estimates the fluctuations of underlying assets. This paper aims to investigate the application of Black Scholes model in the real-world financial markets.

Currently, the Black Scholes model is used to calculate and forecast option prices. Another way that Black Scholes model was used is to compute the implied volatility. The implied volatility can then be used to draw implied volatility surface when combines implied volatility, time to maturity and moneyless. Thus, when looking at the implied volatility surface, investors can see the expectation volatility of underlying assets over the life of the option. In this paper, I will perform two tasks. In the first part, I will draw the implied volatility surface based on the real financial data so that we can observe the expectation of investors in the lifetime of option. Then in the second part, I will use historical implied volatility to calculate option price and compare it with the market price. This calculation will be performed in three different sectors including Banking, Energy and Technology to see how the consistency of Black Scholes model in different sectors.

In order to achieve the goals mentioned above, the rest of this paper will be presented in four parts. The first part is related to works. In this part, we can summary past research that has the same topic as my paper. This can help me to have deeper knowledge about implied volatility and know how it is currently applied in the market. The next part is methodology that will mention my dataset and the analysis process that I applied in my paper. Then in the third part, I will present the results. In the last part, based on the results analysis in above part, we can have some conclusions and some recommendations for future paper to workout.

2 Related work

The Black Scholes model was first published in 1973 and was used to evaluate option price and this formular had strong impact to financial market in this time series. However, the initial Black Scholes model omits the impact of dividend to option price and then dividend yield was quickly added to the formular to adapt for the real market [1]. Since then, various studies have tried to apply Black Scholes in different ways. Beck performed research in 1980 to test if the historical instantaneous volatility of the underlying stock corelate with stock price or not. The dataset included the data of S&P 500 index from 1972 to 1977 and concluded an inverse relationship between these two variables [4]. Until 2006, Yang found the unbiased impact of implied volatility in forecasting future option price [5].

Certain papers investigated the application of Black Scholes model in financial market. One paper used the model to test the dataset of 30 stocks within 18 trading days and concluded that this model has significant accuracy on the real market [2]. Another study that used data in 5 years from 2003 to 2007 from European call option on Australia market to assess the useful of Block Scholes models [3]. The results indicated that the model can be used in the real financial world. Besides, this study also indicated that implied volatility can also be used to manage the investment portfolio.

Besides using Black Scholes model to evaluate option price, various papers also investigated the use of implied volatility in financial. One paper published in 2003 investigated the method to reduce the error when estimating the implied volatility. It constructed a feasible GLS estimator that can be used to reduce the error and bias when calculate implied volatility [6]. One present study also indicated a technique to estimate implied volatility by developing a robust grid-based inverse algorithm with high accuracy [7]. Besides, lagged implied volatility also can be used as a trading signal to predict stock return on the exchange market. This was indicated in a study published in 2009, when the authors use numbers of factors such as firm size, market valuation and lagged implied volatility to analysis US equity options [18]. The significant relationship between stock return and implied volatility was also pointed out in many other researches and in many different dataset. Such as an investigation on Japan exchange market data from 2000 to 2017 was done in 2020 and shown the strong relationship between stock market implied volatility and stock volatility [19]. Feng and his friends have deeper analysis by analyzing the stock return and implied volatility smile slope of call and put options. The paper then proved that the slope–stock return relation is strongest for stocks with high belief differences [20].

Come with implied volatility, implied volatility surface (IVS) can also be used for analysis purposes. A study in 2022 developed an implied volatility surface-based trading system for the data extracted from SPY option data. The system performs well while it has a high return compared to the return of trading underlying assets [8]. Badshah published a paper that plots the dynamics of implied volatility surfaces. This paper concludes con three main factors explained in the implied volatility surfaces. First is the volatility level factor that moves the entire IVS systematically in the same direction. The second factor can be interpreted as term structure factor that generates shifts in the slope of the term structure of different implied volatilities. The third factor can be interpreted jump-fear factor that changes the steepness of IV smirk/skew [16]. These three effects are also indicated in other studies such as the paper in 2010 by Kim and his authors [17]. A recent study that uses dynamics implied volatility surface to improve the price banding efficiency for Fat finger problem. The system performs well and can outperform other similar prediction systems [21].

