2015

Dynamically Hedging Oil and Currency Futures Using Receding Horizontal Control and Stochastic Programming

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Abstract

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MBA, Wayne State University, 2008

BS, Wayne State University, 2007

Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Philosophy

Finance

Walden University

February 2015

Abstract

There is a lack of research in the area of hedging future contracts, especially in illiquid or very volatile market conditions. It is important to understand the volatility of the oil and currency markets because reduced fluctuations in these markets could lead to better hedging performance. This study compared different hedging methods by using a hedging error metric, supplementing the Receding Horizontal Control and Stochastic Programming (RHCSP) method by utilizing the London Interbank Offered Rate with the Levy process. The RHCSP hedging method was investigated to determine if improved hedging error was accomplished compared to the Black–Scholes, Leland, and Whalley and Wilmott methods when applied on simulated, oil, and currency futures markets. A modified RHCSP method was also investigated to determine if this method could significantly reduce hedging error under extreme market illiquidity conditions when applied on simulated, oil, and currency futures markets. This quantitative study used chaos theory and emergence for its theoretical foundation. An experimental research method was utilized for this study with a sample size of 506 hedging errors pertaining to historical and simulation data. The historical data were from January 1, 2005 through December 31, 2012. The modified RHCSP method was found to significantly reduce hedging error for the oil and currency market futures by the use of a 2-way ANOVA with a *t* test and post hoc Tukey test. This study promotes positive social change by identifying better risk controls for investment portfolios and illustrating how to benefit from high volatility in markets. Economists, professional investment managers, and independent investors could benefit from the findings of this study.

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Dedication

This dissertation is dedicated in memory of Daniel Cottrell.

Acknowledgments

I would like to thank the many people that have encouraged me to pursue a Ph.D. They are too numerous to list, but I would like to extend a special thanks to my dog, Puglet.

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Chapter 1: Introduction to the Study

Introduction

Many investors were affected by the financial crisis of 2008. In a financial crisis, there are many types of assets that diminish in value together, creating negative returns for investors. The real-world problem is how to offset falling asset prices in a dynamic way, whereby the variability of portfolio returns is stable. Investigating how to solve this real-world problem is important not just for year-over-year portfolio performance, but to mitigate the exposure for investors to extreme market selloffs. During a financial crisis, energy and currency markets usually exhibit extreme volatility and return variance.

This research study investigated how to improve hedging performance when investing in oil or the foreign exchange futures markets. The major sections of this chapter are the : (a) introduction, (b) problems statement, (c) research questions and hypothesis, (d) theoretical framework for the study, (e) nature of the study, (f) definitions, (g) assumptions, (h) scope and delimitations, (i) limitations, (j) significance, and (k) summary.

The sections for this chapter represent the following. In the introduction section a brief summary of the literature review is presented and gaps identified. The next section is the problem statement section representing the research problem. The research questions and hypotheses are presented in the research questions and hypothesis section. The following section is the theoretical framework for the study and identifies the theoretical framework used in this study and the major theoretical propositions. The rationale for the research design and the key variables are offered in the nature of the study sections. In the definitions section I articulate the relevant definitions. The assumptions section articulates the assumptions used to studying hedging oil and foreign exchange futures. In the scope and delimitations section I will present the boundaries of the study. I offer in the limitations section the research design and methodology limitations. The significance section describes what the significance of this research study is to the body of knowledge related to hedging future contracts. The last section pertains to the summary of this chapter.

The following important research provides some background to this research topic. Meindl (2006) proposed using a receding horizontal control and stochastic programming (RHCSP) method to improve on hedging error compared to other common hedging methods. Meindl used the RHCSP method on corporate bonds, vanilla options, and multidimensional options. No comprehensive backtesting was performed on assets in the Meindl study, however, nor was a better understanding on how the RHCSP method performs in illiquid conditions investigated. Price and return volatility increase as supply and demand are disrupted in the oil market, which has a direct effect on currency fluctuations for the United States dollar (USD). Matilla-García (2007) investigated the chaotic nature of light crude oil markets, which has a direct effect on hedging performance. More investigations are being performed on the concept of peak oil, whereby Holland (2008) proposed four models to understand the supply and demand dynamics of the oil market, which allows for fundamental analysis of the real amount of producible oil. Electronic trading also has affected trading volume over maturity dates and has evolved over time for oil futures on the New York Mercantile Exchange

(NYMEX), which effects future pricing (Ye, Zyren, Shore, & Lee, 2010). Hagens (2010) proposed that energy return on investment (EROI) should be used to consider best energy methods to use, which changes the dynamics of possible replacements for oil—again affecting the price of the futures market. Through these researchers a better understanding on why we need to eliminate risk when investing in the oil and currency market can be reached.

I have chosen five scholarly works to provide a background on modeling and explaining the oil futures market. Holland (2008) discussed peak oil production, using the prevailing assumption that oil has reached a production peak, after which oil production will decline year-over-year. Many developed regions of the world have exhibited this peak oil phenomenon; this study examined the debate on actual resources remaining. The two camps on the causes of peak oil are: (a) due to actual reserves, or (2) due to price of production. Holland concluded that price is a better indicator of resource scarcity than supply and that peak production can be reached within the range of 0% to 100% of resource exhaustion.

To explain and model the nonlinearity of energy futures, Matilla-García (2007) investigated the natural gas, unleaded gasoline, and light crude oil markets. In the Matilla-García study, returns on energy futures showed nonlinearity but was inconclusive if these returns exhibited chaotic dynamics. Matilla-García used genetic algorithms to model short-term price movements, whereby this method produced smaller forecasting errors compared to well-established stochastic methods.

Hassan (2011) modeled asymmetric volatility in oil prices. Hassan's study showed that shocks are persistent and there is asymmetric behavior with new information to oil prices. When bad news is presented to the market there is a stronger effect than good news of the same magnitude. Future traders can use this asymmetric behavior to plan their market position and hedging strategy.

Ye et al. (2010) investigated if oil futures can be used as an indicator of market change. The Ye et al.'s (2010) study showed that electronic trading affected the term structure of the oil futures prices—but more research should be conducted to understand what other variables contributed to this term structure change, such as excess production relative to demand or affects of peak oil. The results from this study can help with using correlations between volume and price to predict if the oil futures market is in a speculative equilibrium and how to hedge such conditions.

The last article I investigated for this section was by Theriault (2007), which dealt with studying the oil and gas futures and options market. Theriault used the nonlinear asymmetric generalized autoregressive conditional heteroskedasticity (GARCH) process coupled with using the Samuelson effect and contract switching for hedging rollover. Theriault concluded that lower pricing errors were obtained using the nonlinear asymmetric GARCH process compared to the constant volatility model and the GARSCH option-pricing model.

Problem Statement

In terms of gaps and deficiencies in prior research, there still remains the lack of understanding for the reasons of volatility in the oil futures or currency markets and how to risk manage those volatility dynamics. Current studies are missing a robust behavioral finance model to describe system dynamics in the oil futures market. Current studies are also missing a robust dynamic-hedging method that reduces hedging error in the oil and currency futures markets. A better behavioral finance method would help hedge energy and currency future positions for market participants. It is important to understand the volatility of the oil market because it is a very important sector in the global economy. By understanding these dynamics better predictions of inflationary or deflationary conditions can be obtained, which can lead to increased performance of hedging strategies. This research would be valuable to economists, policymakers, and market participants.

Thus, there is a lack of scholarly literature, research, and understanding in the area of hedging future contracts, especially in illiquid or very volatile market conditions. There is a lack of understanding for the reasons of volatility in the oil futures or currency markets and how to risk manage those volatility dynamics. Current studies are missing a robust behavioral finance method to describe system dynamics in the oil futures market involving concepts such as: fundamental and speculative equilibrium; chaotic attractions; tipping points; and mean reversions. Current studies are also missing a robust dynamic hedging method that reduces hedging error in the oil and currency futures markets.

Purpose of the Study

The purpose of this research was to fill gaps in the literature by providing a comprehensive study on how to utilize and improve the performance of the RHCSP method pertaining to the oil and currency markets. This research study considered the following time periods for the oil and currency market: (a) precrisis, (b) during the global financial crisis of 2008, and (c) postcrisis. The crisis is defined as the financial crisis of 2008. This research also contributed to the body of knowledge by improving on a dynamic hedging strategy used in illiquid markets. Another way that this research contributes to the body of knowledge is by improving on the dynamic hedging strategy in an illiquid market.

The study followed two basic precepts: that it is important to understand the volatility of the oil and currency market because they are very important financial sectors for the global economy, and that by understanding these dynamics better predictions of inflation or deflationary conditions can be obtained, potentially leading to increased performance of hedging strategies. By lowering the portfolio volatility the returns can be much more stable. This study utilizes dynamic hedging as a strategy of reducing volatility of price movement.

Research Questions and Hypothesis

The research questions and the hypotheses were the following for this study.

RQ1–Quantitative: Can the RHCSP hedging method improve hedging error compared to the Black–Scholes, Leland, and Whalley and Wilmott methods when applied to a simulated market, oil futures market, and currency futures market?

RQ2–Quantitative: Can a modified RHCSP method significantly reduce hedging error under extreme market illiquidity conditions when applied to a simulated market, oil futures market, and currency futures market?

The null and alternative hypothesis was:

H_o: There are no significant differences in hedging error among RHCSP, modified RHCSP, Black–Scholes, Leland, and Whalley and Wilmott methods when applied to a simulated market, oil futures market, and currency futures market.

H_a: There are significant differences in hedging error among RHCSP, modified RHCSP, Black–Scholes, Leland, and Whalley and Wilmott methods when applied to a simulated market, oil futures market, and currency futures market.

Theoretical Framework for the Study

The theoretical foundation used in this research study was based on chaos theory and emergence. I chose these due to an assumption that oil and currency markets are nonlinear systems that exhibit chaotic attributes, as suggested by Mastro (2013). Taleb (1997) argued that it is common practice to implement a hedging strategy to reduce portfolio variance due to possible price swings in the futures market. Therefore the research used in this study pertained to risk management techniques in corporate finance theory. But this study applied the assumptions that markets are not efficient and that investors are not rational utility maximizing. The oil and currency markets seem to exhibit chaotic behavior due to investor behavioral characteristics, which are in large measure irrational.

One way to model asset markets is to use parameters that define the drift, volatility, and jump diffusion of the asset in consideration. These parameters are determined from historical time series. When the system changes momentum a new price pattern emerges, suggesting that modeling from historical datasets will lead to a lagged forecast. Investors need a method to mitigate these unexpected price changes, such as dynamic hedging. Taleb (1997) argued that investors need to hedge for unexpected price movement (p. 3).

Nature of the Study

This quantitative study was designed to compare different hedging methods by using a hedging error metric by using an experimental research design. It specifically was designed to implement and test a variation on the RHCSP method that utilized the London interbank offered rate (LIBOR) and the Levy process to perform better in illiquid markets. It used two independent variables: markets and hedging methods. The first independent variable had three categorical values: simulated market, oil market, and currency market. The second independent variable was the five categorical values pertaining to the hedging methods used.

- BMS,
- Leland,
- Whalley and Wilmott,
- RHCSP, and
- Modified RHCSP.

The dependent variable was the absolute hedging error. There were no covariate, mediating, or moderating variables considered in this research study.

For the simulated market, I calculated the categorical values by running a stochastic simulation using the De Grauwe and Grimaldi behavioral finance model of an underlying asset and compared the difference between the simulated value of the hedged portfolio, $V(T)$, and the shorted derivative, $c(T)$; the absolute hedging error was $|V(T)$ -

$c(T)\,|$. T designates the time of expiration of the derivative. I calculated the absolute hedging error for each categorical value for each day then took the 4-day average over an 8-year time span.

To understand how the different hedging methods actually perform in real world conditions, I used backtesting using historic price series to determine which hedging method performed better in terms of hedging error. The next phase of analysis consisted of backtesting each of the hedging methods used in this study with real world data from the oil and currency futures market. The selected sample period for this data spanned from January 1, 2005 to December 31, 2012, and determined the actual hedging error performance. Then the absolute hedging error was calculated every 4 days.

In extreme illiquid conditions, such as the financial crisis of 2008, certain dynamic hedging may not help reduce losses in a portfolio because of co-movements of assets. This study was accordingly designed to examine the performance of hedging before, during, and after the financial crisis of 2008, so as to ascertain an optimized hedging rebalancing period. Through this rebalancing period investigation a modified RHCSP method was developed to reduce hedging error in illiquid markets, similar to the financial crisis of 2008. I performed a backtest on the oil and currency future markets to determine actual absolute hedging error using the modified RHCSP method. Significance testing was done through a two-way ANOVA and Tukey testing on absolute hedging error every 4 days to determine which method performed better statistically.

Definitions

This section defines the terminology that would need special definitions.

Backtesting. A method used to test the performance of a model with real world data from a previous time period (Investopedia, n.d.).

Black–Scholes Method. A method used to price options using drift and volatility (Investopedia, n.d.).

Bubble. In the context of this study, a term used to describe the over-appreciation of an asset's market value (Investopedia, n.d.).

Burst. A term used to describe the rupturing of a bubble. In a burst phase, the value of an asset starts to decline (Investopedia, n.d.).

Contract Switching. This is a term when investors close out their current contract and open another contract that expires in the future. Usually investors close out their current month expiring contract and initiate a new contract that is in the next available month (Theriault, 2007).

Crash. This is a term used to describe when the market is in a major selloff (Investopedia, n.d.).

Drift. A parameter that defines the degree of a trend. A higher weight with this parameter means a stronger drift. A negative number for this parameter represents a lower price trend (Black & Scholes, 1973).

Dynamic Hedging. A hedging strategy where a rebalance is implemented throughout different time periods. This Strategy can be at discrete or non-discrete time periods (Risk Encyclopedia, n.d.).

Efficient Market Hypothesis. A hypothesis wherein markets are assumed to be priced with all available information and that investors are not able to beat the market in the long run (Investopedia, n.d.).

Fat Tails. A term used to describe the ends of a distribution curve with high kurtosis (Kaya, Lee,& Pornrojnangkool, 2011).

Futures Contracts. A contract whereby the owner of the contract is obligated to either sell or buy at a certain price for a specified amount of a commodity (Investopedia, n.d.).

Futures Market. This is the market where buyers and sellers meet to exchange future contracts (Investopedia, n.d.).

Generalized Autoregressive Conditional Heteroskedasticity(GARCH). This is a model to estimate volatility in financial markets (Investopedia, n.d.).

Heteroskedasticity. When volatility is time varying (Investopedia, n.d.).

Homoskedasticity. When volatility is constant through time (Investopedia, n.d.).

Illiquid Markets. A market where little volume is being traded and it is difficult to find a buyer or seller.

Initial Margin Requirement. This is the amount of money needed to initiate a futures contract (The Free Dictionary, n.d.).

Jump Diffusion. This is a parameter that describes a process when the prices of an asset suddenly jump higher or lower from its previous price level. This parameter may or may not be activated. If this process is not activated then a normal Brownian motion dynamic is present in the price curve (Kennedy, 2007).

Levy Process. A model to describe the movement of asset prices that goes beyond a typical Brownian motion or Black–Scholes method. This process is described through drift, volatility, and jump diffusion parameters (Kennedy, 2007).

Liquid Markets. This is a market where buyers and sellers are in equilibrium (Investopedia, n.d.).

London Interbank Offered Rate (LIBOR). This is a common lending rate used in financial contracts and lending between banks (Investopedia, n.d.).

Maintenance Margin Requirement. This is the amount of money needed to maintain a contract in the futures market. If your account balance falls below this margin then additional money is needed to maintain a position in the futures contract (Investopedia, n.d.).

Monte Carlo Simulation. This is a computer simulation, whereby the evolution of price is generated for each time period (Investopedia, n.d.).

Options Contract. This is a contract that gives the owner the opportunity to fulfill the contract at a certain price for a specified amount of an underlying asset (Investopedia, n.d.).

Options Market. This is the market where option contracts are bought and sold (InvestorWords, n.d.).

Rebalancing. This is the term used when a hedged position is adjusted based on the hedging strategy (Investopedia, n.d.).

Receding Horizontal Control and Stochastic Programming. This is a method to hedge a financial position, whereby Monte Carlo simulations are calculated to predict the movement of an asset price. When a threshold is reached a rebalancing is initiated (Meindl, 2006).

Samuelson Effect. This is the phenomena of higher volatility when a futures or option contract nears expiration (Theriault, 2007).

Static Hedging. A hedging strategy where rebalancing throughout time is not implemented (Moneyterms, n.d.).

Volatility. This is a parameter that defines the degree of variance. The higher the weight with this parameter then the more volatile the price dynamics are for a particular asset. This parameter can also describe the mean reversion of a price curve (Investopedia, n.d.).

Assumptions

I assumed that markets are not meeting the standard model in finance. The standard model is that markets are efficient, whereby the current market price has all possible information. The efficient market hypothesis (EMH) does not hold due to the lack of predictability with extreme movements in market prices. The EMH fails to explain why bubbles and crashes happen frequently in financial market. The standard model in finance suggests that future prices are not affected by past prices, also known as market memory, and that returns are Gaussian distributed. Financial markets have high kurtosis and are skewed, whereby exhibiting non-Gaussian distributions. Soros (2003) conveyed that a whole field of finance, called behavioral finance, has explained market behavior as reflexive and exhibiting herd characteristics (p. 54).

Other key assumptions are that financial markets do not exhibit constant volatility and correlation. Assets tend to have clustered volatility, or heteroskedasticity, in the price curve. This heteroskedasticity can represent extreme movements in asset value. In terms of correlation of assets throughout a time series, different assets might trade with negative correlation, but in extreme cases these assets might trade in tandem. If a portfolio is designed with certain assumed correlations, this portfolio is at risk of correlation breakdown and a fat tail event. Again, I cannot assume that financial market returns to be Gaussian distributional.

In this research study the assumption is that markets are not well behaved and can exhibit nonlinear characteristics. Therefore a means to reduce financial risk due to asset price fluctuation is desired. To risk manage a portfolio, hedging can be utilized. This research study utilized different hedging strategies to determine which method has the least hedging error, whereby volatility of the portfolio is mitigated. Lastly, I assumed that markets also move in a Levy process, whereby I described the dynamics through drift, volatility, and jump diffusions. These parameters in the Levy process were assumed to be time varying. To improve on the RHCSP method, I utilized the Levy process and the LIBOR. I assumed that the LIBOR represented banking stress in the financial system.

Scope and Delimitations

The scope of this research study was to study different hedging methods and evaluate their performance relative to hedging error. The time period considered for historical backtesting was from January 1, 2005 through December 31, 2012. This time period captures the market dynamics during the asset bubble, crash, and recovery of the financial crisis of 2008. The hedging methods investigated were the BSM, Leland, Whalley and Wilmott, RHCSP, and the modified RHCSP. The two futures contracts that were considered in this research study were the light sweet crude oil contract and the EUR/USD contract. These future contracts were considered due to their importance in the global economy. Oil is the life blood of modern society and the EUR/USD is a very important currency relative to the dollar index. Both of these future contracts exhibited extreme volatility during the financial crisis of 2008.

The boundaries of the study were related to the two types of futures contracts investigated. The current month future contract was used for light sweet crude and the EUR/USD contracts. The light sweet crude contract was year round and has a designation of CL. The EUR/USD contract was quarterly and has a designation of 6E. Both future contracts were standard size. I did not include other futures contracts in the study due to the scope of the research questions investigated. I chose the time period of this study to find out how to improve hedging performance in extreme market conditions. The most current data available was the years running up to and through the recovery from the financial crisis of 2008. The starting time period of January 2005 was due to the beginning of the housing boom. Previous years leading up to January 2005 seemed to be extraneous for this research study.

In this study I addressed generalizations by showing that hedging error could be reduced in multiple markets—in this case energy and currency markets. The largest traded energy futures contract in the United States of America is the CL contract, and the

6E currency contract is a very important global currency futures contract. This research study was not concerned with a specific financial return for these contracts when comparing different hedging methods. This research study was concerned specifically if I could reduce hedging error in different market dynamics and which hedging method was best for that task.

Further studies would need to be conducted on actual financial returns when utilizing certain hedging methods and future contracts. Another generalization to consider is how the hedging methods would perform in non-future related assets. It is possible to hedge in the spot market without utilizing futures or options. I do not recommend hedging the spot market with different assets because of the correlation and volatility breakdown of the hedging leg, which might breakdown faster when compared to hedging with future or option strategies of the underlying.

Limitations

There were limitations in this study relative to the research design and methodology implemented. This research was based on an experimental design, whereby stochastic simulation and backtesting of futures markets were used. The limitation of this research design approach was that the backtesting was only on light sweet crude oil and the EUR/USD contracts; therefore I could only establish conclusions from this research for these two futures contracts for the periods examined. As for the simulation process, the limitation is computational time to run the numerous Monte Carlo simulations. But I can establish validity of the instrument via the comparison of the hedging error in a simulated environment and a real world environment.

This research study employed the use of quantitative methods. A limitation of this approach was based on dataset size. Does the dataset have a large enough time period to represent the nonlinear market dynamics? This research evaluates 8 years of market data and establishes hedging method performance via their respective hedging error.

Due to the time period of interest for the backtesting there were extreme conditions that were represented in the dataset, especially during the crisis of 2008. When using moving averages—for returns, volatility, correlations, or drift—datasets can be biased due to these large swings in the prices of the futures market. But the whole point of this research was to develop a way to improve hedging performance in illiquid markets. So simple averaging and elimination of all the outliers is not acceptable and masks the true fragility of the market. These nonlinear dynamics are essential to properly developing and evaluating dynamic hedging strategies for real world conditions, such as fat tail events. This bias was overcome by using a moving average window to parameterize the Levy process and the use of the LIBOR for the modified RHCSP method—reducing the bias of the illiquid market condition. I evaluated the hedging methods only on their hedging error. Because each hedging method is compared to each other in an ANOVA test for the same time period the hedging performance can be established in liquid and illiquid markets.

To address the limitations of the research design and methodology used in this study the following are considered. Backtesting only an energy and currency contract prevents immediate conclusions to be drawn on other asset classes and future contracts.

But this limitation was partially mitigated by simulating price curves via a stochastic process, whereby showing external validity of the performance of different hedging methods when compared to each other relative to hedging error. The main purpose of this research was to establish which hedging method can reduce hedging error in liquid and illiquid markets. I could mitigate the limitations in the quantitative method used because the dataset used was over an 8-year period that covers pre-, during, and postcrisis of 2008. Therefore an asset bubble, crash, and recovery were represented in the data. Another way to mitigate the limitation of the datasets was that the hedging evaluation, in terms of hedging error, was calculated at different discrete time intervals throughout the 8 years to establish a realistic hedging performance evaluation. For example, calculating hedging error only at the end of 8 years compared to calculating the cumulative hedging error every month or every quarter produces different hedging error results; therefore this research uses discrete time interval evaluation to match what real traders and portfolio managers report to establish return performance to their client.

Significance

A comprehensive study using RHCSP on oil and currency futures is necessary to improve portfolio performance and possibly protect from black swan effects such as the financial crash of 2008. Markets are approaching higher volatility episodes, which leads investors to question how to manage their investment portfolio. The sophisticated investors and professional investment managers need access to better risk management tools, such as dynamic hedging, to mitigate market corrections or crashes.

Being able to incorporate the RHCSP to the oil and currency futures market will allow for better risk management within investment portfolios involved in these financial instruments. Since the oil futures market is heavily linked to the USD, understanding how to dynamically hedge currency markets is also important. In theory, even governments might be able to use the RHCSP techniques to smooth out pricing swings, similar to how the Federal Reserve affects interest rates by intervening in the Treasury market. The positive social change that this research might present is a better risk control on investment portfolios and how to benefit from high volatility in markets, instead of being a casualty of financial markets.

A better behavioral finance method would help hedge energy future positions for market participants. It is important to understand the volatility of the oil market because it is a very important sector in the global economy. By understanding these dynamics better predictions of inflationary or deflationary conditions can be obtained, which can lead to increased performance of hedging strategies. This research can be valuable to economists, policymakers, and market participants.

Summary

This chapter introduced the purpose and problem statement of this research study. The research questions and hypotheses were presented with an introduction to the theoretical framework for the research study. The nature of the study was quantitative to evaluate hedging error. Definitions were defined and assumptions were presented to articulate the research design direction. I presented the scope and the limitations of this research design. Lastly, I presented the significance of the design on why a comprehensive study needs to be made in hedging oil and currency futures.

In Chapter 2, I discuss a review of the important literature pertaining to this research study. Key items discussed in the literature review are the theoretical framework, the basis for the hedging method evaluation, and the need for an improved hedging method in illiquid markets.

