Stock Price Forecasting Models

A Major Qualifying Project

Submitted to the Faculty of

Worcester Polytechnic Institute

In partial fulfillment of the requirements for the

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In

Mathematical Sciences

By

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Abstract

Using historical stock data, we developed two models to make short-term predictions for a stock price. The models were refined by including the influence of NASDAQ index. Advanced mathematical techniques were used to formulate these models. Investors can use these models to obtain suggestions and pointers. To test these models we compared the predictions with actual performance of several stocks and obtained trustworthy results. In a period where the market went 5% down our model yielded a gain of 4.35%.

Executive Summary

This project used different mathematical techniques in order to create a trustworthy model which forecasted the price of stocks for a period of thirty business days. Ultimately, we produced two models which were tested during the MQP. The first model used Least Squares approximation and Fourier series expansions. The second model used Autoregressive Integrated Moving Average (ARIMA) modeling. An attempt was made to refine the first model by using moving averages to smoothen the raw data. However, the refined model gave less accurate predictions. In addition, we found an effective way to account for the general market impact by incorporating the NASDAQ index in the first model, which made it more precise.

We decided to use ten stocks from the technology sector to help us create our models. The technology sector, however, is huge and it is hard to represent it by a few stocks. For this reason we focused on ten stocks from the Internet Information Providers Industry of the technology sector. We applied both our models on these data sets to obtain an accurate predictions with a 95% confidence interval. In order to check, whether the NASDAQ modification for the first model worked for stocks with high prices we made additional observations. We found out that the inclusion of NASDAQ modification in the first model yielded better predictions for stocks with value less than $100.

The two models gave accurate forecasts for stocks, the best results were obtained for stocks which were less volatile. We found out that the first model with the NASDAQ modification was able to overcome the stock volatility and random noise that were incorporated in the data and lead to trustworthy predictions. The second, ARIMA, model had closely comparable results. We tested the effectiveness of the prediction by comparing its yielded value to the actual price. The inaccuracy percentage for most stocks was found to be in the 95% confidence interval.

We made a reality test of the models using virtual investment. We decided to test our models by choosing several stocks based on our variables, external information and suggested behavior of the stock price by other competent sources. $100,000 of virtual money was invested with no transaction or broker fees. In a period where the market went 5% down our model yielded a gain of 4.35%.

We believe our stock forecasting models will be useful for individual investors and retirees looking for a stable future who have no access to detailed information about the performance of the companies behind the stocks.

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Introduction

My course of study at WPI is mathematics with computational concentration. For my major qualifying project (MQP) I did a project to predict the prices of stocks. Working on this project allowed me to use most of the material I have gone through in my major field. Methods used in math modeling and numerical analyses classes were helpful in approximating the appropriate data. Statistics classes helped me to understand and evaluate this data. This project deals with advanced math modeling tools and addresses a very complex and popular area of the financial sector. Since my career goals are to go into the financial sector and get involved in the stock market, I think this project helped me move forward intellectually. It provided me with a strong academic base and a positive experience regarding the stock market.

In the market an investor can trade with stocks, options and futures. Option is a contract that sets a price that you can either buy or sell a certain stock at a subsequent time. Future is a contract to sell or buy a commodity at a later date, at a price agreed upon in advance. The difference is that for a futures contract an investor is legally bound to sell or buy the commodity, while the options contract gives you the choice to trade.

With a large part of the society trying to predict the stock prices, the market is very popular in the modern day. They do so in order to either guarantee a financially safe retirement, earn a living or beat the market. A strong stock portfolio will help achieve these goals. With this project we created a mathematical model that predicts the price of shares. This model can help anyone pick out potentially successful stocks and create a strong portfolio. Even though it is impossible to predict the future with a 100% certainty, this complex mathematical model should achieve a level of precision acceptable by investors and brokers alike.

Beating the market means that you are actually beating someone else. Someone else has to lose in order for you to win. This someone else can be a person just like you or it can be a large financial organization. These financial corporations have multiple analysts and a much larger capital to invest. Accomplishing this project from the financial and mathematical perspective will help investors not to lose to the market thus leveling the fields. We believe our stock forecasting models will be useful for individual investors and retirees looking for a stable future who have no access to detailed information about the performance of the companies behind the stocks.

The stock market includes a wide scope of sectors, ranging from information providers to financial corporations. Lots of people think that the market constitutes from finances and mathematics and they are right, however, that is not all of it. When you try to beat the market you should take under consideration the social psychology. For example, year 2000 created controversial predictions about how the computers would react, which even though assumption was far-fetched, caused dumping of shares in nuclear energy sector. You should also understand the corporate and global politics, for example, the drop in oil prices due to military/political crisis with Russia. Projects in general are limited to analyzing the financial and mathematical part of the stock market, which is why it is almost impossible to make a 100% precise prediction. We are trying to make the most accurate representation of what the future holds for specific stocks. We are trying to generate accurate forecasts from fifteen to thirty business days.

This project will constitute 3-4 stages in order to create a sophisticated model. The first stage of creating this model will be this MQP. I am planning to continue working on this project after I am done with my studies at WPI.

We decided to look mostly at NASDAQ, since it contains most of the stocks from the technology sector, the target of our interest. The Stock market encompasses a huge number of companies and is divided into different sectors. We decided to look at the technology sector. The reasoning behind this is that we live in the technological era and our lives are shaped by it every day. It is an area very popular in the society and we also have a personal interest. The technology sector, however, is hard to represent by modeling few stocks. That is why we started working on the project by choosing ten stocks from the Internet Information Providers Industry of the technology sector.

There were a few restrictions set from the beginning for picking out the stocks. First, the company stocks should be relatively stable, thus most of the stocks we chose have gone public for several years now. The stock price data for these companies is available for each working day for the past year. Second, the price range of the stocks is above five dollars and below hundred dollars. We chose the ten stocks by looking at their prices and putting them in 3 divisions. A price range of 5 – 20, 20 – 50 and above 50. These stocks with their ticker symbols are: Facebook Inc. (FB), Yahoo! Inc. (YHOO), Twitter Inc. (TWTR), IAC/InterActiveCorp (IACI), GROUPON Inc. (GRPN), TechTarget Inc. (TTGT), ChinaCache Ltd (CCIH), Blucora Inc. (BCOR), J2 Global Inc. (JCOM), and eBay Inc. (EBAY). We decided to avoid small market capitalization stocks with a price of less than five dollars at first because their price can be changed easily by an investor with a large capital. We decided to avoid large market cap stocks with a price of more than 100 dollars since they are not an accurate representation of the industry, for example, Google is considered a market maker and cannot represent a specific industry of a sector.

Least Squares Approximation plus Fourier Expansion Model

For our first model we used linear Least Squares Approximation (LSA) and the third order Fourier series, however, if number of days obtained from autocorrelation is 50 or less we used second order Fourier series. There are two versions of this model. Version one works on the raw close price data and tries to approximate the future price. Version two uses moving averages to smoothen the raw price data and afterwards works on the new data to try and forecast the stock price. Thus, we called the first version non-smoothed and the second version smoothed. The steps constitute:

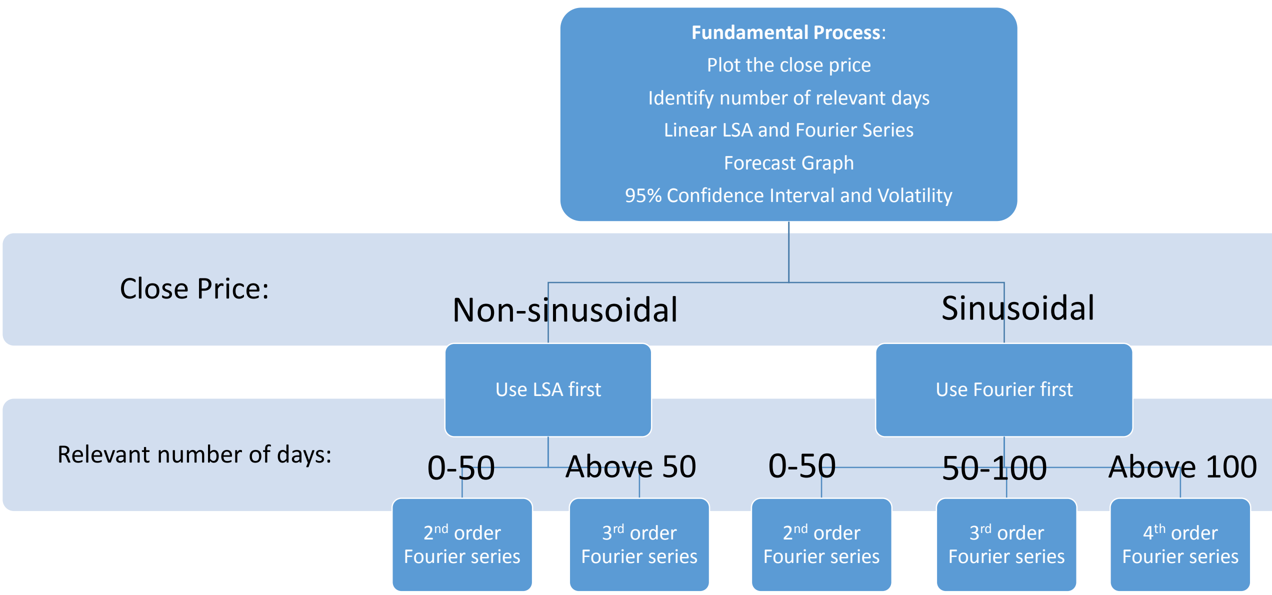
1) After choosing the stock, we looked at the close prices and plotted simple raw data graphs.
2) For the next step we decided to chart the autocorrelation of the close price data. This gave us the date range of the relevant data. This relevant data will be used in the approximation tools. This method correlates the price data to itself going backwards in time. Thus 0 is the last day of the price data provided (which is September 12th) and 50 (for example) represents the autocorrelation value for the price fifty days ago. If the autocorrelation is positive, above the x-axis, it means the price data for that time range is relevant. We only take into consideration the starting region before the autocorrelation graph dives under the x-axis and becomes negative for the first time. Any later instance of a positive autocorrelation is considered as noise and disregarded.
3) We use the linear LSA using the number of relevant days obtained in the previous method and plot its graph on the relevant data. We did not use a quadratic, cubic or higher order least squares approximations. Even though the higher order LSA might fit the close price data precisely, in the future it diverges from the actual price significantly. It is very difficult to keep a high power of a number under control and in the area of

approximation. But, the linear least squared approximation alone still has issues representing the actual data.

4) In order to find a good approximation for the data divergent from the linear LSA, we will now subtract and plot the linear least squares approximation data from the actual close price data to obtain the difference in price. The price difference will be used in future calculations to obtain the Fourier series and the Noise.
5) Using the data from the difference, we create a Fourier series of order two, three or four for the stock. It depends on the number of relevant days for the stock close price. The Fourier series supports the linear LSA by trying to nullify its disadvantages. By fitting the Fourier series to the divergent close price, we created a precise function to represent the raw data. We will use this function to obtain a forecast graph. We will plot this function for the next 30 business days, following September 12th. The model, however, is not completed.
6) The Fourier series function is now subtracted from the price difference. This will give us the Noise. Noise represents the data that randomly oscillates the price of a stock. We will use the Noise to create an area of approximation for our model in order to give us an accurate representation of where the actual price will be heading. We take the average of the absolute value of the Noise. If we add and subtract the average from the price forecast graph (linear LSA plus Fourier series) we will obtain the upper and the lower bounds of the area of approximation.
7) The Fourier series function and the LSA are summed to obtain the price forecast function. Then we take the average of the absolute value of the Noise. We add and subtract the average Noise from the forecast function to obtain the upper and lower bounds of the prediction area. We plot close price data, price forecast, area of approximation and the actual price after 12th of September to determine whether the model was accurate.
8) We calculated the percentage deviation of the predicted line from the actual price. The maximum, minimum and average inaccuracy percentage of the prediction line is obtained. We calculated how far away the max and min inaccuracy is from the area of approximation in dollar value and weather they fit in the area of approximation.

9) Using the previous calculations, we decided that the average accepted inaccuracy would be within a 95% Confidence Interval (CI). We derived logarithmic price changes and used it to find the standard deviation of different stocks. We took two standard deviations in order to identify a 95% confidence interval and compare it to the average percentage inaccuracy of the stocks.
10) The volatility was calculated in order to see its relation to the effectiveness of the model. We looked at the historical volatility for the price data to understand how volatile the graphs were and whether it effected the model.

Flow chart for stock price forecasting:



We modeled the non-smoothed and the smoothed versions for each of the ten chosen stocks, with each stock having a summary of the findings and analysis. Finally, we compared the two versions, gave conclusions with respect to maximum tolerated inaccuracy obtained by a 95% Confidence Interval and decided which version of the model was superior.

Since the stocks presented here are chosen from NASDAQ, we decided to include the NASDAQ index in the model and found out what kind of effect it has on the stock forecasting. We modified the superior version of the model through incorporation of NASDAQ in prediction process of the stock prices. We correlated the NASDAQ data to the close price data of a given stock for the relevant number of days for the given stock price. The index, however, has huge numbers thus we decided to normalize it between 0 and 1. We used the combination of correlation and normalized NASDAQ to obtain the new forecast graph.

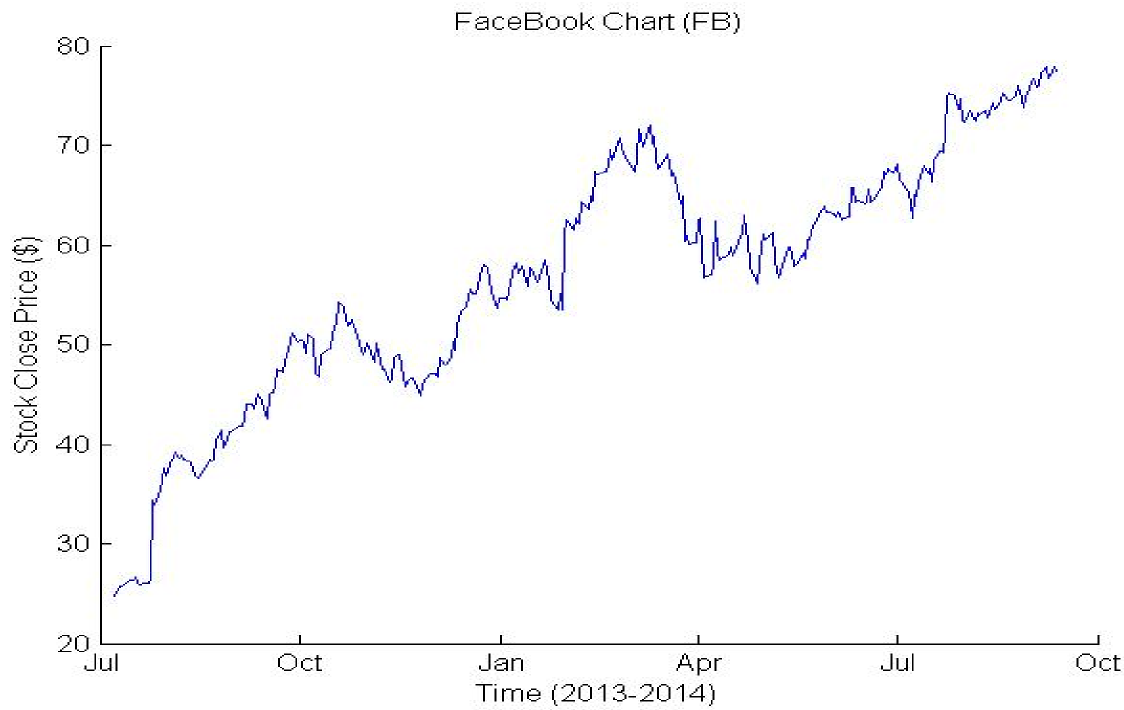
Non-Smoothed Version

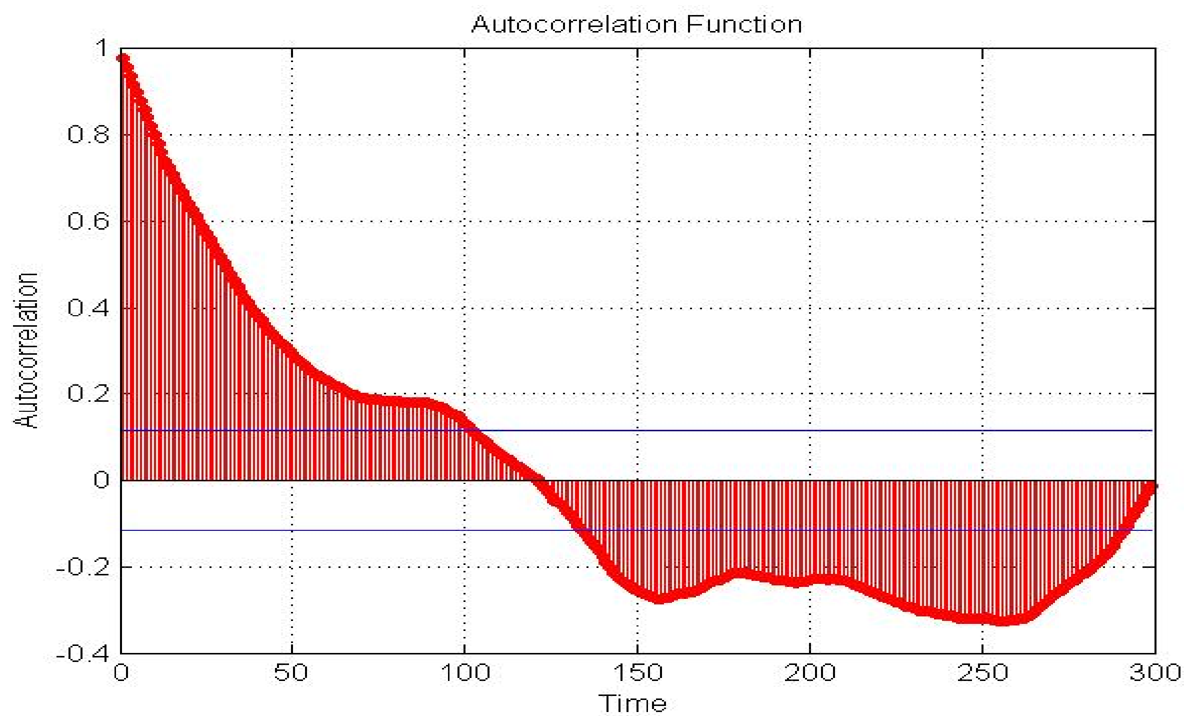
We decided to predict 30 business days in the future, following September 12. We depict the graphs showing the 30 business days, however, we also calculated the accuracy of the model for 15 business days. We found that the length of the period we make predictions for effects the accuracy significantly. The model is acceptable, meaning the average inaccuracy is low enough and the forecast graph still fits in the 95% confidence interval, for eight out of ten stocks, given 15 business days. The model for 30 business days is acceptable for five out of ten stocks.

Facebook (FB):

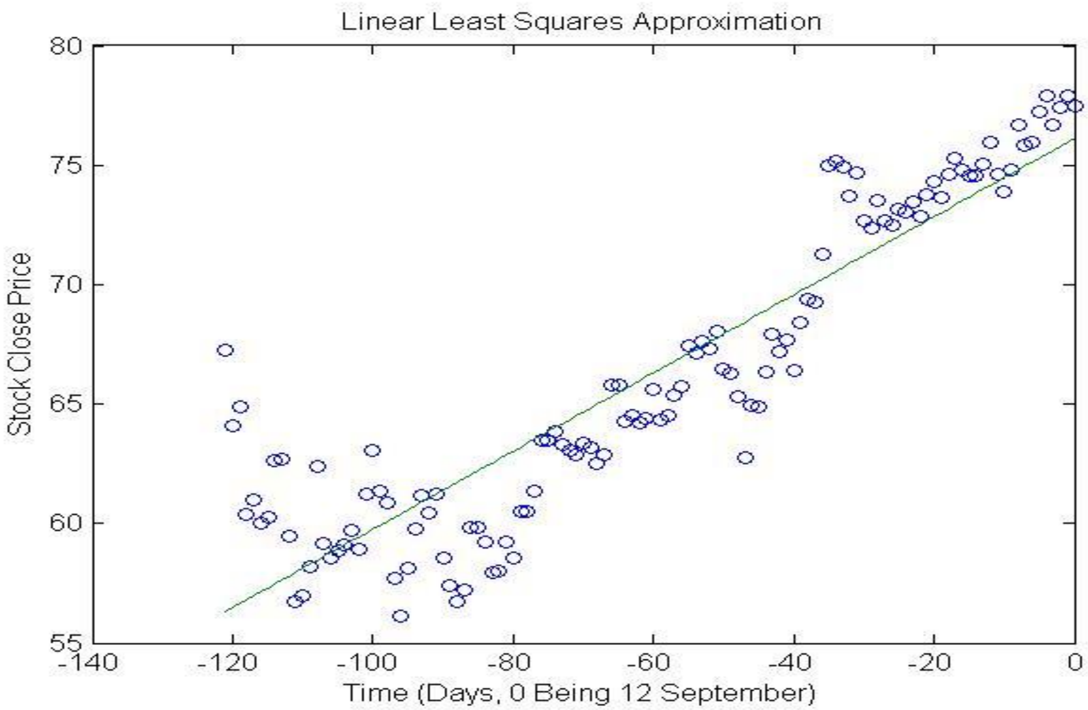
We observed that a part of the actual price is in the approximation range of the function. The forecast line shows a positive slope, thus an upper trend. Even though the price experienced non-predicted sudden drop, the stock is headed in the right direction. The average percent of inaccuracy is 1.9% for 15 business days and 4.8% for 30 business days. Both of them are below the area of approximation. The 95% CI is 5.6%, and since both inaccuracy is lower than 5.6 we obtained acceptable results. The general predicted trend is correct and the average inaccuracy is really low for the 15 business day forecast so it is preferred. The historic volatility for relevant number of days was 35% and the visible upper trend of the close price before September 12th constituted to the stability of the model.

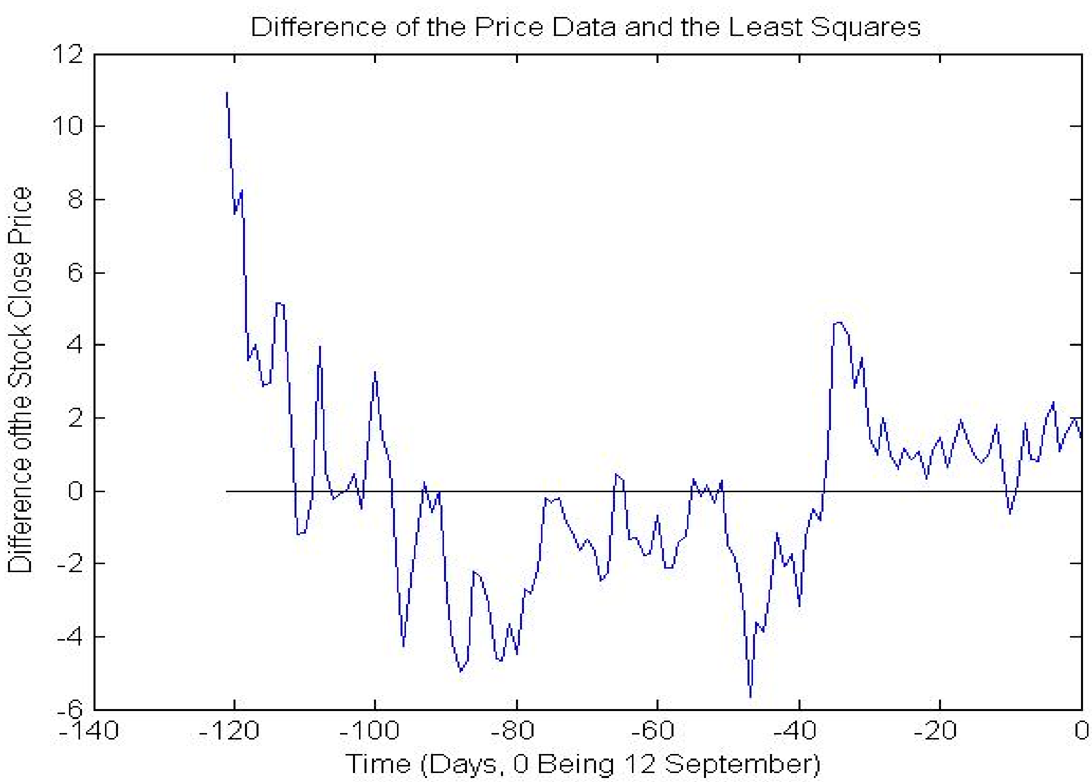
We plot the close price data of Facebook Inc. and use the autocorrelation function to identify relevant data.



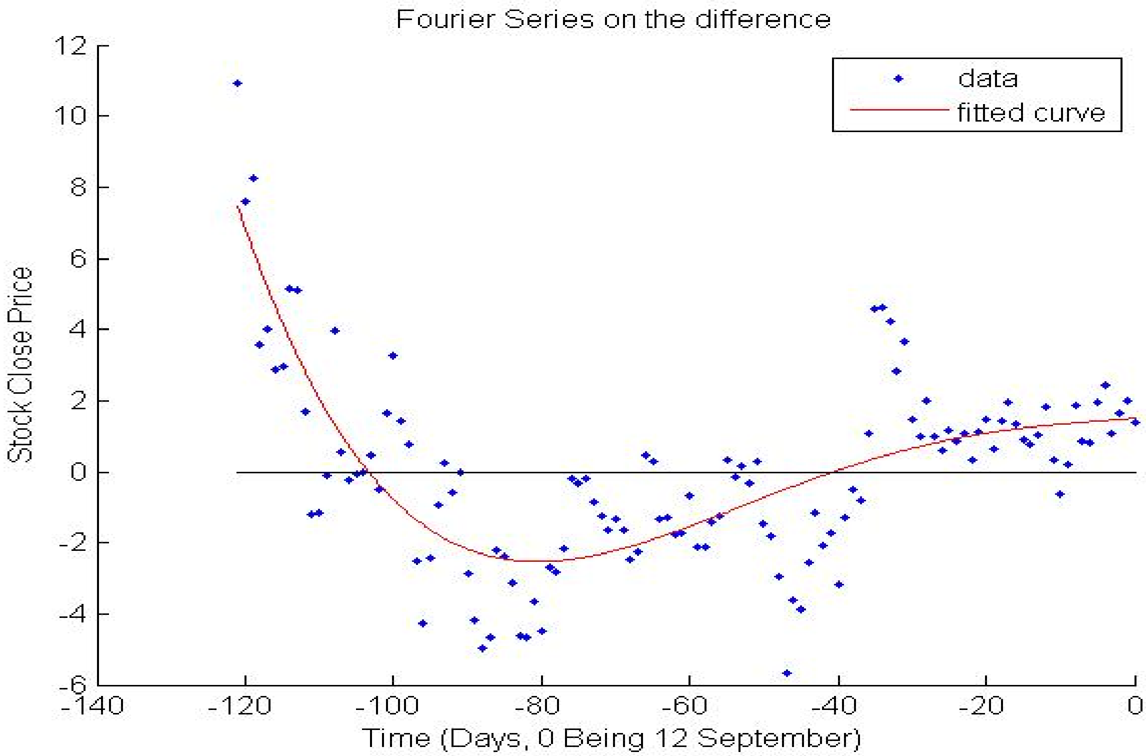


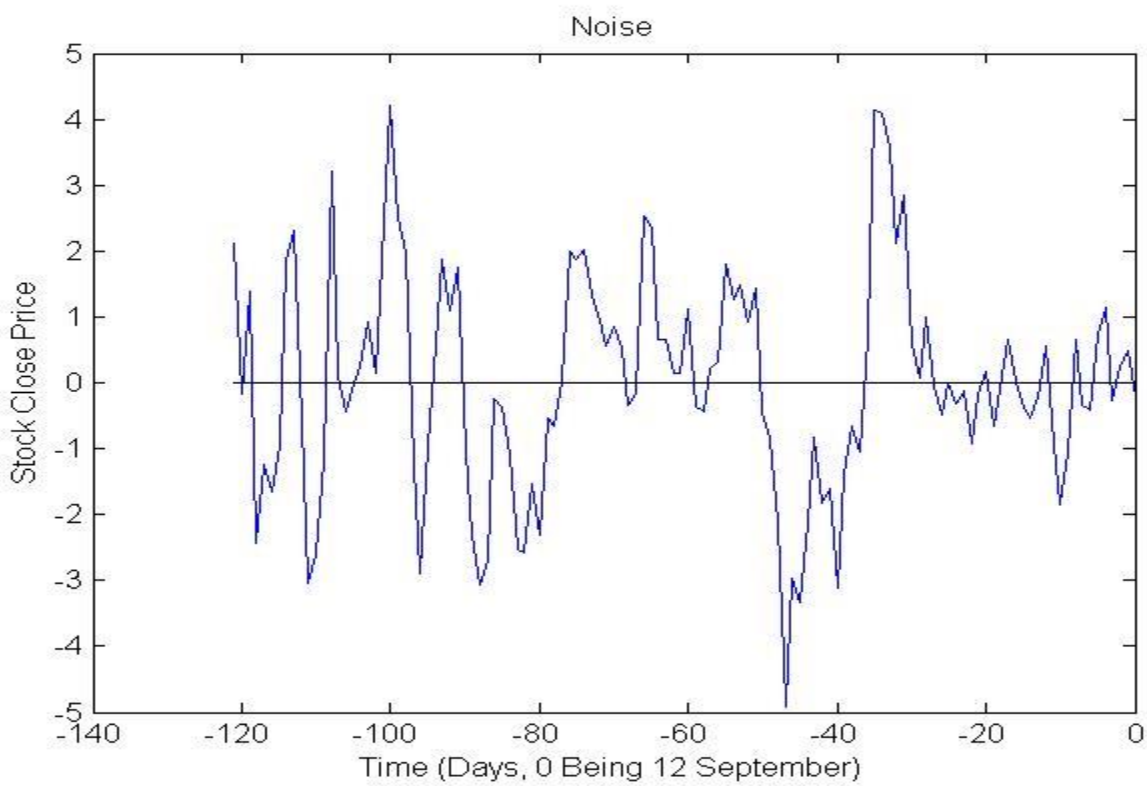
The number of days that are relevant and will be used in the future approximation tools is 122. We use the 122 close price of the stock before 12th of September and plot the Linear LSA. We then subtract the LSA from the stock close data and obtain the price difference.



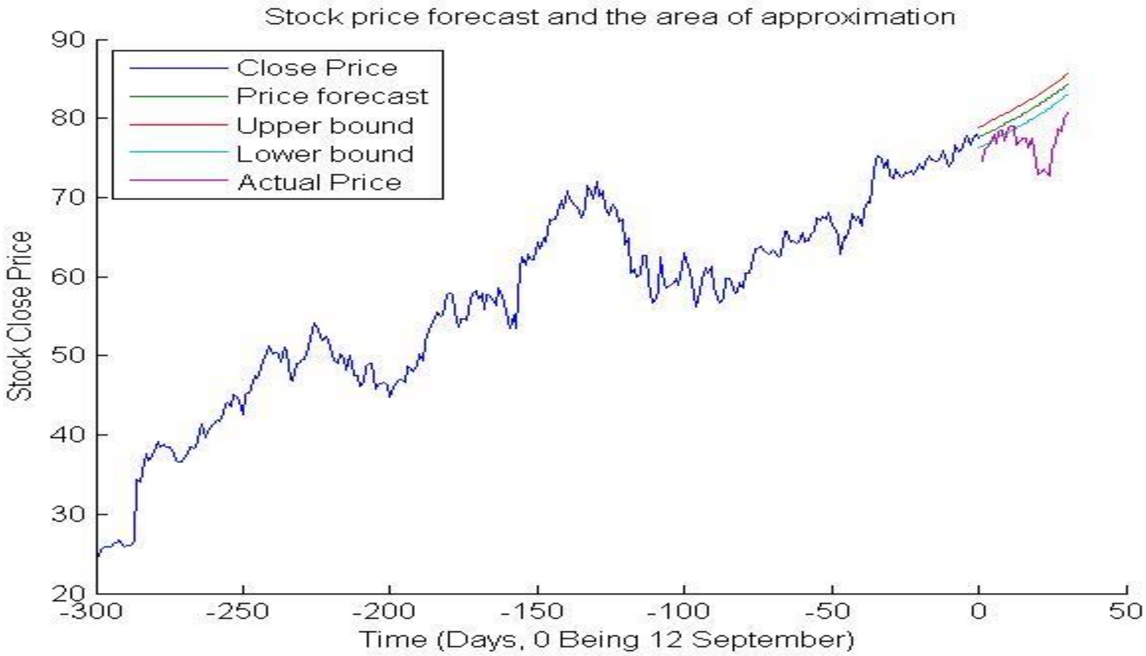


We plot the third order Fourier series on the price difference and then subtract the series from the price difference to obtain the Noise.

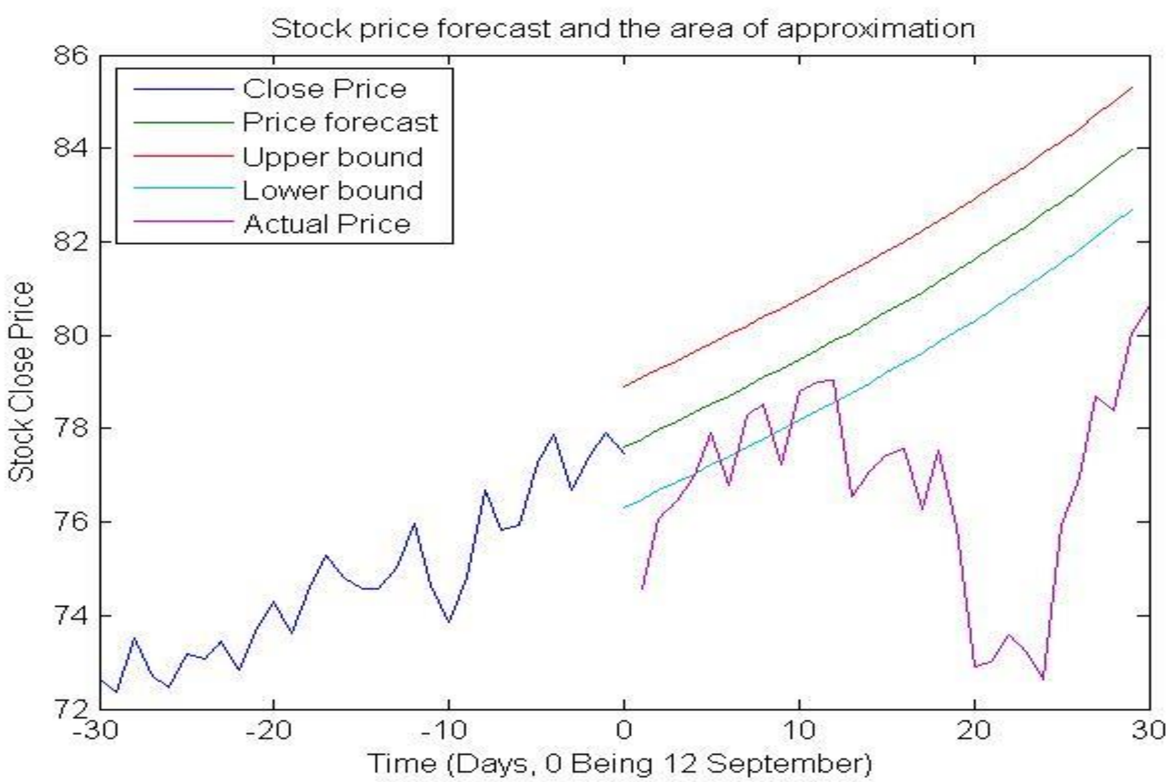

Fourier Series on the difference
data
fitted curve
Stock Close Price
Time (Days, 0 Being 12 September)


Noise
Stock Close Price
Time (Days, 0 Being 12 September)

We sum the Fourier series function and the LSA to obtain the price forecast function. Then we take the average of the absolute value of the Noise. We add and subtract the average Noise from the forecast function to obtain the upper and lower bounds of the prediction area.



Below is the zoomed in version of the graph.

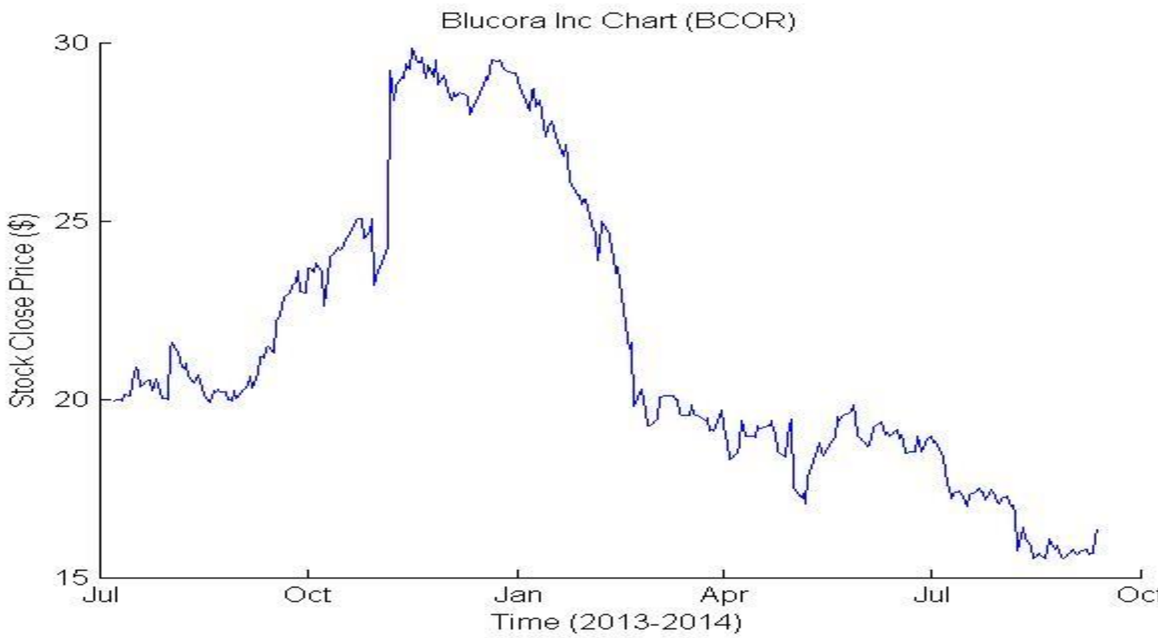


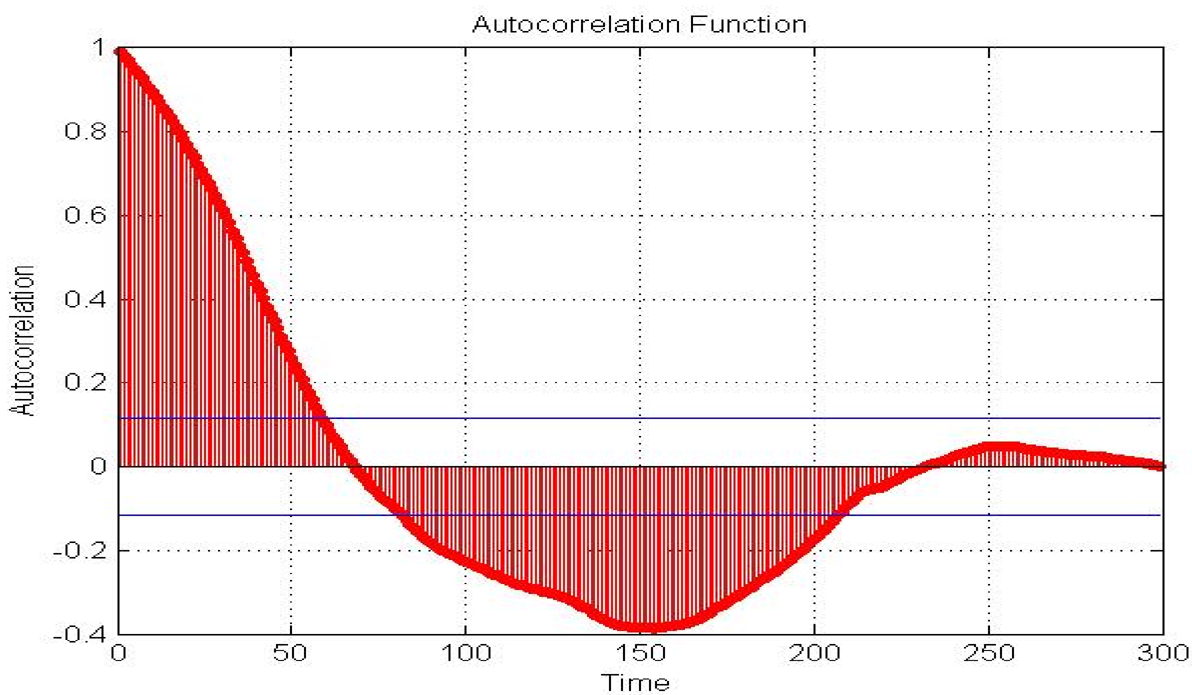
We calculated the percentage of how much predicted line deviates from the actual price. The max percentage for 15 business days is 4.3% and the stock price is 2.02$ below the area of approximation. The min percent is 0.4% and the stock price is inside the area of approximation. The average percent of inaccuracy is 1.9% for 15 business days and 4.8% for 30 business days. Both of them are below the area of approximation. The 95% CI is 5.6%, thus we obtained an acceptable results. The general predicted trend is correct and the average inaccuracy is really low for the 15 business day forecast so it is preferred. The volatility of the data was 45%, while the volatility for the 122 relevant days was 35%. Thus, the model was stable and produced a good forecast.

Blucora Inc. (BCOR):

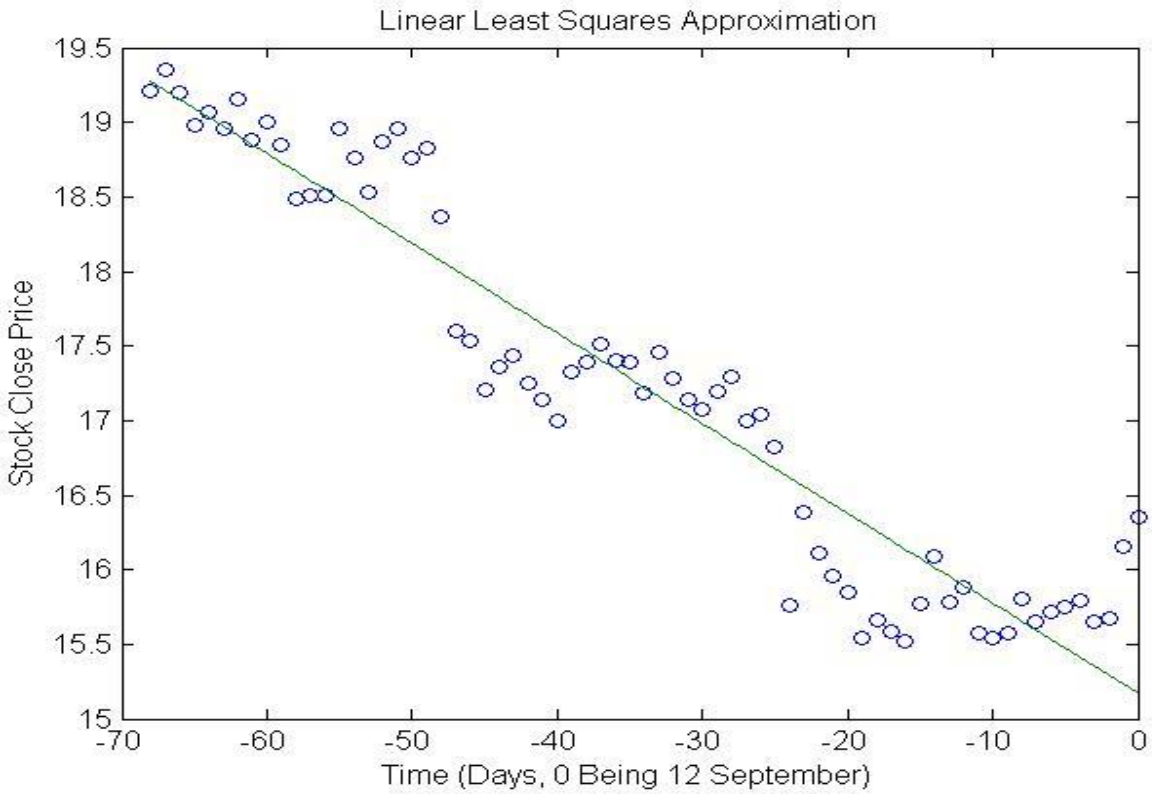
The trend of the forecast line is going downwards and so is the actual price. But, the actual close price after September 12^{th} does not fall in the forecast area. Even though, the volatility for the relevant days was 25%, the model produced an inaccurate prediction. The sudden uptrend of the stock before September 12^{th} for a few days caused the model to destabilize and was only able to correctly determine the slope indicating the direction in which stock price was heading. The average percent of inaccuracy is 5.5% for 15 business days and 6.7% for 30 business days above the area of approximation. The Confidence Interval is 4.3%, which makes the model not acceptable at all.

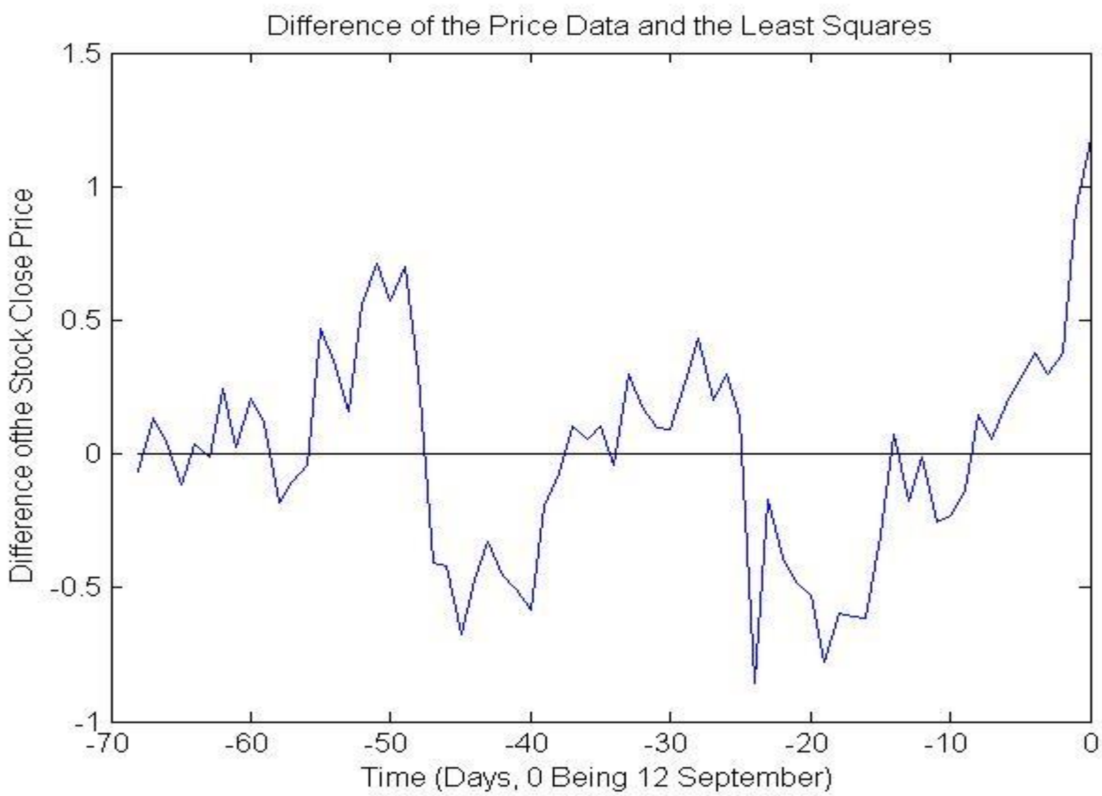
We plot the close price data of Blucora Inc. and use the autocorrelation function to identify relevant data.



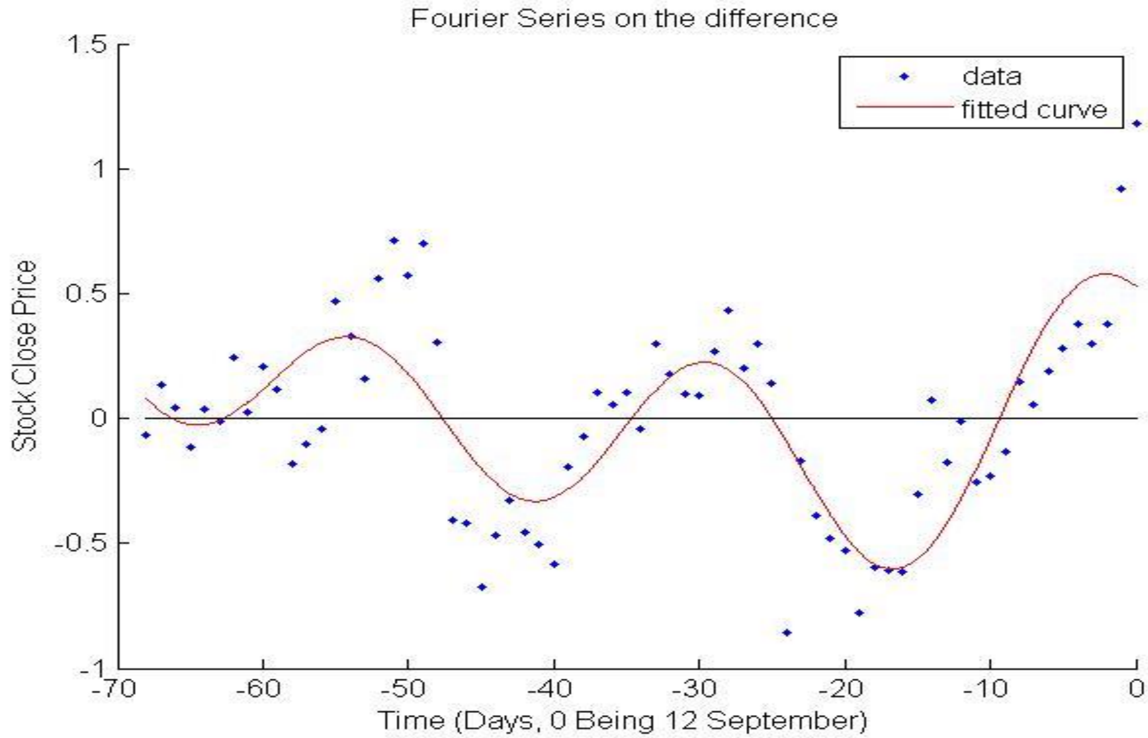


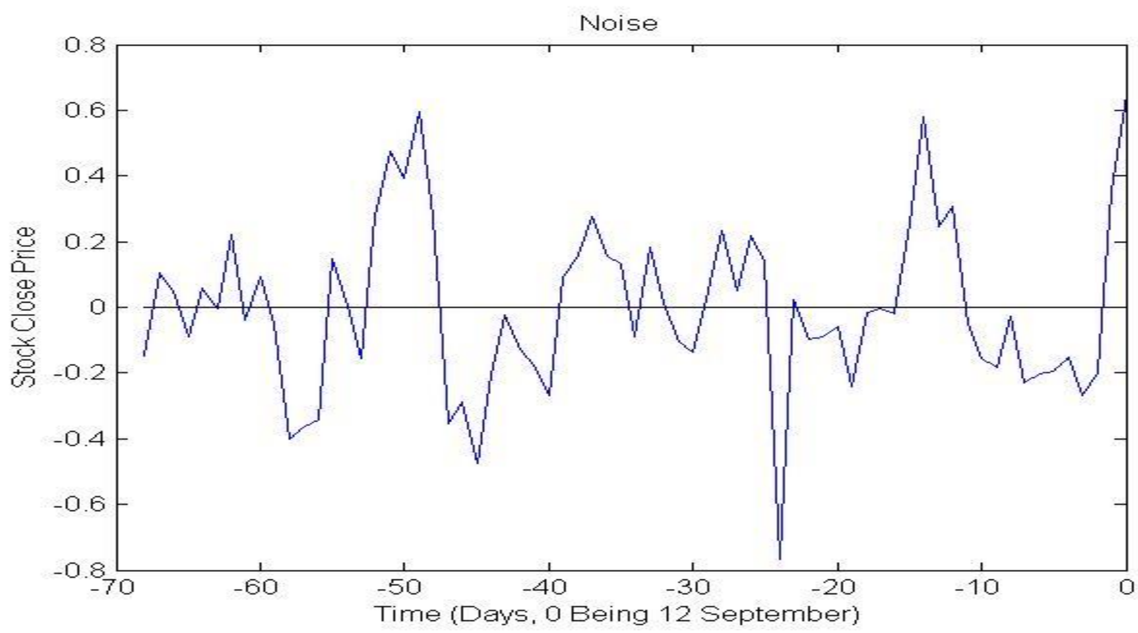
The number of days that are relevant and will be used in the future approximation tools is 69. We use the 69 close price of the stock before 12 September and plot the Linear LSA. We then subtract the LSA from the stock close data and obtain the price difference.


Linear Least Squares Approximation
19.5
19
18.5
18
17.5
17
16.5
16
15.5
15
-70
-60
-50
-40
-30
-20
-10
0
Stock Close Price
Time (Days, 0 Being 12 September)

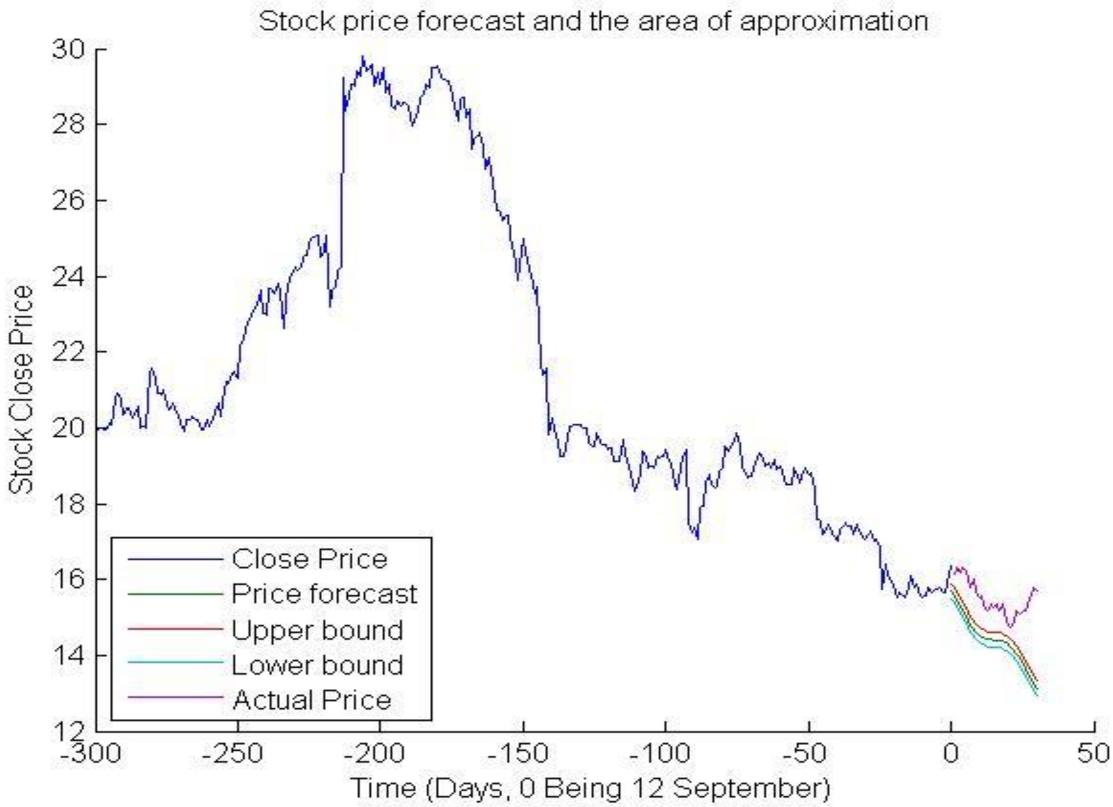

Difference of the Price Data and the Least Squares
1.5
1
0.5
0
-0.5
-1
-70
-60
-50
-40
-30
-20
-10
0
Difference ofthe Stock Close Price
Time (Days, 0 Being 12 September)

We plot the third order Fourier series on the price difference and then subtract the series from the price difference to obtain the Noise.

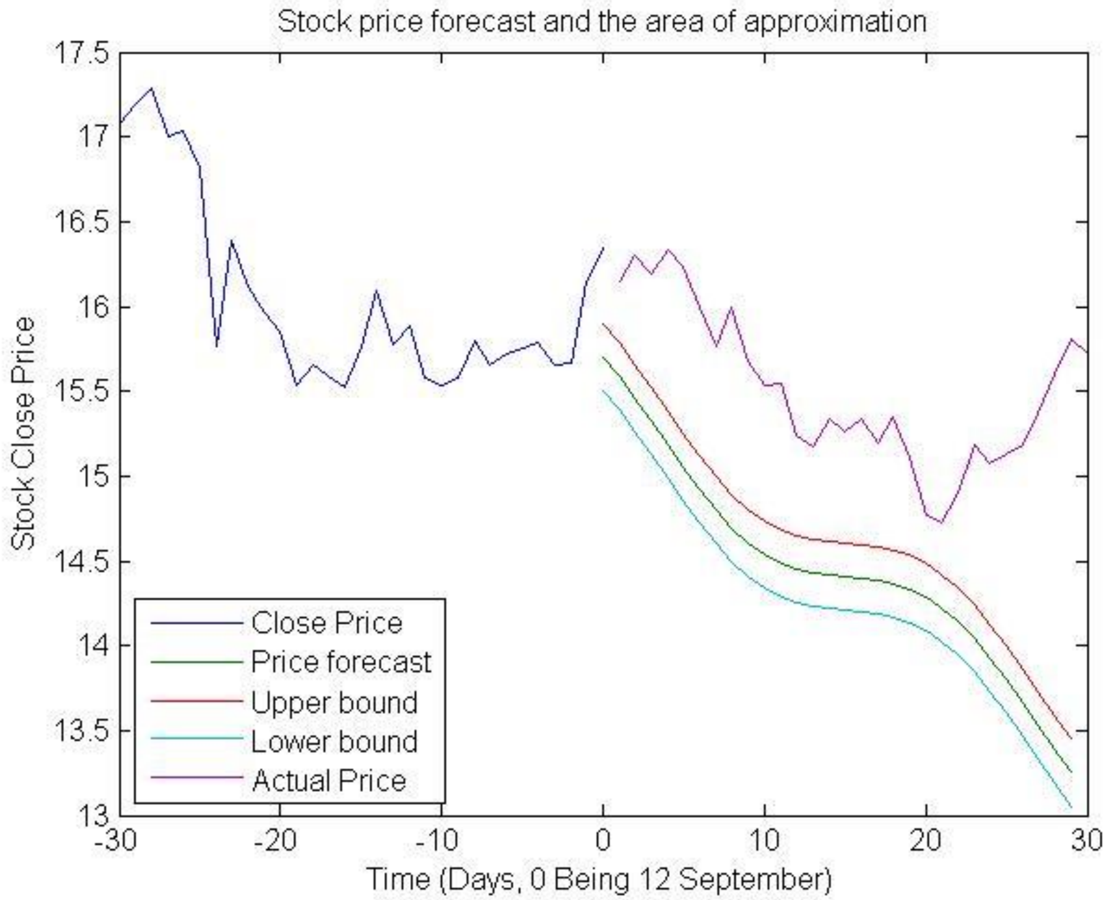




We sum the Fourier series function and the LSA to obtain the price forecast function. Then we take the average of the absolute value of the Noise. We add and subtract the average Noise from the forecast function to obtain the upper and lower bounds of the prediction area.



Below is the zoomed in version of the graph.



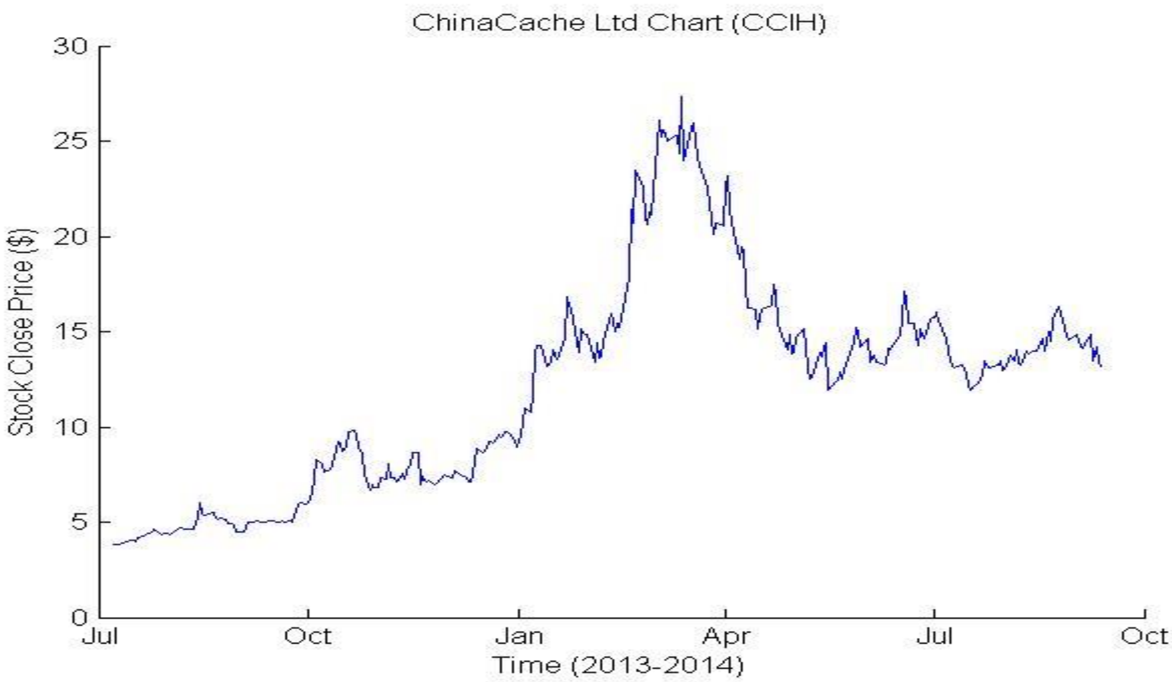
The actual close price after 12 September is off of the forecast area and the only correct assumption the model gave us was the direction of the trend. The sudden uptrend of the stock before 12 September for a few days was the reason that caused the model to produce inaccurate prediction. We calculated the percent deviation of the predicted line from the actual price. The max percentage deviation is 7.5% and the stock price is 1.00$ above the area of approximation. The min percentage is 2.8% and the stock price is 0.25$ above the area of approximation. The average percent of inaccuracy is 5.5% for 15 business days and 6.7% for 30 business days above the area of approximation. The Confidence Interval of 4.3%. The historical volatility of the stock was 34% and for 69 relevant days it was 25%, but a destabilized model was only able to predict the slope of the trend. The model is not acceptable.

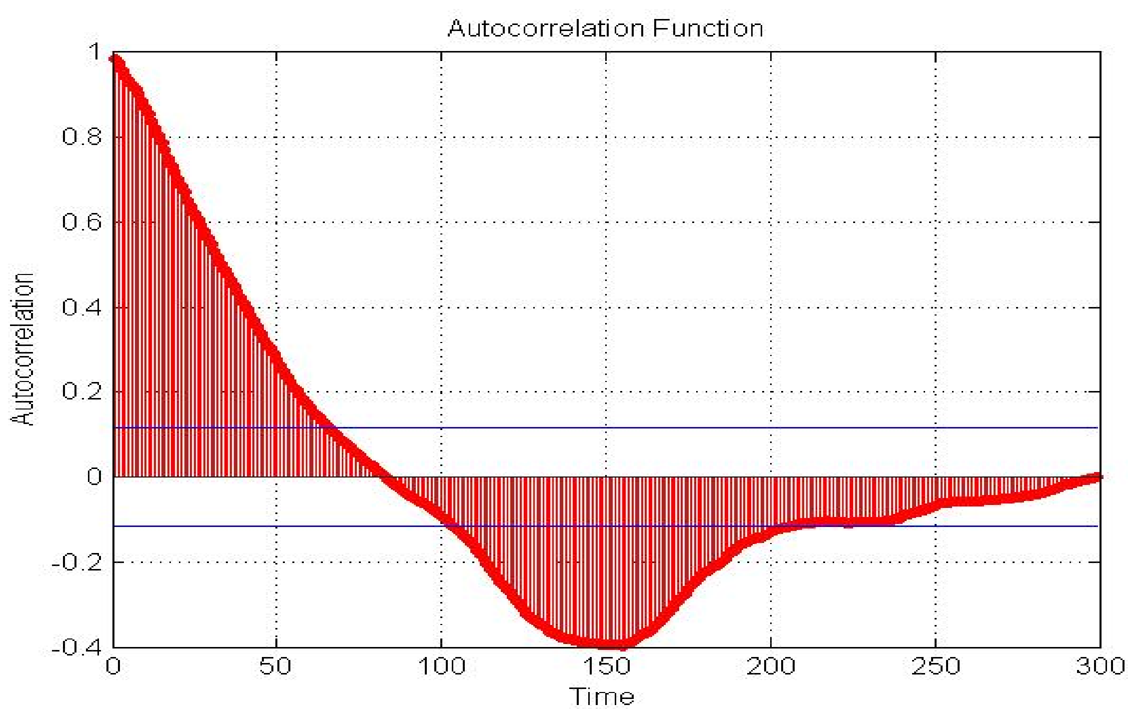
ChinaCache Ltd (CCIH):

We can see that the actual future price is well in the approximation area. The average percent of inaccuracy is 3.2% for 15 business days and 8.1% for 30 business days, which is less than the Confidence Interval of 11.5% and is acceptable. The volatility for the relevant days is

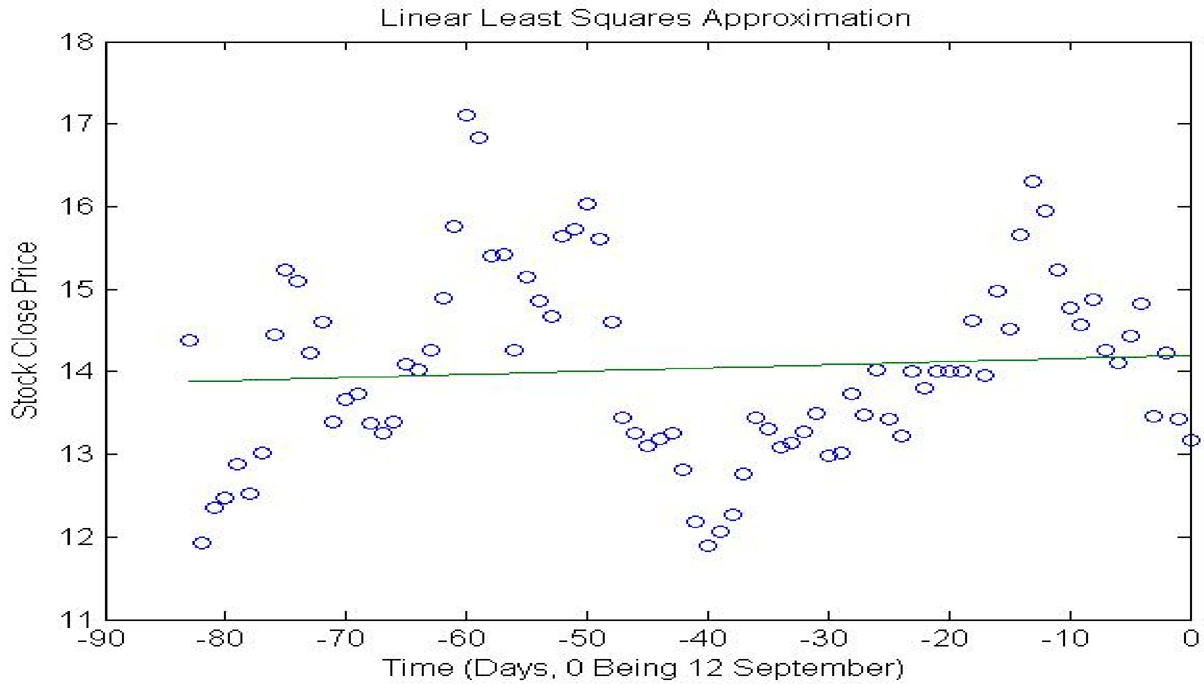
74%. The model is still stable and precise. The historical volatility is 91% and the price change is between 5 and 30, so the relevant number of days represents the stock really well and stabilizes the model. Thus, it is acceptable.

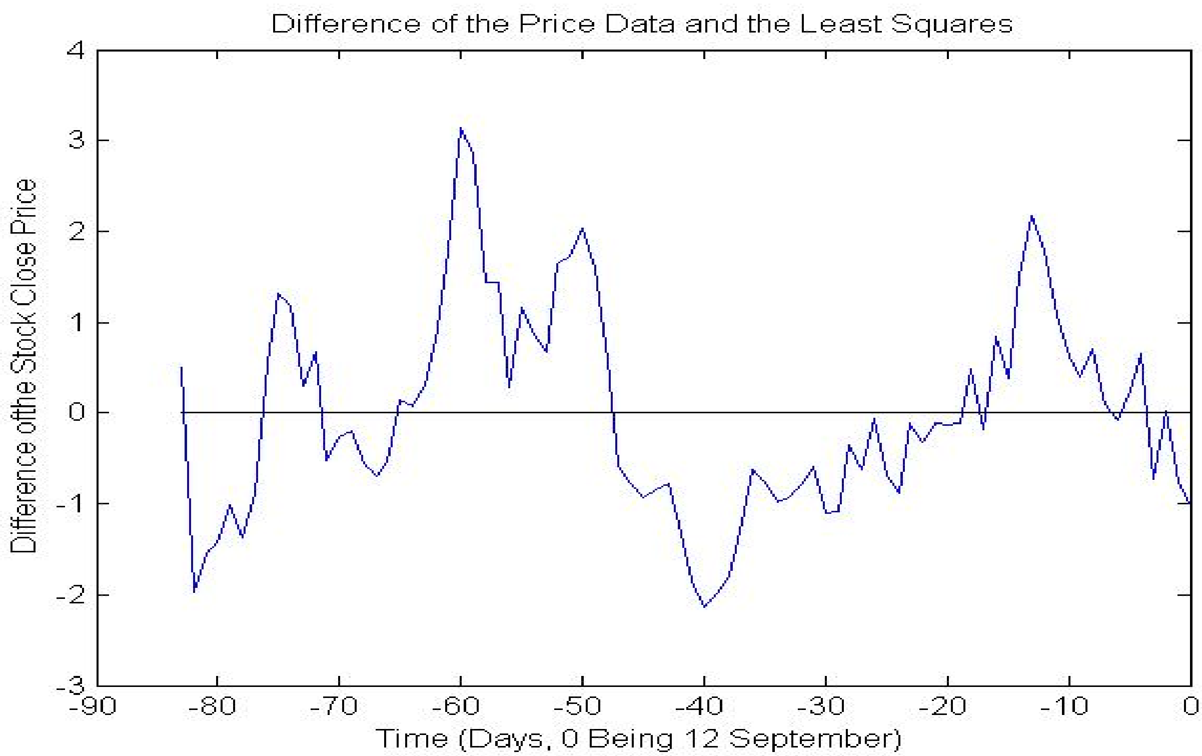
We graph the close price for ChinaCache Ltd and use the autocorrelation data to identify relevant data.



