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Investigating Volatility Trends of Silver Through an Analysis of Stock Options Prices

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ABSTRACT

Volatility is a statistical measure that describes the amount of fluctuation in prices for a given investment; generally, the higher the volatility for an investment, the riskier it is perceived to be. Traders study volatility history so that they can make informed decisions on how to invest capital. The purpose of this article is to analyze implied volatility values, which are derived from the investment's price and are considered the market's estimate of the investment's actual volatility, for silver electronically traded fund (ETF) options in periods of both high and low price movement. In doing so, we desired to see whether or not the general market perception of silver ETF options demonstrated significantly different trends between periods of high and low price movement. Our results demonstrated that implied volatility trends did not show any significant differences between the periods of low and high price movement, and therefore market perception of iShares Silver Trust (SLV) options did not radically change, regardless of the price changes of SLV.

Introduction to Derivatives and Options

The notional value of securities traded in the derivatives market was $1.2 quadrillion in 2010, or 20 times the size of the world economy; to put this in perspective, the world's gross domestic product (GDP) was between $50 trillion and $60 trillion for that same year (Cohan, 2010). This market is not limited to those who consider themselves traders; it is becoming a more common practice for employers to give stock options, which are derivatives, to employees as a job benefit (Udell, 2008). As such derivative markets as the stock options market become more widespread, so does understanding trends within these markets.

Individuals who participate in any type of investment market are most likely interested in finding trends that may enhance their investment portfolio's returns and minimize its risks.

The derivatives market is a risky investment market that has had a substantial impact on the world's economy. This market is composed of derivatives—financial agreements between two parties that have a value based on an asset. Stock options and electronically traded funds (ETFs) are examples of derivatives in these markets because their payoff is directly related to the price of the core asset that it represents (Baken & Nandi, 1996). Stock options are contracts to buy or sell shares of stock at a certain fixed price based on the trading price at the time of purchase (Lardner, 1999). They are particularly attractive because they have the potential to perform incredibly well with a lower risk than buying the stock itself (Sloan & Perrucci, 2003).

Stock option volatilities attract a lot of interest from investors and researchers because they can influence how both private investors and industries choose to buy and sell options. Volatility is generally described as a measure that determines the amount of risk in relation to the number of changes in an investment’s value. Generally, the higher the volatility, the riskier the investment is perceived to be by investors. Investments with lower volatility levels are seen to be more stable. Without a doubt, financial risk is one of the most important factors in determining how people invest. Chance (2004) argues that the origin of financial risk is derived from uncertainty. Uncertainty can exist within many different markets from interest rates and exchange rates to stock prices.

With the recent recession, uncertainty in investments has increased; people are more cautious about investing in financial markets and weigh heavily financial risks. Clapperton (2010) studies the recent recession’s effects on investor perception as well as the types of investments in which individuals are choosing to invest. His findings suggest that such precious metals as gold and silver have never been a safer bet for investors and more people are taking notice. Because there is reasonable interest in investing in precious metals, it is important to understand what drives their prices.

Schoenberger (2011) states that gold’s “artificial scarcity,” the large amount of physical work required to produce gold, and such social implications as power and control drive the value of gold to be more than just monetary value. Coulson (2005) further states that gold has the potential to perform incredibly well simply because the U.S. dollar has had a history of representing weak value in proportion to other currencies.

Cross (2005) analyzes various data, including the prices of U.K. gold product in ETFs, the amount of U.S. jewelry sales, and the percent of total durable goods in the U.S. She uses these data to argue that gold is a very “emotional” metal that behaves akin to the stock market. It is estimated by her studies that the gold market is a small, isolated market that is very unstable and she does not recommend gold as an investment. Her claim that gold holds emotional characteristics, however, supports Schoenbeger’s claim that the value of gold is more than just monetary value.

Borzykowski (2011) takes a somewhat neutral position and argues that what people should invest in depends on the type of investor they are (conservative, middle-of-the-road, or aggressive). He makes his case by citing other respectable economists, such as Michael White. Borzykowski suggests that conservative investors hold on to their investments for the long term with their main goal being the preservation of existing capital. For middle-of-the-road, or balanced, investors, it is recommended by Borzykowski that they invest in the financial sector. For aggressive investors, however, Borzykowski argues that they should consider gold bars or gold ETFs. When smart investors choose to invest in such precious metals as gold and silver, they examine the metals’ historical volatility levels.

The method that finance experts use to analyze volatility levels involves using traditional statistical studies on any given financial time series. This analysis leads to historical volatility, a method for estimating risks based on historical information on the portfolio's recent performance. When calculating historical volatility, financial experts may use the exponentially weighted moving average (EWMA) because it assigns higher weights to more recent prices. This is particularly useful when an investor cares much more about an option's recent history than its older history. The generalized autoregressive conditional heteroskedasticity (GARCH) is another model that superseded the EWMA and is frequently used to calculate volatilities. There are many methods that financial experts can exploit to conduct analyses on various time series and historical volatilities. There is, however, another volatility level that is heavily studied by investors and tested by these formulas: implied volatility. This type of volatility is explained later in this article and is one of the key concepts of this project.

Black-Scholes Model

In order to set a standard to estimate the volatilities of the gold and silver ETF options, a pricing model must be used. Black and Scholes (1973) use mathematical data to construct a theoretical pricing model that can value options. This model is still used frequently by economists so that they can reduce financial risk by hedging properly. The company from which we obtained our analyzed data computed their implied volatility values based on the Black-Scholes model.

The mathematical formulas for the Black-Scholes are as follows:

$$c = S_0 N(d_1) - K e^{-rT} N(d_2)$$

$$p = K e^{-rT} N(-d_2) - S_0 N(-d_1)$$

where

$$d_1 = (\ln(S_0 / K) + (r + \sigma^2/2)T) / (\sigma \sqrt{T})$$

$$d_2 = d_1 - (\sigma \sqrt{T})$$

c = call option price
p = put option price
S_0 = stock price at time zero
K = strike price
R = risk-free rate
σ = volatility of the stock price
T = time to maturity

$N(x)$ is the cumulative probability distribution function for a standard normal distribution (Hull, 2012). Thus, given these equations, it is possible to solve for σ, the volatility of the stock price, if we know the call and put prices of the options. These allow companies to calculate implied volatility values. Call options are contracts that allow an investor to buy assets at an agreed price on or before a specific date. Put options are very similar to call options, the only difference being that it deals with the selling of assets. The Black-Scholes model accounts for both types of options in its formulas. In addition, the results of our programs contain data for both call and put options.

Implied Volatility

Implied volatility (IV) can be described as the standard deviation attained when the price of an option equals a particular model's price for that same option (Chance, 2004). Implied volatilities solve for volatility based on the market's prices. Understanding volatility is imperative for both individuals and corporations who wish to be successful with investment portfolios that contain such assets as stock options (Baken & Nandi, 1996).

Before the emergence of behavioral finance, financial experts believed that social factors were not significant in determining implied volatilities. Cont (2001) identifies and addresses problems that are common to all statistical studies of financial time series. He defies conventional pricing models by proposing that there are "stylized facts" that produce errors within them. The author reveals that stylized empirical facts consist of nontrivial properties that are common across a wide range of instruments, markets, and time periods. He concludes that these properties are model-free and that they result from a general hypothesis of qualitative nature. In essence, even though investors may have had ample information regarding the economic forecast for the option or security, volatilities demonstrated stylized facts that contradict what economists would traditionally predict.

Shiller (2003) provides an extensive literature review, gathering data of stock volatility, stock prices, and real dividends in order to determine if such findings as Cont's are true and relevant. He concludes that ordinary investors often make decisions that are not based on economic equations or data, which supports Cont's argument that stylized empirical facts exist.

Thus, the theory of behavioral finance was created so that the relationship between investors' perceptions of option volatilities (implied volatility) and the actual volatilities of these options could be better understood. It seeks to explain the investors' reasoning behind their financial behavior. Studies in behavioral finance have become more prevalent over the past few years and focus on psychological factors that may influence investor spending.

Behavioral finance is driven by the logic that perceived volatility is likely affected by emotional and social factors. In addition, it shows that investors may make decisions for various reasons that are independent of what pricing models, such as Black-Scholes, predict. Because of the recent recession, many investors are now turning to gold and silver ETFs. With the exception of the experiment on which this project is based, there have been no recent studies of investors' perceptions on the volatilities of these securities; additionally, there have been no recent studies on the actual volatilities of these securities.