Chapter 2: Literature Review

Introduction

This study was designed to address a lack of scholarly literature, research, and understanding related to hedging future contracts related to oil and currency markets. The study followed two basic precepts: that it is important to understand the volatility of the oil and currency market because they are very important financial sectors for the global economy, and that by understanding these dynamics better predictions of inflation or deflationary conditions can be obtained, potentially leading to increased performance of hedging strategies. By lowering the portfolio volatility the returns can be much more stable. This study utilizes dynamic hedging as a strategy of reducing volatility of price movement.

This literature review investigated three related areas of concern to this study: oil and currency volatility, the need to develop hedging strategies to reduce hedging error in the oil and currency markets, and the use of receding horizontal control and stochastic programming.

There was increased volatility in all global financial markets due to the global financial stress caused by the financial crisis of 2008, albeit this volatility of financial markets are characteristic of market crashes of the past, (e.g., crash of 1929). This global financial stress has affected foreign exchange and warrants the need for methods to hedge such volatility risk. Peak oil is also a major concern for the energy sector. Peak oil is the concept that production of oil per barrel has reached maximum and that oil production will continue to decline. Peak oil can be caused by supply or demand dynamics. In terms of supply dynamics, the peak oil concern is caused by reduced recoverable oil reserves, whereas the demand curve is affected by population growth, technological change, and the growth of switching to new energy sources. When the costs are too high for oil extraction compared to the futures market, oil companies usually decide to close the well, which leads to less oil supply. When oil supply is curtailed prices climb causing price volatility in the futures market. Due to these volatility dynamics, investors need to develop ways to hedge in the oil and currency markets—whereby hedging error is reduced leading to better portfolio performance.

Hedging errors occur when a portfolio is not completely immunized by a hedging strategy despite the intent to immunize the volatility of a portfolio return. Some degree of hedging error exists for most hedging strategies. Receding horizontal control and stochastic programming has been shown to reduce hedging error relative to standard hedging methods for simulated short positions on a derivative.

This literature review is divided into five major sections: (a) risk management, (b) pricing models, (c) artificial intelligence and trading systems, (d) behavior finance, and (e) economics. Risk management should be used as a tool to assess risk exposure in a portfolio. This risk exposure might be related to counterparty risk. Other risk exposures are from endogenous or exogenous shocks. Risk managers use scenario and stress testing to help determine their risk exposure in a portfolio. The primary risk management themes examined in this review are: (a) hedging, (b) options, (c) monitoring volatility, and (d) liquidity.

The next major section covered in this literature review examines literature on pricing models. Pricing models are a means to determine expected value of assets. These pricing models are used to determine if the market price is above or below expected price, enabling an investor to determine to enter or exit a position in the market. Investors can also use this pricing model information to establish a hedged position. The topics covered pertaining to pricing models are: (a) option pricing, (b) other derivative pricing, (c) volatility modeling, (d) variance gamma, (e) threshold model for forecasting accuracy, (f) exchange rate modeling, (g) real option valuation, and (h) correlation modeling.

The third major section examines pertinent literature on artificial intelligence and trading systems. This section discusses methods to build automated trading systems. These artificial intelligent systems contain algorithms to help parameterize a model for price expectation or market direction expectation. This section involves the following topics: (a) currency market trading using volatility dynamics, (b) genetic algorithms for optimization, (c) technical trading strategies, (d) pattern association, (e) use of vector machines to predict volatility, (f) use of artificial neural networks, and (g) high frequency trading.

The fourth major section examines literature on behavioral finance. The behavioral finance field provides theories on investor behavior in terms of investment decisions and market characteristics. These market characteristics relate to market bubbles, crashes, and liquidity issues in trading. Key topics examined in this section include: (a) risk aversion, (b) investor psychology, (c) behavioral bias, (d) segmentation of investors, (e) behavioral finance with efficient markets, (f) market behavior, (g) game theory, and (h) financial crises.

The last major section covers pertinent literature on economics. The field of economics has produced many theories to help understand international trade effects, other macroeconomic situations, and market dynamics. This section pertains to the following topics: (a) futures markets, (b) exchange rates, (c) financial crises in Asia, (d) efficient market hypothesis, (e) carbon taxing, (f) macroeconomics, and (g) central banking.

Literature Search Strategy

The literature search was conducted using three major library databases: (a) ProQuest's business and dissertation databases, (b) Science Direct, and (c) EBSCO Host's academic search complete database. The primary search terms and combinations were:

- Dynamic hedging and oil
- Dynamic hedging and currency
- Oil futures and energy or currency
- Behavioral finance
- Economics or macroeconomics
- Quantitative finance and oil or currency
- Risk management
- Value-at-Risk or copulas
- Black Scholes
- Levy process
- Option pricing

The search period examined material from 1985 to 2012, with most literature selected around the most recent 5-year period. The types of literature examined included dissertations, peer-reviewed journals, and textbooks. The textbooks were in the fields of economics, risk modeling, hedging, volatility, and correlation modeling. The seminal literatures used in this research study were:

- Black and Scholes (1973)
- Leland (1985)
- Whalley and Wilmott (1997)
- Meindl (2006)

Black and Scholes (1973) showed how to use an option pricing function to hedge. Leland (1985) modified the Black–Scholes method by utilizing a volatility function capturing transaction costs. Whalley and Wilmott (1997) hedged using a tolerance band; where as Meindl (2006) utilized a RHCSP method.

Theoretical Foundation

Possible Selection Set of Theories to Use

There are many theories available to guide portfolio management. Some of the theoretical foundations available are corporate finance, behavioral finance, prospect theory, intertemporal choice theory, and chaos theory and emergence. Theories in corporate finance pertain to concepts in managing corporations, portfolio management, and risk management. Managing corporations is relatively axiomatic, but an explanation of portfolio management and risk management needs some clarification. In terms of portfolio management, the efficient market hypothesis is assumed and that investors and economies maximize their utility functions. Risk management assumes that there are ways to improve profitability by reducing volatility in asset returns.

Behavioral finance theories relate to concepts that explain investor behavior, such as, reflexivity, animal spirits, and speculative or fundamental equilibriums. Reflexivity, in this context, refers to feedback loops into the investment decision, whereby a herd mentality can result; herd mentalities can be positive or negative. Herd mentality is when investors move together in their investment positions. The term animal spirits is used to describe when a market has momentum. This momentum refers to the strong direction of the price of a financial asset. This momentum can be from a positive outlook on the economy or a negative outlook. Speculative and fundamental equilibriums are where an asset class is trading either near its fundamental value or is in a speculative long or short pattern.

Prospect theory tries to explain investor behavior related to their risk aversion characteristics. The main point of prospect theory is that investors tend to hold losing positions and close profitable positions. The reason for this seemingly irrational behavior is that financial losses are too psychologically damaging to realize. Intertemporal choice theory pertains to time period discounting. When valuing an asset many investors might assume a constant discount factor to calculate the net present value of an asset. In intertemporal choice theory, an investor’s behavior seems to suggest time varying discounting.

The last theoretical foundation to consider is chaos theory and emergence. Concepts in chaos theory and emergence try to explain nonlinear behavior of complex systems. These complex systems tend to exhibit fixed and chaotic attractions. A fix attraction is when a system seems to attract to a fix point or a set of points. It is possible when the growth of a system reaches a certain threshold that the complex system exhibits chaotic attractions, whereby the system seems to move in an erratic behavior with little predictability. When certain thresholds are reached a phase transition can result in a system leading to different system dynamics and other evolutionary phenomena.

Theory to Use in Research Study

The theoretical foundation used in this research study was chaos theory and emergence. The reason for choosing chaos theory and emergence as a theoretical foundation was due to the assumption that oil and currency markets are nonlinear systems that exhibit chaotic attributes. To reduce the possible price swings in the futures market a hedging strategy should be implemented. Therefore the research used in this study pertains to risk management techniques in corporate finance theory, but applies the assumptions that markets are not efficient and that investors are not rational utility maximizing because the oil and currency markets seem to exhibit chaotic behavior due to investor behavioral characteristics. One way to model these asset markets is to use parameters that define the drift, volatility, and jump diffusion of the asset in consideration. These parameters are determined form historical time series. It is important to note that when the system changes momentum a new price pattern emerges, which suggests that modeling from historical datasets will lead to a lagged forecast. Thus, an investor needs to hedge for unexpected price movement.

Origins of the Theory

The origins of chaos theory, in terms of financial markets, come from the observation that markets seemed to be irrational at times. Greenspan (2013), Taleb (2012), Taleb (2007), Shiller (2005), and Soros (2003) suggested that irrational characteristics are seen in asymmetric price movements; whereby in a selloff, prices depreciated faster than in the price appreciation. This can be referred to as panic selling. During selloffs a market can become illiquid and price depreciates rapidly. Another consideration is the asymmetric effects of news on price movements that were proposed by De Grauwe and Grimaldi (2006) when analyzing currencies. Some news unpredictably affects price, while in other time periods, news has a significant weight on price movements. This suggests that systems may be in some equilibrium phase, whereby the news does not have significant effects until some other system dynamic is present (De Grauwe & Grimaldi, 2006, p. 128).

Another reason to consider the use of chaos theory and emergence as a theoretical foundation was due to the characteristics of the price charts in the oil and currency markets. Mandelbrot (2004) thought that there seems to be fractal characteristics in financial price charts. For example, a one-hour price chart shows similar characteristics as a four-hour or day-price chart. This principle is called self-similarity. Brown (2008) investigated another interesting but related phenomena of price charts and found that price movements exhibit Fibonacci sequences (p. 10).

Investors can use technical analysis to determine price retracements. Price seems to mean revert to a more stable level after an asset bubble. The mean reversion might be due to a phase transition or attraction point for the nonlinear dynamic. In large asset bubbles, the nonlinear dynamics are more pronounced leading to larger asset losses. The financial crisis of 2008 is a great example of exaggerated home price appreciation and how a bubble burst can be catastrophic to the larger economy. During the financial crisis of 2008 it seemed that the system was going into a chaotic attraction during the selloff.

As prices moved lower there were sporadic mean reversions to slow the selloff, but that was fleeting. During this selloff period the volatility of returns were extremely high, leading to unpredictable price movements—again characteristics of a chaotic attraction state. Mandelbrot (2004), Taleb (2007), and Sornette (2003) considered that this chaotic state of affairs seems to represent a complex Lorenz system, whereby the prices are unpredictable and move wildly by not settling down to a new energy level.

Major Proposition of the Theory

In chaos theory and emergence, financial systems can be considered nonlinear with fractal characteristics. Within chaos theory and emergence there are reflexive properties charged by investor behavior, which leads to magnification or demagnification of price movements. Another proposition of chaos theory pertaining to financial markets is the price asymmetry with selloffs and that mean reversions can be very violent, but some are quite benign.

Correlation between assets do change, especially in illiquid conditions, and that chaos theory provides a theoretical foundation to explain these changing correlations that the efficient market hypothesis seems to not explain. In addition to time varying correlations, volatility is not constant and exhibits heteroskedasticity. Assumed in chaos theory and emergence is that the rate of growth or decline has a maximum level, whereby price reversals result. In this theoretical foundation, the proposition exists that financial volatility is possible to hedge using derivatives.

How the Theory Has Been Applied In Studies

Black and Scholes (1973) provided a means to model option prices using Brownian motion. The Black–Scholes method (BSM) also allows investors to model how to hedge an option position or hedge with an option position. Investors typically use the BSM method to delta hedge, but gamma or vega hedging is also possible—but less common in the financial industry. The main assumptions of the BSM are that transaction costs were not included and volatility is constant.

To provide a hedging method that includes transaction costs and constant volatility, Leland (1985) developed a method to utilize the volatility variable in the BSM. The key approach by Leland was to model transaction costs as a function of volatility; therefore the Leland hedging method still utilizes the Brownian motion characteristics of the BSM hedging strategy.

Whalley and Wilmott (1997) proposed a hedging method that included transaction costs, time varying volatility, and hedging threshold levels. These threshold levels provide a way to reduce rebalancing costs in dynamic hedging situations. There are two different types of hedging: static and dynamic. In static hedging there is only a one-time hedging position that remains active until the portfolio is liquidated. In dynamic hedging strategies there are many rebalancing periods, which usually incur transaction costs. The key to dynamic hedging is to reduce unwarranted transaction costs by reducing the number of rebalancing periods.

Meindl (2006) proposed a method to improve hedging error by using a process called RHCSP, whereby this method utilizes objective functions and Monte Carlo simulations. RHCSP also utilizes different threshold levels, which improves upon the Whalley and Wilmott method.

Rationale for the Choice of the Theory

The rationale for utilizing chaos theory and emergence as a theoretical foundation for this research project is due to five reasons. Firstly, the futures market is a nonlinear system and I needed a framework that can describe unexpected system dynamics. Secondly, financial markets exhibit bubbles and bursts. Investors need to be able to reduce their market risk exposure by trying to forecast probabilities of mean reversion. Thirdly, financial systems seem to have an asymmetrical price movement characteristic, whereby selloffs are more violent than rallies. Fourthly, contingency claims among institutional investors can produce nonlinear behavior at certain key price points. Lastly, the need to reduce return volatility—especially near a mean reversion point—is mission critical to an investor for capital preservation. Volatility can be reduced using certain hedging methods.

The Selected Theory Relates To the Research Study

I selected chaos theory and emergence as a theoretical foundation because, by realizing that markets have erratic behavior at certain points in time, reducing risk is important to investors. By using hedging methods to reduce risk, investors can reduce the chaotic movements of the futures market. Since initial minor fluctuations in the price path can produce large possible price ranges, there needs to be tools developed to reduce forecasting error.

To understand the nonlinear dynamics and path dependencies chaos theory and emergence holds some promise. These developed tools to reduce forecasting error can lead to reduced hedging error and provide more stable portfolios. The research questions proposed in this research study builds on existing theory in two ways. First, this research study develops a way to reduce hedging error in the oil and currency markets, especially in illiquid conditions. Secondly, by utilizing receding horizontal control and stochastic programming to fine tune hedging positions an investor can produce more stability and less fragile portfolios, which should reduce the typical investor stress from investing in volatile underlying markets.

Literature Review Related to Key Variables

Studies Related to Chosen Methodology

This research expands on research from Meindl (2006), Whalley and Wilmott (1997), Leland (1985), and Black and Scholes (1973). In the Meindl study different hedging methods were compared to determine lowest hedging error. Meindl found that RHCSP was a better method to improve hedging error for dynamic hedging, but the study was based primarily on simulated data.

In the Whalley and Wilmott (1997) study their hedging method used time varying volatility and threshold levels before rebalancing hedged positions. The Leland (1985) method used transaction costs that were imbedded into the volatility function to determine the BSM delta hedge. The problem with the Leland method is that volatility is also assumed constant.

The Black and Scholes (1973) study provided a method to delta hedge an investment position but assumes that volatility is constant, no transaction costs are incurred, and that asset prices move in a Brownian motion dynamic.

How Others Have Approached the Problem

Other researchers have approached volatility in a portfolio in a few ways. Kennedy (2007) used dynamic hedging utilizing a regime switching process. Kennedy leveraged the Levy process by dynamically hedging while considering price movements that exhibit jump diffusion characteristics.

In terms of artificial intelligence price expectation can be calculated. Kim, Han, and Lee (2004) used artificial intelligence to predict price by utilizing fuzzy logic and genetic algorithms. These fuzzy logic and genetic algorithms were used to integrate information from multiple sources and helped with processing cognitive uncertainties. By predicting price, a hedged portfolio can be established to offset predicted returns.

Technical analysis is a very common trading practice. Many traders solely rely on this behavioral finance method of price prediction. Modovan, Moca, and Nitchi (2011) used technical indicators, such as Moving Average Convergence and Divergence (MACD), Rate-of-Change (ROC), and stochastic oscillation. Their study used these three indicators to develop an automated trading system. Modovan et al. used trading algorithms to produce a trading signal. These signals can be used to determine when to enter a trade, exit a trade, or hedge a leg in a portfolio. By using genetic algorithms a researcher can determine the best indicator combination and optimized parameters for each indicator. The parameterization is based on historical datasets.

To investigate a high volatile market, Fleten, Bråthen, and Nissen–Meyer (2010) studied the Nordic hydropower market. Electric power is a highly volatile market due to storage issues. Producers need to hedge for price volatility and Fleten et al. found that using forward contracts to reduce risk was viable. They compared the use of static and dynamic hedging. The Fleten et al.'s study established that hedging in a super high volatile market is possible and effective.

Justification of Variables and Concepts

The first independent variable was the type of market, whereby the following are the markets analyzed:

- Simulated
- Oil
- Currency

The second independent variable for this research study on dynamic hedging was based on five hedging methods:

- BMS
- Leland
- Whalley and Wilmott
- RHCSP
- Modified RHCSP

The justification of using these hedging methods for the second independent variable was due to the industry practice. The BMS method is one of the most common hedging methods utilized, but volatility is assumed to be constant and that transaction costs are not included—which does not seem to be helpful in a dynamic hedging situation. The Leland method helps with transactions costs, but volatility is still constant.

The Whalley and Wilmott method helps in the dynamic hedging strategy with threshold bands and the RHCSP methods help with better control of tracking the asset price path—which is critical in dynamic hedging.

The dependent variable was the hedging error. Hedging error is a metric to determine how much deviation a hedging strategy has to the position being hedged. A hedging error of zero means that the hedged leg of the portfolio matches to the non-hedged leg perfectly. Therefore, the net value of the portfolio has not changed in a perfectly hedged situation. It is industry practice to evaluate hedge strategies via the hedging error performance; allowing for portfolio managers to determine the hedge efficacy.

The main concept of hedging a portfolio is to attempt to immunize volatility of an asset market. In reality, hedging strategies break down due to changes in correlation, volatility, and liquidity. There are two main types of hedging: static and dynamic. A static hedge is when the hedge position is not adjusted throughout the life of the portfolio. In dynamic hedging the hedge position is adjusted throughout the life of the portfolio.

Review and Synthesis of the Study

Risk Management. The first main theme to review was related to risk management. Lautier and Raynaud (2012) thought that there seemed to be market integration in the energy sector and other future markets might also exhibit similar dynamics (p. 215). Lautier and Raynaud investigated if there was evidence of market integration within the energy, agricultural, and financial futures (p. 215). By using recurrent neural network-based prediction systems for option trading and hedging, Quek, Pasquier, and Kumar (2008) found that direction of change for the next day of trading was 90% predictable for the gold commodity and GBP/USD currency pair between 2000 and 2002 (p. 150).

Kroner and Sultan (1993) showed that a bivariate error correction GARCH model can be used to improve risk management (p. 550). Kroner and Sultan tested the GBP/USD, USD/CAD, DEM/USD, USD/JPY, and USD/CHF from February 8, 1985 through February 23, 1990 and confirmed that conditional hedging outperforms (p. 540). Humphreys (1997) showed that by using GARCH models for energy commodities that dynamic hedging was better than standard hedging for West Texas Intermediate (WTI) and Brent oil contracts from April, 1991 to March, 1996 (pp. 68–72). Humphreys compared naïve hedging, standard hedging, and dynamic hedging relative to variance of returns for the WTI and Brent contracts—which are commodities with high volatility (p. 70). Naïve hedging is hedging without consideration of an optimal level for the hedging leg of the portfolio and standard hedging is when considering constant variance and a covariance ratio.

During periods of extreme volatility oil futures prices are very non-stationary. How efficient is the oil futures market in these extreme conditions? This question can be answered by studying the difference between symmetric and asymmetric GARCH models in the oil market during extreme market conditions (El-Khoury, 2006, p. 6). In the El-Khoury's study, NYMEX light sweet crude oil contracts from January, 1986 to April, 2005 showed that future oil prices were unbiased predictors of future spot prices; therefore they were efficient markets even in volatile conditions (p. 24). Pan (2009) conveyed that speculation on the oil market increased since oil commodity trading became electronic, and it over time became a very important explanatory variable for market volatility (p. 33). Pan concluded that the variation of future price volatility could be explained by speculation variance measured by a speculative index (p. 33). Ludkovski (2005) investigated on how to incorporate tolling agreements in hedging and pricing models (p. 1). Tolling agreements are temporary lease agreements between the energy buyer and energy generator and are important to energy contracts because they allow for risk reduction.

Modeling jumps in the market is becoming more popular as a pricing strategy. Kennedy (2007) found that hedging under a Levy process can be effective even for path-dependent American options (p. 192). Kennedy used simulation data and concluded that many different Levy processes can be incorporated into a hedging strategy (p. 192).

According to Frey and Schmidt (2012), risk management is also necessary in the credit derivative markets and this type of derivatives market can set a chain reaction that ripples through the energy and currency markets. They found that it is possible to use unobservable market information through a filtration process to price and hedge credit derivatives (pp. 125–127). The Frey and Schmidt's study using nonlinear filtering is important because it suggests that there are endogenous signals in the credit markets that might allow for better dynamic hedging performance.

Due to the fact that the correlation of assets is not fixed, having a portfolio of many different assets might produce unexpected diversification characteristics. Modeling the changing dynamics of the pair of assets in a portfolio is extremely important, especially when dynamically hedging. Cross hedging is when taking a long position on a certain asset and hedging with a different asset that trades inversely. Ankirchner and Heyne (2012) showed how to cross hedge with stochastic correlation models (pp. 41–42).

With the Cao and Guo (2012) study it was shown that for Google, Inc. standard error was smaller for higher hedging frequencies, but average gains were higher with a variance–gamma process (p. 32). Cao and Guo also discovered that the higher hedging frequencies produced higher average values for net gains (p. 32). The Cao and Guo study makes sense, but there is the concern of over hedging by rebalancing too many times. Over rebalancing induces higher transaction costs, so there is a balance between rebalancing using a dynamic process—but only enough to minimize the rebalancing costs.

Looking at tail risk for portfolios is very important, especially when trying to hedge risk. How to model tail risk? The use of Value-at-Risk and Conditional Value-at-Risk are two approaches that can help model tail risk (Kaya et al., 2011, p. 343). Kaya et al. found that persistence in volatility can be filtered with GARCH models to reach a stationary condition for fat tail and dependency modeling (p. 355). Kaya et al. also showed that out-of-sample testing of the USD/JPY, EUR/USD, GBP/USD, AUD/USD, and USD/CAD showed that managing risk can be done with mean variance but only a non-normal model with tail risk control appears to reduce the size of the drawdowns (pp. 345–347). Kaye et al. showed that bivariate normal distributions can be a poor approximation for joint behavior of certain currency pairs; therefore one should model currency pairs with a marginal distribution by fitting fat-tailed distributions to the residuals of the Glosten-Jagannathan-Runkle GARCH (GJR) process and calibrate a t–copula to join the marginal distributions (p. 350).

There are many different hedge fund strategies. Viebig and Poddig (2010) found that there are dependency structures between several different hedge fund strategies, which produce asymmetric behavior in the hedge fund indexes (p. 44). Viebig and Poddig showed that extreme value theory and copula theory can be used to model multivariate daily return distributions of hedge fund strategies and that there is clustering behavior due to increased volatility and credit spread widening (p. 51). Their study is important due to the empirical evidence that as stress in the financial system increases the probability of co-movement of different assets increases, leading to higher portfolio value loss. In financial crises a supposed diversified portfolio might actually trade in a non-diversified way.

The main point of modeling tail risk is that standard statistical tools do not model the dynamics efficiently enough. It was the purpose of this research not to model the actual tail risk of the CL or the 6E futures contracts, but to hedge the risk associated with these contracts.

Liquidity-adjusted Value-at-Risk (L-VaR) is an exciting but underutilized model in the world of finance. Al Janabi (2009) demonstrated that due to the asymmetric behavior in the distribution of returns in the commodity space, L-VaR calculations with stress-testing or scenario analysis can add clarity to the risk in the market (p. 36).

Default term structure models can be used to help understand and risk-manage bonds. By using the price of a zero-coupon defaultable bond as a dependent variable and using discounted growth, jump intensity, short rate, and mean jump sizes as the independent variables one can measure credit risk based on real-world probability measures (Bruti–Liberati, Nikitopoulos–Sklibosios, Platen, & Schlögl, 2009, p. 22). Understanding credit default risk can be a possible exogenous measure for a market correction in the commodities market, because credit default risk might lead to contagious market situations—which were exhibited during the Lehman collapse of 2008.