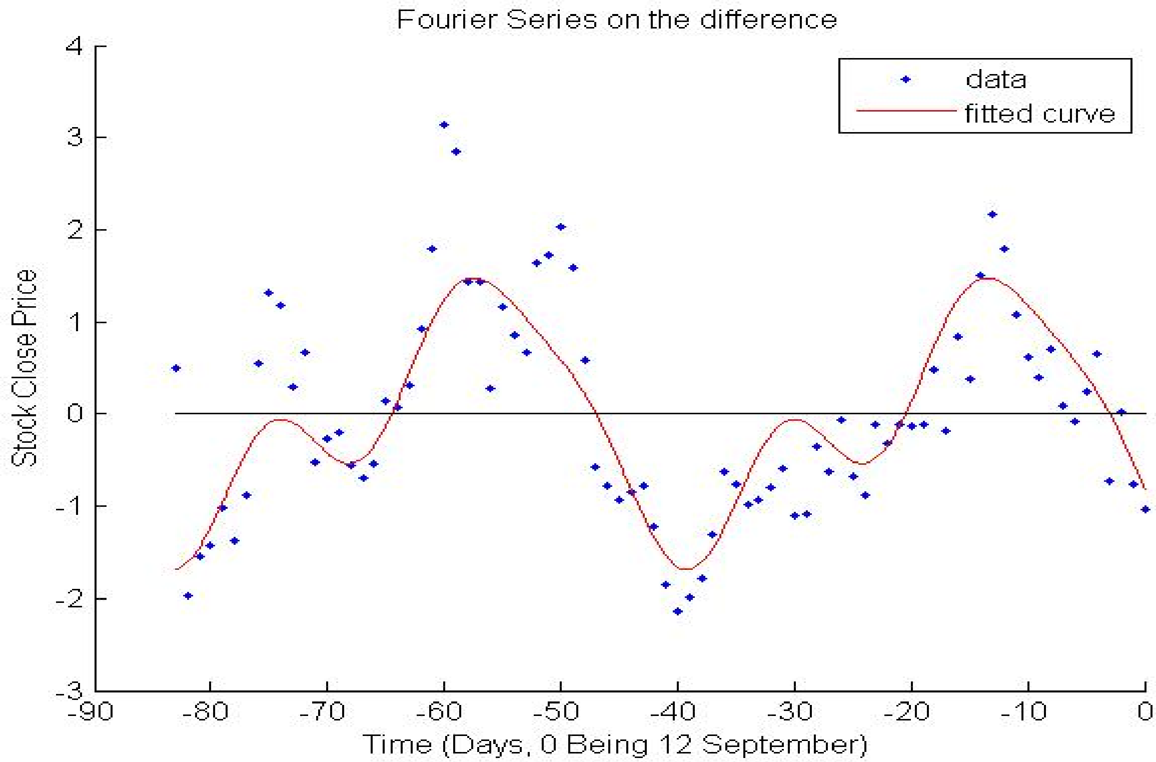


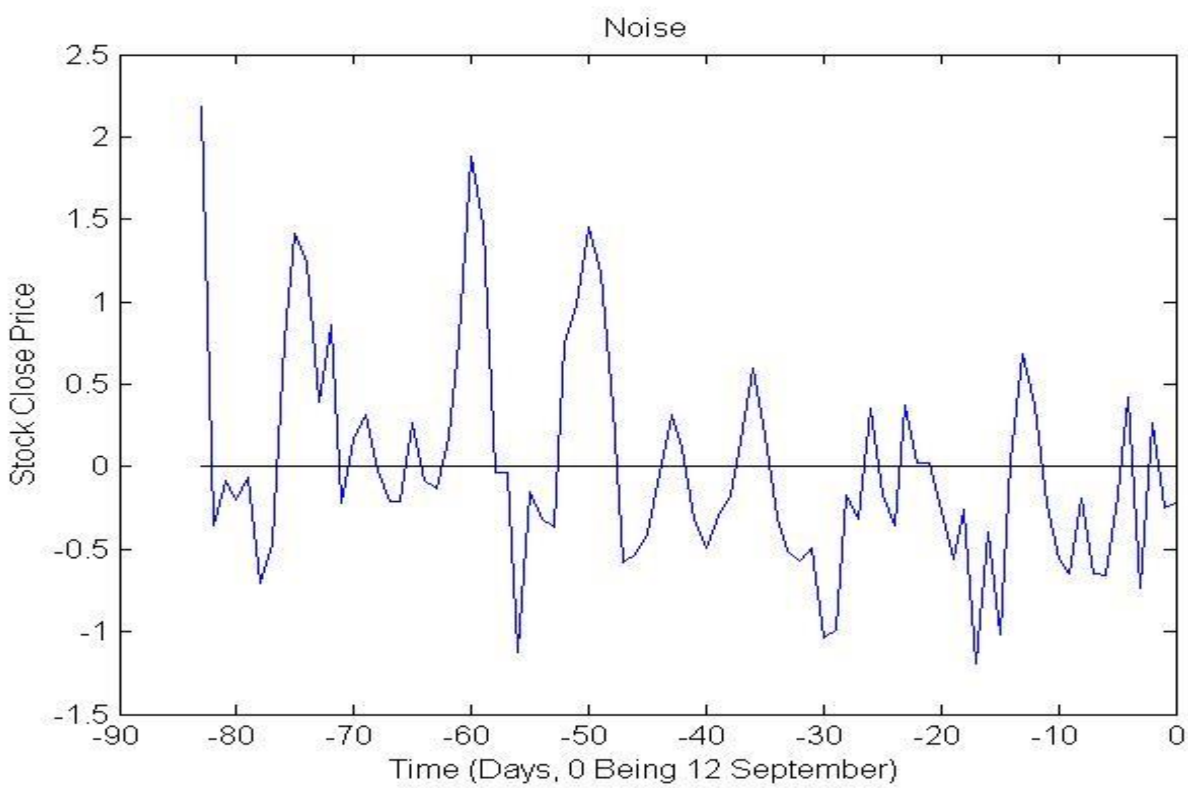
The number of days obtained is 84. Thus, the close price for 84 days before 12 September is what we will use for our future calculations. We plot the linear LSA for the relevant data and subtract it from the data to obtain price difference.





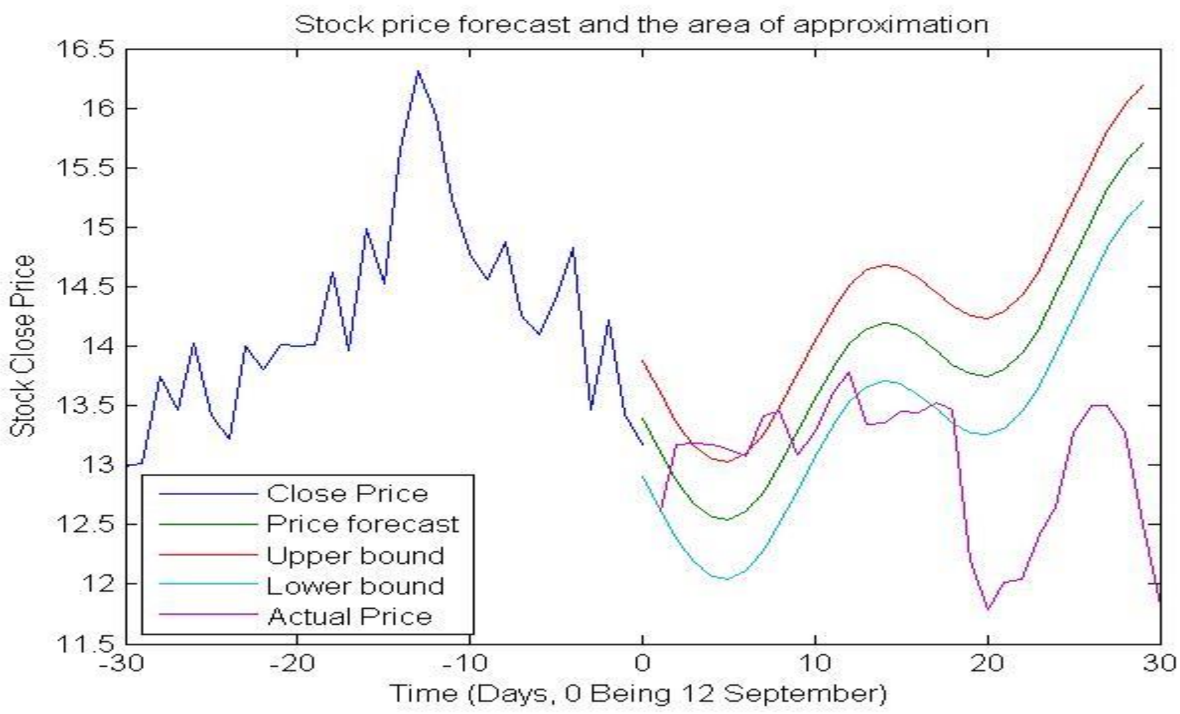
We plot a third order Fourier series and subtract it from the price difference to obtain Noise.





We sum the Fourier series function and the LSA to obtain the price forecast function. Then we take the average of the absolute value of the Noise. We add and subtract the average Noise from the forecast function to obtain the upper and lower bounds of the prediction area. Below is a plot of the close price data before and after 12 September.

Below is the zoomed in version of the graph.

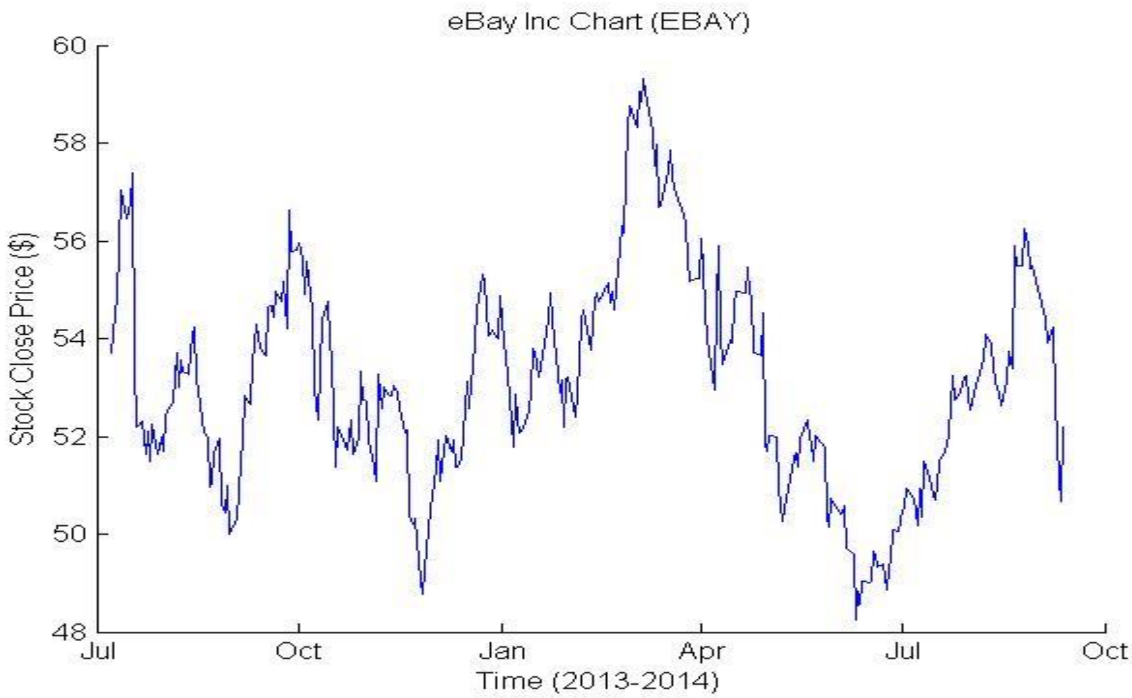


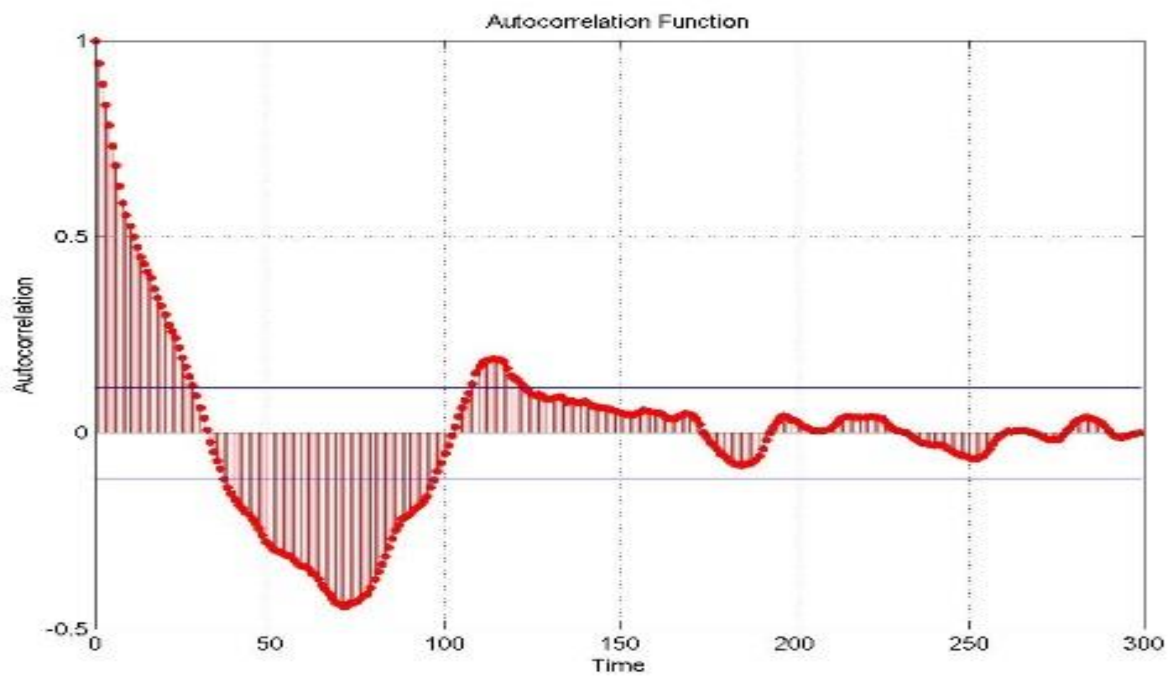
The max percentage of inaccuracy is 6.2% and the stock price is 0.31$ below the area of approximation. The min percent is 0.01% and the stock price is inside the area of approximation. The average percent of inaccuracy is 3.2% for 15 business days and 8.1% for 30 business days, while the 95% CI is 11.5%. We can see that the actual future price is well in the approximation area. The historical volatility for this stock was 91% and for the last 84 relevant days it was 74%. The model is still stable and precise because the price change, during the relevant day period, is between 13 and 16. The historical volatility price change is between 5 and 30, so the relevant number of days represents the stock really well and stabilizes the model. The model is acceptable.

EBay Inc. (EBAY):

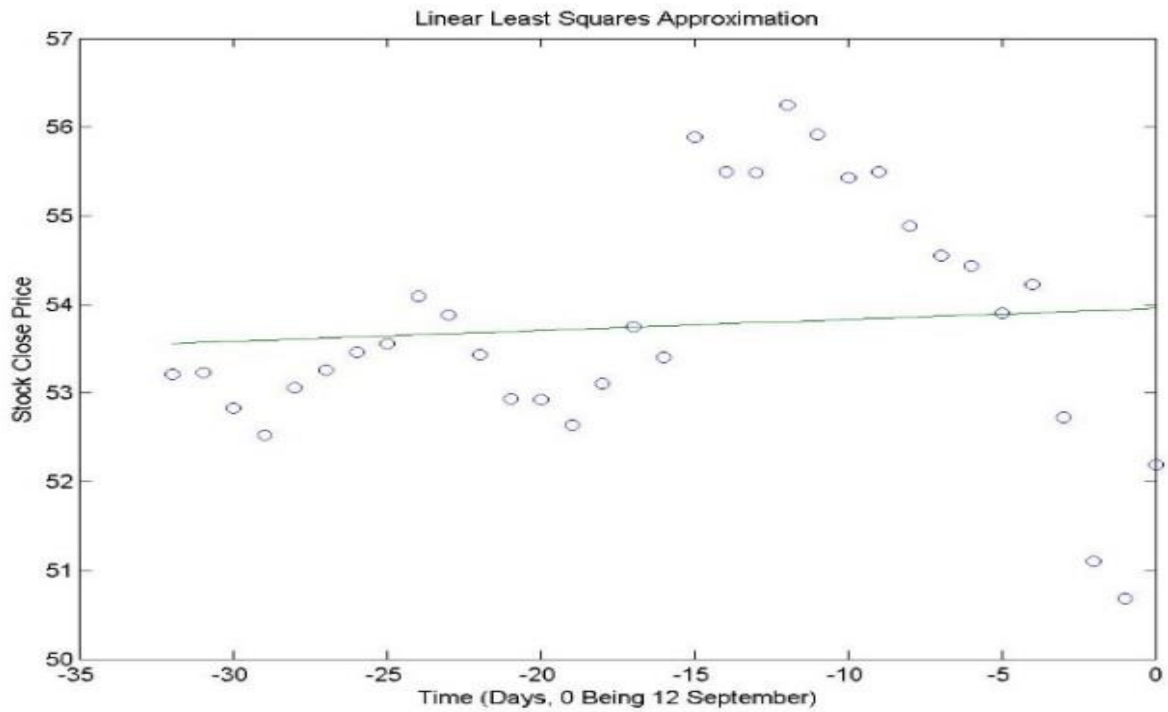
The actual price after 12 September starts off in the area of approximation. The graph predicts a strong positive momentum. EBay is an interesting stock because the forecast graph diverges below the stock price. This means that if the model predicted a rise in price, an investor should have bought the stock in order to have sold it at a later date. The actual future price making a steeper jump than the forecasted line is a much better result and the investor made a lot more capital. The average percent of inaccuracy is 1.6% for 15 business days and 4.6% for 30 business days, CI is 2.8%, and volatility for relevant days is 22%. The model is only acceptable for 15 business day forecasting.

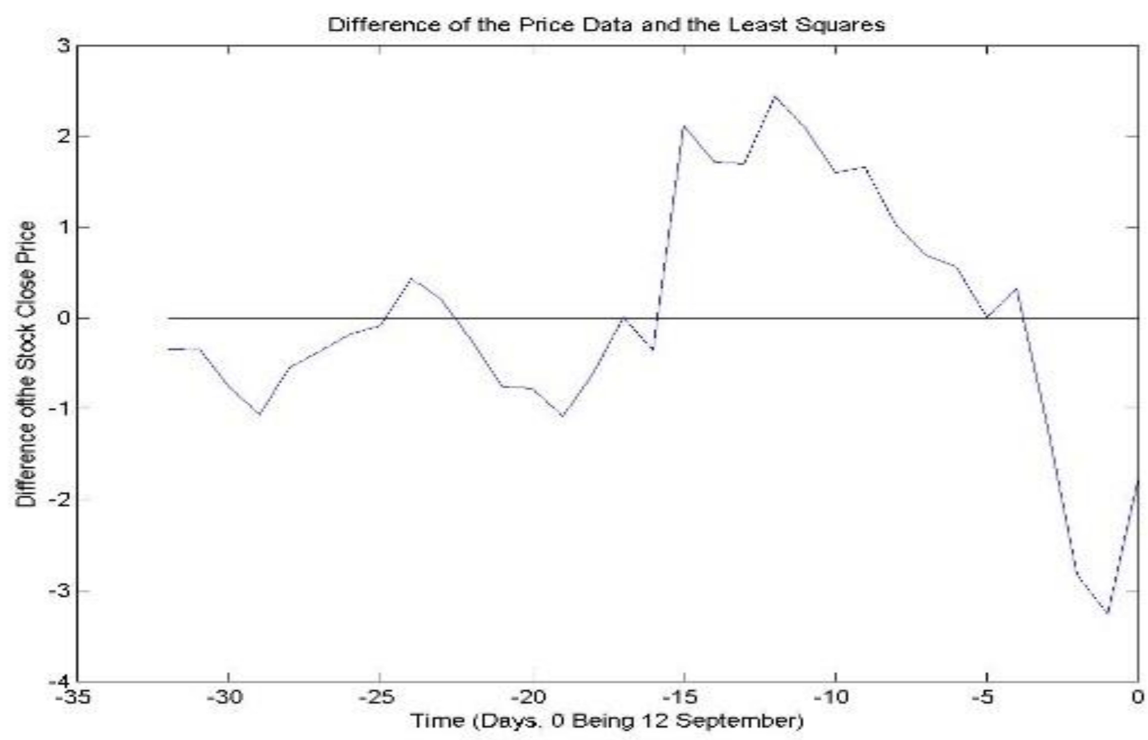
We graph the close price for eBay Inc. and use the autocorrelation data to identify relevant data.



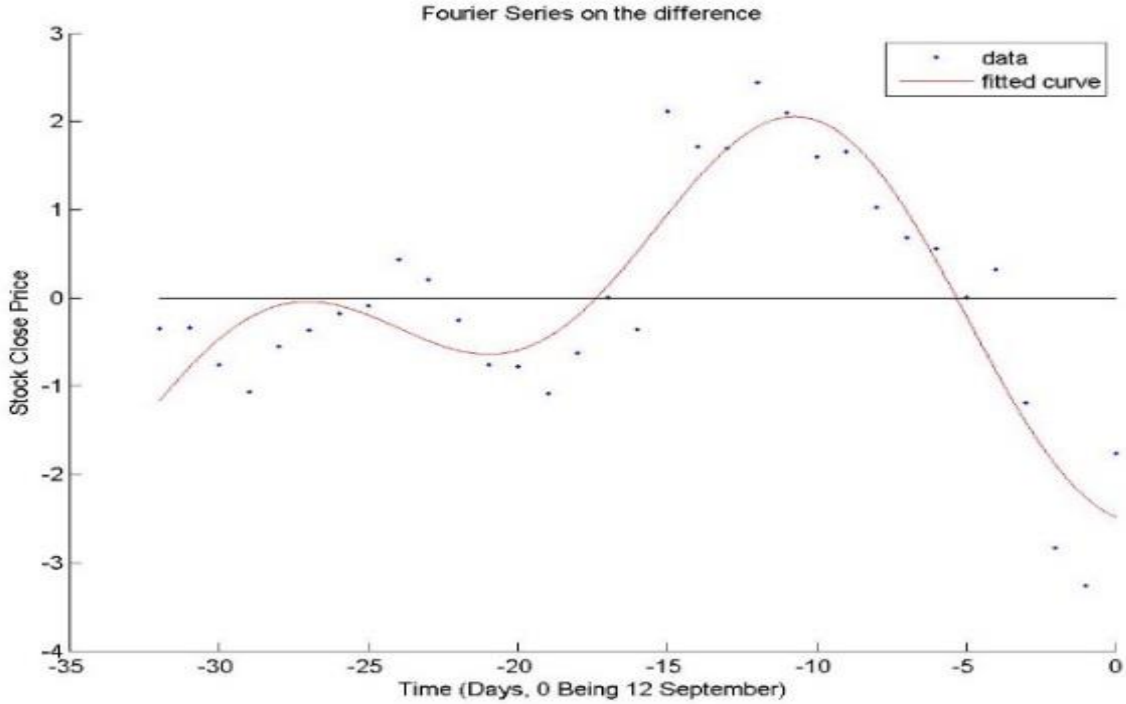


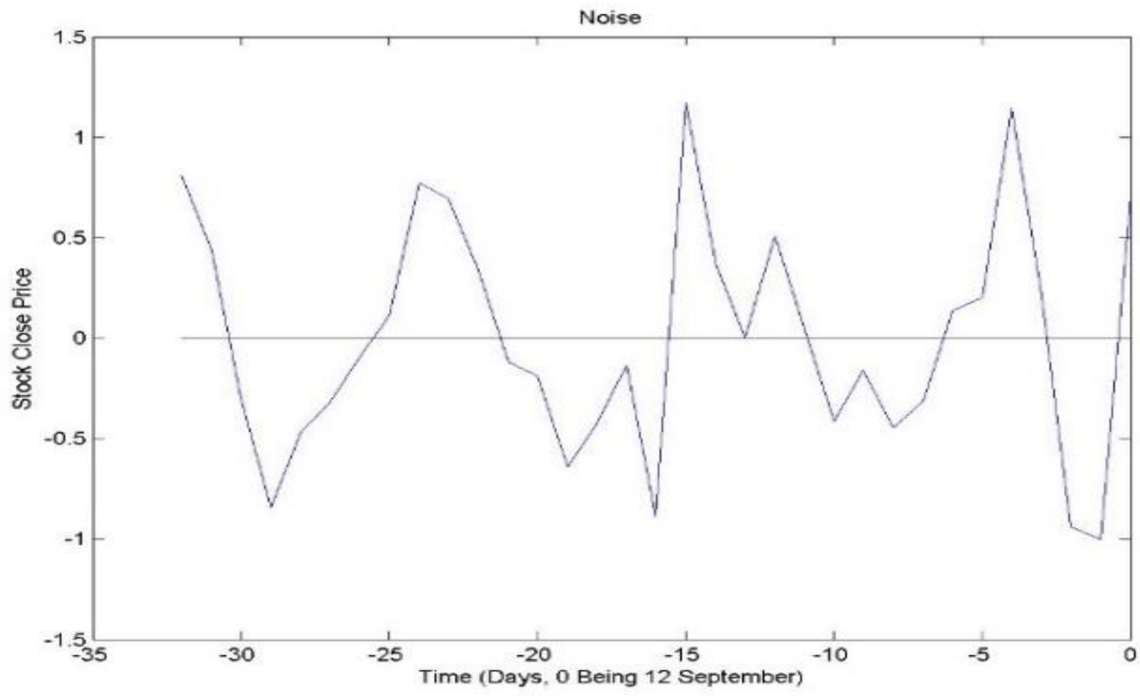
The number of days that are relevant and will be used in the future approximation tools is 33. We use the 33 close price of the stock before 12 September and plot the Linear LSA. We then subtract the LSA from the stock close data and obtain the price difference.



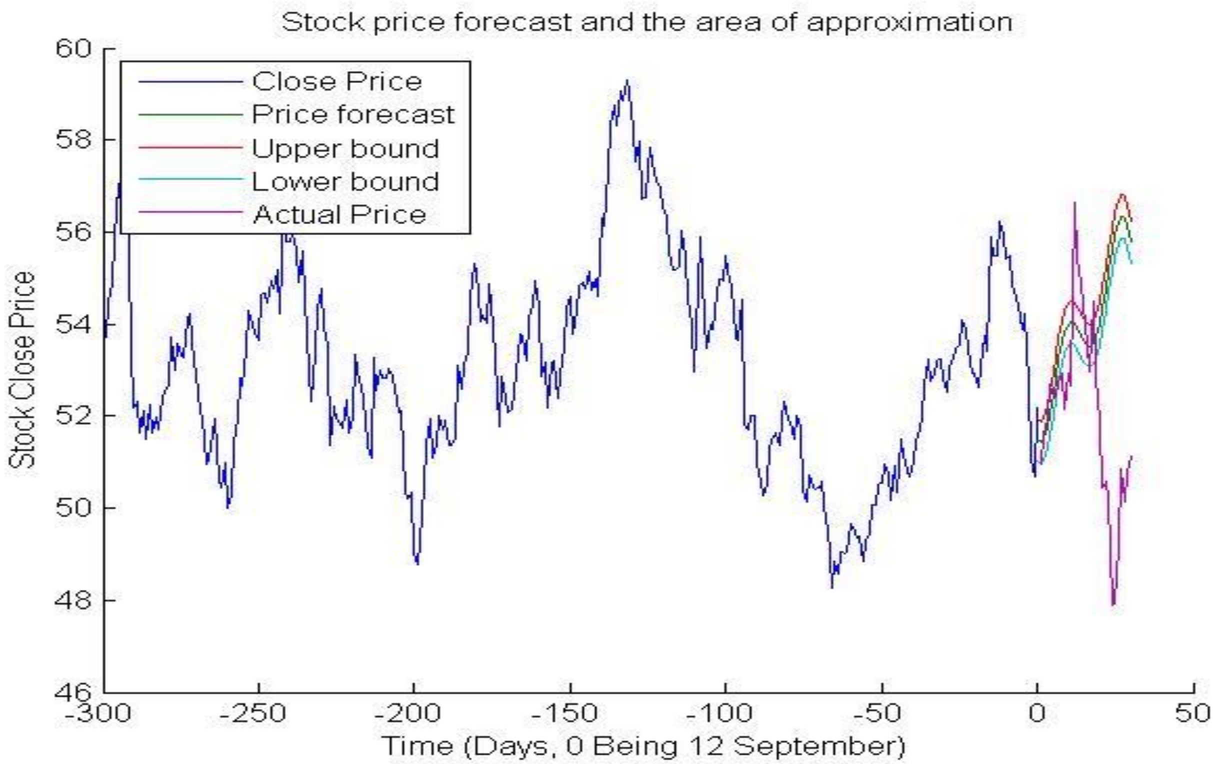


Due to autocorrelation being 33, which is a small number. We will use second order Fourier series for eBay instead of third order. We then subtract the obtained Fourier function from the price difference to obtain the Noise.

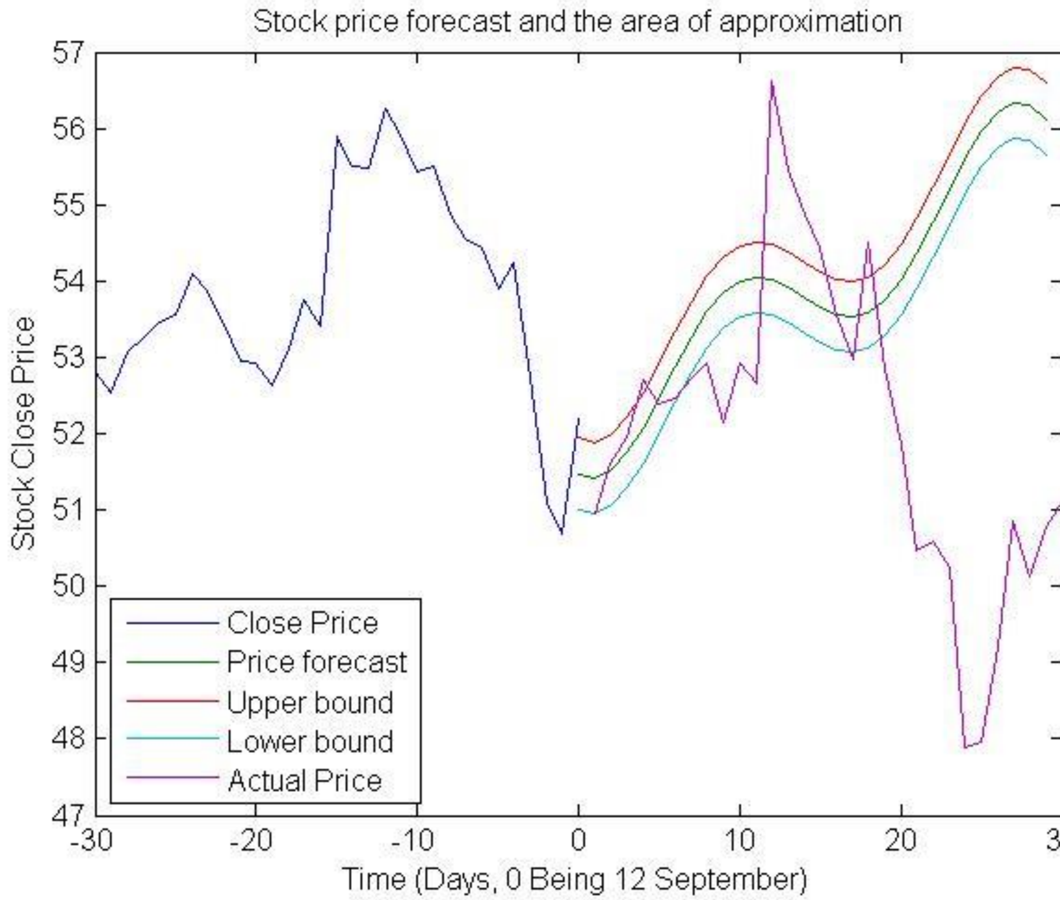




We sum the Fourier series function and the LSA to obtain the price forecast function. Then we take the average of the absolute value of the Noise. We add and subtract the average Noise from the forecast function to obtain the upper and lower bounds of the prediction area.



The zoomed in version of the graph is represented below.

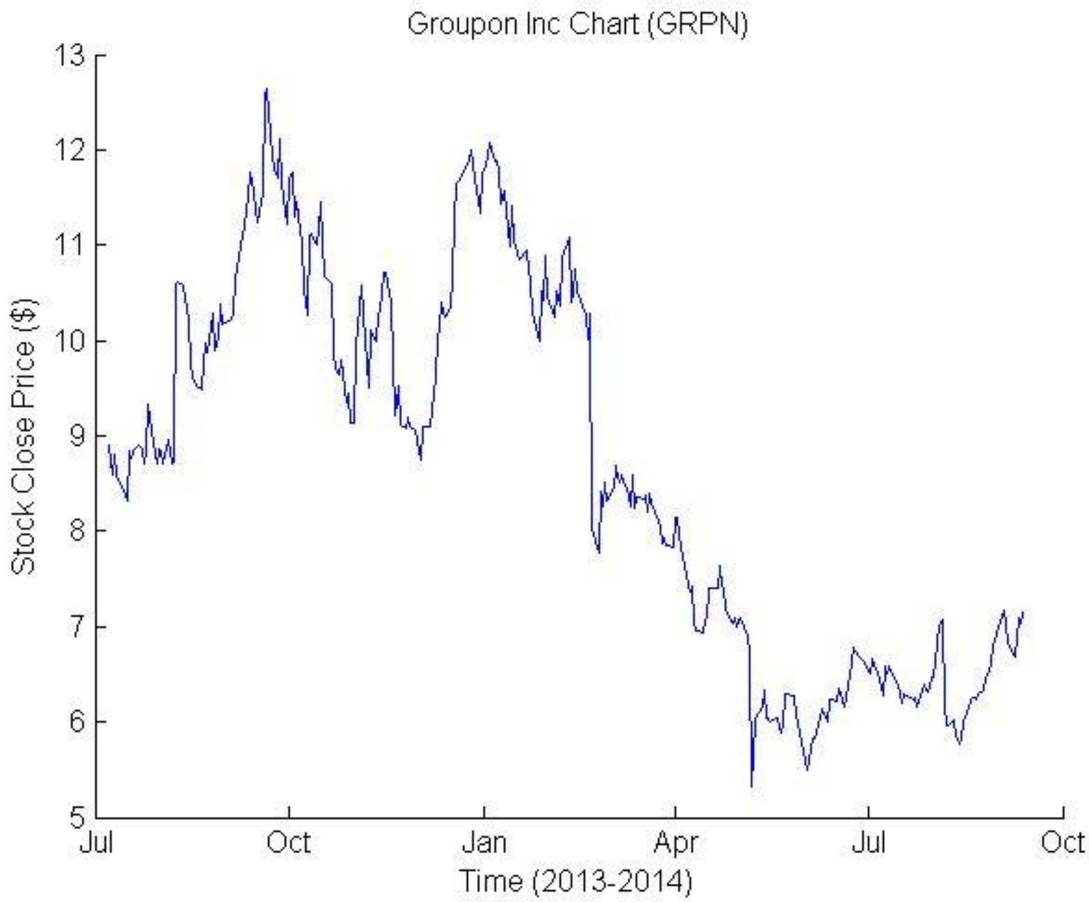


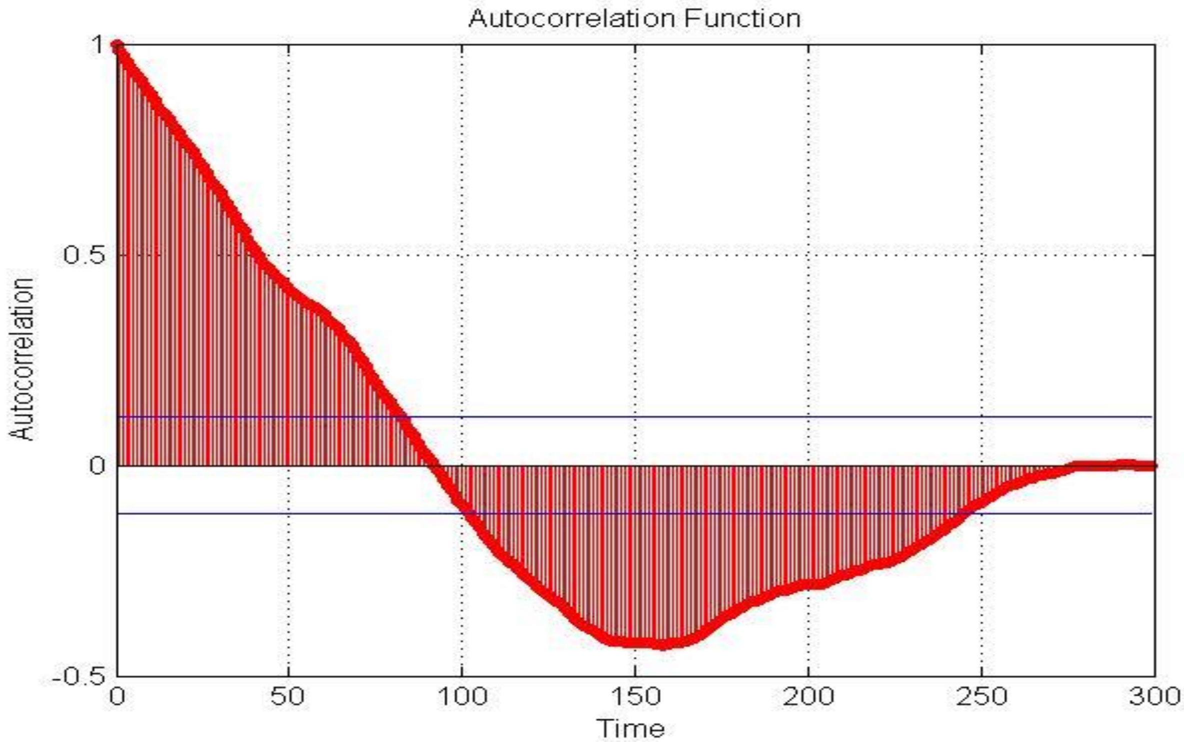
We calculated the percentage of how much predicted line deviates from the actual price. The max percentage is 4.6% and the stock price is 2.11$ above the area of approximation. The min percent is 0.005% and the stock price is inside the area of approximation. The actual price after 12th of September starts off in the area of approximation. The graph predicts a strong positive momentum. EBay is an interesting stock because the forecast graph diverges below the stock price. This means that if the model predicted a rise in price, an investor should have bought the stock in order to have sold it at a later date. The actual future price making a steeper jump than the forecasted line is a much better result and the investor made a lot more capital. The average percent of inaccuracy is 1.6% for 15 business days and 4.6% for 30 business days, CI is 2.8%, and historical volatility and volatility for 33 relevant days are 22%. The model is only acceptable for 15 business day forecasting.

Groupon Inc (GRPN):

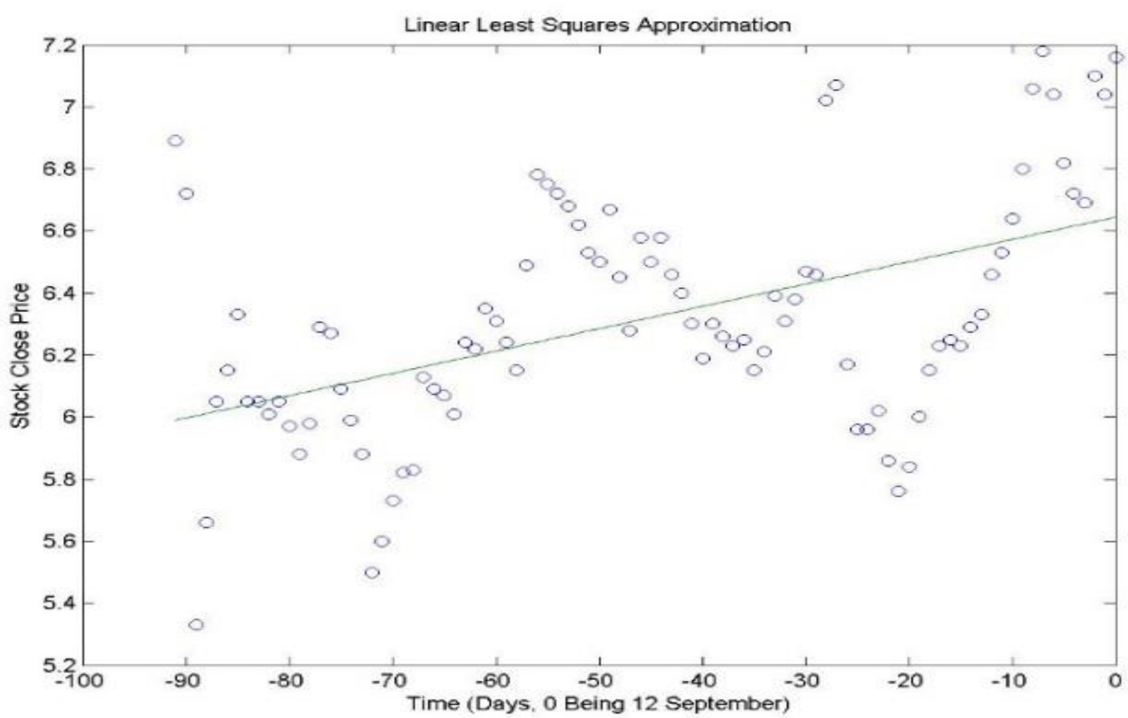
The Groupon close price data after 12th of September is well within the area of approximation and follows the price forecast function with minimal divergence. This is an excellent forecast and the average percent of inaccuracy is 1.1% for 15 business days and 4.1% for 30 business days. Even though, the volatility for relevant data was 60% and the confidence interval 7.5%, the maximum price movement was between 5 and 7 dollars. The historical close price experienced sharp movement ranging from 5 to 13 dollars thus the model was well represented.

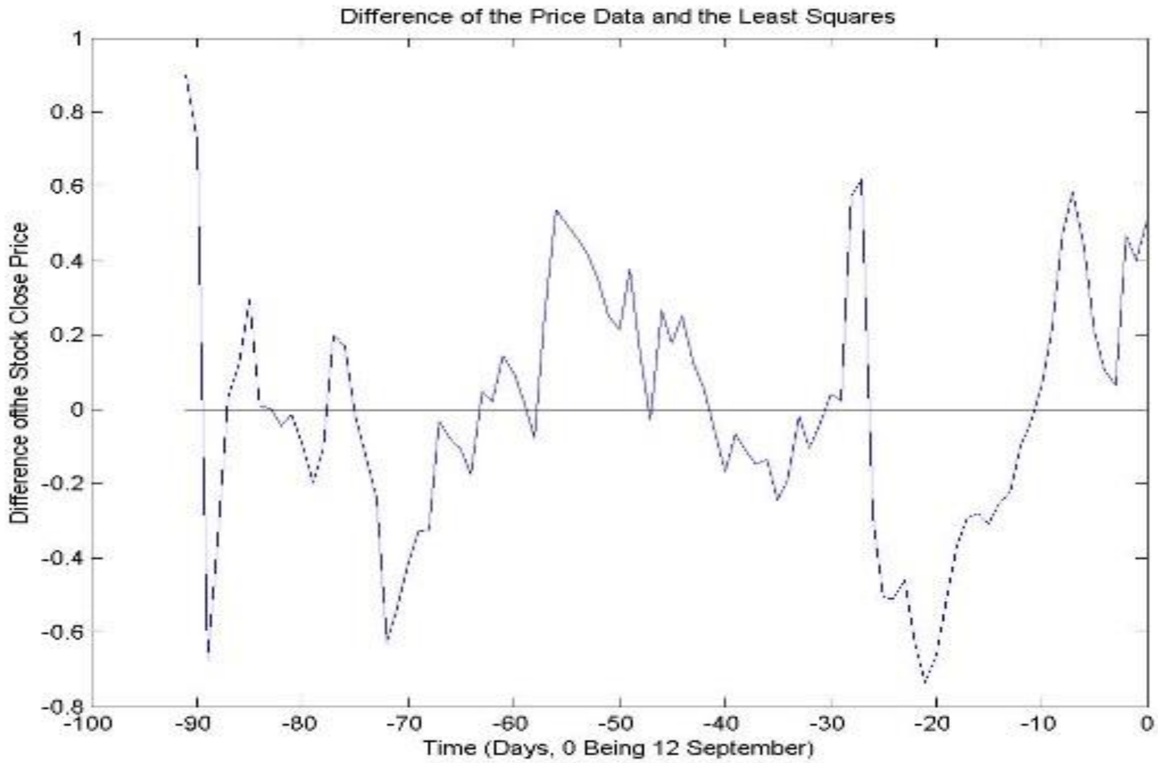
We graph the close price for Groupon Inc. and use the autocorrelation data to identify relevant data.



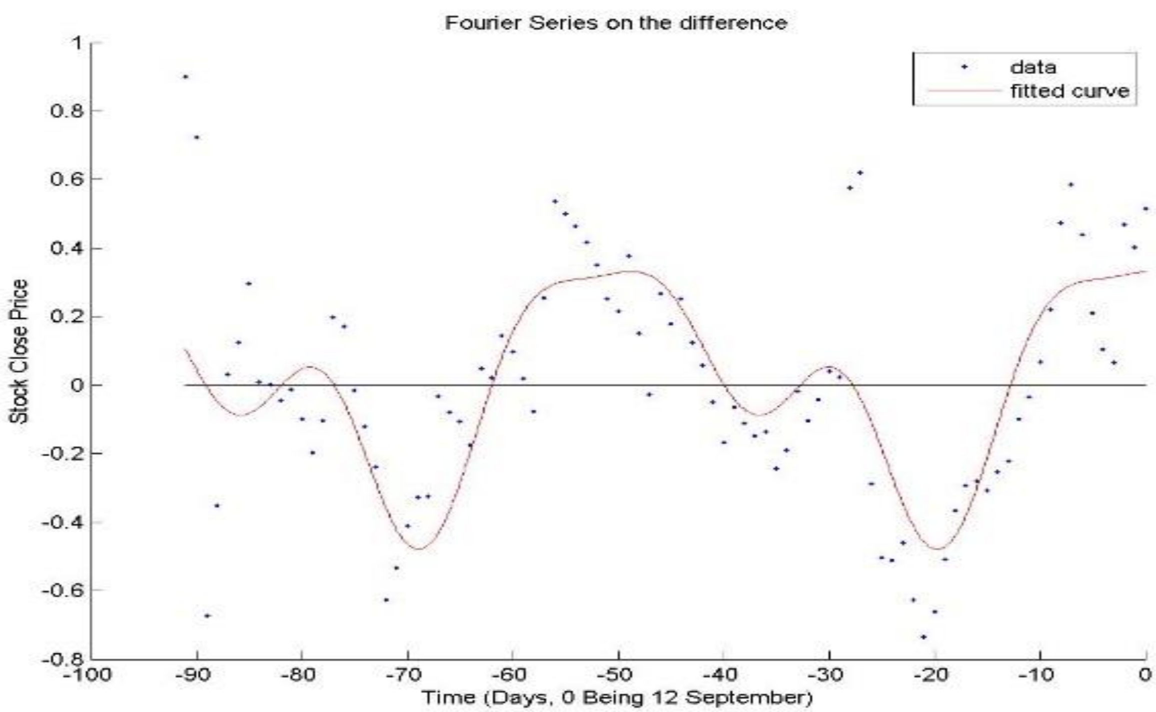


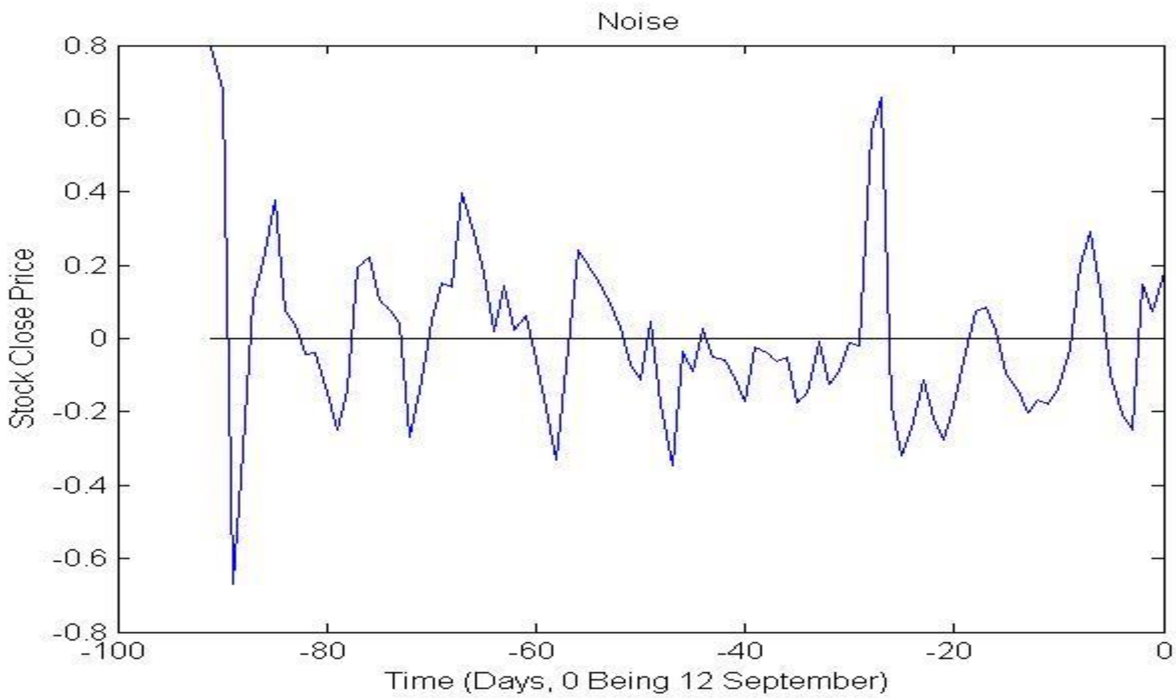
The number of days obtained is 92. Thus, the close price for 92 days before 12th of September is what we will use for our future calculations. We plot the linear LSA for the relevant data and subtract it from the data to obtain price difference.



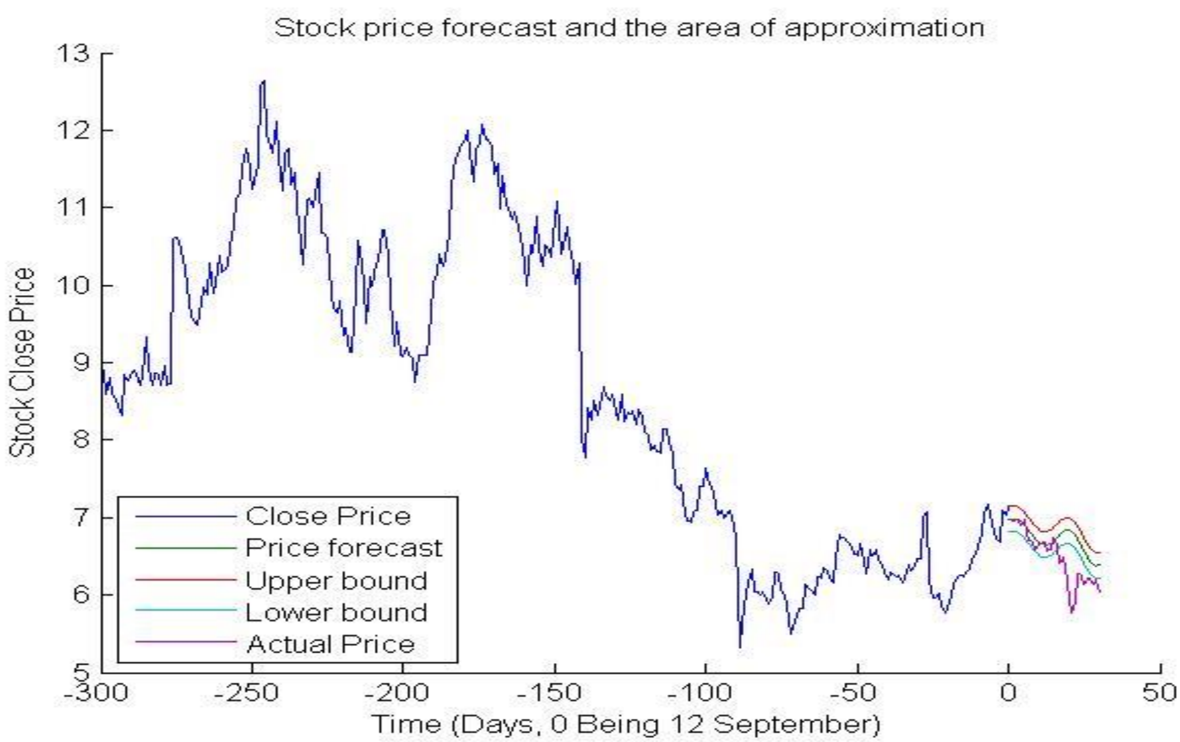


We plot a third order Fourier series and subtract it from the price difference to obtain Noise.

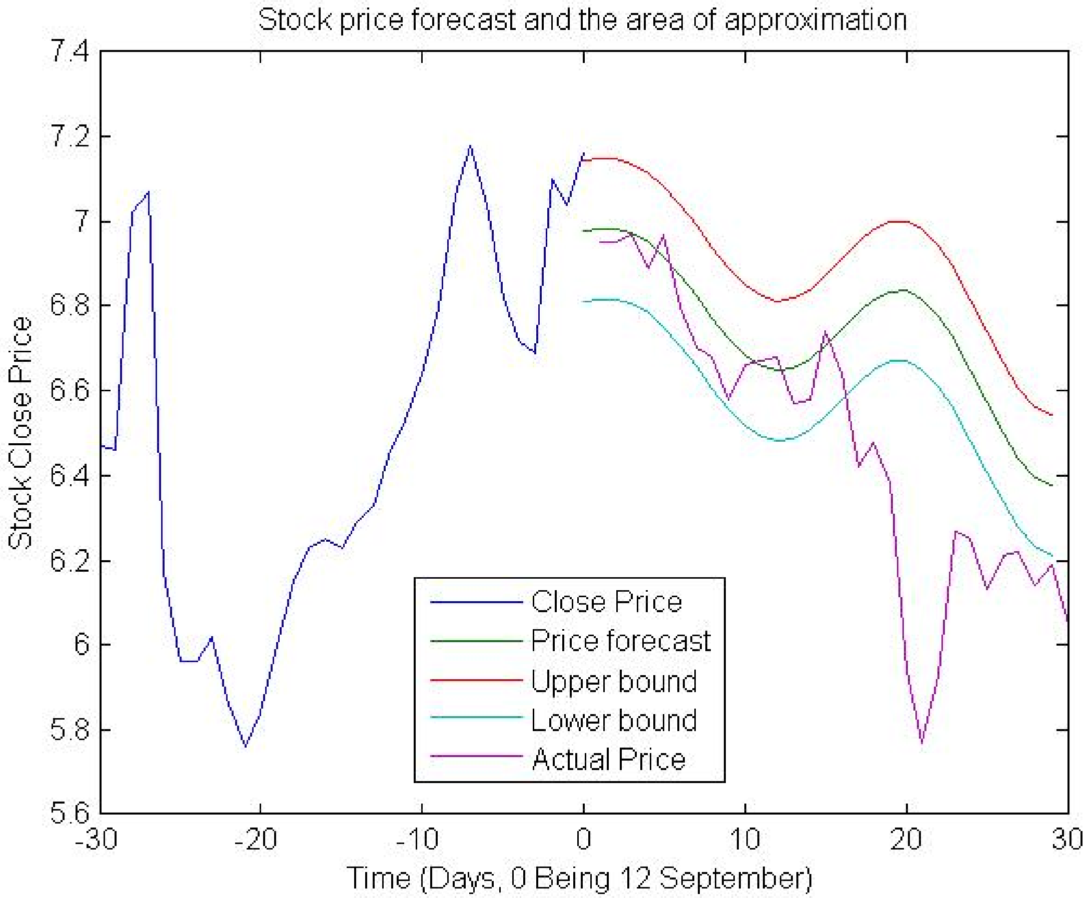




We sum the Fourier series function and the LSA to obtain the price forecast function. Then we take the average of the absolute value of the Noise. We add and subtract the average Noise from the forecast function to obtain the upper and lower bounds of the prediction area.



Below is the zoomed in version of the graph.



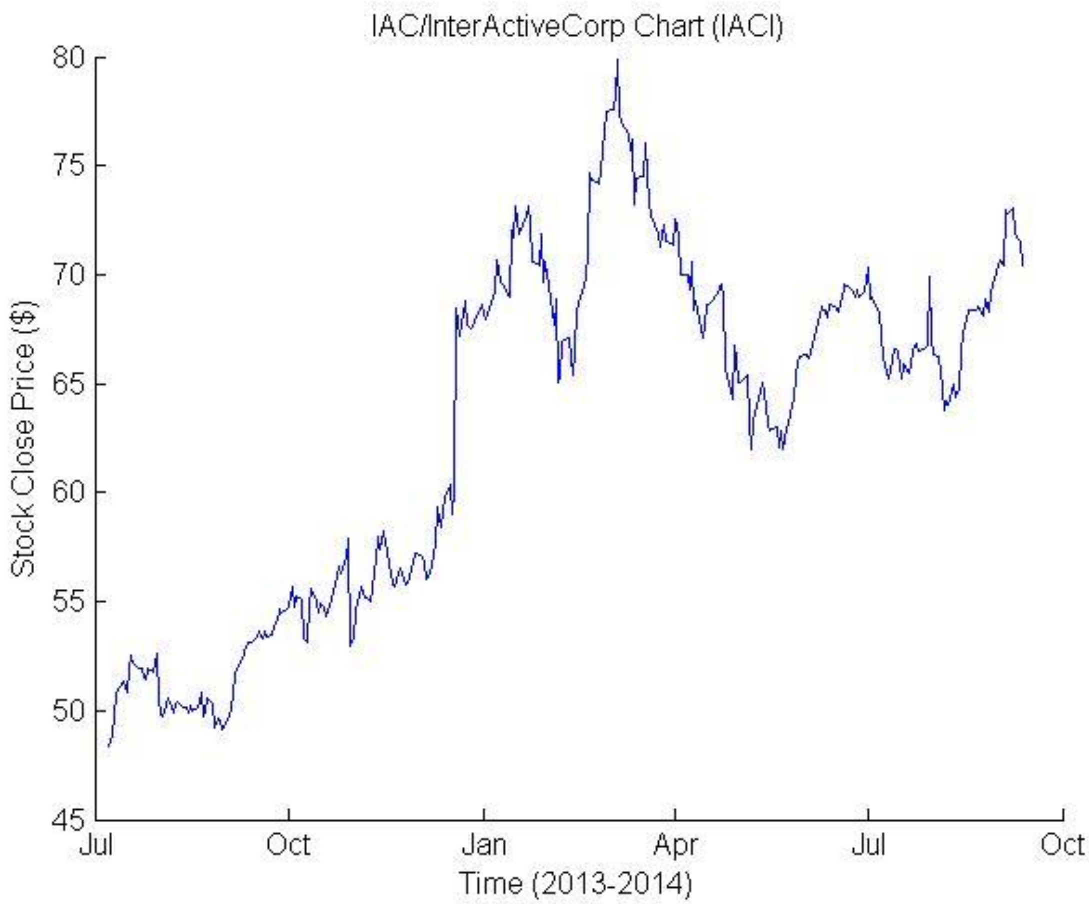
The max percentage of inaccuracy is 2.9% and the stock price is 0.03$ below the area of approximation. The min percent is 0.18% and the stock price is inside the area of approximation. The average percent of inaccuracy is 1.1% for 15 business days, 4.1% for 30 business days and the CI is 7.5%. The Groupon close price data after 12th of September is well within the area of approximation and follows the price forecast function with minimal divergences. This is an excellent forecast. Even though, the volatility for 92 relevant data was 60% the maximum price movement was between 5 and 7 dollars. The historical close price experienced sharp movement ranging from 5 to 13 dollars for a volatility of 59%, thus the model was well represented.

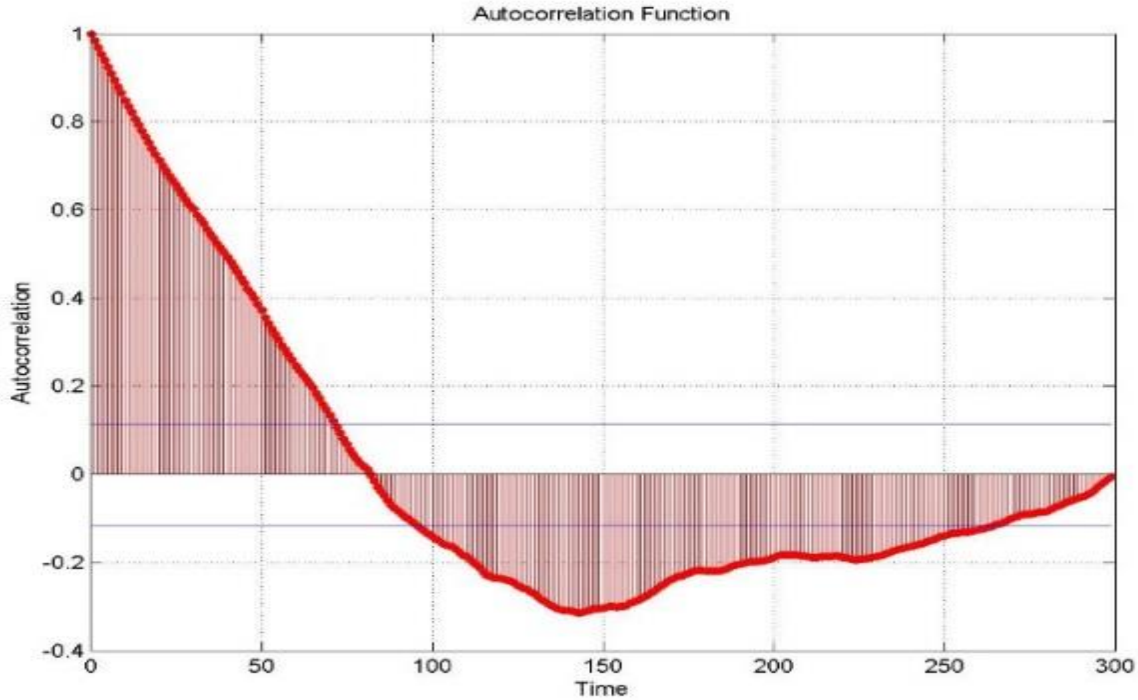
IAC/InterActiveCorp (IACI):

The actual price is well approximated, however, it is important to note that we changed the method of modeling a bit. After calculating the number of relevant days, we first plotted the Fourier series and afterwards we plotted the linear least squares approximation on top of the graph representing the difference between Fourier series and the actual price data. The reason is that for the last 82 relevant days the plot of the actual price data behaves like a sine graph, thus a

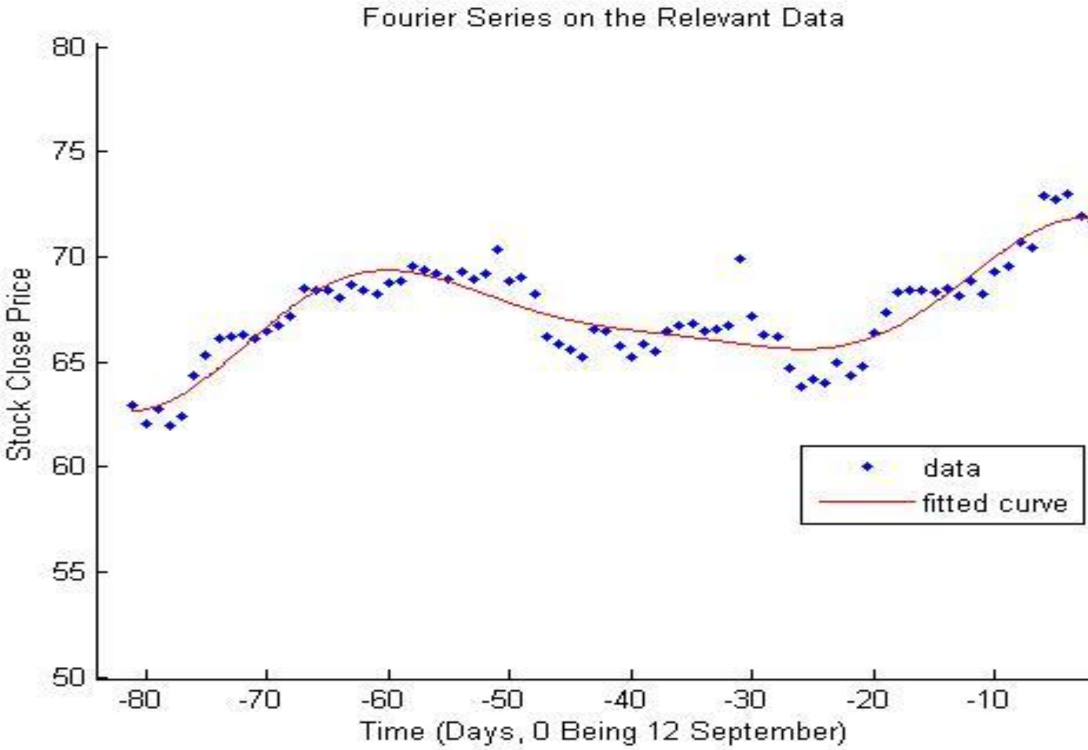
Fourier series was the best fit in this case. The average percent of inaccuracy is 2.4 % for 15 business days and 3.6% for 30 business days. The CI is 3.5%, thus, only 15 business day forecasting is well represented by the model, even though in the last month before 12th of September the price has experienced a 10$ jump.

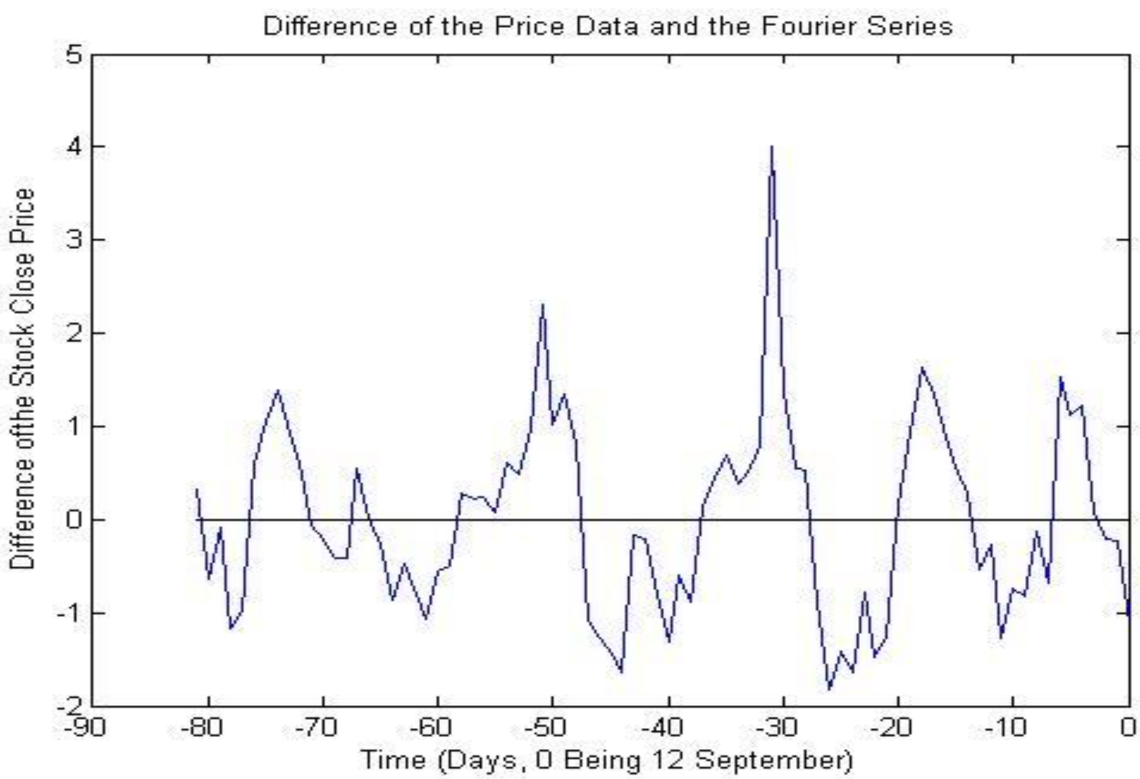
We graph the close price for IAC/InterActiveCorp and use the autocorrelation data to identify relevant data.



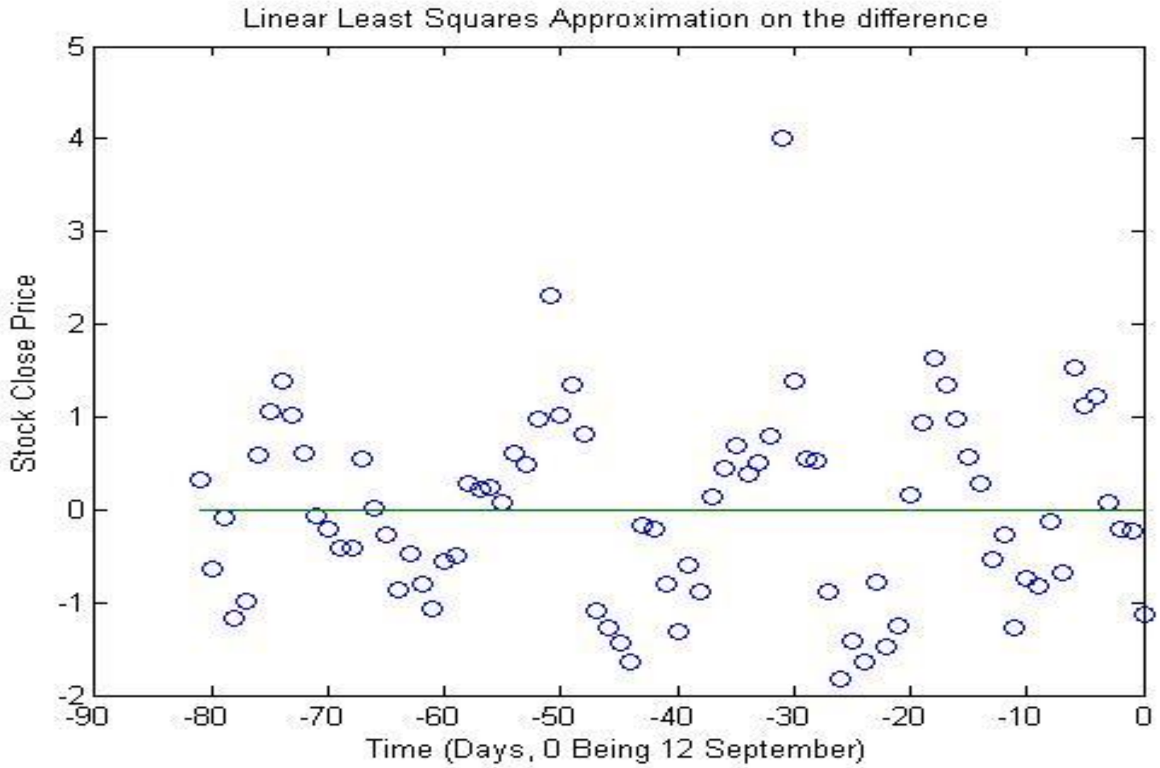


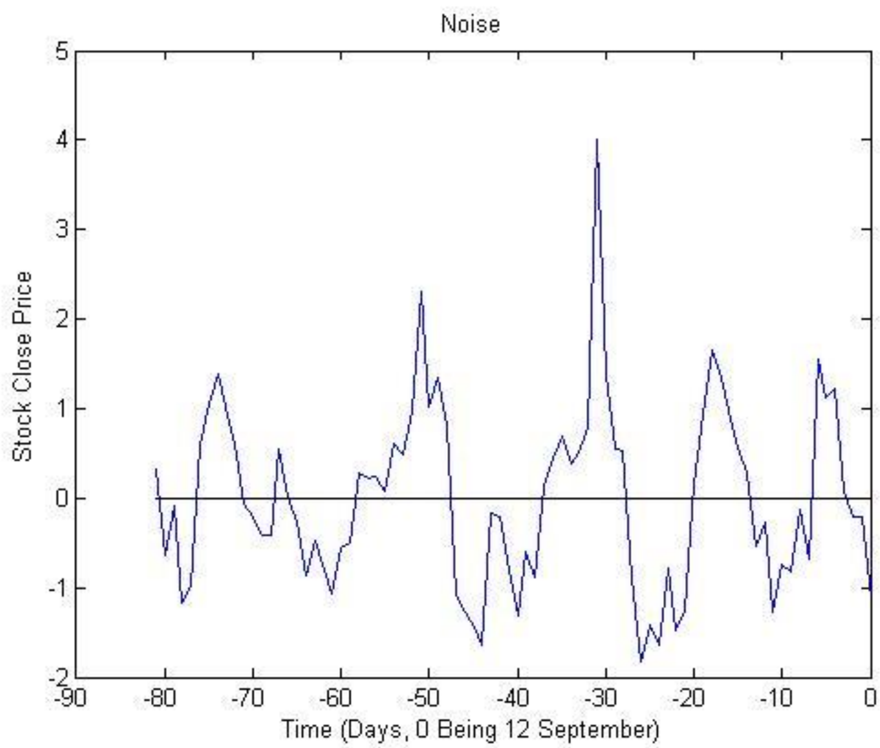
As already mentioned above, the number of days that are relevant and will be used in the future approximation tools is 82. We use the 82 close price of the stock before 12th of September and plot the Linear LSA. We then subtract the LSA from the stock close data and obtain the price difference.