A previous study conducted by Downey (2011) implemented the Black-Scholes model to compare the volatility of silver prices to investors' speculation of the volatility. The question posed by the authors is whether or not these views agreed with the data on actual volatility. The authors then analyzed historical data on the rising and falling of silver prices, and compared both the historical and implied volatilities to the expectations of investors. An investigation of stock option prices for the silver ETF supports their argument that investors viewed silver as being unusually volatile in January 2010 and December 2011. They then conclude that volatility had been consistent throughout the period, and that low or high prices of silver options do not affect the actual volatility of silver.

This investigation expanded on Downey's study to cover a 12-month time series. Instead of conducting a hypothesis test between two sets of data, a complete analysis using Excel Visual Basic for Applications (VBA) was conducted to determine the behavioral characteristics of volatility for silver ETFs by graphing the volatility smirks for periods of low and high price movement. If investors expand their knowledge on the behavior of options in the derivative market, then it will allow them to make better decisions on their investments.

Methods

In this study, prices for the iShares Silver Trust (SLV) ETF were analyzed so that we could identify the periods of high and low price movement. Additionally, we examined implied volatility values for these options for noticeable trends. First, we obtained spreadsheets containing documented data on price histories of silver ETFs for the year 2010. These data were downloaded from Yahoo! Finance and included open, close, high, low, and adjusted close prices. Upon obtaining the spreadsheets, we used

Microsoft Excel to find the four weeks of both lowest and highest activity (volatility) in closing prices. We determined which weeks to analyze by calculating the standard deviation of each week's five-day returns; the higher values determined the high price volatility weeks, while the lower values determined the low price volatility weeks. For each of these weeks, we computed the volatility smirks for both put and call options separately.

After identifying these periods, we pulled in-depth, corresponding options data, both call and put options, for each period. These data were very extensive and included put/call option, closing price, strike price, expiration date, and implied volatility level. Our data sets were purchased from http://historicaloptiondata.com. After obtaining the data sets, we wrote programs in the Excel VBA programming language to compare the volatility smirks during periods of high/low price volatility for both put and call options to see if there were any significant differences in behavior. Because there is no standard method to do this, it was imperative that we wrote original programs to address this problem. Our programs will be explained later in the article. Finally, we used Excel to compute and graph our results.

System Design

As noted above, this article required original programs to be written so that we could address our research questions. Because Excel VBA has the ability to open and manipulate Excel spreadsheets, we decided that it would be our language of choice. Our algorithm includes several functions for the purpose of modularity with the main benefit being the reduction in redundancy and increase in reusability. Therefore, our overall template for our program consists of a subroutine and several functions. The following programs are written with the purpose of returning corresponding implied volatility (IV) values for certain strike prices for a week of data. In addition to executing a macro with the code, it is necessary to compute the overall average of each strike price's IV values and then use Excel to graph the relationship between strike prices and average IV values to get the volatility smirk.

Below is the base subroutine that implemented the algorithm to compute the volatility smirk. The code remains mostly the same throughout all of the weeks analyzed; the only components that change are the day variables. In these variables, a file path must be specified to a comma separated values (CSV) file that contains option data from http://historicaloptiondata.com. This must be repeated for each of the five variables that represent the five-day period.

After the basic variables were declared, a variable named CellCount was allocated to memory so that the program could keep track of rows that had been used. This was important to ensure that data from multiple days did not overlap. The code below retrieves implied volatility values for "call" options only. In order to modify the program to retrieve implied volatility values for "put" options, it is required to modify each conditional statement (if statements) in the program to include "call instead of "put."

```
Sub GetVolatilitySmirk()
    Dim StrikePrice As Double
    Dim CellCount As Integer
    Dim ClosingPrice As Double
    Dim ResultBook As Workbook
    Dim Status As Double
    Set ResultBook = ActiveWorkbook
    CellCount = 2

    Dim Day1 As Workbook
    Dim Day1OptionStrikePrice As Double
```

```
    Set Day1 = Workbooks.Open("")
    ClosingPrice = FindClosingPrice(Day1)
    Day1OptionStrikePrice = GetOptionStrikePrice(Day1, ClosingPrice)
    CellCount = PrintStrikePrices(ResultBook, CellCount, Day1OptionStrikePrice)
    Status = MatchIVValues(Day1, ResultBook, (CellCount - 15), CellCount)
    Day1.Close

    Dim Day2 As Workbook
    Dim Day2OptionStrikePrice As Double
    Set Day2 = Workbooks.Open("")
    ClosingPrice = FindClosingPrice(Day2)
    Day2OptionStrikePrice = GetOptionStrikePrice(Day2, ClosingPrice)
    CellCount = PrintStrikePrices(ResultBook, CellCount, Day2OptionStrikePrice)
    Status = MatchIVValues(Day2, ResultBook, (CellCount - 15), CellCount)
    Day2.Close

    Dim Day3 As Workbook
    Dim Day3OptionStrikePrice As Double
    Set Day3 = Workbooks.Open("")
    ClosingPrice = FindClosingPrice(Day3)
    Day3OptionStrikePrice = GetOptionStrikePrice(Day3, ClosingPrice)
    CellCount = PrintStrikePrices(ResultBook, CellCount, Day3OptionStrikePrice)
    Status = MatchIVValues(Day3, ResultBook, (CellCount - 15), CellCount)
    Day3.Close

    Dim Day4 As Workbook
    Dim Day4OptionStrikePrice As Double
    Set Day4 = Workbooks.Open("")
    ClosingPrice = FindClosingPrice(Day4)
    Day4OptionStrikePrice = GetOptionStrikePrice(Day4, ClosingPrice)
    CellCount = PrintStrikePrices(ResultBook, CellCount, Day4OptionStrikePrice)
    Status = MatchIVValues(Day4, ResultBook, (CellCount - 15), CellCount)
    Day4.Close

    Dim Day5 As Workbook
    Dim Day5OptionStrikePrice As Double
    Set Day5 = Workbooks.Open("")
    ClosingPrice = FindClosingPrice(Day5)
    Day5OptionStrikePrice = GetOptionStrikePrice(Day5, ClosingPrice)
    CellCount = PrintStrikePrices(ResultBook, CellCount, Day5OptionStrikePrice)
    Status = MatchIVValues(Day5, ResultBook, (CellCount - 15), CellCount)
    Day5.Close

End Sub
```

In addition to a main subroutine, functions are used so that redundancy in the code could be limited. The function below, FindClosingPrice, takes a single workbook as a parameter. Then, it looks at the relevant option data (hardcoded as SLV) and finds the closing price.

```
Function FindClosingPrice(x As Workbook)
  Dim RowCount As Double
```

```
    RowCount = x.ActiveSheet.UsedRange.Rows.Count
    For i = 1 To RowCount
        If x.ActiveSheet.Range("A" & i).Value = "SLV" And x.ActiveSheet.Range("F" & i).Value = "call"
Then
            FindClosingPrice = x.ActiveSheet.Range("B" & i).Value
            Exit For
        End If
    Next i
End Function
```

The function below, GetOptionStrikePrice, takes two parameters: a workbook and a double that represents the closing price (obtained by using the function above). This function simply iterates through all the rows in the specified workbook and finds the option strike price that is closest to the day's closing price.

```
Function GetOptionStrikePrice(x As Workbook, ClosingPrice As Double)
    Dim TempOptionStrikeDifference As Double
    Dim TempOptionStrikeDifference2 As Double
    Dim OptionStrikePrice As Double
    TempOptionStrikeDifference2 = 10

    Dim RowCount As Double
    RowCount = x.ActiveSheet.UsedRange.Rows.Count

    For i = 1 To RowCount
        If x.ActiveSheet.Range("A" & i).Value = "SLV" And x.ActiveSheet.Range("F" & i).Value = "call"
Then
                TempOptionStrikeDifference = Abs(ClosingPrice - x.ActiveSheet.Range("I" & i).Value)\
                If TempOptionStrikeDifference < TempOptionStrikeDifference2 Then
                    OptionStrikePrice = x.ActiveSheet.Range("I" & i).Value \
                    TempOptionStrikeDifference2 = TempOptionStrikeDifference
                End If
        End If
    Next i

    GetOptionStrikePrice = Round(OptionStrikePrice, 0)

End Function
```