Chang, McAleer, and Tansuchat (2009) found that when modeling conditional correlations for risk diversification in the energy market you could find that univariate ARCH and GARCH components of GARCH(1,1) and GJR(1,1) were statistically significant for all returns on the Brent, WTI, and Dubai crude oil markets from January 2, 1991 to November 10, 2008 (p. 50). Chang et al. also concluded that asymmetric effects using GJR(1,1) were not significant (p. 50). Therefore it might be prudent to model with symmetric GARCH models for the energy sector instead of asymmetric GARCH models.

In terms of credit default swaps, understanding default spreads might provide a signal for risks building up in a financial system. A credit default swap market signal might allow for rebalancing to be initiated in a hedged portfolio. Errais (2006) concluded that parameters in a LIBOR model can capture the skew observed in the cap market (p. 93). Errais also found that the affine point process is flexible enough to account for cyclical dependencies in the economy and contagion in the market with random recoveries (pp. 52–53).

Jabbour, Kramin, and Young (2009) conveyed that by using copula functions one can model a basket of default swaps and default correlations (p. 44). Jabbour et al. concluded that assumptions are critical to the valuation of the basket of default swaps, and the type of copula that is chosen also has a pricing impact on the default swap basket (p. 43). Again, understanding the model assumptions in the credit and default swap markets should help provide insight on looking for a signal in the market for adjusting hedging rebalancing timeframes.

The hydroelectric power industry has a common practice on hedging pricing risk. Fleten et al. (2010) discovered that optimized positions vary over time and hedging with the use of forward contracts significantly reduces risk; but that this added hedge protection only reduces mean revenue slightly (p. 28). In the energy market there are speculators and hedgers. Knowing that energy producers and key industrial users of energy are active in the market helps one to understand the true demand for that particular energy product.

It has been established that, at least in the Saudi financial markets, investor managers' behaviors are key to understanding financial market behavior. Masood, Aktan, and Chaudhary (2009) showed that Saudi risk managers favor experience and personal judgment over quantitative models (p. 118). Having models that incorporate investor behavior should provide endogenous risk insight for hedging rebalancing.

How can I better model financial losses that evade controls? Hybrid Bayesian networks can successfully model event dependencies in complex environments that evolve over time (Neil, Häger, & Andersen, 2009, p. 27). Neil et al. used hybrid

Bayesian networks to model a financial institution's operational risk (pp 11–16). This is important because without proper control of risk within a financial institution then operational risk can build up and might lead to a firm failure or possible economic collapse. The Neil et al.'s study sheds light onto how to utilize Bayesian models to understand endogenous risk formation.

The stochastic mesh method can be used to calculate potential future risk exposure (Ng, Peterson, & Rodriguez, 2010, p. 152). Ng et al. found that in multi-dimensional problems stochastic meshes yielded accurate potential risk exposure much faster than nested Monte Carlo simulations (p. 152). This study could be useful in developing a computationally efficient modeling regime that captures endogenous and exogenous risk formation in the financial markets.

Complexity science can also help in modeling financial market risk. Smith (2009) demonstrated that fuzzy logic and genetic algorithms can provide nonlinear dynamic equilibriums (p. 72). The Smith study presents an innovative modeling technique utilizing complexity science and emergence to understanding risk dynamics. Perhaps it is possible to use fuzzy logic and genetic algorithms to produce machine learning to recognize risk patterns in historical data and forecast out a potential hedging rebalancing.

The Asian markets can be indicators of world financial stress, therefore modeling risk in the Asian markets are important to hedging portfolios. According to So and Tse (2009), the Hong Kong stock market has a high Tail Dependency Coefficient (TDC) for property stocks and a low TDC for consumer stocks; therefore property stocks have more price action in a severe downturn (p. 208). So and Tse also showed that the Chinese stock exchanges also have strong contagious effects with other markets when there are abnormal price dynamics (p. 208).

GARCH modeling is a common industrial practice for forecasting volatility. Which GARCH type model is best to use? Srinivasan (2011) found that symmetric GARCH models are better in reduced forecasting variance in the S&P 500 index than asymmetric GARCH models (p. 63). This seems to confirm results found in the Chang et al. (2009) study when using GARCH for the energy sector.

Pricing Models. In quantitative finance being able to price different assets is very important to determine if markets are mispricing or to be able to price an illiquid asset to determine proper valuation. Many of these models involve volatility. In terms of currency options, what is the best volatility model to use for pricing? Manzur, Hoque, and Poitras (2010) showed that implied volatility, realized volatility, and the GARCH model can be used in pricing currency options (pp. 81–83). Manzur et al. discovered that realized volatility outperformed implied volatility and GARCH modeled volatility for currency option pricing for the GBP/USD, USD/CHF, EUR/USD from July 22, 2002 to June 30, 2006 (p. 84). Wang (2009) found that it is better to model GBP/USD and USD/JPY with a variance–gamma process for valuing options (p. 90).

Kristensen and Mele (2011) found that it is possible to use a close approximation model when there lacks a closed form solution for pricing derivatives (p. 410). Kristensen and Mele used Taylor series approximations in their study (p. 391).

When modeling international financial markets it is important to know what the volatility is in these markets. Georgiev (2007) concluded that realized volatility in many international markets is approximately log-normally distributed and this volatility exhibits long memory (p. 32). Georgiev also found time series that are modeled with realized volatility show strong predictive effectiveness (p. 32).

In terms of forecasting accuracy of a pricing model, what are the impacts of a Latent Threshold Model (LTM)? According to Nakajima (2012), LTM can outperform non-threshold models for cumulative returns for GBP/USD.EUR/USD, USD/JPY, USD/CAD, AUD/USD, and USD/CHF based on the time period from January 2006 through December of 2009—which was from daily returns of the currency exchange rates (p. 103). Nakajima defined a latency threshold model as a model framework that can shrink elements of the parameter process and collapse elements fully to zero when redundancy or irrelevance is present (p. 1).

There are many GARCH models to utilize for calculating volatility, but what GARCH model works best for currency pair modeling? Koubida (2007) found that a fractional integrated GARCH (FIGARCH) works well for developing countries, but GARCH is more accurate for developed countries' currency (p. 19). This might be due to the liquidity differences between developed and developing countries. Therefore, when considering hedging a currency pair position using GARCH modeling for volatility calculations the researcher or investor should consider the level of development the country has achieved before deciding on which GARCH model is appropriate.

Molodtsova (2008) found that using a simple Taylor rule can significantly increase predictability for the Organization for Economic Co-operation and Development (OECD) countries' currency rates (p. 104). Molodtsova defined the Taylor rule as the condition when central banks set targets for nominal interest rates due to changing conditions for inflation and output gaps (p. 2).

It is possible to model volatility in commodity prices by using a three-factor stochastic volatility model (Hughen, 2007, pp. 40– 41). More research needs to be conducted on historical data before implementing the Hughen study since the solution is only theoretical.

By utilizing a regression analysis on future contract returns, Dincerler (2001) found that storage costs and hedging pressure can explain the risk premium with future contracts (p. 161). Real options can also be used in energy market valuation. Real options are used when calculating a non-exchange traded asset, whereby knowing the current market value is difficult to discern. Real options methods use the Black–Scholes model for evaluating the value of exercising a particular set of possible investment options. Zhou (2010) utilized a generalized Gaussian Quadrature model against a Monte Carlo simulation and found that the former outperforms the Monte Carlo simulation in terms of efficiency, accuracy, and flexibility (p. 106).

Vector error correction model (VECM) performs better than random walks when applied to forecasting foreign exchange markets (Jiang, 2010, p. 31). Jiang also showed that VECM performs well in a one week prediction horizon (p. 31). The Jiang study might be useful in hedging risk in the currency market and a possible endogenous indicator for rebalancing a hedged position before a regime switch.

The term structure in the oil futures market is an important consideration in determining how to possibly hedge an oil position. Zha (2011) found that backwardation in the oil futures curve is not as persistent as in previous years and that contango occurs much more often in recent years due to more volatility in the energy markets (p. 130). The Zha study is important because a simple future contract rollover will not help hedge an energy position very effectively.

Another method when utilizing pricing models is the Kaurtz polynomial. Mahajan (2011) showed an analytical solution that was computationally stable for pricing options involving the BSM (p. 61). But a more applicable pricing model for option pricing is the use of a hidden Markovian jump diffusion process. Elliot and Siu (2013) showed analytically that the stochastic intensity of a random jump and the distribution of the random jump sizes are modulated through a hidden Markov chain (p. 24).

In the energy sector it is common practice to pair trade commodities, (e.g., oil–gas or coal–electricity.) Joint modeling these energy commodities is important for hedging risk. How to joint model the gas and electricity markets? Frikha and Lemaire (2013) recommended the following being important in any joint model: (a) capturing cross correlations; (b) long-term dependencies between gas and electricity; and (c) the stylized characteristics of the spot prices (p. 91). Frikha and Lemaire used maximum likelihood estimators and a least squares procedure for parameter estimation of their model (p. 91).

Frikha and Lemaire also showed that there is no need for multiple price drivers and that their model is close to a multifactor model based on jump diffusion processes (p. 91).

It was shown analytically that it is possible to use geometric dynamic programming to price American options (Bouchard & Vu, 2010, p. 243). But more research needs to be conducted if this actually works with historical datasets. Geometric dynamic programming is a method for solving stochastic targeted problems. In Hinnerich (2013), when pricing equity swaps in an economy with jump diffusion dynamics, it was shown that using a Martingale method and calculating convexity correction terms that an extended general pricing model for equities can be utilized (p. 114).

Being able to model asymmetric volatility in the energy sector would help to determine when to adjust a hedging rebalancing timeframe. According to Hassan (2011), shocks are persistent because the alpha and beta terms in the GARCH models are close to one and that bad news affects price more than good news because the sigma term is negative (p. 75). In terms of electronic trading on the oil market, it has been documented that electronic trading has a large impact on price volatility (Ye et al., 2010, p. 267). Theriault (2007) showed that GARCH models can perform better than constant volatility models and that maturity effects are important in pricing oil and gas commodity futures and options (pp. 32–33).

Due to the nonlinear dynamics in the energy markets it is important to model the volatility accordingly. Matilla-García (2007) started the pursuit by testing if there are nonlinear and chaotic behaviors in the natural gas, unleaded gasoline, and light crude oil markets; and concluded nonlinearity cannot be rejected (p. 27).

Artificial intelligence and trading systems. Artificial intelligence strategies and trading systems are evolving to a level that even retail traders can benefit from this technology. When developing a hedging system, incorporating an artificial intelligence algorithm should improve returns on an investment.

Extracting information from a streaming price of an asset is a common way to help automate a trading system. How to extract information about market expectations of future volatility from traded option prices? Guo (2000) suggested that ISVR models under predict low priced options and over predict high priced options (p. 144). Guo (2000) also found that GARCH models over predict call options, but put options can be over or under predicted (p. 145). The main take away from the Guo's study is that volatility modeling might under predict or over predict the pricing action; therefore a threshold level for rebalancing might be useful.

It is common practice among traders to follow a momentum strategy, especially in currency markets. Menkhoff, Sarno, Schmeling, and Schrimpf (2012) showed that momentum strategies can deliver high excess returns in the foreign exchange markets (p. 682). Menkhoff et al. attributed the high excess returns in momentum strategies due to the fact that currencies are harder to hedge and have high country risk, which is similar to corporate bonds with non-investment grade level and stocks with high credit risk (p. 682).

Genetic algorithms are starting to become more popular in implementing them into a trading strategy. Fan, Brabazon, O'Sullivan, and O'Neill (2009) found that a Quantum Inspired Evolutionary Algorithm (QIEA) obtained competitive results versus a standard genetic algorithm in static testing, but QIEA performed much better in dynamic tests (p. 509). When selecting a portfolio, genetic algorithms can also be used for optimization. By using genetic algorithms based on Markowitz mean variance theory a portfolio optimization can be performed. Yu, Wang, and Lai (2009) found that genetic algorithms perform better than equal weighted portfolios (p. 28).

When training certain algorithms with datasets, overfitting can be an issue with genetic algorithms and artificial neural networks. By using S&P 500 closing prices from June 6, 1988 to March 12, 1997 it was established in Fernandez Garcia, dela Cal Marin, and Ouiroga Garcia (2010) that incremental training diminishes overfitting and this increases the financial return of the trading rule, especially when trying to minimize market risk (p. 105). In Tian, Quan, Zhang, and Cai (2012), Chinese stock indexes showed increased profitability using an ACD optimized model, but ACD seems to work well in environments with high liquidity and low transaction costs (p. 283). ACD stands for the A, C, and D points for a certain technical trading method.

In terms of pattern recognition, researchers have investigated the Hang Seng Index. First one finds a set of patterns in a dataset and then determines if there are associated relationships amongst the patterns (Lui, Hu, & Chan, 2010, p. 280). Lui et al. suggested their pattern recognition method is good to determine if a pattern has significance but is not good for price prediction (p. 283). Other researchers have used relevant vector machines (RVM) to predict volatility. When using the Shanghai Composite Index from January 2001 to December 2006, Ou and Wang (2010) discovered that RVM yielded better predictive capability than normal GARCH(1,1) models since it is a dynamic process and incorporates longer memory of past information (p. 16). Lee, Ahn, Oh, and Kim (2010) discovered that Real-Time Rule Based Trading (RRTS) with the Korea Composite Stock Price Index (KOSPI) can be used to determine ideal number of trading indicators to use in a trading system (pp. 373–374).

Artificial intelligence in trading systems is being deployed at an increased rate. Kablan (2009) mentioned that artificial intelligence seems to be able to increase returns when using technical indicators, but when combining neural networks with fuzzy logic better results can be achievable (p. 226). Perwej and Perwej (2012) investigated the Bombay Stock Exchange and concluded that artificial neural networks can be robust with nonlinear dynamics (p. 118).

Currency trading can utilize artificial intelligence in a trading system. Intelligent trading systems are significantly better when compared to traditional trading rules (Thinyane & Millin, 2011, p. 373). Can artificial neural networks and genetic algorithms improve forecasting? Samanta and Bordolio (2005) studies the Indian stock market and concluded that out-of-sample tests showed that artificial neural networks improved forecast accuracy compared to a random walk model (p. 184). Kim et al. (2004) demonstrated that when using multiple sources to determine a decision, fuzzy genetic algorithms can be used in a trading strategy for the Korean stock market (p. 59). Another example of using genetic algorithms for portfolio selection was conducted in the Sefiane and Benbouziane (2012) study, whereby the weights of a portfolio can be optimized for maximum return (pp. 150–152). Sefiane and Benbouziane also concluded that the use of genetic algorithms for portfolio optimization can be computationally efficient (p. 153).

Technical indicators can be utilized in an artificial intelligence trading system. In Modovan et al. (2011) it is possible to use genetic algorithms to determine the closest to the best technical indicators to use and which will change over time (p. 187). Tan (2010) investigated how a trading system can produce long term and short term profits; and concluded that there is a higher probability of longer trade profits than shorter trade profits (p. 7).

In terms of ultra high frequency trading, data cleaning is important. Verousis and Gwilym (2010) utilized a special filter technique to clean ultra high frequency data (p. 324). Verousis and Gwilym suggested using minimum tick size, price level effect, daily price range effect, and return effect (p. 324).

Behavioral Finance. Behavioral finance is becoming more popular to help explain the reflexivity of the financial markets and understand the dynamics between speculators and hedgers. Spyrou (2006) investigated how investors react to price shocks and concluded that investors can over and under react to price shocks (p. 58). In terms of news, Aissia (2009) found that negative information defuses into the market slowly; but repeated bad news will lead to negativity by the investor and overreactions to financial markets can result (p. 22). Collective sentiment among investors plays a significant role in asset bubbles and crashes (Ildiko & Lefer, 2007, pp. 458–459).

In higher frequency trading is there a difference in investor behavior? Iyengar and Ma (2010) developed a tick-by-tick model utilizing a behavior financial based framework and concluded their model can predict price and volume, but more research needs to be conducted to improve external validity (p. 75). Neoclassical economics fails to explain the true behavior of the market due in part to the fact that investors are not rational agents and have asymmetric information. Harvey (2006) suggested that to explain the volatility in the foreign exchange markets only non-rational behavior models can help shed light (p. 153).

What makes certain trade decisions in the currency market? Kaiser and Kube (2009) found four key results in determining currency trade decisions: (a) interest differences across countries play a significant role in trade decisions, (b) trades are more profitable when using only interest rate differentials, (c) technical analysis is poor as a currency exchange predictor, and (d) when future rates are unknown you should use key economic data (pp. 48–50).

Kasilingam and Jayabal (2010) found it useful to categorize investors based on convenience, risk protection, return, and liquidity (p. 88). There is an open debate as to validity of the efficient market and behavioral finance theories. Konté (2010) used evolutionary models to reconcile behavioral finance and efficient market theories (p. 28). Understanding the motives of an investor can help understand the dynamics of price movements, whereby better hedging strategies can be developed. Paudel and Laux (2010) suggested that overall sentiment is not significant in terms of financial decisions (p. 104).

Rating agencies are important for assessing risk of certain investments. Pedro (2009) found that rating agencies are subject to cognitive limitations, erroneous beliefs, factors related to the cost of acquiring information, and conflict of interest—which all produces noise in financial information for an investor (p. 127).

Rizzi (2008) mentioned that identifying potential negative scenarios through stress testing that these scenario results can provide insight on appropriate portfolio selection (p. 95). In Rupp (2009), game theory is a common practice to understanding the behavior of actors (p. 68). Szyszka (2009) (2010) used behavioral finance to explain imperfections of the human mind and how asset prices can be distorted.

Economics. Economic theory and econometrics are important when developing a hedging strategy. Macro and micro indicators might be useful in determining endogenous and exogenous risk. I need to understand currency exchange fluctuations to adequately develop a rebalanced hedged strategy. Tsuji (2012) studied the Japanese automobile industry after the Lehman crash relative to yen fluctuations (p. 78). Tsuji found that in the post Lehman crash era the exchange rate sensitivities of the stocks for the automobile companies have increased (pp. 86–87).

There seems to be a correlation between the oil prices and the US dollar. Most likely the correlation is due to most oil contracts are in USD. Do oil prices and USD rates affect consumption in the United States of America? Devereux, Shi, and Xu (2010) found that there is a slight gain in consumption when oil commodities are priced in USD, but this is highly dependent on monetary policy (p. 543). What about open interest effects on commodities and currency pricing? Hong and Yogo (2012) found that movements in open interest can predict commodity, currency, bond, and stock price movements (p. 490). It is possible to use open interest as an indicator for changing momentum of the currency or oil markets to help rebalance hedged portfolios.

Vargas (2009) developed a model that utilizes a Markov switching VAR model for speculative pressure in the Asian markets (p. 22). The Vargas model might be useful for modeling price action when utilizing a regime switching technique. In Ishii and Nishide (2013) more trading volume was present in the morning and near the closing of the trading day (p. 66). Therefore the timing of the rebalance might be optimized when considering the intraday volume characteristics of the oil or currency market.

When considering the possibility of peak oil production, volatility of the oil markets should increase if energy efficiencies or future energy technologies do not offset the loss of supply. But Holland (2008) suggested that peak production is not evidence for the lack of producible oil, but possible evidence of demand and production cost dynamics (pp. 75–76).

Reimann and Tupak (2007) found that with a sufficiently large degree of dynamic decoupling that returns exhibit extreme volatility clustering when analyzing the Nikkei from January 1990 to December 2004 (pp. 238–239). Reimann and Tupak refer to decoupling as the separation of the fast and slow components of the time series. Perhaps understanding the fast and slow characteristics of the oil or currency market will help develop a better hedging strategy.

In terms of central bank policies, the behavior of these institutions can have a profound economic effect. Trow (2010) describes the following three main behaviors of central banks that make credit crisis inevitable: (a) short term rates are held low for too long, (b) current account surpluses from other countries keep long term borrowing rates too low for other countries, and (c) the skewed regulatory incentives favor debt to equity financing (p. 16). In van der Cruijsen and Eijffinger (2010) they stated that the European Central Bank has transparency issues (p. 389). Van der Cruijsen and Eijffinger mentioned that perceptions matter for trust in the European Central Bank's policy signals and that the central bank needs to be clear in their communication to improve the perceived transparency issue (pp. 397–398). By having the central bank release clearer communication on policy decisions and changes to such monetary policy, it is possible to use these releases as an economic indicator for adjusting a hedging strategy in a portfolio.

Summary and Conclusion

Major Themes

There were five literature themes discussed in this chapter: (a) risk management; (b) pricing models; (c) artificial intelligence and trading systems; (d) behavioral finance; and (e) economics. Risk management is a way to assess risk exposure in a portfolio. When that risk exposure has been identified there are methods for hedging and monitoring volatility. I can utilize pricing models to price different types of assets. These pricing models allow for correlation modeling and are important in derivative pricing. By implementing a pricing model an investor can compare the market price to the model price and determine if the asset is overvalued or undervalued.

Artificial intelligence and trading systems allow an investor to build automated trading decisions and execution of buy or sell orders. Artificial intelligence algorithms such as Artificial Neural Network (ANN) or Genetic Algorithm (GA) can help parameterize models for price or directional expectation. Behavioral finance is a field within finance that helps to understand investor behavior to allow for intelligent investment decisions. Behavioral finance also describes market characteristics and has predictive models to establish entry and exit points for a trading portfolio. Lastly, economics is a way to understand international trade, central banking policy, exchange rates, and macroeconomic trends. But it is important to note that many economic theories do seem to breakdown under extreme market events, partially due to irrational behavior of market participants. This irrational behavior does not seem to maximize an investor's utility function. Standard economic theory suggests that market participants on average are maximizing their utility curves.

Summary of Known and Unknown

The known information related to this thesis is the following. The Levy processes can help describe price curve characteristics using drift, volatility, and jump diffusion variables. RHCSP has been shown to work in simulations per the Meindl (2006) study, which reduced hedging error compared to standard hedging methods. Artificial intelligence can be used to improve parameterization using fuzzy logic, artificial neural networks, and genetic algorithms. Artificial intelligence techniques can also be used to optimize models.

Another known fact is that dynamic hedging can at certain times reduce risk. Markets are nonlinear, whereby they have asymmetric characteristics. Due to volatility and correlations not remaining constant in financial markets, models that predict asset prices can fail. Behavioral finance can describe how markets behave irrationally; therefore investors are not always utility maximizing. It has been well established that transaction costs can be prohibitive in dynamic hedging when rebalancing is frequent, especially in volatile markets. Lastly, Monte Carlo simulations have been implemented to simulate path dependencies and produce probability cones.

Some unknowns related to this research are the following. How to improve hedging error in illiquid markets efficiently? How to improve on hedging error in the oil and currency futures market utilizing RHCSP? How to easily and accurately provide a way to measure endogenous risk in an asset? By understanding the illiquid component of the price decline it seems to be possible to improve the RHCSP. Perhaps by modifying the RHCSP with metrics utilizing the LIBOR and the Levy process then adjustments to the periodicity of the rebalancing can be efficiently established.

How This Research Study Fills Literature Gaps

This research study fills gaps in the literature by providing a comprehensive study on how to utilize the performance of the RHCSP method pertaining to the oil and currency markets. This research study considers the following time periods for the oil and currency market: (a) precrisis, (b) during the crisis, and (c) postcrisis. I define the crisis as the financial crisis of 2008. Another way that this research contributes to the body of knowledge is by improving on the dynamic hedging in an illiquid market.

Backtesting the improved RHCSP method to the financial crisis of 2008 was expected to reduce hedging error. This improved RHCSP method utilizes the LIBOR and the Levy process to signal a need to adjust the rebalancing time horizon to allow for better hedge tracking. The LIBOR is a gauge on the endogenous risks within the interbank lending sector of the economy, but exogenous to the oil and currency markets.

The Levy process is a model to describe a price curve. The characteristics of the price curve can be defined by drift, volatility, and jump diffusion activation.

Going Forward

In the literature review section I presented an introduction to the purpose and problems. A synopsis of the current literature that establishes the relevance was portrayed. I also presented a discussion on the search strategy to establish how the gap in the literature was determined. I conducted a detailed dialogue on the possible theoretical foundations. Why chaos theory and emergence was chosen as a theoretical foundation for this research study was put forth. Discussions on the origins of chaos theory and emergence provided historical insight on this theoretical foundation. I have offered an investigation on the proposition of chaos theory and emergence in terms of financial systems. I performed a literature review on how to apply chaos theory to hedge in the financial markets and the rationale for choosing chaos theory for this research study. Other aspects of the literature review was to show how the research study will build on existing knowledge, and what are the related key variables to consider. Lastly, a summary of the literature landscape was carried out.

Now I will turn to the methodology of this research study. Part of the methodology section will cover how to evaluate the performance of the different hedging methods considered in this research study. By evaluating hedging error of different hedging methods and using an ANOVA analysis I can establish if certain hedging methods statistically perform better than others.