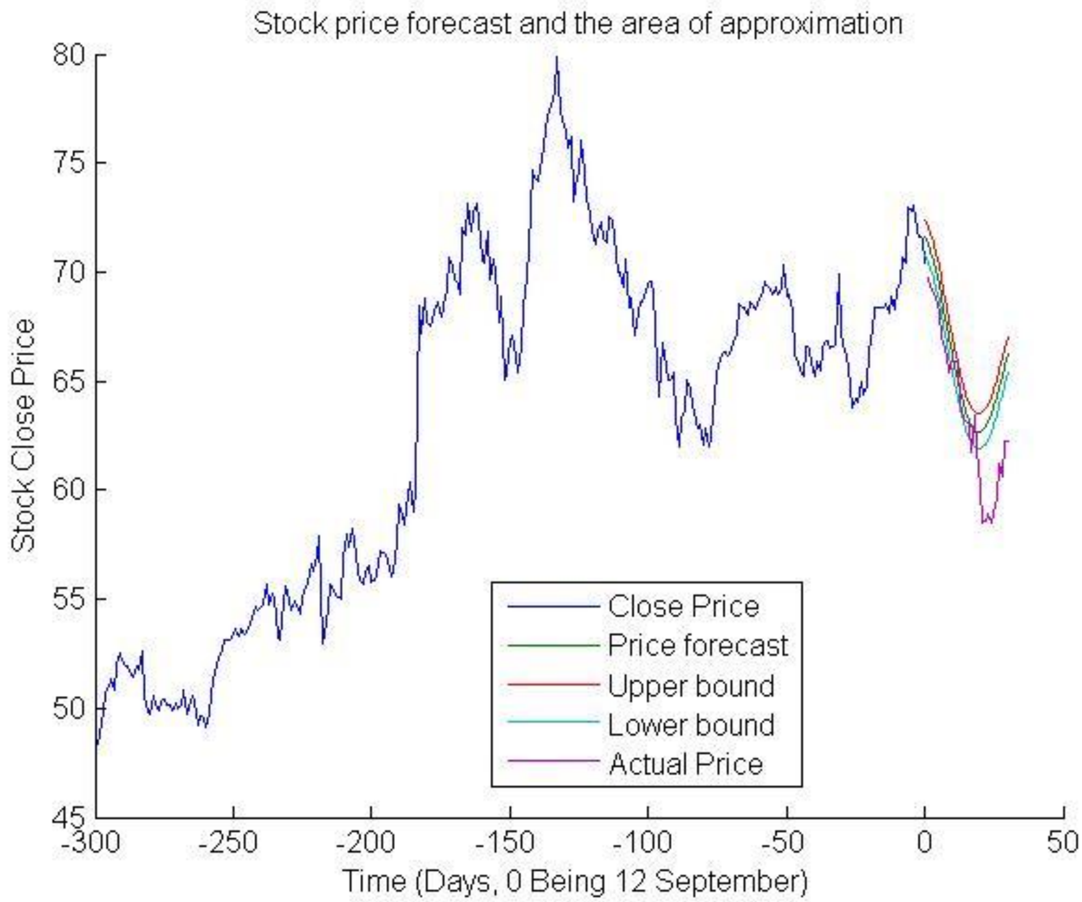


We plot a third order Fourier series and subtract it from the price difference to obtain Noise.

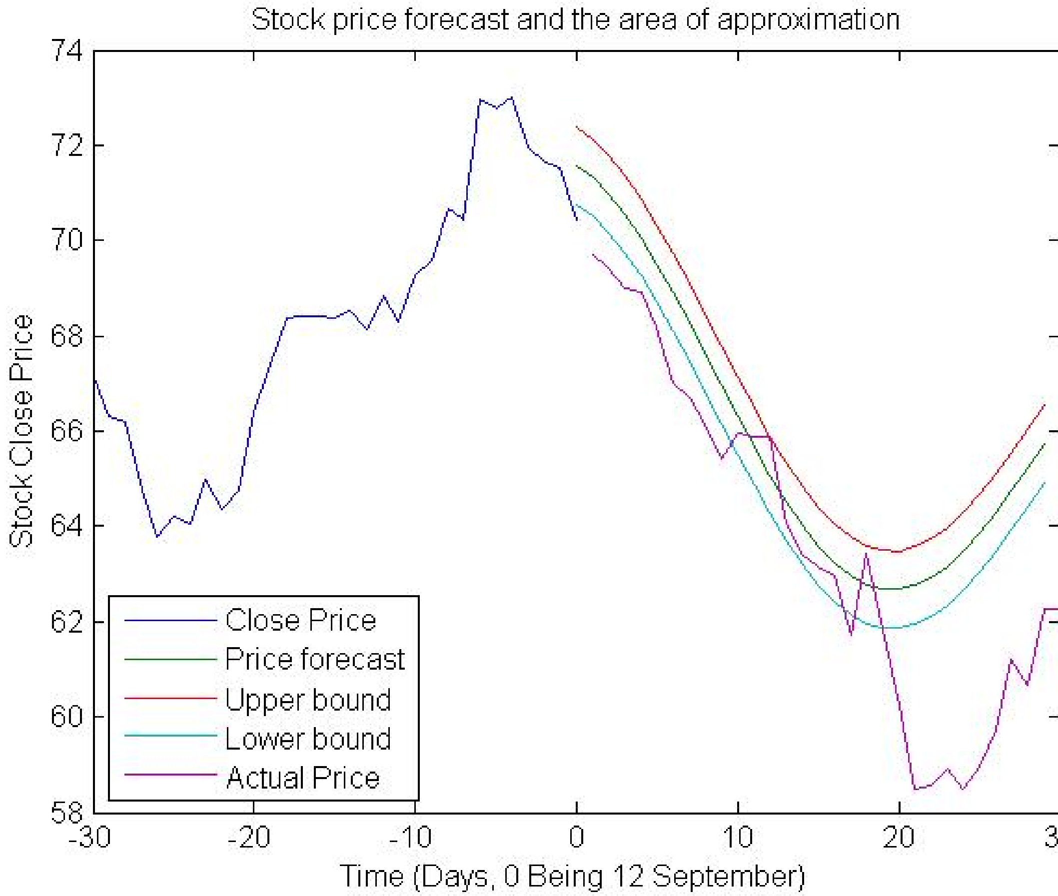

Linear Least Squares Approximation on the difference
Stock Close Price
Time (Days, 0 Being 12 September)
5
4
3
2
1
0
-1
-2
-90
-80
-70
-60
-50
-40
-30
-20
-10
0


Noise
Stock Close Price
Time (Days, 0 Being 12 September)
5
4
3
2
1
0
-1
-2
-90
-80
-70
-60
-50
-40
-30
-20
-10
0

We sum the Fourier series function and the LSA to obtain the price forecast function. Then we take the average of the absolute value of the Noise. We add and subtract the average Noise from the forecast function to obtain the upper and lower bounds of the prediction area.



Below is the zoomed in version of the graph.



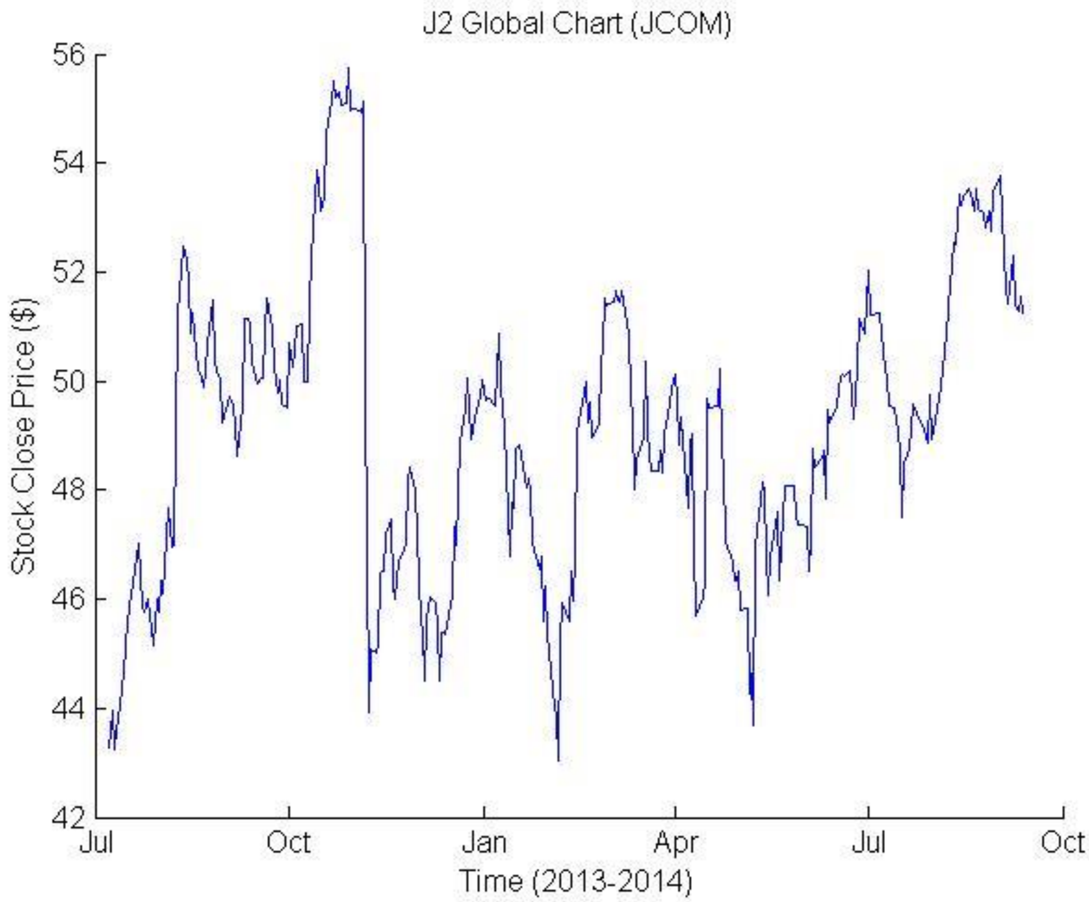
The max percentage of inaccuracy is 3.7% and the stock price is 1.69$ below the area of approximation. The min percent is 0.3% and the stock price is inside the area of approximation. The average percent of inaccuracy is 2.4%. The actual price is well approximated, however, it has already been noted we changed the method of modeling a bit. After calculating the number of relevant days, we first plotted the Fourier series and afterwards we plotted the linear least squares approximation on the difference of Fourier series and the actual price data. Again the reason being that, for the last 82 relevant days the plot of the actual price data behaves like a sine graph, thus a Fourier series was the best fit in this case. The historical volatility is 28%, while the 82 relevant day volatility is 21%. The average percent of inaccuracy is 2.4% for 15 business days and 3.6% for 30 business days. The CI is 3.5%, thus, only 15 business day forecasting is well represented by the model, regardless of the $10 jump in price before 12th of September.

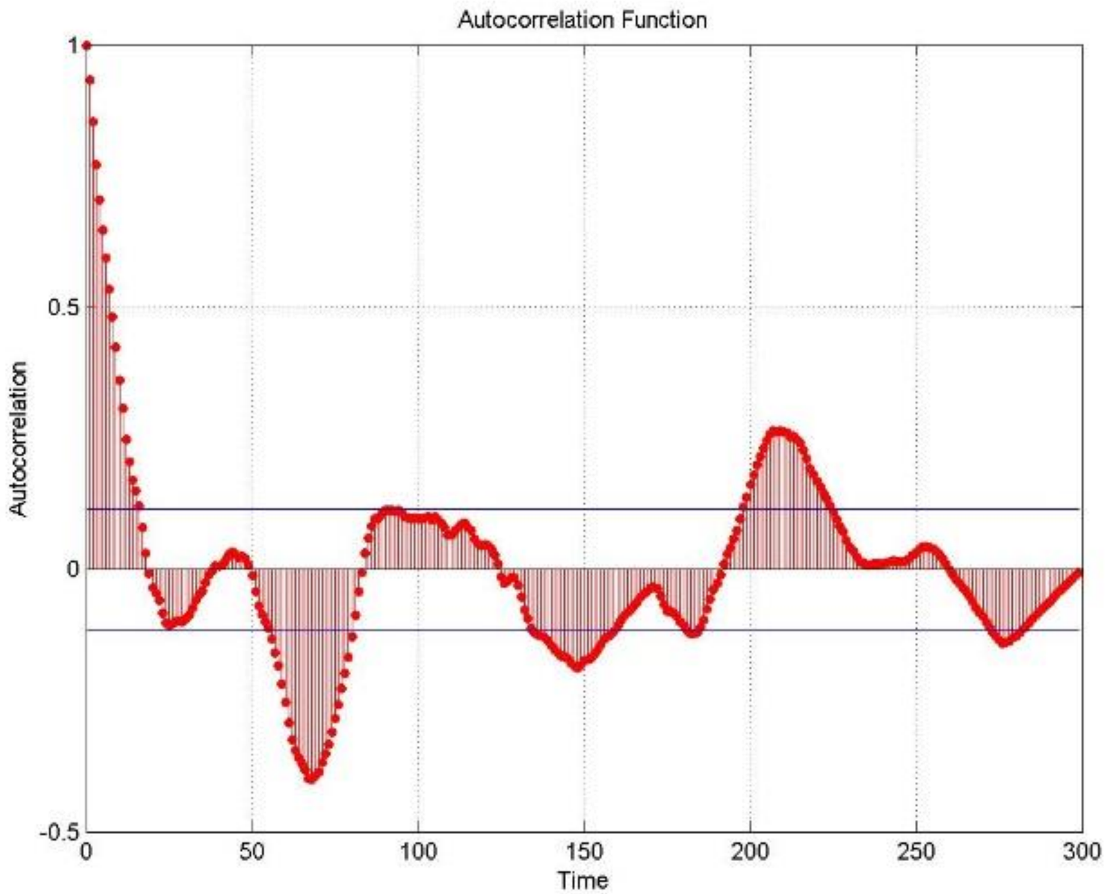
J2 Global (JCOM):

Choosing a lower order Fourier series gave a much more accurate representation of the stock close price data. The average percent of inaccuracy is 1.0% for 15 business days and 1.7%

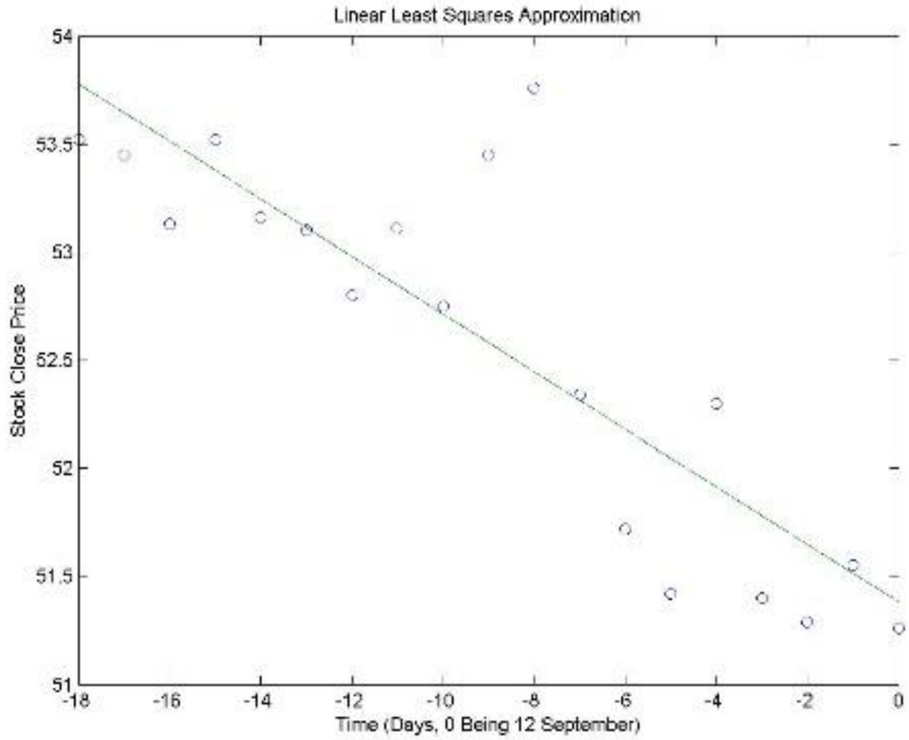
for 30 business days, while the CI gave us 3.8%. The actual price crosses the area of approximation twice and ends up following the trend. With 19 relevant day volatility being at 16% the forecast line is really accurate and follows the trend. The model is acceptable.

We graph the close price for J2 Global and use the autocorrelation data to identify relevant data.

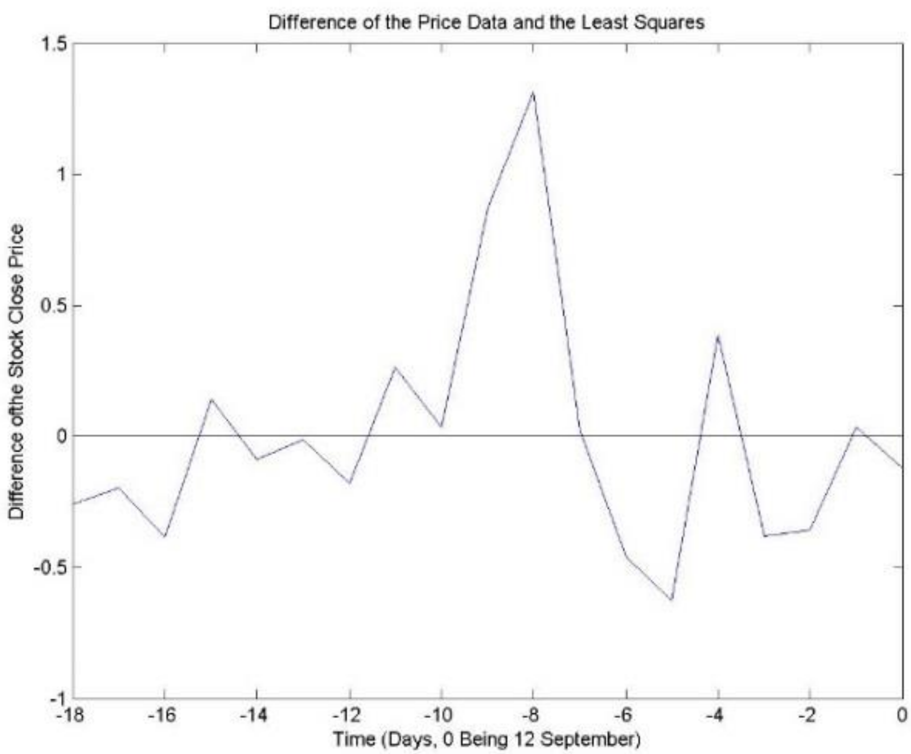




The number of days obtained is 19. Thus, the close price for 19 days before 12 September is what we will use for our future calculations. We plot the linear LSA for the relevant data and subtract it from the data to obtain price difference.

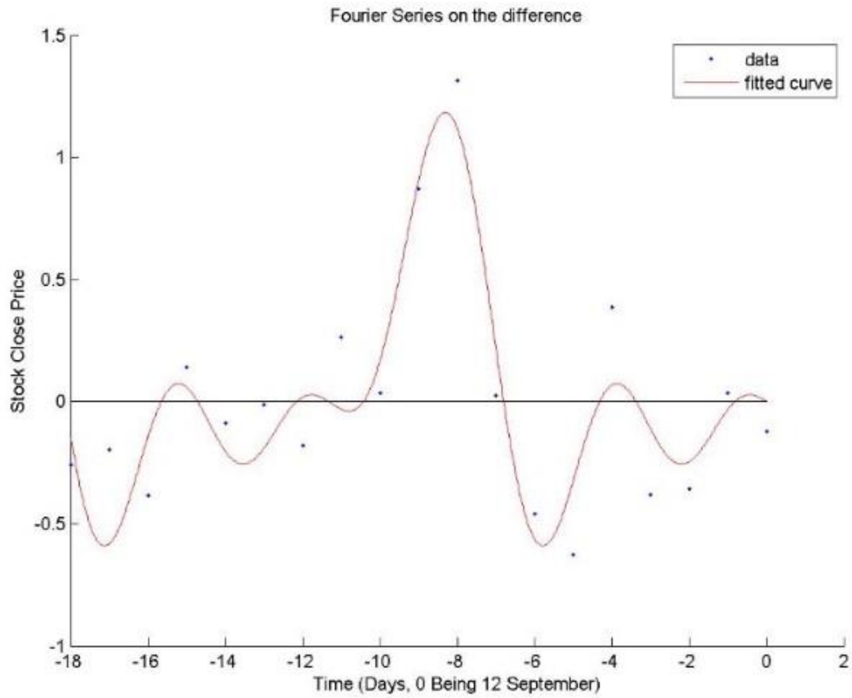


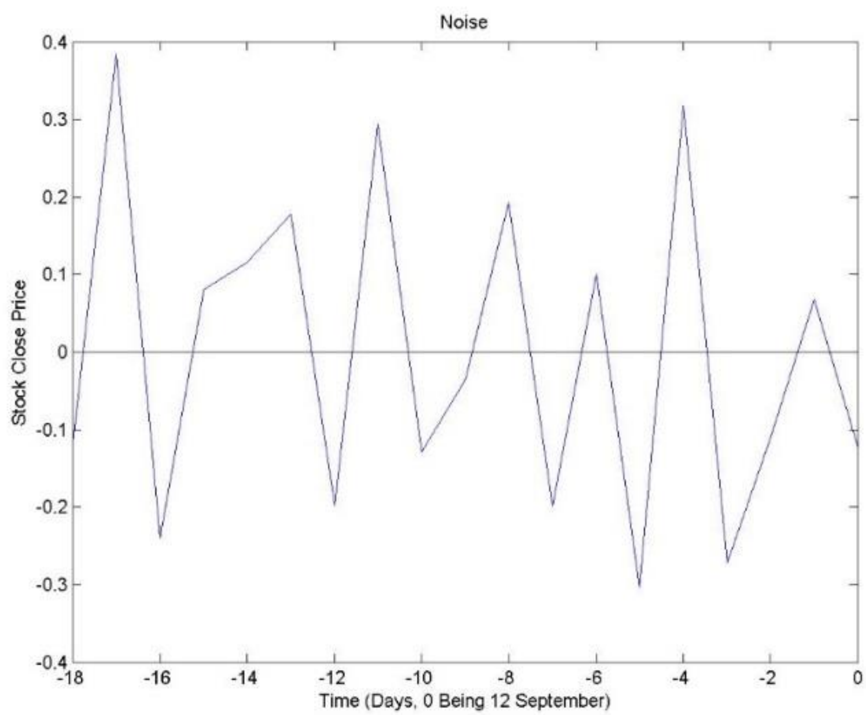
Linear Least Squares Approximation
Stock Close Price
54
53.5
53
52.5
52
51.5
51
-18
-16
-14
-12
-10
-8
-6
-4
-2
0
Time (Days, 0 Being 12 September)



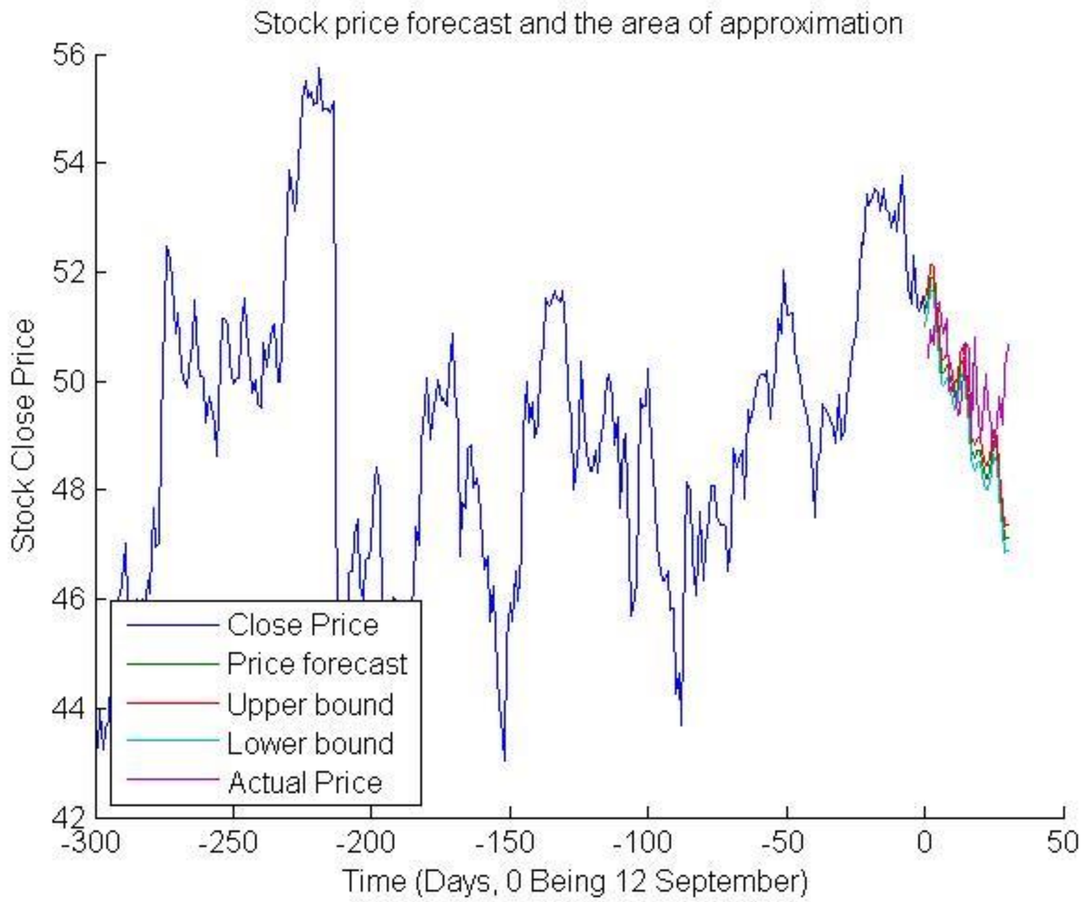
Difference of the Price Data and the Least Squares
Difference ofthe Stock Close Price
1.5
1
0.5
0
-0.5
-1
-18
-16
-14
-12
-10
-8
-6
-4
-2
0
Time (Days, 0 Being 12 September)

Due to autocorrelation being 19, which is a small number. We will use second order Fourier series for J2Global instead of third order. We then subtract the obtained Fourier function from the price difference to obtain the Noise.

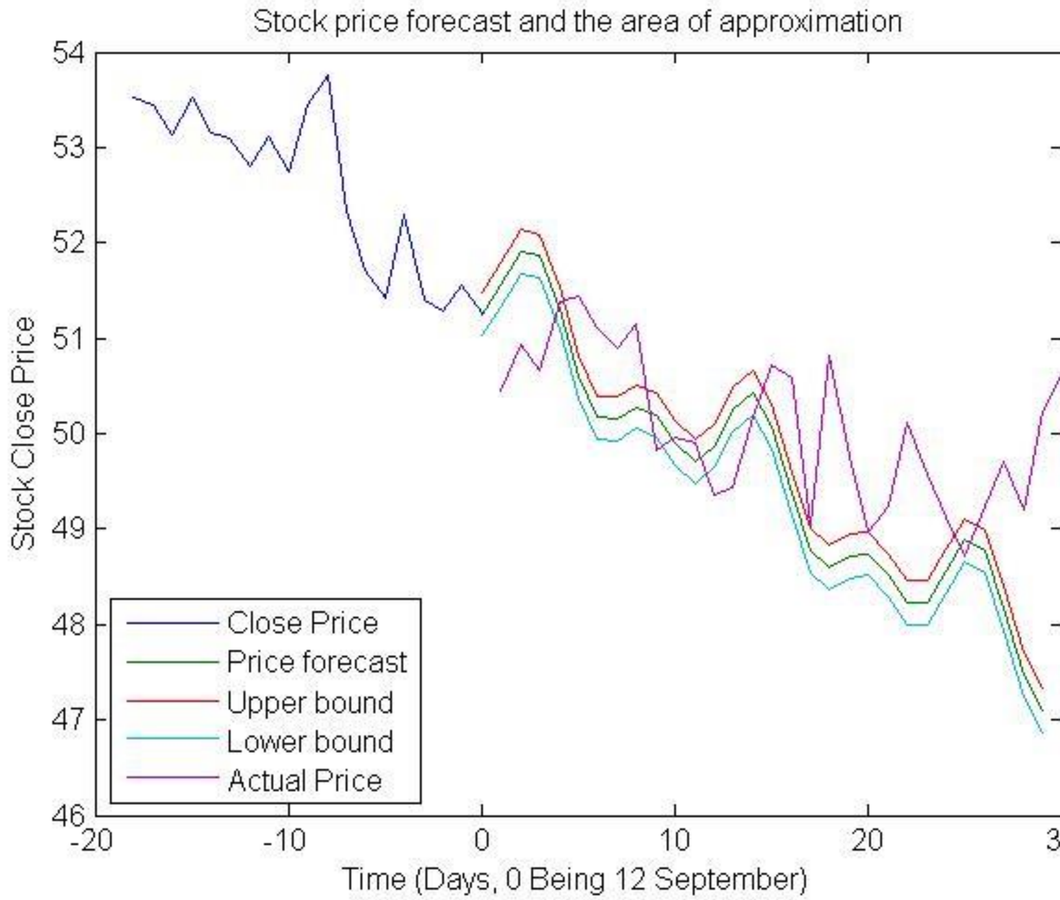




We sum the Fourier series function and the LSA to obtain the price forecast function. Then we take the average of the absolute value of the Noise. We add and subtract the average Noise from the forecast function to obtain the upper and lower bounds of the prediction area.



Below is the zoomed in version of the graph

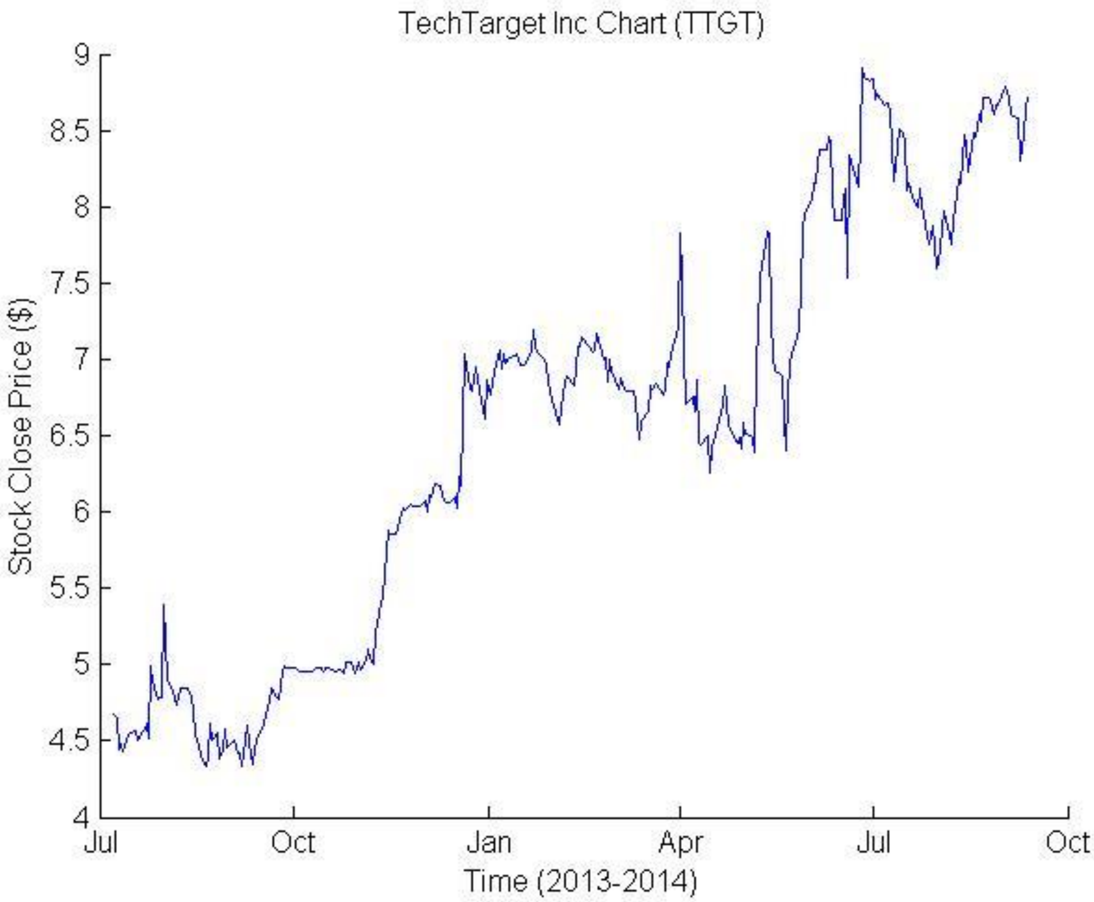


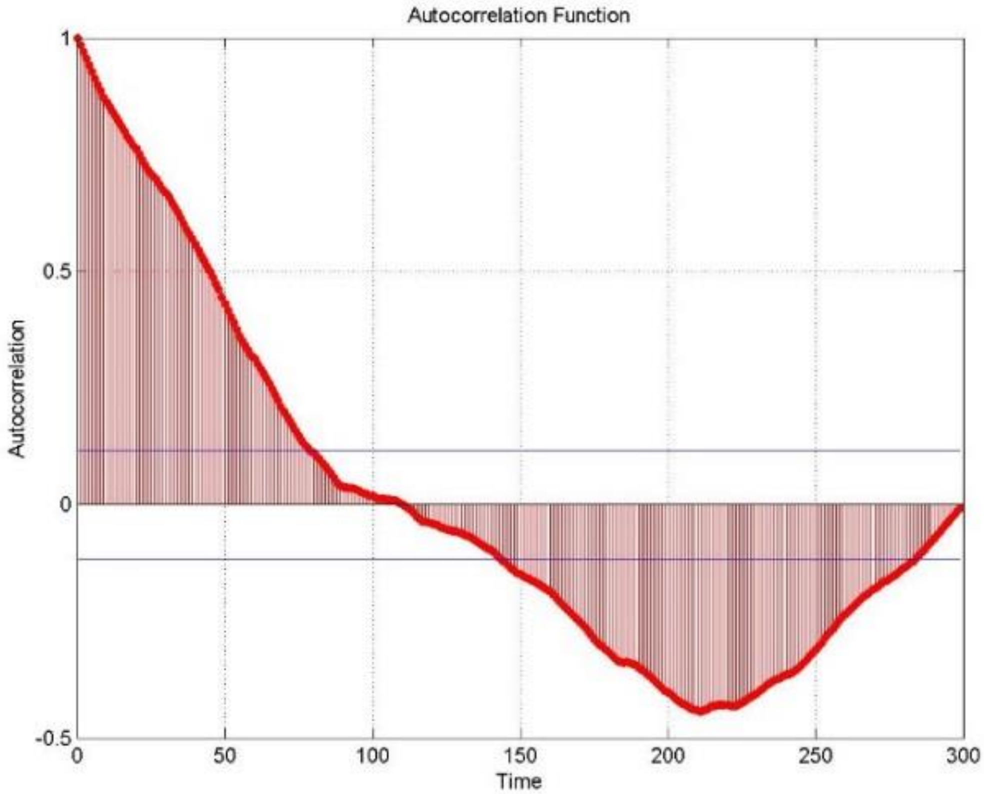
We calculated the percentage of how much predicted line deviates from the actual price. The max percentage deviation is 2.5% and the stock price is 1.02$ below the area of approximation. The min percent is 0.001% and the stock price is inside the area of approximation. The average percent of inaccuracy is 1.0% for 15 business days and 1.7% for 30 business days. The CI delivered a 3.8% inaccuracy threshold. Choosing a lower order Fourier series gave a much more accurate representation of the stock close price data. The actual price crosses the area of approximation twice and ends up following the trend. With historic volatility of 30% and 19 relevant days volatility being at 16% the forecast line is really accurate and follows the trend, thus the model is acceptable.

TechTarget Inc. (TTGT):

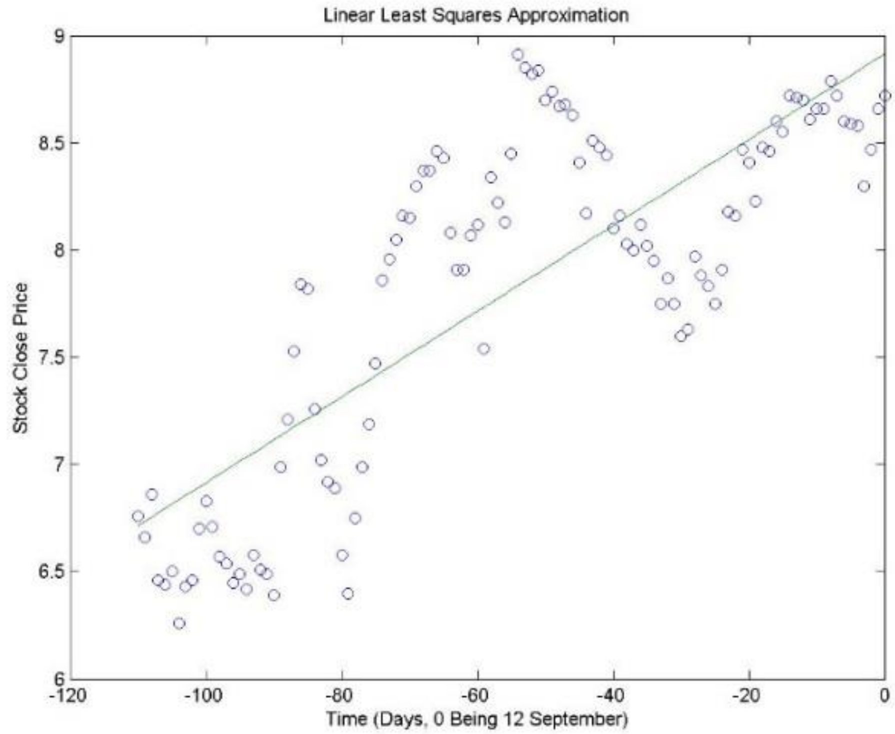
The average percent of inaccuracy is 1.5% for 15 business days and 2.8% for 30 business days. The 95% CI gave us 5.1% inaccuracy threshold. The actual price after 12th of September is well predicted for the first few days with the exception of last day. This upward divergence by the actual future price at the last day is actually a good sign, especially when the area of approximation predicted a rising trend. The investor following this model would expect the price to rise after 12th of September, and in our case the price rose more than expected, which means a lot more capital return for the investor. The model is acceptable.

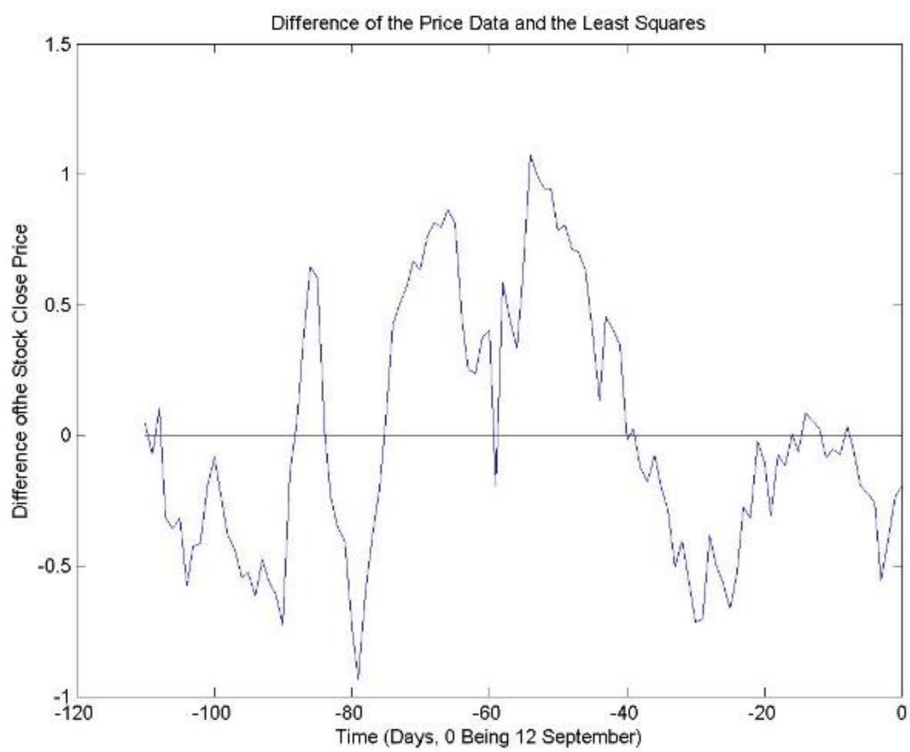
We graph the close price for TechTarget Inc. and use the autocorrelation data to identify relevant data.



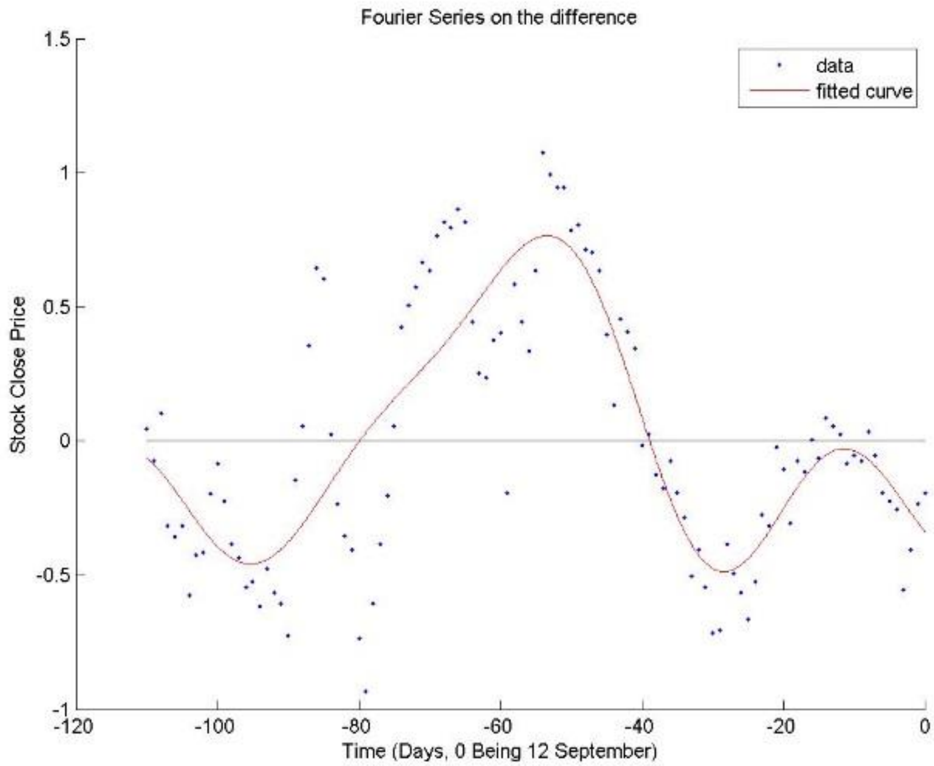


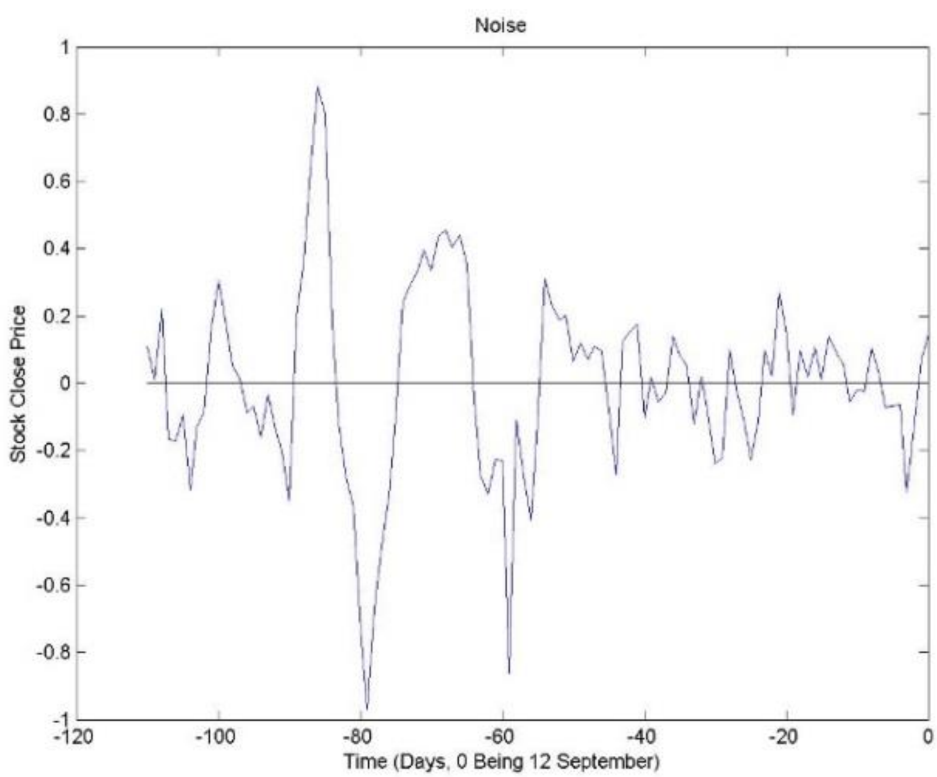
The number of days that are relevant and will be used in the future approximation tools is 111. We use the 111 close price of the stock before 12th of September and plot the Linear LSA. We then subtract the LSA from the stock close data and obtain the price difference.



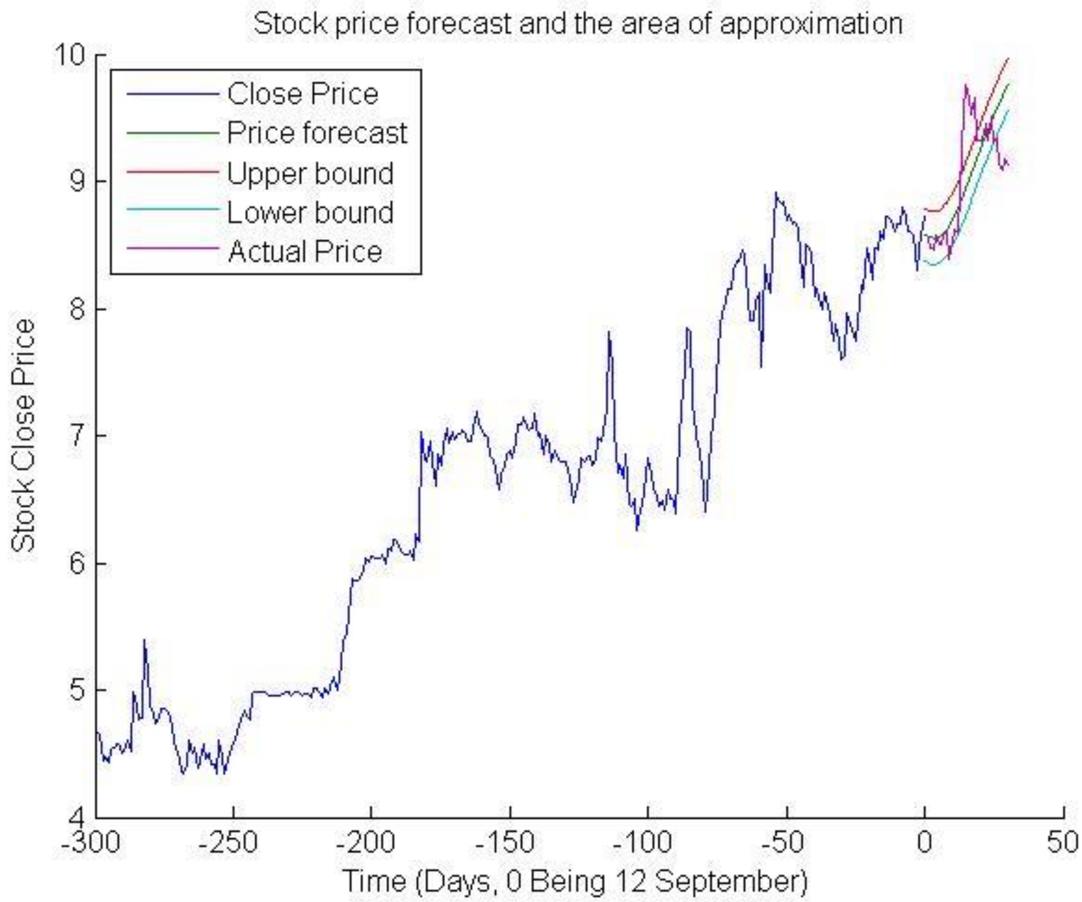


We plot the third order Fourier series and subtract it from the price difference to obtain Noise.

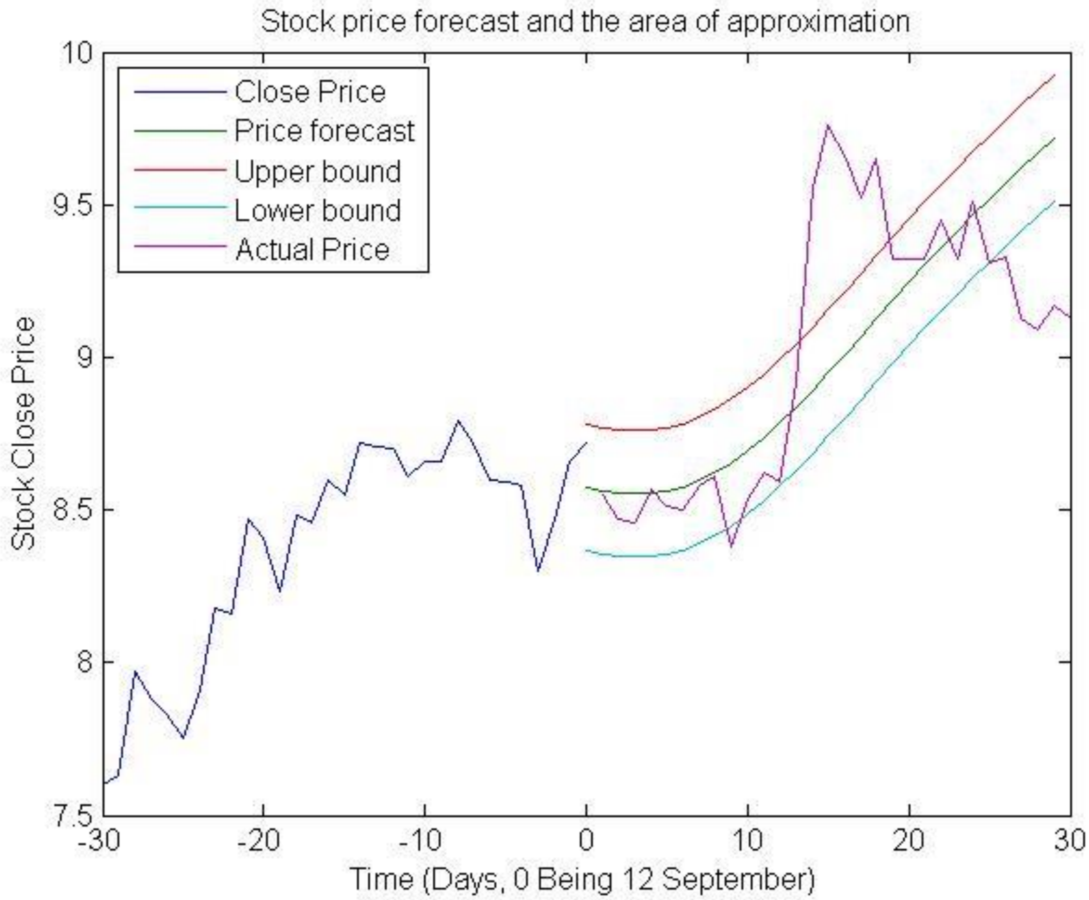

Fourier Series on the difference
data
fitted curve
Stock Close Price
Time (Days, 0 Being 12 September)


Noise
Stock Close Price
Time (Days, 0 Being 12 September)

We sum the Fourier series function and the LSA to obtain the price forecast function. Then we take the average of the absolute value of the Noise. We add and subtract the average Noise from the forecast function to obtain the upper and lower bounds of the prediction area.



Below is the zoomed in version of the graph.

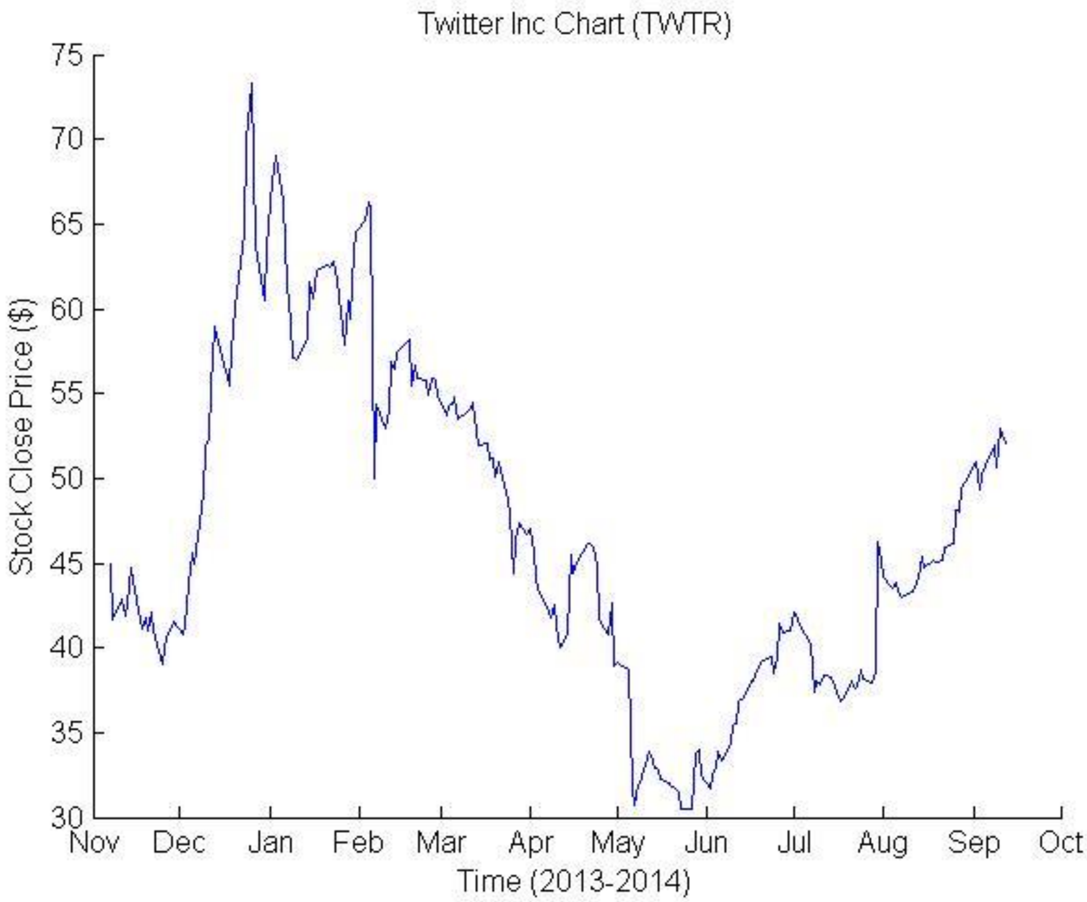


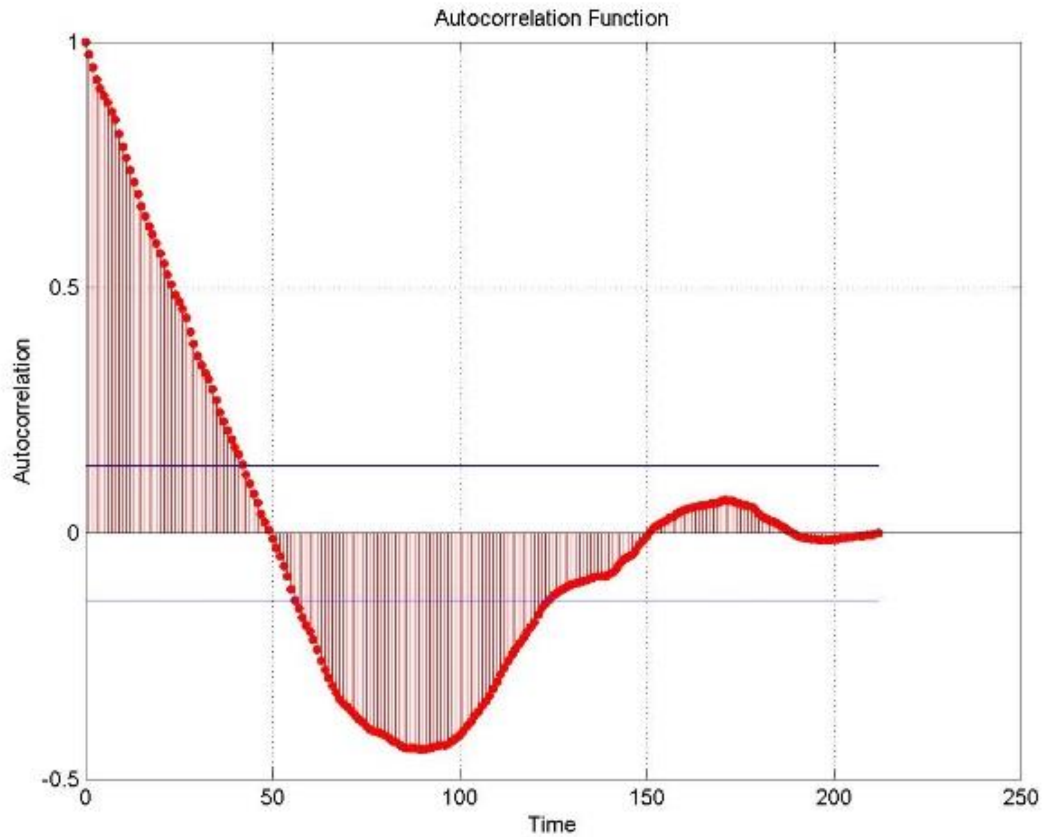
The max percentage of inaccuracy is 7.5% and the stock price is 0.51$ above the area of approximation. The min percent is 0.04% and the stock price is inside the area of approximation. The average percent of inaccuracy is 1.5% for 15 business days and 2.8% for 30 business days. The confidence interval gave us 5.1% max acceptable inaccuracy. The actual price after 12th of September is well predicted for the first few days, the only notable exception was the last day, which showed an upward deviation. This upward divergence of the actual future price on the last day is actually a good sign, especially when the area of approximation predicted a rising trend. The investor following this model would expect the price to rise after 12th of September, and in our case the price rose more than expected, which means a notably more capital return for the investor. The historical volatility was 40% and 111 relevant day volatility was 44%. The model is acceptable

Twitter Inc. (TWTR):

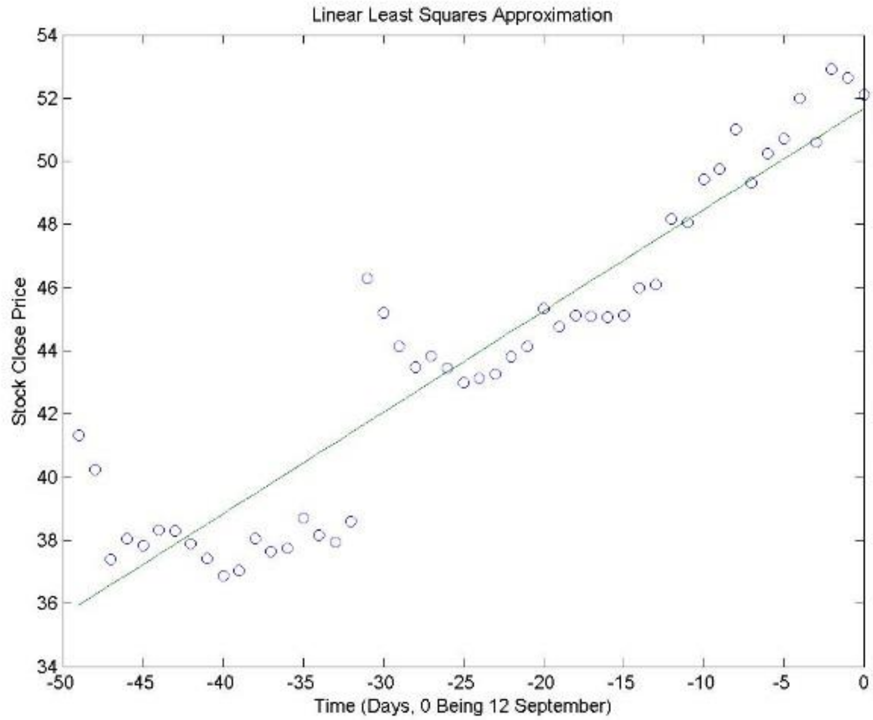
The sudden drop in the price was not predicted at first, however, the price followed the trend with slight divergences. The actual price fluctuations after 12th of September is chaotic, however, it concentrates around the area of predictions. The forecast graph rises quickly for the next consecutive days and becomes unrealistic, thus it quickly diverges from the actual stock price. The average percent of inaccuracy is 3.4% for 15 business days and 9.1% for 30 business days with a CI of 8.5%, and the model is acceptable for 15 business day forecasting. Relevant days being 50 and the volatility 52% had an effect on the accuracy of the model. The model is still acceptable because effects of volatility did not yield results with considerable discrepancies from the actual prices.

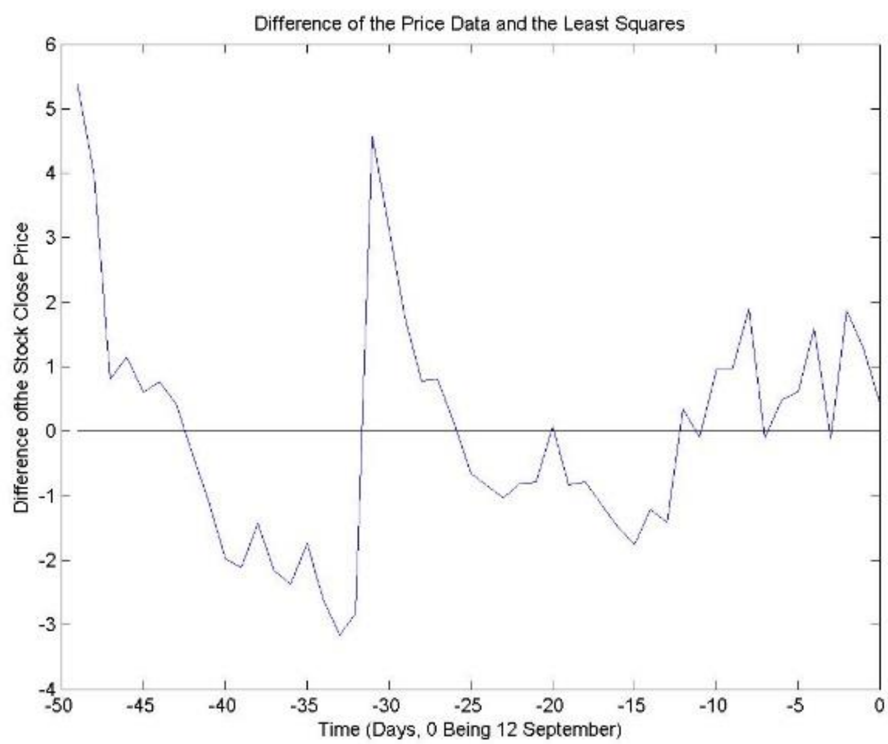
We graph the close price for Twitter Inc. and use the autocorrelation data to identify relevant data.



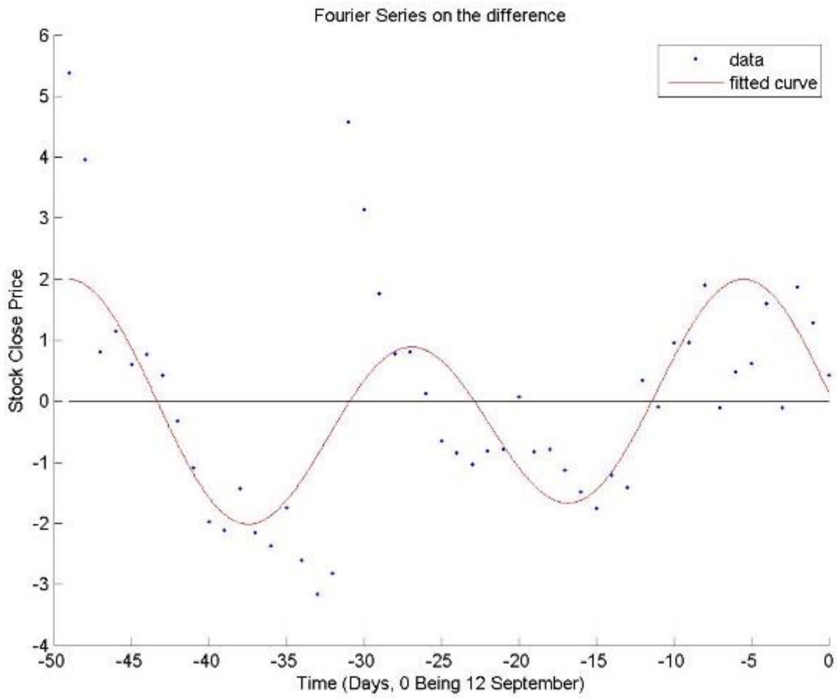


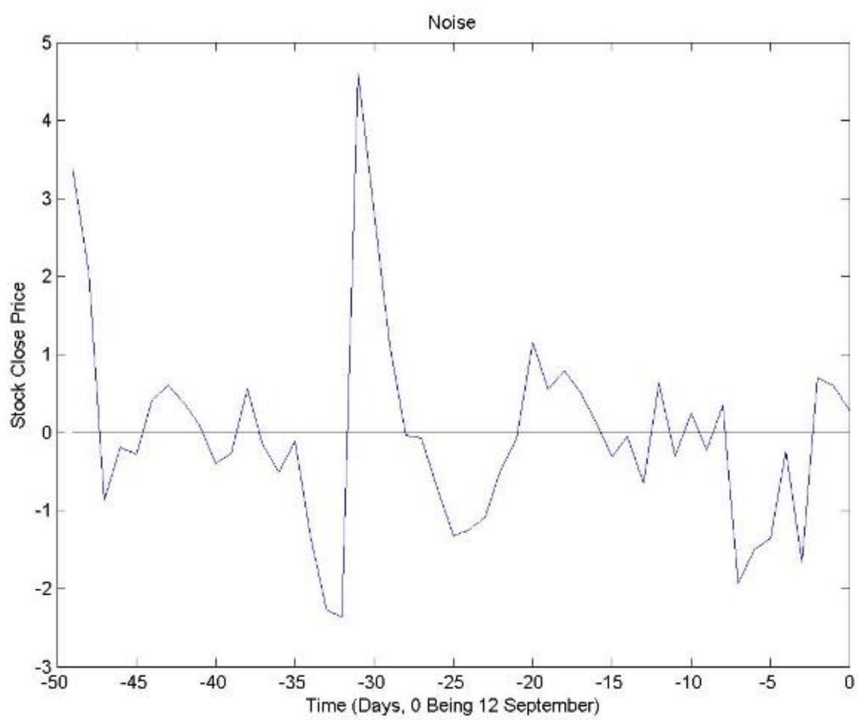
The number of days that are relevant and will be used in the future approximation tools is 50. We use the 50 close price of the stock before 12th of September and plot the Linear LSA. We then subtract the LSA from the stock close data and obtain the price difference.