The function below takes three parameters: the workbook on which the various strike prices should be printed, CellCount (keeps track of the rows that are used in the program), and StrikePrice (the price that needs to be printed, along with seven prices below and above the StrikePrice). Using the StrikePrice parameter, the function uses an iteration statement in the form of a for{ loop to print out the StrikePrice, as well as seven prices below and above it to the specified workbook. Lastly, the function returns a new value for CellCount, since the function prints out additional strike prices on the rows of the result workbook.

```
Function PrintStrikePrices(ResultBook As Workbook, CellCount As Integer, StrikePrice As Double)
    For i = 7 To 1 Step -1
        ResultBook.ActiveSheet.Range("A" & CellCount).Value = StrikePrice - i
        CellCount = CellCount + 1
```

```
    Next i
    ResultBook.ActiveSheet.Range("A" & CellCount).Value = StrikePrice
    CellCount = CellCount + 1
    For i = 1 To 7
        ResultBook.ActiveSheet.Range("A" & CellCount).Value = StrikePrice + i
        CellCount = CellCount + 1
    Next i
    PrintStrikePrices = CellCount
End Function
```

The function shown below, MatchIVValues, takes four parameters: a workbook to analyze, a workbook to print results, and the start and end rows of the result workbook, which allow the results to be printed out to a particular range in the result workbook. Using this function allows the program to get the implied volatility (IV) values that correspond with each strike price defined earlier in the PrintStrikePrices function. The program obtains the last IV value available that corresponds with the strike price specified (these are obtained in the function above).

```
Function MatchIVValues(Workbook As Workbook, ResultBook As Workbook, StartRow, EndRow)
    Dim RowCount As Double
    RowCount = Workbook.ActiveSheet.UsedRange.Rows.Count
    For i = StartRow To EndRow 'representing strike prices on resultbook's activesheet -7 and + 7
        For x = 1 To RowCount
            If Workbook.ActiveSheet.Range("A" & x).Value = "SLV" And Workbook.ActiveSheet.Range("F"
& x).Value = "call" Then
            If ResultBook.ActiveSheet.Range("A" & i).Value = Workbook.ActiveSheet.Range("I" & x).Value
Then
                    ResultBook.ActiveSheet.Range("B" & i).Value = Workbook.ActiveSheet.Range("O" &
x).Value
                    'Exit For
                End If

            End If
        Next x
    Next i
MatchIVValues = 1
End Function
```

Results

The results of the programs are shown below in Figures 1-16. The first eight graphs represent the four weeks of high price volatility with each week's call and put options shown in separate graphs. Figures 1-4 represent call options for the weeks of high price volatility, and Figures 5-8 represent the same weeks as Figures 1-4 but show put options. The last eight graphs represent the four weeks of low price volatility with each week's call and put options also shown in separate graphs. Figures 9-12 represent call options for the weeks of low price volatility, and Figures 13-16 represent the same weeks as Figures 9-12 but show put options. Each graph demonstrates the volatility smirk of the call or put option that corresponds with the week it represents. It is important to take note that for the weeks of both low and high price volatility, the call option graphs are shown first followed by the put option graphs.

The first noticeable trend with the results can be observed in the four weeks of high price volatility with call options, which are presented in Figures 1-4. It can be seen that the volatility smirk becomes more normalized as the price volatility decreases. This can be observed specifically in Figures 3-4. SLV put options in these same periods (Figures 5-8) showed a very similar trend to the call options.

As it is in Figures 1-4, which outlined call options rather than put options, the volatility smirks become more standard as the overall price volatility of each week decreases. However, unlike Figures 3-4, the put option volatility smirks in Figures 7-8 have a noticeable trough and two fairly akin peaks.

Figures 9-16 represent the volatility smirks of SLV call options for the weeks of low price volatility for the year. Call options are listed first and then put options follow. Figures 9-12 showed fairly normal trends for three out of four graphs and did not produce much of a pattern. Figure 11, which represented the third week of highest volatility, was the graph that produced some anomalies. The call options for these weeks can be found below in Figures 9-12.

Like the call options, the put options in the periods of lowest price movement (Figures 13-16) demonstrate fairly normal results with the third graph being the exception. The overall results show that there were no highly distinguishable differences between the volatility smirks of the weeks of high price volatility (Figures 1-8) and those of the corresponding weeks with low price volatility (Figures 9-16). As noted previously, data for some weeks were not available.

Conclusion

This project was an application of computational finance. Computational finance uses programming techniques and analytical methods to make better financial predictions on option pricing (Yingsaeree & Treleaven, 2010). As additional technologies are utilized by financial companies, the opportunities for formulating new programs for financial analysis are expanding.

We examined whether or not the volatility smirks of put and call SLV options presented similar trends among periods of high and low price movement. Since the volatility smirks among high and low price movement periods presented very similar trends, we can infer that SLV volatility behavior in high and low price movement periods is similar as well for the year 2010. In addition, we can infer that SLV volatility in the year 2010 is independent of price and may instead depend on qualitative factors that do not depend on economic equations or data. This is consistent with Downey's analysis of 2010 SLV stock option prices, as well as Cont's and Shiller's arguments that investors often make decisions that are based on factors that are not quantitative.

Supplementary studies could be done by further analyzing IV values for additional dates to see how similar these trends are with other weeks of low and high price movement.

Figures

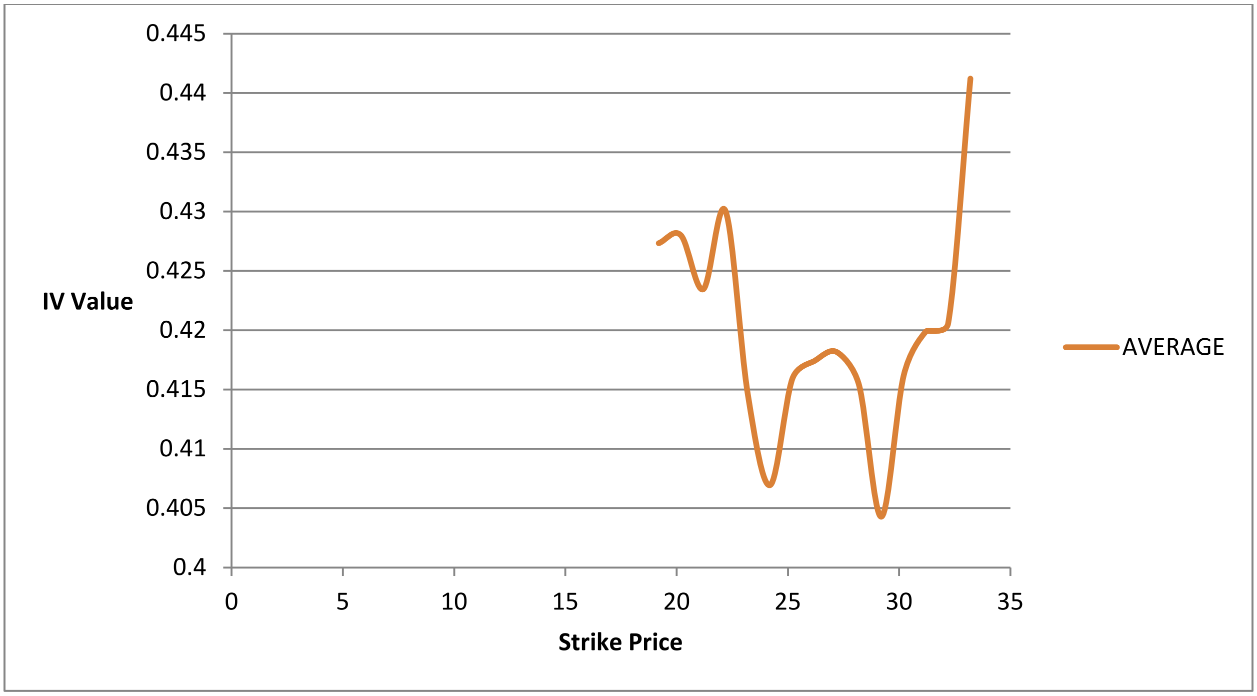

Figure 1. Volatility Smirk for SLV Call Option for the Week of Highest Price Volatility (11/9/10-11/15/10)