Chapter 3: Research Method

This study was designed to address a lack of scholarly literature, research, and understanding concerning hedging future contracts related to the oil and currency market. The study followed two basic principles: that it is important to understand the volatility of the oil and currency market because they are very important financial sectors for the global economy, and that by understanding these dynamics better predictions of inflation or deflationary conditions can be obtained, potentially leading to increased performance of hedging strategies.

There are six major sections in this chapter. Firstly, the research design and rationale section explains the research design and the study’s independent and dependent variables. Secondly, the methodology section defines the population, sampling, procedures in archival data, and the research instruments used for this research study. Thirdly, the hedging method section explains how each hedging method is used and the mathematics of these methods. The next section pertains to threats to validity, whereby an internal and external validity is evaluated. The fifth section covers ethical procedures and considerations in this research study. Lastly, a summary of the methodology is reviewed.

Research Design and Rationale

The Study Variables

This study employed two independent variables: markets and hedging methods. The first independent variable had three categorical values: simulated market, oil market, and currency market. The second independent variable had five categorical values pertaining to the hedging methods used:

- BMS,
- Leland,
- Whalley and Wilmott,
- RHCSP, and
- Modified RHCSP.

The dependent variable in this study was the absolute hedging error. There were no covariate, mediating, or moderating variables to consider in this research study.

Research Design

This study utilized an experimental design incorporating stochastic simulations and backtesting of futures markets. The two separate futures markets that were chosen were the light sweet crude and the EUR/USD contracts. The choice of an experimental design for this research project was consistent with meeting the needs to advance the knowledge of risk management. There is a gap in the literature on how RHCSP performs in illiquid markets, such as high volatility epochs. This study was designed to identify how to reduce return variance, responding to the need to reduce or manage volatility in the oil and currency futures markets. I utilized backtesting as an instrument to show how to reduce hedging error in the real world. This study focused on evaluating hedging error with different hedging methods in two actual markets (the oil market and the currency market) and one simulated market, making an experimental design strategy especially suitable.

Methodology

Population

The defined target population for backtesting was all possible light sweet crude oil futures for the CL contract. The CL contracts are available for every month of the year. The CL contract started in 1981 and remains an active futures contract. The defined target population for currency backtesting was all possible EUR/USD futures for the 6E contract. The 6E contracts are only available for March, June, September, and December. The 6E contract started in around year 2000 and remains an active futures contract.

The targeted population for backtesting the light wweet crude oil futures and the EUR/USD currency futures contracts are from a time period from January 1, 2005 through December 31, 2012. This time period includes the main time periods of interest: precrisis, during, and postcrisis of 2008. A CL contract is a standard size of 1,000 barrels of oil per contract. A 6E contract is also a standard size of 125,000 Euros per contract. Positions are rolled over to the next available contract when expiring, which incurs rollover costs.

The stochastic simulation generated a separate price curve and the dependent variable calculated from 506 samples yielding a mean absolute hedging error over a simulated 8-year period. This stochastic simulation was performed before the backtesting of the oil and currency markets. The secondary data was also evaluated with 506 samples for each contract. Samples were generated using a 4-day average of hedging error.

Sampling and Sampling Procedure

I created the primary study data by using a simulation approach to determine the performance of each hedging model relative to hedging error. This simulated price curve is compared for each method. This study also used secondary data consisting of historical data for light sweet crude oil and EUR/USD future price curves. The secondary data were needed to determine hedging method performance relative to real world conditions. I obtained the LIBOR for the modified RHCSP method.

The procedure for drawing the primary data was through a stochastic process utilizing the De Grauwe and Grimaldi (2006) model. The De Grauwe and Grimaldi model incorporates fundamentalist and chartist traders to represent a behavioral finance framework for modeling asset price dynamics. For my research, the model produced prices for each time step utilizing the De Grauwe and Grimaldi stochastic process. Each time period represented a trading day and the number of trading days per year was approximately 250 days. Each run of the stochastic model produced primary data representing 8 years' worth of price evolution. Only one 8-year price curve was simulated for the primary data analysis, whereby a 4-day average of hedging error was calculated yielding 506 samples. Only one curve was simulated for proper statistical comparison with oil and currency datasets within this study.

The secondary data collection, which was used for backtesting, was procured from a market data warehouse vendor. The name of that vendor is IQFEED. IQFEED has serviced over 80,000 customers for data streams. IQFEED stores the market data generated from different exchanges, such as NYSE, Nasdaq, ICE, CBOT, CME, OPRA, NYMEX (IQFEED, n.d.).

The sample framing for the primary data from the stochastic model generated the same time scale as the backtesting data, which consisted of 8 years' worth of price data. The sample framing for the secondary data, utilized by the backtesting phase of this research study, included 3 years of market data on the CL and EUR/USD futures of monthly futures contracts before the financial crisis of 2008. The next time period corresponds to the actual time during the financial crisis of 2008. The last time period consisted of data representing 4 years of mean reversion after the financial crisis of 2008.

This research study used an effect size of 0.20, alpha of 0.05, and power of 0.95; whereby the sample size needed a minimum of 501 hedging error calculations for each market. The minimum sample size of 501 was met by calculating the 4-day average hedging error for 8 years, yielding 506 hedging error samples.

Archival Data

The procedure for obtaining the market data for backtesting and simulation generation is stated in this section. The generated data from the stochastic simulation utilizes the De Grauwe and Grimaldi model to determine price evolution and the data was stored in a matrix through the use of MATLAB software. The procured secondary data from IQFEED for backtesting was accomplished through a query of their database on the EUR/USD spot prices, CL contracts, and 6E contracts for periods from January 1, 2005 through December 31, 2012. A downloaded file from IQFEED was stored in a matrix in MATLAB for further computation. The LIBOR prices were also obtained through

IQFEED for the modified RHCSP method for the same time period as the CL and 6E contracts.

There was no special permission or process required to gain access to IQFEED besides payment of a nominal fee to download market data. The only data that I needed to obtain was the futures data on the CL contracts, 6E contracts, EUR/USD spot prices, and the LIBOR prices. The secondary dataset consisted of historical price data. To establish IQFEED's credibility their credentials are: (a) services over 80,000 customers that trade the financial markets professionally and (b) the company stores market data from the exchanges for over 30 years.

Instrumentation and Operationalization of Constructs

The basis for utilizing hedging performance as the instrument was due to the successful use by Meindl (2006). Reliability in this research instrument was shown when hedging methods perform similarly in a simulated and real world environment in terms of relative hedging error.

Establishing external and internal validity is important. I did establish external validity by showing that hedging error can be reduced in multiple future markets such as oil and currency markets. I did establish internal validity by showing the hedging error of five different hedging methods evaluated over an 8-year period. During this 8-year period different price dynamics are represented pre-, during and postcrisis of 2008.

I presented two considerations to establish the sufficiency of hedging performance as a research instrument. Measuring hedging error to determine performance of hedging strategies is a relatively common financial industry practice, as demonstrated in Chapter

2. Also hedging strategies are judged on the ability of the method to track the targeted leg of the portfolio. If the hedging error is low, then better risk control is accomplished. If hedging error is high, then a better hedging method should be investigated.

Operational Definition

The operational definitions of the independent variables are the following. The first independent variable was the market, which was comprised of three categorical values: simulated, oil, and currency markets. The second independent variable was the hedging method, which was comprised of five categorical values: Black–Scholes, Leland, Walley and Wilmott, RHCSP, and modified RHCSP methods. The simulated market data was produced using a stochastic simulation based on the De Grauwe and Grimaldi model.

The Black–Scholes method is the most common quantitative finance model used for pricing options and hedging portfolios. Modern finance in terms of pricing derivatives is based on the Black–Scholes theoretical framework. The Black–Scholes method delta hedges at each re-hedging point, whereby the hedging is accomplished by holding a certain amount of underlying shares. The Black–Scholes method does not include transaction costs, assumes constant volatility, and uses discrete time rebalancing.

The Leland method was also a delta hedging method but uses a modified volatility calculation, whereby transaction costs increased the volatility. The Leland delta hedging method also uses the Black–Scholes framework but that volatility is incorporated with transaction costs. As with the Black–Scholes method, hedging is done at discrete time periods with the Leland method.

The Whalley and Wilmott hedging method can establish thresholds for re-hedging as an alternative to discrete time periods. The problem with the Whalley and Wilmott hedging method is that it assumes certain exponential utility functions, but it is questionable that real world conditions meet this utility function assumption. Meindl (2006) showed a method that can adjust the utility function via an objective function during the hedging rebalancing, which should improve performance (p.24).

The RHCSP method proposed by Meindl (2006) projects out from the current timeframe to a few timeframes ahead, which determines the number of shares to hold for the hedging strategy. It is similar to the threshold method by Whally and Wilmott, but any objective function can be used to determine an optimized hedging position. Due to computational efficiency, usually three time periods are projected out to determine the optimized hedging position in the RHCSP method.

The modified RHCSP uses endogenous and exogenous sensors that the previous RHCSP did not implement. Endogenous risk factors are assumed to be represented in the Levy process; whereby the drift, volatility, and jump diffusions can be captured in the previous time periods of the asset being investigated. For example, the time series will have a certain quantity and intensity of jumps which allows for the development of probability density functions (PDF) and cumulative distribution functions (CDF). These PDF and CDF curves can provide the probability of a jump state. The exogenous risk factors were assumed to be in the LIBOR because the LIBOR is a major indicator of banking stress, especially among intrabank lending arrangements. If the exogenous or endogenous risk factors reach a certain threshold then I adjusted the time step for calculating a potential rebalancing.

The operating definition of the dependent variable for the absolute hedging error was as follows. The value of the hedged portfolio was represented by V(T) and the shorted derivative was represented by c(T). By taking the $|V(\mathrm{T}) - c(\mathrm{T})|$ one calculates the absolute hedging error. In this study each of the three markets are evaluated over an 8-year period, producing 506 4-day average absolute hedging error samples.

The second independent variable consisted of five categorical values calculated for each of the five stated hedging methods. Each of these hedging methods calculated the amount of positions to hold in the hedged leg of the portfolio. In terms of the dependent variable, I calculated the absolute hedging error for each day in the time series within each market investigated. Then a 4-day average absolute hedging error was derived and compared amongst the remaining hedging methods to determine the best hedging method performance. I evaluated the independent variables and the dependent variable with simulated and historical data.

Lower absolute hedging error represents better hedging strategy or portfolio performance. With lower absolute hedging error, reduced financial risk of loss for the portfolio is accomplished.

The data analysis plan was as follows. I used SPSS software for the statistical data analysis. I utilized MATLAB for producing simulation and historical backtesting, as well as producing charts and other graphical representations. The data cleaning and screening procedures were as follows. In cases when missing data was in the historical dataset for the LIBOR, CL, or 6E contracts, an interpolation method was used to fill the gap. This interpolation method was just a simple averaging between the adjacent prices from the gap.

The research questions and the hypotheses were the following for this study.

RQ1–Quantitative: Can the RHCSP hedging method improve hedging error compared to the Black–Scholes, Leland, Whalley and Wilmott methods when applied to a simulated market, oil futures market, and currency futures market?

RQ2–Quantitative: Can a modified RHCSP method significantly reduce hedging error under extreme market illiquidity conditions when applied to a simulated market, oil futures market, and currency futures market?

The null and alternative hypothesis was:

H_o: There are no significant differences in hedging error among RHCSP, modified RHCSP, Black–Scholes, Leland, and Whalley and Wilmott methods when applied to a simulated market, oil futures market, and currency futures market.

H_a: There are significant differences in hedging error among RHCSP, modified RHCSP, Black–Scholes, Leland, and Whalley and Wilmott methods when applied to a simulated market, oil futures market, and currency futures market.

In terms of data analysis, the statistical tests that were used to test the hypothesis were the following. I performed a two-way ANOVA on 4-day average absolute hedging error to determine which hedging method performs better statistically for each of the three markets investigated. *F*–tests were reported for the overall performance of a particular market; and *t*–tests and Tukey post hoc tests were reported for each of the mean hedging error differences amongst the different hedging methods. The reason for statistical testing on historical data is to help understand how the different hedging methods perform in different market conditions, (e.g., pre-bubble, bubble, and post-bubble conditions.) In this research study covariate variables were not used. The results were interpreted by the value of absolute hedging error. Lower absolute hedging error represents better portfolio performance, reduced market risk, and lower volatility for the portfolio value over the investigated timeframe. The statistical significant was at 95% with the power determined at 0.95.

Hedging Method

The intent of this section is to describe each of the five hedging methods used in this study.

Black–Scholes delta hedging. Shown in equation 1 was the delta hedge using the Black–Scholes method (Meindl, 2006, p. 21).

$$\Delta(t) = N\left(\frac{ln\left(\frac{S(t)}{K}\right)+\left(r+\frac{\sigma^2}{2}\right)(T-t)}{\sigma\sqrt{(T-t)}}\right) \quad (1)$$

Δ represents the number of shares to hold of the underlying asset at time t. $N(\cdot)$ was the cumulative distribution function which was Gaussian distributed. The volatility was represented by σ, T was the time of expiration, r was the risk free rate, K the strike price, and S was the price of the underlying at time t.

I used equation 1 to determine the number of underlying positions to hold to hedge the portfolio. The CL contracts were considered the underlying while the options on the CL contract were considered the other side of the hedged portfolio. For the 6E futures contract the currency spot price was the underlying.

For simulated prices, equation 1 was used to determine the number of positions to hold on the underlying and the portfolio was rebalanced at discrete time periods. The hedging error was calculated for every day before any rebalancing should take place. Equation 1 was calculated at each discrete time period to adjust the amount of underlying needed to accomplish a hedged portfolio.

It is important to note that volatility is assumed constant and that no transaction costs were used. I calculated a transaction cost during each rebalancing period and subtracted it from the portfolio value. A moving average of the actual volatility was calculated at each rebalancing period to update equation 1.

Leland delta hedging. To include transaction costs Leland (1985) proposed modifying the Black–Scholes method and embedded the transaction cost into a volatility calculation. Equation 2 was the Leland formula for calculating volatility with transaction costs used in the Mendel study (Meindl, 2006, p. 22).

$$\hat{\sigma} = \sigma\left(1 + \frac{g}{\sigma}\sqrt{\frac{8}{\pi\delta t}}\right)^{1/2} \qquad (2)$$

Transaction costs were represented by the variable g, δt was the time step between discrete rebalancing periods, σ was the volatility used in the standard Black–Scholes method, and $\hat{\sigma}$ was the new volatility with transaction costs. It is important to note that this new volatility was then used in equation 1 to determine the correct number of units to hold for delta hedging.

Why does increasing volatility increase with transaction costs? The assumption that was made in equation 2 was that transaction costs increased the buy price and reduces the net gain on selling of an asset, therefore the Black–Scholes delta hedge calculation utilized a higher asset price leading to more assets being purchased or sold to balance correctly (Meindl, 2006, p. 22).

Equation 2 was calculated for each discrete time period to update the volatility window. A moving average of the actual volatility was calculated at each rebalance period to update equation 2.

I assumed that transaction costs remained constant. This new volatility from equation 2 was then plugged into equation 1. I then used equation 1 to determine the number of underlying positions to hold for hedging the portfolio. The CL contracts were considered the underlying while the options on the CL contract were considered the other side of the hedged portfolio. For the 6E futures contract the currency spot price was the underlying.

For simulated prices I used equation 1 to determine the number of positions to hold on the underlying and the portfolio was rebalanced at discrete time periods. The hedging error was calculated for each period before any rebalancing took place at the time of the hedging error calculation. I calculated equation 1 at each discrete time period to adjust the amount of the underlying needed to accomplish a hedged portfolio.

Whalley and Wilmott delta hedging. When considering the bandwidth that rebalancing should be initiated the Whalley and Wilmott (1993) method for delta hedging was considered, which was used in the Meindl study and shown in equation 3 (Meindl, 2006, p. 23).

$$\Delta(t) \pm \left(\frac{3gS(t)e^{-r(T-t)} \left| \Gamma - \frac{e^{-r(T-t)}(\mu - r)}{\gamma S(t)^2 \sigma^2} \right|}{2\gamma} \right)^{1/3} \tag{3}$$

$\Delta(t)$ was calculated by the standard Black–Scholes method from equation 1, and Γ was the gamma from the Black–Scholes method. Gamma equals the second derivative of the option value relative to the change in underlying price. γ represented risk aversion from an exponential utility function, r was the risk free rate, μ was the drift, T time of expiration, t current time, $S(t)$ was the value of the underlying at time t, g was the transaction cost, and σ was the volatility.

When an underlying asset breaches the boundary represented in equation 3 a rebalancing was initiated and a new hedged position was held at the border of this boundary (Meindl, 2006, p. 23). The problem with the Whalley and Wilmott method was that an exponential utility function was assumed and that performance of the boundary calculation could be inaccurate if the utility function was different. Therefore Meindl (2006) proposed a method that allowed for any utility function to be implemented in calculating hedging boundaries.

The reason why the Whalley and Wilmott method was very useful was that total transaction costs were reduced because discrete period hedging was not utilized—rebalancing was only performed when outside the calculated boundary. Therefore overall portfolio value was usually enhanced when comparing the Whalley and Wilmott method to the standard Black–Scholes method for delta hedging.

The simulated market, CL, and 6E future contracts are hedged the same way as in the previous hedging methods.

RHCSP. The RHCSP hedging method was based on the issue that computing a dynamic program with continuous state spaces for the entire duration of the investment would be too computationally intense or impossible to solve (Meindl, 2006, p. 35). Meindl also considered the suboptimal solution for hedging portfolios using instantaneous horizons, whereby hedging heuristics are computational efficient but do not provide good hedging error characteristics with complex environments such as crashes and transaction cost structures (p. 35).

The RHCSP method was not an instantaneous horizon method, but looked over a multi-period horizon. Meindl (2006) used a multi-period horizon, which is a computationally solvable problem (p. 35). The objective in dynamic hedging problems is to deduce the absolute hedging error as much as possible, therefore a set of decisions needs to be determined to minimize hedging error. Meindl considered that this minimization can be accomplished by taking the current asset price at time t and estimate the value of the portfolio at time T, $V(T)$, when one rebalances the portfolio h times within each time step (p. 36). A stochastic program simulates possible paths and a decision is made as to how to hedge the current period. This process is continued with a new stochastic program simulating possible paths and hedging decisions are made for the entire time continuum until the investment horizon is reached. Meindl viewed that the beauty of the RHCSP method is that any system dynamic that enters into the current price can be incorporated in the stochastic program simulation (p. 36).

To demonstrate the RHCSP method used in this study I used the method proposed by Meindl, which used a large time step to reach time *T* utilizing a 3 period lattice (Meindl, 2006, p. 38). See Figure 1 for an illustration of the RHCSP.

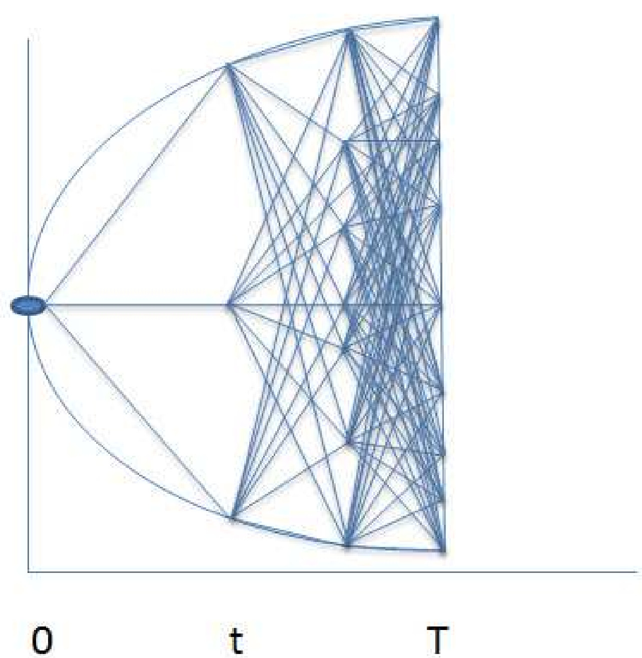

Figure 1. Three period lattice. Source: Meindl (2006).

How to define the optimization model within RHCSP? Many Monte Carlo simulations were produced throughout the 3 period lattice and a stochastic program was built based on these asset paths from the Monte Carlo simulation with decision variables representing the number of shares to hold for hedging the portfolio (Meindl, 2006, p. 38). Meindl (2006) used the following method to build the stochastic program of decision variables, shown in Figure 2 (p. 39).

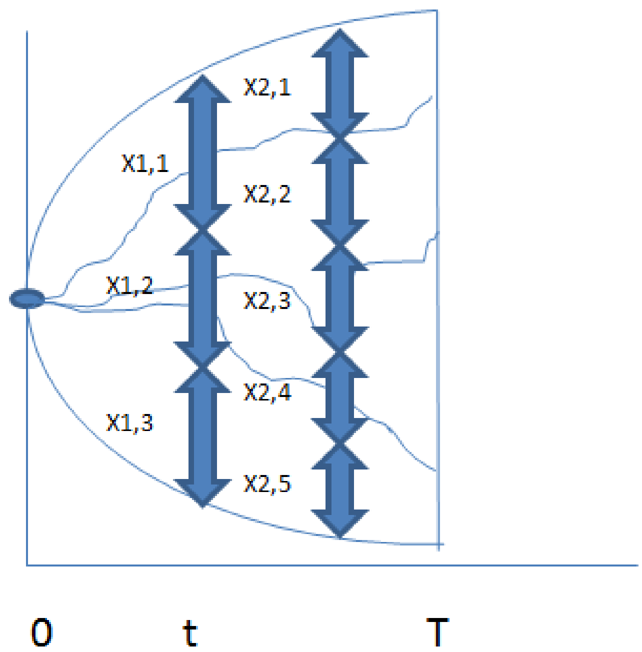

Figure 2. Stochastic program with decision variables. Source. Meindl (2006).

In this study for dynamic hedging the simulated, oil, and currency markets I used a three-time step with the number of bins at each time step being [1,3,5]. A bin is the amount of assets to hold for a hedged position. Therefore if I were in time step 2 there were 3 bins to consider for possible hedging ratios. The total number of simulations from the Monte Carlo model provided a cone of possible prices and the number of bins for each time step set price ranges evenly. This procedure was the same as used in the Meindl (2006) study. Meindl used 200 simulations for each receding time period which was the strategy in this study. Probabilities were assessed for each of the bins and used to determine how much to hedge in the current time period. I hedged at this high probability zone because I want to reduce the hedging error in the next time frame. I performed this procedure throughout the full portfolio horizon. Each bin had a calculated delta hedge from the Black–Scholes method. Transaction costs were accounted for each time a rebalancing was initiated. The first independent variable was treated the same way as in the previous hedging methods.

Modified RHCSP. The modified RHCSP method was utilizing the RHCSP method described in the previous section but included a much more sophisticated parameterization method. I used the simulated and historical data to parameterize a Levy process. This Levy process constituted three main parameters: (a) drift, (b) volatility, and (c) jumps. The drift was the overall direction that the price curve was moving in. The volatility was the fluctuation of the asset returns. The jumps were defined with two additional parameters: intensity and frequency. The intensity was the level of the jump and the frequency was defined as the number of times a jump can occur. Jumps can produce higher or lower prices. The intensity and frequency parameters were developed for each price curve by using a moving average. Drift, volatility, and jumps were parameterized with a moving average window.

The Monte Carlo simulations for each receding time point utilized the parameterized drift, volatility, and jumps from the asset price curve to make possible price paths. Using these parameters in the Monte Carlo simulation usually improved the accuracy probability values for each bin and usually improved on hedging error. The standard Levy process is shown in equation 4.

$$\mu S(t) + \sigma W(t) + J(t) \qquad (4)$$

μ was the drift, $S(t)$ was the price at time t, σ was the volatility, $W(t)$ represented a stochastic process, and $J(t)$ defined the jump diffusion.

Besides using a Levy process to determine endogenous risk factors in the price curve, I also needed to involve exogenous risk factors. The study proposed that the exogenous risk factors in the banking industry were important aspects to incorporate in a hedging strategy. I used the LIBOR rate to determine if banking stress was increasing.

If the LIBOR rate seemed to increase or the jump diffusion functions seemed to be close to activation then a hedging adjustment was made. If the LIBOR rate seemed to decrease or the jump diffusion functions seem to be low in probability for activation then hedge adjustments were set at normal evaluation levels.