Linear Least Squares Approximation
Stock Close Price
Time (Days, 0 Being 12 September)
54
52
50
48
46
44
42
40
38
36
34
-50
-45
-40
-35
-30
-25
-20
-15
-10
-5
0

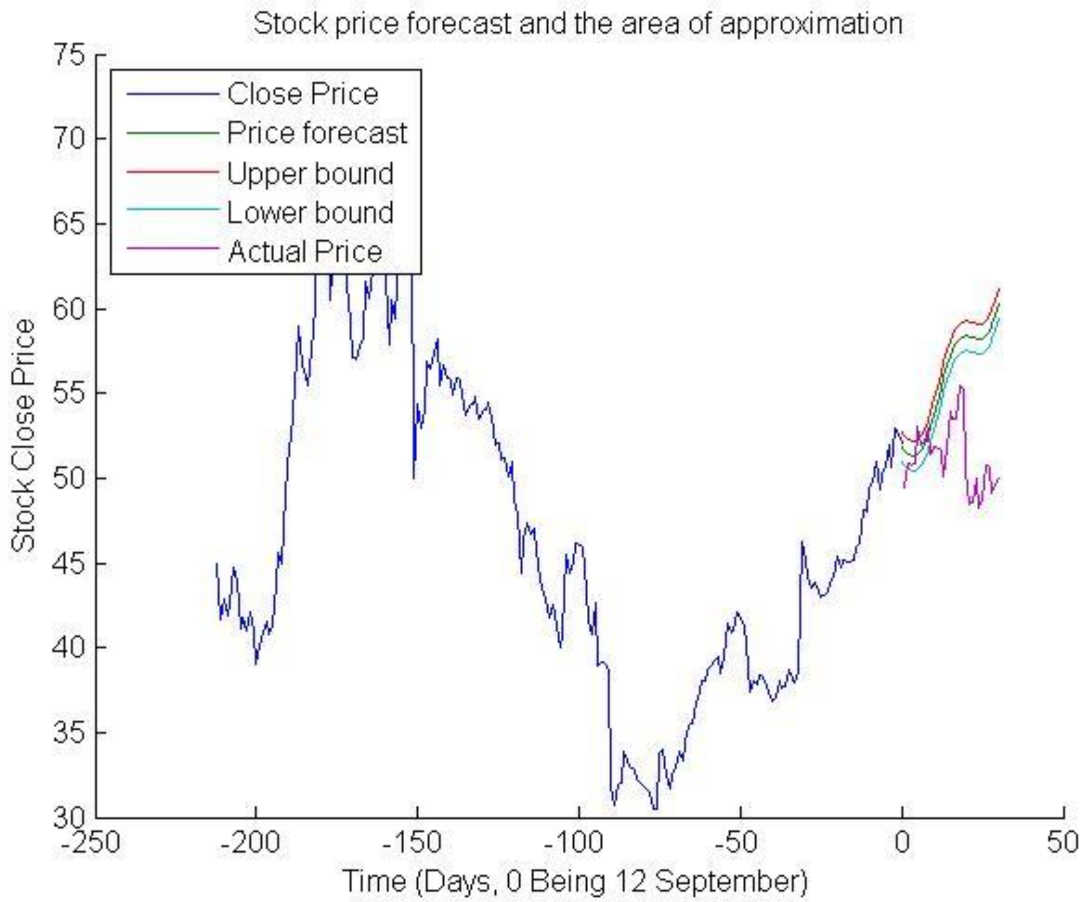

Difference of the Price Data and the Least Squares
Difference ofthe Stock Close Price
Time (Days, 0 Being 12 September)
6
5
4
3
2
1
0
-1
-2
-3
-4
-50
-45
-40
-35
-30
-25
-20
-15
-10
-5
0

Due to autocorrelation being 50, which is a small number. We will use second order Fourier series for Twitter instead of third order. We then subtract the obtained Fourier function from the price difference to obtain the Noise.

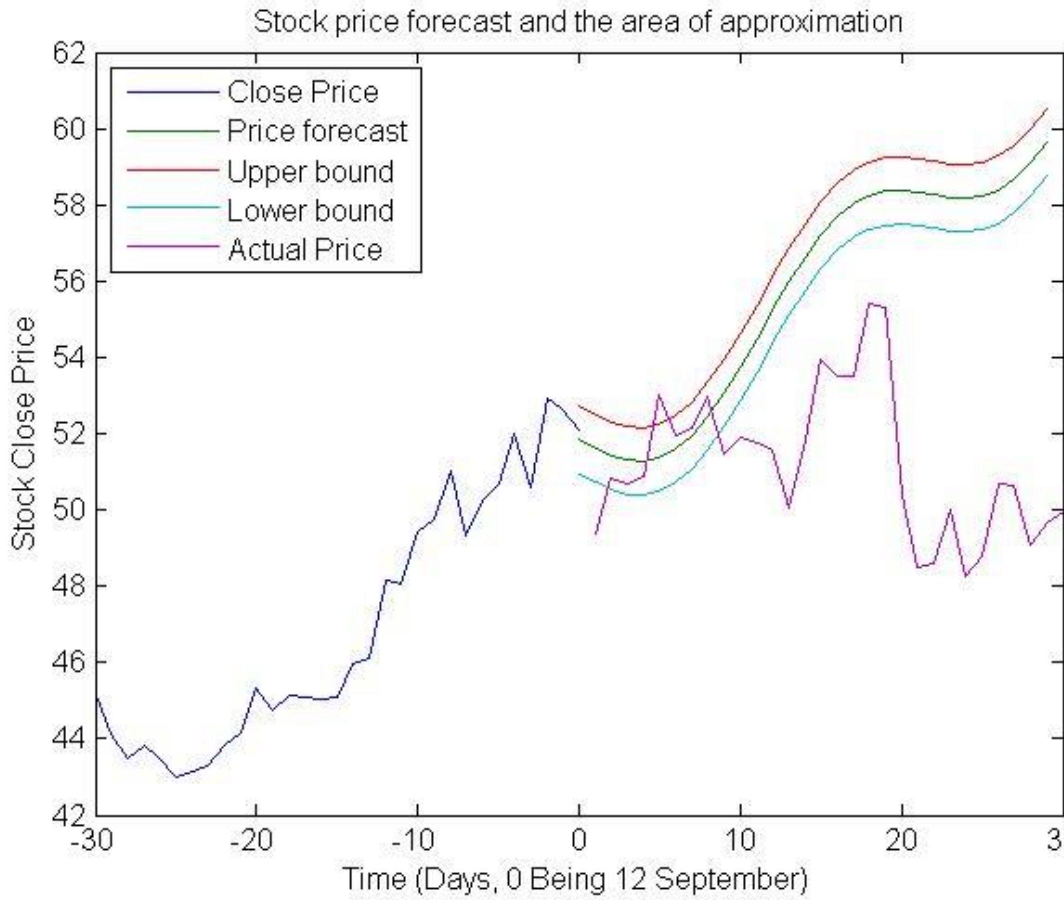




We sum the Fourier series function and the LSA to obtain the price forecast function. Then we take the average of the absolute value of the Noise. We add and subtract the average Noise from the forecast function to obtain the upper and lower bounds of the prediction area.



Below is the zoomed in version of the graph.

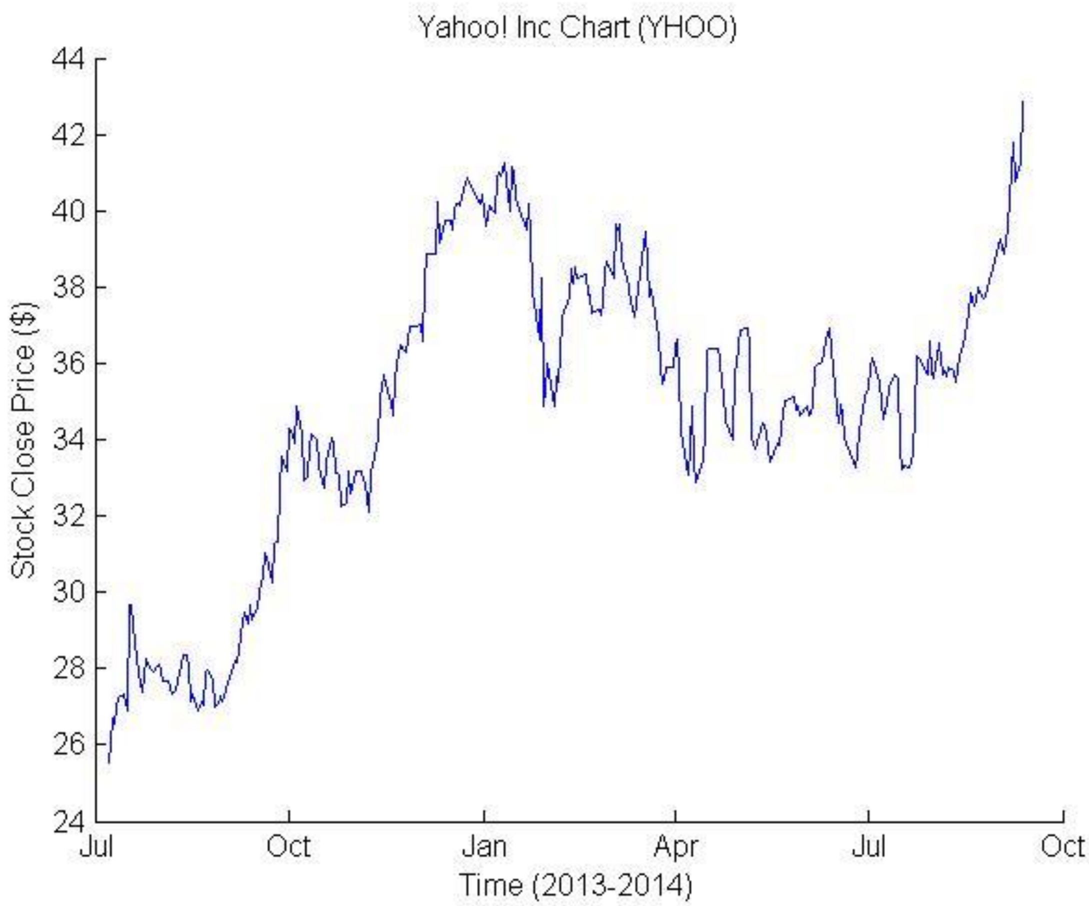


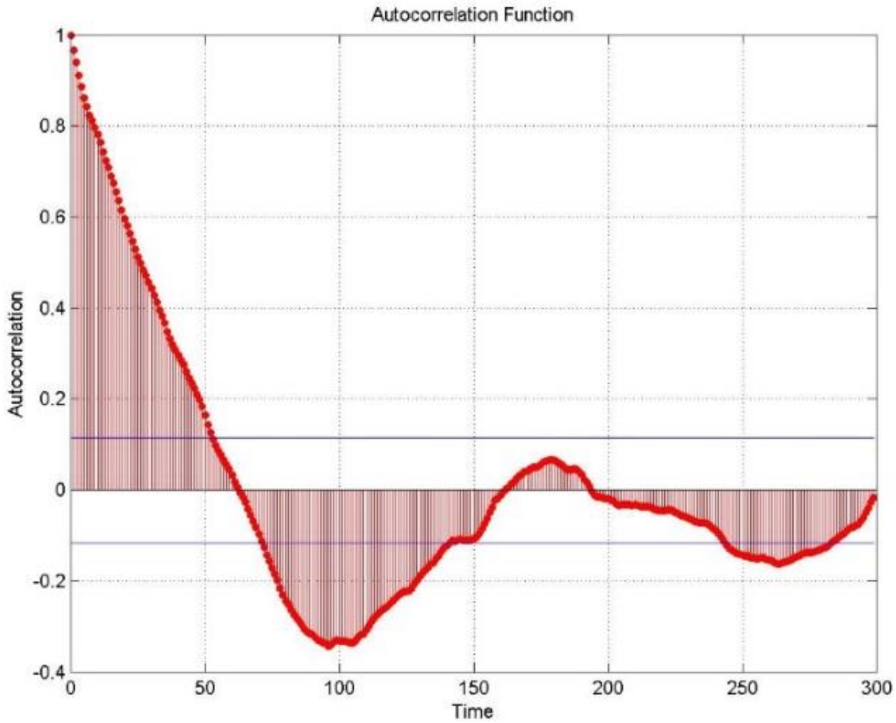
We calculated the percentage of how much the predicted line deviates from the actual price. The max percentage is 10.4% and the stock price is 4.31$ below the area of approximation. The min percent is 0.8% and the stock price is inside the area of approximation. The average percent of inaccuracy is 3.4% for 15 business days and 9.1% for 30 business days, while the CI gave us 8.5%. The sudden drop in the price was not predicted at first, however, the price followed the trend with slight divergences for the first 15 business days. The actual price after 12th of September is chaotic, however, it is around the area of predictions. The forecast graph rises quickly in the upcoming days and becomes unrealistic, thus it quickly diverges from the stock price. Relevant days being 50 and the volatility 52% had an effect on the accuracy of the model. The historic volatility being 68% and the stock having a history of price change between 30 and75 dollars destabilized the model in the later days, however, it is still acceptable for the first 15 business days, since the percent inaccuracy is less than the 95% confidence interval.

Yahoo! Inc. (YHOO):

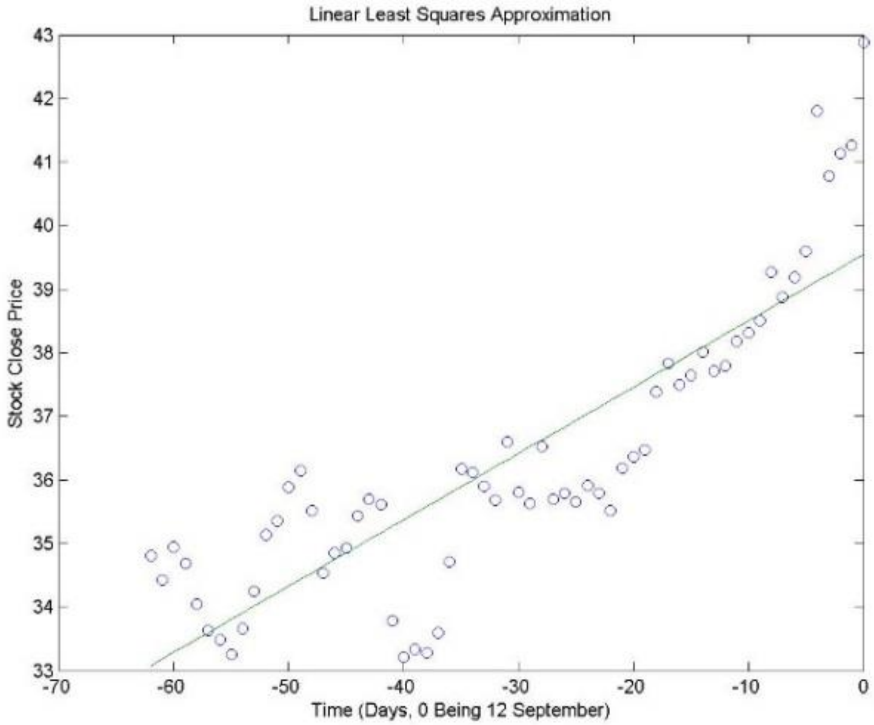
The price drop was not predicted by the model, though it started off well. This happened due to Alibaba's (BABA) initial public offering. Since Yahoo had a large number of assets in Alibaba Group Holding it experienced a sudden drop. However, critics are saying that Yahoo will stabilize and we will keep observing the future prices to see if they will start fitting predicted trend. Right now, however, the average percent of inaccuracy is 6.9% for both 15 and 30 business days, while the CI gave us 4.0% inaccuracy threshold, thus the model is not acceptable.

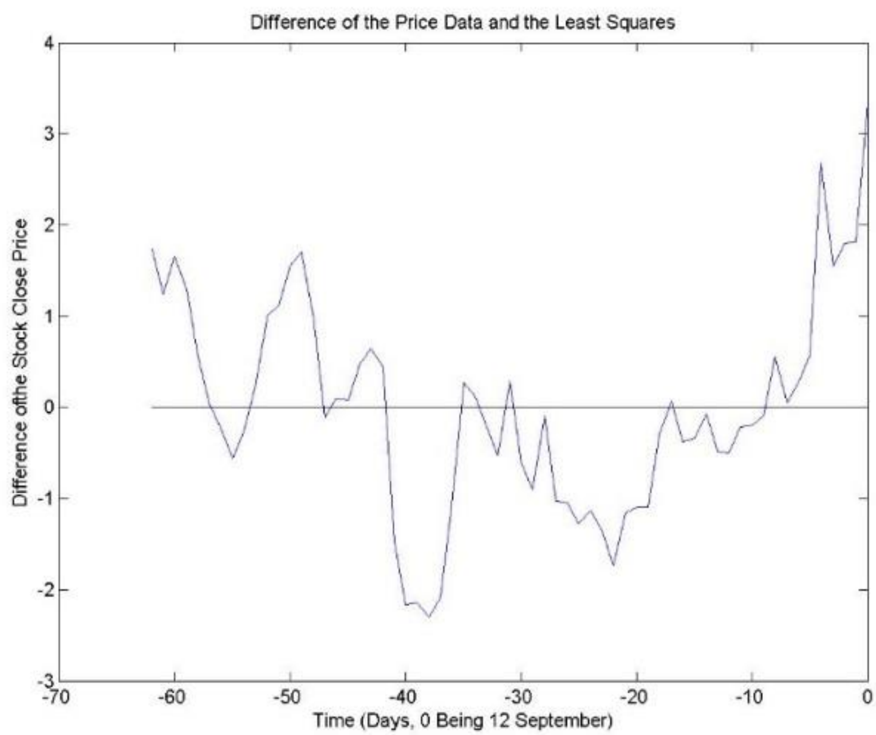
We graph the close price for Yahoo! Inc. and use the autocorrelation data to identify relevant data.



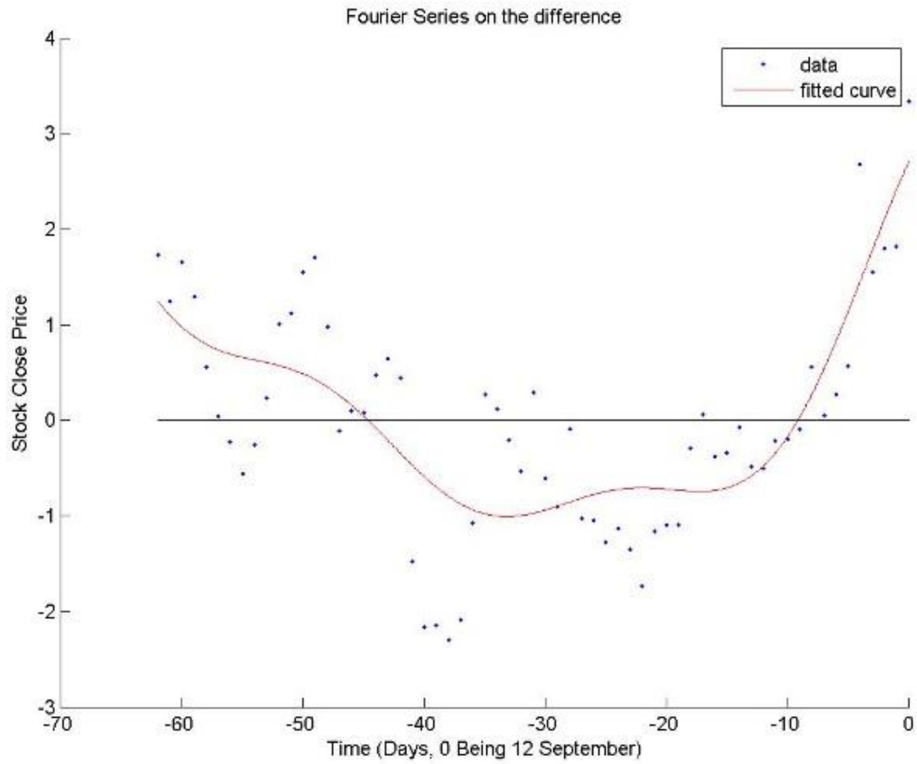


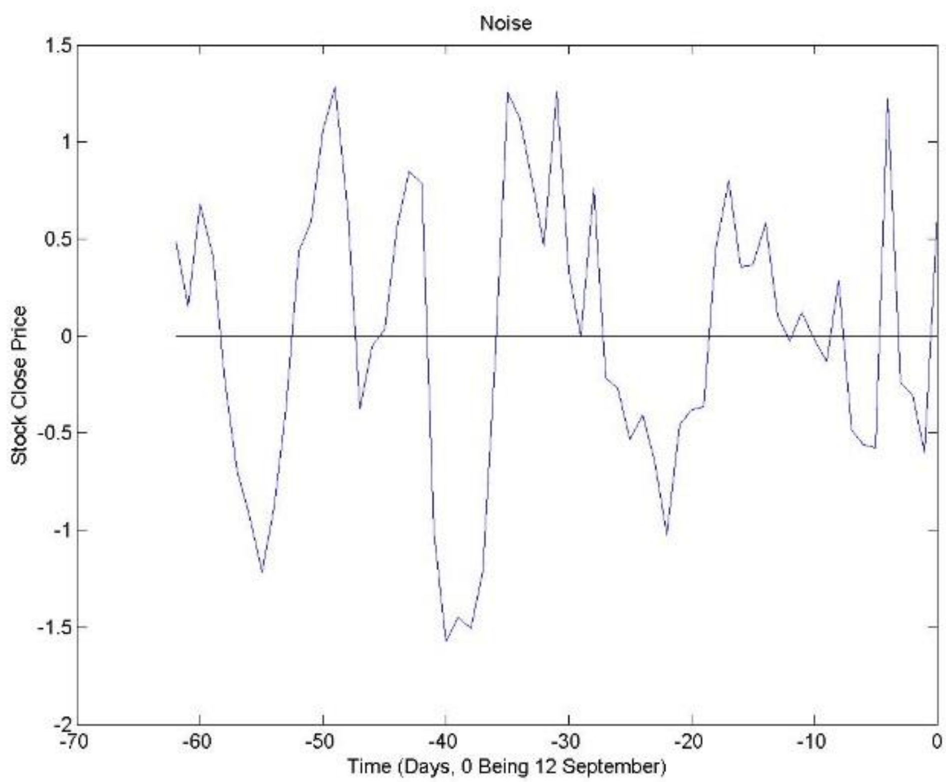
The number of days that are relevant and will be used in the future approximation tools is 63. We use the 63 close price of the stock before 12^{th} of September and plot the Linear LSA. We then subtract the LSA from the stock close data and obtain the price difference.



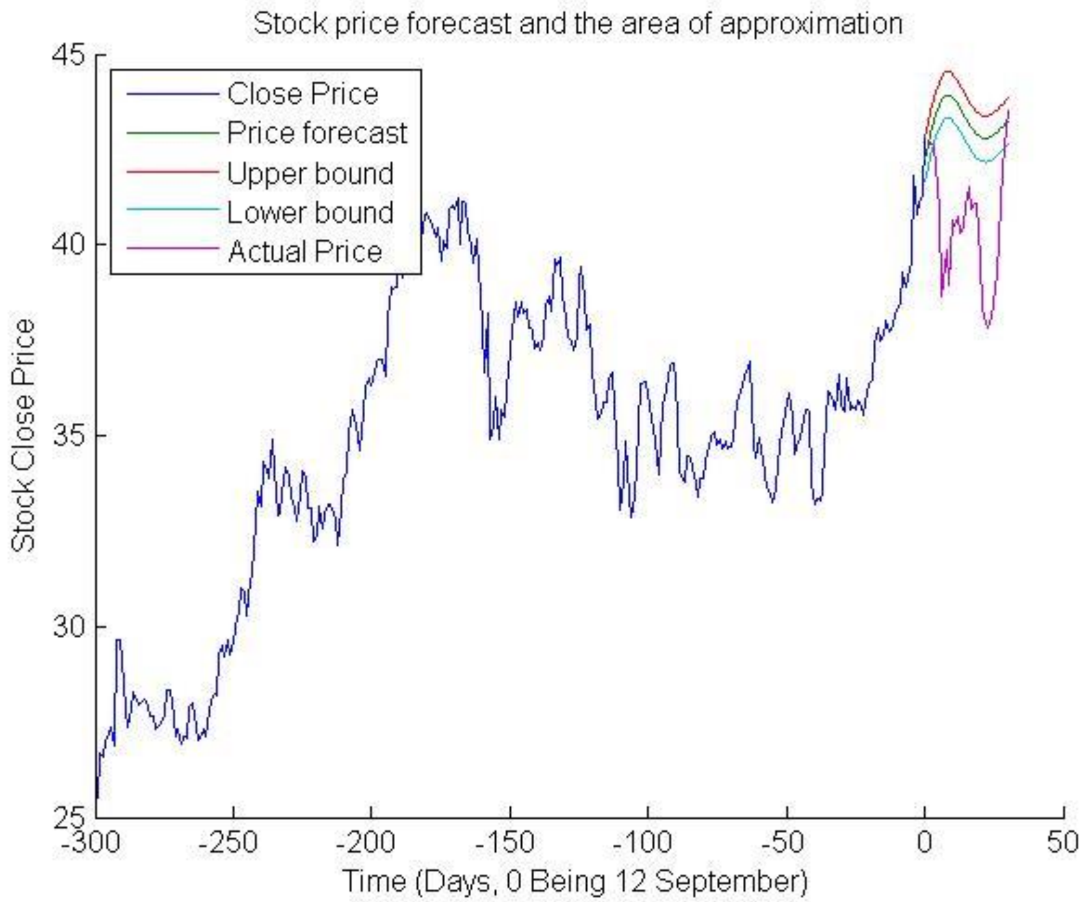


We plot a third order Fourier series and subtract it from the price difference to obtain Noise.

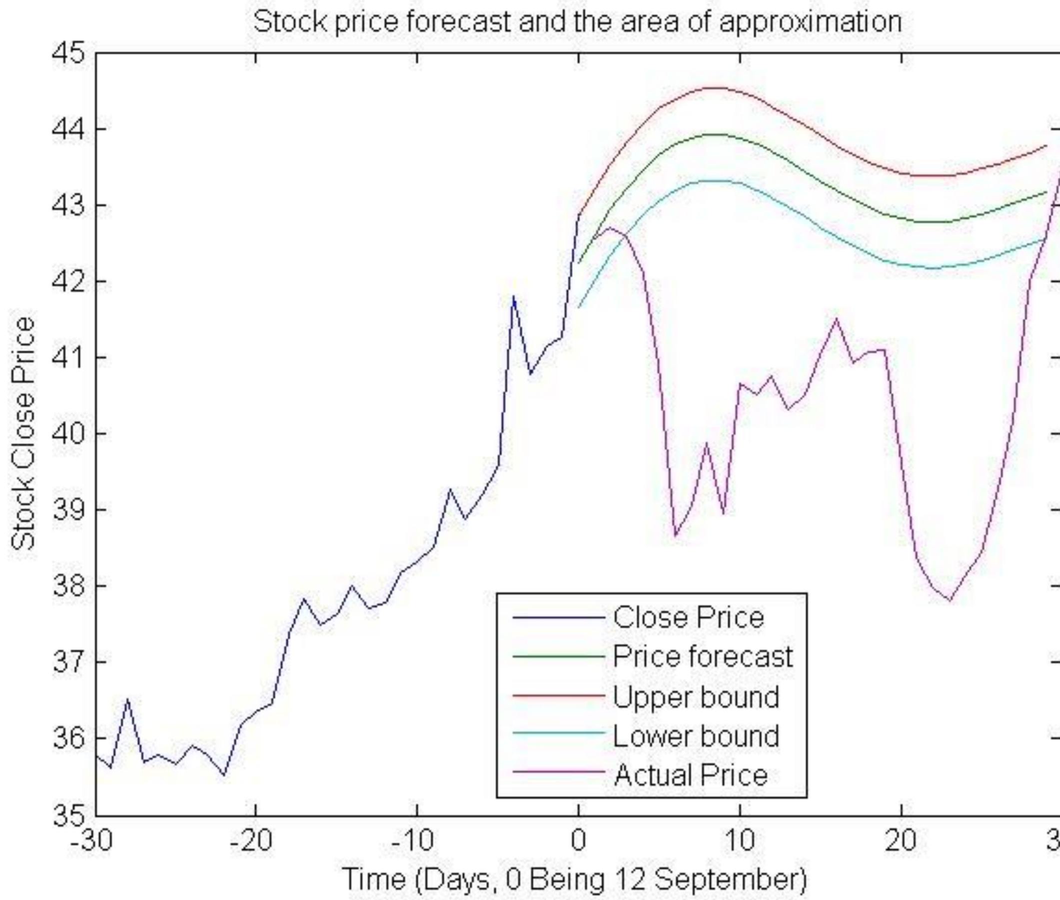

Fourier Series on the difference
data
fitted curve
Stock Close Price
Time (Days, 0 Being 12 September)
4
3
2
1
0
-1
-2
-3
-70
-60
-50
-40
-30
-20
-10
0


Noise
Stock Close Price
Time (Days, 0 Being 12 September)
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-70
-60
-50
-40
-30
-20
-10
0

We sum the Fourier series function and the LSA to obtain the price forecast function. Then we take the average of the absolute value of the Noise. We add and subtract the average Noise from the forecast function to obtain the upper and lower bounds of the prediction area.



Below is the zoomed in version of the graph.



We calculated the percentage of how much the predicted line deviates from the actual price. The max percentage divergence is 12.9% and the stock price is 4.40$ below the area of approximation. The min percent is 0.2% and the stock price is inside the area of approximation. The historical volatility was 32% and 63 relevant day volatility was 30%. The price drop was not predicted by the model, though it started off well. It was due to Alibaba's (BABA) initial public offering. Since Yahoo had a large number of assets in Alibaba Group Holding it experienced a sudden drop. However, critics are saying that Yahoo will stabilize and we will keep observing the future prices to see whether it will go back to following the predicted trend. Right now, however, the average percent of inaccuracy is 6.9% for both 15 and 30 business days, while maximum acceptable inaccuracy according to a 95% confidence interval is 4.0%, thus the model is not acceptable.

Conclusion:

We compared the 15 business day forecast with the 30 business day forecast and the model is more accurate for 15 day period.

Below is the statistics for 30 business days.

Stock Ticker	Slope of Trend	Max % Inaccuracy	Max $ Difference	Min % Inaccuracy	Min $ Difference	Average % Inaccuracy	95% CI
FB	Positive	13.4%	8.41$ below AOA*	0.4%	Inside AOA	4.8%	5.6%
BCOR	Negative	15.7%	2.27$ above AOA*	2.8%	0.24$ above AOA	6.7%	4.3%
CCIH	Positive	32.9%	3.40$ below AOA*	0.01%	Inside AOA	8.1%	11.5%
EBAY	Positive	15.9%	7.19$ below AOA*	0.004%	Inside AOA	4.6%	2.8%
GRPN	Negative	18.5%	0.90$ below AOA*	0.18%	Inside AOA	4.1%	7.5%
IACI	Negative	8.0%	3.88$ below AOA*	0.3%	Inside AOA	3.6%	3.5%
JCOM	Negative	7.0%	3.33$ above AOA*	0.001%	Inside AOA	1.7%	3.8%
TTGT	Positive	8.9%	0.66$ above AOA*	0.04%	Inside AOA	2.8%	5.1%
TWTR	Positive	20.7%	9.08$ below AOA*	0.8%	Inside AOA	9.1%	8.5%
YHOO	Negative	13.1%	4.40$ below AOA*	0.2%	Inside AOA	6.9%	4.0%

* AOA – Area of Approximation

Below is the statistics for 15 business days.

Stock Ticker	Slope of Trend	Max % Inaccuracy	Max $ Difference	Min % Inaccuracy	Min $ Difference	Average % Inaccuracy	95% CI

FB	Positive	4.3%	2.02$ below AOA	0.4%	Inside AOA	1.9%	5.6%
BCOR	Negative	7.5%	1.00$ above AOA	2.8%	0.25$ above AOA	5.5%	4.3%
CCIH	Positive	6.2%	0.31$ below AOA*	0.01%	Inside AOA	3.2%	11.5%
EBAY	Positive	4.6%	2.11$ above AOA*	0.005%	Inside AOA	1.6%	2.8%
GRPN	Negative	2.9%	0.03$ below AOA*	0.18%	Inside AOA	1.1%	7.5%
IACI	Negative	3.7%	1.69$ below AOA*	0.3%	Inside AOA	2.4%	3.5%
JCOM	Negative	2.5%	1.02$ below AOA*	0.001%	Inside AOA	1.0%	3.8%
TTGT	Positive	7.5%	0.51$ above AOA*	0.04%	Inside AOA	1.5%	5.1%
TWTR	Positive	5.5%	2.15$ below AOA*	0.6%	Inside AOA	2.7%	8.5%
YHOO	Negative	12.9%	4.40$ below AOA*	0.2%	Inside AOA	6.9%	4.0%

Below we make comparison to demonstrate for which stocks has the model proven to be acceptable. More specifically, we demonstrate the stocks for which the average inaccuracy has fallen below the 95% confidence interval.

Stock Ticker	Overall Quality for 15 Business Days	Overall Quality for 30 Business Days
FB	Acceptable	Acceptable
BCOR	Not Acceptable	Not Acceptable
CCIH	Acceptable	Acceptable
EBAY	Acceptable	Not Acceptable

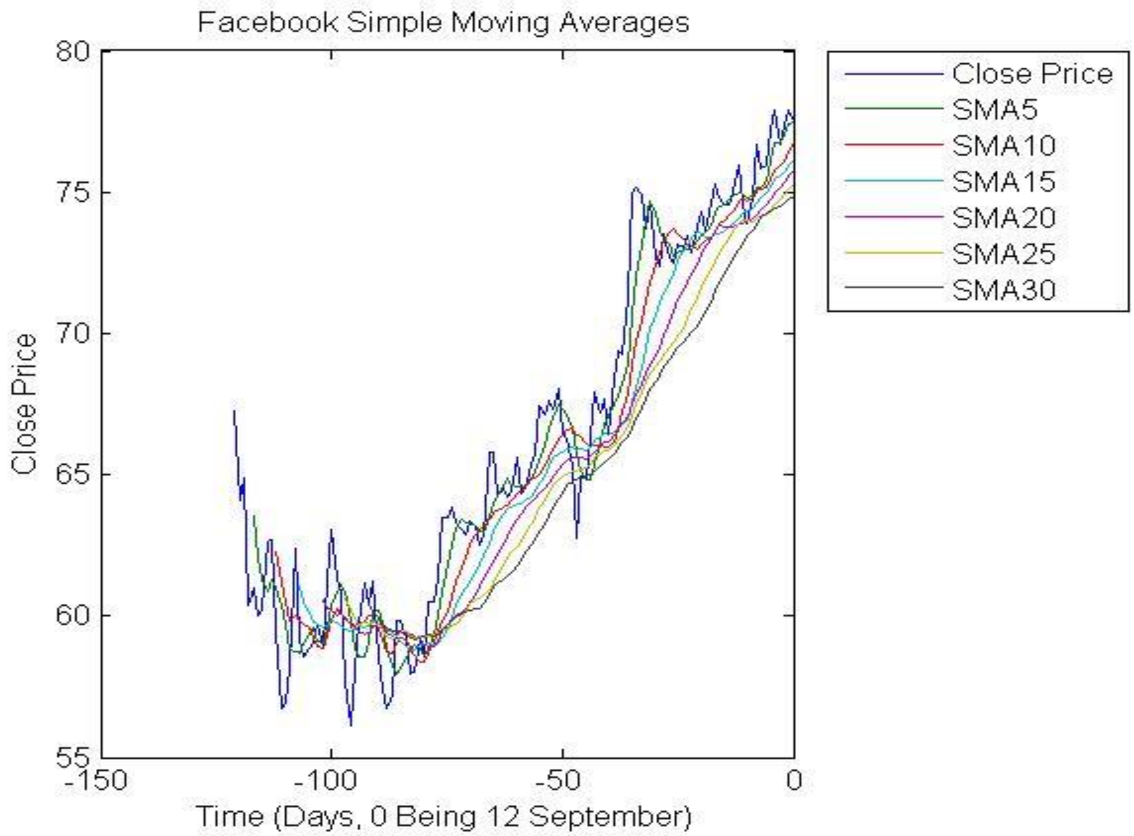
GRPN	Acceptable	Acceptable
IACI	Acceptable	Not Acceptable
JCOM	Acceptable	Acceptable
TTGT	Acceptable	Acceptable
TWTR	Acceptable	Not Acceptable
YHOO	Not Acceptable	Not Acceptable

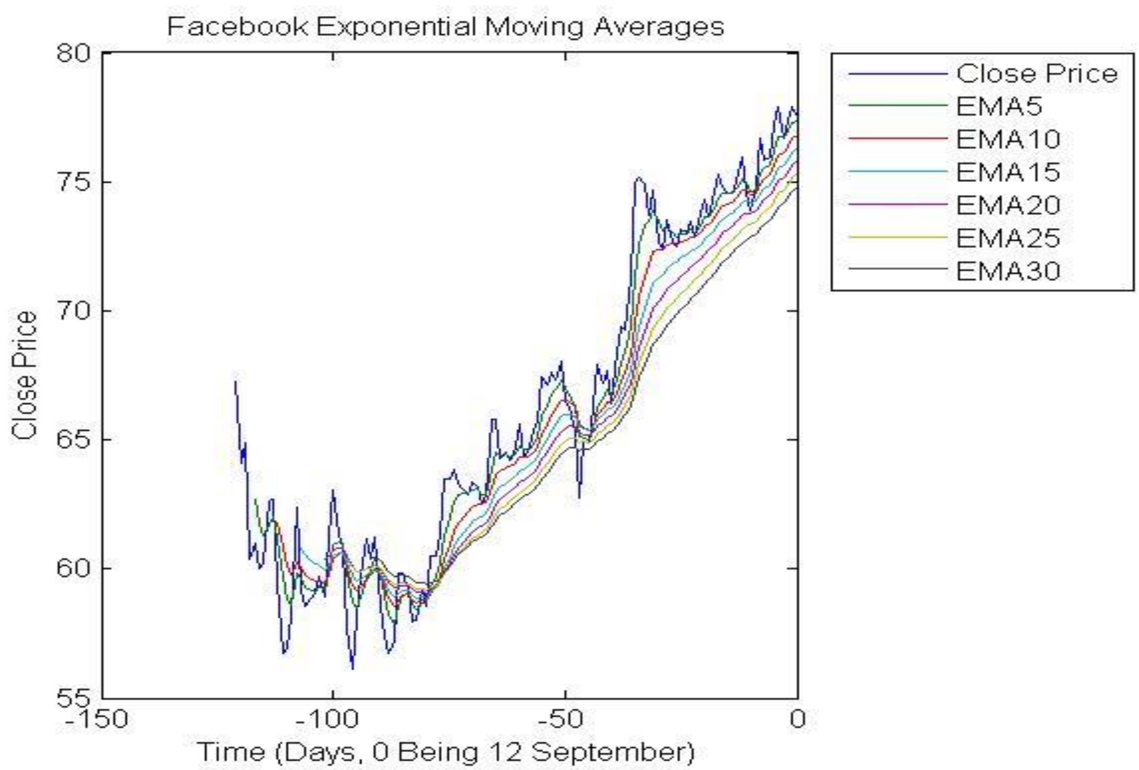
The difference in level of precision of predictions for 15 and 30 business days is significant. For 15 days the model is acceptable for eight out of ten stocks, while, for thirty days the model is acceptable for 5 out of ten stocks. For the purpose of accurately forecasting stock prices we suggest using this model for 15 business days. Moving forward, we will use the 15 business day approximation statistics to compare the two versions of the model.

Smoothed Version

Since the non-smoothed version was more accurate for 15 business day forecasting we will use this timeframe value for the smoothed version to predict the price of the stock.

We chart the moving averages of the close prices to decide which moving average will be the best choice for smoothing the raw data. We used both simple and exponential moving averages for 5, 10, 15, 20, 25, and 30 days.


Facebook Simple Moving Averages
Close Price
SMA5
SMA10
SMA15
SMA20
SMA25
SMA30
80
75
70
65
60
55
-150
-100
-50
0
Time (Days, 0 Being 12 September)

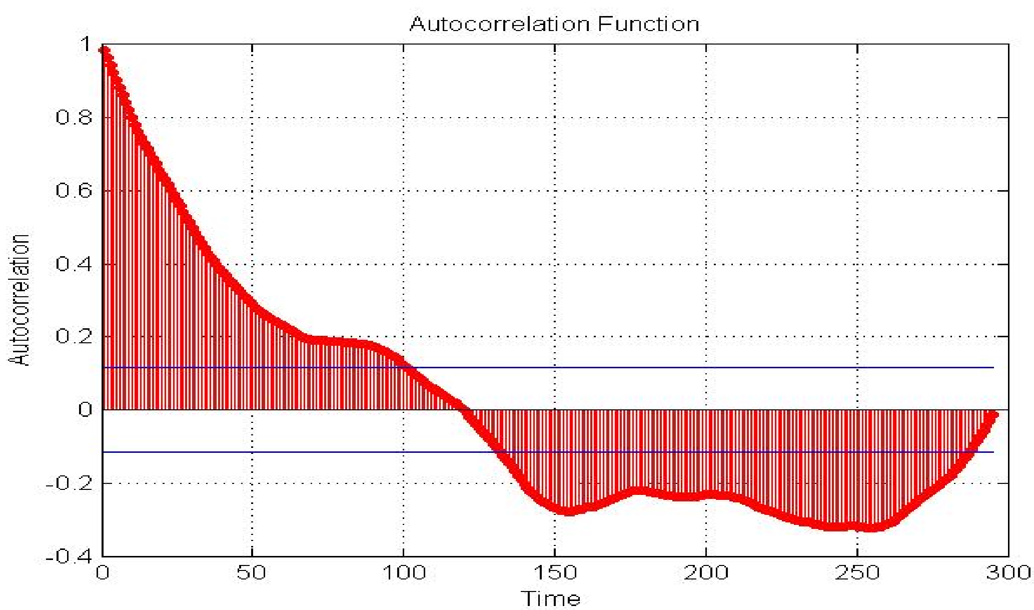

Facebook Exponential Moving Averages
Close Price
EMA5
EMA10
EMA15
EMA20
EMA25
EMA30
80
75
70
65
60
55
-150
-100
-50
0
Time (Days, 0 Being 12 September)

We decided to use 5 day simple moving average since it gets rid of sufficient noise from the raw data to plot a precise autocorrelation function. We disregarded any moving averages above five days along with the exponential moving averages since they smooth the data too much and are inaccurate representations of stock close price.

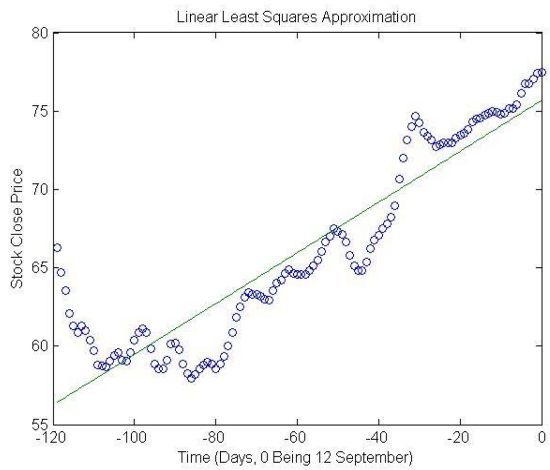
Facebook:

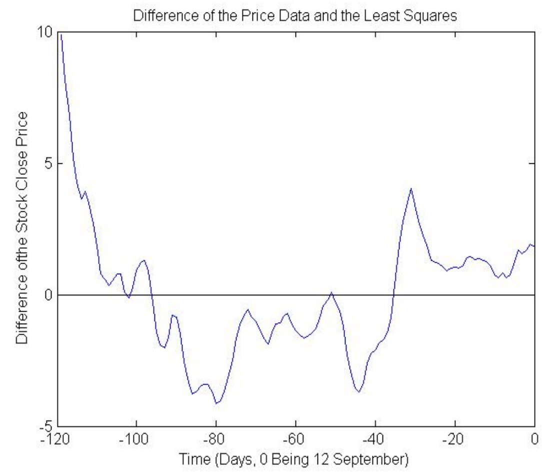
We observed that a part of the actual price is in the approximation range of the function. The forecast line shows a positive slope, thus an upper trend. Even though the price experienced a sudden drop at first, which was a slight mismatch to the prediction, the stock is headed in the right direction. In the end it started to diverge. The average percent of inaccuracy is 2.1% below the area of approximation. Overall, this is not an acceptable result. The general predicted trend was correct at first, but the trend of the area of approximation is too steep and started to quickly diverge from the actual price.

We do not plot the close price data since it is already presented in the non-smoothed version. We take the Facebook close price and smooth it using five day moving average.

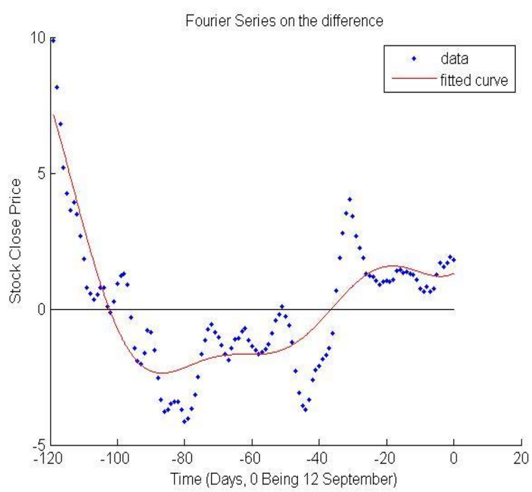


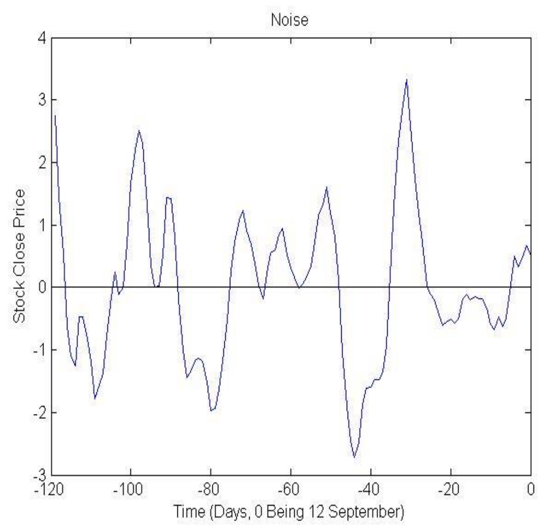
The autocorrelation of the smoothed data gave us a positive area for the first 120 days, which is two days less than that of the raw data from the non-smoothed autocorrelation. We plot a Linear Least Squares Approximation function on the relevant smoothed data and we will subtract the LSA from the data to obtain the difference.





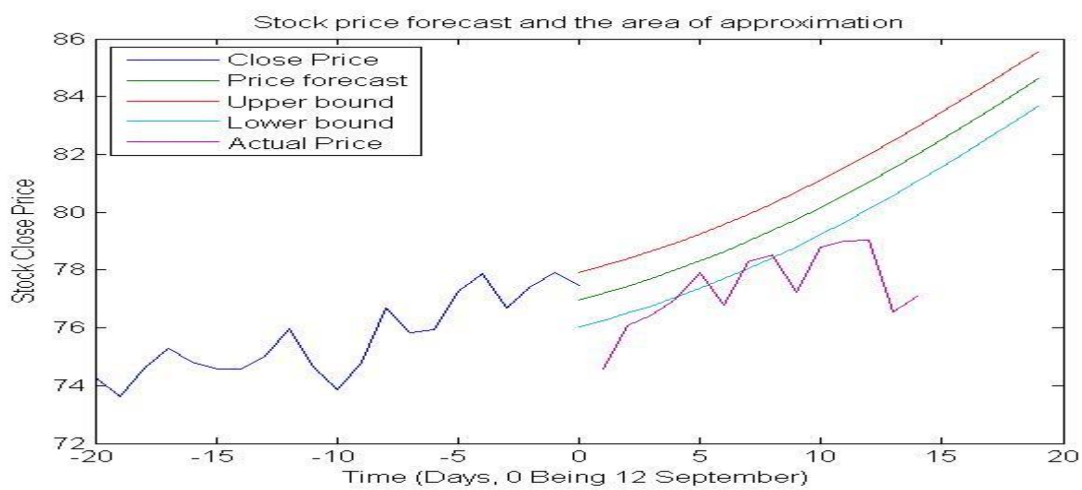
We use the acquired difference value and create a third order Fourier series to fit the divergent data and we subtract the Fourier series function from the price difference to obtain the Noise.





We sum the Fourier series function and the LSA to obtain the price forecast function. Then we take the average of the absolute value of the Noise. We add and subtract the average Noise from the forecast function to obtain the upper and lower bounds of the prediction area.

Below is the zoomed in version of the plot.

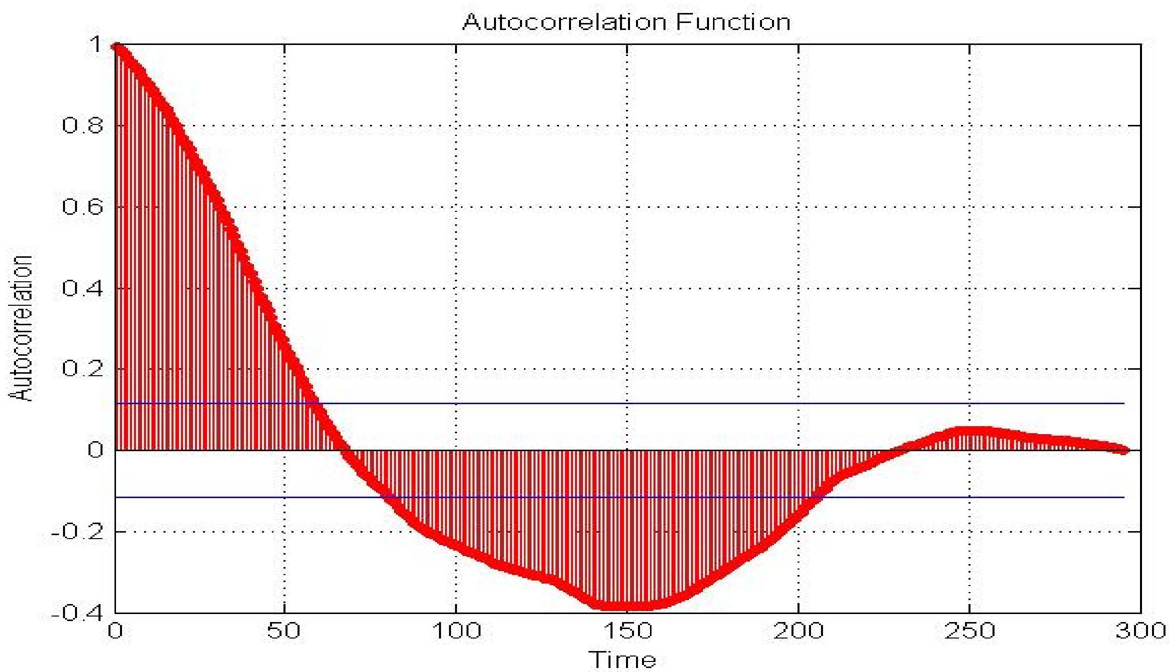


We calculated the percentage divergence of the predicted line is from the actual price. The max percentage is 5.9% and the stock price is 3.56$ below the area of approximation. The min percent is 0.1% and the stock price is inside the area of approximation. The average percent of inaccuracy is 2.1%. The stock was close and inside the area of approximation, however, the prediction line started diverging from the actual price. The volatility for the close price data was 45%, while the 122 relevant day volatility was 35%. The model is not acceptable even though the percentage inaccuracy is low, since it started to diverge from the actual price.

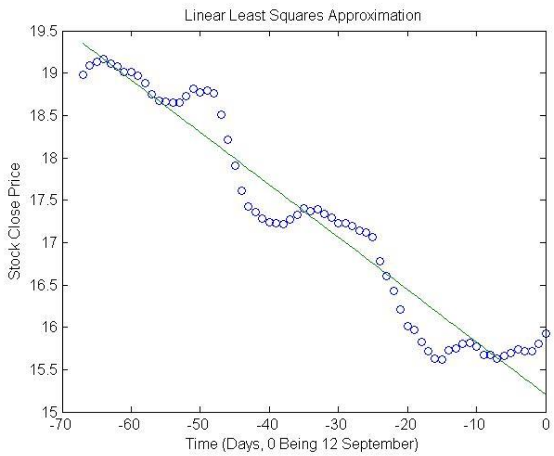
Blucora Inc:

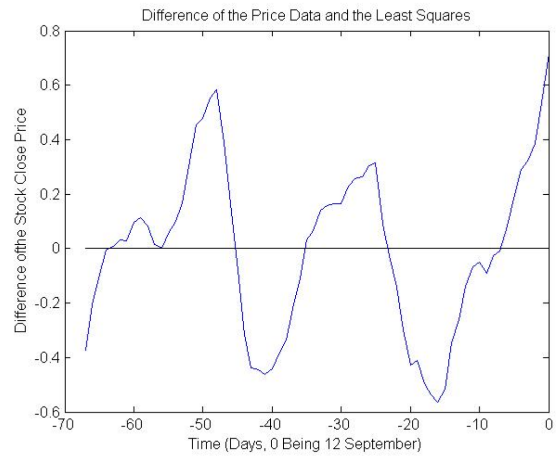
The trend of the forecast line is going downwards and so is the actual price. But, the actual close price after 12th of September does not fall under the forecast area. Even though, the volatility for the relevant days was 25%, the model produced an inaccurate prediction. The sudden uptrend of the stock before 12th of September for a few days caused the model to destabilize and was only able to correctly determine the slope of the direction the stock price was heading. The average percent of inaccuracy is 6.2% above the area of approximation, which makes the model not acceptable.

We do not plot the close price data since it is already presented in the non-smoothed version. We take the Blucora Inc. close price and smooth it using five day moving average.

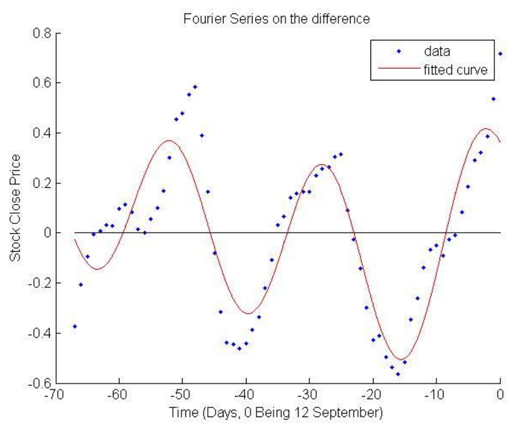


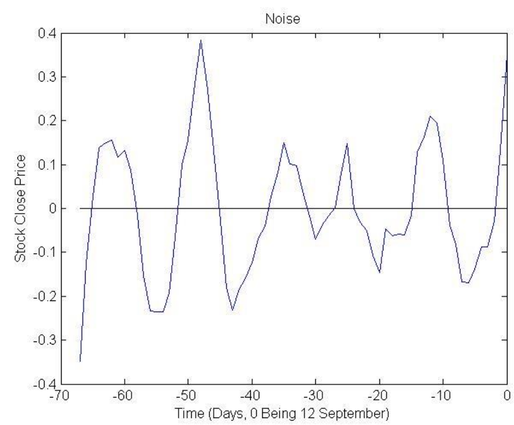
The autocorrelation of the smoothed data gave us a positive area for the first 68 days, which is one day less than that of the raw data from the non-smoothed autocorrelation. We plot a Linear Least Squares Approximation function on the relevant smoothed data and we will subtract the LSA from the data to obtain the difference.



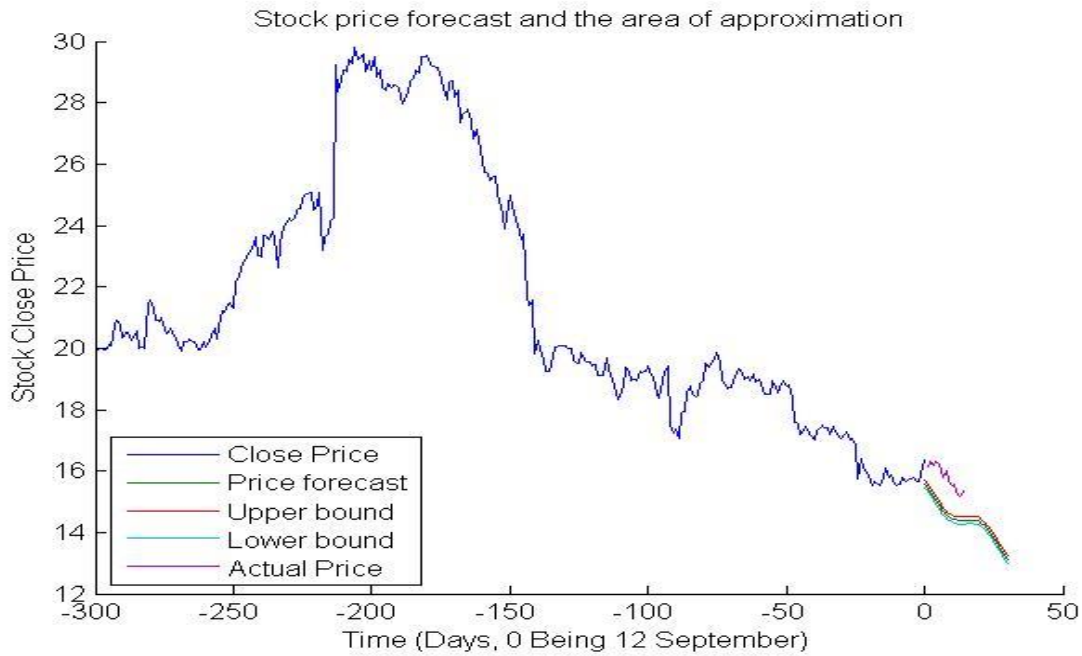


We use the difference and create a third order Fourier series to fit the divergent data and we subtract the Fourier series function from the price difference to obtain the Noise.

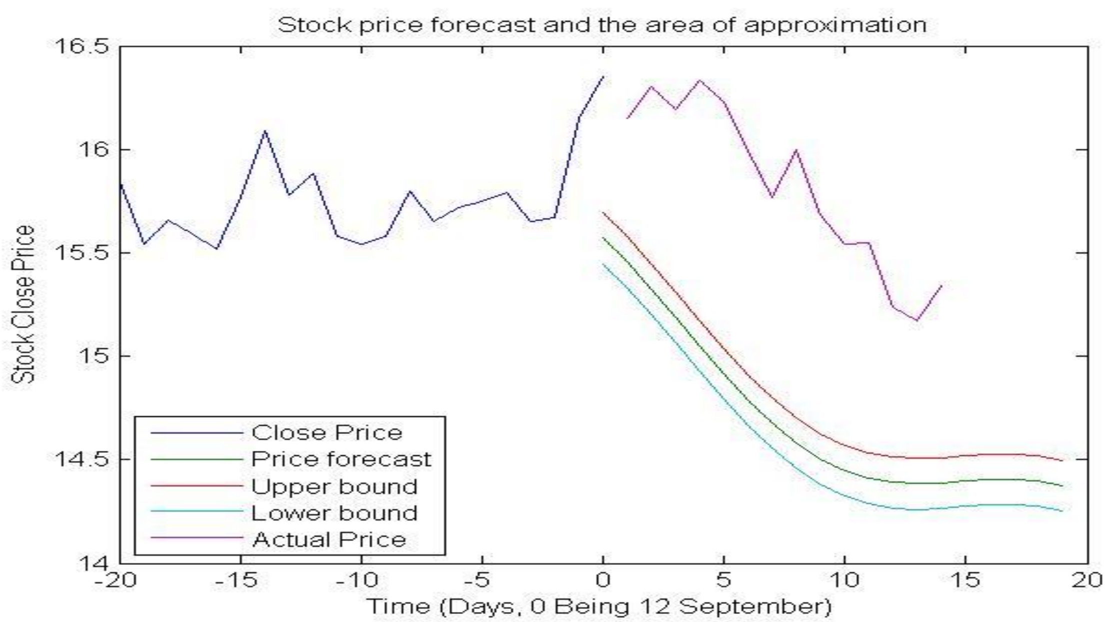




We sum the Fourier series function and the LSA to obtain the price forecast function. Then we take the average of the absolute value of the Noise. We add and subtract the average Noise from the forecast function to obtain the upper and lower bounds of the prediction area.



Below is the zoomed in version of the graph.

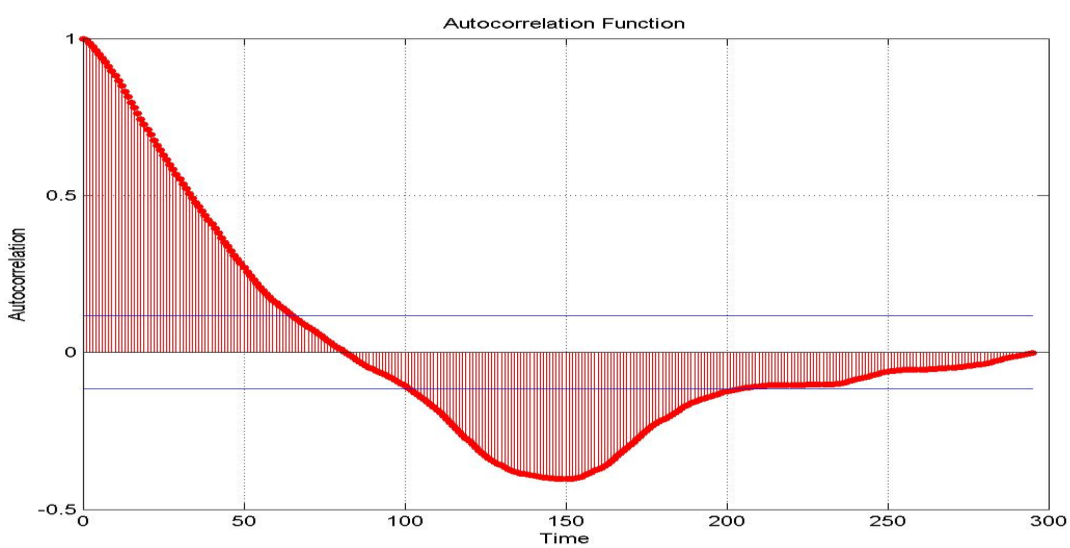


The actual close price after 12th of September does not fall under the forecast area and the only correct assumption the model gave us was the direction of the trend. The sudden uptrend of the stock before 12th of September for a few days was the reason that caused the model to produce inaccurate prediction. We calculated the percentage deviation of the predicted line from the actual price. The max percentage is 8.3% and the stock price is 1.20$ above the area of approximation. The min percent is 3.6% and the stock price is 0.46$ above the area of approximation. The average percent of inaccuracy is 6.2%. The historical volatility of the stock was 34% and for 69 relevant days it was 25%, but a destabilized model was only able to predict the slope of the trend. The model is not acceptable.

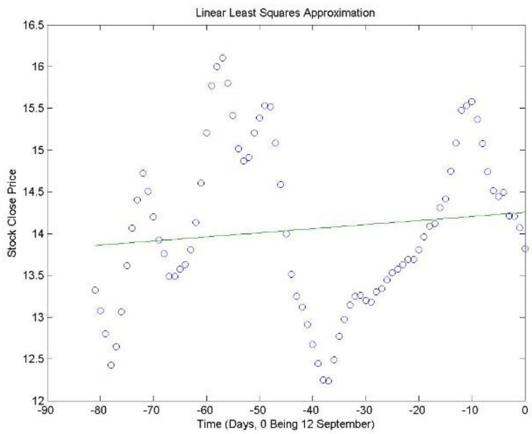
ChinaCache Ltd:

The forecast line is not accurate at first, however, the actual future price heads well into the approximation area. The average percent of inaccuracy is 4.4. The volatility for the relevant days is 74%. The model is still stable and precise because the price change, during the relevant day period, is between 13 and 16. The historical volatility is 91% and the price change is between 5 and 30, so the relevant number of days represents the stock really well and stabilizes the model. Thus, it is acceptable.

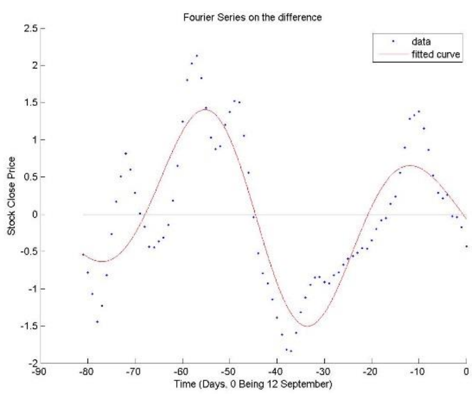
We do not plot the close price data since it is already presented in the non-smoothed version. We take the ChinaCache Ltd close price and smooth it using five day moving average.

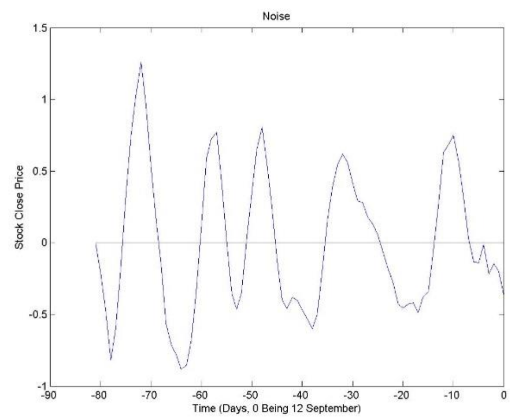


The autocorrelation of the smoothed data gave us a positive area for the first 82 days, which is two days less than that of the raw data from the non-smoothed autocorrelation. We plot a Linear Least Squares Approximation function on the relevant smoothed data and we will subtract the LSA from the data to obtain the difference.



We use the acquired difference and create a third order Fourier series to fit the divergent data and we subtract this Fourier series function from the price difference to obtain the Noise.

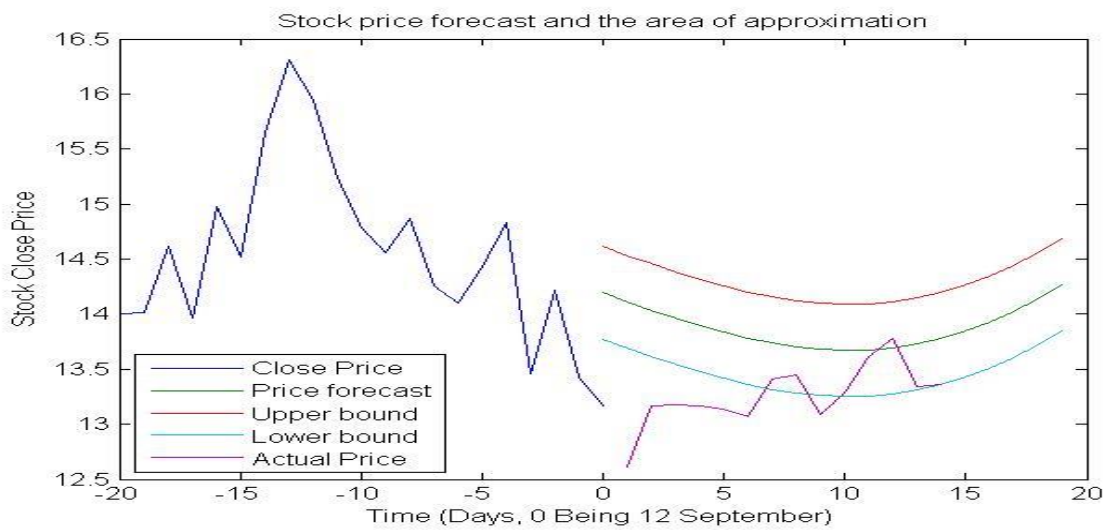




We sum the Fourier series function and the LSA to obtain the price forecast function. Then we take the average of the absolute value of the Noise. We add and subtract the average

Noise from the forecast function to obtain the upper and lower bounds of the prediction area.

Below is the zoomed in version of the graph.

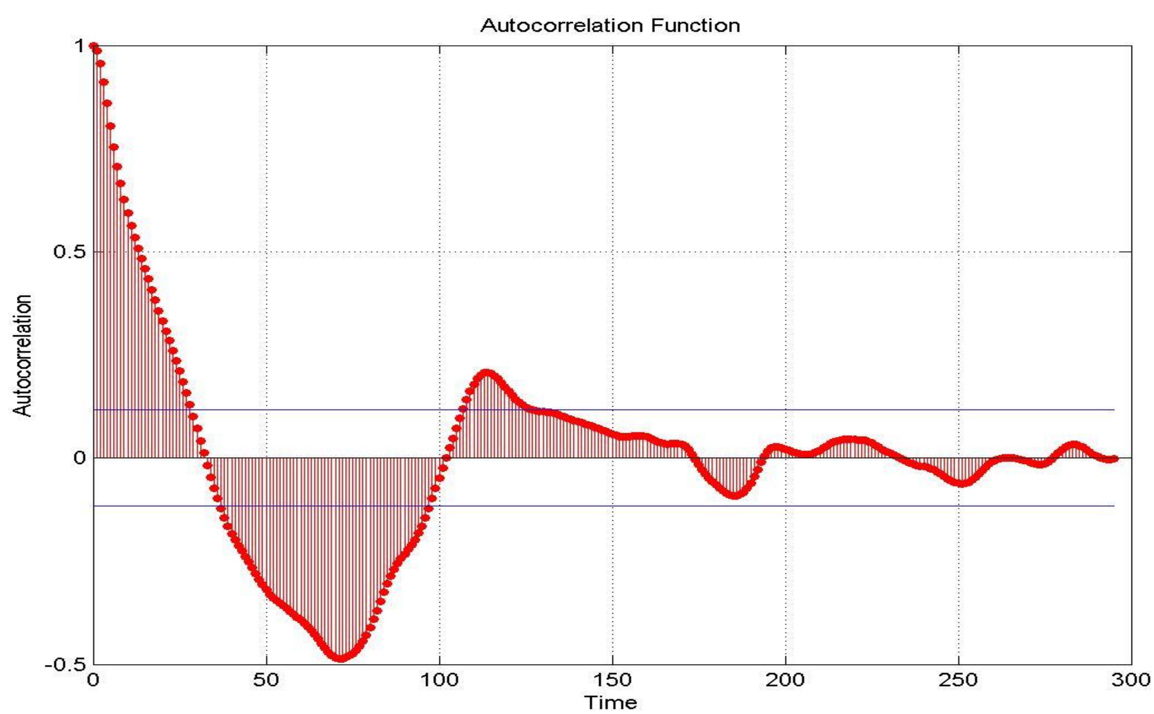


The max percentage of inaccuracy is 12.6% and the stock price is 1.16$ below the area of approximation. The min percent is 0.4% and the stock price is inside the area of approximation. The average percent of inaccuracy is 4.4%. The forecast line is not accurate at first, however, the actual future price heads well into the approximation area. The historical volatility for this stock was 91% and for the last 84 relevant days it was 74%. The model is still stable and precise because the price change, during the relevant day period, is between 13 and 16. The historical volatility price change is between 5 and 30, so the relevant number of days represents the stock really well and stabilizes the model. The prediction area had a bad start, however, it moved close to the actual price value and in the end the stock was well forecasted. The model is acceptable.

EBay Inc.:

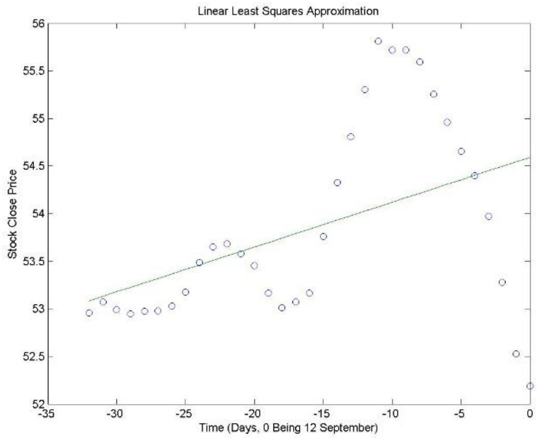
The actual price after 12th of September starts off in the area of approximation. The graph predicts a strong positive momentum. EBay is an interesting stock because the forecast graph diverges below the stock price. This means that if the model predicted a rise in price, an investor should have bought the stock in order to have sold it at a later date. The actual future price making a steeper jump than the forecasted line is a much better result and the investor made a considerably bigger profit. The average percent of inaccuracy is 3.8%, volatility for relevant days is 22% and the model is acceptable.

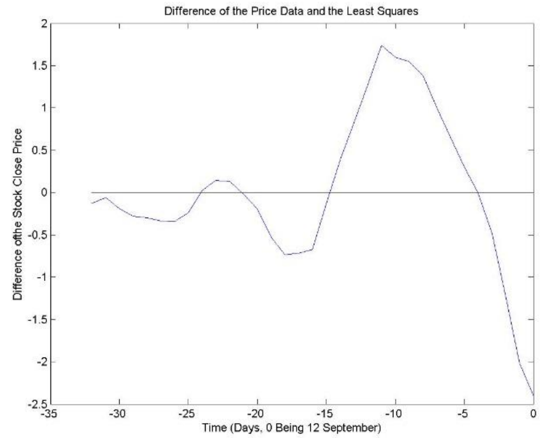
We do not plot the close price data since it is already presented in the non-smoothed version. We take the eBay Inc. close price and smooth it using five day moving average.