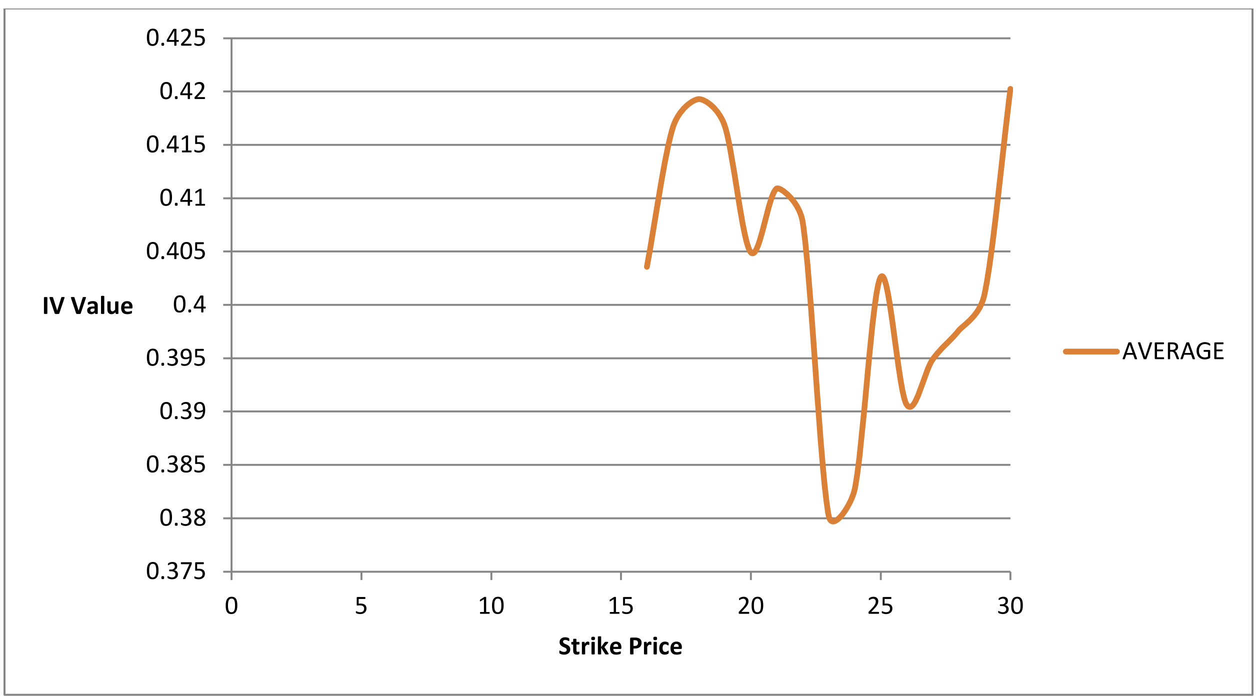

*Figure 2***.** Volatility Smirk for SLV Call Option for the Week of Third Highest Price Volatility (10/19/10-10/25/10)[1]

[1]Data for the week of second highest price volatility were not available.

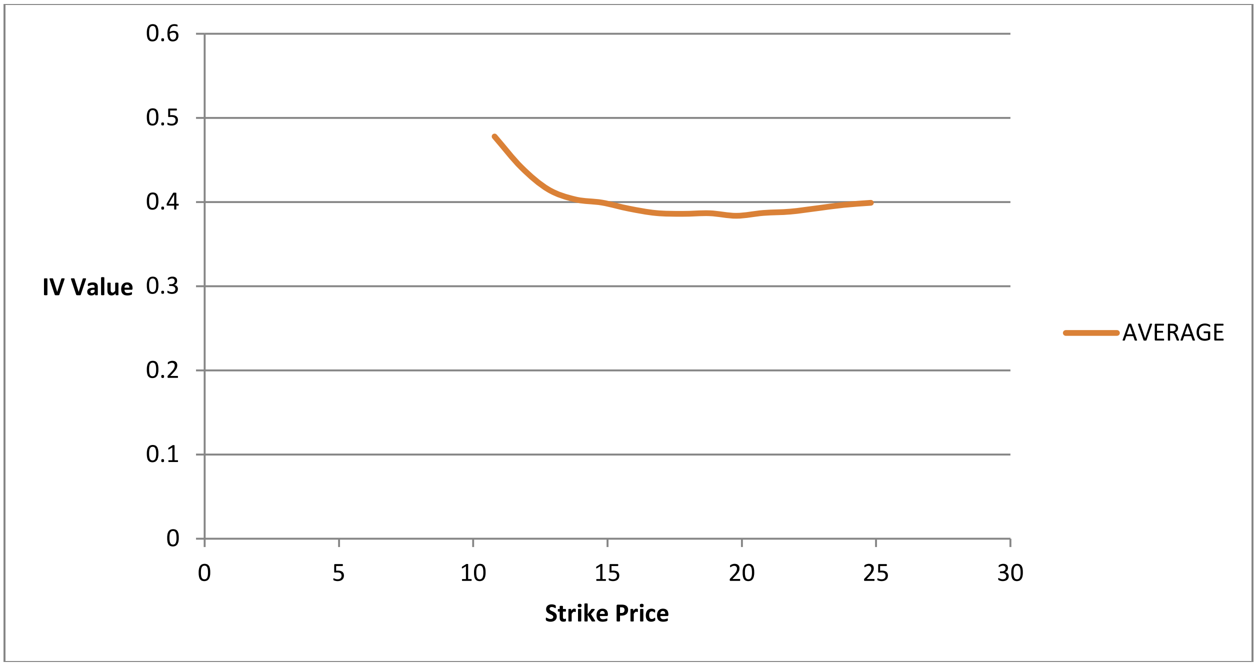

Figure 3. Volatility Smirk for SLV Call Option for the Week of Fourth Highest Price Volatility (6/4/10-6/10/10)

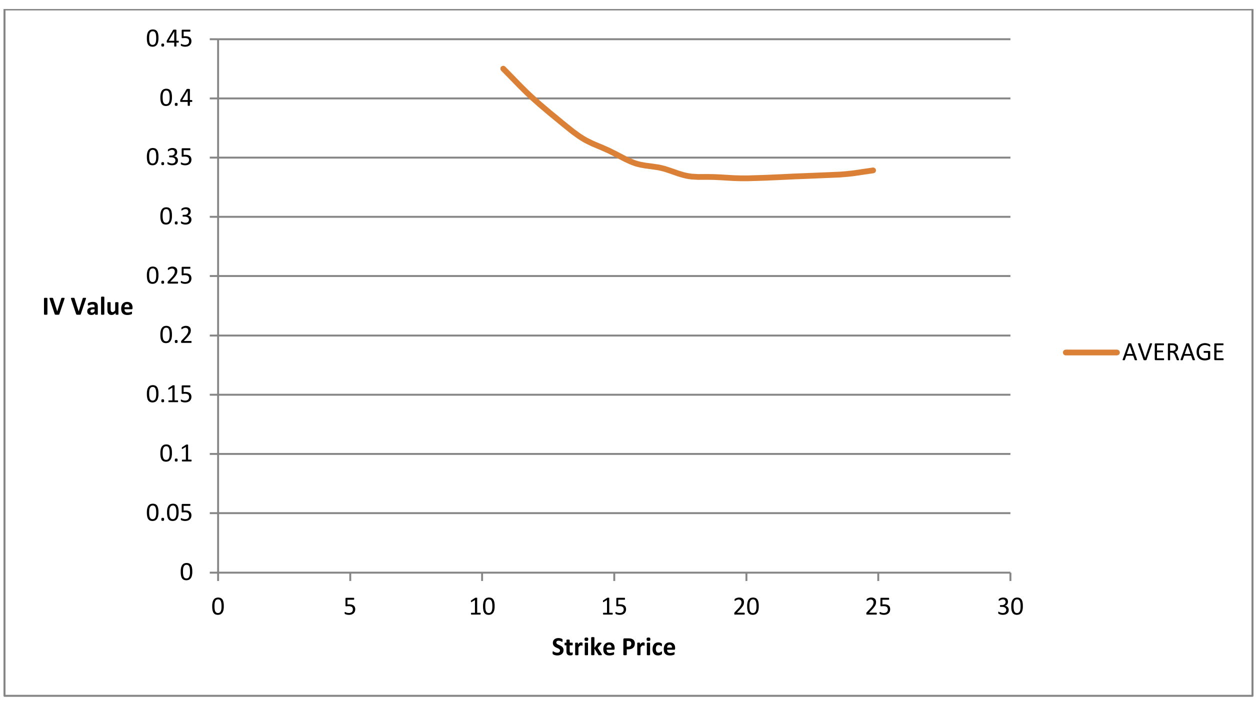

Figure 4. Volatility Smirk for SLV Call Option for the Week of Fifth Highest Price Volatility (4/29/10-5/5/10)

Figure 5. Volatility Smirk for SLV Put Option for the Week of Highest Price Volatility (11/9/10-11/15/10)

Figure 6. Volatility Smirk for SLV Put Option for the Week of Third Highest Price Volatility (10/19/10-10/25/10)[2]

[2]Data for the week of second highest price volatility were not available.