Threats to Validity

The threats to external validity were: (a) when developing a hedging method, (b) addressing particular market relevance, and (c) the boom–bust cycle of asset markets. When developing a hedging method one needs to make sure to maintain external validity by showing that a particular hedging method performs in different asset markets and at different time periods. In this research project, I investigated three different asset markets: simulated market, energy market, and the currency market. In terms of external validity relative to time periods, this study covers over three distinct time periods: (a) pre 2008 financial crisis, (b) during the crisis, and (c) post financial crisis.

The threats to internal validity were in terms of the measuring instrument. The instrument for measuring hedging performance had strong validity because the purpose of hedging a portfolio is to reduce risk. Lower hedging error means higher asset protection. By using simulation data and historical data this study increased the internal validity of the measuring instrument with the five categorical variables for the second independent variable. By using simulation and historical data, the results should have similar hedging error characteristics.

In terms of threats to the validity of statistical conclusions, perhaps hedging is not useful in extreme crash conditions when measuring with just a 4-day average hedging error. I calculated hedging performance on the simulation and historical data over a 4-day average basis. When hedging with monthly contracts it seemed appropriate to measure portfolio performance on a near weekly basis to determine if intra-month hedging rebalancing needed to be performed. Measurement of the portfolio performance on a monthly basis is a standard financial industry practice, but I wanted to understand the hedging error dynamics within a particular month or week.

Ethical Procedures

There were no special agreements to gain access to participants or data because either simulation data was generated or historical market data was public information. Since this study did not involve human participants no special considerations were needed. Also since there were only simulation and historical market data used in this study no special institutional permission from the Internal Review Board (IRB) was needed. There were no remaining ethical concerns in terms of recruitment of materials or data collection because either data was simulated or obtained in a public domain. In terms of confidential or anonymous data none was used in this study, therefore no special provisions were needed. The IRB number for this study is 09-16-14-0228753.

Summary

This chapter introduced the problem and purpose of this study with a major section review of this study. I discussed the research design and rationale pertaining to the variables used in this study. The research design in the study was an experimental approach, whereby a simulated market was generated and backtesting were performed on energy and currency contracts. The methodology section discussed the targeted population, whereby CL and 6E future contracts between January 1, 2005 and December 31, 2012 were to be used, but I also evaluated simulated data over an 8-year time period as well. I presented an articulation of the different hedging methods in the hedging method section of this chapter. In terms of threats to validity, external and internal validity considerations were addressed for this dynamic hedging study for the simulated, energy, and currency markets. Ethical considerations are important in any research study and were ascertained in the ethical procedures section.

In Chapter 4, I present a description of the data collection for simulated prices and for historical data pertaining to the CL future contracts, CL option contracts, 6E future contracts, EUR/USD spot prices, and the LIBOR rates. I presented results describing the hedging performance of each of the hedging methods for the simulated and the historical datasets. This chapter also presented how to use the Levy process and the LIBOR prices to improve dynamic hedging in asymmetric price movements. I presented these results using a two-way ANOVA and Tukey testing. Results from historical datasets contain bubble, crash, and recovery market dynamics—which allowed the presentation of the performance characteristics in financial crises for each hedging method tested in this study.

Chapter 4: Results

The study followed two basic precepts: that it is important to understand the volatility of the oil and currency market because they are very important financial sectors for the global economy, and that by understanding these dynamics better predictions of inflation or deflationary conditions can be obtained, potentially leading to increased performance of hedging strategies.

The research questions are developed to help explore dynamic hedging in different financial markets and if it is possible to reduce volatility in asset returns. The research questions and the hypotheses were the following for this study.

RQ1–Quantitative: Can the RHCSP hedging method improve hedging error compared to the Black–Scholes, Leland, and Whalley and Wilmott methods when applied to a simulated market, oil futures market, and currency futures market?

RQ2–Quantitative: Can a modified RHCSP method significantly reduce hedging error under extreme market illiquidity conditions when applied to a simulated market, oil futures market, and currency futures market?

The null and alternative hypothesis was:

H_o: There are no significant differences in hedging error among RHCSP, modified RHCSP, Black–Scholes, Leland, and Whalley and Wilmott methods when applied to a simulated market, oil futures market, and currency futures market.

H_a: There are significant differences in hedging error among RHCSP, modified RHCSP, Black–Scholes, Leland, and Whalley and Wilmott methods when applied to a simulated market, oil futures market, and currency futures market.

This chapter discusses the data collection, the treatment of the data, results from this study, and summary of the answers to the research questions. The time frame and how representative the samples are to the population of interest are discussed within the data collection section. In the second section, a description of the treatment of the dataset is described. The following are in the results section: (a) report on descriptive statistics, (b) evaluating of the statistical assumptions, and (c) reporting statistical analysis of the findings. In the last section of this chapter, a summary of the answers to the research questions are presented on how well different hedging methods perform in different markets.

Data Collection

Description and Review

The time frame examined by this study was an 8-year span from January 1, 2005 to December 31, 2012 involving LIBOR, CL, and 6E contracts. There were no discrepancies in the data collection from the proposed data collection plan. There were a total of 2,022 daily closing prices in each contract. The 2,022 daily closing prices allowed for the resulting sample size of 506 of 4-day average absolute hedging error calculations for a total of 8 years. These samples are very representative of the population of interest because within this study I was concerned with the precrisis, during the crisis, and the postcrisis cycle—especial with the recent financial crisis of 2008.

There were three dynamics of the global financial crisis of 2008: the boom, bust, and mean reversion for economies. The precrisis period encompasses all samples from January 1, 2005 to August 9, 2007. The crisis period encompasses from August 10, 2007 to March 3, 2009, while the remainder of the samples comprise the postcrisis years. There were no covariates within this study.

Interpolation was used to replace missing data in the historical dataset for the LIBOR, EUR/USD, CL, or 6E contracts. This data cleaning using the interpolation method was a simple averaging using the adjacent prices from the gap. These gaps were usually due to certain asset markets being closed on holidays or emergencies. I added 5 closing prices for the CL contract, 9 closing prices for the EUR/USD spot market, and 1 closing price for the LIBOR. The percentages for the additional closing prices that were interpolated were: CL 0.2%, EUR/USD 0.4%, and LIBOR 0.05% relative to the total dataset.

I used the closing prices to calculate the log return, drift, volatility of the log return, intensity of the jump for the Levy process, and the number for jumps. I used the following thresholds to constitute a jump within the log returns to calculate the jumps for the CL, 6E, EUR/USD, and simulation data: CL +/- 1.0%, 6E +/- 0.3%, EUR/USD +/- 0.3%, and simulated data +/- 0.0055%. These different jump thresholds were used to maintain approximately 25% of the total dataset for each asset to be classified as a jump within the log return. The jump intensity and frequency of jumps were used in the modified RHCSP to signal endogenous risk for each asset.

The volatility of the log returns and the drift were calculated using a 5-day window. The risk free rate for the Black–Scholes option pricing was the 1-month Treasury rate published from the Federal Reserve and converted using a monthly continuously compound rate. For example, a rate of 1.99% for a 1-month Treasury bill was calculated using the natural log of 1.0199, which equals 1.97%. This 1.97% was used in the option pricing model, which is standard option modeling practice. To harmonize the data for the risk free rate with the other asset closing prices, I interpolated 19 closing rates, corresponding to 0.9% of the dataset.

The descriptive statistics of the datasets are summarized in Table 1. Notably, the asset that had the highest kurtosis within the full 8-year dataset was the CL contract of 6.892 relative to log returns. The LIBOR log returns exhibited extremely high kurtosis at 40.45, which is used as an exogenous risk signal for the modified RHCSP method. Since the simulated market used a normal distribution stochastic process, the kurtosis was at 3.299, which is around the normal range of expectations. In terms of skewness, most assets were slightly skewed negatively in terms of log returns; but the LIBOR was extremely skewed positively, due to the extreme fear among the banking industry during the 2008 financial crisis.

Table 1

Descriptive Statistics of the Dataset

Dataset	Max	Min	*M*	Median	Mode	*SD*	Var	Kurtosis	Skewness
CL	145.29	33.98	78.38	76.25	88.28	20.19	407.74	3.10	0.48
CLDrift	0.018	-0.025	0.000	0.000	0.000	0.003	0.000	7.383	0.018
CLLogRet	0.067	-0.057	0.000	0.000	0.000	0.010	0.000	6.892	-0.031
CLVolLog	0.042	0.000	0.009	0.008	0.000	0.006	0.000	9.421	2.160
EUFut	1.60	1.17	1.34	1.33	1.27	0.09	0.01	2.72	0.53
EUFutDrift	0.003	-0.006	0.000	0.000	0.000	0.001	0.000	4.658	-0.141
EUFutVolLog	0.011	0.000	0.003	0.002	0.000	0.001	0.000	5.743	1.266
EUFutlogRet	0.014	-0.013	0.000	0.000	0.000	0.003	0.000	4.727	-0.081
EuroSpot	1.5990	1.1668	1.3430	1.3263	1.2035	0.0952	0.0091	2.7589	0.5372
EuroSpotDrift	0.004	-0.006	0.000	0.000	0.000	0.001	0.000	4.813	-0.140
EuroSpotLogRet	0.015	-0.013	0.000	0.000	0.000	0.003	0.000	4.811	0.002
EuroSpotVolLog	0.010	0.000	0.003	0.002	0.000	0.001	0.000	5.980	1.323
LIBOR	5.7750	0.1863	2.1882	0.5725	5.3200	2.0996	4.4083	1.4664	0.4110
LIBORDrift	0.034	-0.038	0.000	0.000	0.000	0.005	0.000	18.443	-0.393
LIBORLogRet	0.190	-0.147	-0.001	0.000	0.000	0.014	0.000	40.450	1.259
LIBORVolLog	0.121	0.000	0.008	0.004	0.000	0.012	0.000	24.588	3.720
Sim	100.20	99.46	99.92	99.95	99.46	0.16	0.02	2.96	-0.67
SimDrift	0.000	0.000	0.000	0.000	0.000	0.000	0.000	3.042	0.010
SimLogRet	0.000	0.000	0.000	0.000	0.000	0.000	0.000	3.299	-0.096
SimVolLog	0.000	0.000	0.000	0.000	0.000	0.000	0.000	3.960	0.789

CL Dataset Description

Shown in Figures 3 through 18 are some notable observations of the CL independent variable. First by using three dimensional graphs I can view the surface dynamics relative to three variables, (e.g., price, time, and normal return volatility shown in Figure 3). The three dimensional graphs use a biharmonic surface fitting function. I can see in several of the figures of the heteroskedastic characteristics of the CL contract between January 1, 2005 and December 31, 2012. In Figure 4 the financial crisis of 2008 is shown around the time period between 800 and 1,000. Extreme volatility was exhibited between the 800 and 1,000 time periods, as well as 1,500 to 1,600. This later volatility is the aftershock of the financial crisis of 2008.

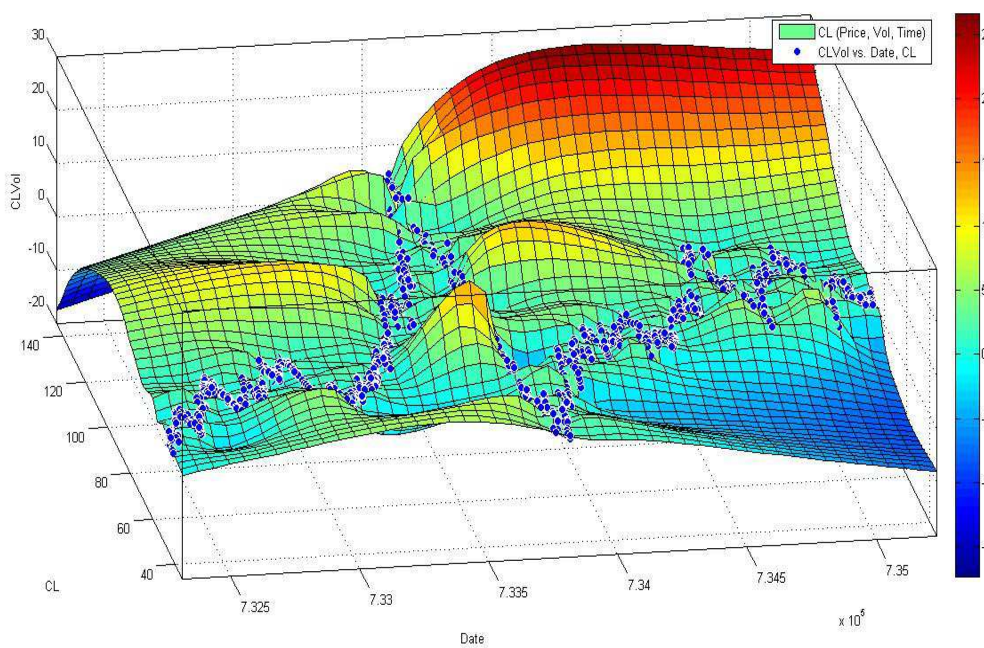

Figure 3. CL contract for price, volatility, and time.

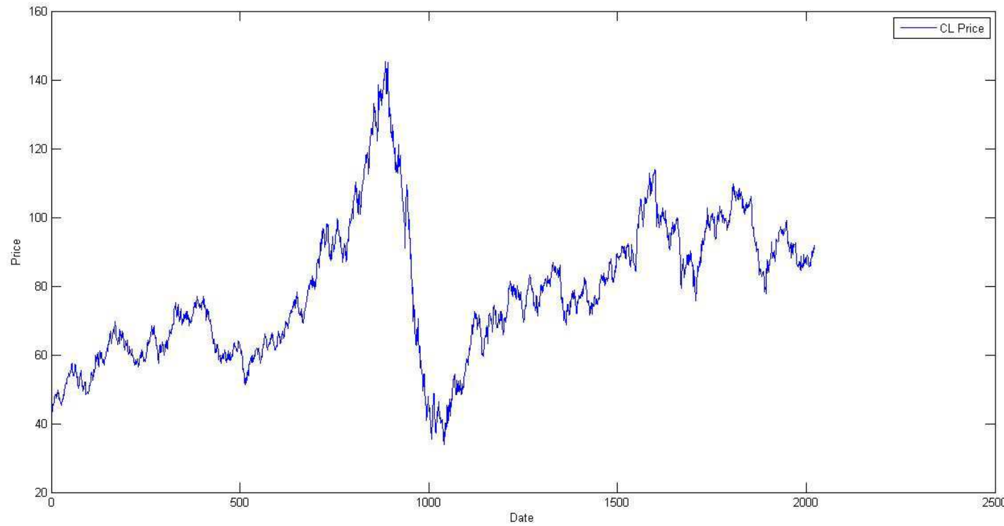

Figure 4. CL contract for price and time.

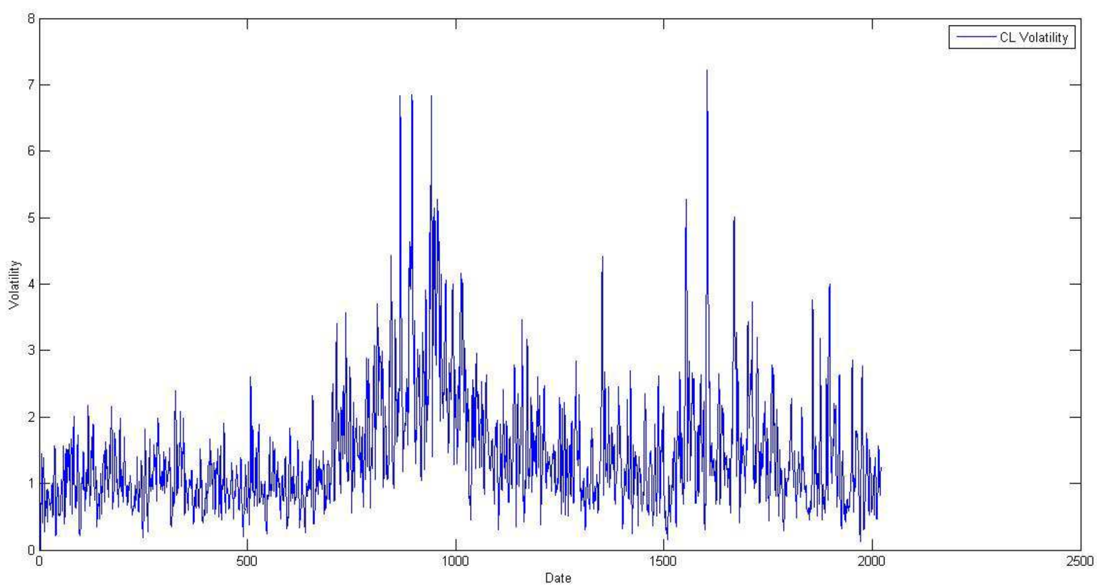

Figure 5. CL contract for normal return volatility and time.

As shown in Figure 6, extreme volatility was graphed in three dimensions with time and log return representing severe surface distortion—meaning that the oil market was in a chaotic attraction. For the Levy process used in the modified RHCSP method, the parameters used were drift, log return volatility, and jumps. This Levy process was meant to quantify the price movements of the CL contract for use in the Monte Carlo simulation for price forecasting.

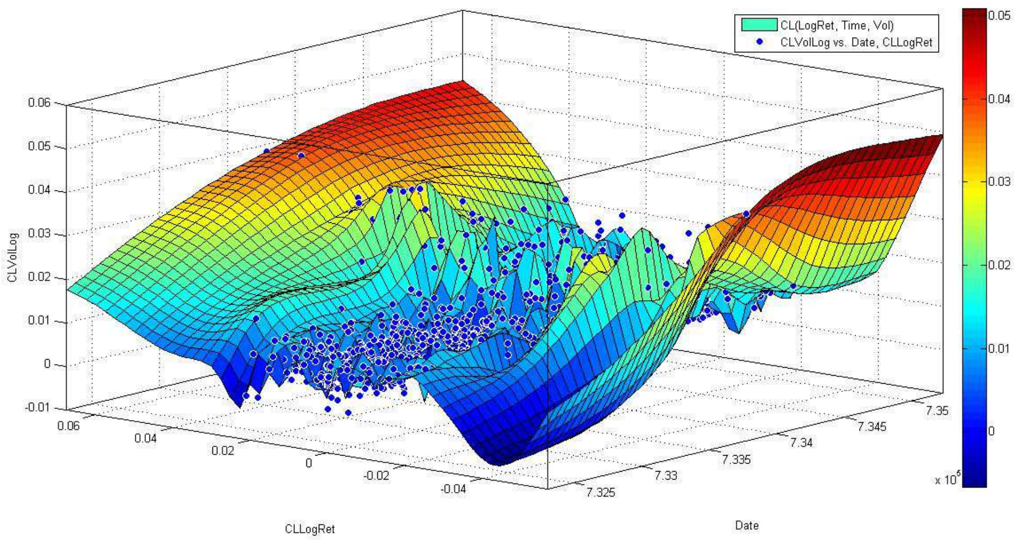

Figure 6. CL contract for log return, log return volatility, and time.

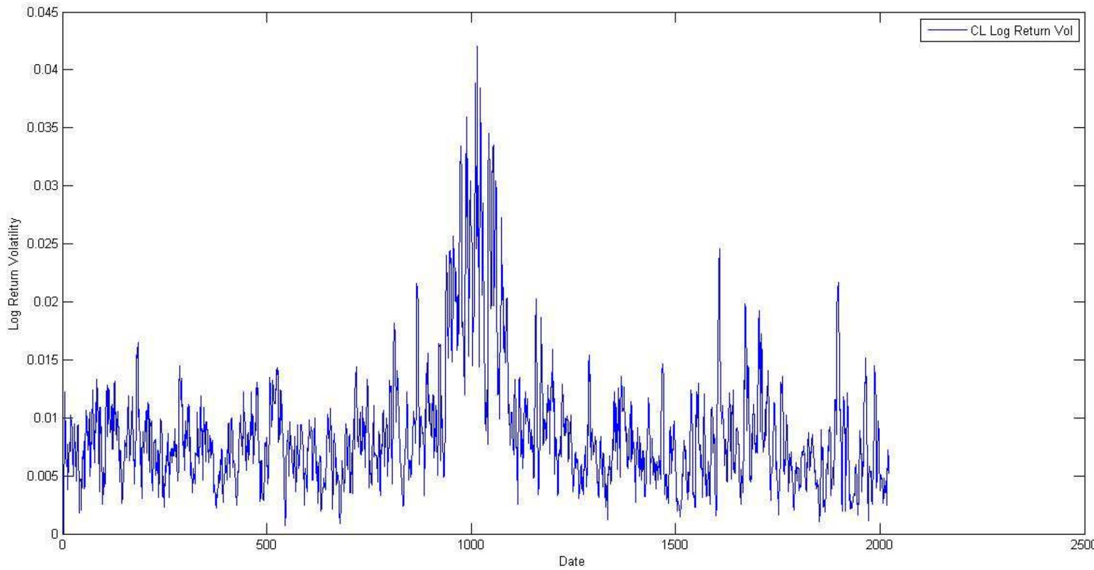

Figure 7. CL contract for log return and time.

I represent the Levy process calculations in Figures 8 through 10. As shown in Figure 8, there are similar characteristics to the surface shape as of Figure 6 because drift was calculated from the log returns within a 5-day moving window. In Figures 9 and 10 shows clearly the heteroskedatic characteristics of the CL contract. Figure 10 can be considered the filtered signal of stress within the CL contract through the investigated 8-year period. The jump intensity for the CL contract was filtered with a 1.0% threshold. A moving average of 30 days was used in the modified RHCSP to determine the probability of a jump and the intensity when calculating the expected price of the CL during the Monte Carlo simulation.

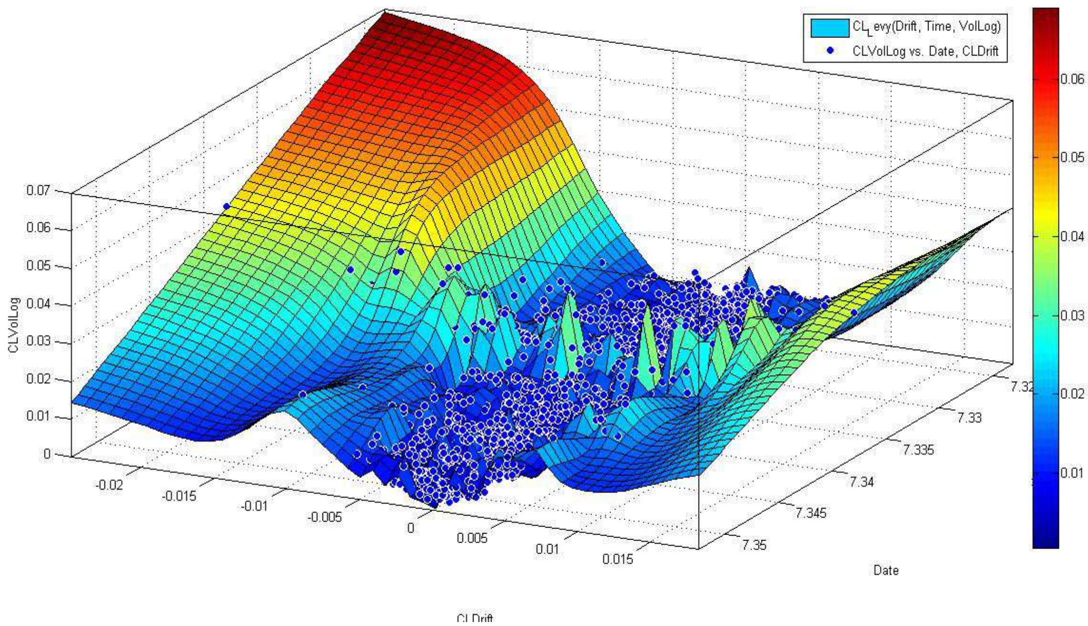

Figure 8. Levy process on the CL contract for drift, log return volatility, and time.