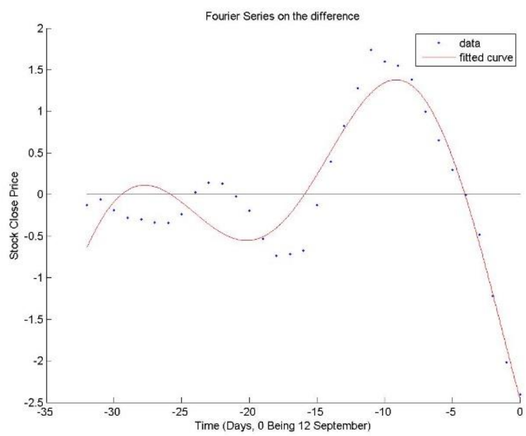
The autocorrelation of the smoothed data gave us a positive area for the first 33 days, which is the same as the raw data from the non-smoothed autocorrelation. We plot a Linear Least

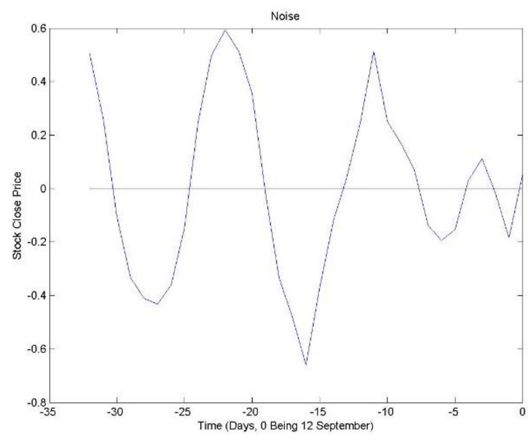
Squares Approximation function on the relevant smoothed data and we will subtract the LSA from the data to obtain the difference.



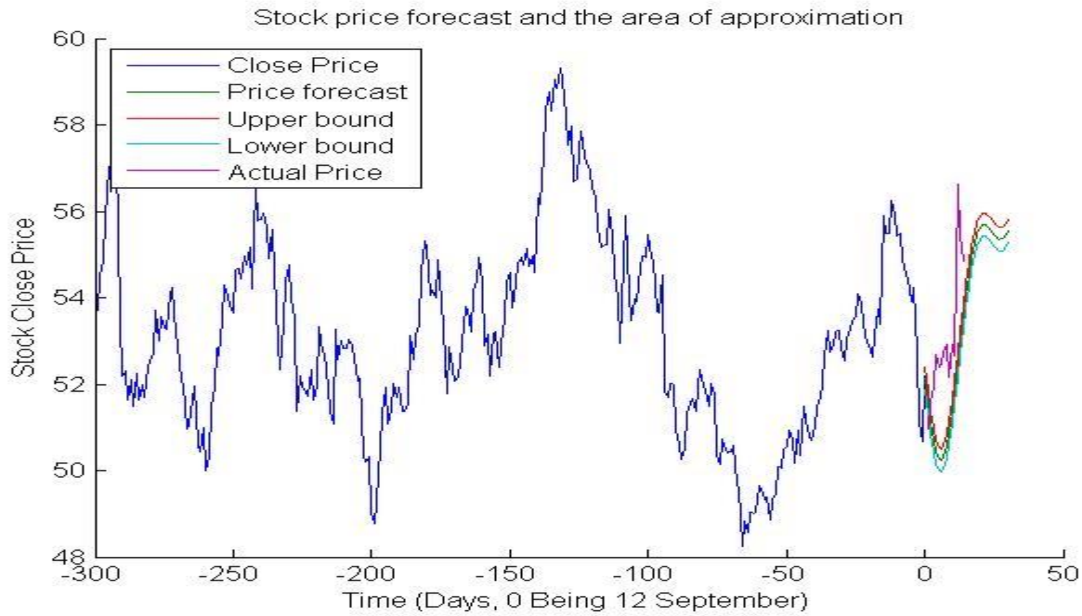


We use the difference and create a third order Fourier series to fit the divergent data and we subtract the Fourier series function from the price difference to obtain the Noise.

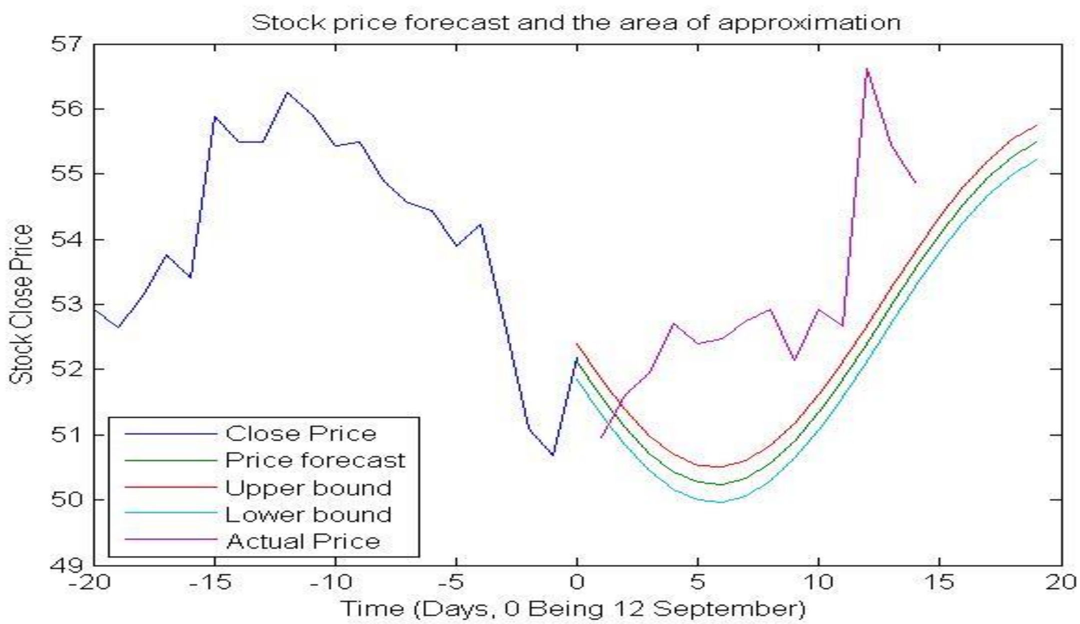




We sum the Fourier series function and the LSA to obtain the price forecast function. Then we take the average of the absolute value of the Noise. We add and subtract the average Noise from the forecast function to obtain the upper and lower bounds of the prediction area.



Below is the zoomed in version of the graph.

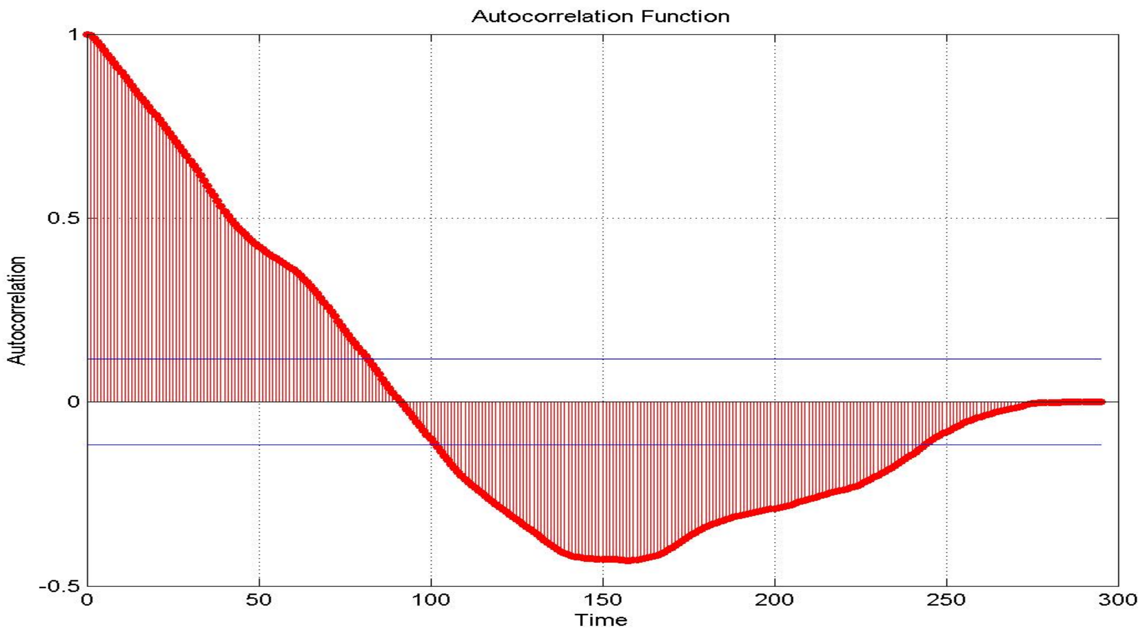


The max percentage of inaccuracy is 8.4% and the stock price is 4.51$ below the area of approximation. The min percent is 0.5% and the stock price falls in the area of approximation. The actual price after 12th of September starts off in the area of approximation. The graph predicts a strong positive momentum. EBay is an interesting stock because the forecast graph diverges below the stock price. This means that if the model predicted a rise in price, an investor should have bought the stock in order to have sold it at a later date. The actual future price making a steeper jump than the forecasted line is a much better result and the investor made a lot more capital. The average percent of inaccuracy is 3.8%, volatility for 33 relevant days is 22% and the historical volatility is 22% as well. The model is acceptable.

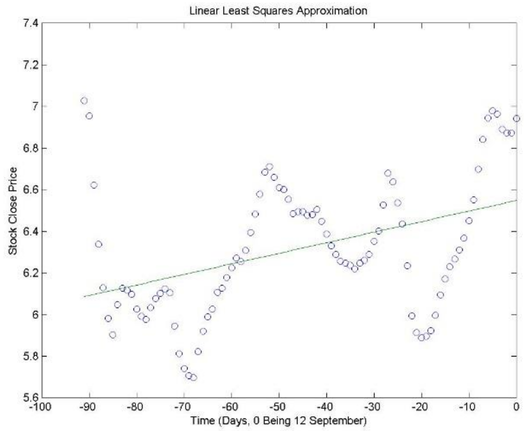
Groupon Inc.:

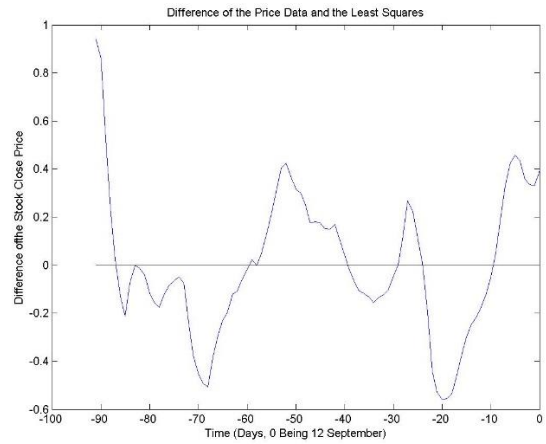
The Groupon close price data after 12th of September is well within the area of approximation and follows the price forecast function with minimal divergences. This is an excellent forecast and the average percent of inaccuracy is 1.1%. Even though, the volatility for relevant data was 60% the maximum price movement was between 5 and 7 dollars. The historical close price experienced sharp movement ranging from 5 to 13 dollars thus the model was well represented.

We do not plot the close price data since it is already presented in the non-smoothed version. We take the Groupon Inc. close price and smooth it using five day moving average.

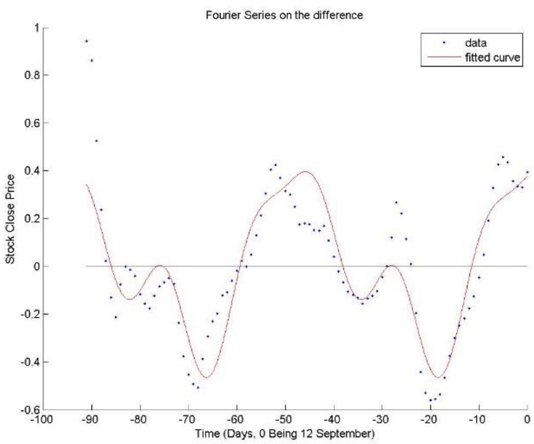


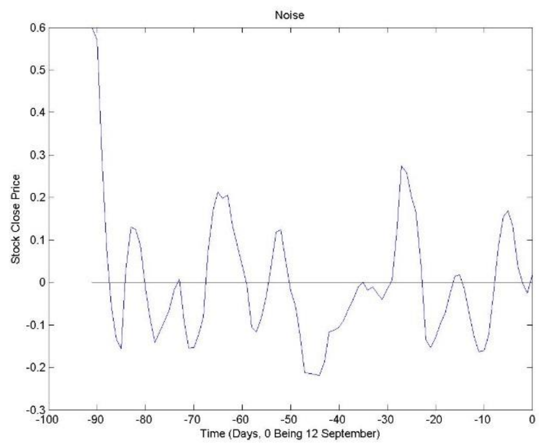
The autocorrelation of the smoothed data gave us a positive area for the first 92 days, which is the same as the raw data from the non-smoothed autocorrelation. We plot a Linear Least Squares Approximation function on the relevant smoothed data and we will subtract the LSA from the data to obtain the difference.





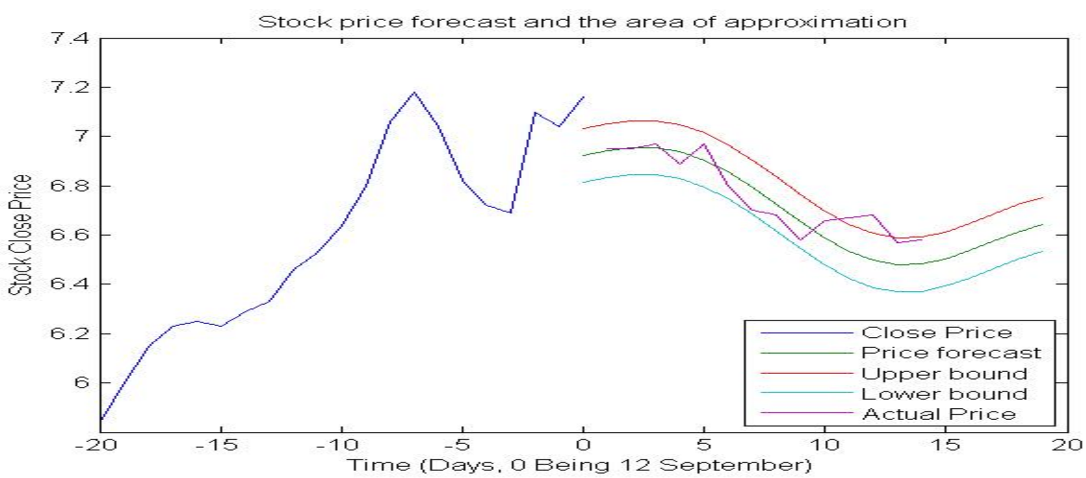
We use the difference and create a third order Fourier series to fit the divergent data and we subtract the Fourier series function from the price difference to obtain the Noise.





We sum the Fourier series function and the LSA to obtain the price forecast function. Then we take the average of the absolute value of the Noise. We add and subtract the average Noise from the forecast function to obtain the upper and lower bounds of the prediction area.

Below is the zoomed in version of the graph.

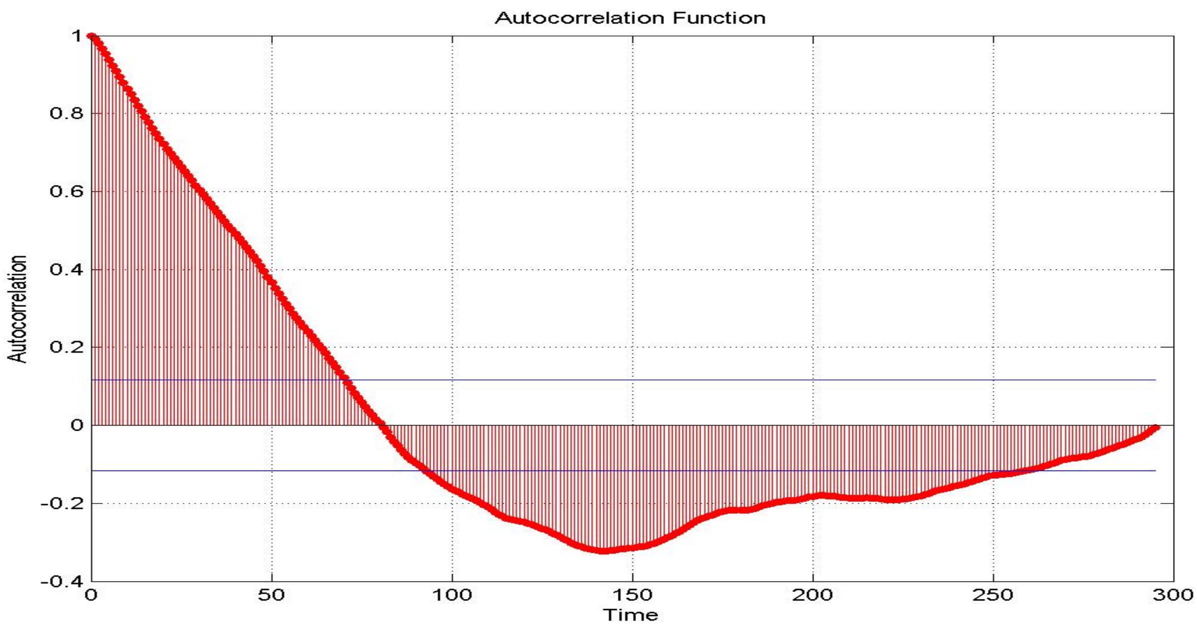


The max percentage of inaccuracy is 2.3% and the stock price is 0.05$ above the area of approximation. The min percent is 0.08% and the stock price is in the area of approximation. The average percent of inaccuracy is 1.1%. The Groupon close price data after 12th of September is well within the area of approximation and follows the price forecast function with minimal divergences. This is an excellent forecast. Even though, the volatility for 92 relevant data was 60% the maximum price movement was between 5 and 7 dollars. The historical close price experienced sharp movement ranging from 5 to 13 dollars for a volatility of 59%, thus the model was well represented.

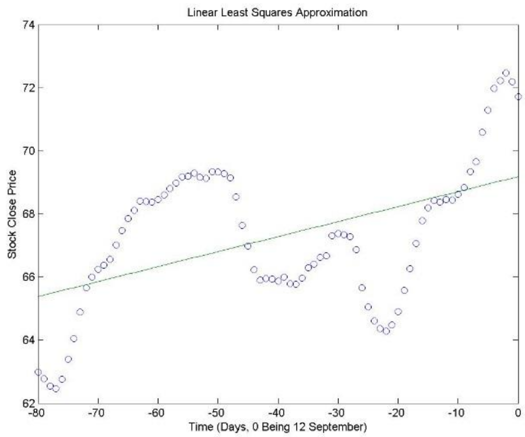
IACI:

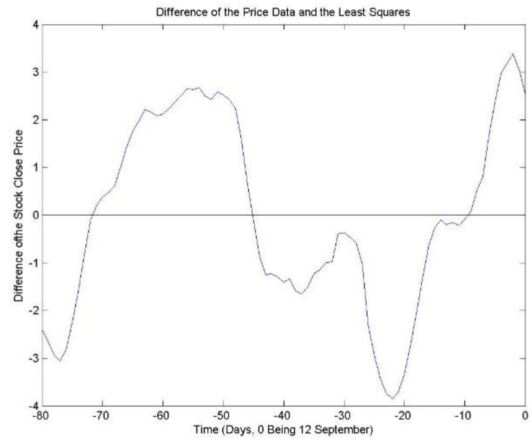
The forecast graph was completely off this time. The average percent of inaccuracy is 6.6%, which already makes the model not acceptable. The inaccuracy of this model is caused by rapid changes in the stock price. In the last month alone the price has experienced a 10$ jump, while last year, the stock experienced a 30 dollar fluctuations.

We do not plot the close price data since it is already presented in the non-smoothed version. We take the IACI close price and smooth it using five day moving average.

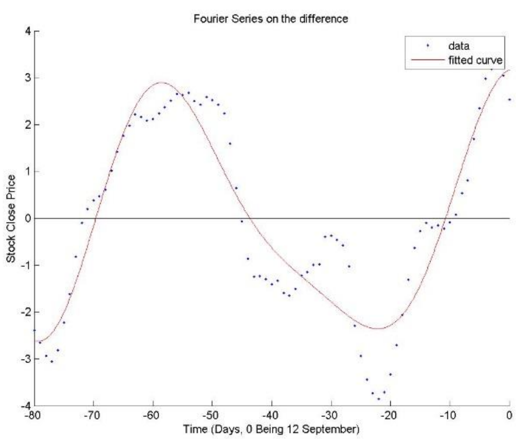


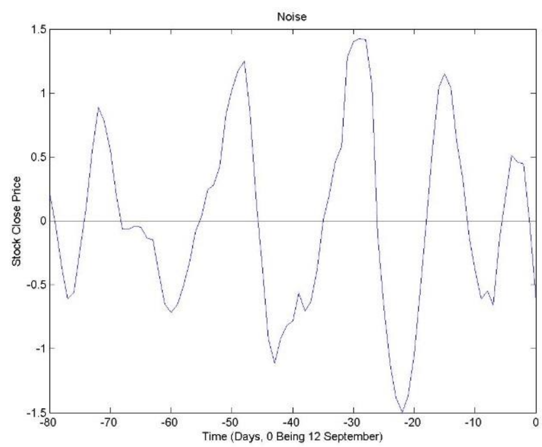
The autocorrelation of the smoothed data gave us a positive area for the first 81 days, which is one day less than that of the raw data from the non-smoothed autocorrelation. We plot a Linear Least Squares Approximation function on the relevant smoothed data and we will subtract the LSA from the data to obtain the difference.



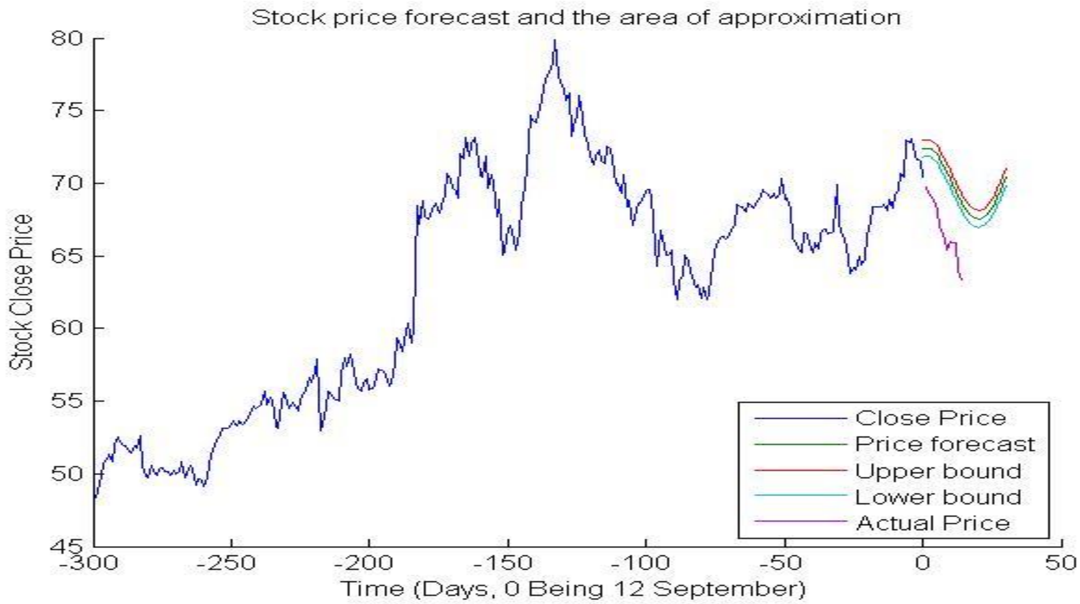


We use the difference and create a third order Fourier series to fit the divergent data and we subtract the Fourier series function from the price difference to obtain the Noise.

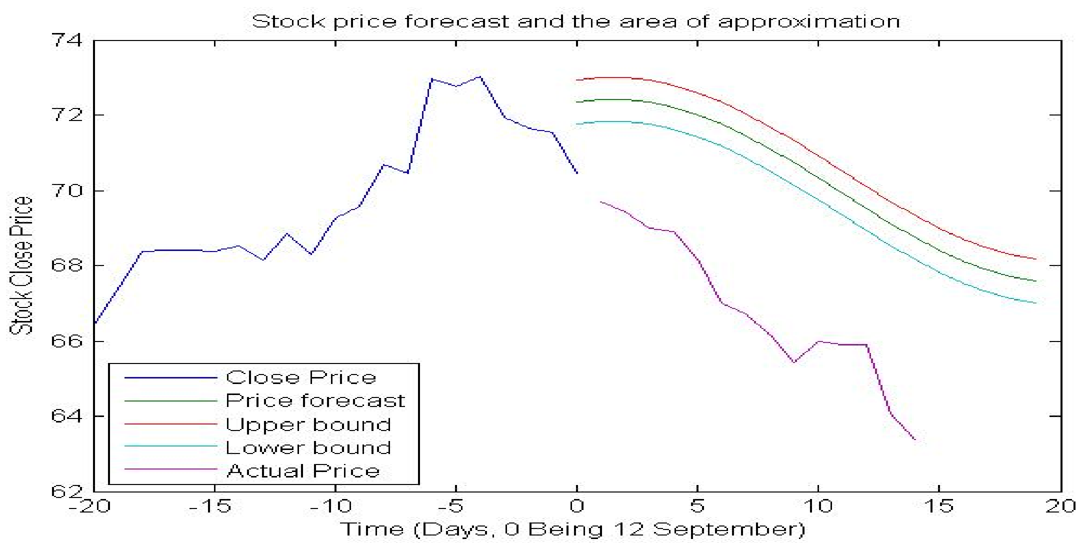




We sum the Fourier series function and the LSA to obtain the price forecast function. Then we take the average of the absolute value of the Noise. We add and subtract the average Noise from the forecast function to obtain the upper and lower bounds of the prediction area.



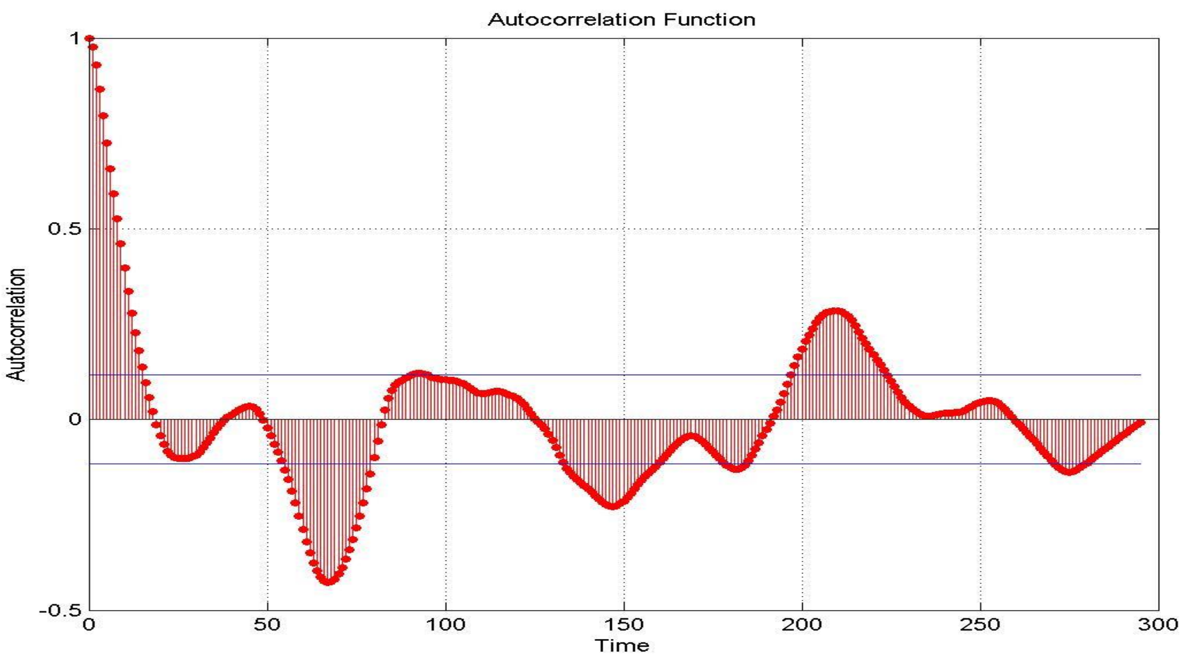
Below is the zoomed in version of the graph.



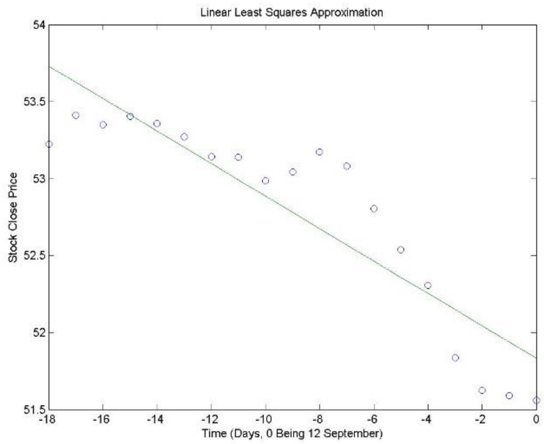
The max percentage of inaccuracy is 9.1% and the stock price is 5.16$ above the area of approximation. The min percent is 3.8% and the stock price is 2.06$ above the area of approximation. The average percent of inaccuracy is 6.6%. Even though, the forecast line is realistic, it completely inaccurate. The model is not acceptable. The inaccuracy of this model is caused by rapid changes in the stock price. In the last month alone the price has experienced a 10$ jump, while last year, the stock experienced a 30 dollar fluctuations.

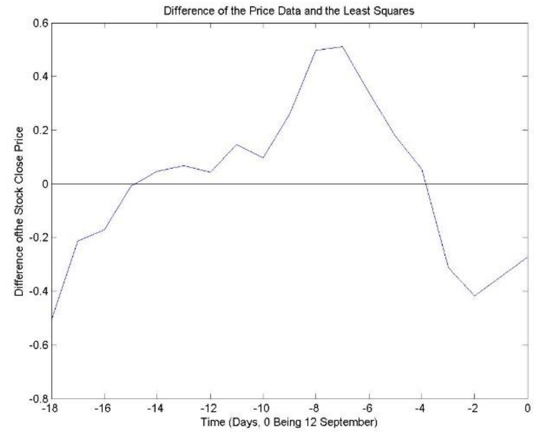
J2 Global:

Choosing a lower order Fourier series gave a much more accurate representation of the stock close price data. The average percentage of inaccuracy is 1.6%. The actual price crosses the area of approximation twice and even though it is not in the area of approximation, the future price ends up following the trend and the forecast graph with a good accuracy. Relevant day volatility being at 16% the forecast line is really accurate and follows the trend. The model is acceptable.

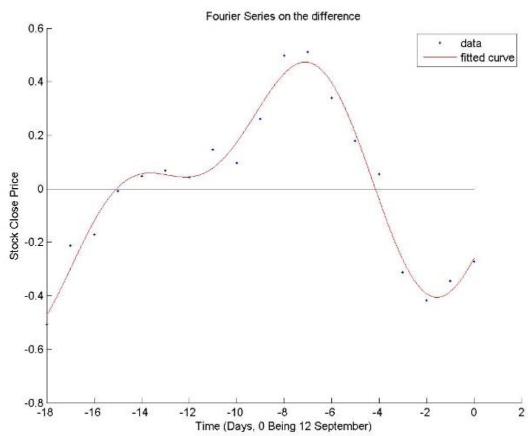


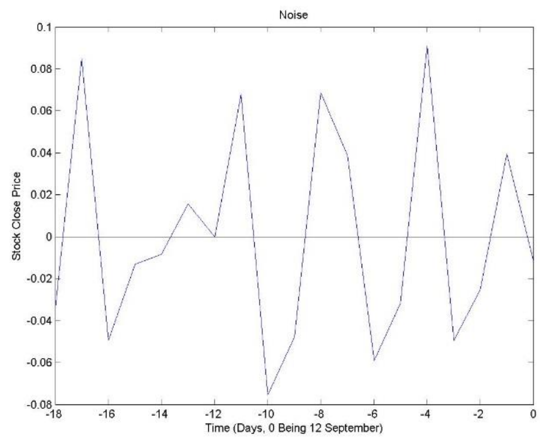
The autocorrelation of the smoothed data gave us a positive area for the first 19 days, which is the same as the raw data from the non-smoothed autocorrelation. We plot a Linear Least Squares Approximation function on the relevant smoothed data and we will subtract the LSA from the data to obtain the difference.



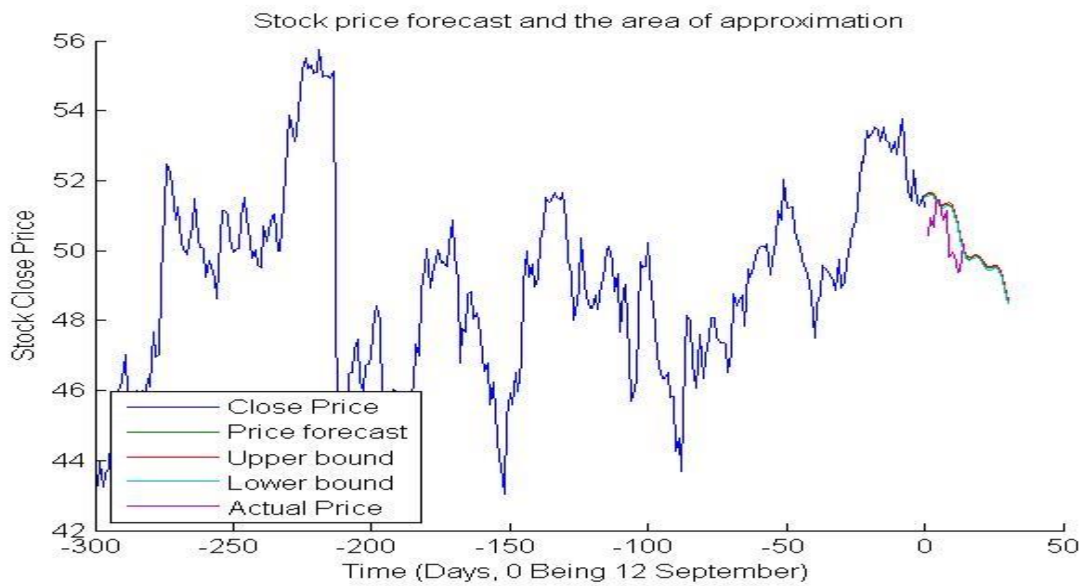


We use the difference and create a third order Fourier series to fit the divergent data and we subtract the Fourier series function from the price difference to obtain the Noise.





We sum the Fourier series function and the LSA to obtain the price forecast function. Then we take the average of the absolute value of the Noise. We add and subtract the average Noise from the forecast function to obtain the upper and lower bounds of the prediction area.



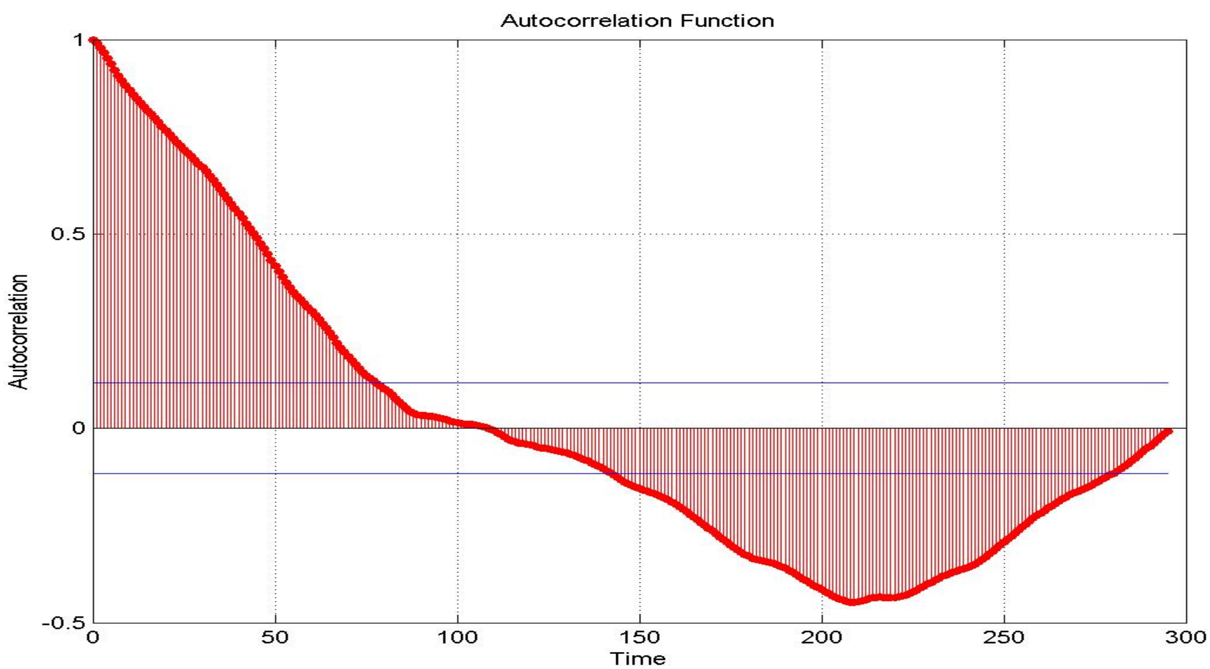
Below is the zoomed in version of the graph.

The max percentage of inaccuracy is 3.4% and the stock price is 1.65$ below the area of approximation. The min percent of deviation is 0.05% and the stock price is inside the area of approximation. The average percent of inaccuracy is 1.6%. Choosing a lower order Fourier series gave a much more accurate representation of the stock close price data. The actual price crosses the area of approximation twice and even though it is not in the area of approximation, the future price ends up following the trend and the forecast graph with a good precision. Historical volatility is 30% and relevant day volatility being at 16% the forecast line is really accurate and follows the trend. The model is acceptable.

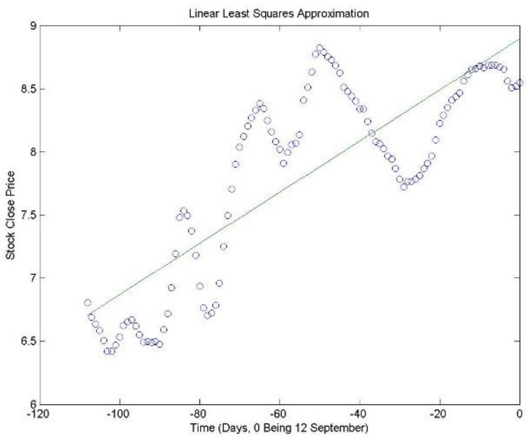
TechTarget Inc.:

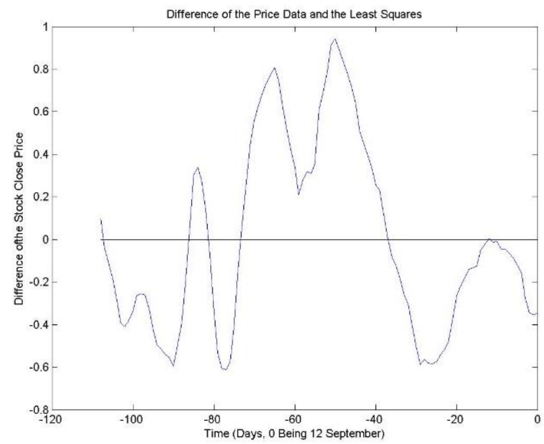
The average percent of inaccuracy is 1.6%. The actual price after 12 September is well predicted for the first few days with the exception of the last day. This upward divergence by the actual future price at the last day is actually a good sign, especially when the area of approximation predicted a rising trend. The investor following this model would expect the price to rise after 12 September, and in our case the price rose more than expected, which mean a lot more capital return for the investor. The model is acceptable.

We do not plot the close price data since it is already presented in the non-smoothed version. We take the TechTarget Inc. close price and smooth it using five day moving average.

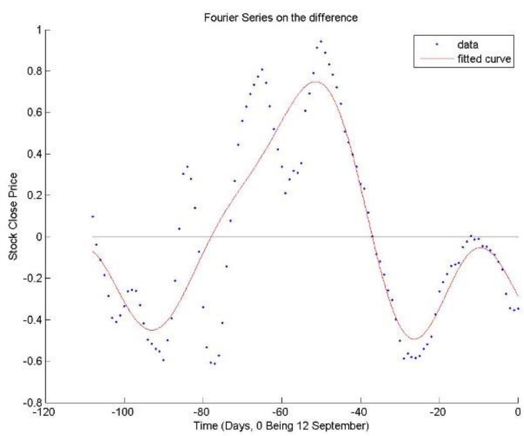


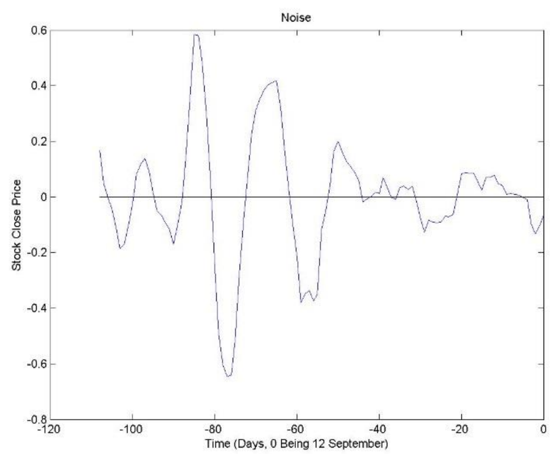
The autocorrelation of the smoothed data gave us a positive area for the first 109 days, which is two days less than that of the raw data from the non-smoothed autocorrelation. We plot a Linear Least Squares Approximation function on the relevant smoothed data and we will subtract the LSA from the data to obtain the difference.



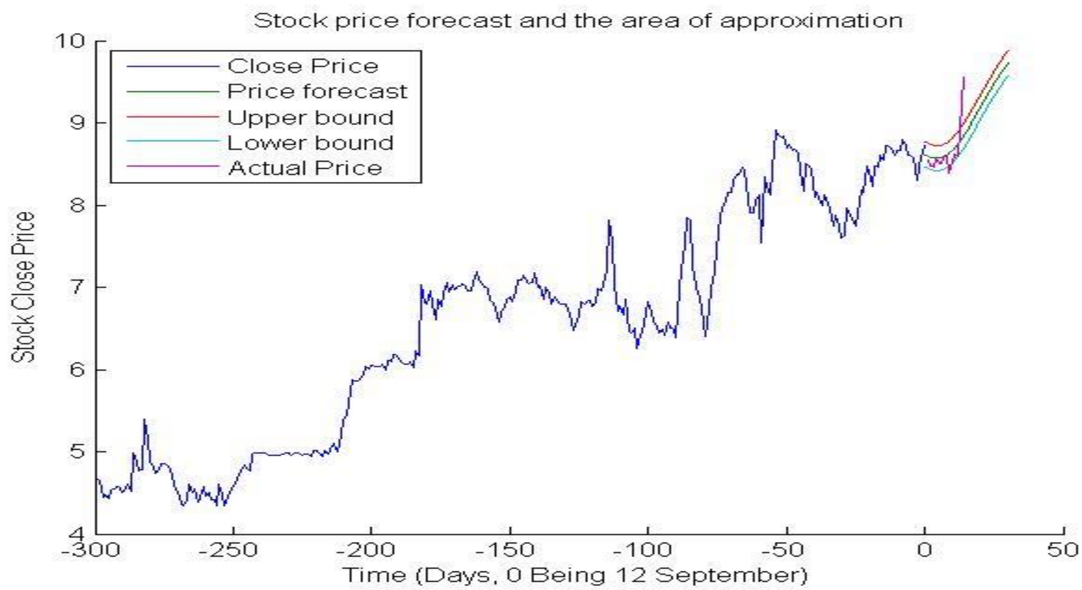


We use the difference and create a third order Fourier series to fit the divergent data and we subtract the Fourier series function from the price difference to obtain the Noise.

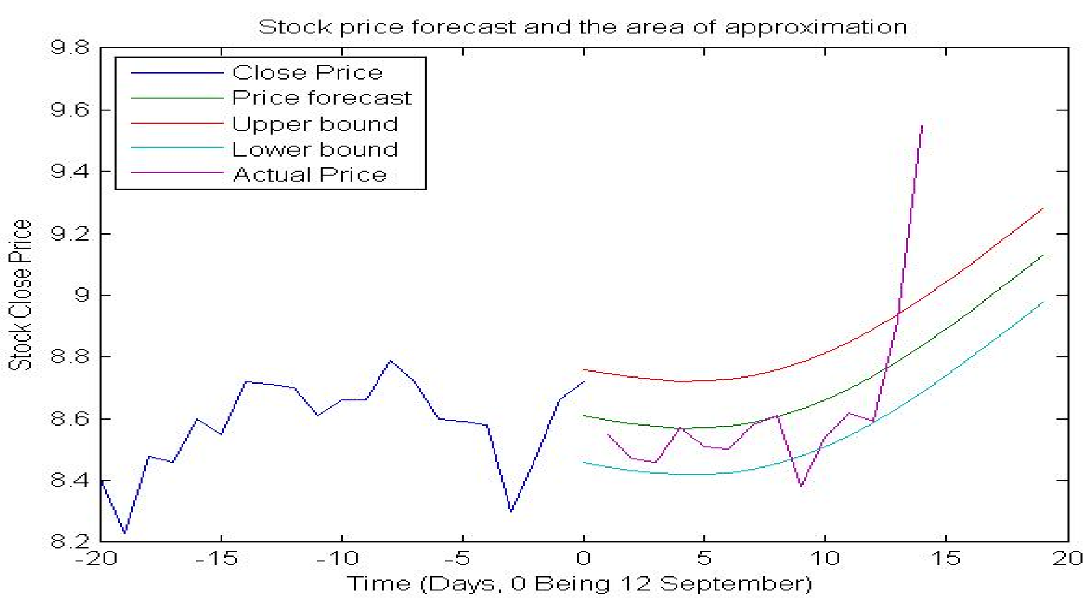




We sum the Fourier series function and the LSA to obtain the price forecast function. Then we take the average of the absolute value of the Noise. We add and subtract the average Noise from the forecast function to obtain the upper and lower bounds of the prediction area.



Below is the zoomed in version of the graph.

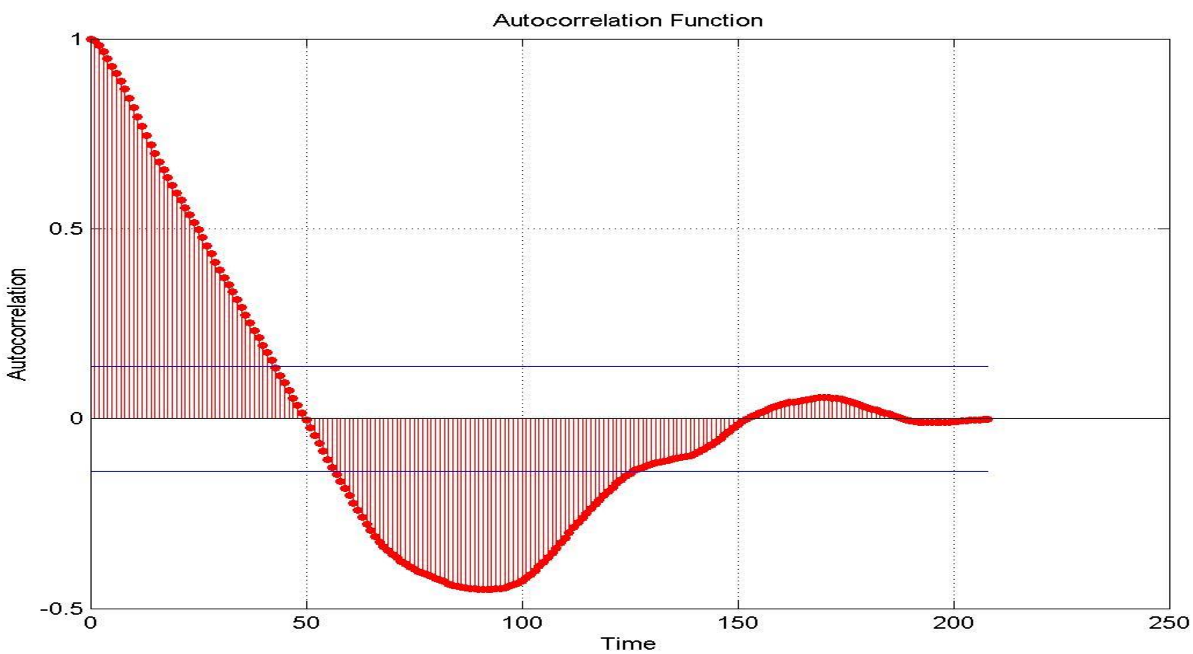


The max percentage of inaccuracy is 8.0% and the stock price is 0.61$ above the area of approximation. The min percent is 0.04% and the stock price is inside the area of approximation. The average percent of inaccuracy is 1.6%. The actual price after 12 September is well predicted for the first few days with the exception of last day. This upward divergence by the actual future price at the last day is actually a good sign, especially when the area of approximation predicted a rising trend. The investor following this model would expect the price to rise after 12 September, and in our case the price rose more than expected, which mean a lot more capital return for the investor. The historical volatility was 40% and 111 relevant day volatility was 44%. The model is acceptable.

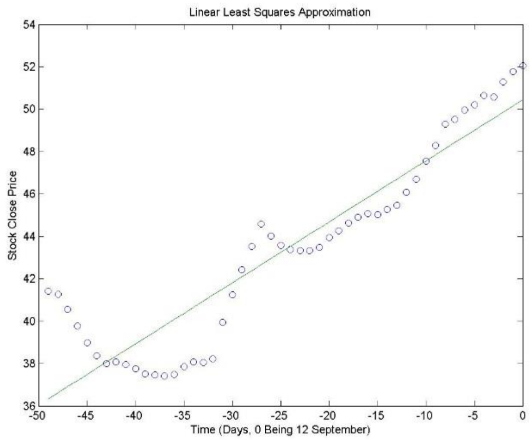
Twitter Inc.

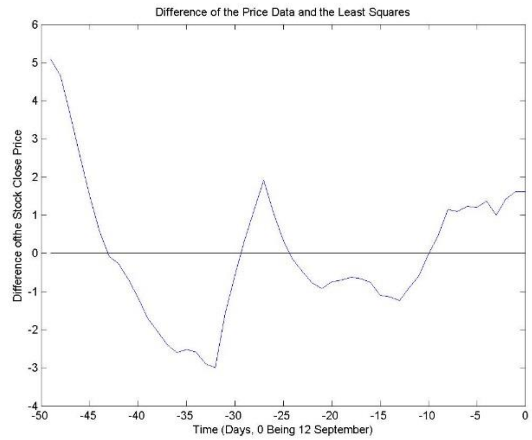
The sudden drop in the price was not predicted at first, however, the price followed the trend with slight divergences. The actual price after 12 September is chaotic, however, it is around the area of predictions. The forecast graph rises quickly in the upcoming days and becomes unrealistic, thus it quickly diverges from the stock price. The average percentage is 2.7%. Relevant days being 50 and the volatility 52% had an effect on the accuracy of the model. The historic volatility being 68% and the stock having a history of price change between 30 and75 dollars destabilized the model in the later days, however, it is still acceptable.

We do not plot the close price data since it is already presented in the non-smoothed version. We take the Twitter Inc. close price and smooth it using five day moving average.

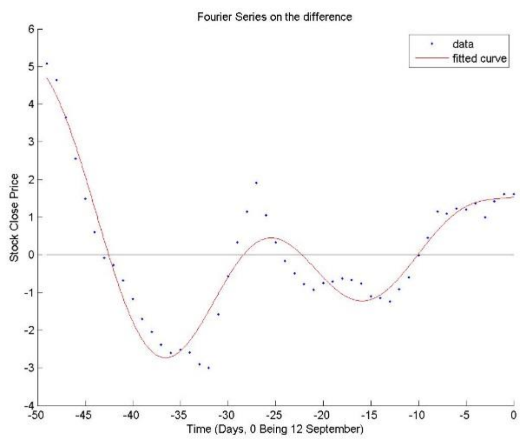


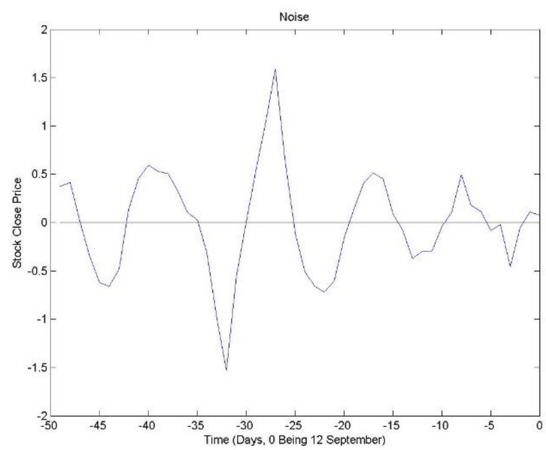
The autocorrelation of the smoothed data gave us a positive area for the first 50 days, which is the same as the raw data from the non-smoothed autocorrelation. We plot a Linear Least Squares Approximation function on the relevant smoothed data and we will subtract the LSA from the data to obtain the difference.



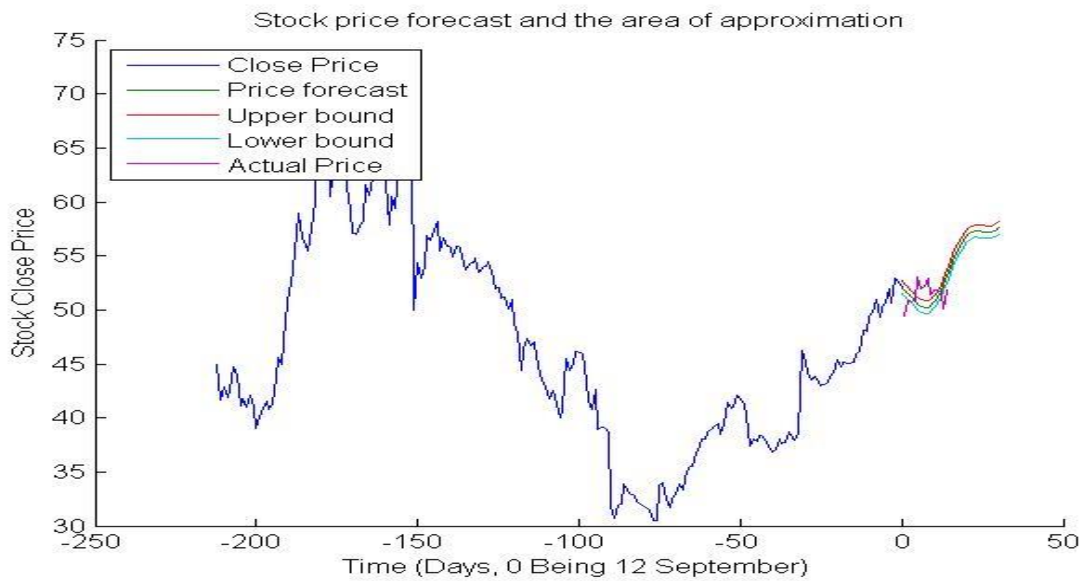


We use the difference and create a third order Fourier series to fit the divergent data and we subtract the Fourier series function from the price difference to obtain the Noise.

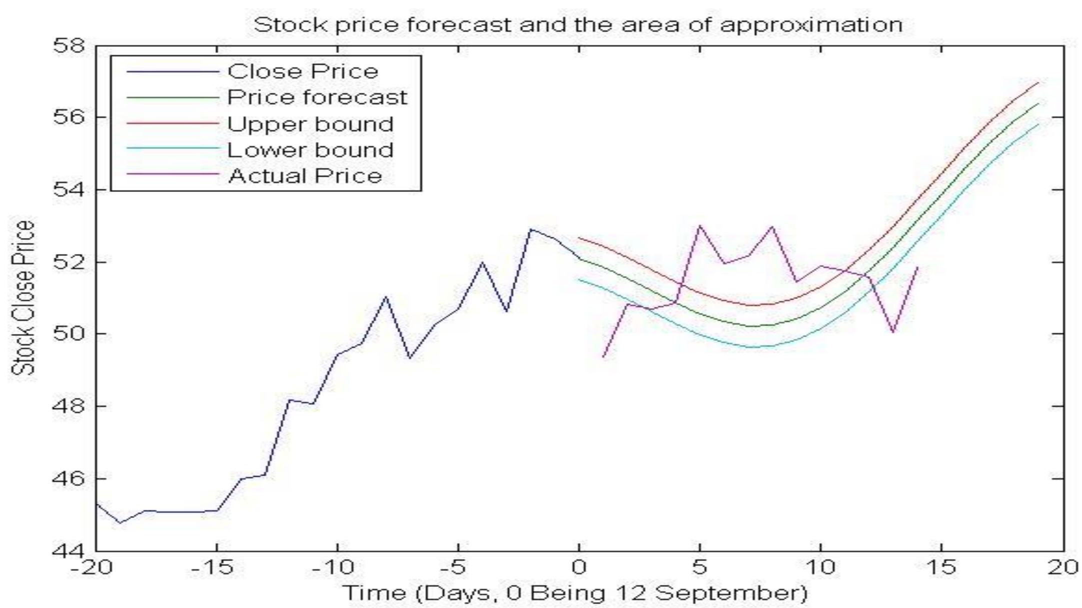




We sum the Fourier series function and the LSA to obtain the price forecast function. Then we take the average of the absolute value of the Noise. We add and subtract the average Noise from the forecast function to obtain the upper and lower bounds of the prediction area.



Below is the zoomed in version of the graph.



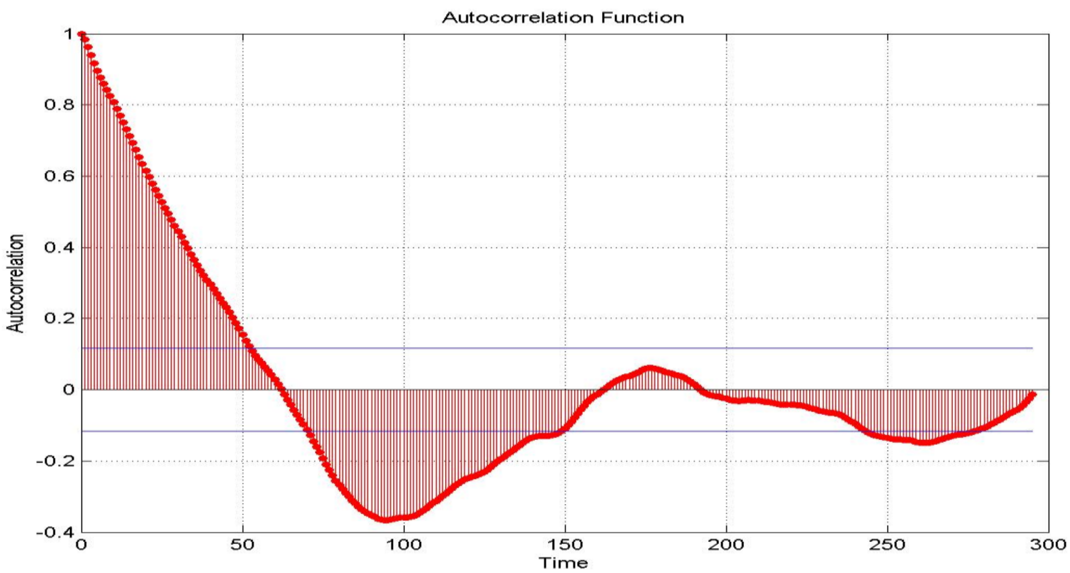
The max percentage of inaccuracy is 5.5% and the stock price is 2.15$ above the area of approximation. The min percent is 0.6% and the stock price is inside the area of approximation. The average percent of inaccuracy is 2.7%. The sudden drop in the price was not predicted at first, however, the price followed the trend with slight divergences. The actual price after 12 September is chaotic, however, it is around the area of predictions. The forecast graph rises quickly in the upcoming days and becomes unrealistic, thus it quickly diverges from the stock price. Relevant days being 50 and the volatility 52% had an effect on the accuracy of the model.

The historic volatility being 68% and the stock having a history of price change between 30 and75 dollars destabilized the model in the later days, however, it is still acceptable.

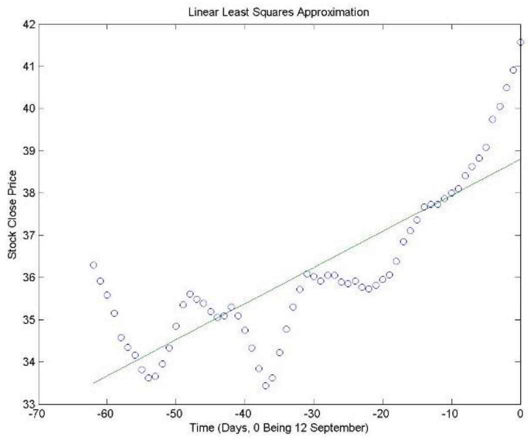
Yahoo! Inc.:

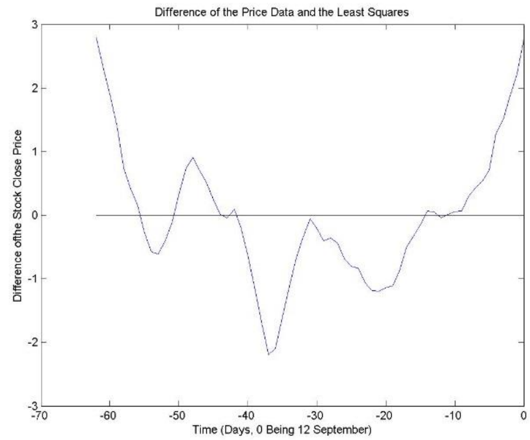
The average percent of inaccuracy is 37.2%. The price forecast graph is completely unrealistic. It was caused due to a quick rise of stock price right before 12 September, which destabilized the model. The model is not acceptable.

We do not plot the close price data since it is already presented in the non-smoothed version. We take the Yahoo! Inc. close price and smooth it using five day moving average.

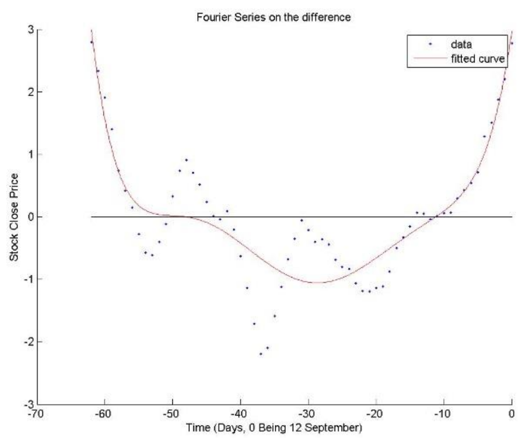


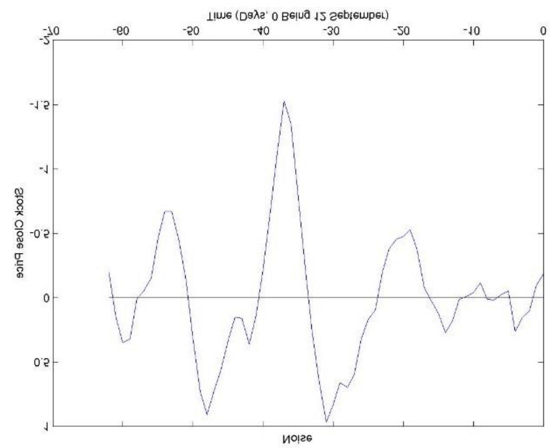
The autocorrelation of the smoothed data gave us a positive area for the first 63 days, which is the same as the raw data from the non-smoothed autocorrelation. We plot a Linear Least Squares Approximation function on the relevant smoothed data and we will subtract the LSA from the data to obtain the difference.



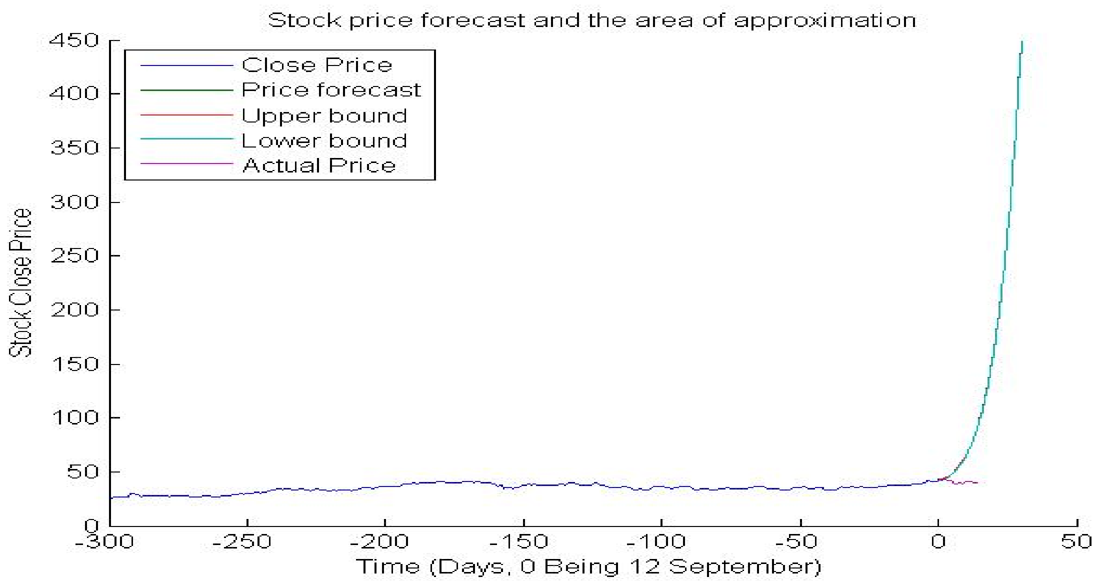


We use the difference and create a third order Fourier series to fit the divergent data and we subtract the Fourier series function from the price difference to obtain the Noise.

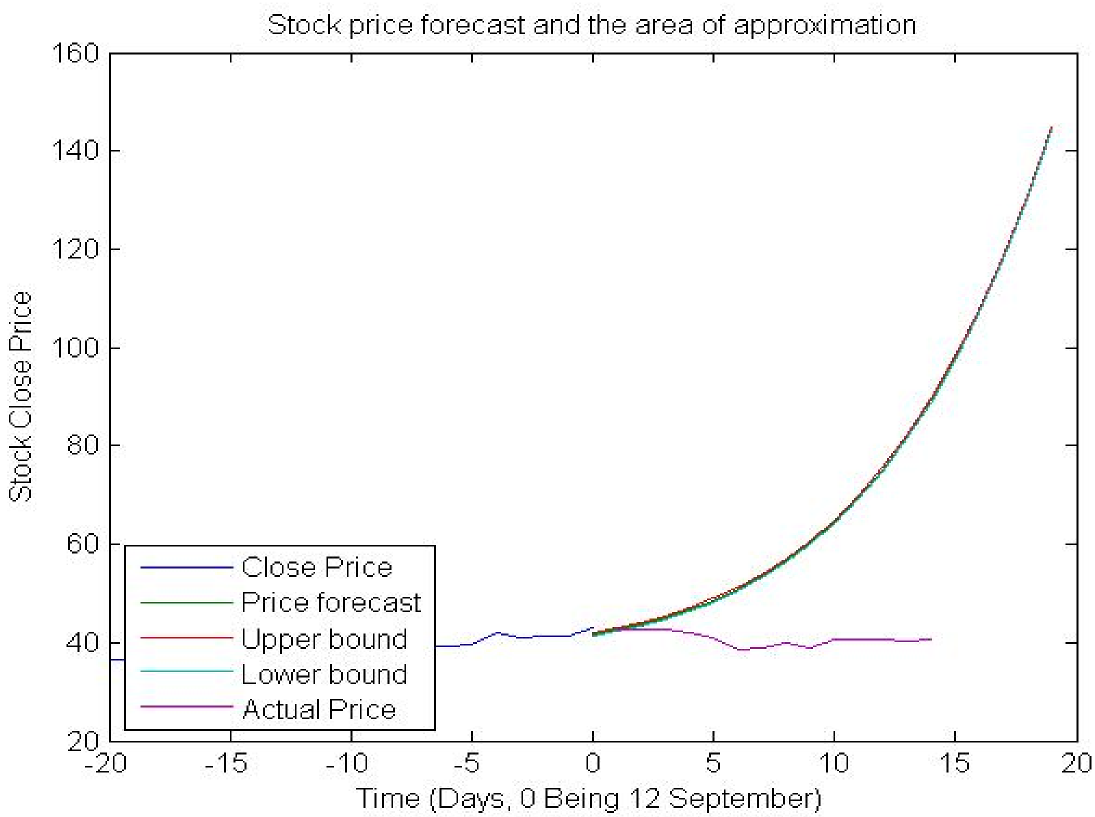




We sum the Fourier series function and the LSA to obtain the price forecast function. Then we take the average of the absolute value of the Noise. We add and subtract the average Noise from the forecast function to obtain the upper and lower bounds of the prediction area.



Below is the zoomed in version of the graph.



The max percentage of inaccuracy is 101.7% and the stock price is 40.83$ above the area of approximation. The min percent is 0.1% and the stock price is inside the area of approximation. The average percent of inaccuracy is 37.2%. The historical volatility was 32%

and 63 relevant day volatility was 30%.The price forecast graph is completely unrealistic. It was caused due to a quick rise of stock price right before 12 September, which destabilized the model. The model is not acceptable.

Comparison

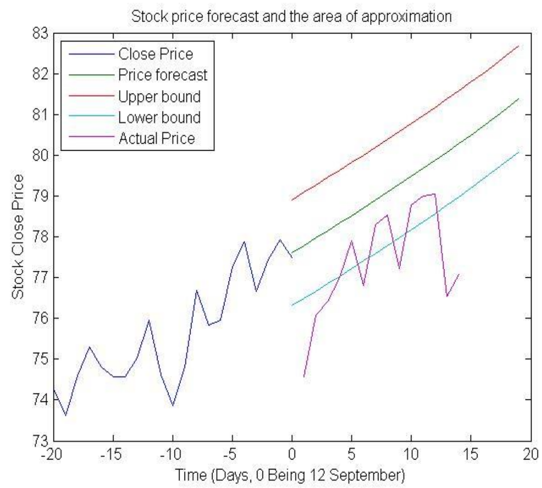
We will compare the two versions of our models for each of the stock. We will evaluate each stock and conclude which version of the LSA plus Fourier model is the better of the two. We will use the statistics for 15 business day forecasting since it is significantly more accurate than the 30 business day forecasting.