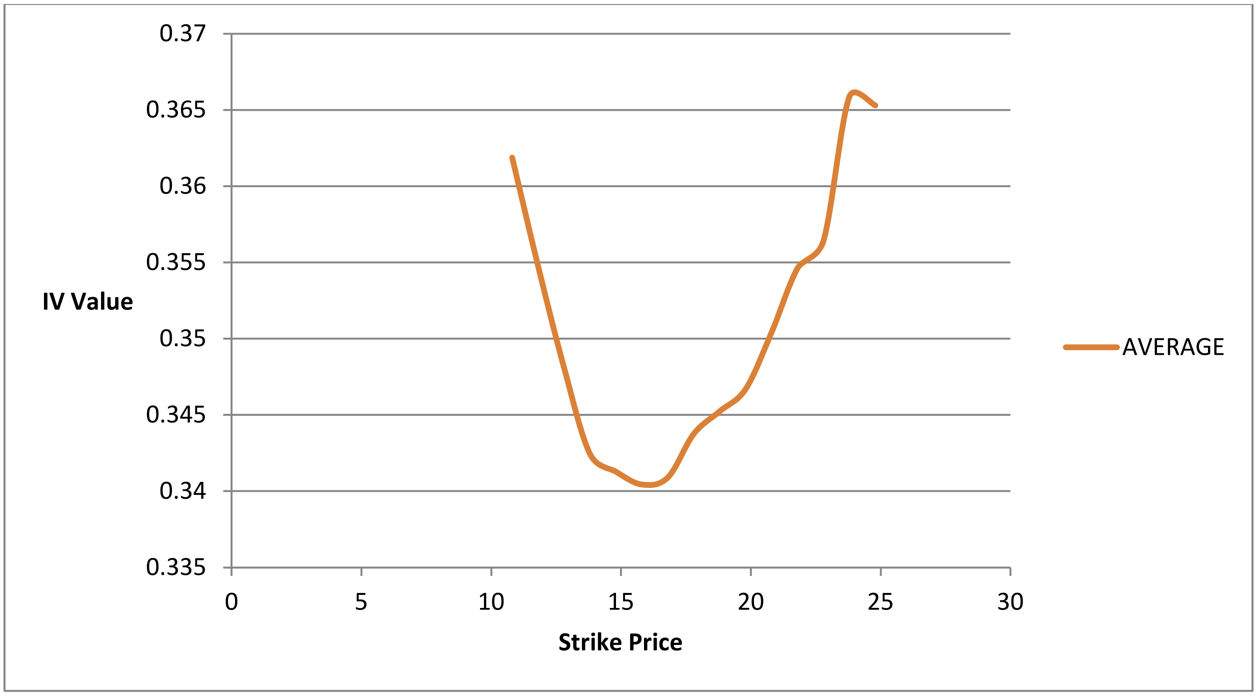

Figure 7. Volatility Smirk for SLV Put Option for the Week of Fourth Highest Price Volatility (6/4/10-6/10/10)

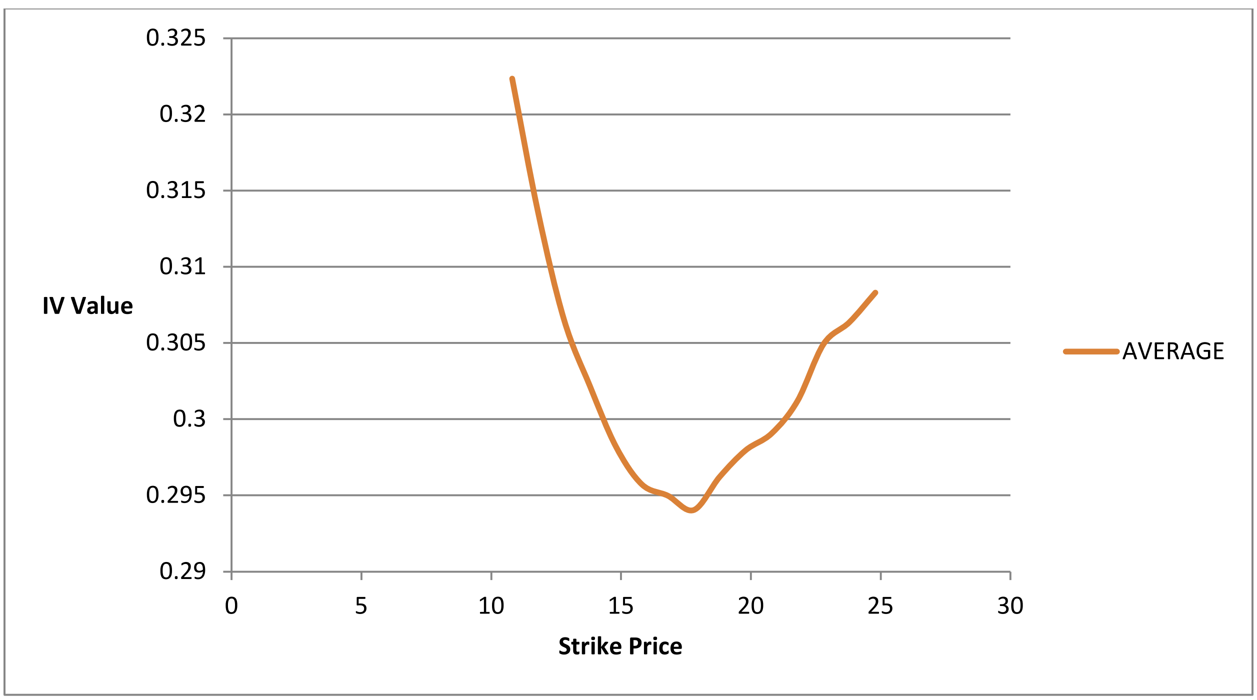

Figure 8. Volatility Smirk for SLV Put Option for the Week of Fifth Highest Price Volatility (4/29/10- 5/5/10)