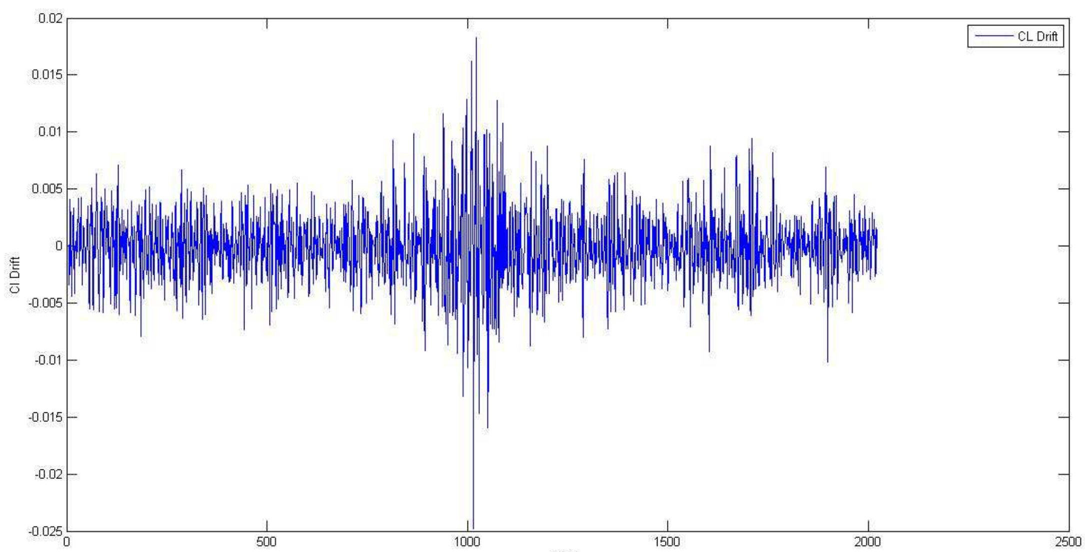

Figure 9. Levy process on the CL contract for drift and time.

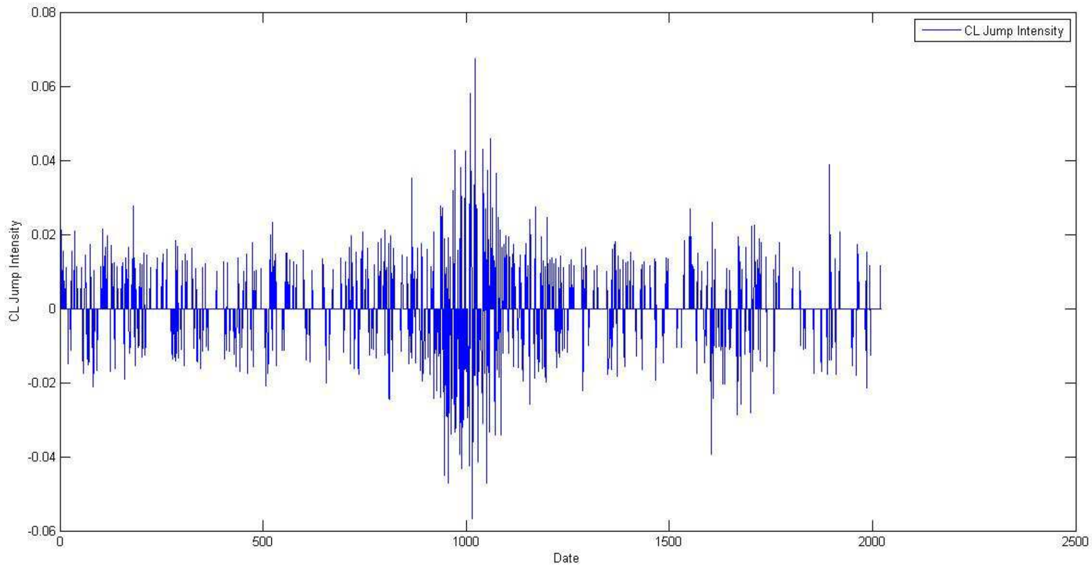

Figure 10. Levy process on the CL contract for intensity and time.

Shown in Figures 11 through 18 are the probability density functions and the cumulative distribution functions for the CL contract and its Levy process calculations. The PDF and CDF graphs show the level of skewness, kurtosis, and the probability of a certain variable to be in the CL contract dataset. I used a random number generator to determine if a jump was activated based on the jump average count within a 30-day window. If a jump was activated then another random generator was used to determine the size of the jump. I set the intensity threshold to be around 25% of the total log return distribution to allow for enough of the signal to be in a 30-day window.

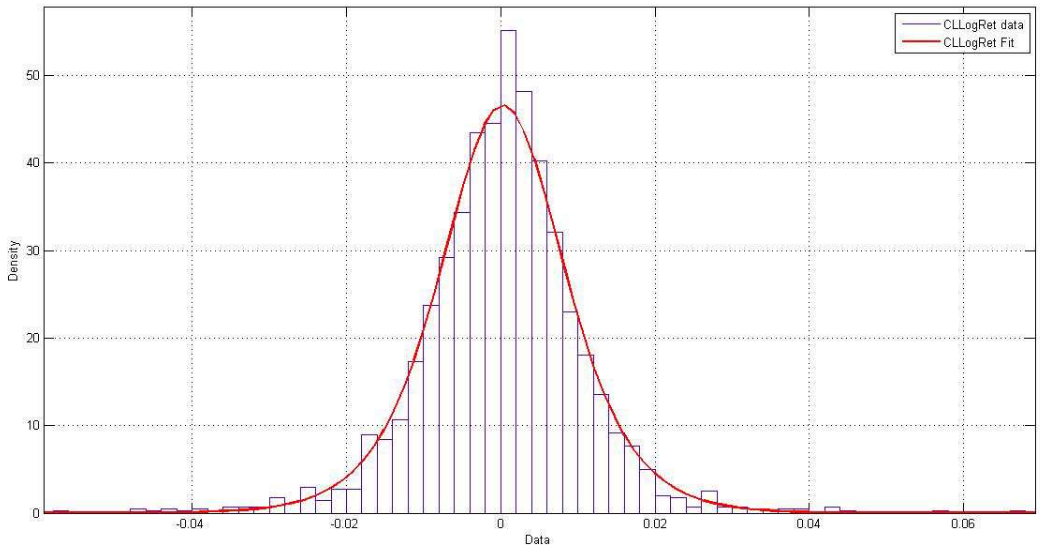

Figure 11. PDF on the CL contract for log returns.

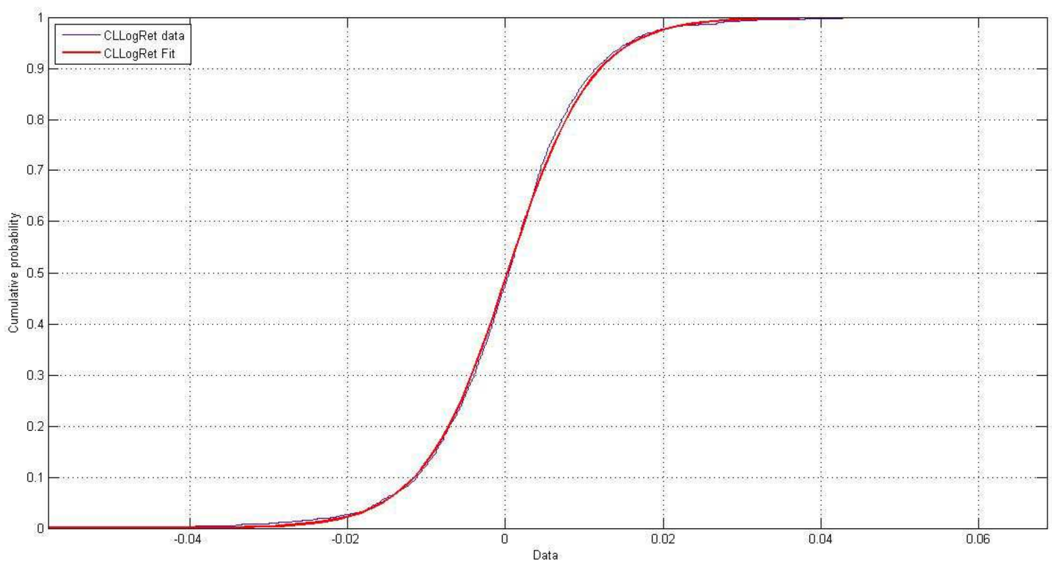

Figure 12. CDF on the CL contract for log returns.

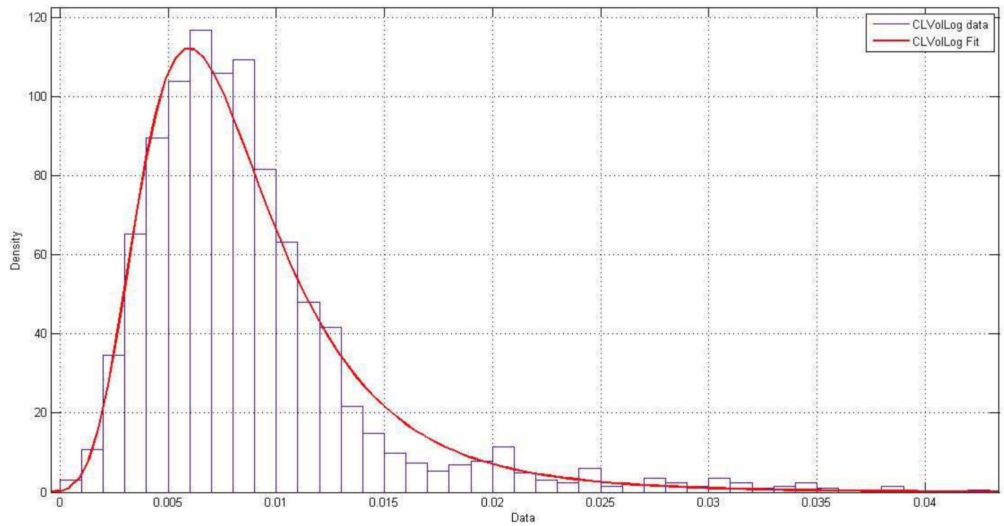

Figure 13. PDF on the CL contract for volatility.

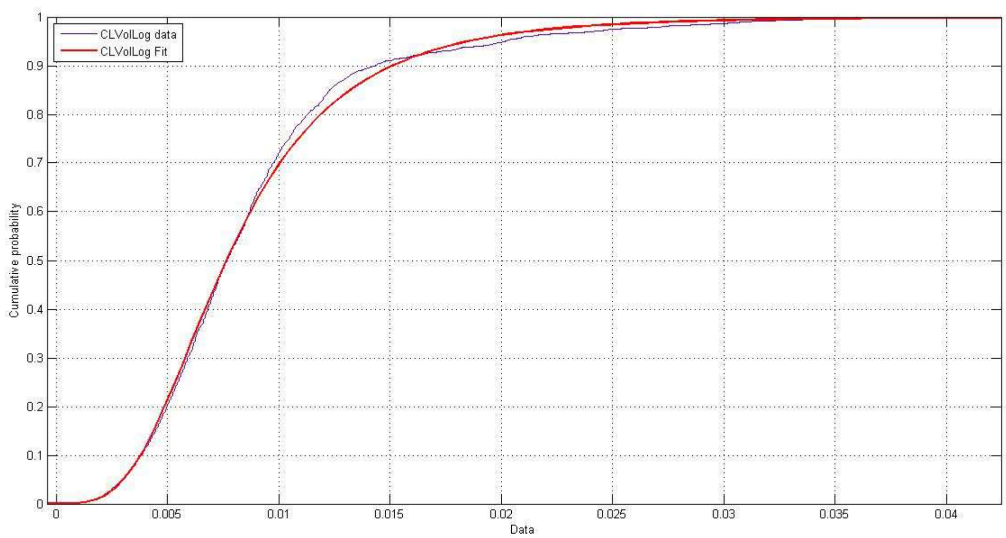

Figure 14. CDF on the CL contract for volatility.

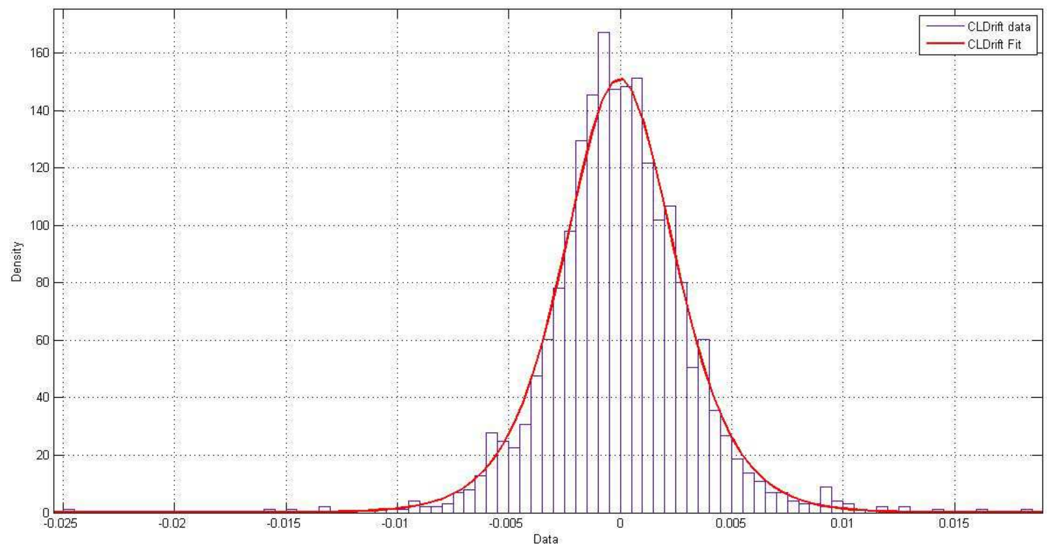

Figure 15. PDF on the CL contract for drift.

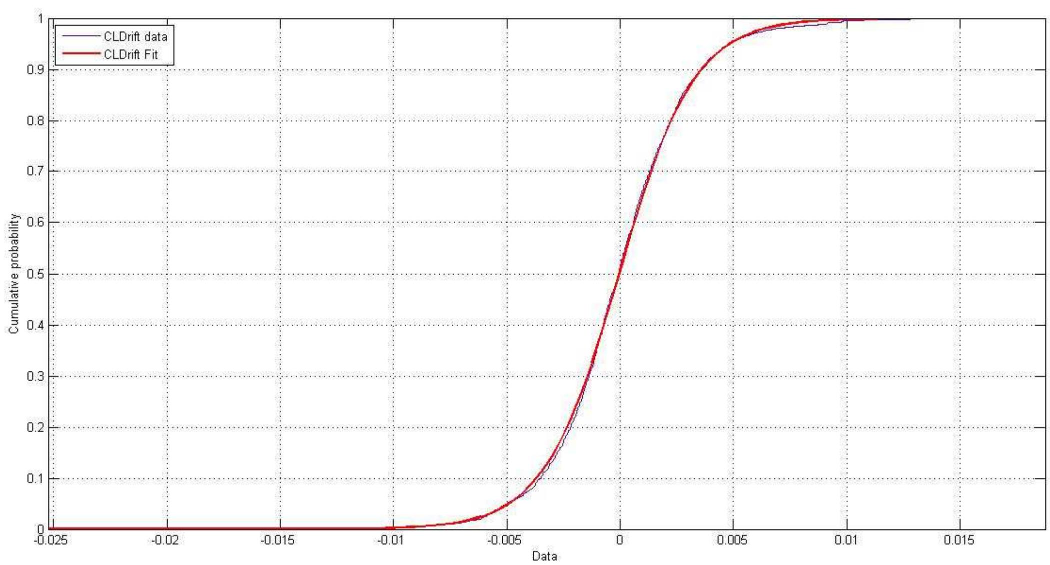

Figure 16. CDF on the CL contract for drift.

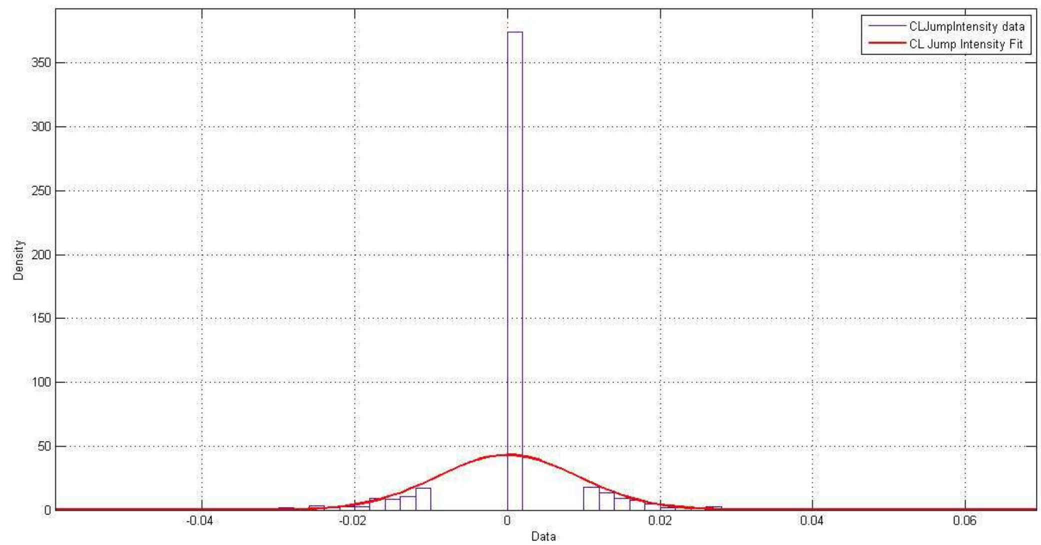

Figure 17. PDF on the CL contract for jump intensity.

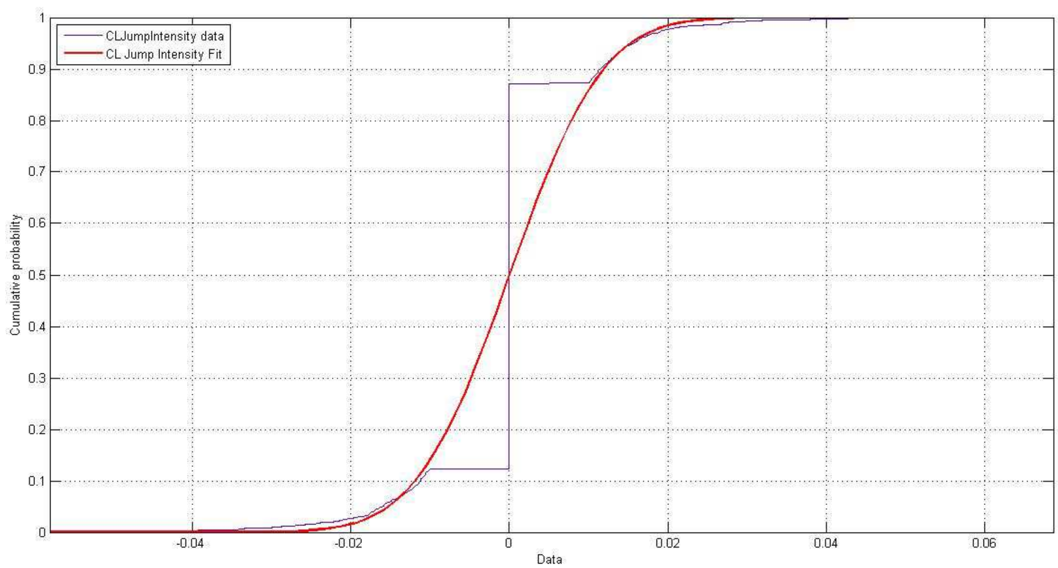

Figure 18. CDF on the CL contract for jump intensity.

6E Dataset Description

Shown in Figures 19 through 34 are some notable observations of the 6E independent variable. The three dimensional graphs for the 6E contract were prepared the same way as described for the CL contract and the time span were the same as well. In Figure 20 the financial crisis of 2008 is shown around the time period between 800 and 1,000. Extreme volatility was exhibited during the 800 and 1,000 time periods, but remained elevated. This later volatility was the aftershock of the financial crisis of 2008, which included the European zone sovereign debt crisis. This sovereign debt crisis spilled over into the banking sector within the European region.

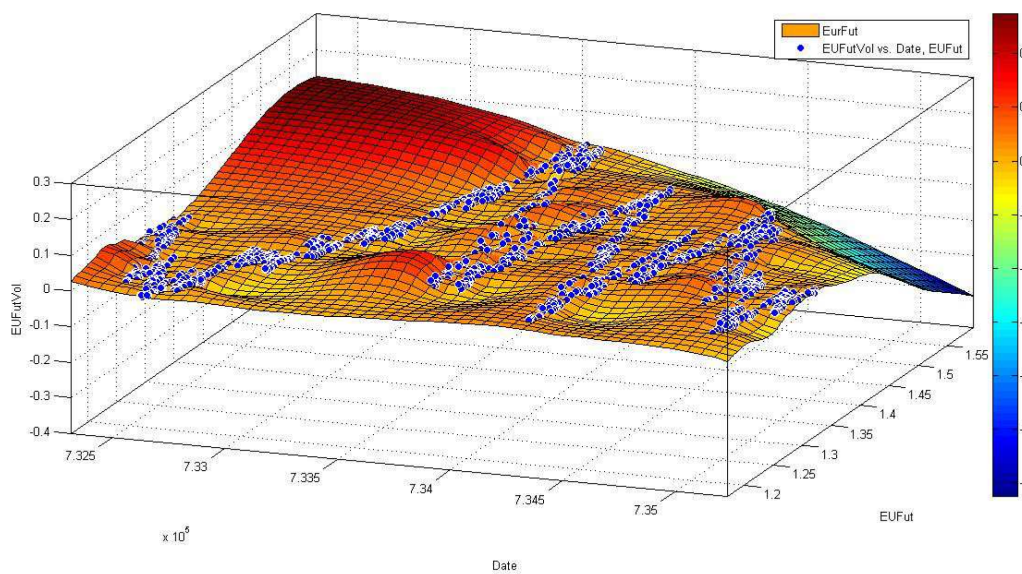

Figure 19. 6E contract for price, normal return volatility, and time.

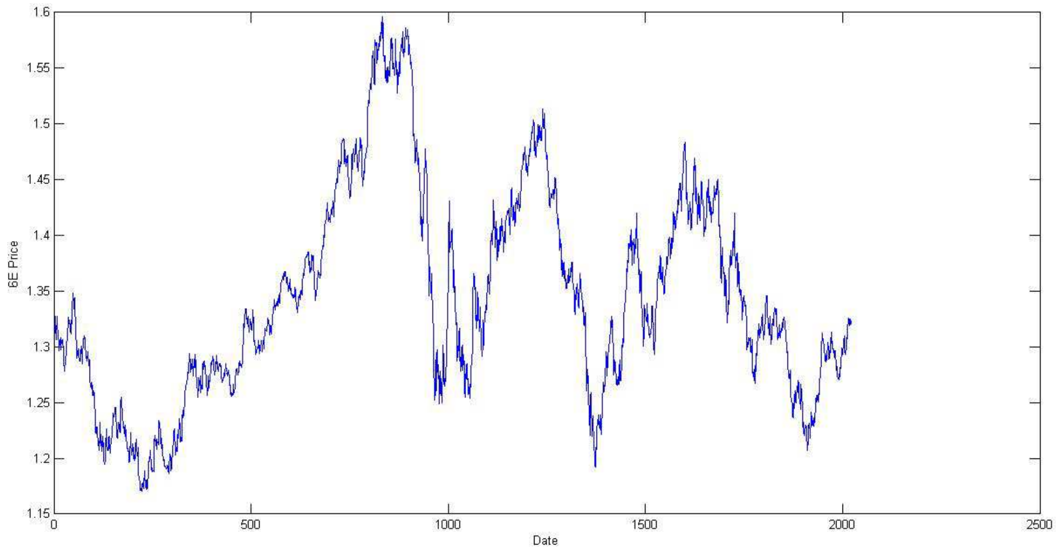

Figure 20. 6E contract for price and time.

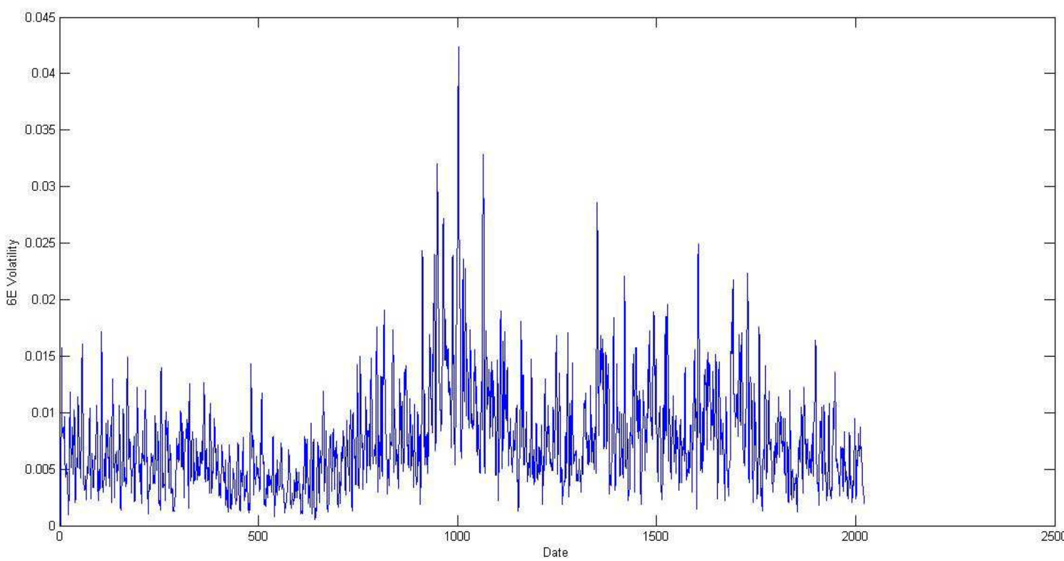

Figure 21. 6E contract for normal return volatility and time.