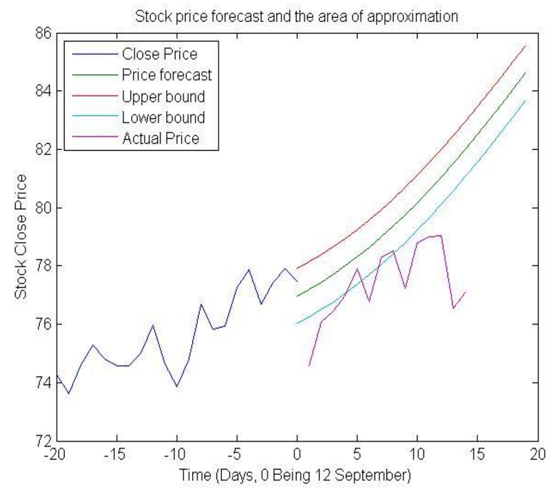
Facebook:

We observed that there is a slight difference between the two methods. Below on the left is the non-smoothed version and on the right is the smoothed version using five day moving averages. In our instance, the area of approximation using the raw data is slightly more accurate. We observed that a portion of the actual price data is in the approximation range of the function. The forecast line shows a positive slope, thus an upper trend. Even though at first the price experienced an unpredicted sudden drop, the stock is headed in the right direction. The average percent of inaccuracy is 1.9% below the area of approximation. Overall, this is an acceptable result, since the general predicted trend is correct and the average inaccuracy is really low. A larger portion of the actual price after September 12 is in the non-smoothed area of the approximation.

The smoothed forecast line experiences a much sharper rise in the price. The average percent of inaccuracy is 2.1% below the area of approximation. Overall, this is not an acceptable result. The general predicted trend was correct at first, but the trend of the area of approximation is too steep and started to quickly diverge from the actual price. Overall this could have been expected, smooth version takes into account less accurate data, since it discards variables that deviate from others.

Even though, there is only 0.2% difference between the two methods the non-smoothed version is the better choice. The historic volatility for relevant number of days was 35% and the visible upper trend of the close price before 12 September constituted to the stability of the model.



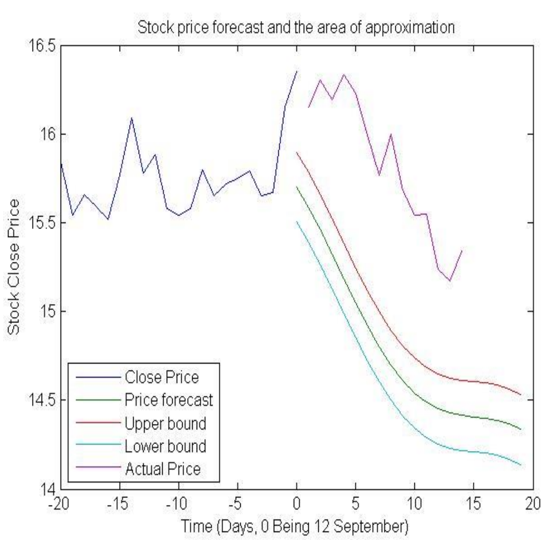


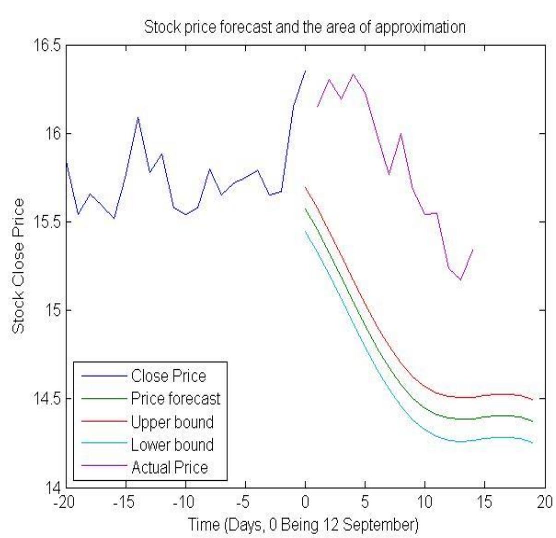
Non-smoothed

Smoothed

Blucora Inc.:

The trend of the forecast line is going downwards and so is the actual price. But, the actual close price after 12th of September does not fit in the forecast area. Even though, the volatility for the relevant days was 25%, the model produced an inaccurate prediction. The sudden uptrend of the stock before 12th of September for a few days caused the model to destabilize and was only able to correctly determine the slope of the direction stock price was heading. The average percent of inaccuracy for non-smoothed version is 5.5% above the area of approximation and for smoothed version is 6.2% above the area of approximation. Which makes the model not acceptable, however, we observed that the non-smoothed version is slightly more accurate than the smoothed graph.



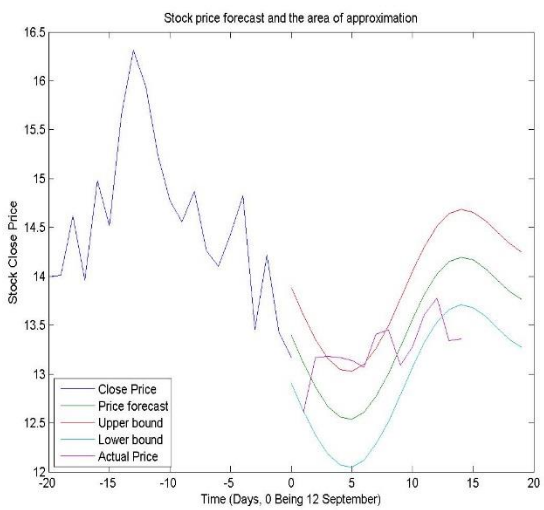


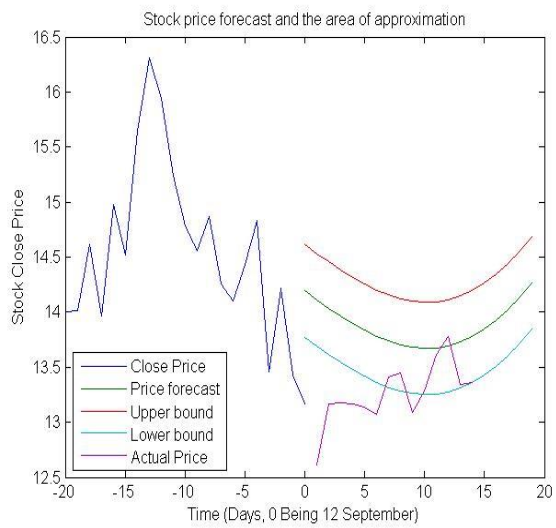
Non-smoothed *Smoothed*

ChinaCache Ltd:

We observed that there is a clear difference between the two versions. The average percent of inaccuracy is for non-smoothed is 3.2% and for smoothed is 4.4%, thus both are less than 11.5% and acceptable. The volatility for the relevant days is 74%. The model is still stable and precise because the price change, during the relevant day period, is between 13 and 16 dollars. The historical volatility is 91% and the price change is between 5 and 30, so the relevant number of days represents stock really well and stabilizes the model. Thus, it is acceptable.

The non-smoothed version, on the left, predicts the price well. The smoothed version, however, does not depict the actual price after 12th of September, the actual price enters the smoothed region of approximation at the later stages of predicted close price. The average percent of inaccuracy is 1.2% less for the smoothed version and even though both version are acceptable, overall, the non-smoothed version is more accurate.

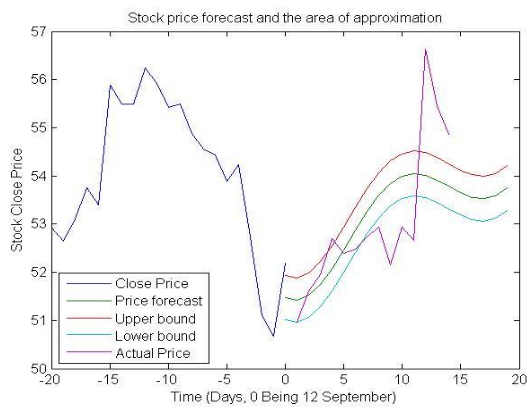




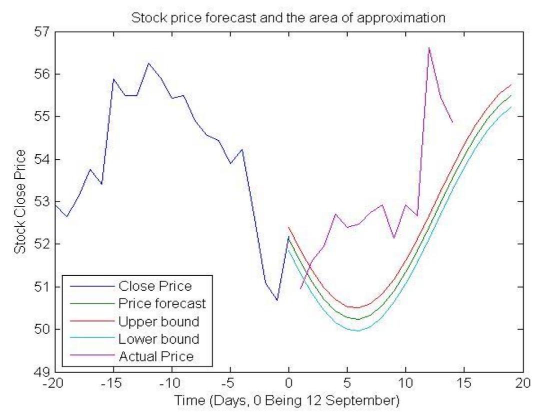
Non-smoothed *Smoothed*

EBAY Inc.:

The actual price after 12 September starts off in the area of approximation. The graph predicts a strong positive momentum. EBay is an interesting stock because the forecast graph diverges below the stock price. This means that if the model predicted a rise in price, an investor should have bought the stock in order to have sold it at a later date. The actual future price making a steeper jump than the forecasted line is a much better result and the investor made a lot more capital. The average percent of inaccuracy is 1.6% for non-smoothed version and 3.8 for smoothed version. The model is acceptable for both versions, but difference between the two versions is clearly visible. The non-smoothed version starts off well with most of the actual data being inside the area of approximation and then it diverges from the forecast graph. The actual price in the smoothed version cuts the area of approximation and is constantly divergent afterwards. The non-smoothed model is 2.2% less inaccurate. For the EBAY stock the non-smoothed version is more accurate.



Non-smoothed

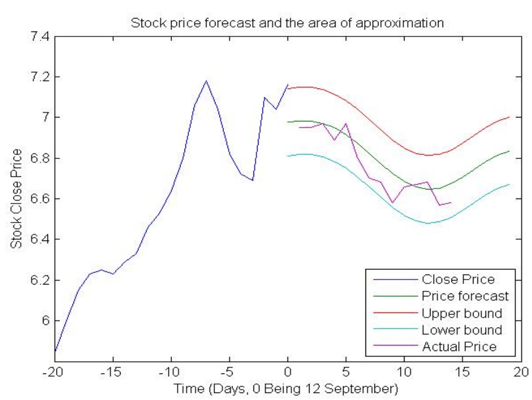


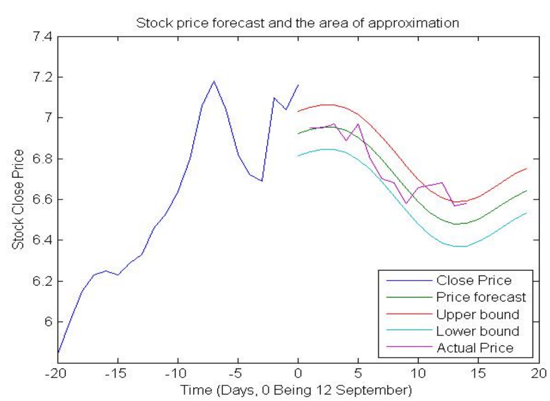
Smoothed

Groupon Inc.:

The Groupon close price data after 12th of September is well within the area of approximation for both versions of the model and follows the price forecast functions with minimal divergences. These are excellent forecasts and the average percent of inaccuracy is 1.1% for both smoothed and non-smoothed. Even though, the volatility for relevant data was 60% the maximum price movement was between 5 and 7 dollars. The historical close price experienced sharp movement ranging from 5 to 13 dollars thus the model was well represented.

There are minimal differences between the two methods and both are acceptable.

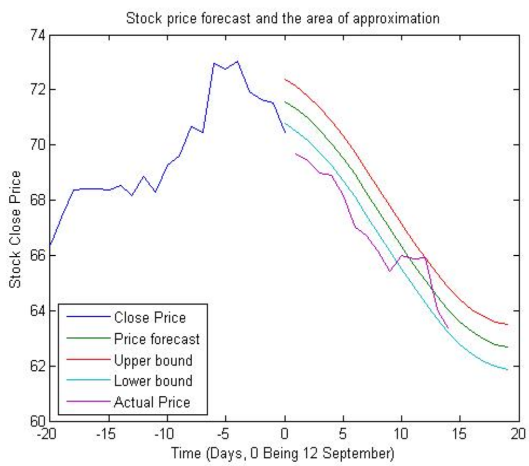


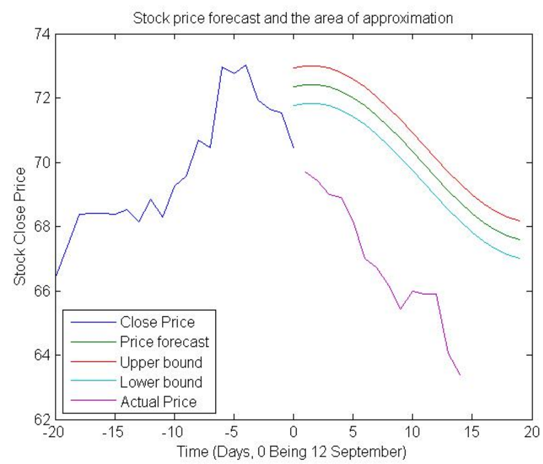


Non-smoothed *Smoothed*

IACI:

The difference between the two versions is clearly visible. The actual price of the stock is well approximated in the non-smoothed version of the data. The smoothed version, on the other hand, gives us a realistic area of prediction, however, it is not accurate at all. This is connected to the rapid price change of the stock, since the smoothed model could not handle the rapid alteration of the stock price before September 12. Non-smoothed version had an average percent inaccuracy of 2.4%, less than 3.5% CI, and correctly predicted the direction of the trend. Even though, it quickly becomes an unrealistic representation of the actual price, the non-smoothed version is preferred for IACI stock.

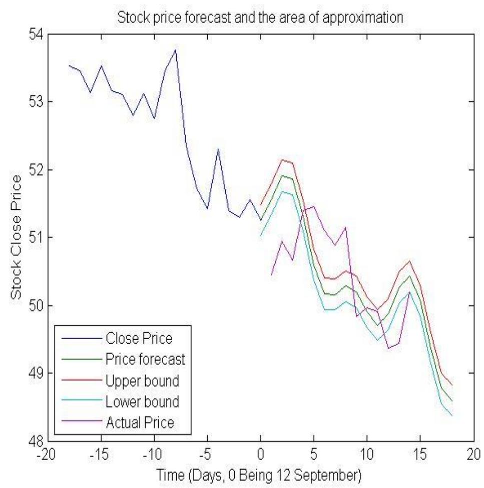


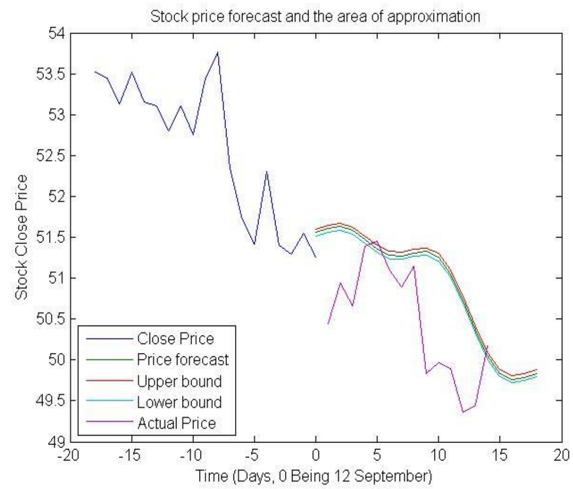


Non-smoothed *Smoothed*

J2 Global:

Choosing a lower order Fourier series gave a much more accurate representation of the stock close price data. The difference between the two versions is visible. But, the average percentage of inaccuracy is really low for both of them: non-smoothed is 1.1% and smoothed is 1.6%. The actual price crosses the area of approximation twice and even though the smoothed version is not in the area of approximation, the future price ends up following the trend and the forecast graph with a good accuracy. Relevant day volatility being at 16% the forecast line is really accurate and follows the trend. The model is acceptable for both versions. The non-smoothed trend approximates the actual price graph much better with average inaccuracy being 46.8% less than the smoothed forecast. The non-smoothed version is preferred.

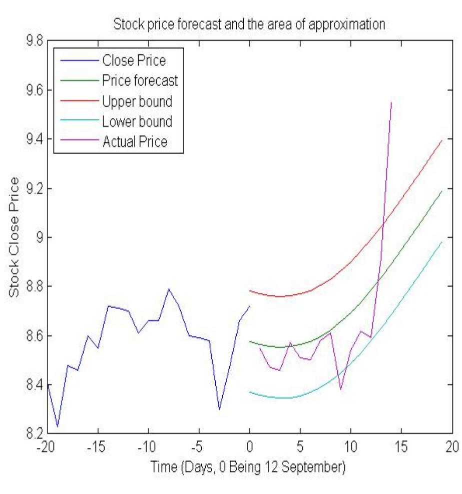


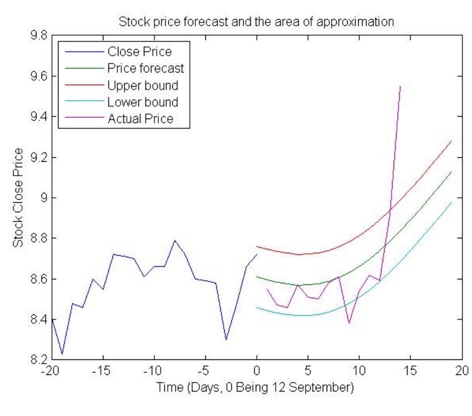


Non-smoothed *Smoothed*

TechTarget Inc.:

There is no significant difference between the two versions. Both of them approximate the data well and barely diverge from the price forecast graph. Both of them have a large number of relevant days to represents the stock for the last year. Their volatility for relevant days is 44%. The forecast graph predicts a rising direction for the stock price. The actual price rising sharply is a good result for an investor too see if someone decided to buy a stock on the 12 of September.

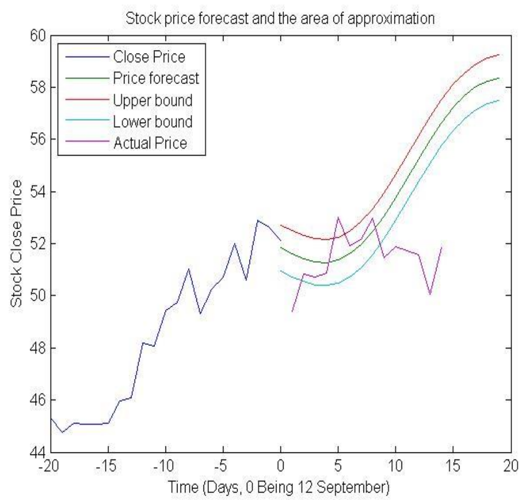




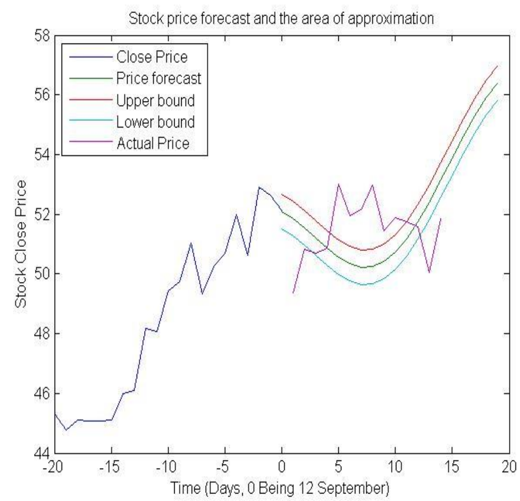
Non-smoothed *Smoothed*

Twitter Inc.:

The sudden drop in the price was not predicted at first, however, the price followed the trend with slight divergences. The actual price after 12 September is chaotic, however, it is around the area of predictions. The forecast graph rises quickly in the upcoming days and becomes unrealistic, thus it quickly diverges from the stock price. The difference between the two methods is easy two notice. Even though neither version was able to predict the sudden drop in the price, the non-smoothed version did an overall better job at predicting the actual data for the first week and a half after 12 September. At the later stages, the actual price diverges from the non-smoothed area of approximation, but it diverges towards the smoothed forecast graph. The highly volatile nature of this stock and the sudden rise in the stock price 20 days before 12 September makes the area of approximation unreliable. Since the average percentage inaccuracy for smoothed version is 2.7% and for non-smoothed is 3.6%, the smoothed version is the preferred model.



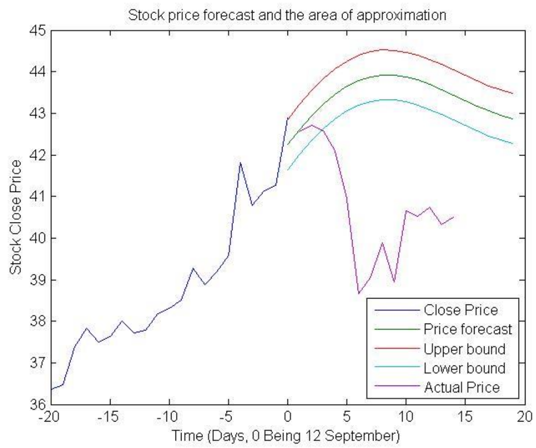
Non-smoothed

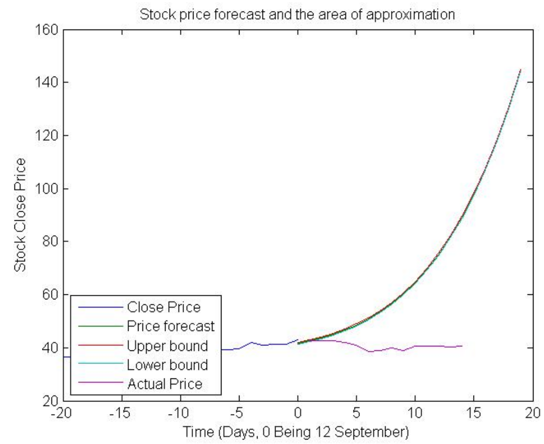


Smoothed

Yahoo! Inc.:

It is easy to notice difference between the non-smoothed and the smoothed versions. The non-smoothed version predicts a realistic area of approximation, while the smoothed forecast graph explodes and is unrealistic. The price drop was not predicted by either version of the model. It was caused by Alibaba (BABA) going public and since Yahoo! Inc. had significant number of BABA shares, it lost quite a capital. In addition, the inaccuracy of the model was caused by the sudden surge of price in the last month before 12 September. This caused the stock to be highly volatile and the smooth forecast graph could not handle it.





Non-smoothed *Smoothed*

Conclusion:

Two stocks were not acceptable: Blucora (BCOR) and Yahoo (YHOO). For these two stocks, however, the non-smoothed version of the model was preferable. The reason was that it offered a realistic prediction compared to smoothed version. All other stocks were acceptable. Only Twitter (TWTR) stock preferred the smooth version of the model.

Approximations that were not precise had several things in common. They shared a highly chaotic history of stock close prices. They had high volatility and thus a small number of relevant days were obtained from the autocorrelation function. This caused problems, since it is hard to represent a large time frame using only about a month's worth of data. Finally, if the price had quickly surged up right before 12th of September, the date after which we plotted the forecast graphs, the model, especially the smoothed version, could not handle it and would produce unrealistic or inaccurate predictions. Below are two tables depicting information about the stocks.

Stock Ticker	Preferred Version of the Model.	Slope of Trend	Max % Inaccuracy	Max $ Difference	Min % Inaccuracy	Min $ Difference
FB	Non-Smoothed	Positive	4.3%	2.02$ below AOA	0.4%	Inside AOA

BCOR	Non-Smoothed	Negative	7.5%	1.00$ above AOA	2.8%	0.25$ above AOA
CCIH	Non-Smoothed	Positive	6.2%	0.31$ below AOA*	0.01%	Inside AOA
EBAY	Non-Smoothed	Positive	4.6%	2.11$ above AOA*	0.005%	Inside AOA
GRPN	Both Excellent	Negative	2.9%	0.03$ below AOA*	0.18%	Inside AOA
IACI	Non-Smoothed	Negative	3.7%	1.69$ below AOA*	0.3%	Inside AOA
JCOM	Non-Smoothed	Negative	2.5%	1.02$ below AOA*	0.001%	Inside AOA
TTGT	Both Excellent	Positive	7.5%	0.51$ above AOA*	0.04%	Inside AOA
TWTR	Smoothed	Positive	5.5%	2.15$ below AOA*	0.6%	Inside AOA
YHOO	Non-Smoothed	Negative	12.9%	4.40$ below AOA*	0.2%	Inside AOA

* AOA – Area of Approximation

Stock Ticker	Historical Volatility	Relevant Days	Volatility for Relevant Days	Average % Inaccuracy	95% CI	Overall Quality
FB	45%	122	35%	1.9%	5.6%	Acceptable
BCOR	34%	69	25%	5.5%	4.3%	Not Acceptable
CCIH	91%	84	74%	3.2%	11.5%	Acceptable
EBAY	22%	33	22%	1.6%	2.8%	Acceptable
GRPN	59%	92	60%	1.1%	7.5%	Acceptable
IACI	28%	82	21%	2.4%	3.5%	Acceptable
JCOM	30%	19	16%	1.0%	3.8%	Acceptable

TTGT	40%	111	44%	1.5%	5.1%	Acceptable
TWTR	68%	50	52%	2.7%	8.5%	Acceptable
YHOO	32%	63	30%	6.9%	4.0%	Not Acceptable

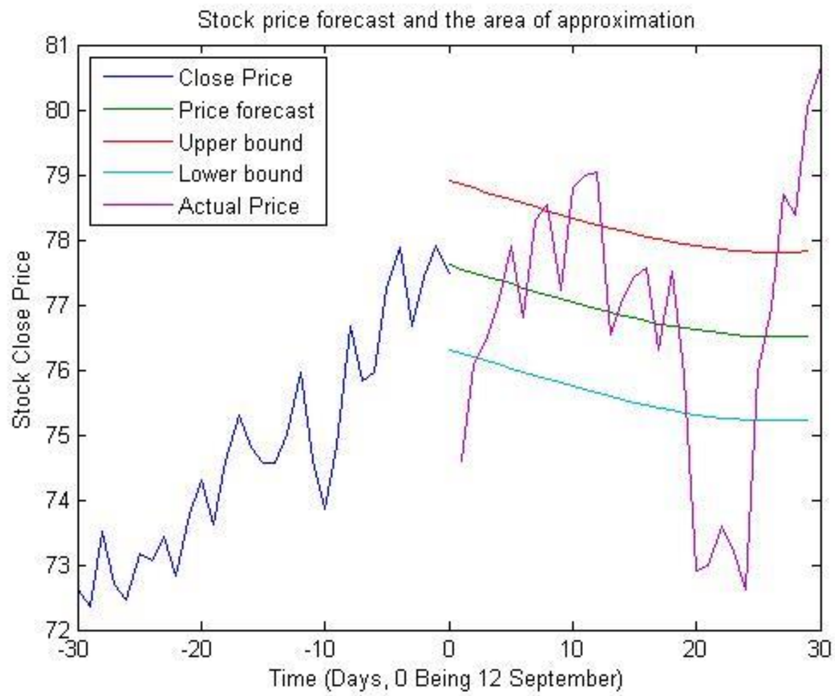
Lastly, we can conclude that the non-smoothed version was a better choice for predicting the price of stocks using the LSA plus Fourier series model. Nine stocks were predicted better with the non-smoothed method, while only one case, Twitter, yielded forecasted predictions with the smoothed version. We took under consideration a 95% Confidence Interval to obtain a maximum acceptable inaccuracy between the forecast line and the actual close price after 12th of September. Eight stocks were acceptable and two were not. Ultimately, majority of the stocks had accurate predictions.

NASDAQ Modification

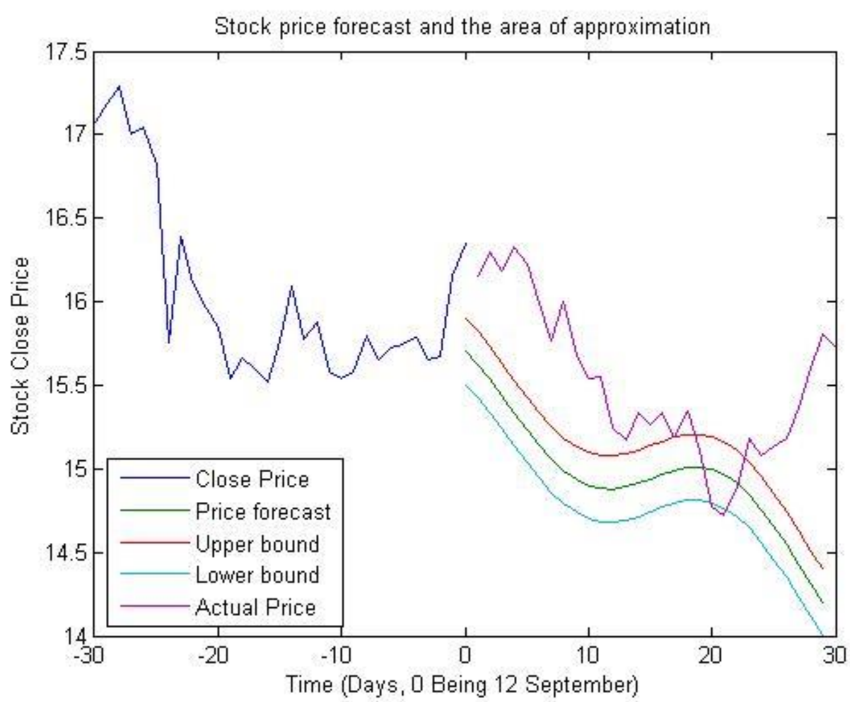
Since the non-smoothed version for 30 business days was not acceptable we decided to modify it by using NASDAQ composite. Due to time constraints we could only look at NASDAQ and we did not implement any other index. Since the stocks presented here are chosen from NASDAQ, we decided to include the NASDAQ index in the model and find out what kind of effect it has on the stock forecasting. We modified the superior version of the model by incorporation of NASDAQ to predict the price of stocks. We correlated the NASDAQ data to the close price data of a given stock for the relevant number of days for that stock price. The index, however, has huge numbers thus we decided to normalize it between 0 and 1. We multiplied the normalized NASDAQ, the correlation and a constant variable. This constant variable was calculated implicitly to be 0.1, this gave weight to NASDAQ and how much it could influence a given stock. We subtract this number from 1 and multiply it by the old forecast data to obtain a modified prediction.

Formula: `newforecast = forecast*(1-0.1*correl*nasdaq)`

Facebook:



Blucora:



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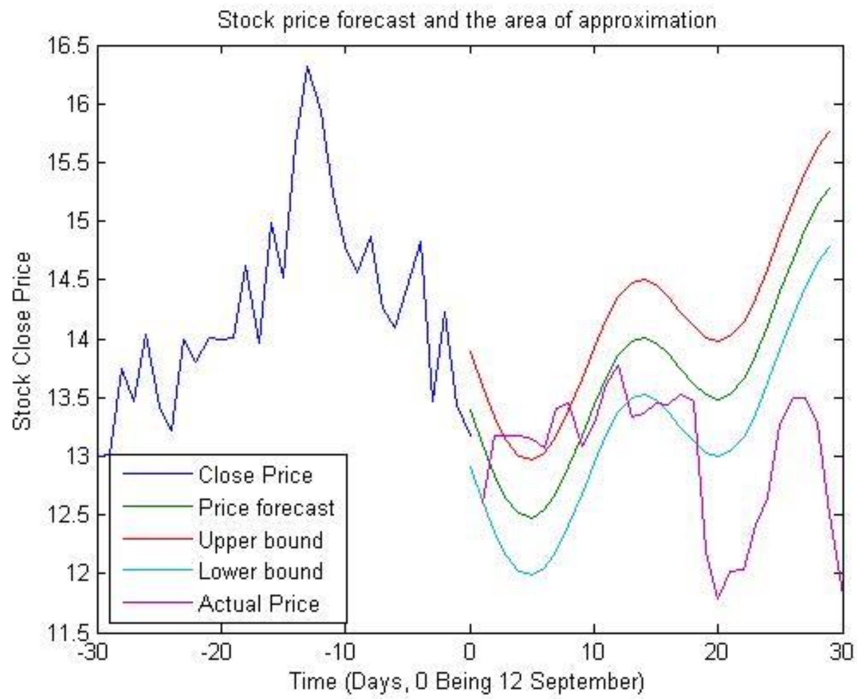

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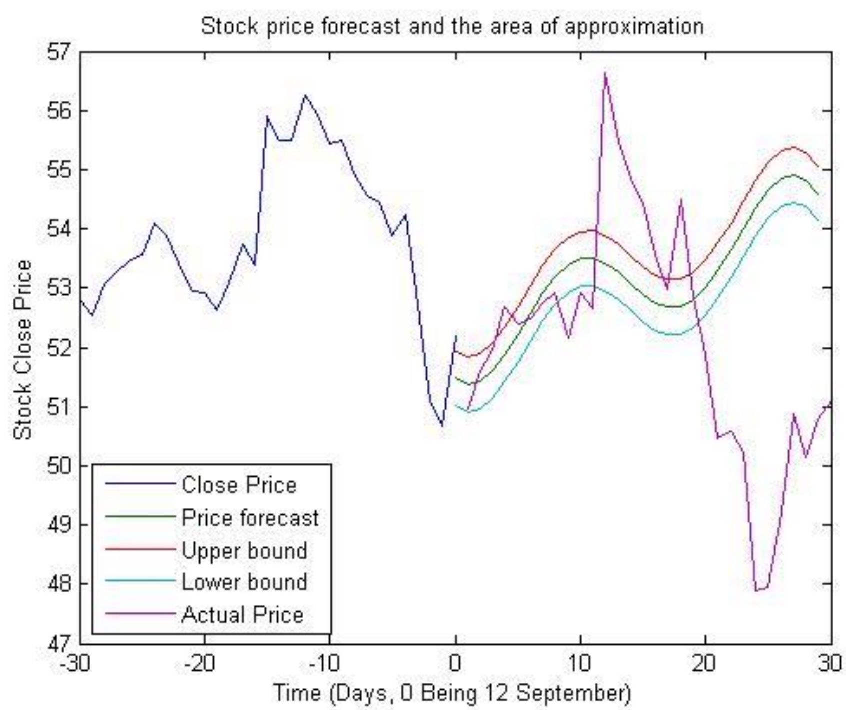
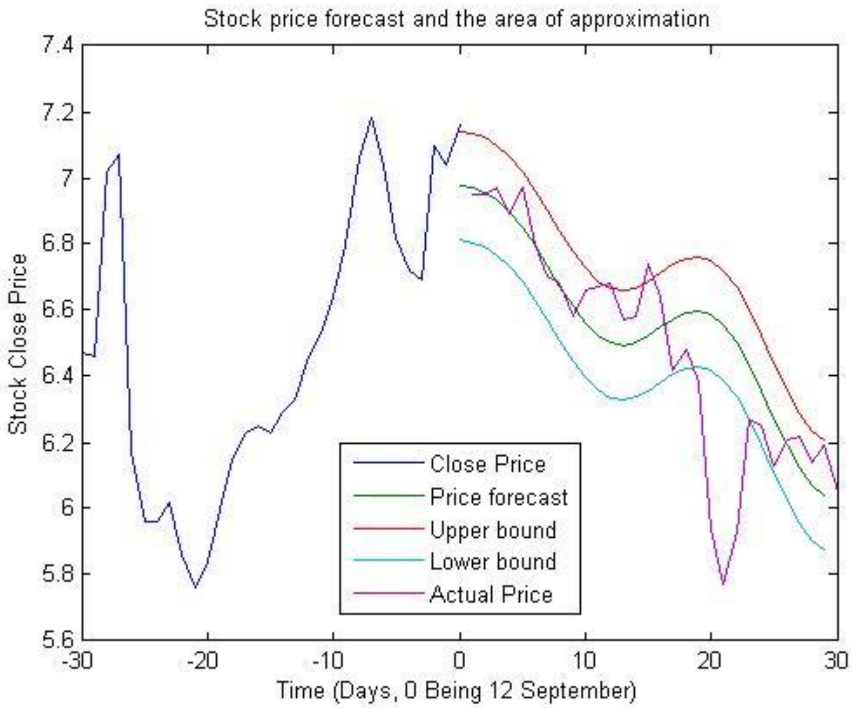
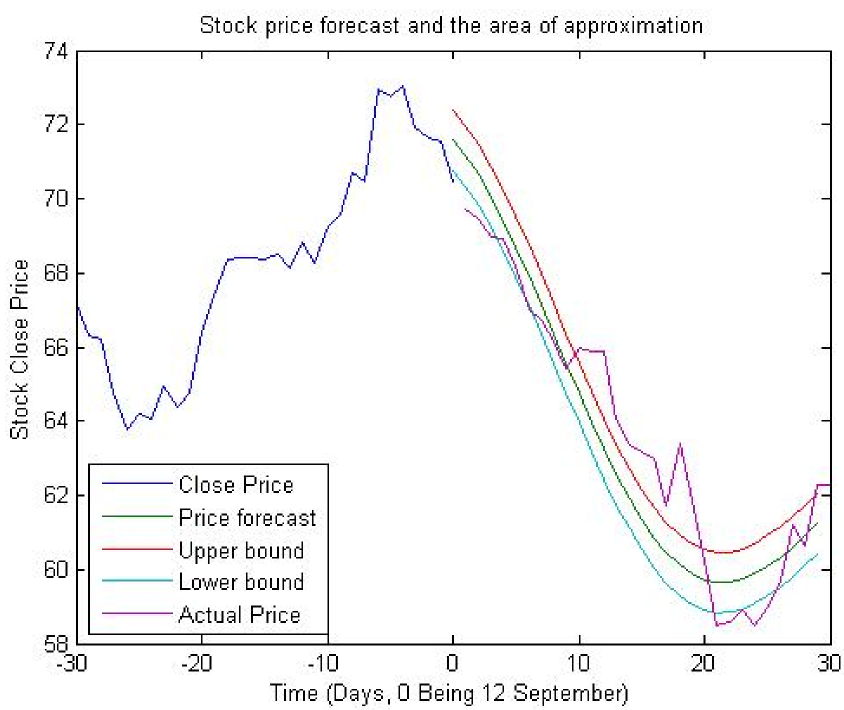


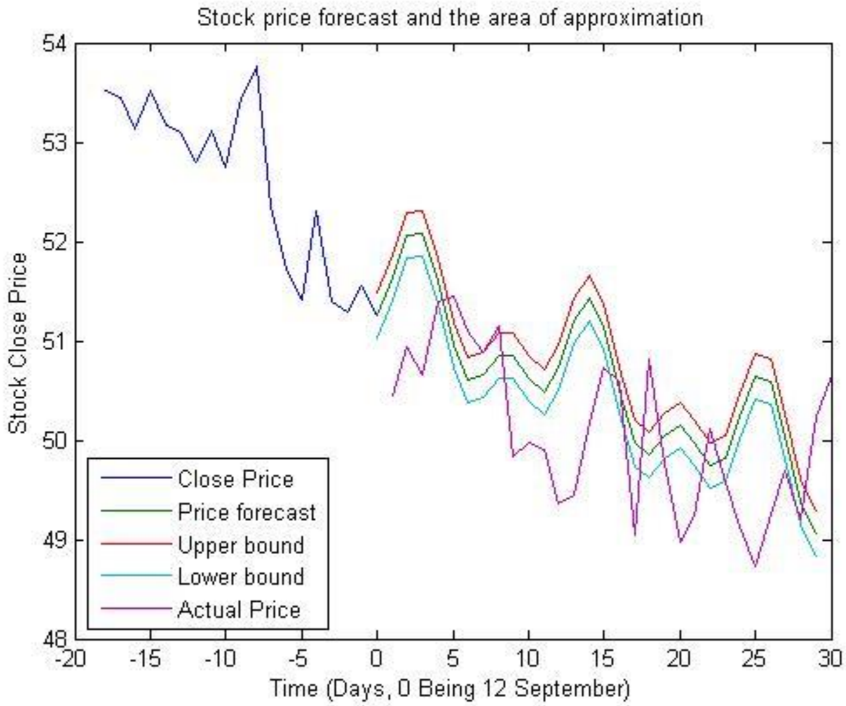
Groupon:



IACI:



J2 Global:



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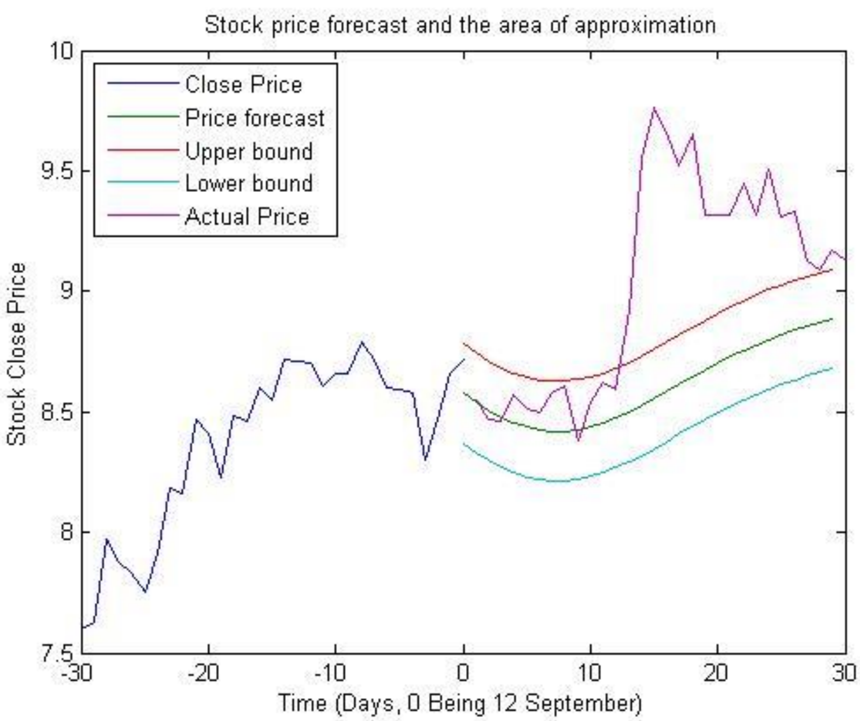
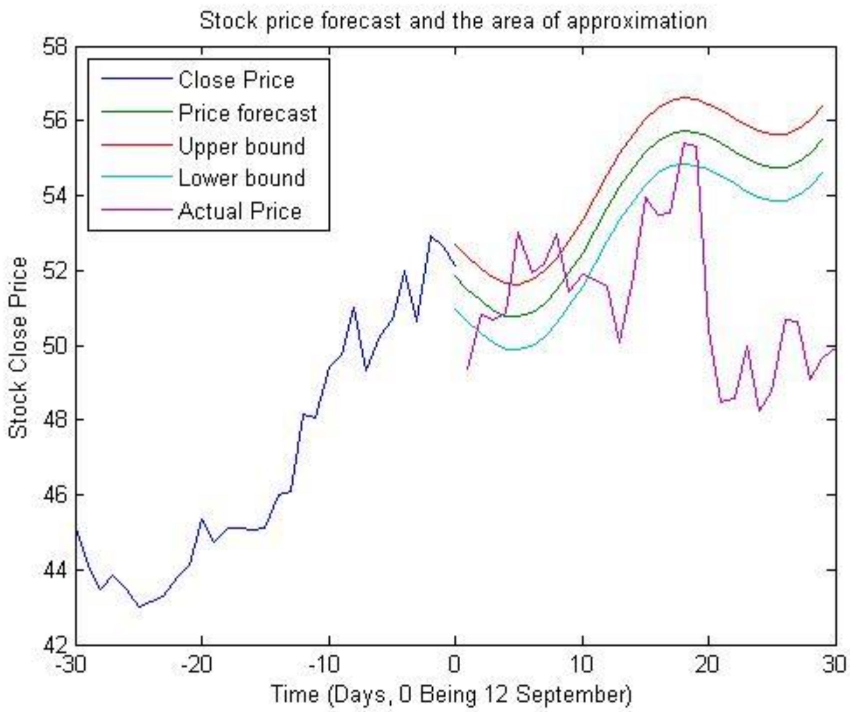
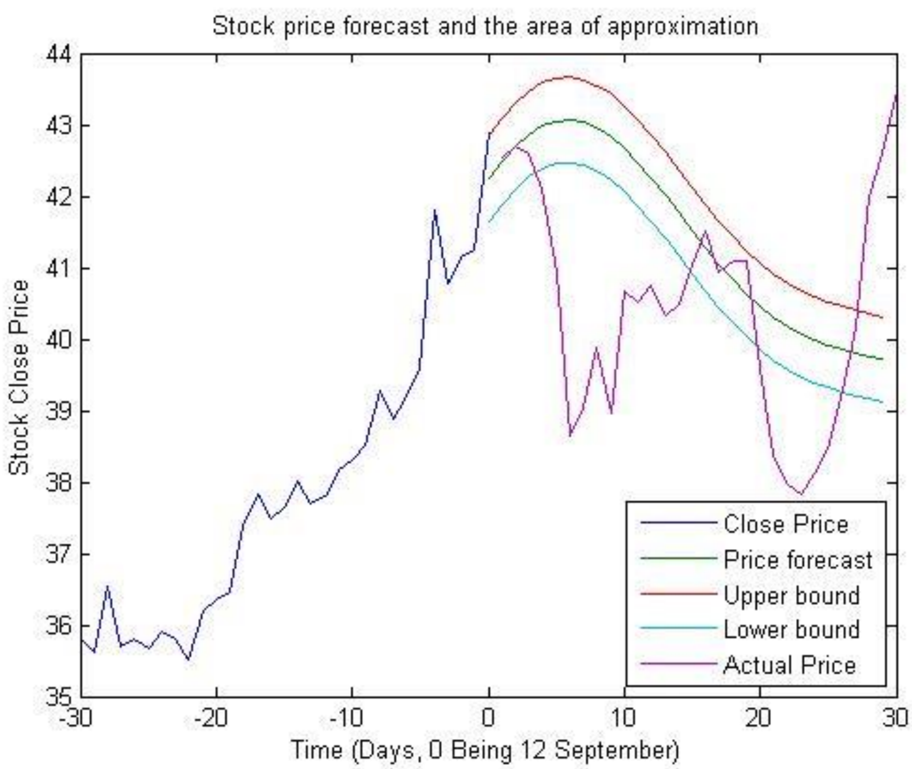


Twitter:



Yahoo:



Conclusion:

The graphs of each stock prediction is more accurate for every stock except for TechTarget (TTGT). Below is the statistics for 30 business day forecasting with and without NASDAQ modification.

30 business day forecasting with NASDAQ modification:

Stock Ticker	Slope of Trend	Max % Inaccuracy	Max $ Difference	Min % Inaccuracy	Min $ Difference	Average % Inaccuracy	95% CI
FB	Positive	5.4%	2.85$ below AOA*	0.1%	Inside AOA	2.1%	5.6%
BCOR	Negative	9.7%	1.32$ above AOA*	0.4%	Inside AOA	3.7%	4.3%
CCIH	Positive	29.4%	2.98$ below AOA*	0.5%	Inside AOA	6.9%	11.5%
EBAY	Positive	13.4%	5.95$ below AOA*	0.03%	Inside AOA	3.9%	2.8%
GRPN	Negative	14.1%	0.65$ below AOA*	0.2%	Inside AOA	2.4%	7.5%
IACI	Negative	4.7%	2.17$ below AOA*	0.1%	Inside AOA	1.9%	3.5%
JCOM	Negative	3.2%	1.37$ above AOA*	0.2%	Inside AOA	1.6%	3.8%
TTGT	Positive	12.7%	1.03$ above AOA*	0.3%	Inside AOA	4.8%	5.1%
TWTR	Positive	14.6%	6.21$ below AOA*	0.01%	Inside AOA	5.6%	8.5%
YHOO	Negative	11.4%	3.80$ below AOA*	0.01%	Inside AOA	4.2%	4.0%

* AOA – Area of Approximation

30 business day forecasting without NASDAQ:

Stock Ticker	Slope of Trend	Max % Inaccuracy	Max $ Difference	Min % Inaccuracy	Min $ Difference	Average % Inaccuracy	95% CI
FB	Positive	13.4%	8.41$ below AOA*	0.4%	Inside AOA	4.8%	5.6%
BCOR	Negative	15.7%	2.27$ above AOA*	2.8%	0.24$ above AOA	6.7%	4.3%
CCIH	Positive	32.9%	3.40$ below AOA*	0.01%	Inside AOA	8.1%	11.5%
EBAY	Positive	15.9%	7.19$ below AOA*	0.004%	Inside AOA	4.6%	2.8%
GRPN	Negative	18.5%	0.90$ below AOA*	0.18%	Inside AOA	4.1%	7.5%
IACI	Negative	8.0%	3.88$ below AOA*	0.3%	Inside AOA	3.6%	3.5%
JCOM	Negative	7.0%	3.33$ above AOA*	0.001%	Inside AOA	1.7%	3.8%
TTGT	Positive	8.9%	0.66$ above AOA*	0.04%	Inside AOA	2.8%	5.1%
TWTR	Positive	20.7%	9.08$ below AOA*	0.8%	Inside AOA	9.1%	8.5%
YHOO	Negative	13.1%	4.40$ below AOA*	0.2%	Inside AOA	6.9%	4.0%

Comparison:

Stock Ticker	Average % Inaccuracy without NASDAQ	Average % Inaccuracy with NASDAQ	Overall Quality without NASDAQ	Overall Quality with NASDAQ	correl
FB	4.8%	2.1%	Acceptable	Acceptable	0.95
BCOR	6.7%	3.7%	Not Acceptable	Acceptable	-0.74

CCIH	8.1%	6.9%	Acceptable	Acceptable	0.28
EBAY	4.6%	3.9%	Not Acceptable	Not Acceptable	0.28
GRPN	4.1%	2.4%	Acceptable	Acceptable	0.54
IACI	3.6%	1.9%	Not Acceptable	Acceptable	0.71
JCOM	1.7%	1.6%	Acceptable	Acceptable	-0.43
TTGT	2.8%	4.8%	Acceptable	Acceptable	0.88
TWTR	9.1%	5.6%	Not Acceptable	Acceptable	0.72
YHOO	6.9%	4.2%	Not Acceptable	Not Acceptable	0.83

Since the non-smoothed version for 30 business days was not acceptable we decided to modify it by using NASDAQ composite. Average inaccuracy percentage for each stock, except for TTGT, was reduced. The model was able to reduce the inaccuracy of Blucora Inc. (BCOR) to the point at which it was acceptable, since the average percentage was below the 95% confidence interval. The Yahoo stock average inaccuracy reached a new time low. But, EBAY and YHOO stock are still not acceptable since they are over their 95% confidence interval.

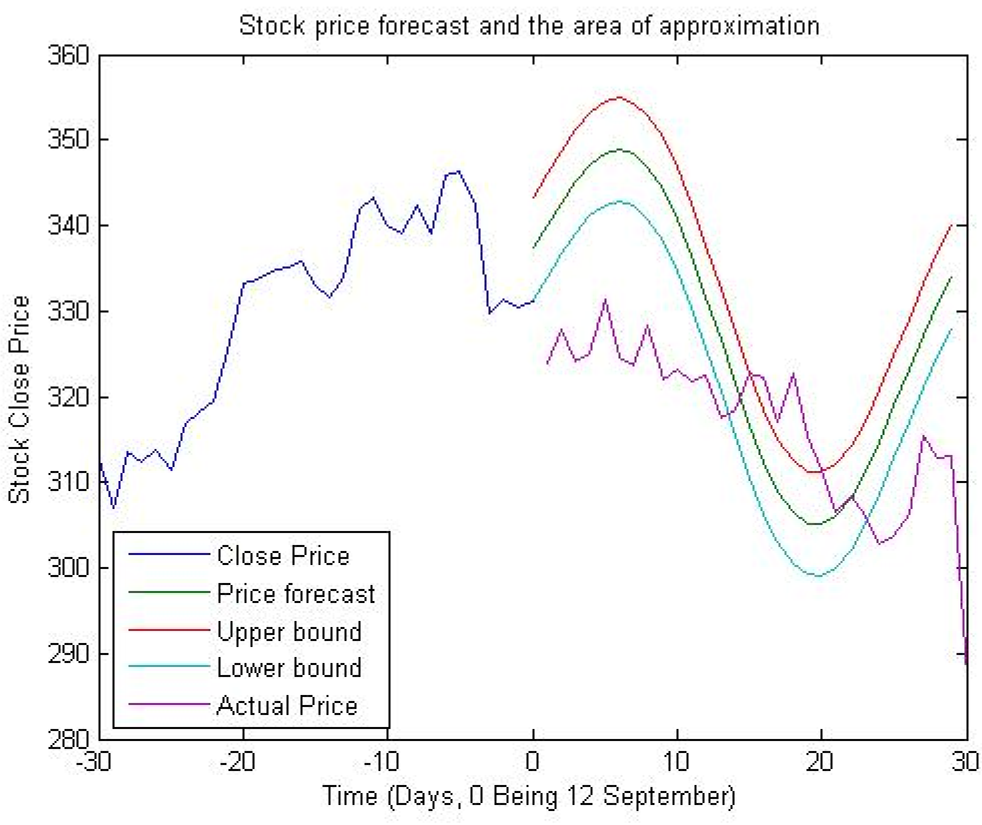
Ultimately, if an investor is interested in forecasting 15 business days in the future he would be well of using the non-smoothed version of the model. If he wishes to extend the prediction range, the NASDAQ modification accurately depicts the behavior of given stocks for the following 30 Business days.

Additional observations

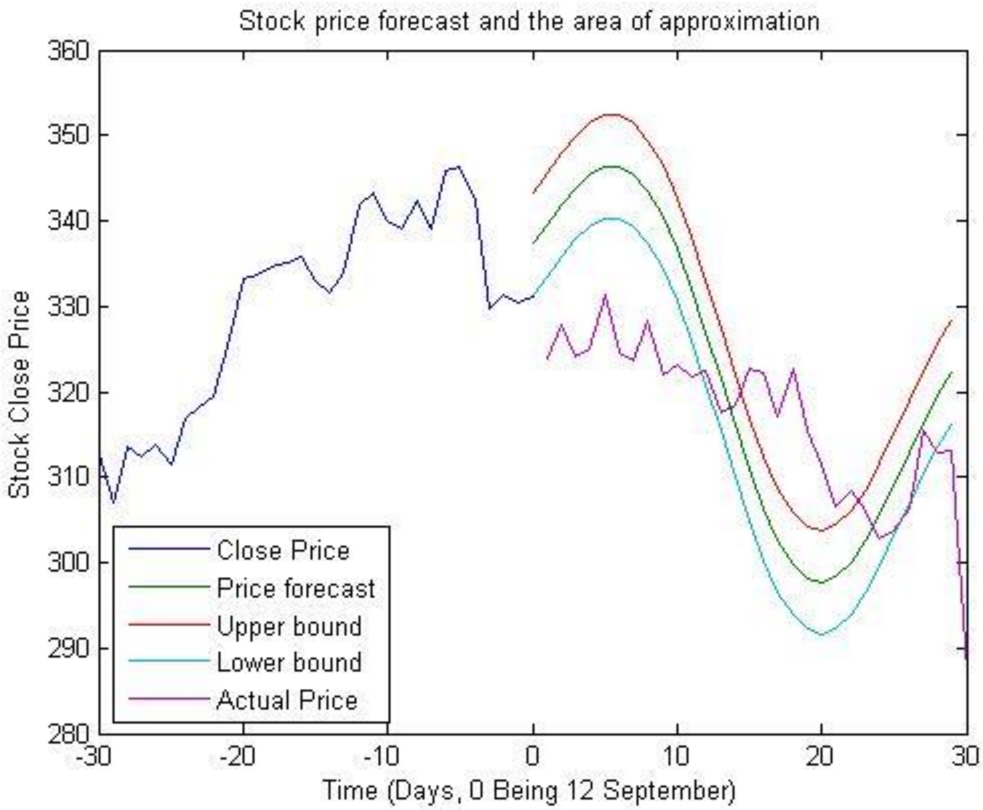
In order to check whether the NASDAQ modification works for stocks with high stock price and higher market capitalization, we made additional observations. We chose five stocks with a stock price above 100$. These stocks are: Baidu Inc. (BIDU), Equinix Inc. (EQIX), Netflix Inc. (NFLX), TripAdvisor Inc. (TRIP), Amazon.com inc. (YY).

AMZN:

The average inaccuracy without using NASDAQ modification was 7.8%. When we used the modification it was 6.2%, while the 95% CI was 4.0%. The close price graph for the stock was not sinusoidal, thus we used Linear LSA first and afterwards the Fourier series to approximate the close price after 12 September. The modification made the forecast better. Below is the forecast without NASDAQ modification:

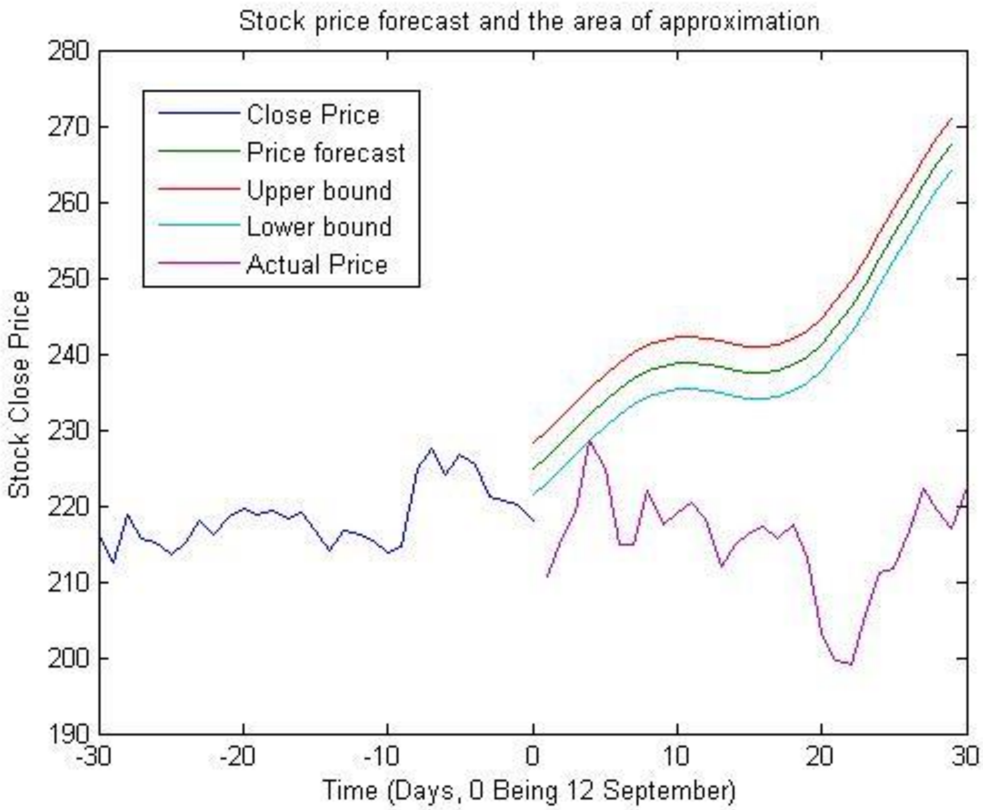


Below is the forecast using NASDAQ modification:

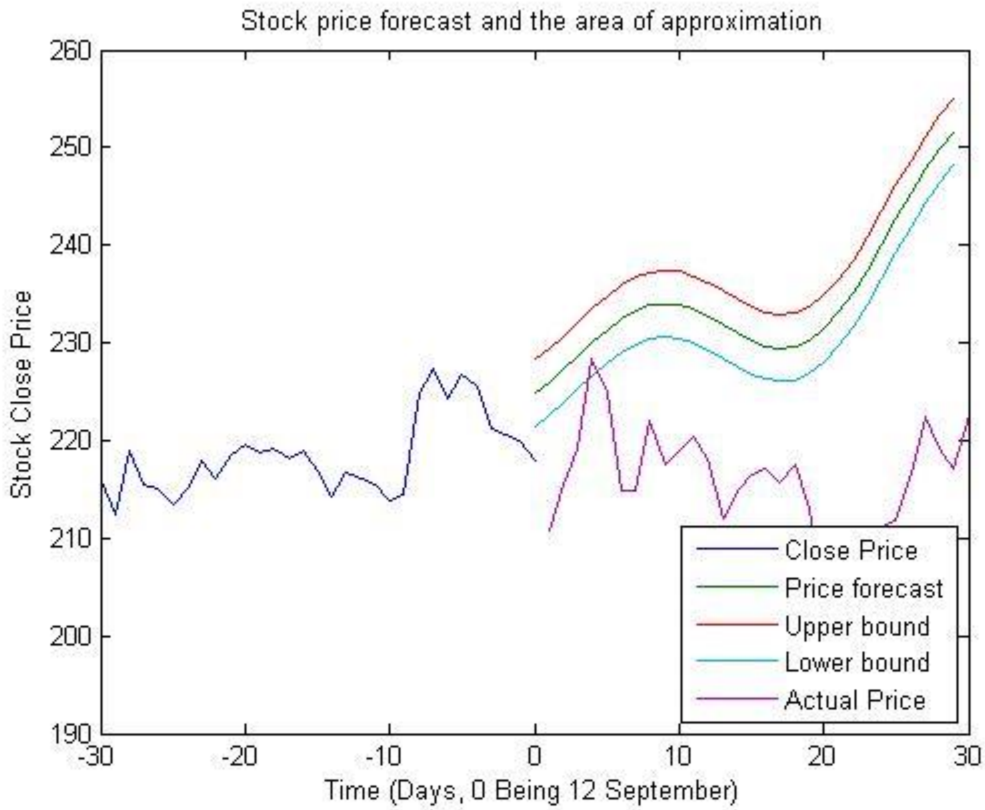


BIDU:

The average inaccuracy without using NASDAQ modification was 12.2%. When we used the modification it was 8.8%, while the 95% CI was 4.7%. The close price graph for the stock was not sinusoidal, thus we used Linear LSA first and afterwards the Fourier series to approximate the close price after 12 September. The modification made the forecast better. Below is the forecast without NASDAQ modification:

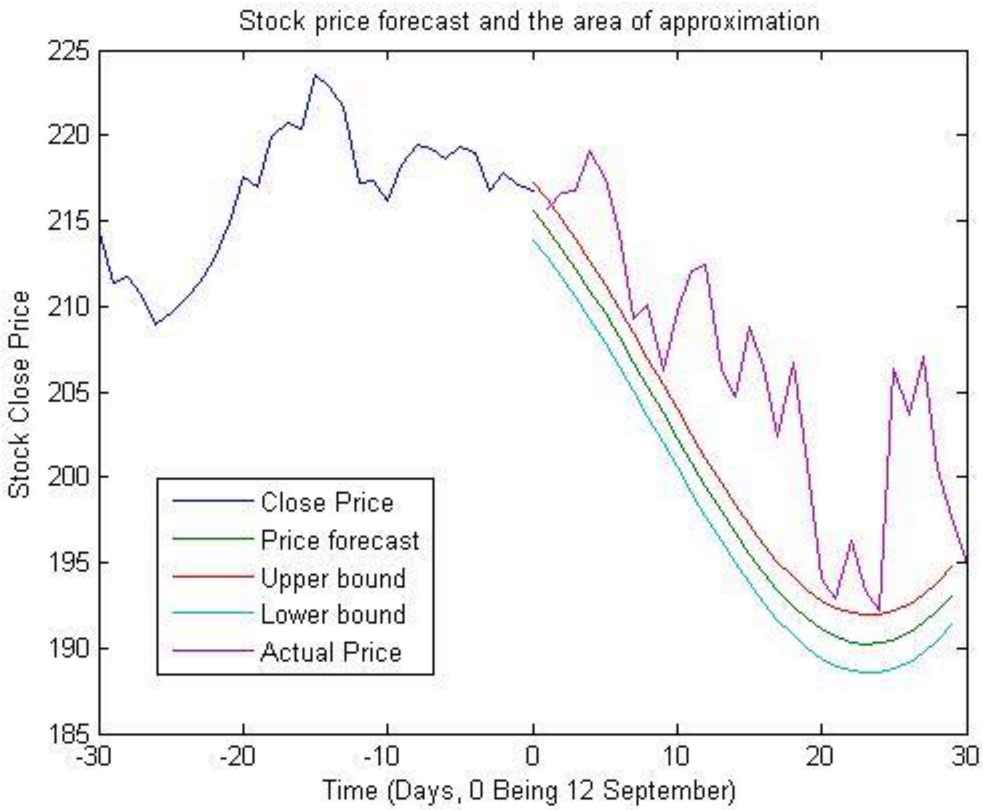


Below is the forecast using NASDAQ modification:

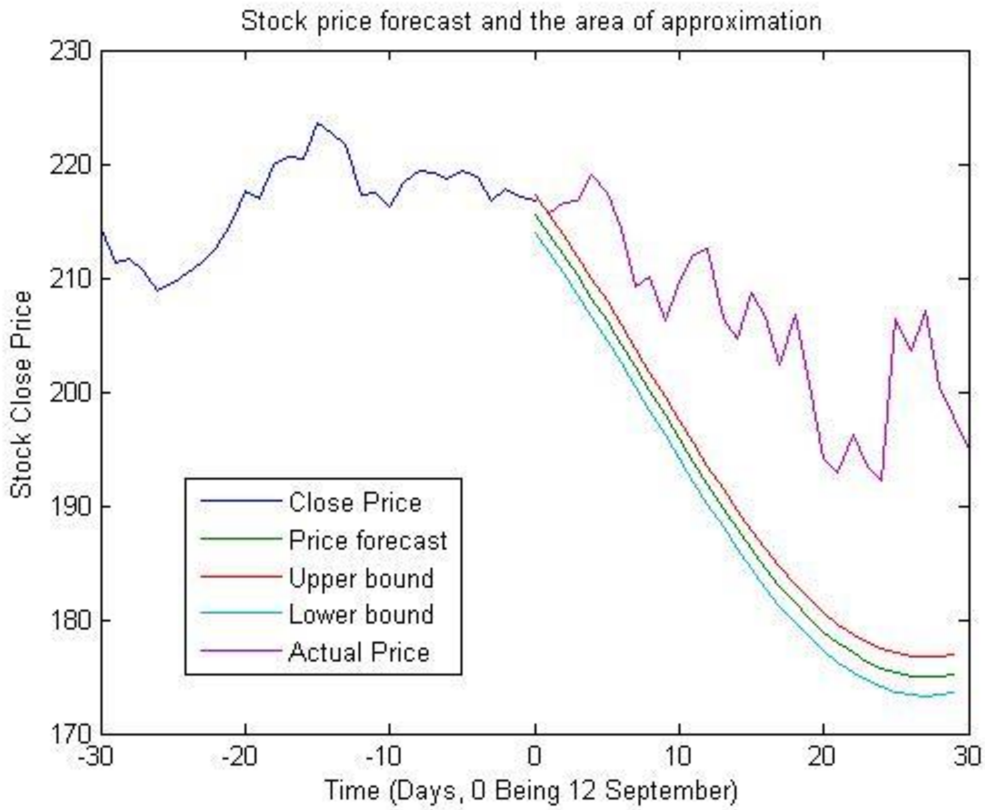


EQIX:

The average inaccuracy without using NASDAQ modification was 5.0%. When we used the modification it was 7.6%, while the 95% CI was 2.7%. The close price graph for the stock was not sinusoidal, thus we used Linear LSA first and afterwards the Fourier series to approximate the close price after 12 September. The modification made the forecast worse. Below is the forecast without NASDAQ modification:

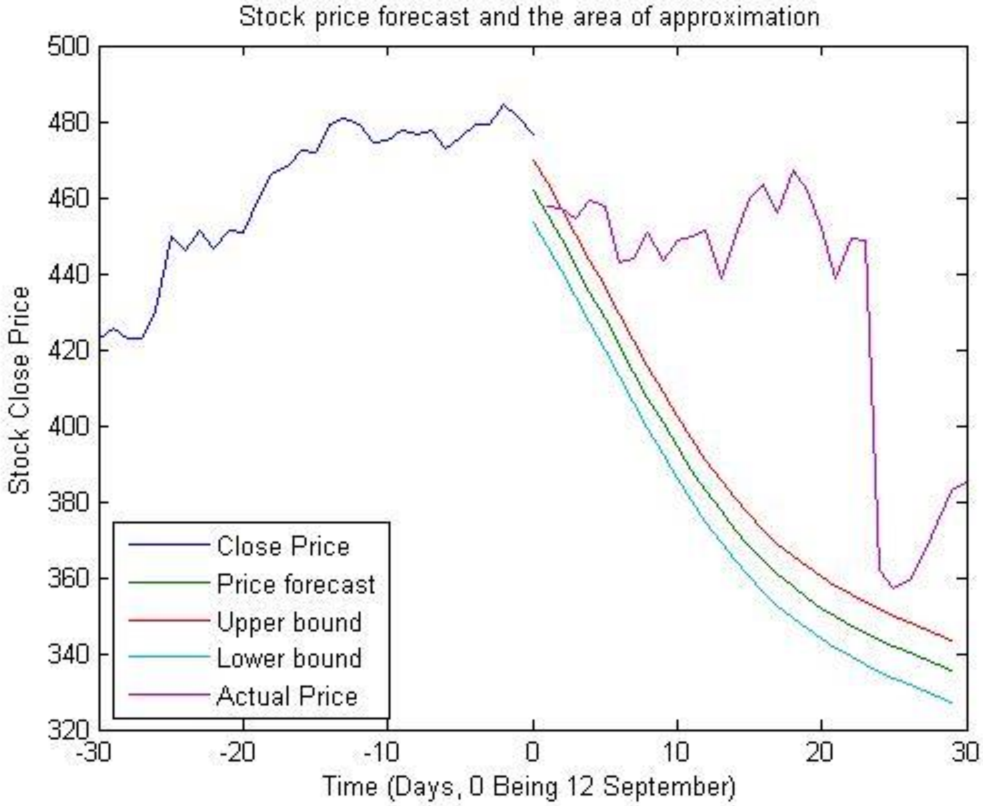


Below is the forecast using NASDAQ modification:

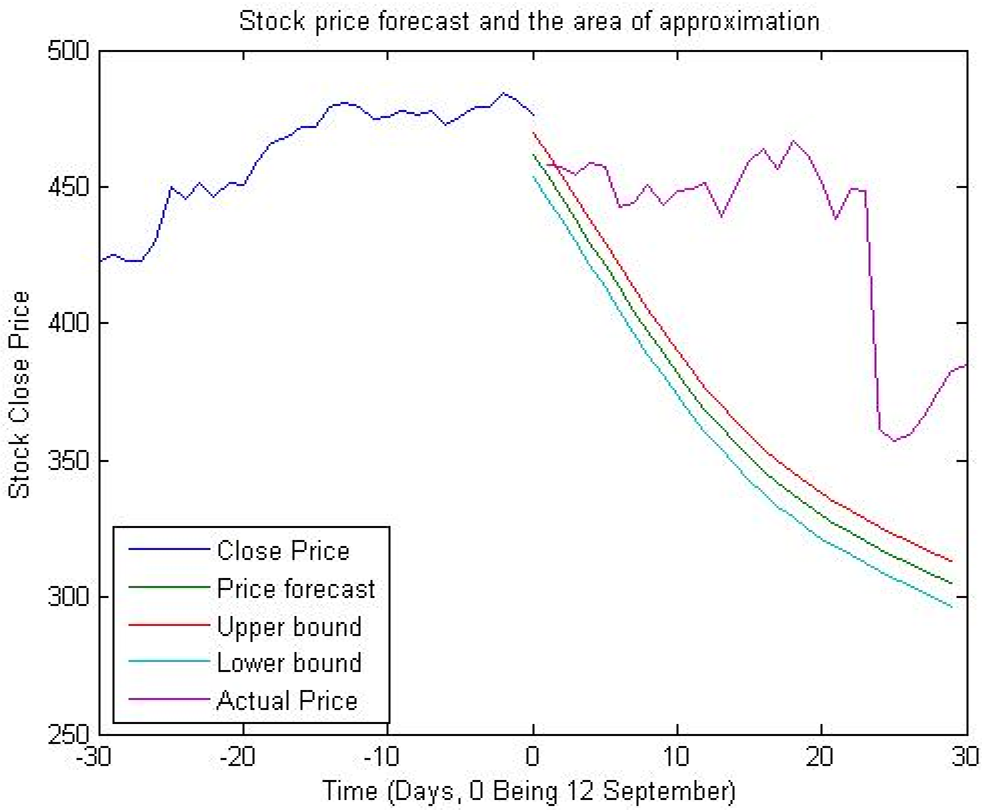


NFLX:

The average inaccuracy without using NASDAQ modification was 11.8%. When we used the modification it was 15.6%, while the 95% CI was 5.0%. The close price graph for the stock was sinusoidal, thus we used Fourier series first and afterwards the Linear LSA to approximate the close price after 12 September. The modification made the forecast worse. Below is the forecast without NASDAQ modification:



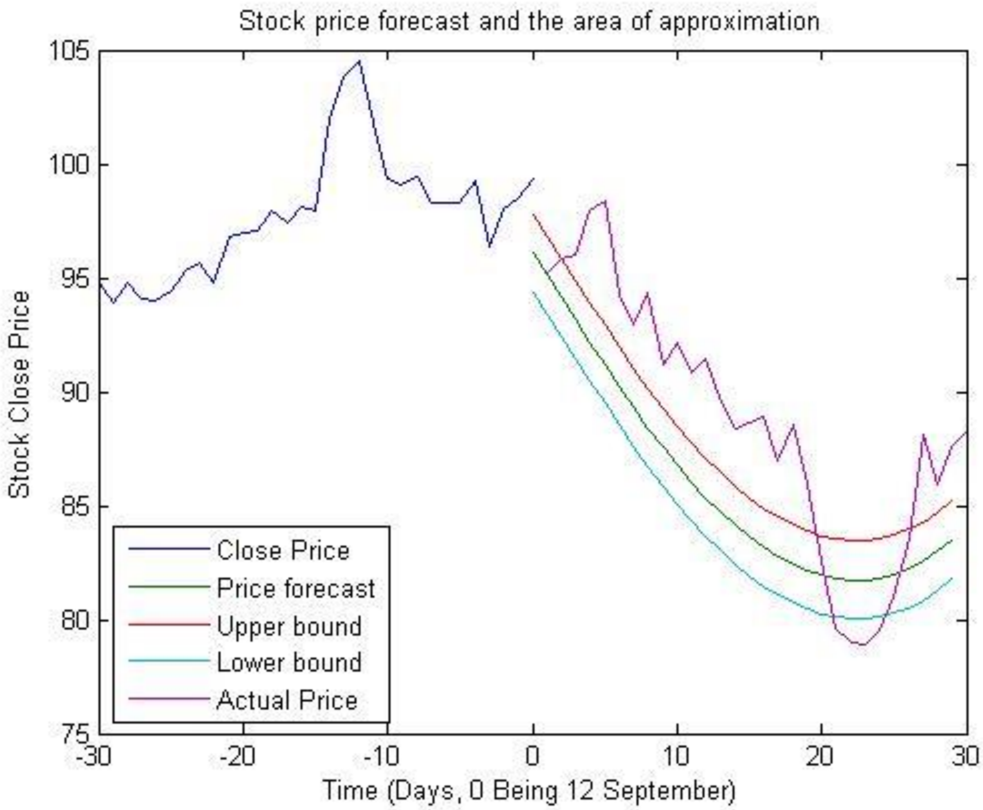
Below is the forecast using NASDAQ modification:



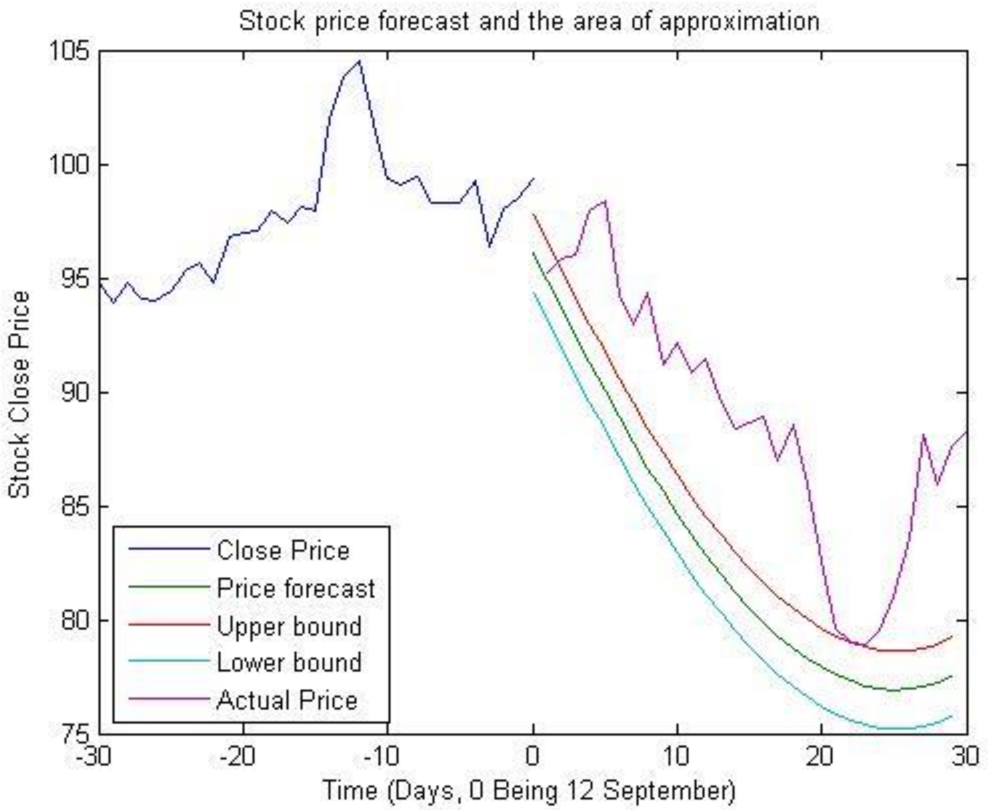
TRIP:

The average inaccuracy without using NASDAQ modification was 3.9%. When we used the modification it was 6.5%, while the 95% CI was 4.9%. The close price graph for the stock was sinusoidal, thus we used Fourier series first and afterwards the Linear LSA to approximate the close price after 12 September. Modification made the forecast worse.