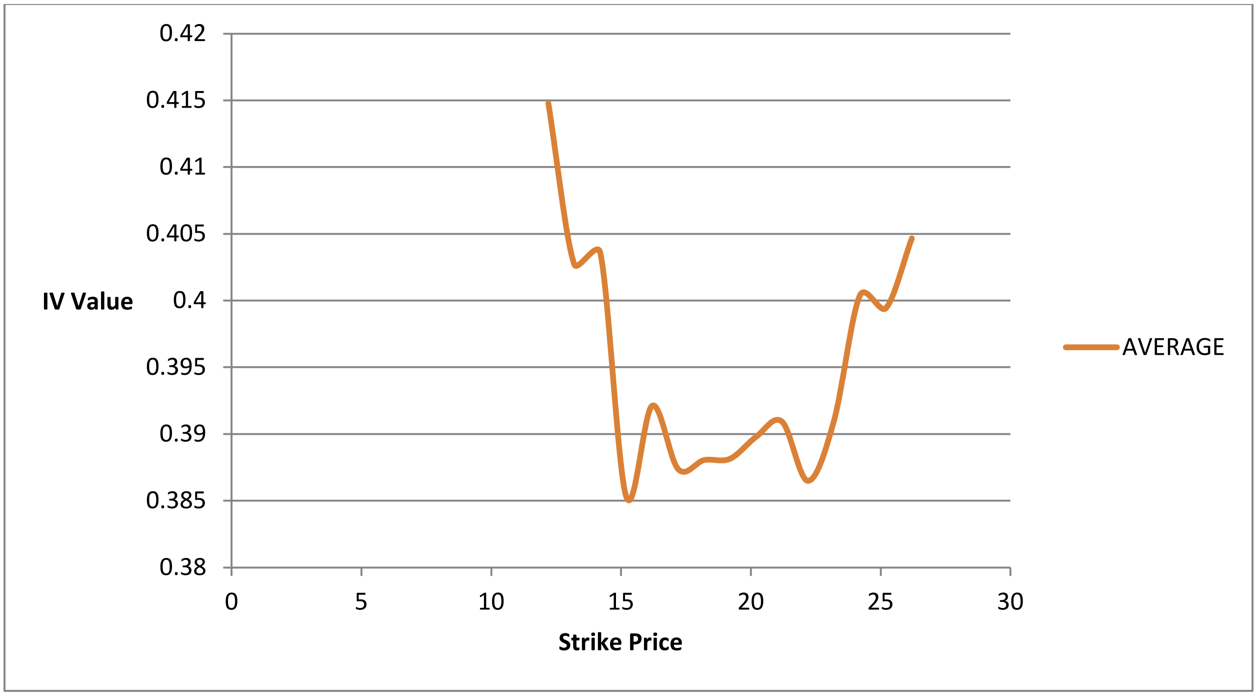

Figure 9. Volatility Smirk for SLV Call Option for the Week of Lowest Price Volatility (9/7/10- 9/13/10)

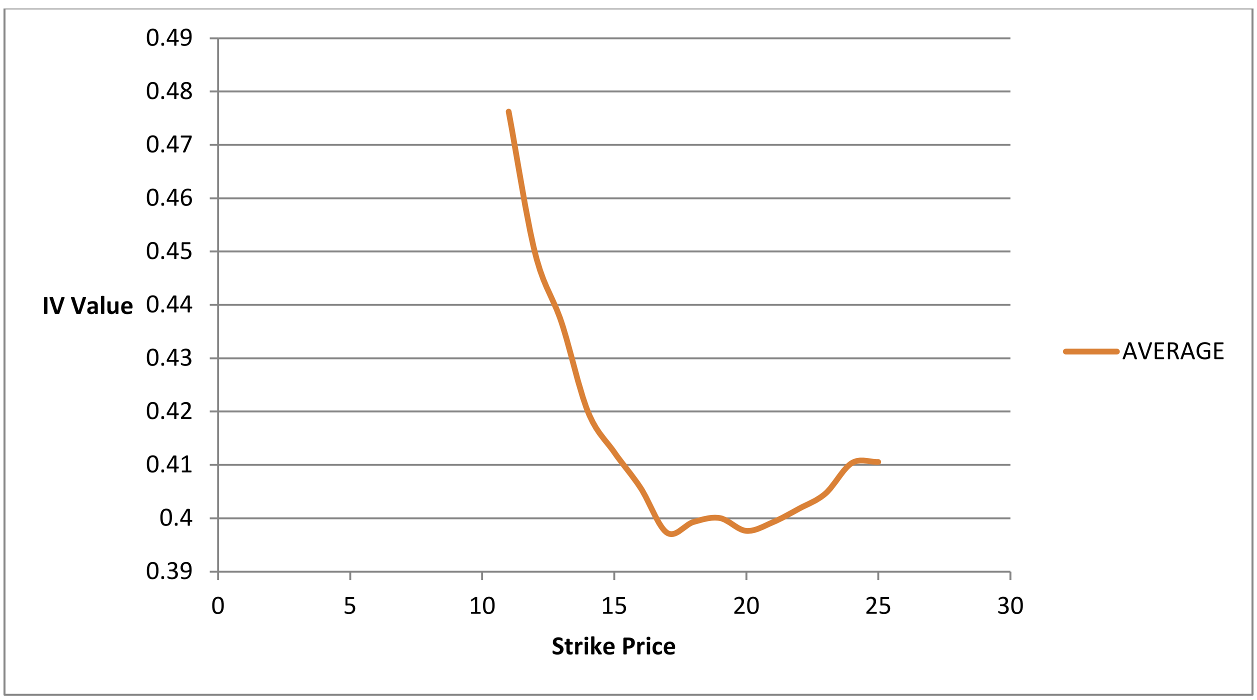

Figure 10. Volatility Smirk for SLV Call Option for the Week of Second Lowest Price Volatility (7/2/10- 7/9/10)

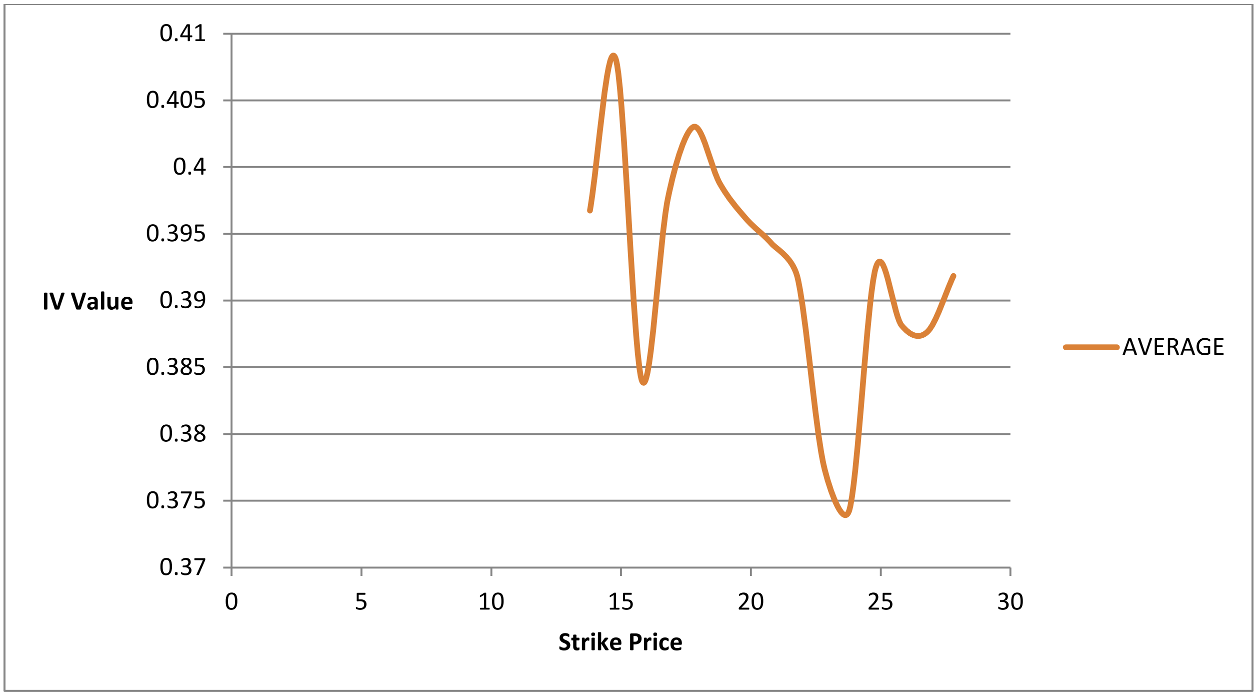

Figure 11. Volatility Smirk for SLV Call Option for the Week of Third Lowest Price Volatility (9/21/10-9/27/10)