As shown in Figure 22, extreme volatility was graphed in three dimensions with time and log returns representing severe surface distortion—meaning that the EUR/USD futures market was in a chaotic attraction. For the Levy process on the 6E contract was processed similar to the CL contract, but with a different threshold amount and was also used in the modified RHCSP method.

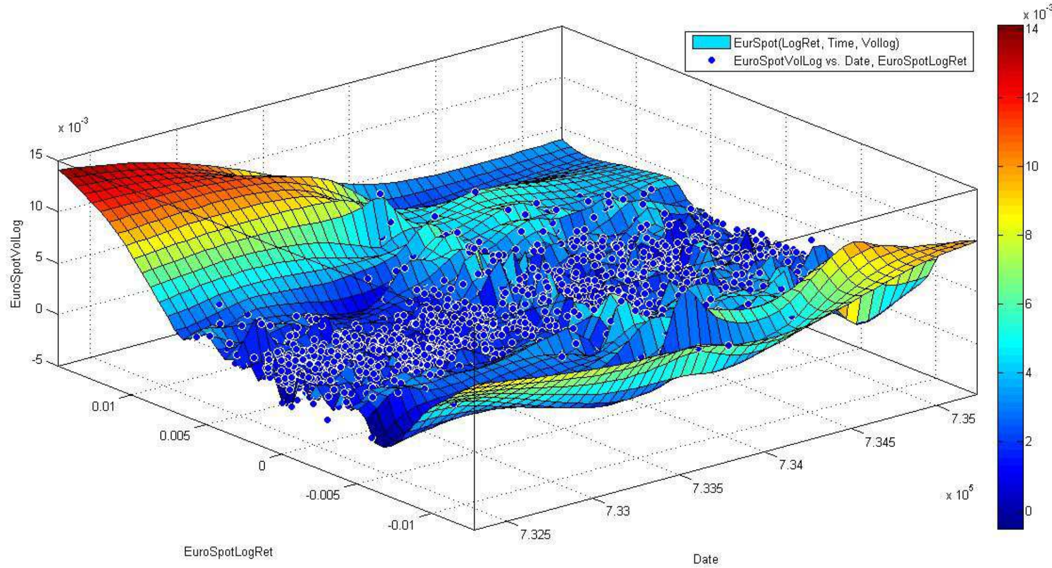

Figure 22. 6E contract for log return, volatility, and time.

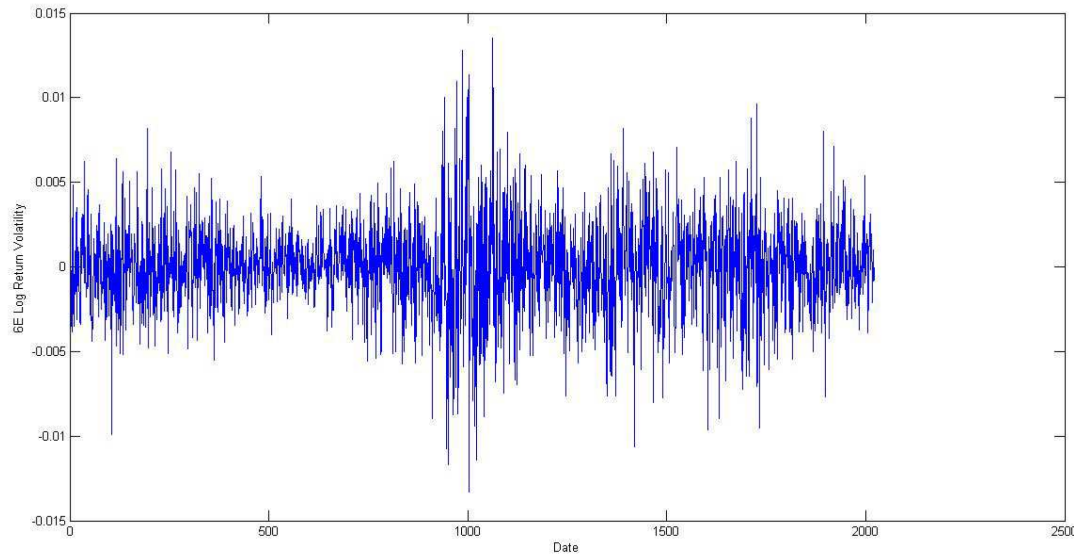

Figure 23. 6E contract for log return and time.

I represented the Levy process calculations in Figures 24 through 26 for the 6E contract. As shown in Figure 24, there were similar characteristics to the surface shape as of Figure 22 because drift was calculated from the log returns within a 5-day moving window. Figures 25 and 26 clearly showed the heteroskedastic characteristics of the 6E contract. Figure 26 can be considered the filtered signal of stress within the 6E contract through the investigated 8-year period. The jump intensity for the 6E contract was filtered with a 0.3% threshold. A moving average of 30 days was used in the modified RHCSP to determine the probability of a jump and the intensity when calculating the expected price of the 6E during the Monte Carlo simulation.

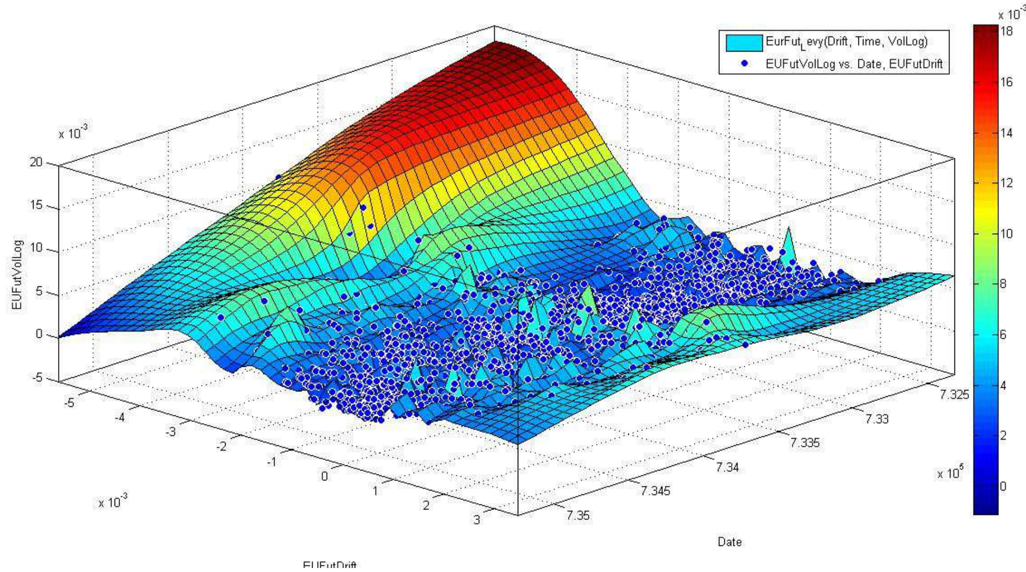

Figure 24. Levy process on the 6E contract for drift, volatility, and time.

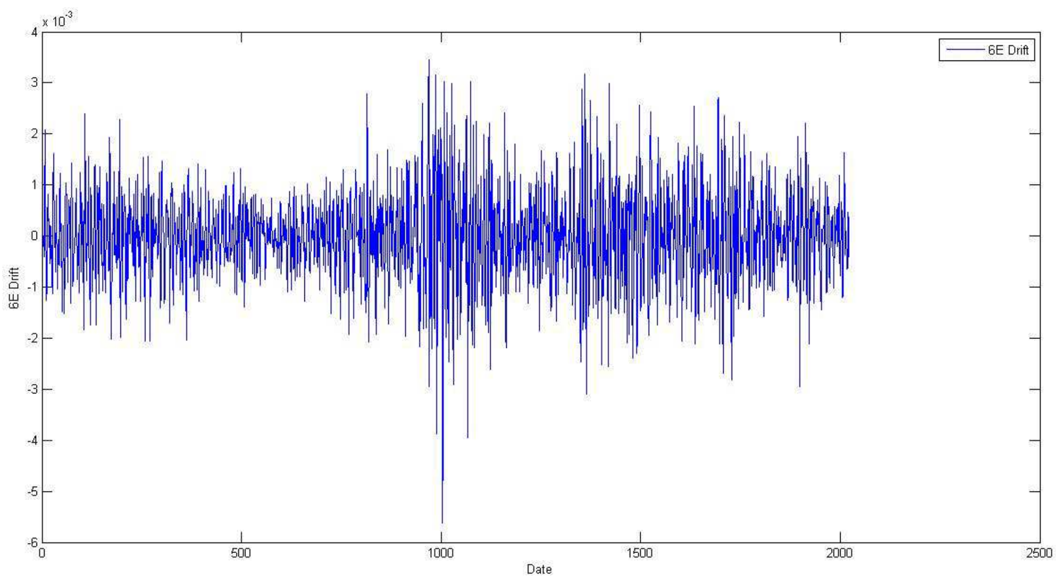

Figure 25. Levy process on the 6E contract for drift and time.

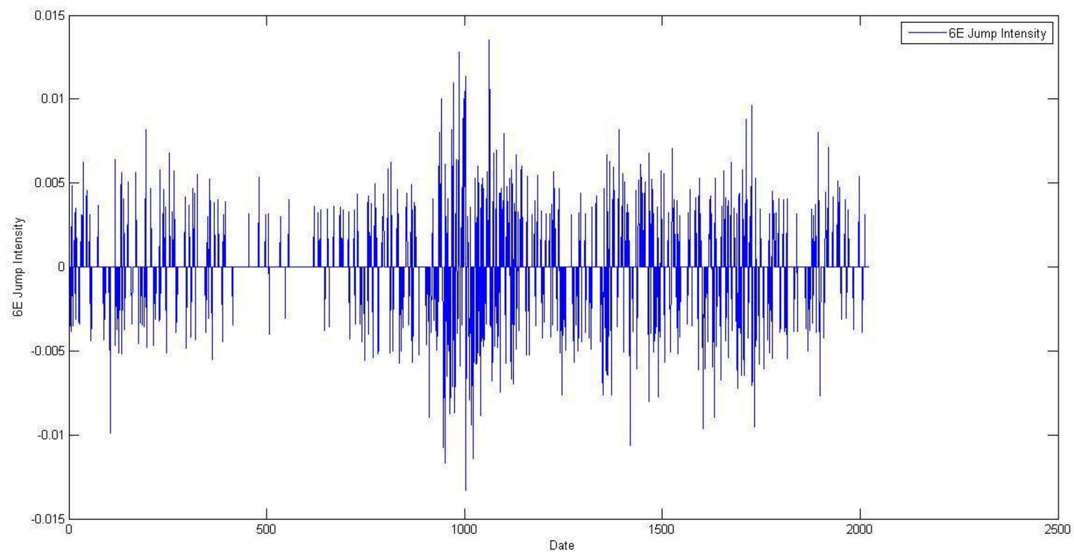

Figure 26. Levy process on the 6E contract for intensity and time.

Shown in Figures 27 through 34 were the probability density functions and the cumulative distribution functions for the 6E contract and its Levy process calculations. The PDF and CDF graphs showed the level of skewness, kurtosis, and the probability of a certain variable to be in the 6E contract dataset. I used a random number generator to determine if a jump was activated based on the jump average count within a 30-day window. If a jump was activated then another random generator was used to determine the size of the jump. I set the intensity threshold to be around 25% of the total log return distribution to allow for enough of the signal to be in a 30-day window.

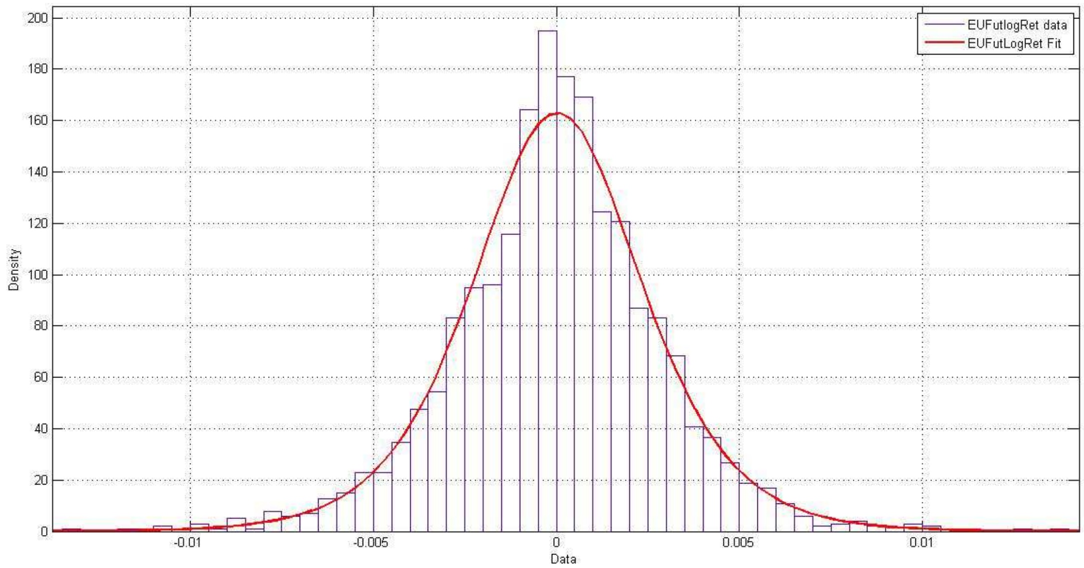

Figure 27. PDF on the 6E contract for log returns.

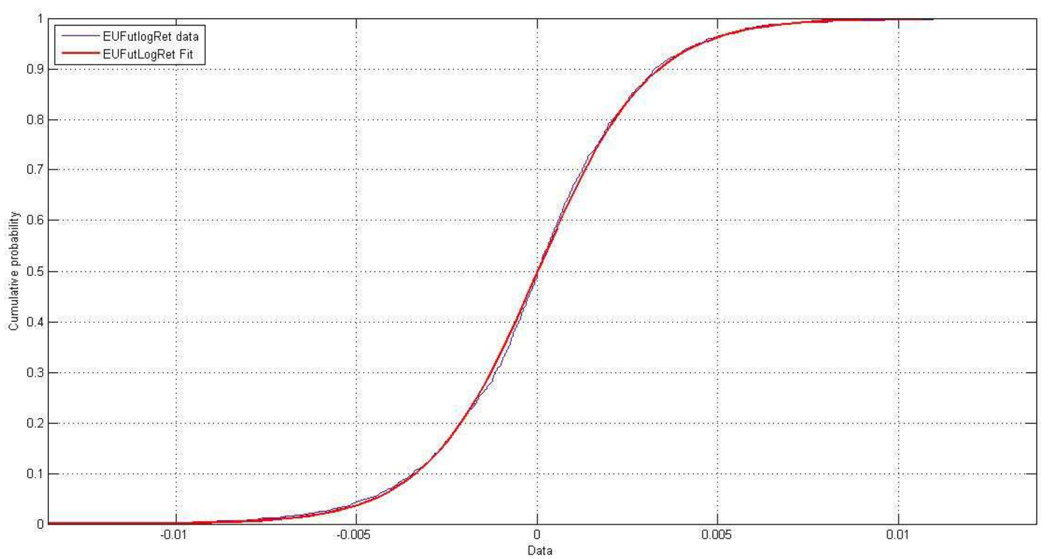

Figure 28. CDF on the 6E contract for log returns.

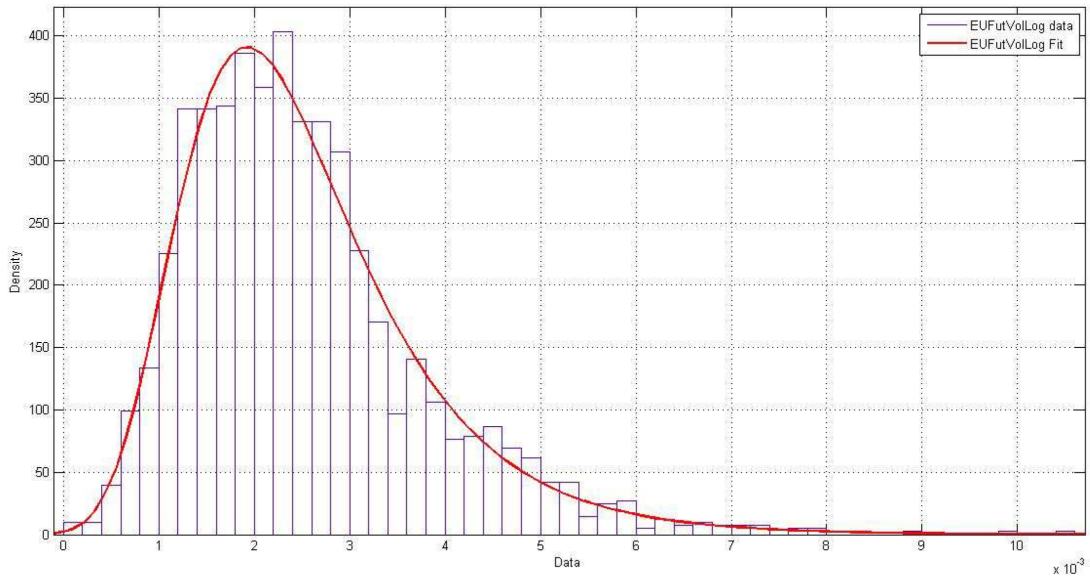

Figure 29. PDF on the 6E contract for volatility.

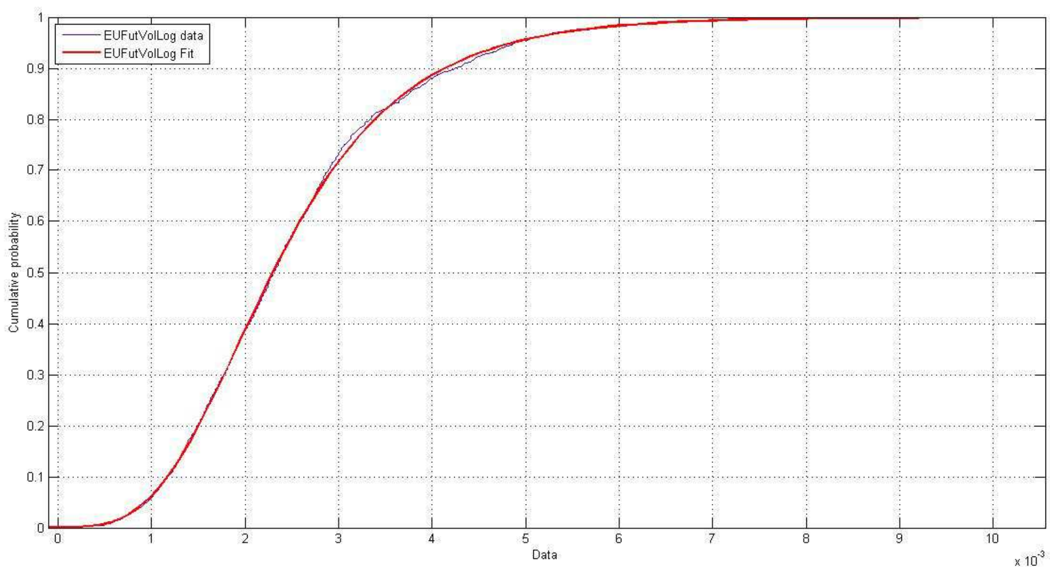

Figure 30. CDF on the 6E contract for volatility.

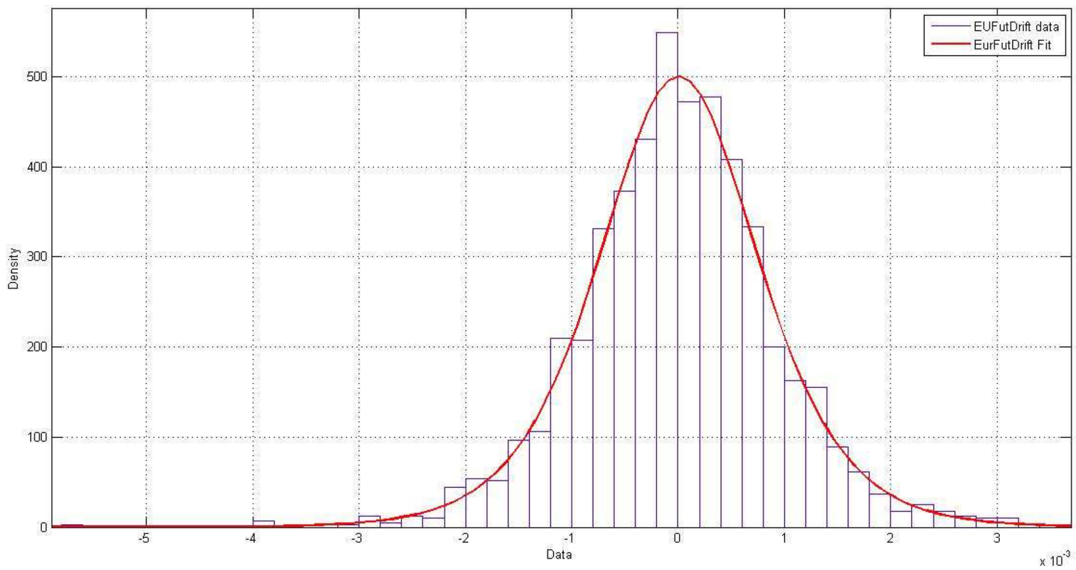

Figure 31. PDF on the 6E contract for drift.

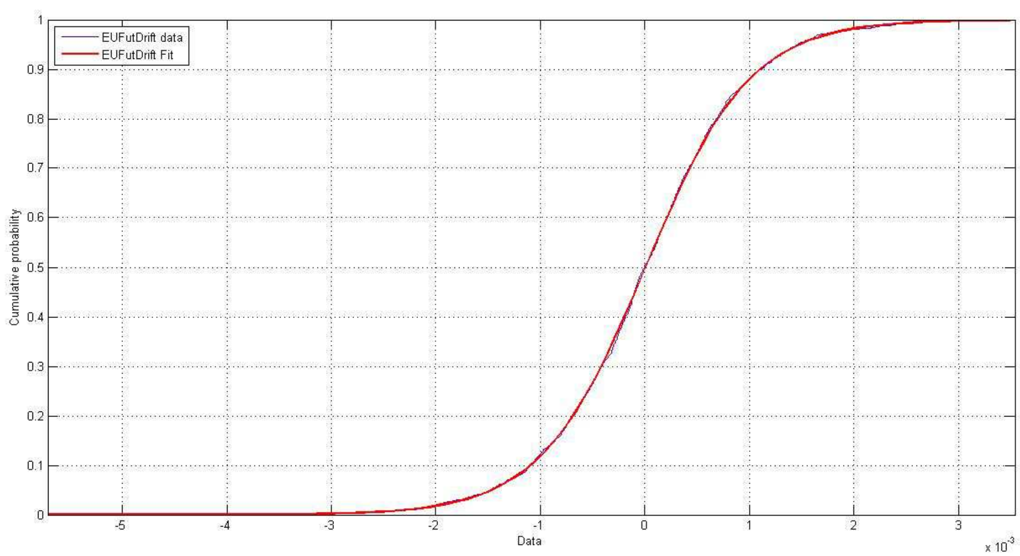

Figure 32. CDF on the 6E contract for drift.