3 Methodology

This paper is divided into 2 parts with two different methodologies so I will mention two methodologies below.

3.1 Methodology for implied volatility surface

Step 1: Crawl data: the dataset used in this study is downloaded directly from Historical Option Data [9]. Besides, risk free rate is one element of Black Scholes formular, so I use 10 years treasury yield export from Quantmod packgage as the risk-free rate [10]. The dividend yield is taken from Macrotrend [11].

Step 2: Data pre-processing: the dataset downloaded from Option Data is one month data including all stocks listed on New York Stock Exchange so it will be too heavy to run on my personal laptop. Thus, in this study, I just use the AAPL data of 01 August 2019 for drawing implied volatility surface. The risk-free rate is also extracted on 01 August 2019 in 10 years treasury yield data. For the dividend yield, I use the dividend yield in 11/8/2018 as this is the nearest day before 01 August 2019 that quoted in the dividend yield chart [11].

Step 3: Scope and application selection: The dataset contains 20 columns of variables. For this part, I just need the data about UnderlyingSymbol, UnderlyingPrice, Type, Expiration, DataDate, Strike, Bid, Ask.

Step 4: Calculating the implied volatility: Based on the data extracted and prepared in above parts, I can calculate the implied volatility. In order to calculate the rate, we can base on past papers as references [12].

Step 5: Draw implied volatility surface: Based on the implied volatility calculated in step 4. I use package Plotly to draw 3D graphs.

3.2 Methodology for calculate option price on different sectors

Step 1: Crawl data: The data needed in calculating option price will be the same as data needed to draw implied volatility surface. Besides, I also need to calculate historical volatility from past trading information [13].

Step 2: Data pre-processing: Unlike the first part where I need to make many calculations steps and it requires very strong infrastructure that my laptop cannot adapt. In the second part, I can make the calculation become a function and make the calculations become much lighter. In this part, I will extract the data about three stocks that belong to three different domains that include Banking (BAC stock), Energy (OXY stock) and Technology (AAPL). The date to extract will be the same as in the first part on 01 August 2019. Risk-free rate and dividend will be used the same as in part 1.

Step 3: Calculate option price: Using the data in step 2 with the function in package Quantmod in R studio, I combine the calculation steps into a function. Then I put the data of Banking (BAC stock), Energy (OXY stock) and Technology (AAPL) into this function to calculate option price.

Step 4: Evaluate the results in step 3: In order to access the result, first, I will use the average of bid and ask price as the market price and then compare the option price calculated from step 3 with the market price.

4 Specification

4.1 Assessing implied volatility surface

In order to assess the results in drawing the implied volatility surface. I will compare it with implied volatility surface that was drawn in the past paper from different sources [14] [12] [15] [16] [17].