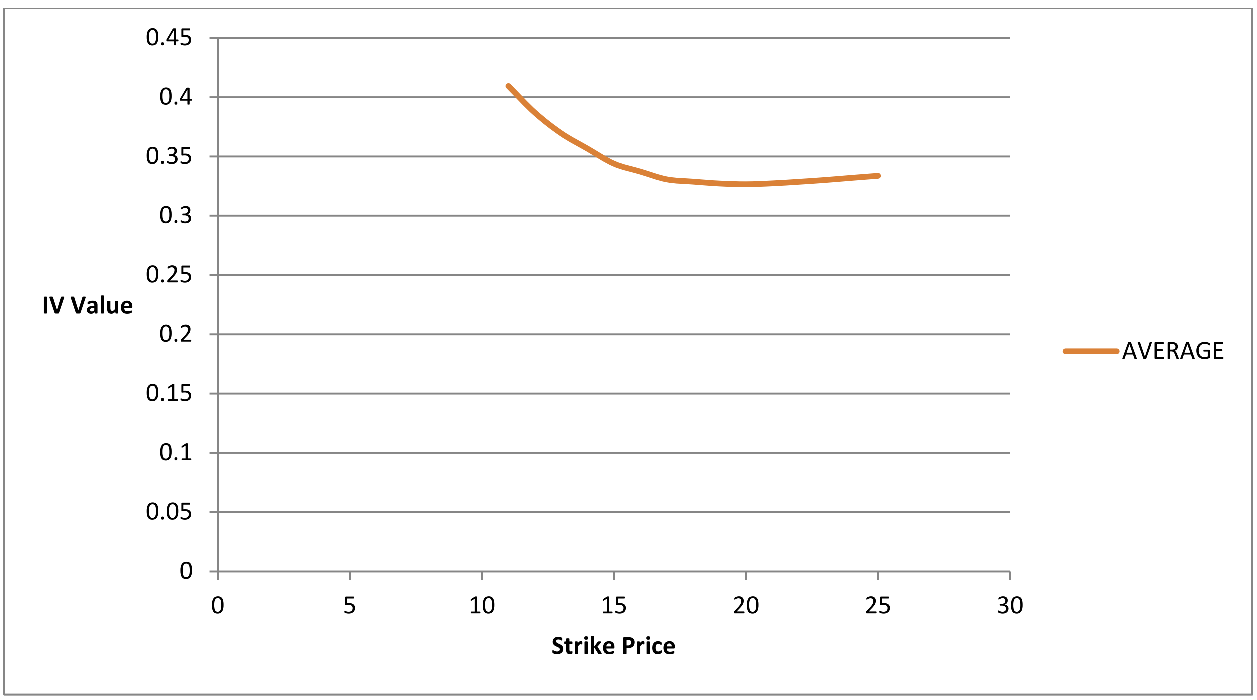

Figure 12. Volatility Smirk for SLV Call Option for the Week of Fifth Lowest Price Volatility (4/22/10-4/28/10)[3]

[3]Data for the fourth lowest price volatility week were not available.

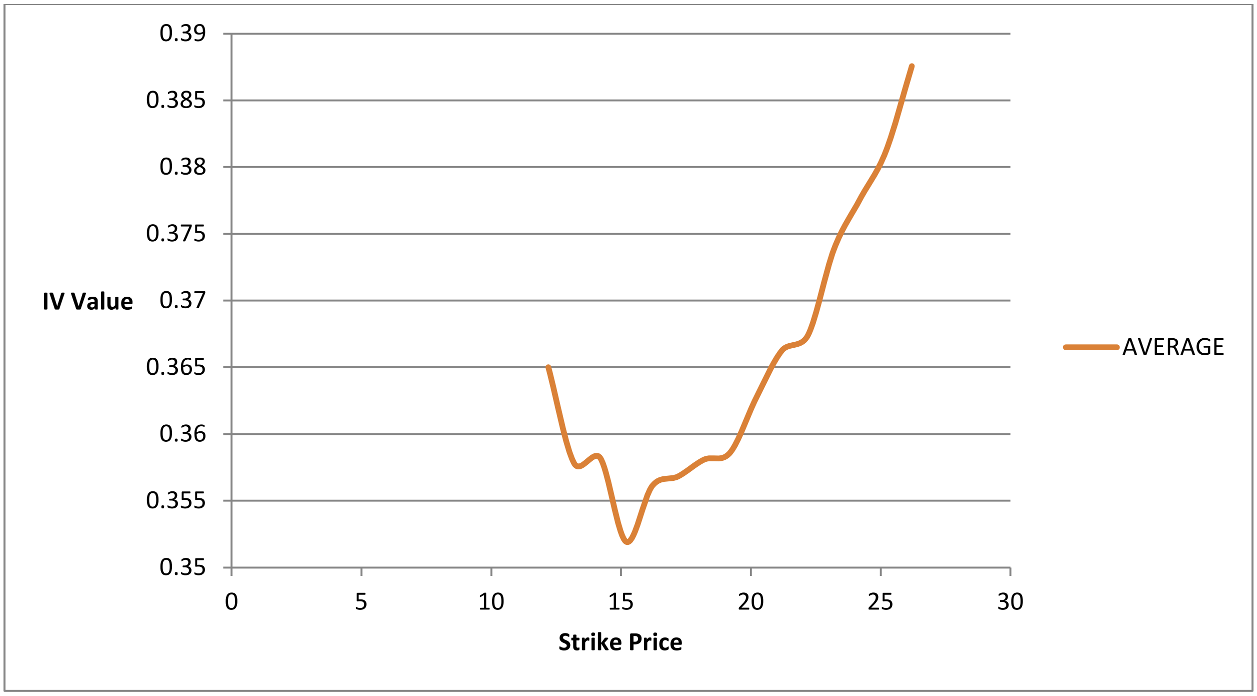

Figure 13. Volatility Smirk for SLV Put Option for the Week of Lowest Price Volatility (9/7/10- 9/13/10)

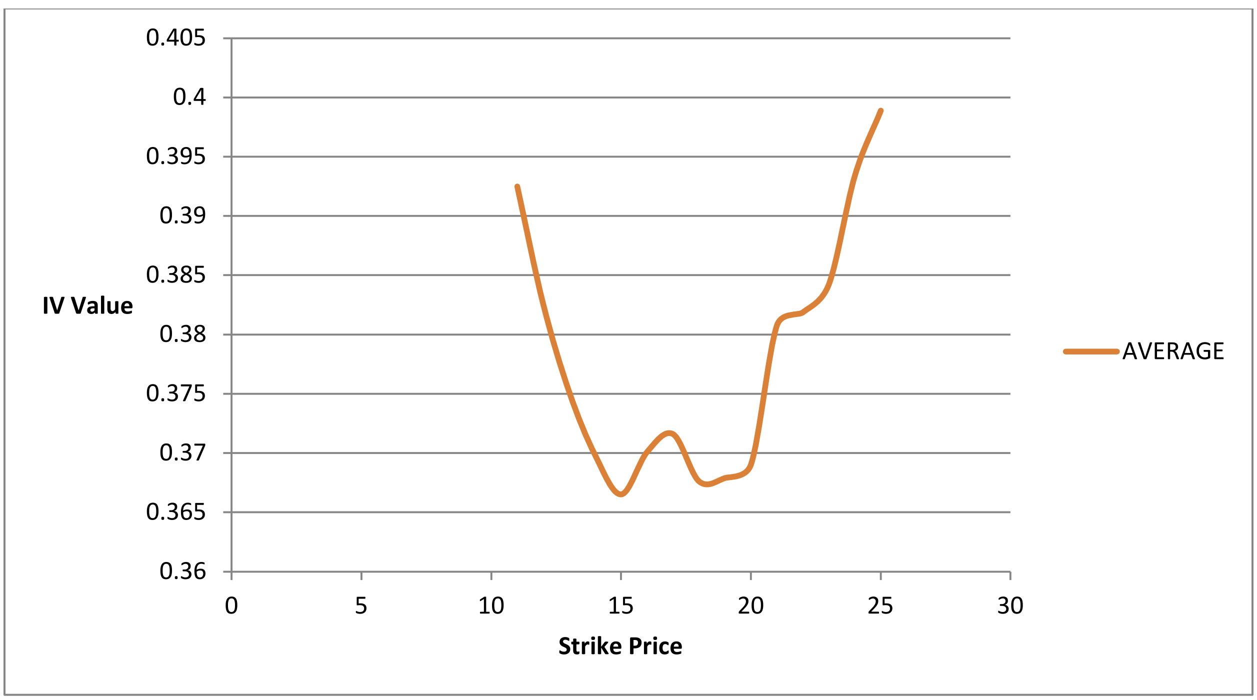

Figure 14. Volatility Smirk for SLV Put Option for the Week of Second Lowest Price Volatility (7/2/10- 7/9/10)