Below is the forecast without NASDAQ modification:



Below is the forecast using NASDAQ modification:



Conclusion:

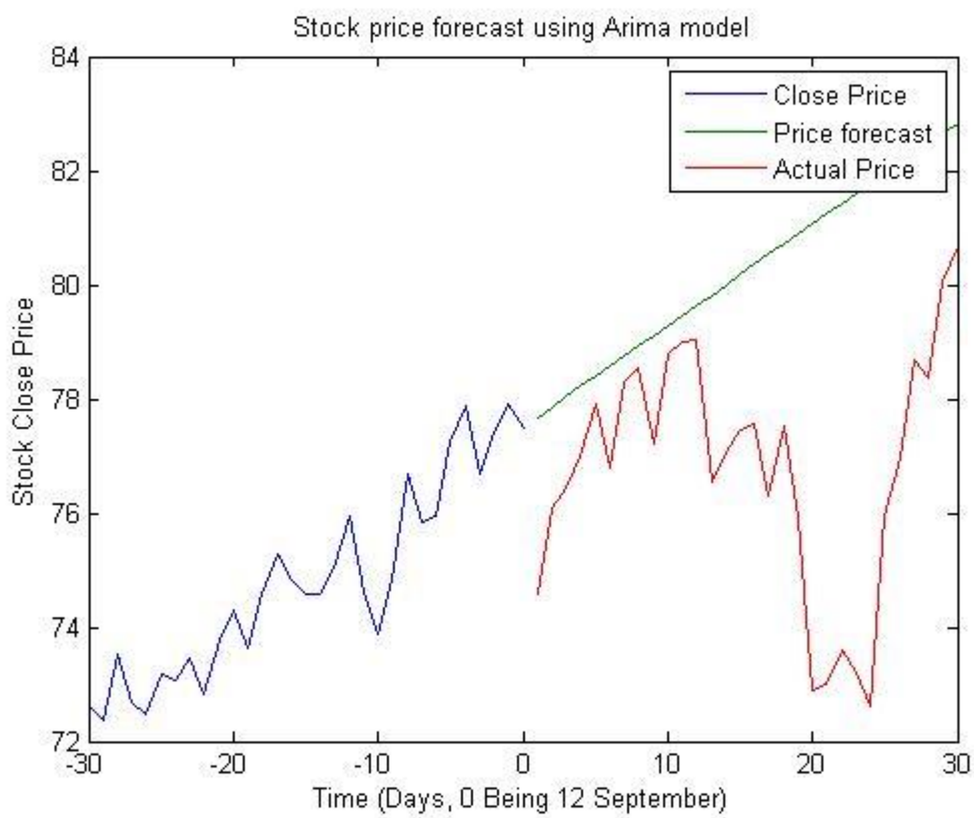
Stock Ticker	Average Inaccuracy without NASDAQ	Average Inaccuracy with NASDAQ	95% CI	Close price
AMZN	7.8%	6.2%	4.0%	330$
BIDU	12.2%	8.8%	4.7%	220$
EQIX	5.0%	7.6%	2.7%	215$
NFLX	11.8%	15.6%	5.0%	480$
TRIP	3.9%	6.5%	4.9%	100$

The forecast using NASDAQ modification was made worse in most of the cases. The modification was helpful if we changed the constant in the function form negative to positive. The model was inaccurate for these five stocks. We concluded that the model is not applicable for stocks with a stock price of a 100 and above.

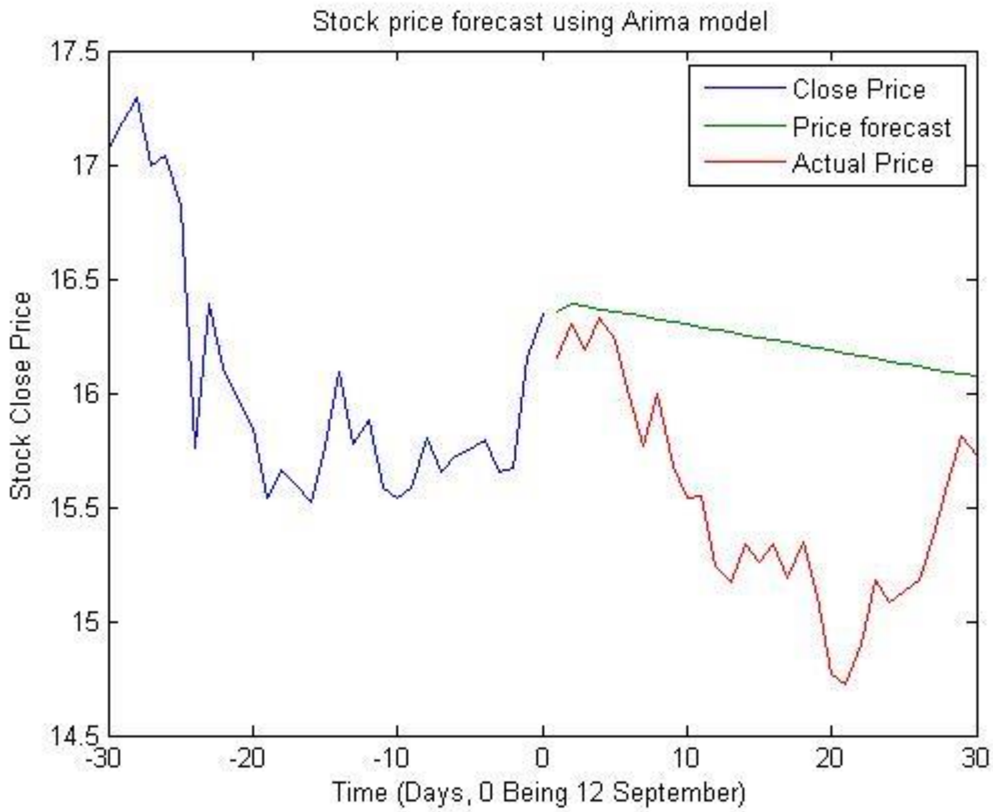
ARIMA Model

As our second model we used ARIMA model in order to predict the price of stocks. ARIMA creates model objects for stationary or unit root non-stationary linear time series model. This includes moving average (MA), autoregressive (AR), mixed autoregressive and moving average (ARMA), integrated (ARIMA), multiplicative seasonal, and linear time series models which on their hand include exogenous covariates (ARIMAX). We will use arima (p, D, q), which creates a non-seasonal linear time series model using autoregressive degree p, differencing degree D, and moving average degree q. For our input arguments we chose arima (1, 1, 3), since it offers the least error in predicting stock prices. We used the estimate and forecast functions in Matlab to predict the price of stocks. Finally, we compared the ARIMA model with the LSA plus Fourier model.

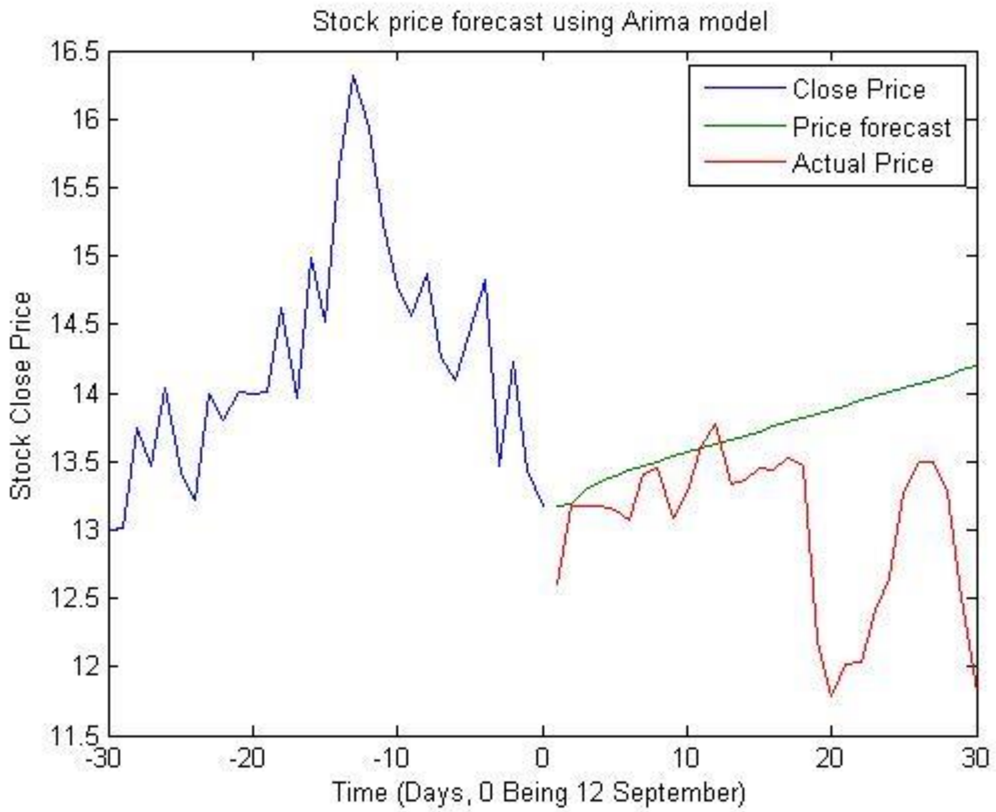
FB:



BCOR:

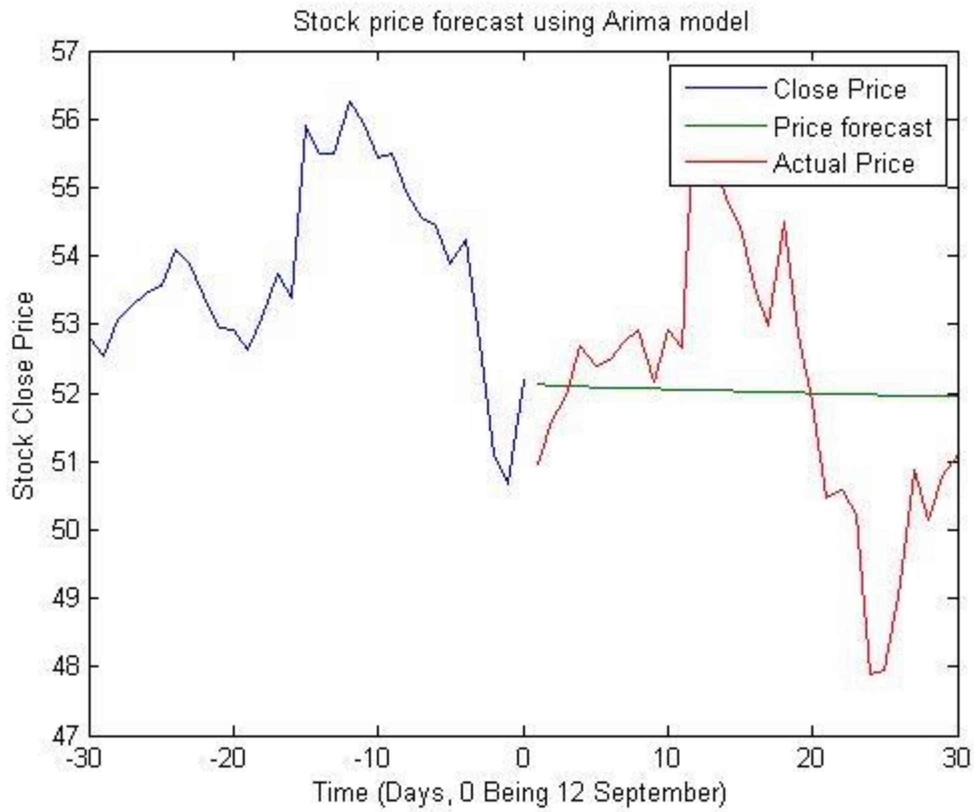

Stock price forecast using Arima model
Close Price
Price forecast
Actual Price
Stock Close Price
Time (Days, 0 Being 12 September)
17.5
17
16.5
16
15.5
15
14.5
-30
-20
-10
0
10
20
30

CCIH:



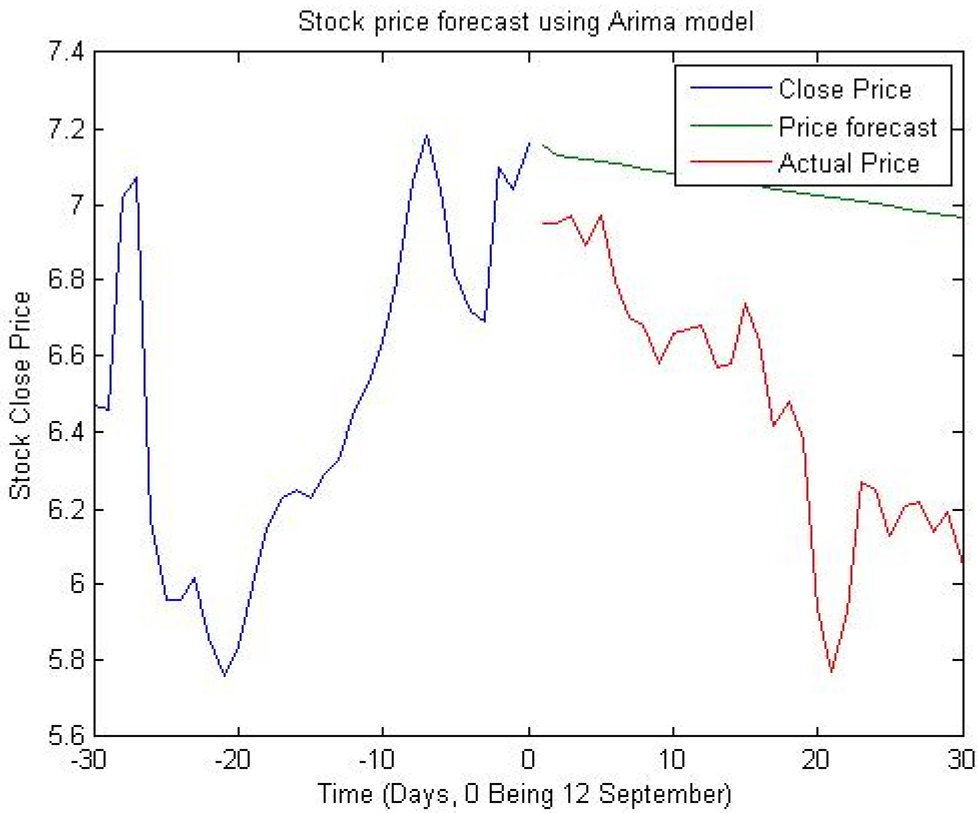
Stock price forecast using Arima model
Close Price
Price forecast
Actual Price
Stock Close Price
16.5
16
15.5
15
14.5
14
13.5
13
12.5
12
11.5
-30
-20
-10
0
10
20
30
Time (Days, 0 Being 12 September)

EBAY:

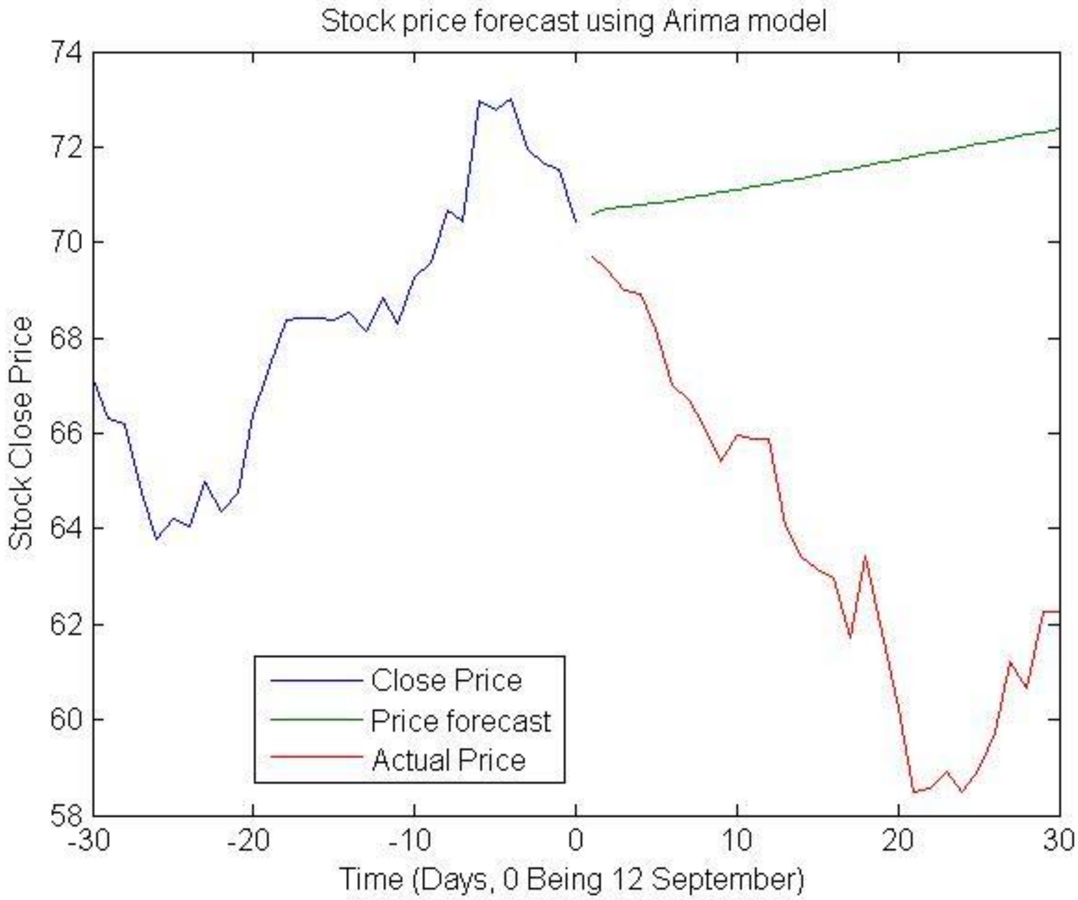


Stock price forecast using Arima model
Close Price
Price forecast
Actual Price
Stock Close Price
Time (Days, 0 Being 12 September)
57
56
55
54
53
52
51
50
49
48
47
-30
-20
-10
0
10
20
30

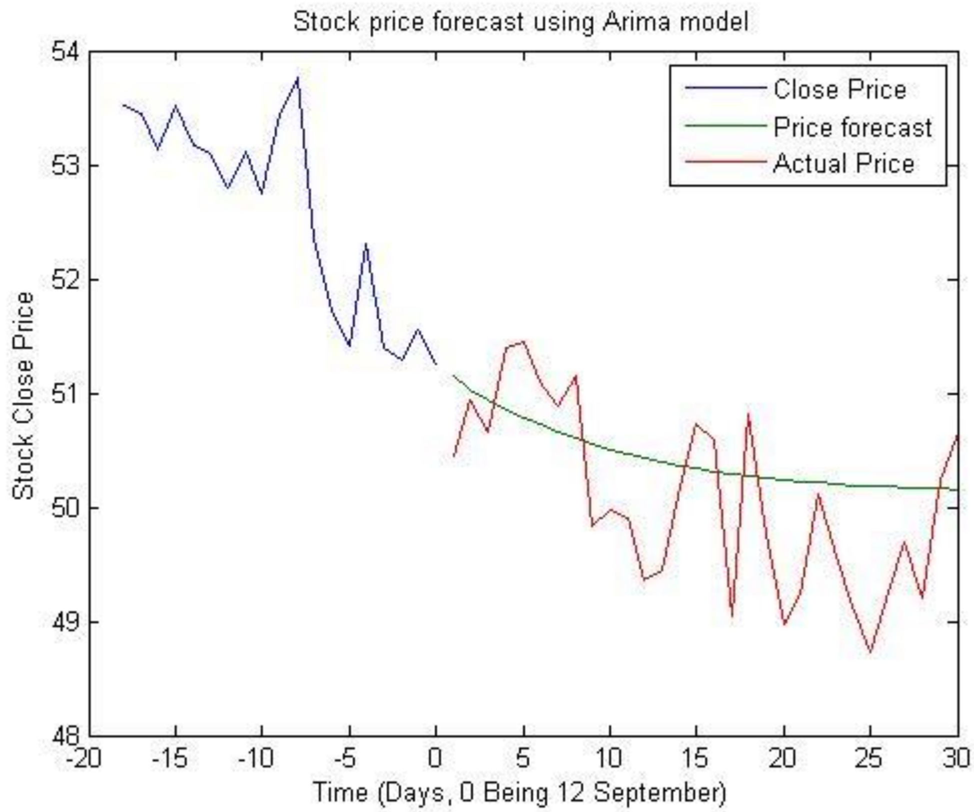
GRPN:


Stock price forecast using Arima model
Close Price
Price forecast
Actual Price
Stock Close Price
Time (Days, 0 Being 12 September)
7.4
7.2
7
6.8
6.6
6.4
6.2
6
5.8
5.6
-30
-20
-10
0
10
20
30

IACI:

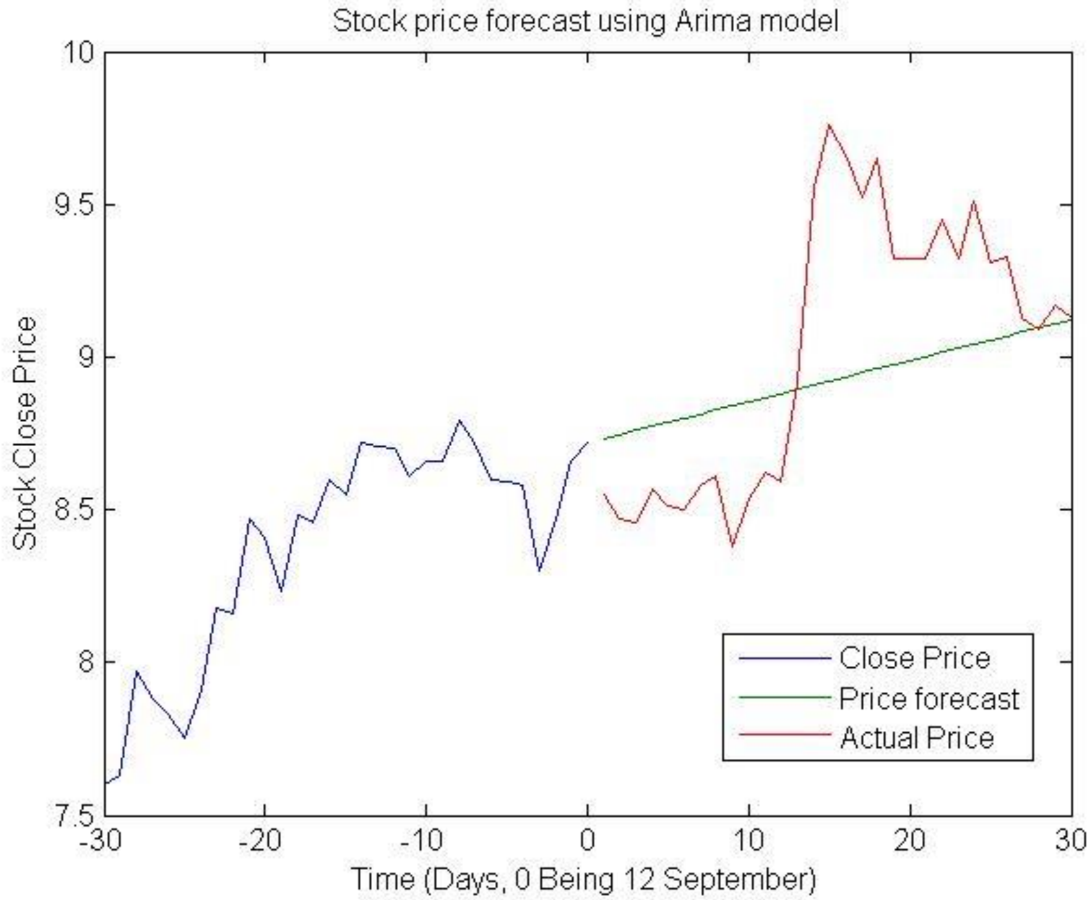

Stock price forecast using Arima model
74
72
70
68
66
64
62
60
58
-30
-20
-10
0
10
20
30
Stock Close Price
Time (Days, 0 Being 12 September)
Close Price
Price forecast
Actual Price

JCOM:



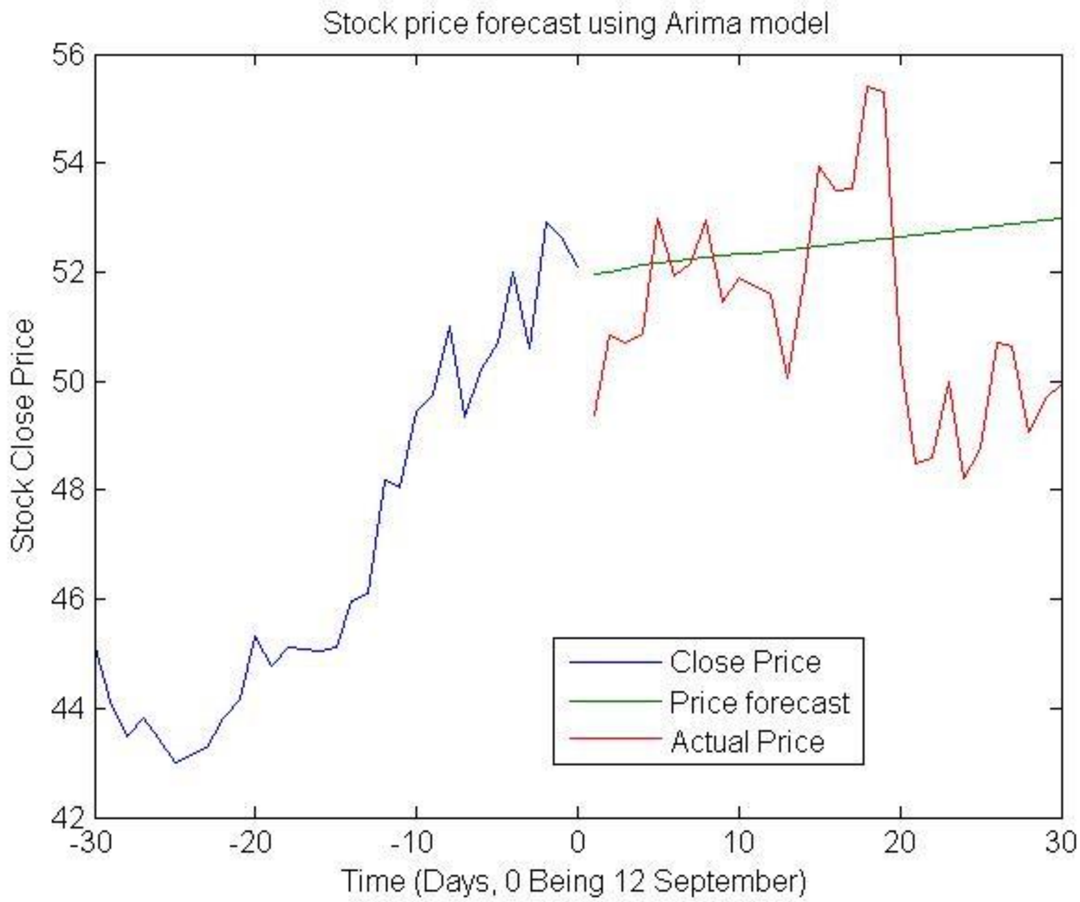
Stock price forecast using Arima model
Close Price
Price forecast
Actual Price
Stock Close Price
Time (Days, 0 Being 12 September)
54
53
52
51
50
49
48
-20
-15
-10
-5
0
5
10
15
20
25
30

TTGT:



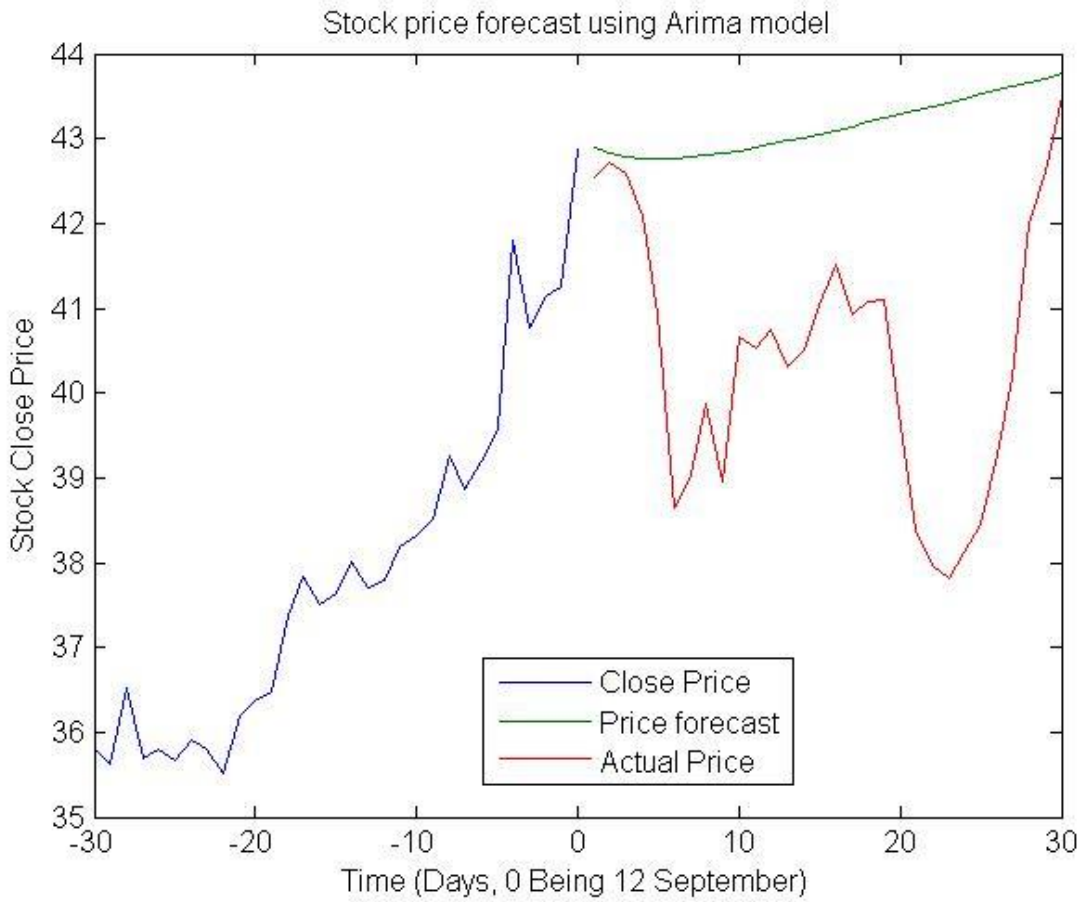
Stock price forecast using Arima model
Stock Close Price
Time (Days, 0 Being 12 September)
Close Price
Price forecast
Actual Price
10
9.5
9
8.5
8
7.5
-30
-20
-10
0
10
20
30

TWTR:



Stock price forecast using Arima model
Stock Close Price
56
54
52
50
48
46
44
42
-30
-20
-10
0
10
20
30
Time (Days, 0 Being 12 September)
Close Price
Price forecast
Actual Price

YHOO:



Conclusion:

Stock Ticker	Max Inaccuracy	Min Inaccuracy	Average Inaccuracy	95% CI	Quality of Prediction
FB	12.6%	0.5%	4.5%	5.6%	Acceptable
BCOR	9.9%	0.2%	4.7%	4.3%	Not Acceptable
CCIH	20.2%	0.1%	5.5%	11.5%	Acceptable
EBAY	8.6%	0.2%	2.8%	2.8%	Acceptable
GRPN	21.6%	2.0%	8.8%	7.5%	Not Acceptable
IACI	23.1%	1.3%	12.3%	3.5%	Not Acceptable
JCOM	3.0%	0.2%	1.3%	3.8%	Acceptable
TTGT	8.6%	0.1%	3.5%	5.1%	Acceptable

TWTR	9.4%	0.1%	3.9%	8.5%	Acceptable
YHOO	14.8%	0.3%	6.6%	4.0%	Not Acceptable

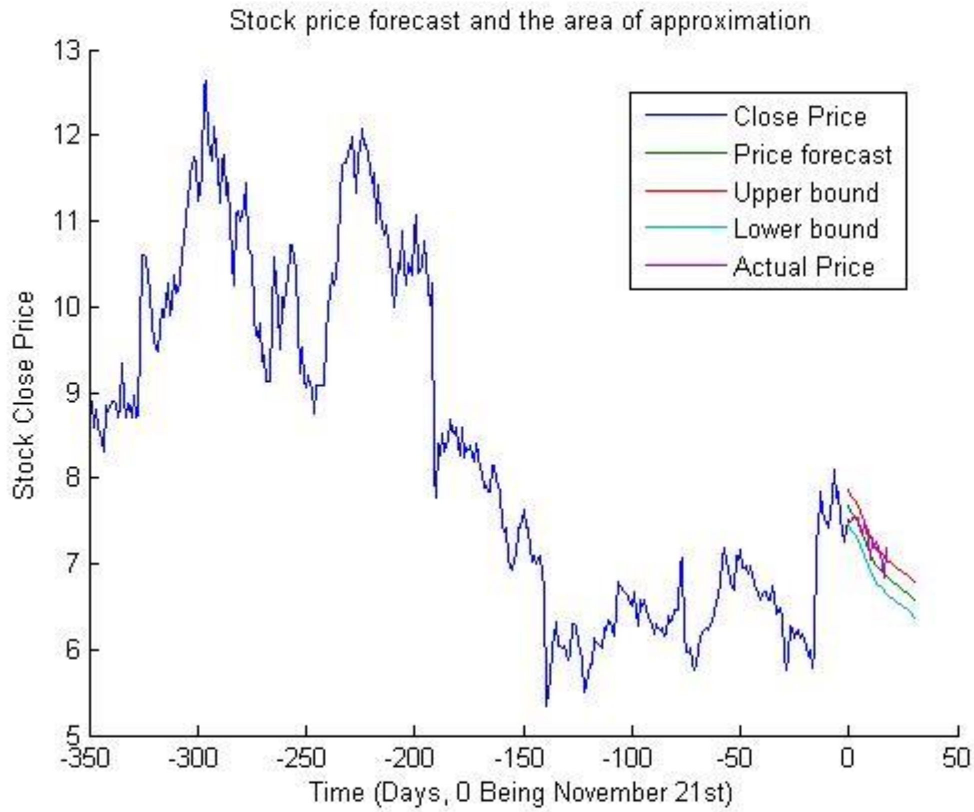
Out of ten stocks, four were not acceptable due to a large percent Inaccuracy. Thus the model is not acceptable for a 30 business day forecasting.

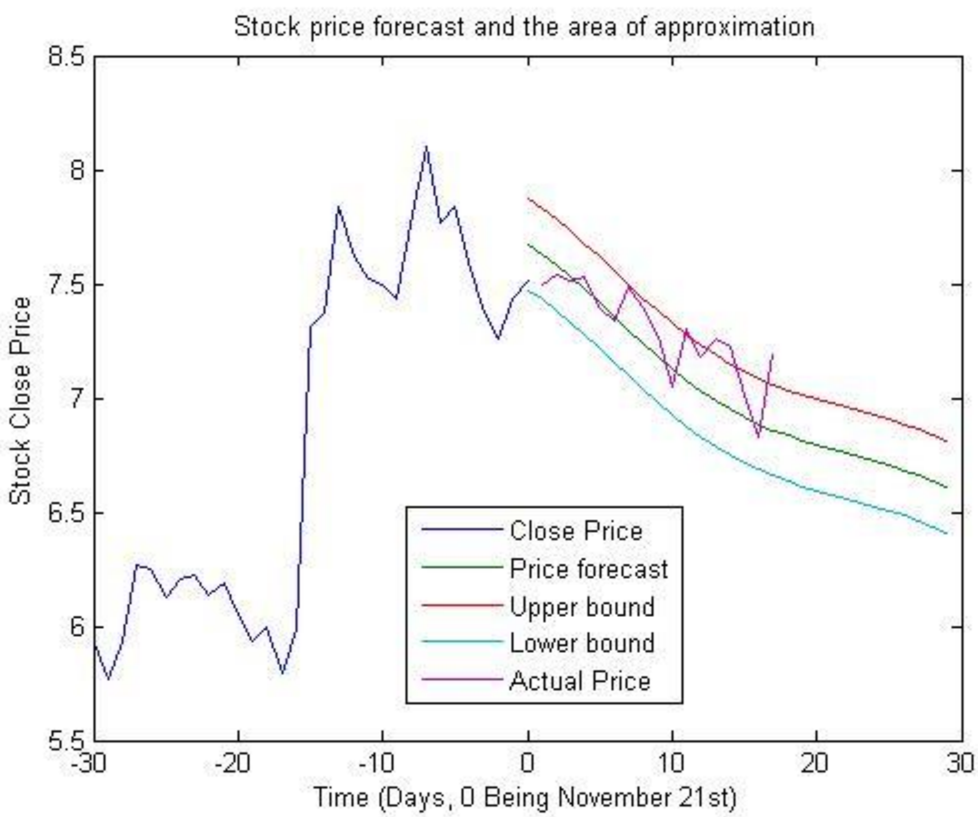
Reality test of Virtual Investment

It was decided to test our models by choosing several stocks and investing in them $100,000 of virtual money with no transaction or broker fees. Our investing strategy was based on careful examination of the predictions provided by our two models that we created. In addition, we looked at their historical close prices and observed general trends as well as the volatility right before November 21st. Furthermore, we used expert advice about the future of the stocks from fool.com, bloomberg.com and seekingalpha.com. We looked for stocks where the predictions of our models conformed to this expert advice. Based on this data, we picked five stocks and invested $20,000 in each of them, regardless of their stock price. We chose the stocks starting from Friday the 21st of November and we will provide the actual stock prices for each of them at the end of 18 business day period. We chose to sell short two stocks and buy three stocks.

GRPN:

We sold short stocks, worth $20,000 with a stock price of $7.51. Historical volatility of 59%, told us that we would expect a relevant change in price. Both of our models predicted that the price of the stock would fall after 21st of November. Sam Mattera at fool.com believes that Groupon share value will fall, if either their Asian assets do not attract interest, initiatives fall short, or guidance continues to disappoint. The alexa.com ranking places fool.com at 413 in the United States according to a site's ratings. Simply the fact that, a website of this scale makes a negative prediction, creates a small catalyst for the fall of the price.


Stock price forecast and the area of approximation
Close Price
Price forecast
Upper bound
Lower bound
Actual Price
Stock Close Price
Time (Days, 0 Being November 21st)
13
12
11
10
9
8
7
6
5
-350
-300
-250
-200
-150
-100
-50
0
50


Stock price forecast and the area of approximation
Close Price
Price forecast
Upper bound
Lower bound
Actual Price
Stock Close Price
Time (Days, 0 Being November 21st)
8.5
8
7.5
7
6.5
6
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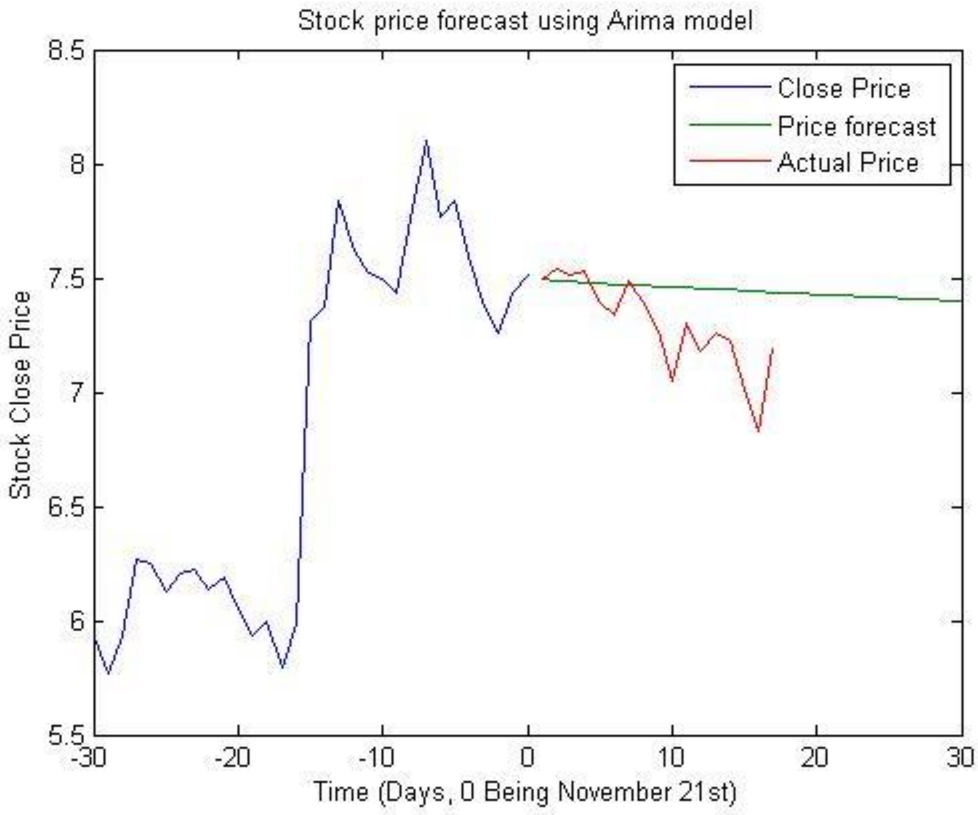
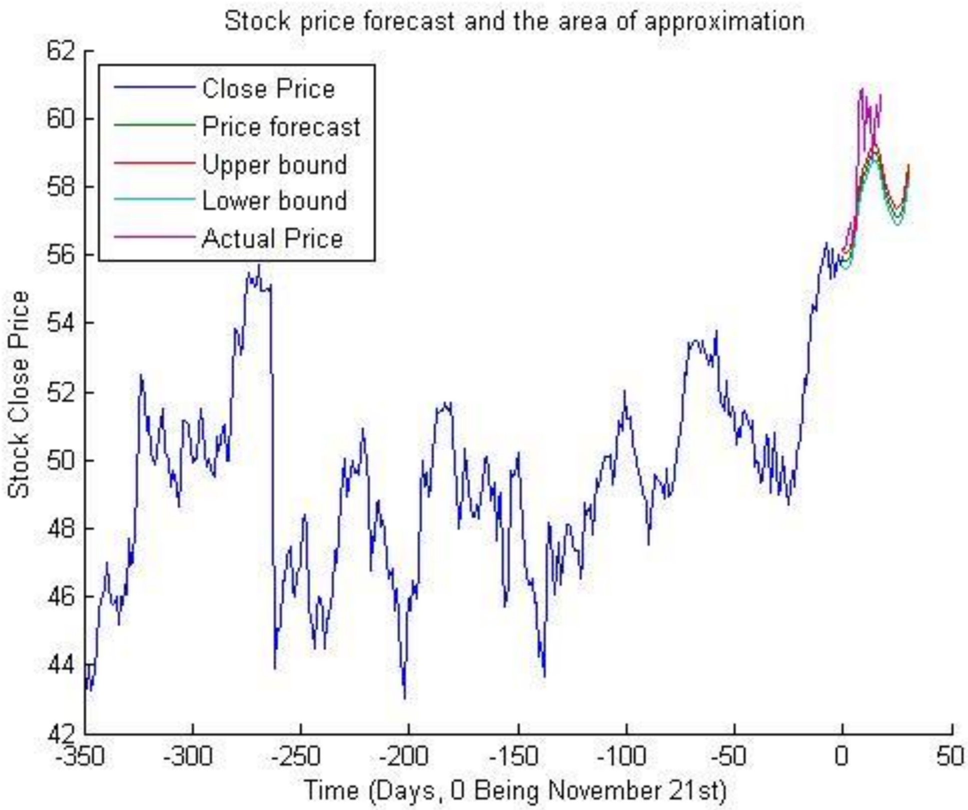
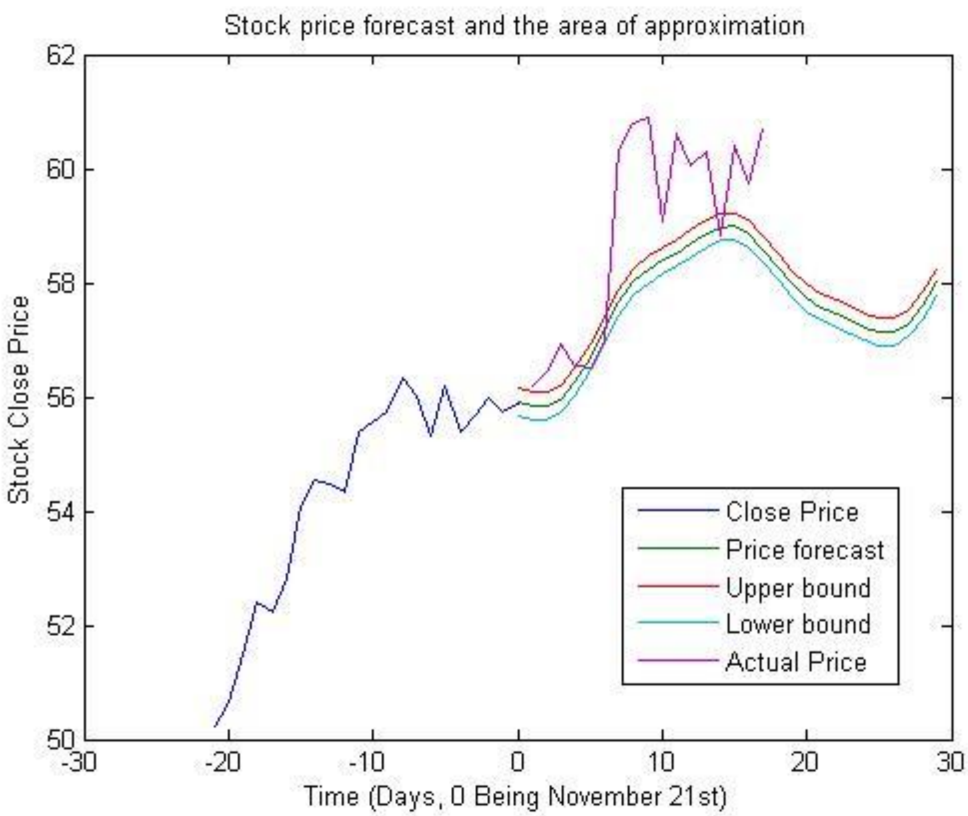
-10
0
10
20
30

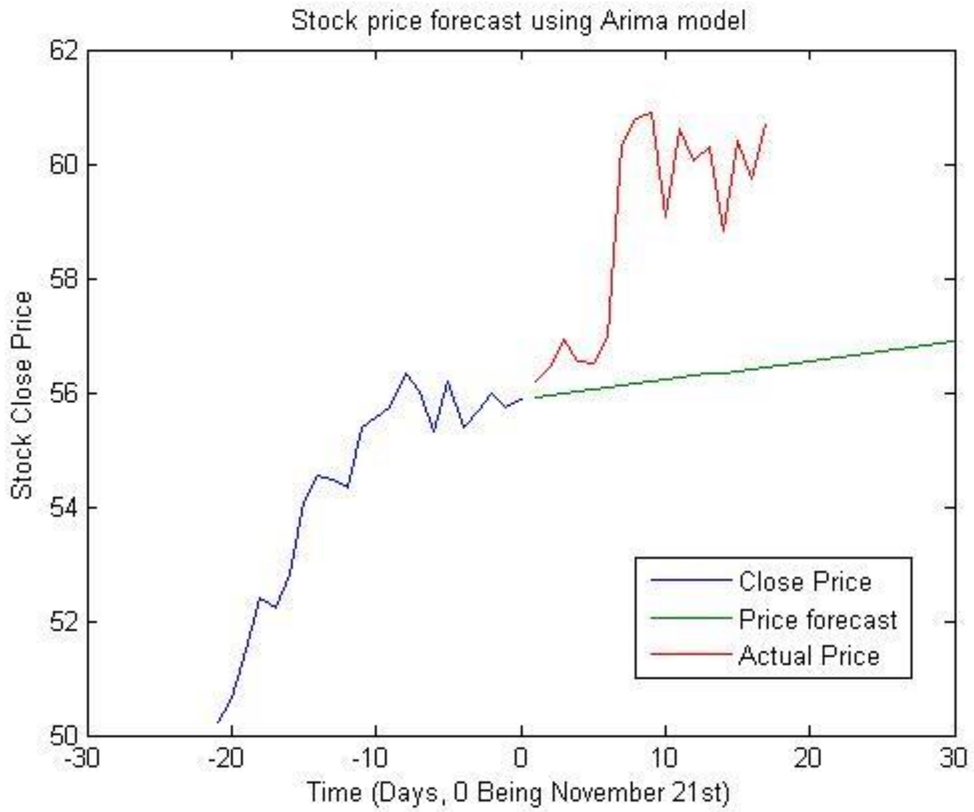


JCOM:

We bought stocks worth $20,000 with a stock price of $55.87. JCOM is acceptable for all three of our models and inherited confidence in its prediction, in addition to the low inaccuracy of less than 2%. Both of our models predicted that the stock price would rise after 21st of November. J2 Global earning per share and the revenue for the quarter beat the consensus estimate. The revenue is 20% higher than the revenue in the same quarter last year.

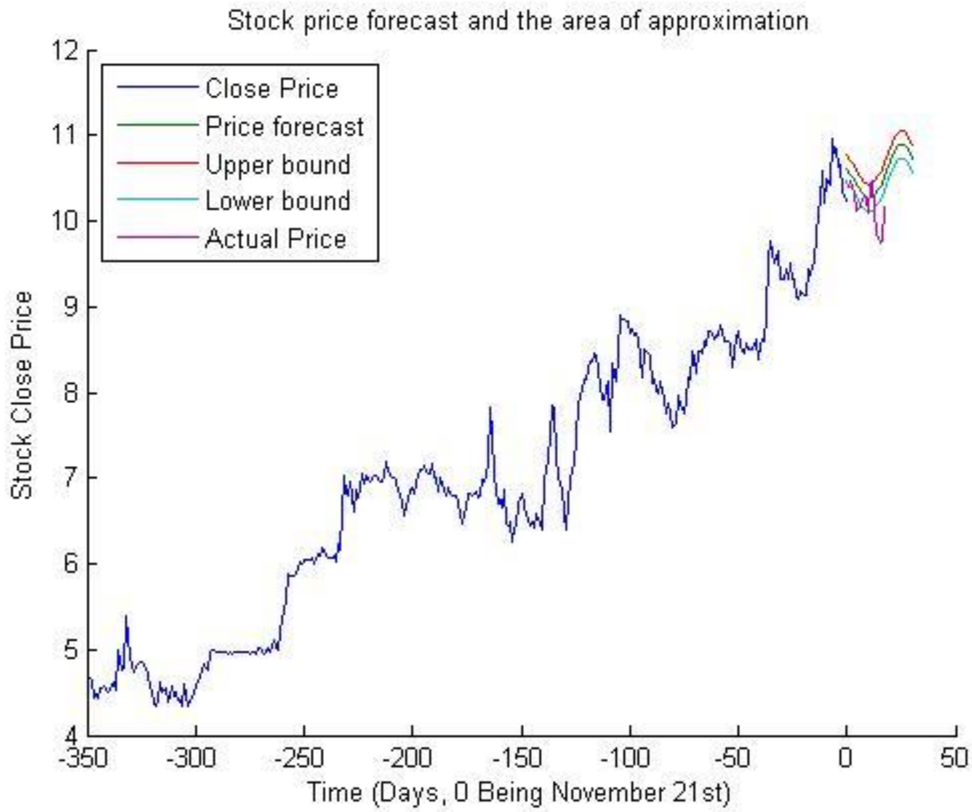

Stock price forecast and the area of approximation
Close Price
Price forecast
Upper bound
Lower bound
Actual Price
Stock Close Price
Time (Days, 0 Being November 21st)
62
60
58
56
54
52
50
48
46
44
42
-350
-300
-250
-200
-150
-100
-50
0
50


Stock price forecast and the area of approximation
Close Price
Price forecast
Upper bound
Lower bound
Actual Price
Stock Close Price
Time (Days, 0 Being November 21st)
62
60
58
56
54
52
50
-30
-20
-10
0
10
20
30

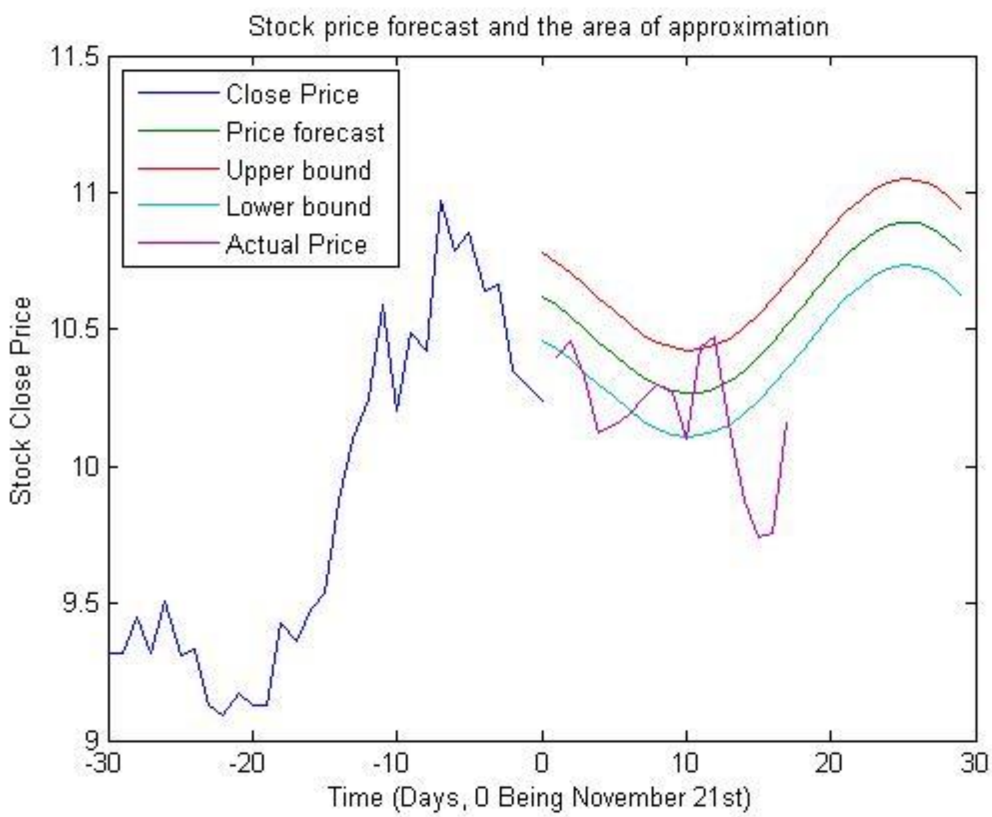


TTGT:

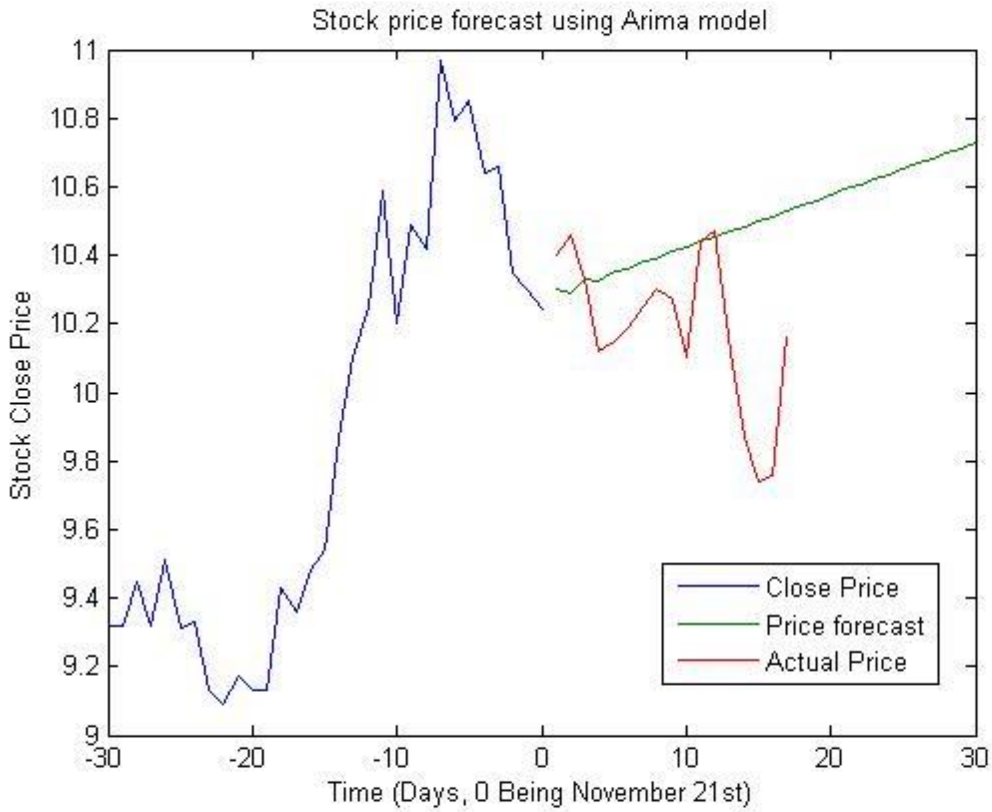
We bought stocks worth $20,000 with a stock price of $10.24. Historical volatility of 44% told us that we would expect a relevant change in price. Being acceptable for both of our models, this case inherited confidence in its prediction. Both models predicted an eventual rise in the price of the stock. We can see a steady increase of share value throughout the last year and we believe the trend will persist. TTGT third quarter earnings beat consensus estimates. Its gross profit margin is higher in the third quarter as compared to same time period of last year. Marshall Hargrave at seekingalpha.com predicts a rise in the price and it agrees with our own forecast. The ranking of seekingalpha.com is 576 in the USA. It provides a small catalyst of potential upward movement of the stock price. We are confident in the investment.



Stock price forecast and the area of approximation
Close Price
Price forecast
Upper bound
Lower bound
Actual Price
Stock Close Price
12
11
10
9
8
7
6
5
4
-350
-300
-250
-200
-150
-100
-50
0
50
Time (Days, 0 Being November 21st)



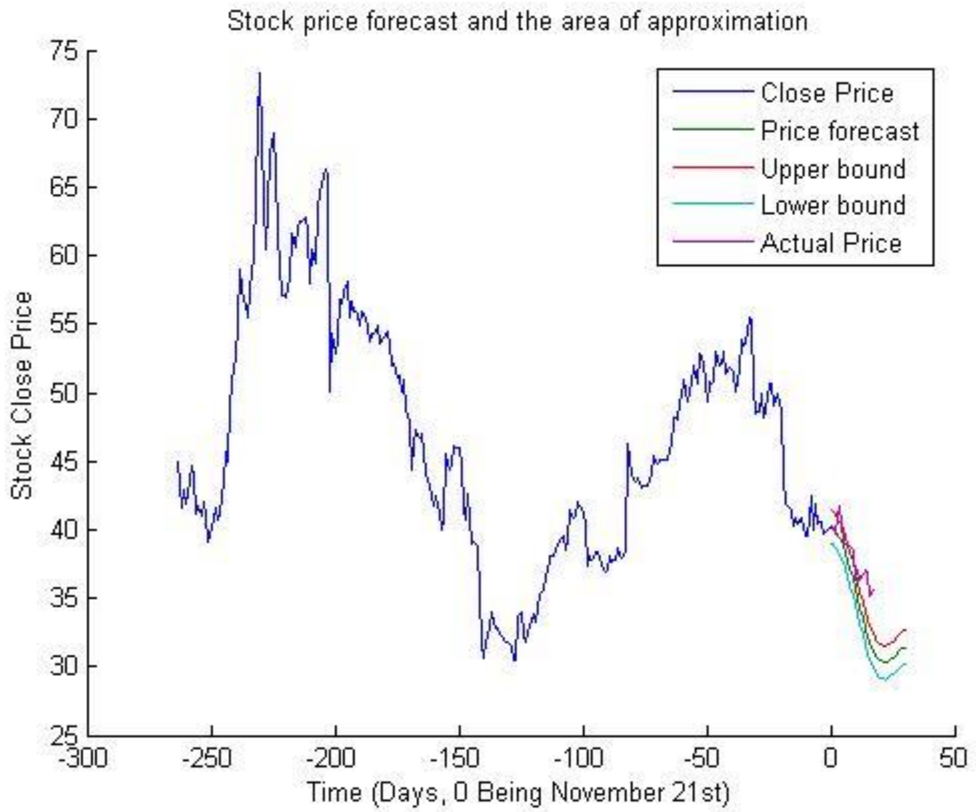
Stock price forecast and the area of approximation
Close Price
Price forecast
Upper bound
Lower bound
Actual Price
Stock Close Price
11.5
11
10.5
10
9.5
9
-30
-20
-10
0
10
20
30
Time (Days, 0 Being November 21st)

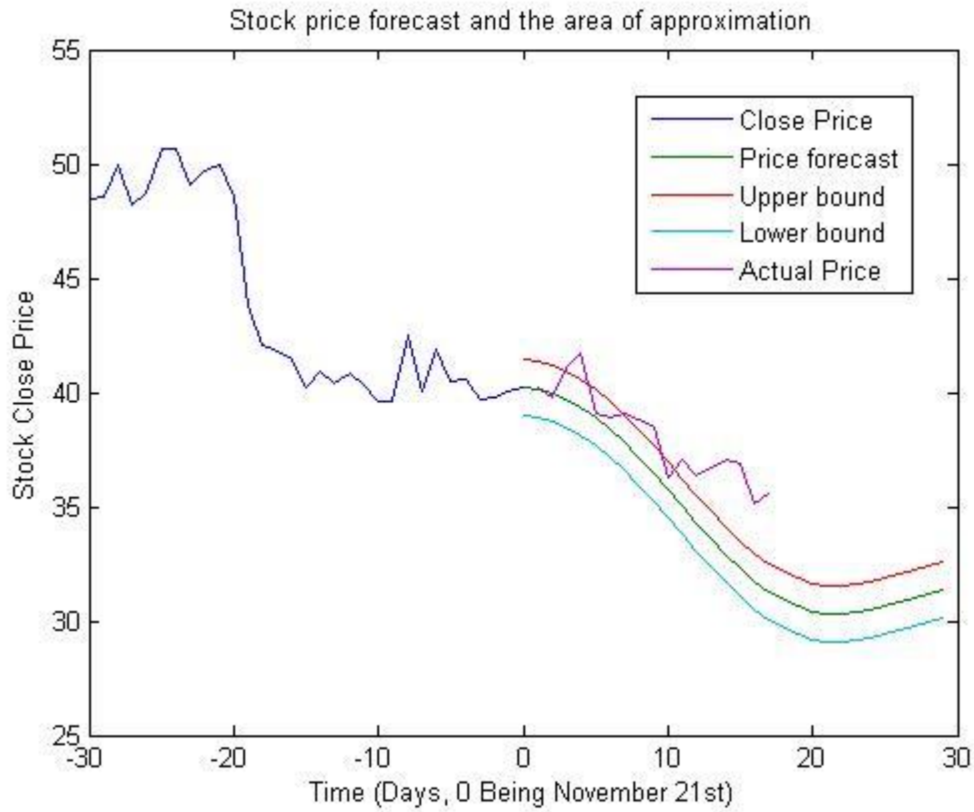


TWTR:

We sold short, stocks worth $20,000 with a stock price of $40.19. Historical volatility of 68% indicates that we should expect a relevant change in price. Both models predicted a downtrend. By observing the close price, we see that the stock has experienced a peculiar, recurrent shift and it is being repeated right before November 21st. One year ago, the stock price rose above $70 which resulted in a steady drop with a few shifts of relative stability of the close price. Same is repeated before Friday, thus we are confident that the stock will experience a decline in its price after a brief period of stability.

Twitter announced that all the messaging can now include public tweets, however, we think this will have no significant effect on their performance. Having no effect means that it is a drawback for the company and the stock price will keep falling. If we look at Twitters competitor, Facebook, it spent billions of dollars to purchase WhatsApp and SnapChat as mentioned by Brendan Byrne. In addition to their own messaging app, with these additional purchases Facebook is massively outperforming Twitter, at the race of developing and adopting a better messaging service. Sarah Frier at Bloomberg.com states that the Twitter user growth rates downward trends and the CEO Costolo replaced the company's top executives. His family trusts sold 283,460 shares, which was 50% of their holdings (valuewalk.com, 2014). We think these actions are not confidence inspiring for the investors and will constitute to the drop of the share value.