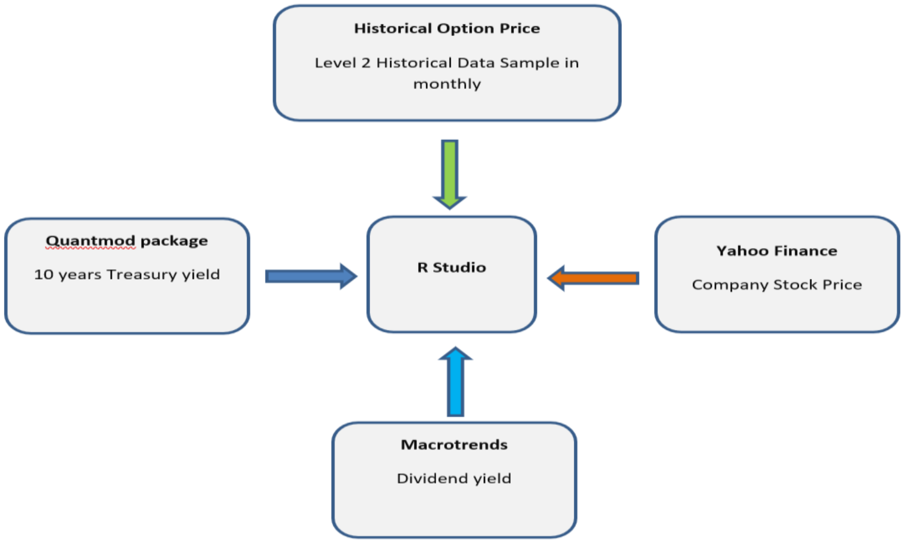
4.2 Assessing option price

In order to compare the accuracy of different sectors, I use root mean square error method. The sector with the lowest root means square error method will be the most consistent sector with the price calculated by Black Scholes formular.

5 Research resource

Databases:

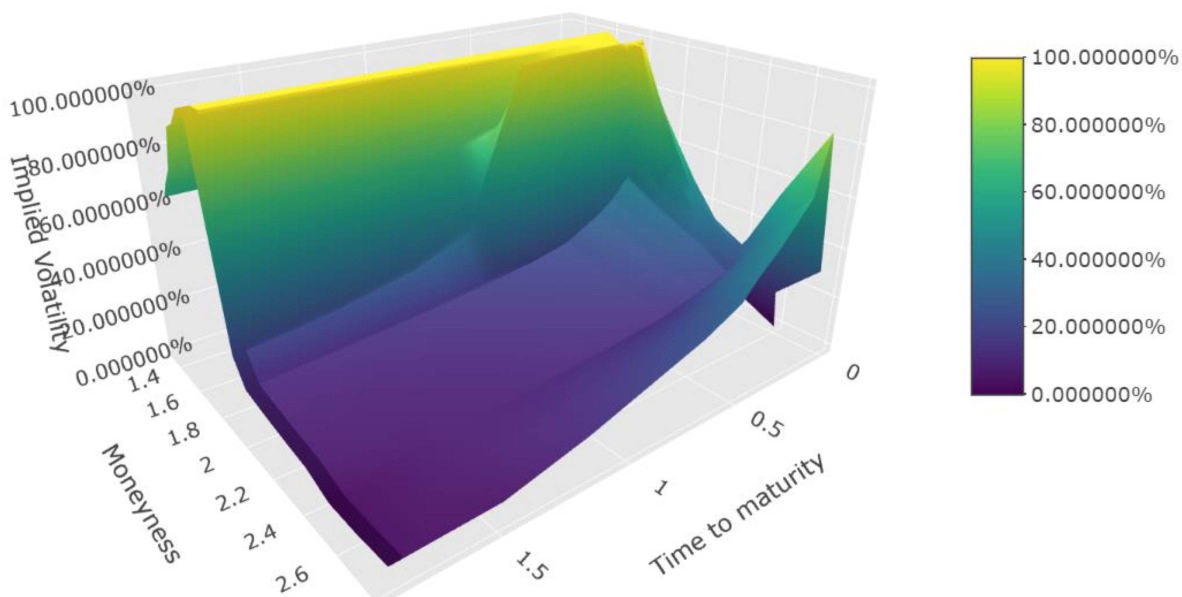
- Historical Option Price
- Yahoo Finance
- Quantmod package
- Macrotrends