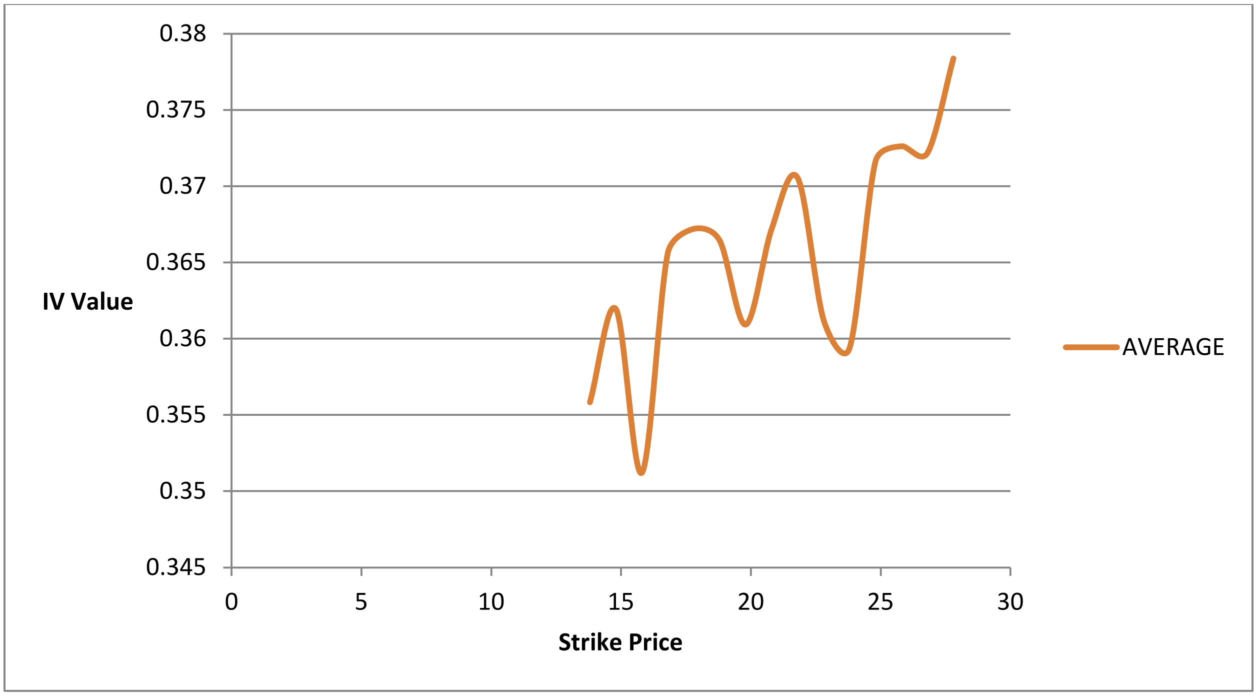

Figure 15. Volatility Smirk for SLV Put Option for the Week of Third Lowest Price Volatility (9/21/10-9/27/10)

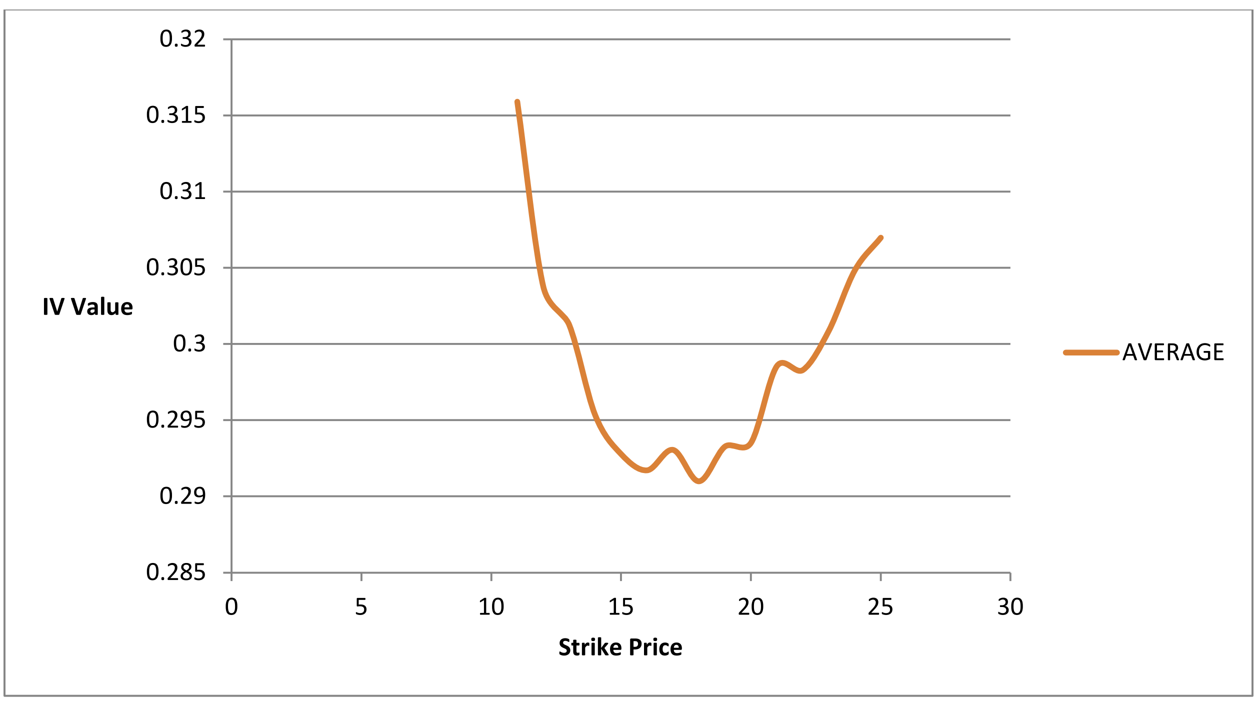

Figure 16. Volatility Smirk for SLV Put Option for the Week of Fifth Lowest Price Volatility (4/22/10-4/28/10)[4]

[4]Data for the fourth lowest price volatility week were not available.

References

Baken, P. A., & Nandi, S. (1996). Options and volatility. *Economic Review*, *81*(3-6), 21.

Black, F., & Scholes, M. (1973). The pricing of options and corporate liabilities. *Journal of Political Economy*, *81*(3), 637-654.

Borzykowski, B. (2011).Volatility survival guide. *Canadian Business, 84*(15), 47-49.

Chance, D. M. (2004). *An introduction to derivatives and risk management.* Mason: South-Western.

Clapperton, G. G. (2010). Raising the gold standard. *Engineering & Technology*, *5*(15), 66-69.

Cohan, P. (2010). Big risk: $1.2 quadrillion derivatives market dwarfs world GDP. *Daily Finance*. Retrieved from http://www.dailyfinance.com/2010/06/09/risk-quadrillion-derivatives-market-gdp/.

Cont, R. (2001). Empirical properties of asset returns: Stylized facts and statistical issues. *Quantitative Finance*, 1, pp.223-236.

Coulson, M. (2005). Gold as an investment. *Applied earth science: Transactions of the institution of mining and metallurgy section b*, *114*(2), 122-128.

Cross, J. (2005). Gold – the emotional metal. *Applied earth science: Transactions of the institution of mining and metallurgy section b*, *114*(2), 101-107.

Downey, J. (2011). Investigating silver ETF volatility. (Unpublished honors thesis). Conway: Coastal Carolina University.

Hull, J. (2012). Options, futures, and other derivatives (8th ed.). Boston, MA: Prentice Hall.

Lardner, J. (1999). OK, here are your options. *U.S. News & World Report*, *126*(8), 44.

Neely, C. J. (2005). Using implied volatility to measure uncertainty about interest rates. *Review*, *87*(3), 407-425.

Schoenberger, E. (2011). Why is gold valuable? Nature, social power and the value of things. *Cultural Geographies*, *18*(1), 3-24.

Shiller, R. J. (2003). From efficient markets theory to behavioral finance. *Journal of Economic Perspectives*, *17*(1), 83-104.

Sloan, A., & Perrucci, D. (2003). Running out of options. *Newsweek*, *142*(3), 40.

Udell, S. (2008). Understanding stock options. *American Journal of Family Law*, *22*(1), 23-27.

Yingsaeree, C., Nuti, G., & Treleaven, P. (2010). Computational finance. *IEEE Computer, 43*(12), 36-43.