Stock price forecast and the area of approximation
Close Price
Price forecast
Upper bound
Lower bound
Actual Price
Stock Close Price
Time (Days, 0 Being November 21st)
55
50
45
40
35
30
25
-30
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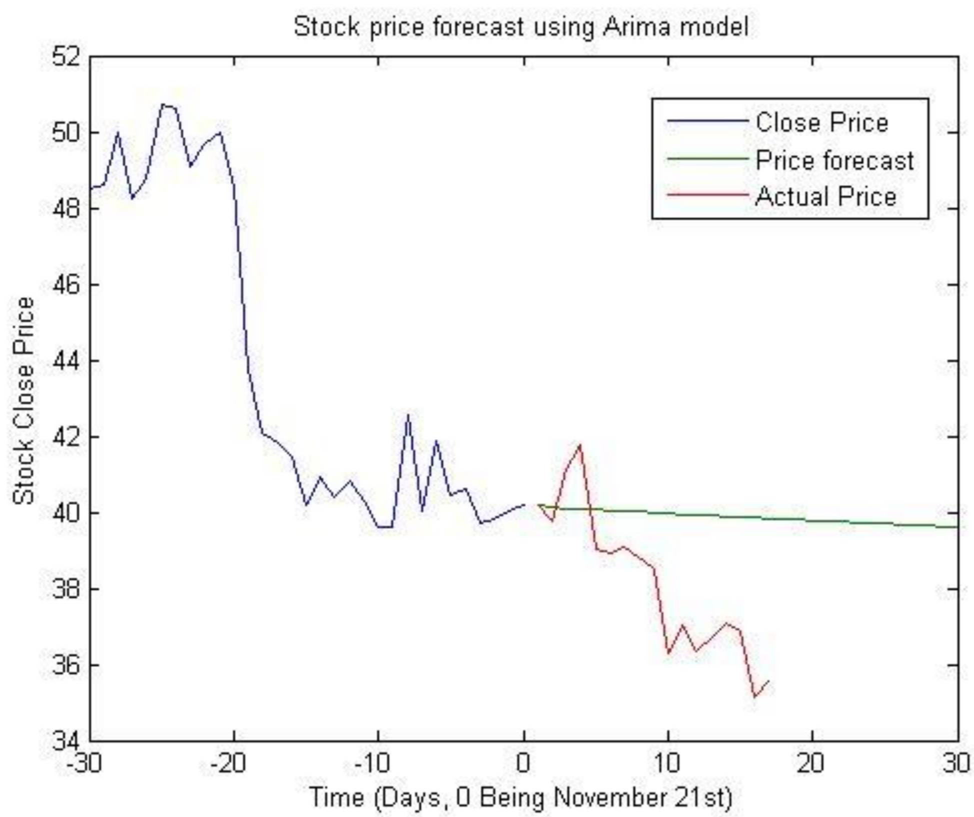
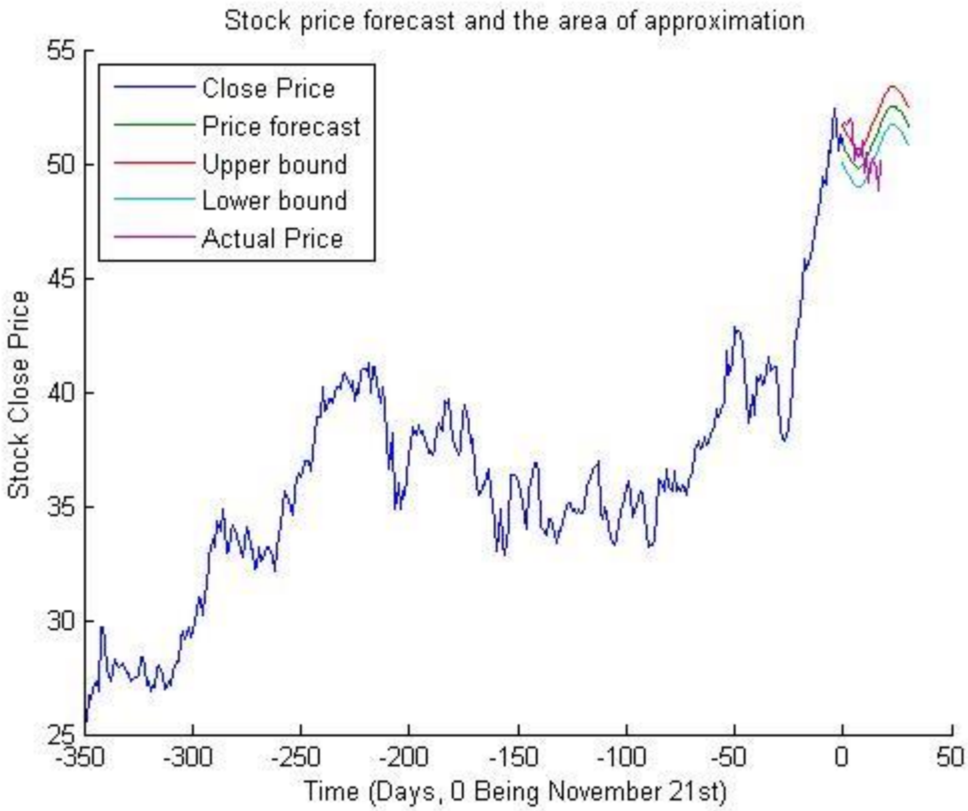
-10
0
10
20
30

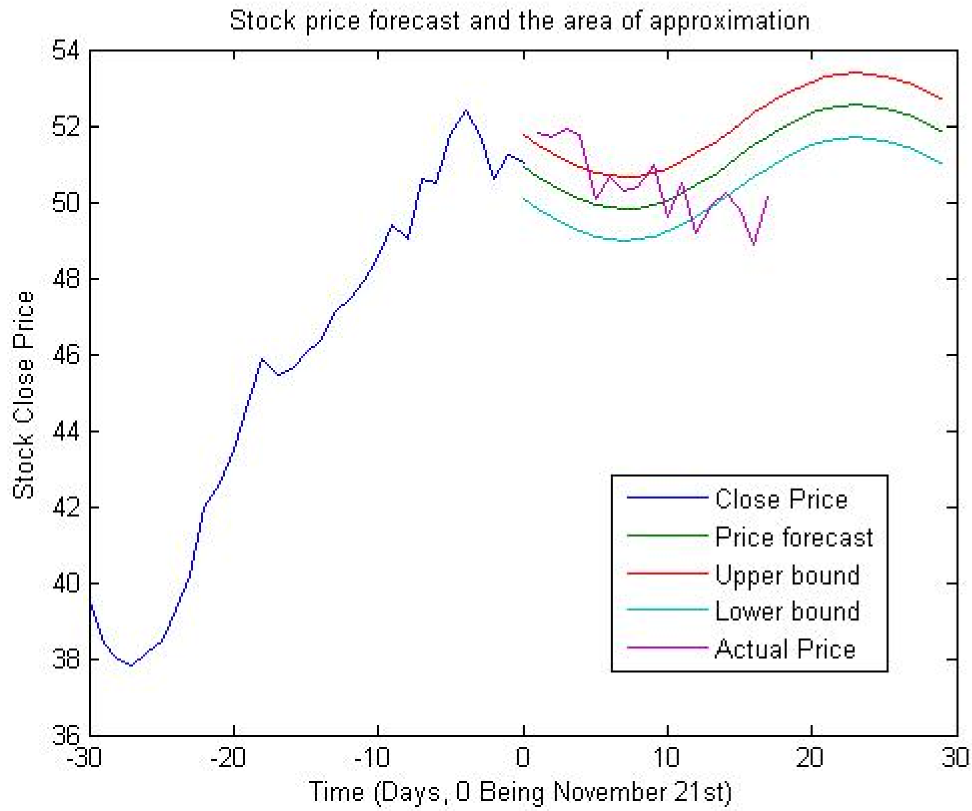

Stock price forecast using Arima model
Close Price
Price forecast
Actual Price
Stock Close Price
Time (Days, 0 Being November 21st)
52
50
48
46
44
42
40
38
36
34
-30
-20
-10
0
10
20
30

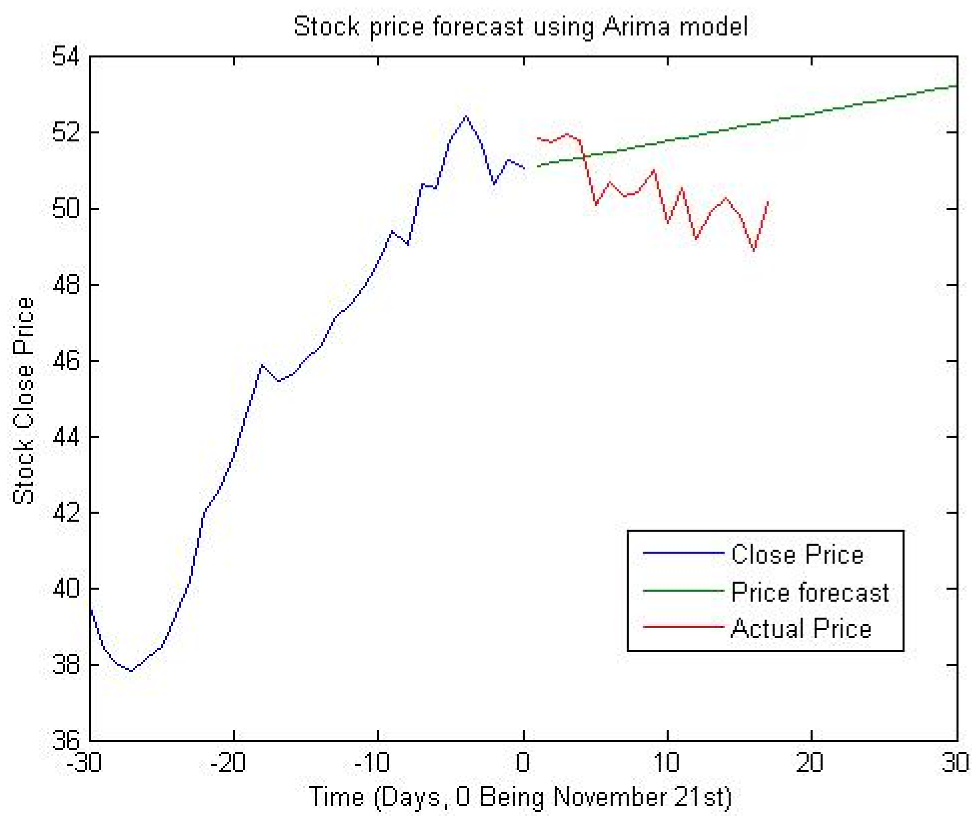
YHOO:

We bought stocks worth \$20,000 with a stock price of \$51.04. Both models predicted the same direction in stock price fluctuations. We can see that the close price has been steadily increasing, even throughout the whole year, without any major drops. Thus, we can expect the price to rise or at least stay at the same level.

Yahoo replaced google as a default search engine for Firefox creating a good catalyst for increase in share value, this in addition to phenomenal third quarter being reported (seekingalpha.com, 2014). The third quarter report attracted several important investors, such as Bill Ackman and a Swedish hedge fund Zenit Asset Management (insidermonkey.com, 2014). Alibaba (BABA) stock rose significantly giving a hand to yahoo which has a 15% share in that company, this constitutes the same amount as their own market capitalization.



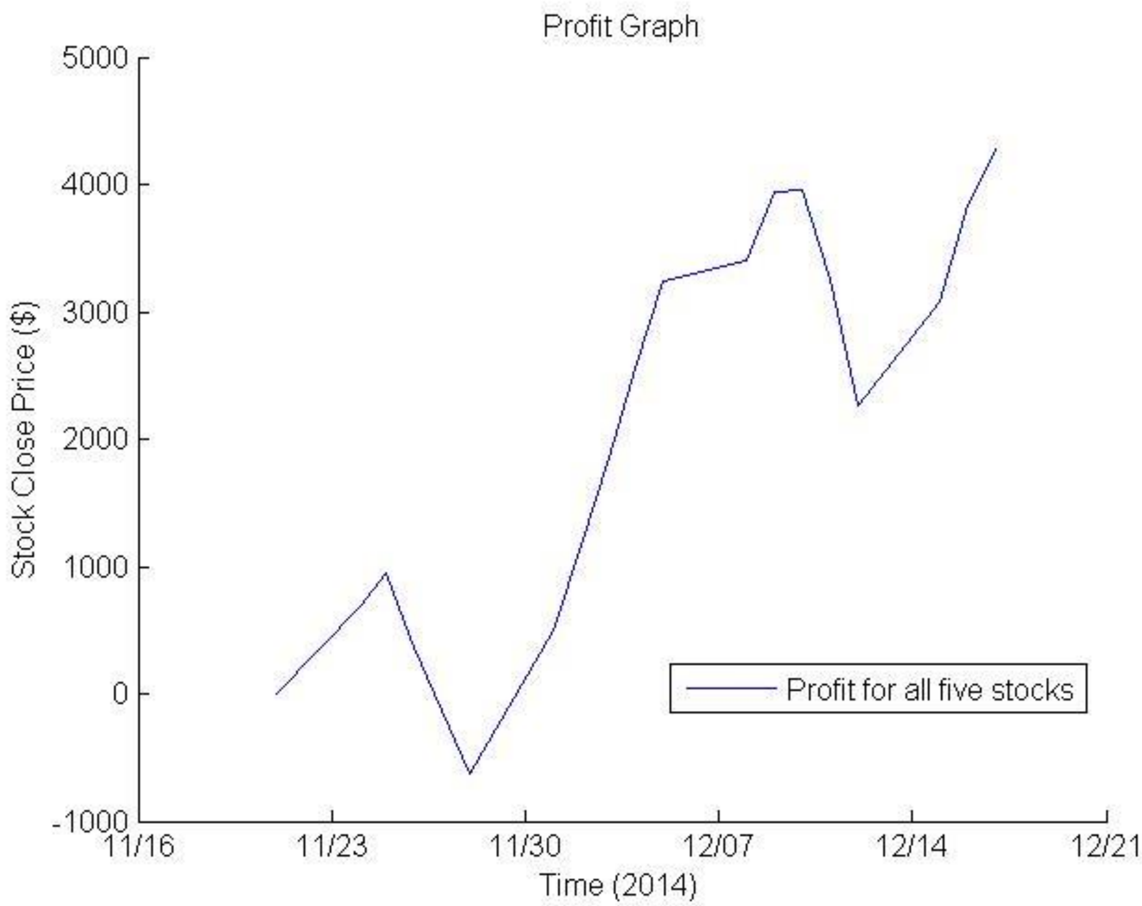

Stock price forecast and the area of approximation
Stock Close Price
Time (Days, 0 Being November 21st)
Close Price
Price forecast
Upper bound
Lower bound
Actual Price


Stock price forecast using Arima model
Stock Close Price
Time (Days, 0 Being November 21st)
Close Price
Price forecast
Actual Price

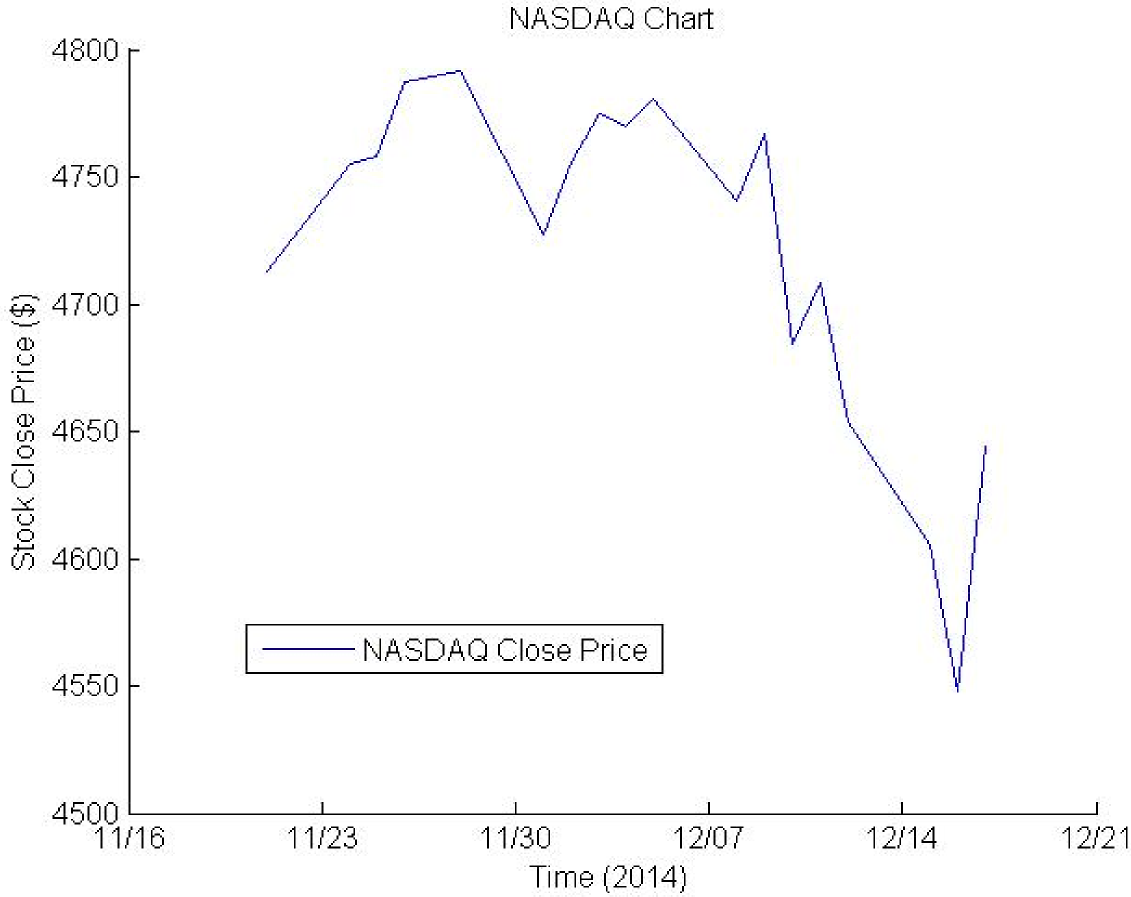
Following table depicts results for the reality test of the virtual investment.

Stock Ticker	Investment Type	Initial Price	Eventual Price	Net Gain
GRPN	Sell Short	$7.51	$7.19	$ 852.20
JCOM	Buy	$55.87	$60.67	$ 1718.28
TTGT	Buy	$10.24	$10.16	-$156.25
TWTR	Sell Short	$40.19	$35.57	$2299.08
YHOO	Buy	$51.04	$50.12	$ -360.50

Below is the profit graph for all five stocks throughout the 18 business days we tested our models.



Below is a NASDAQ close price graph, depicting the sharp fall.



With a virtual $100,000 we made a profit in this short term test with a net gain of $4352.81. In a period where the market went 5% down our model yielded a gain of 4.35%.

Conclusion

In this project we created two models for short-term predictions of stock prices. We compared the different models and summarized the results. To test forecasts of our models in real time, virtual $100,000 was used as an investment in different stocks. In a period of 18 business days, we were able to post a gain of over $4,000 while the NASDAQ index as a whole plummeted over 5%. Based on this performance we are confident that these models deserve the consideration of any individual who might want to invest in the stock market. Finally, after the thorough analysis of the data obtained, we have charted additional considerations for anyone who might decide to pick up on the project and continue working in the same direction.

Model Comparison and Summary:

We will compare the ARIMA model, Linear Least Squares Approximation plus Fouries Series approximation function, and with its NASDAQ modification, thus overall we have three models for evaluation and comparison.

Stock	95% CI	LSA+Fourier	Quality	NASDAQ	Quality	ARIMA	Quality
FB	5.6%	4.8%	Acceptable	2.1%	Acceptable	4.5%	Acceptable
BCOR	4.3%	6.7%	Not Acceptable	3.7%	Acceptable	4.7%	Not Acceptable
CCIH	11.5%	8.1%	Acceptable	6.9%	Acceptable	5.5%	Acceptable
EBAY	2.8%	4.6%	Not Acceptable	3.9%	Not Acceptable	2.8%	Acceptable
GRPN	7.5%	4.1%	Acceptable	2.4%	Acceptable	8.8%	Not Acceptable
IACI	3.5%	3.6%	Not Acceptable	1.9%	Acceptable	12.3%	Not Acceptable
JCOM	3.8%	1.7%	Acceptable	1.6%	Acceptable	1.3%	Acceptable
TTGT	5.1%	2.8%	Acceptable	4.8%	Acceptable	3.5%	Acceptable
TWTR	8.5%	9.1%	Not Acceptable	5.6%	Acceptable	3.9%	Acceptable
YHOO	4.0%	6.9%	Not Acceptable	4.2%	Not Acceptable	6.6%	Not Acceptable

Observations and analysis demonstrated that, for a 30 business day forecast, the LSA and Fourier series model used along with NASDAQ modification, yields the superior results as compared to all the other methods. It produced only two unacceptable stock predictions. The ARIMA model had four unacceptable results, while the raw LSA in unity with Fourier model had five unacceptable results. Moving forward, we suggest using the NASDAQ modification for price forecasting as well as ARIMA modeling. The combination of the two models will provide the best prediction and investment strategy.

We made a reality test of the models using virtual investment. We decided to test our models by choosing several stocks based on our variables (we chose five stocks for which both Nasdaq and ARIMA models agreed on the price trending directions.), external information and predictions on behavior of the stock prices made by other competent sources. $100,000 of virtual money was invested with no transaction or broker fees and we made a profit of $4,352. In a period where the market went 5% down, utilization of our model, yielded the 4.35% gains on invested capital.

Future considerations and improvements:

Due to time constraints we were not able to consider every detail in the model and some areas remain to be explored. For future considerations we suggest:

1) Taking volume under consideration. The number of stocks sold/bought on a given day has a significant impact and changes the stock price. . It has an effect on the volatility of the stock as well and is a promising area worth exploring into more depth.
2) Including other indexes in the model. Even though, NASDAQ has an effect on the stocks, so do the other market indexes. S&P 500, Dow Jones Industrial Average and New York Stock Exchange (NYSE) are just few more examples of what indexes might be included as a modification for the model. Especially impactful can be the utilization of stocks from NYSE.

We believe our stock forecasting models will be useful for individual investors and retirees looking for a stable future who have no access to detailed information about the performance of the companies behind the stocks.

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Appendix

We used Matlab to approximate stock prices by the following tools:

Least Squares Approximation plus Fourier Expansion model

Initialize variables.

```
filename = 'C:\Users\Andro\Documents\MATLAB\SpreadSheets\FB.csv';
delimiter = ',';
startRow = 2;
filename1 = 'C:\Users\Andro\Documents\MATLAB\SpreadSheets\FBfut.csv';
```

Format string for each line of text:
column1: date strings (%s)
column2: double (%f)
column3: double (%f)
column4: double (%f)
column5: double (%f)
column6: double (%f)
column7: double (%f)

```
formatSpec = '%s%f%f%f%f%f%f%[^\n\r]';
```

Open the file.

```
fileID = fopen(filename,'r');
fileID1 = fopen(filename1,'r');
```

Read columns of data according to format string.
This call is based on the structure of the file used to generate this code.

```
dataArray = textscan(fileID, formatSpec, 'Delimiter', delimiter, 'HeaderLines' ,startRow-1,
'ReturnOnError', false);
dataArray1 = textscan(fileID1, formatSpec, 'Delimiter', delimiter, 'HeaderLines' ,startRow-1,
'ReturnOnError', false);
```

Close the file.

```
fclose(fileID);
fclose(fileID1);
```

Convert the contents of column with dates to serial date numbers using date format string (datenum).

```
dataArray{1} = datenum(dataArray{1}, 'mm/dd/yy');
dataArray1{1} = datenum(dataArray1{1}, 'mm/dd/yy');
```

Allocate imported array to column variable names

```
Date = dataArray{:, 1};
Open = dataArray{:, 2};
High = dataArray{:, 3};
Low = dataArray{:, 4};
Close = dataArray{:, 5};
Volume = dataArray{:, 6};
AdjClose = dataArray{:, 7};

Date1 = dataArray1{:, 1};
Open1 = dataArray1{:, 2};
High1 = dataArray1{:, 3};
Low1 = dataArray1{:, 4};
Close1 = dataArray1{:, 5};
Volume1 = dataArray1{:, 6};
AdjClose1 = dataArray1{:, 7};
```

Clear temporary variables

```
clearvars filename delimiter startRow formatSpec fileID dataArray ans;
% plot close price chart
figure
hold on
plot(Date,Close);
datetick('x', 3) % show date into a month format
title('FaceBook Chart (FB)')
xlabel('Time (2013-2014)')
ylabel('Stock Close Price ($)')
hold off

% autoccorrelate close price data to identify number of relevant days
figure
autocorr(Close,length(Close)-1) % plot the autocorrelation
title('Autocorrelation Function')
xlabel('Time')
ylabel('Autocorrelation')
a = autocorr(Close,length(Close)-1);
[row,col]=find(a<0,1,'first'); % row-1 is the number of relevant days
% create a new array for relevant days
x = -(row-2):0;
Closef = fliplr(Close(1:(row-1)).');

% find the linear Least Squares Approximation(LSA) for relevant data
s = polyfit(x,Closef,1); % linear LSA coefficients
f = polyval(s,x); % LSA
% plot LSA and relevant close price data
```

```
figure
plot(x,Closef,'o',x,f,'-')
title('Linear Least Squares Approximation')
xlabel('Time (Days, 0 Being 12 September)')
ylabel('Stock Close Price')

% take the price difference between LSA and close price
diff = Closef-f;
% plot the price difference
figure
plot(x,diff,x,zeros(1,length(x)),'k')
title('Difference of the Price Data and the Least Squares')
xlabel('Time (Days, 0 Being 12 September)')
ylabel('Difference ofthe Stock Close Price')

% find the Fourier series for the price difference
Fourier = fit(x.',diff.','fourier2');
% plot Fourier series on the difference
figure
hold on
plot(Fourier,x,diff)
plot(x,zeros(1,length(x)),'k')
hold off
title('Fourier Series on the difference')
xlabel('Time (Days, 0 Being 12 September)')
ylabel('Stock Close Price')

% obtain Noise by subtracting Fourier series data from the price difference
Noise = (diff.'-Fourier(x));
% plot Noise
figure
plot(x,Noise,x,zeros(1,length(x)),'k')
title('Noise')
xlabel('Time (Days, 0 Being 12 September)')
ylabel('Stock Close Price')
% mean of absolute value of the Noise
NoiseA = mean(abs(Noise));

% create a forecast line
xfut = 0:length(Close1); % 30 days in the future
ffut = polyval(s,xfut); % LSA
forecasts = (ffut.'+Fourier(xfut)); % LSA plus Fourier series

% NASDAQ
[CloseN,nasdaq] = NASDAQ;
CloseNf = fliplr(CloseN(1:(row-1)).');
correl = corrcoef(CloseNf,Closef);
correl = correl(1,2);
forecasts = forecasts.*(1-0.1.*correl.*nasdaq.');

% area of prediction
areatop = forecasts + NoiseA; % area of prediction above forecast line
areabot = forecasts - NoiseA; % area below forecast line
```

```
% actual close price after 12 September
x1=1:length(Close1);
Close1f=fliplr(Close1.');

% plot the close price before 12 September, forecast line, area of
% prediction and the actual close price after 12 September
figure
hold on
plot(-(length(Close)-1):0,fliplr(Close.'),xfut,forecasts,xfut,areatop,xfut,areabot,x1,Close1f)
legend('Close Price','Price forecast','Upper bound','Lower bound','Actual
Price','Location','NorthWest')
title('Stock price forecast and the area of approximation')
xlabel('Time (Days, 0 Being 12 September)')
ylabel('Stock Close Price')
hold off

% Zoomed in version of the final graph on -30 to 30 on the x-axis
if length(x)>30 % if the number of relevant days is more than 30
    xz=x(length(x)-30:length(x));
    Closefz=Closef(length(Closef)-30:length(Closef));
else % if the number of relevant days is less than 30
    xz=x;
    Closefz=Closef;
end
% zoomed in prediction area
xfutz = xfut(1:30);
forecastz = forecasts(1:30);
areatopz = areatop(1:30);
areabotz = areabot(1:30);
% zoomed in actual future price
x1z = x1(1:30);
Close1fz = Close1f(1:30);
% plot the zoomed version
figure
plot(xz,Closefz,xfutz,forecastz,xfutz,forecastz+NoiseA,xfutz,forecastz-NoiseA,x1,Close1f)
legend('Close Price','Price forecast','Upper bound','Lower bound','Actual
Price','Location','NorthWest')
hold off
title('Stock price forecast and the area of approximation')
xlabel('Time (Days, 0 Being 12 September)')
ylabel('Stock Close Price')

% check how off the prediction is from the actual price
forecastlength = forecasts(1:length(Close1f.'));
diffut = abs(forecastlength - Close1f.');
percent = diffut./Close1f.'*100;
% max difference between forecast and actual future price
percentmax = max(percent) % percent difference
checkmax = max(diffut) - NoiseA % dollar difference
% min difference between forecast and actual future price
percentmin = min(percent) % percent difference
checkmin = min(diffut) - NoiseA % dollar difference
% average difference between forecast and actual future price
diffutA = mean(diffut);
```

```
Close1fA = mean(Close1f.');
percentA = diffutA./Close1fA*100 % percent difference
checkA = diffutA - NoiseA % dollar difference
```

NASDAQ Modification:

```
% autocorrelate close price data to find number of relevant days and plot the autocorrelation
a = autocorr(Close,length(Close)-1);
[row,col]=find(a<0,1, 'first'); % row-1 is the number of relevant days
x = -(row-2):0;
Closef = fliplr(Close(1:(row-1)).');

% find the linear Least Squares Approximation(LSA) for relevant data
s = polyfit(x,Closef,1); % linear LSA coefficients
f = polyval(s,x); % LSA

% create the prediction
xfut = 0:30; % number of days in the future
forecasts = polyval(s,xfut); % prediction line

% normalize NASDAQ between 0-1
nasdaq = (forecasts-min(forecasts))./(max(forecasts)-min(forecasts));
```

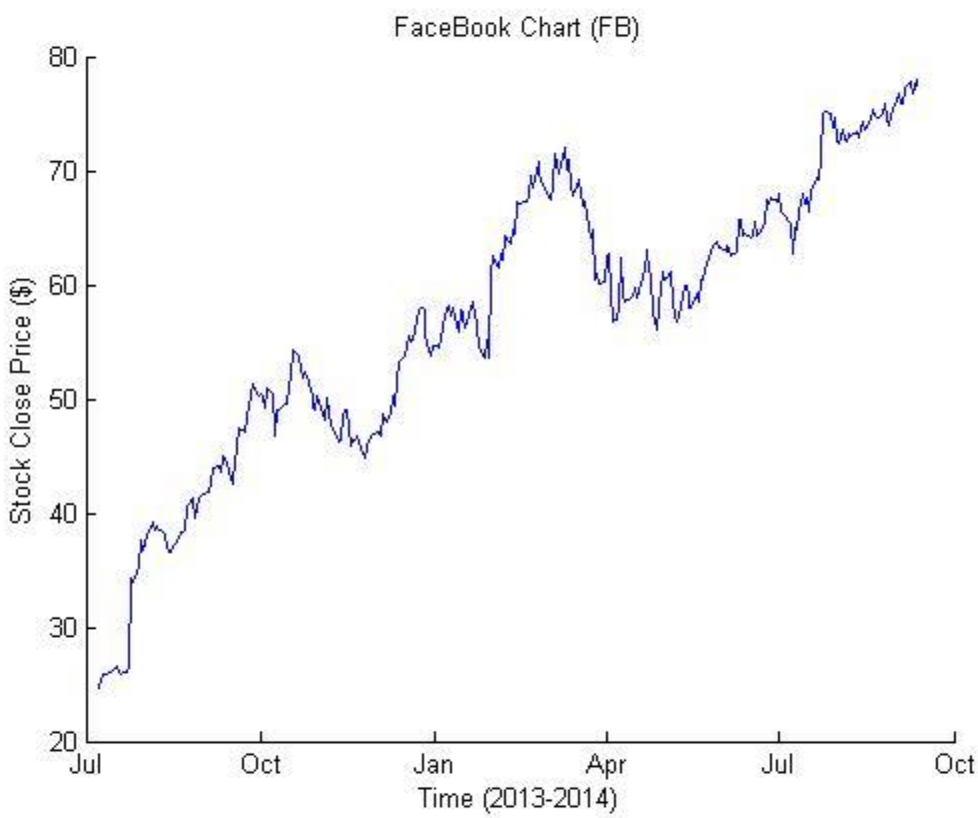
Arima Model

```
Close = fliplr(Close.').';

% create an arima model with given values
model = arima(1,1,3);
% estimate arima model with stock close price
modelfit = estimate(model,Close);
% create an arima forecast function
[Y,YMSE] = forecast (modelfit,30,'Y0',Close);
% find upper and lower 95% confidence interval using arima
lower = Y-1.96*sqrt(YMSE);
upper = Y+1.96*sqrt(YMSE);
% plot arima forecast
figure
plot(xz,Closefz,1:length(Y),Y,x1,Close1f)
% hold on
% plot(1:length(Y),lower,'r:')
% plot(1:length(Y),upper,'r:')
legend('Close Price','Price forecast','Actual Price')
title('Stock price forecast using Arima model')
```

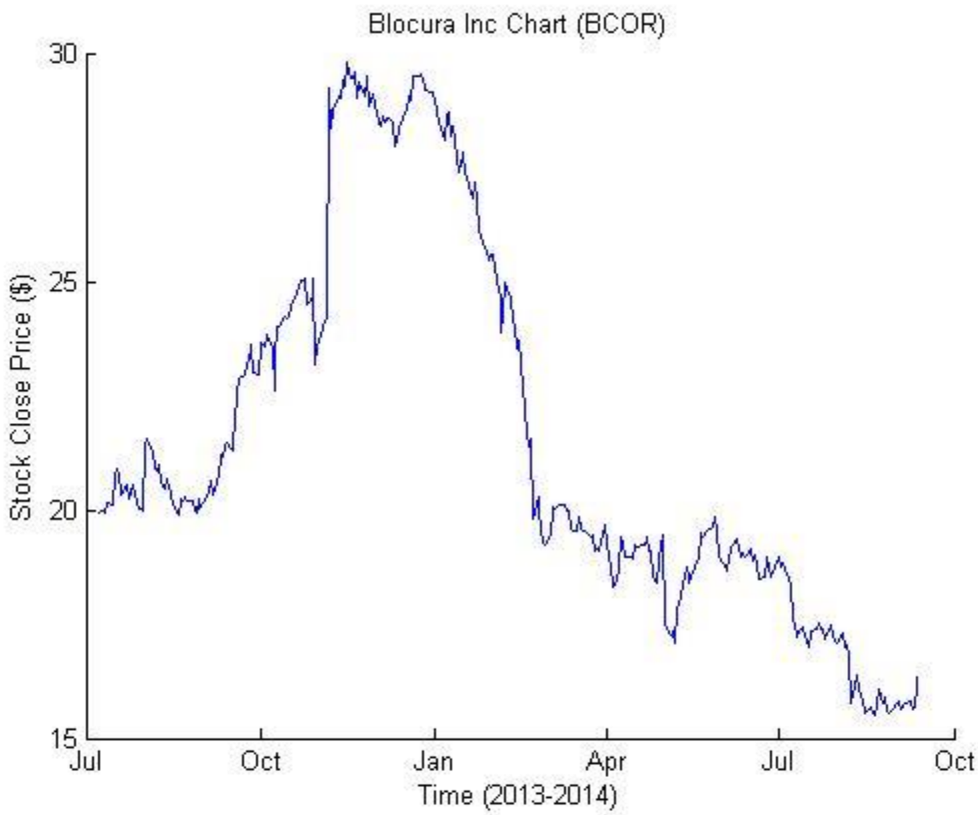
```
xlabel('Time (Days, 0 Being 12 September)')
ylabel('Stock Close Price')

% check how off arima prediction is from the actual price
diffarima = abs(Y-Close1f.');
percentarima = diffarima./Close1f.'*100;
% max percent inaccuracy of arima
maxarima = max(percentarima)
% min percent inaccuracy of arima
minarima = min(percentarima)
% average percent inaccuracy of arima
diffarimaA = mean(diffarima);
percentarimaA = diffarimaA./Close1fA*100
```

Industry data

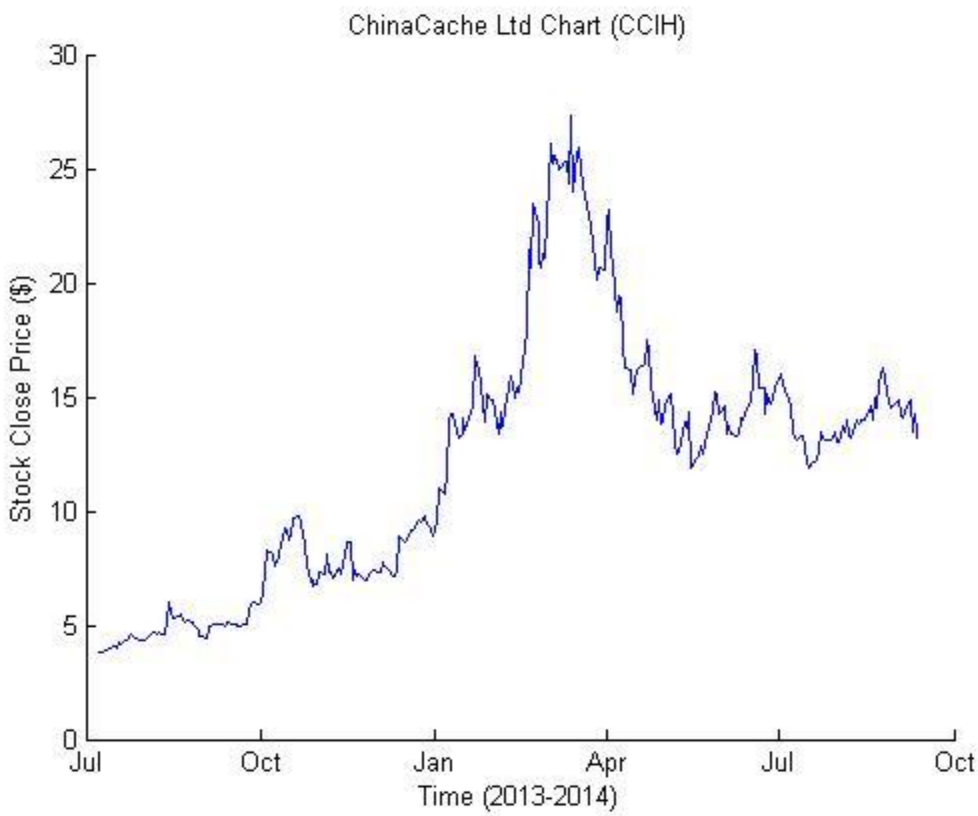
FB:



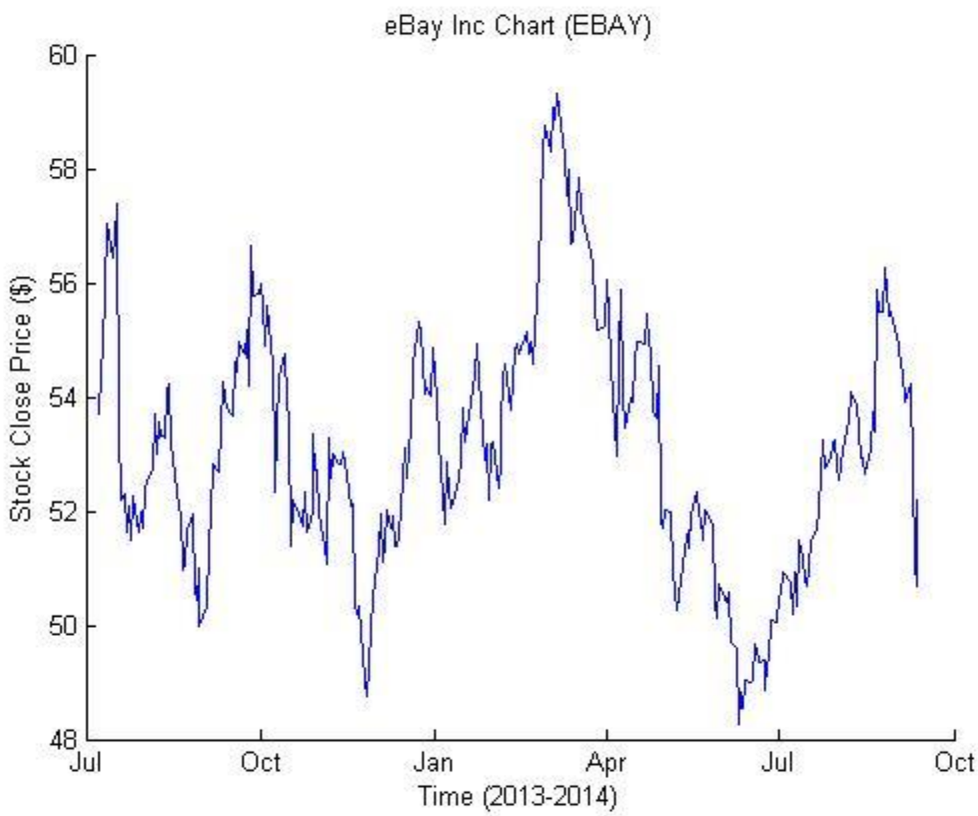
BCOR:


Blocura Inc Chart (BCOR)
30
25
20
15
Stock Close Price ($)
Jul
Oct
Jan
Apr
Jul
Oct
Time (2013-2014)

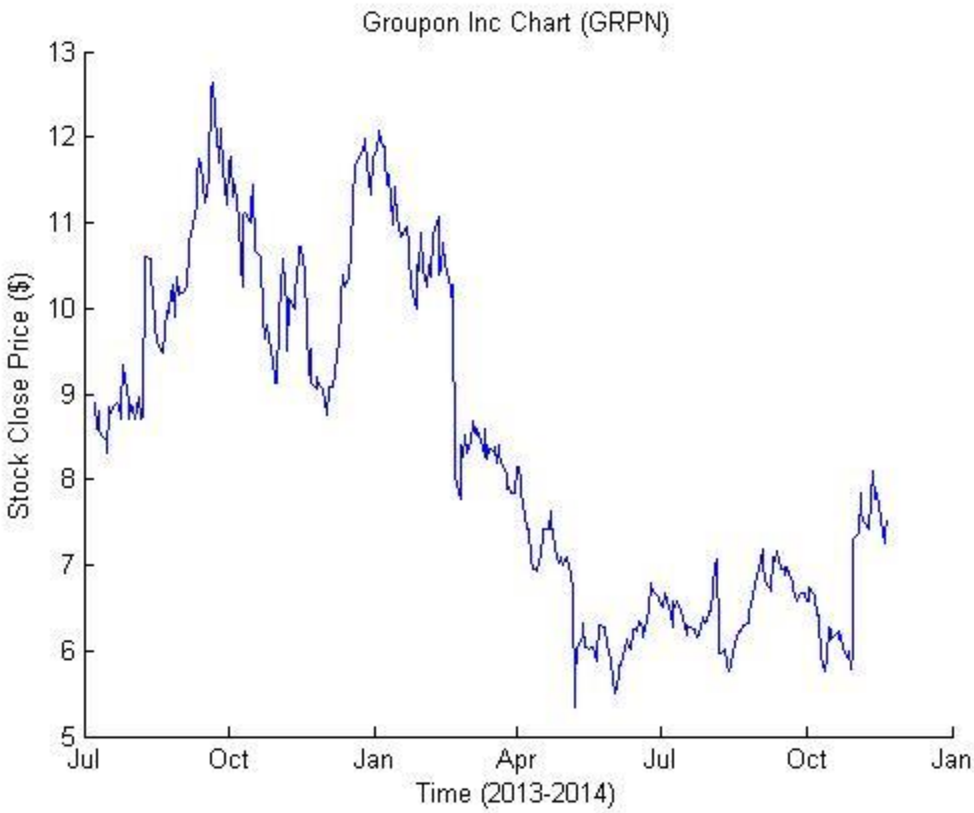
CCIH:


ChinaCache Ltd Chart (CCIH)
Stock Close Price ($)
30
25
20
15
10
5
0
Jul
Oct
Jan
Apr
Jul
Oct
Time (2013-2014)

EBAY:

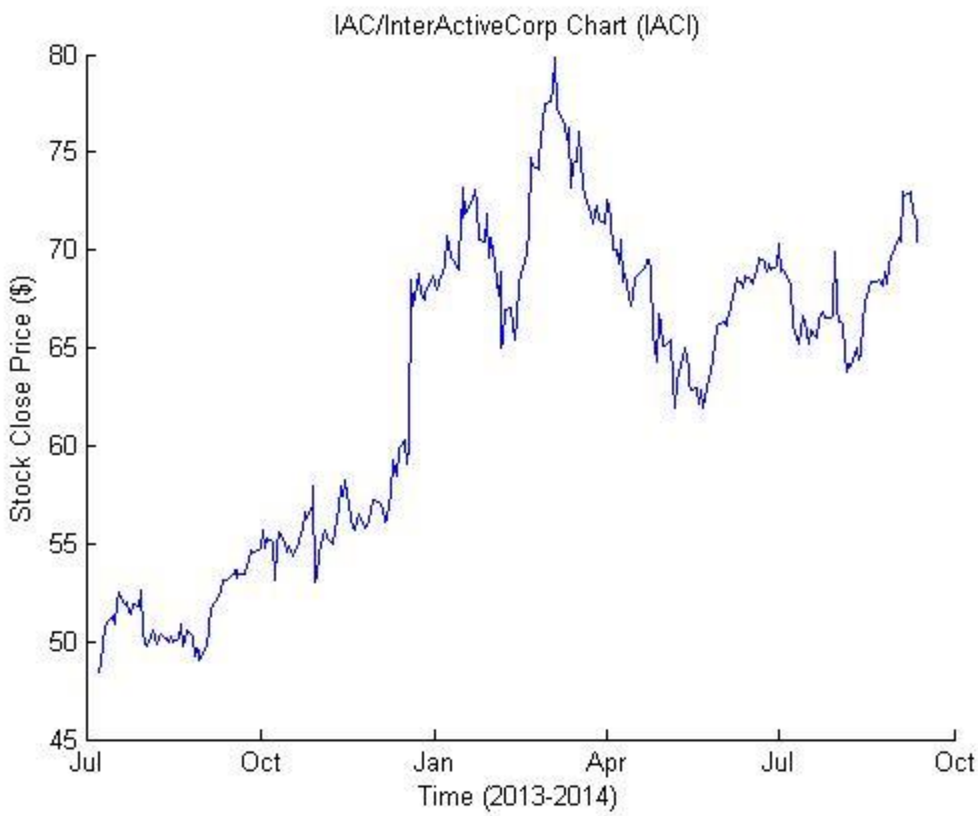

eBay Inc Chart (EBAY)
60
58
56
54
52
50
48
Stock Close Price ($)
Jul
Oct
Jan
Apr
Jul
Oct
Time (2013-2014)

GRPN:

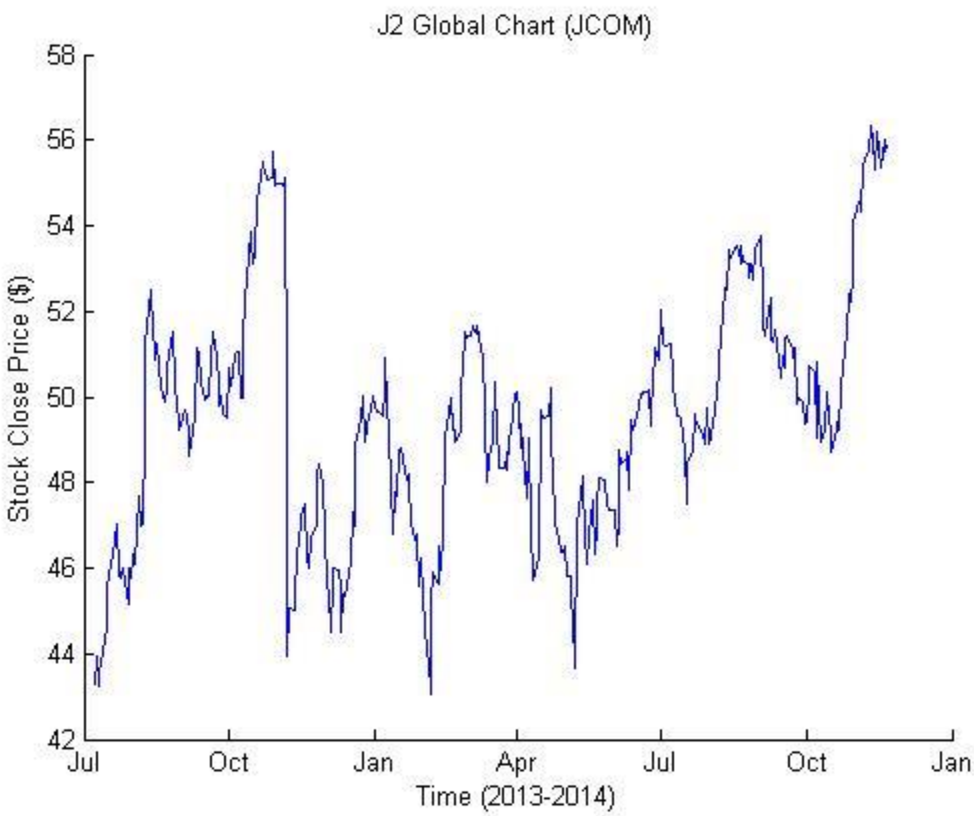


Groupon Inc Chart (GRPN)
Stock Close Price ($)
13
12
11
10
9
8
7
6
5
Jul
Oct
Jan
Apr
Jul
Oct
Jan
Time (2013-2014)

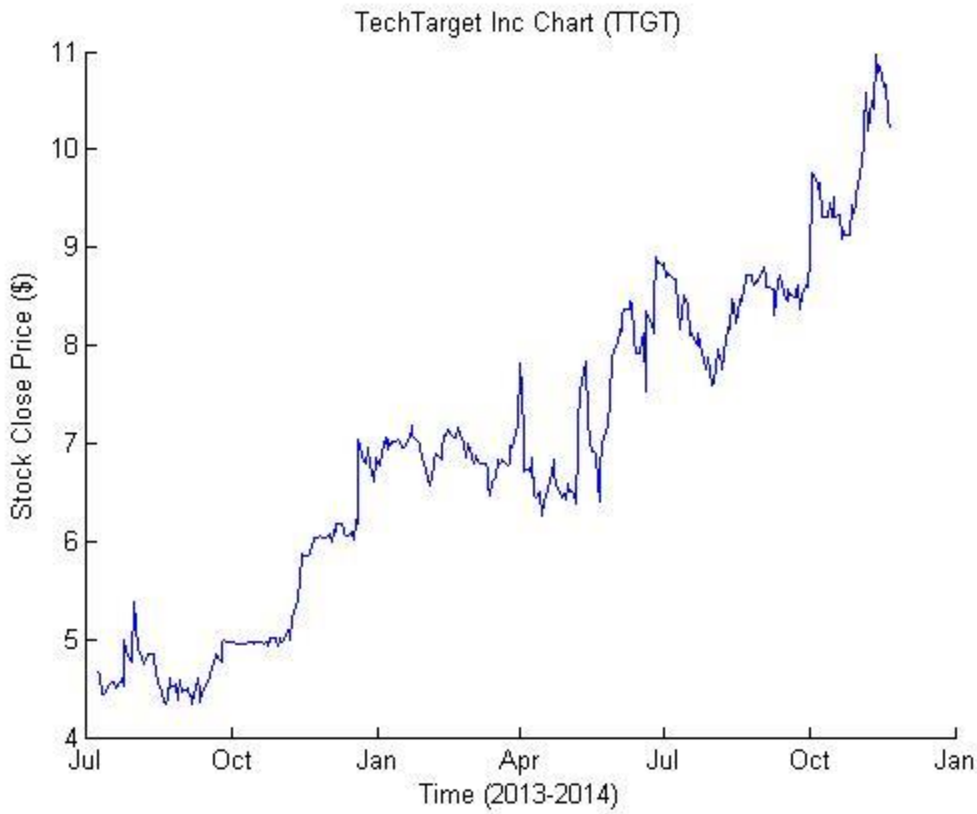
IACI:


IAC/InterActiveCorp Chart (IACI)
Stock Close Price ($)
80
75
70
65
60
55
50
45
Jul
Oct
Jan
Apr
Jul
Oct
Time (2013-2014)

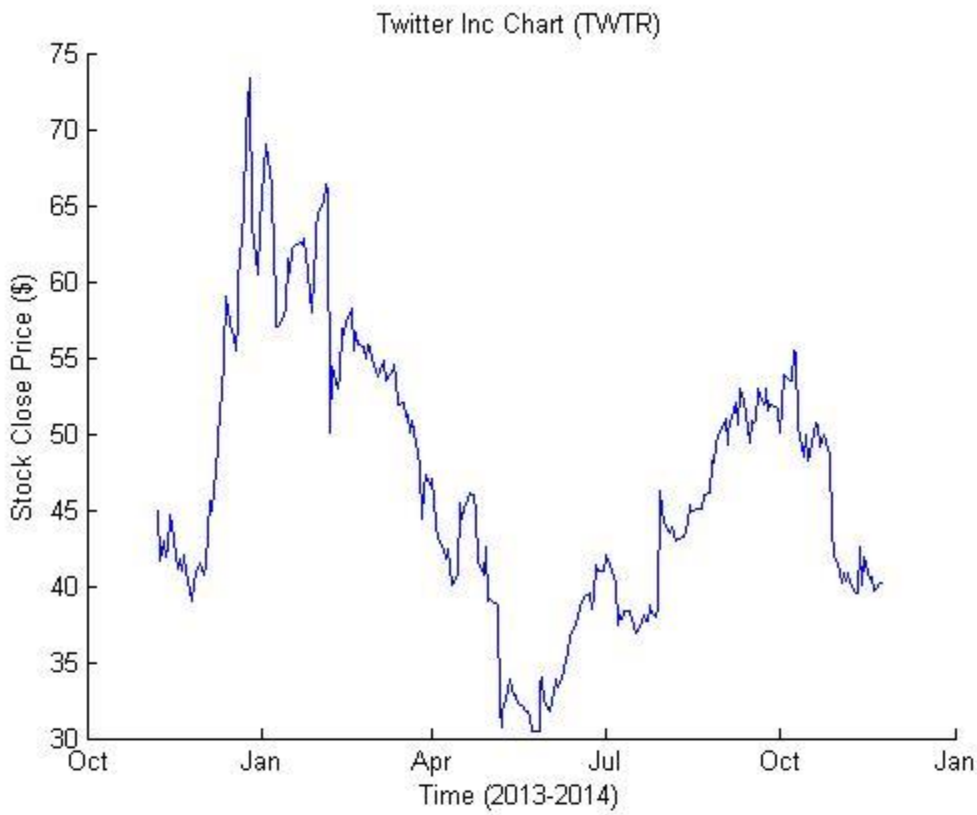
JCOM:


J2 Global Chart (JCOM)
Stock Close Price ($)
58
56
54
52
50
48
46
44
42
Jul
Oct
Jan
Apr
Jul
Oct
Jan
Time (2013-2014)

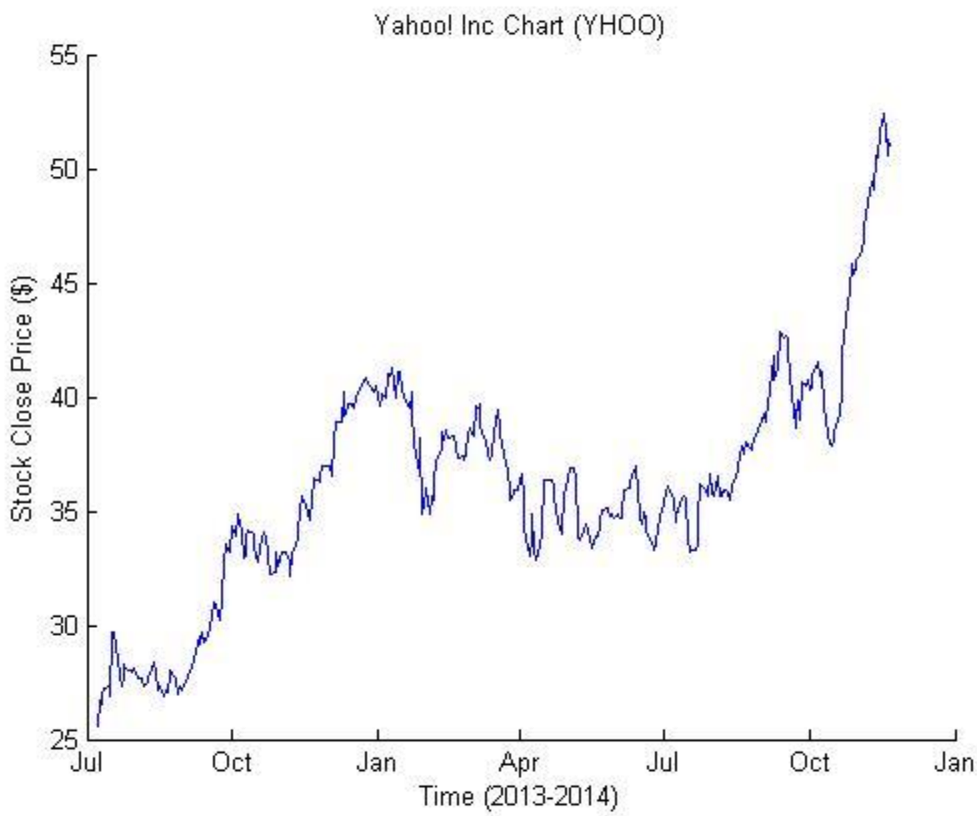
TTGT:


TechTarget Inc Chart (TTGT)
Stock Close Price ($)
11
10
9
8
7
6
5
4
Jul
Oct
Jan
Apr
Jul
Oct
Jan
Time (2013-2014)

TWTR:

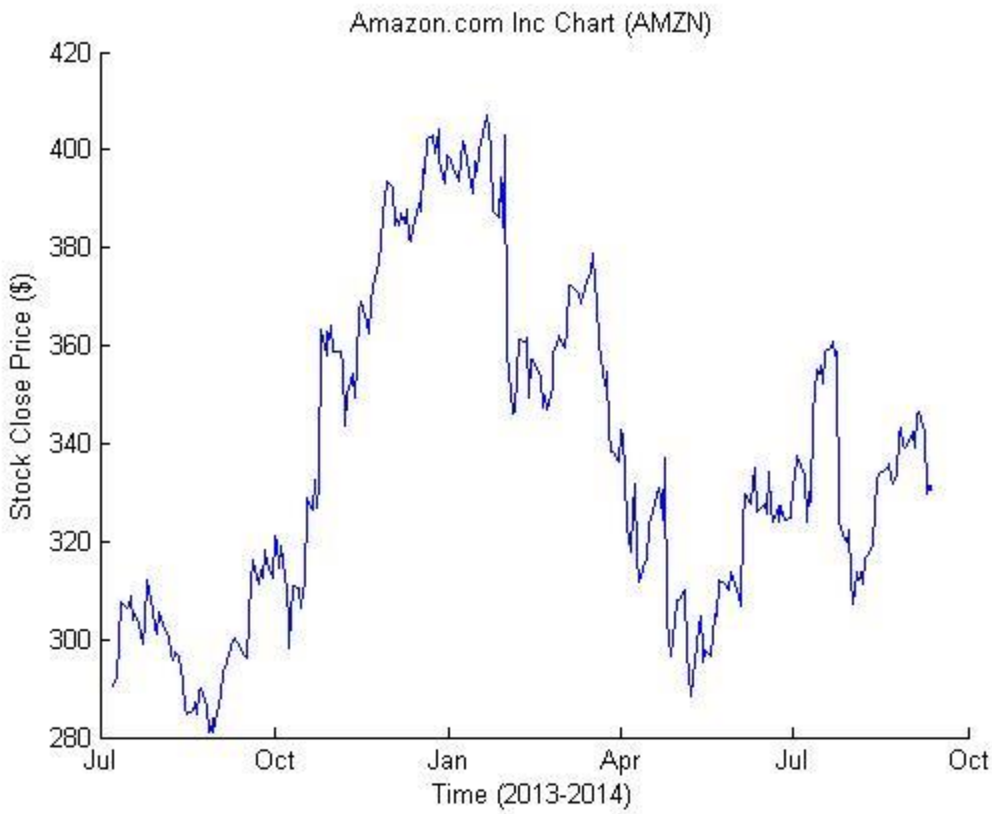

Twitter Inc Chart (TWTR)
Stock Close Price ($)
75
70
65
60
55
50
45
40
35
30
Oct
Jan
Apr
Jul
Oct
Jan
Time (2013-2014)

YHOO:

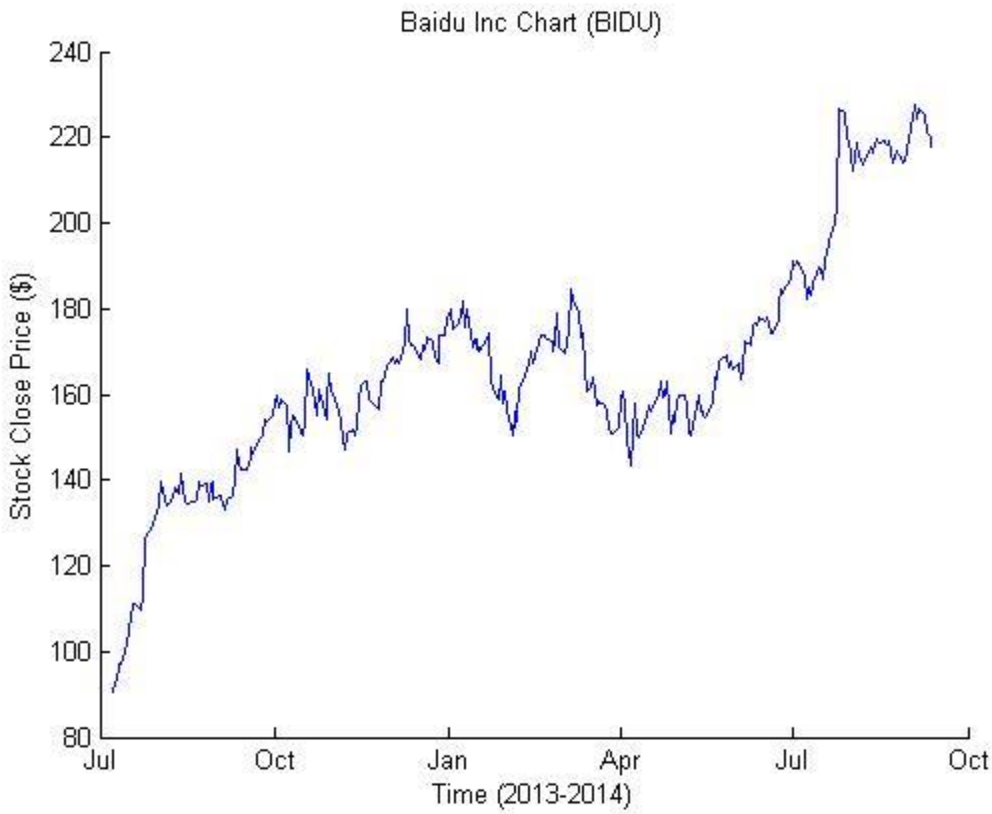

Yahoo! Inc Chart (YHOO)
55
50
45
40
35
30
25
Stock Close Price ($)
Jul
Oct
Jan
Apr
Jul
Oct
Jan
Time (2013-2014)

Additional Observations Data

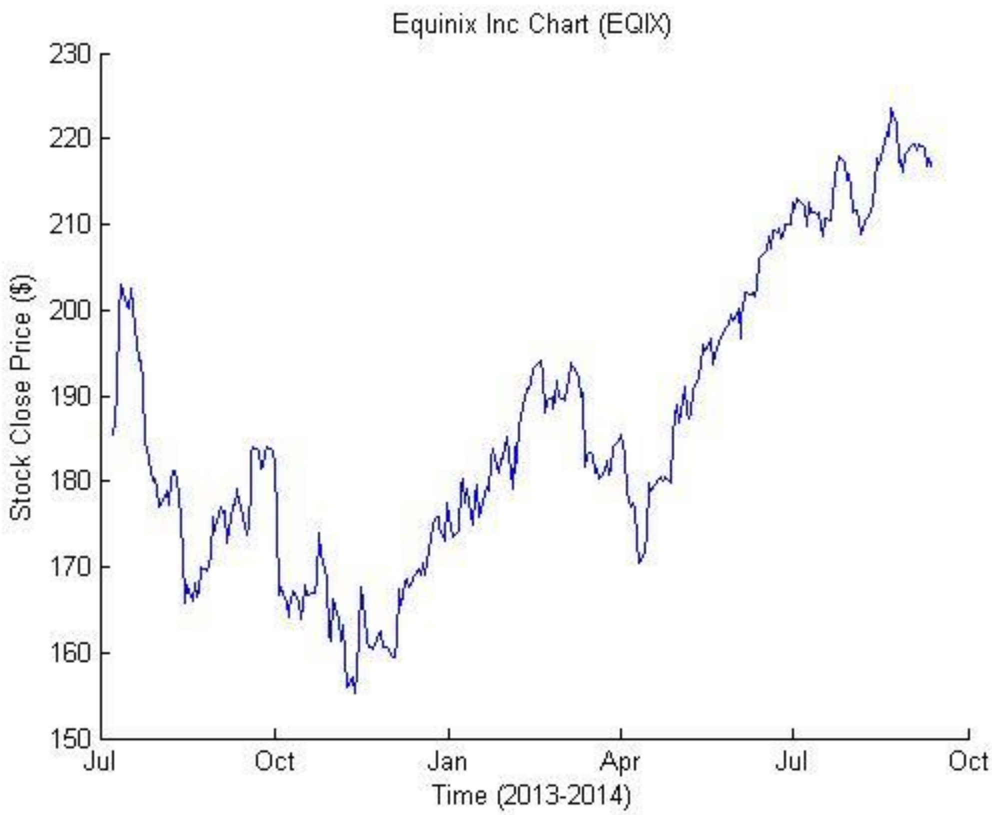
AMZN:



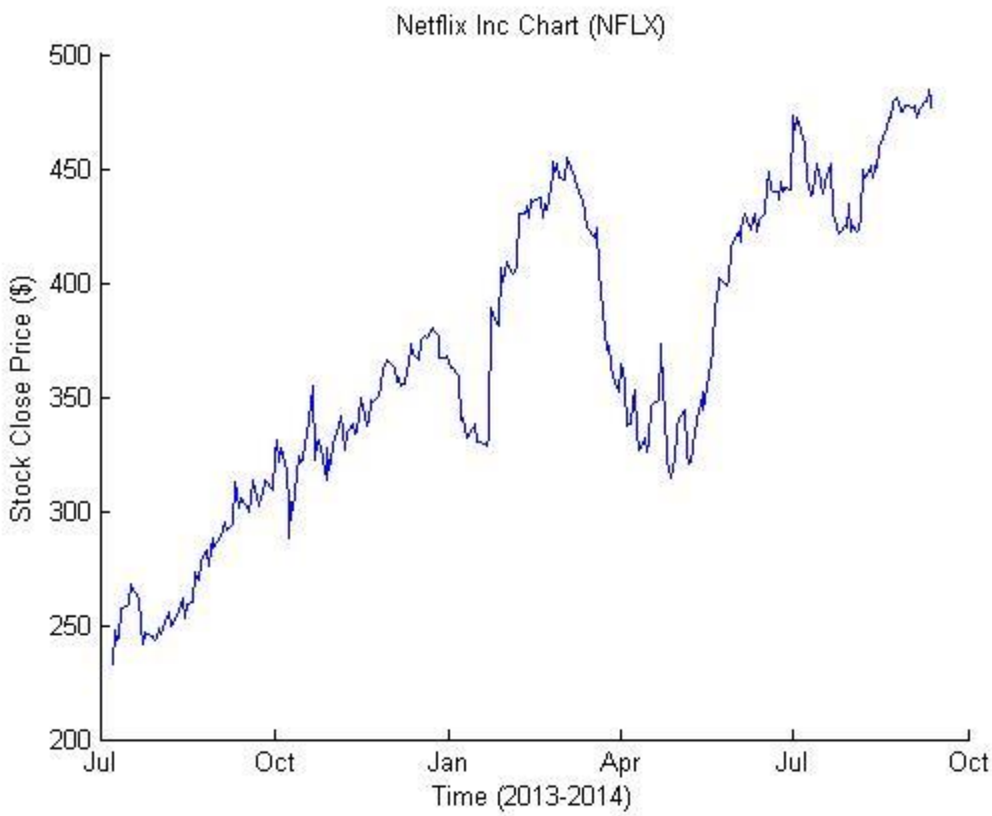
BIDU:


Baidu Inc Chart (BIDU)
240
220
200
180
160
140
120
100
80
Stock Close Price ($)
Jul
Oct
Jan
Apr
Jul
Oct
Time (2013-2014)

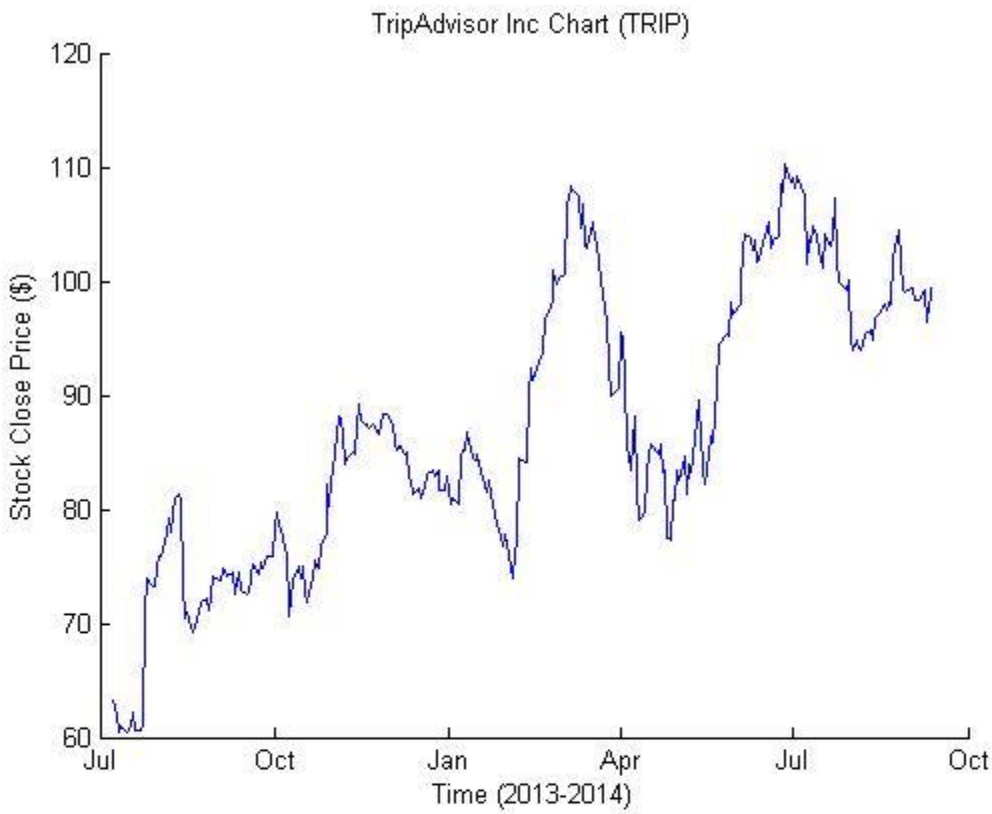
EQIX:


Equinix Inc Chart (EQIX)
230
220
210
200
190
180
170
160
150
Stock Close Price ($)
Jul
Oct
Jan
Apr
Jul
Oct
Time (2013-2014)

NFLX:


Netflix Inc Chart (NFLX)
Stock Close Price ($)
500
450
400
350
300
250
200
Jul
Oct
Jan
Apr
Jul
Oct
Time (2013-2014)

TRIP:



TripAdvisor Inc Chart (TRIP)
Stock Close Price ($)
120
110
100
90
80
70
60
Jul
Oct
Jan
Apr
Jul
Oct
Time (2013-2014)