6 Results

6.1 Implied Volatility Surface

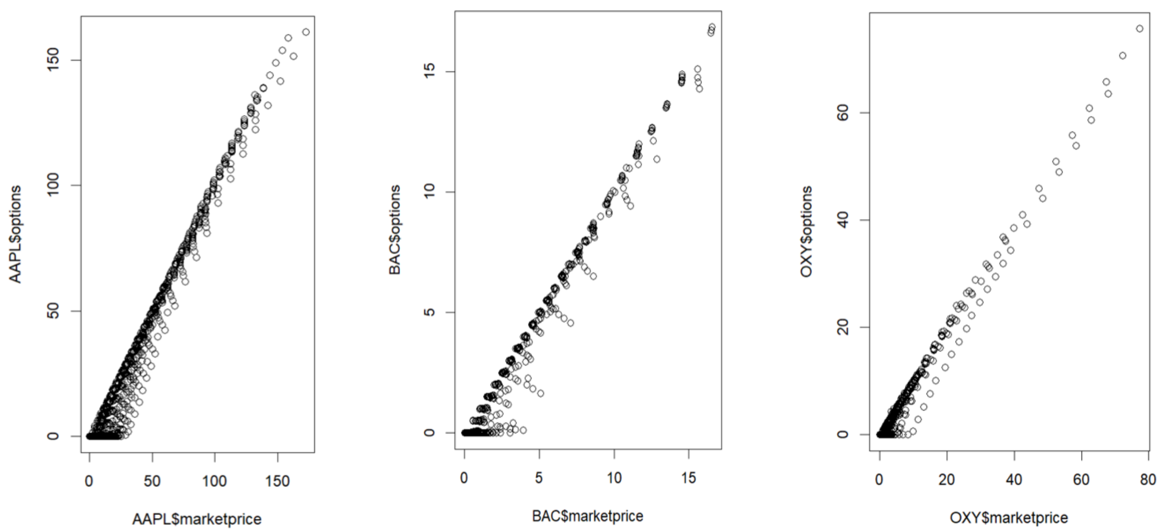
After applying the methodology mentioned in the above part, I plot a 3D graph that shown the implied volatility surface of AAPL stocks. The Implied Volatility Surface was draw as below:



The Implied Volatility Surface that I plot above is not as smooth, but it still shows the dynamics of implied volatility surface. Firstly, the skew shows that as the lower the strikes, the greater implied volatility and the higher the strikes, the lower the implied volatility. Secondly, we can see the smile shapes between implied volatility and strike price. Thirdly, the implied volatility surface above can also confirm the level effect. Compared to other studies that draws and investigate on the dynamics of implied volatility surface, my graph seems not smooth, this problem might occur because the data I use in here is just one day trading data.

6.2 Calculating option price

After the calculating processes, I plot the charts that illustrate the market price and the option price I compute from extracted data. All the charts are added in the pictures below. Note that the x column is market price and y column is the option price.



Looking at the charts above and assessing the distribution of predicting value points and actual points value, we can see that AAPL which present for Technology sector seems to have the most consistent between computed price and market price. In contrast, BAC which present for Banking sector seems to have least accurate between computed price and market price. However, in order to analysis the results in a more statistical way, let's compute root mean square error of all stocks and compare it with the mean of actual value. RMSE is a popular method used to evaluate and compare different models. The results are displayed as in table below:

Sectors	RMSE	RMSE/Mean
Banking	0.59	0.196
Energy	1.54	0.267
Technology	6.12	0.234

Based on the results above, I can conclude that that Banking sector has the most consistency with the option price I calculated. This result is different from the first assessment when we just look at the charts. The reason the low RMSE/Mean displayed in the table above can be explained when we look at the high volatility of Energy and Technology market. It means that price movement of Energy and Technology sectors are very high. We can see the negative oil price when the world faces Covid pandemic and also when the oil price goes above 100 USD per BBL when the pandemic passes. It is one example of how high volatility is in the Energy sector. The same happens with Technology stock because many of these firms have negative cash flow but the growth rate is very high. The strong fluctuations in the market can lead to the less accurate for the computation of historical implied. Thus, the option price calculated from this historical implied volatility will be less consistent with the market price compared to the Banking sector.

7 Conclusion and Future work

After the analysis, we can have some conclusions for this paper. Firstly, we can conclude the theorical dynamics of implied volatility surface in the real financial world. The level effect, skew effect and smile effect are proved through my paper. Secondly, my results from the second part indicate that the banking sector is fitter to apply the Black Scholes model compared with the energy sector and technology sector.

Besides, I also have some recommendations for future work. The dataset I found was very large and includes the option information of all stocks in New York Stock Exchange and the data I use in my paper is just a very small amount extracted from this dataset. For further study, instead of using just AAPL, BAC and OXY stock data, we can use all data in this dataset as the input value for the research. The results with larger dataset in longer time can display and tells us more stories.

- **Note: Link R studio cloud is as here: https://posit.cloud/content/5820351**

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