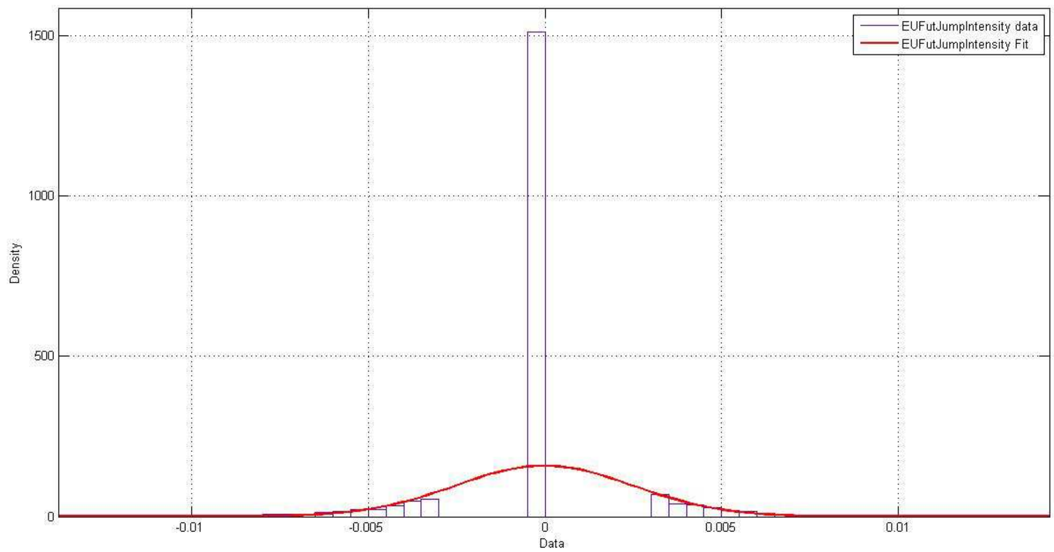

Figure 33. PDF on the 6E contract for jump intensity.

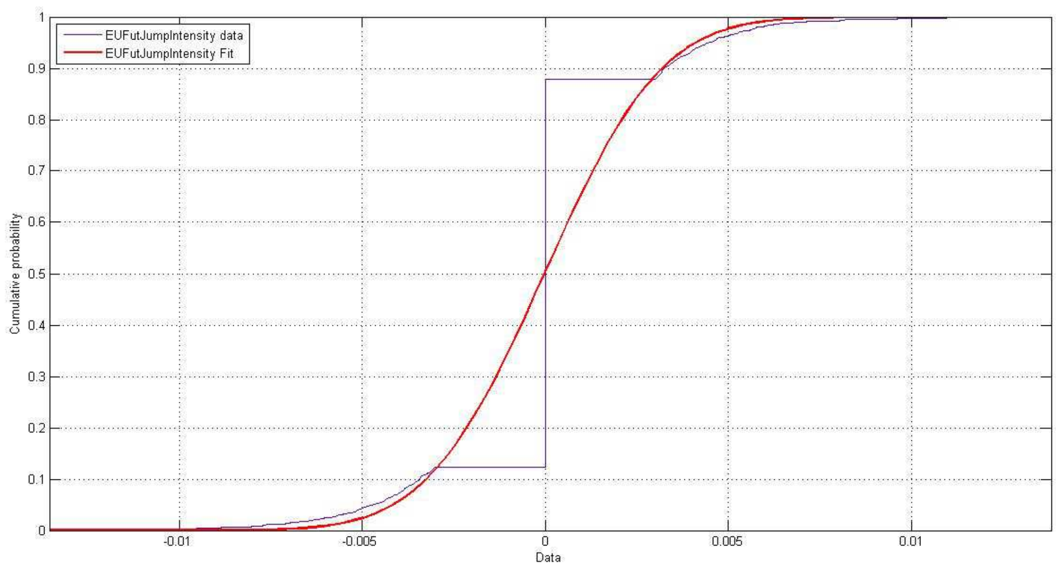

Figure 34. CDF on the 6E contract for jump intensity.

EUR/USD Dataset Description

Shown in Figures 35 through 50 are some notable observations of the EUR/USD spot market independent variable. The three dimensional graphs for the EUR/USD spot were prepared the same way as described for the previous mentioned contracts and the time span were the same as well. In Figure 36 the financial crisis of 2008 was shown around the time period between 800 and 1,000. Extreme volatility was exhibited during the 800 and 1,000 time periods, but remained elevated—similar to the 6E futures contract. This later volatility was the aftershock of the financial crisis of 2008, which included the European zone sovereign debt crisis. This sovereign debt crisis spilled over into the banking sector within the European region.

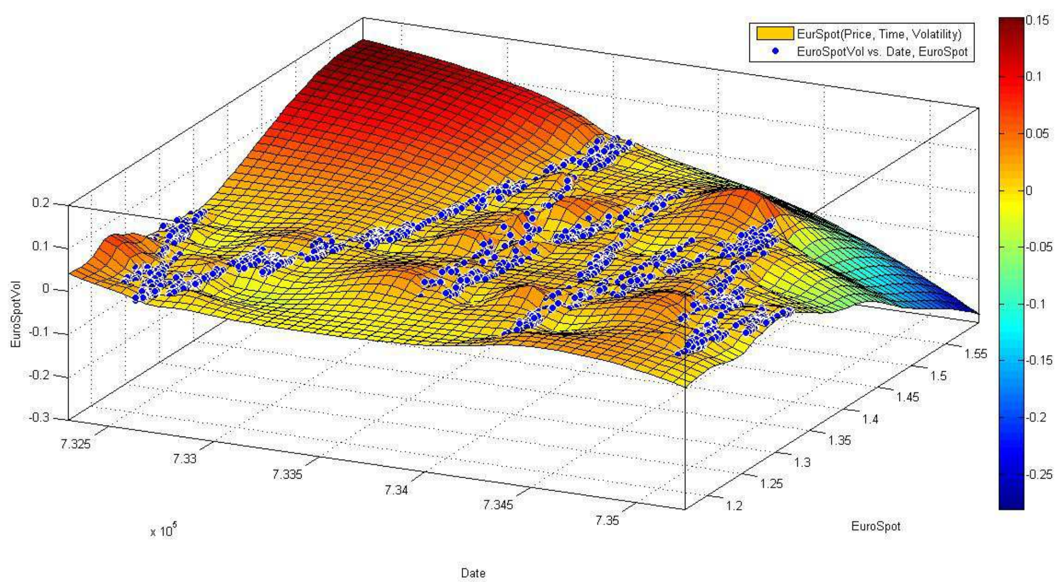

Figure 35. EUR/USD spot for price, volatility, and time.

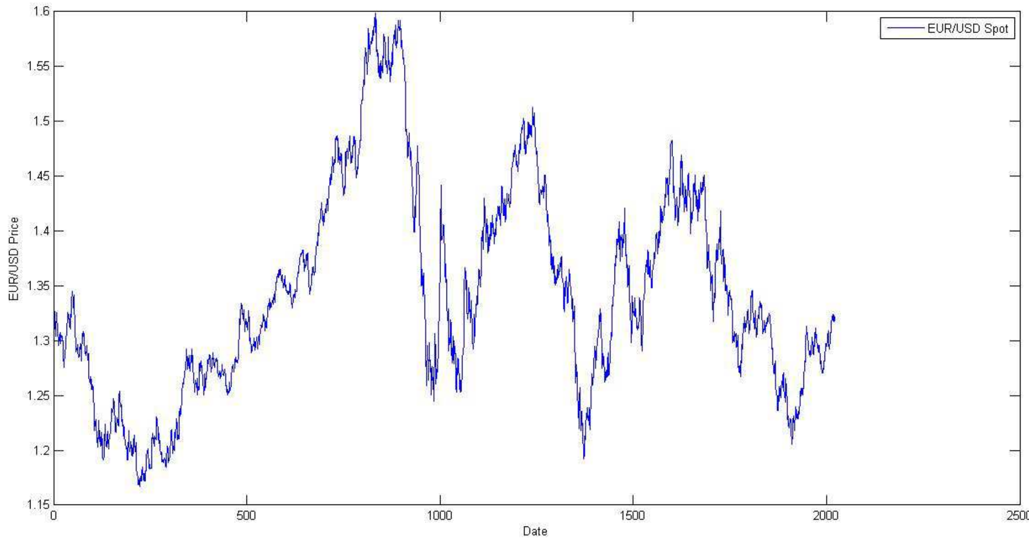

Figure 36. EUR/USD spot for price and time.

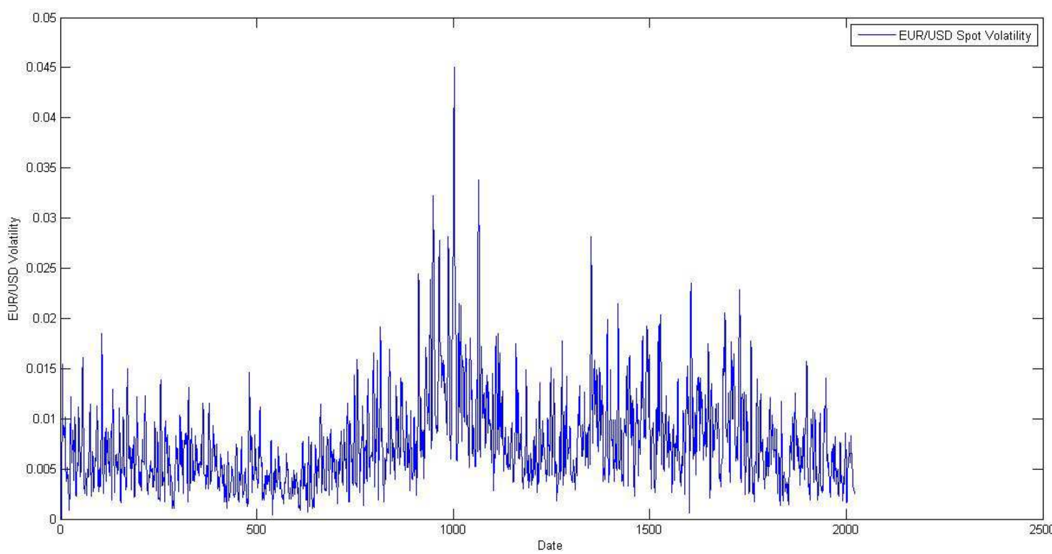

Figure 37. EUR/USD spot for normal return volatility and time.

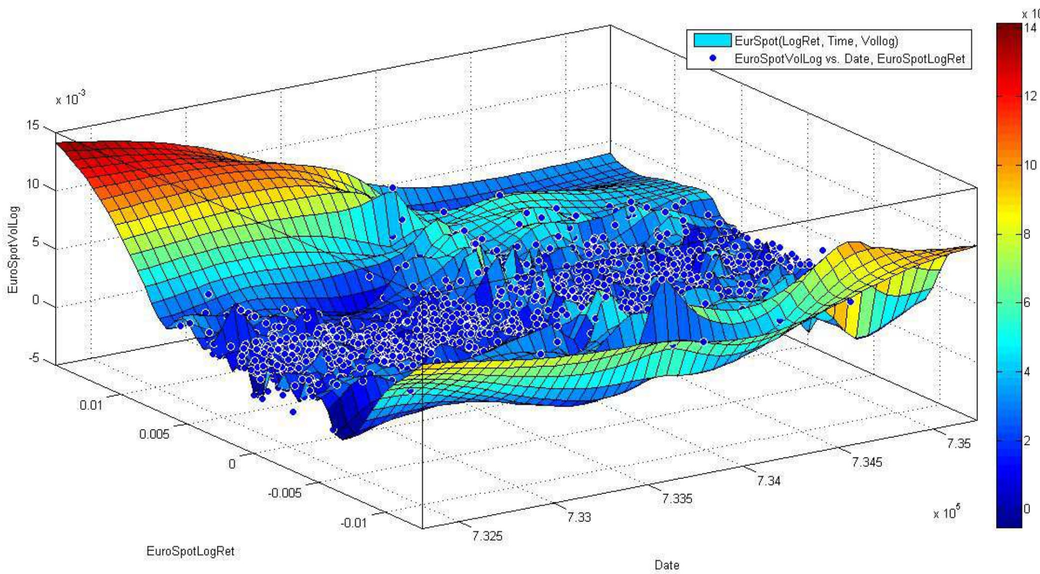

Figure 38. EUR/USD spot for log return, volatility, and time.

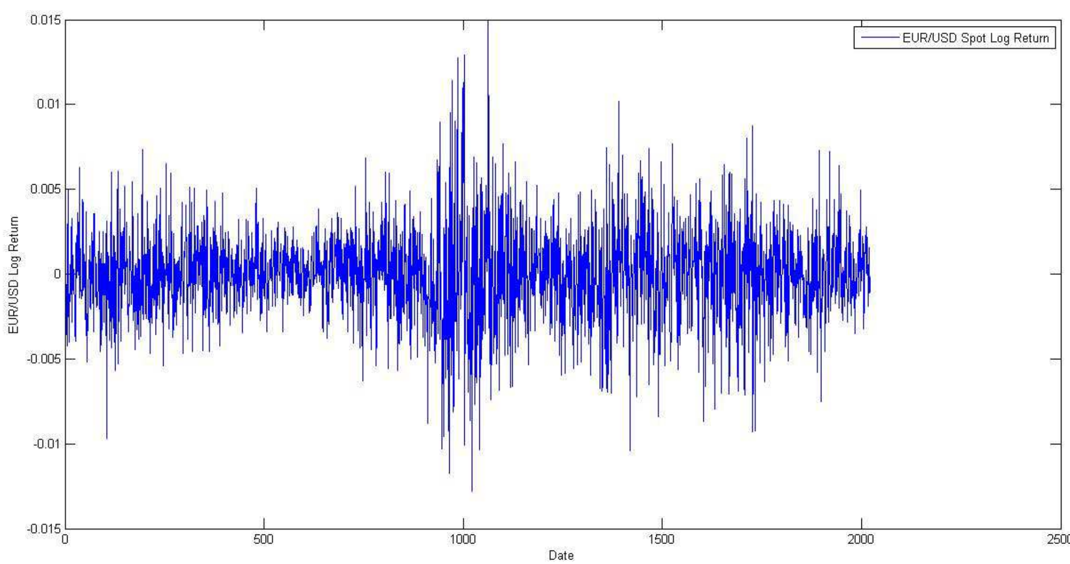

Figure 39. EUR/USD spot for log return and time.

I represented the Levy process calculations in Figures 40 through 42 for the EUR/USD spot. As shown in Figure 40, there were similar characteristics to the surface shape as of Figure 38 because drift was calculated from the log returns within a 5-day moving window. Figures 41 and 42 showed clearly the heteroskedastic characteristics of the EUR/USD spot market. Figure 42 can be considered the filtered signal of stress within the EUR/USD spot through the investigated 8-year period. The jump intensity for the EUR/USD spot was filtered with a 0.3% threshold, which was the same for the 6E contract. A moving average of 30 days was used in the modified RHCSP to determine the probability of a jump and the intensity when calculating the expected price of the EUR/USD spot during the Monte Carlo simulation.

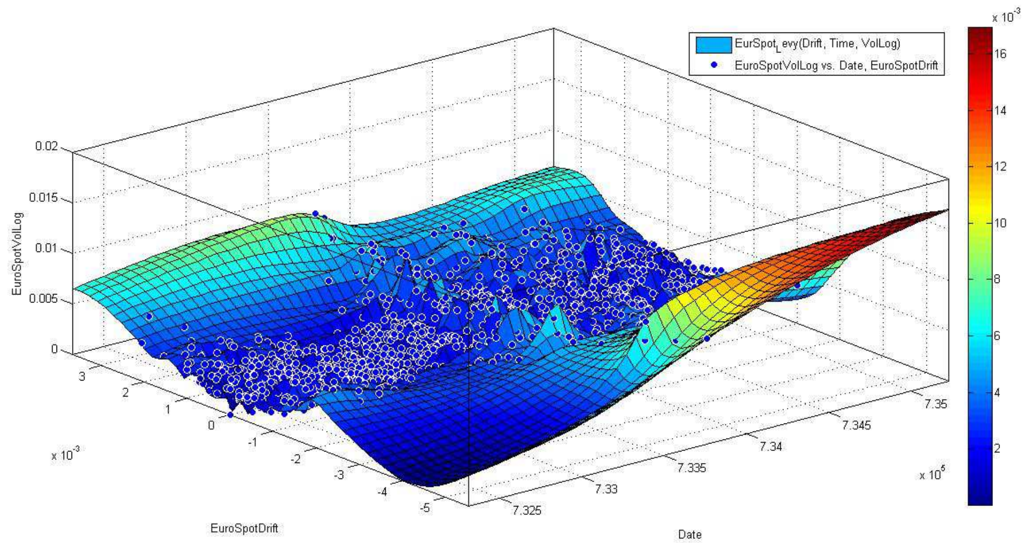

Figure 40. Levy process on the EUR/USD spot for drift, volatility, and time.

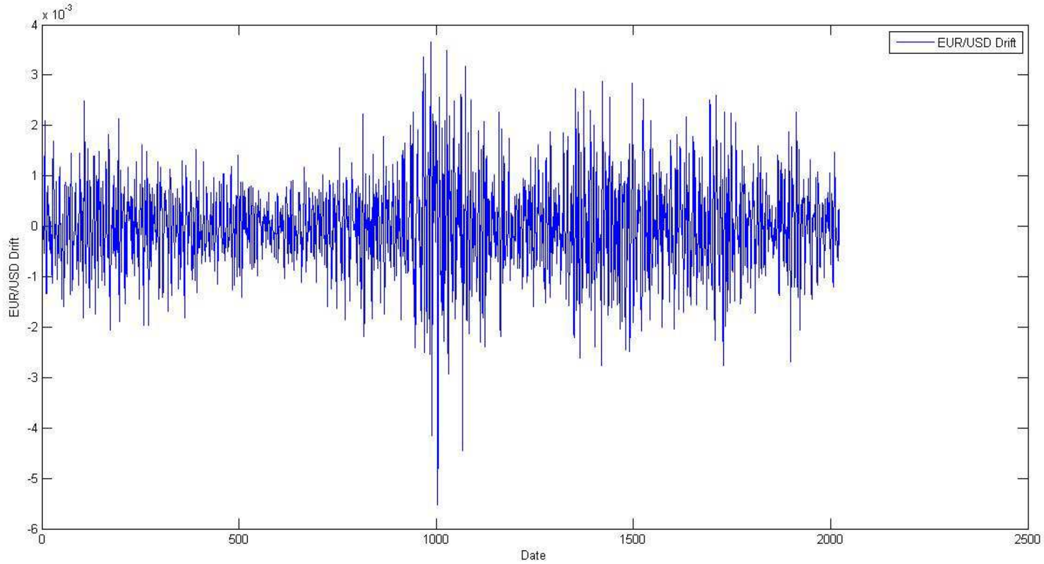

Figure 41. Levy process on the EUR/USD spot for drift and time.

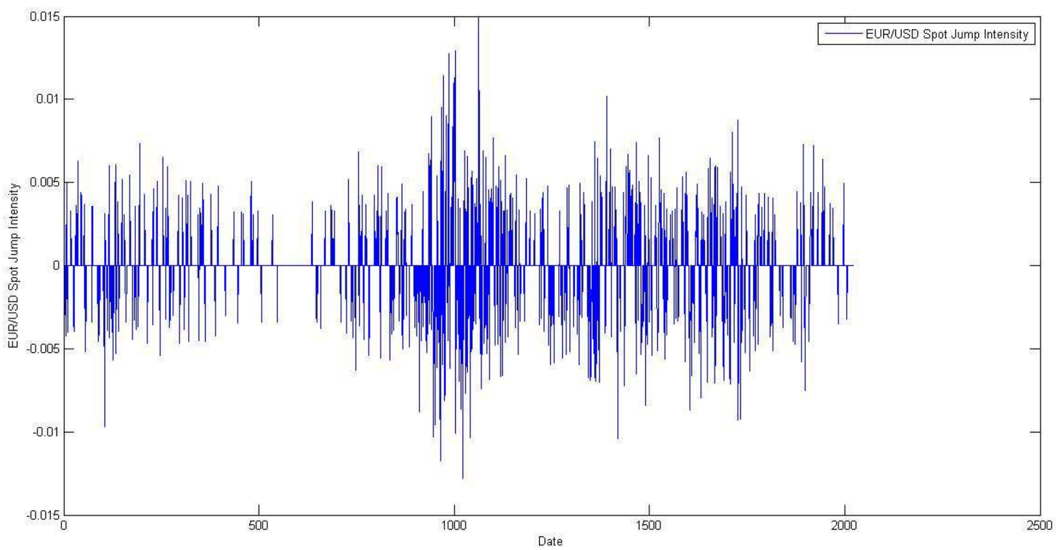

Figure 42. Levy process on the EUR/USD spot for intensity and time.

Shown in Figures 43 through 50 were the probability density functions and the cumulative distribution functions for the EUR/USD spot and its Levy process calculations. The PDF and CDF graphs showed the level of skewness, kurtosis, and the probability of a certain variable to be in the EUR/USD spot dataset. I used a random number generator to determine if a jump was activated based on the jump average count within a 30-day window. If a jump was activated then another random generator was used to determine the size of the jump. I set the intensity threshold to be around 25% of the total log return distribution to allow for enough of the signal to be in a 30-day window.

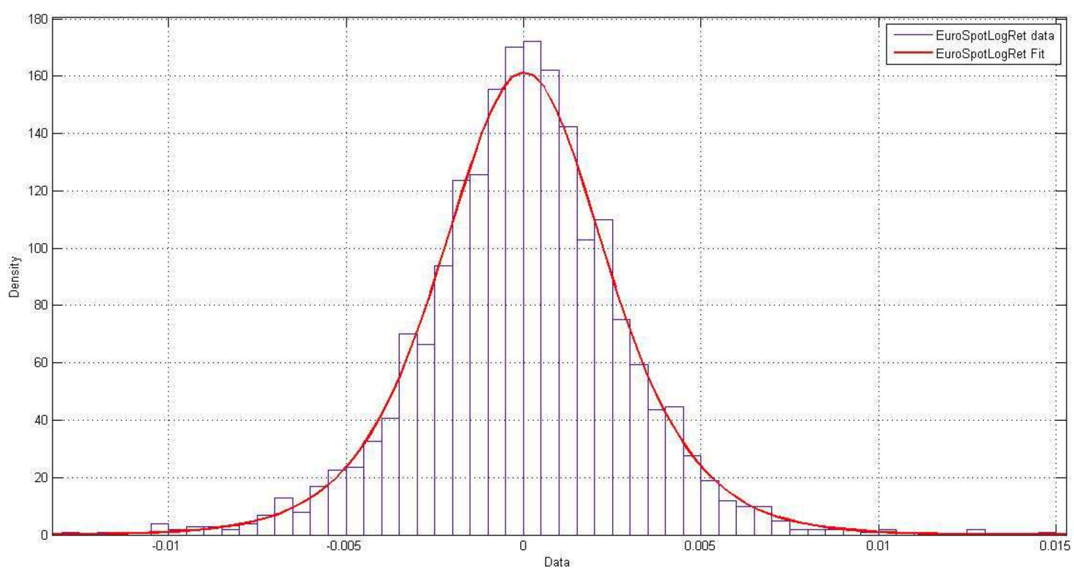

Figure 43. PDF on the EUR/USD spot for log returns.

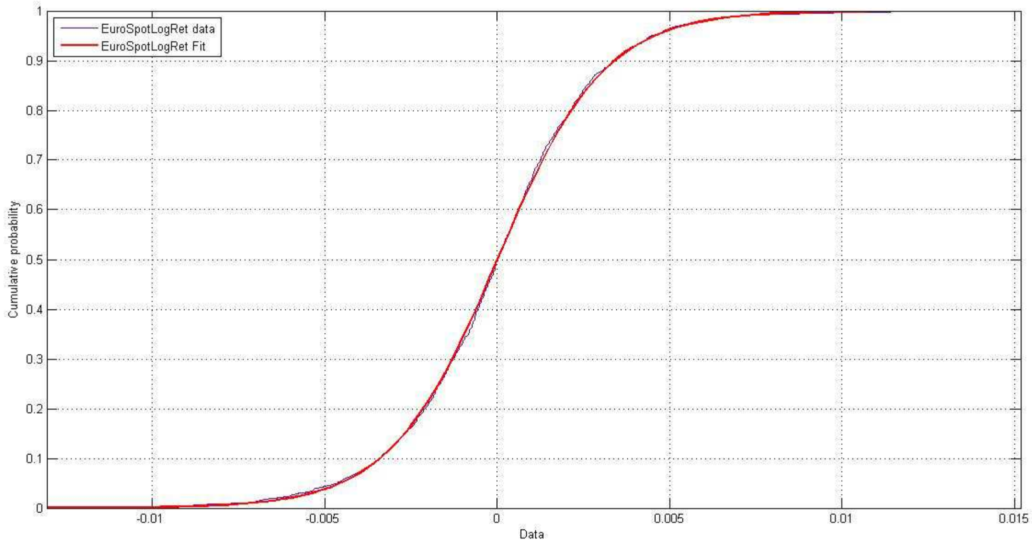

Figure 44. CDF on the EUR/USD spot for log returns.

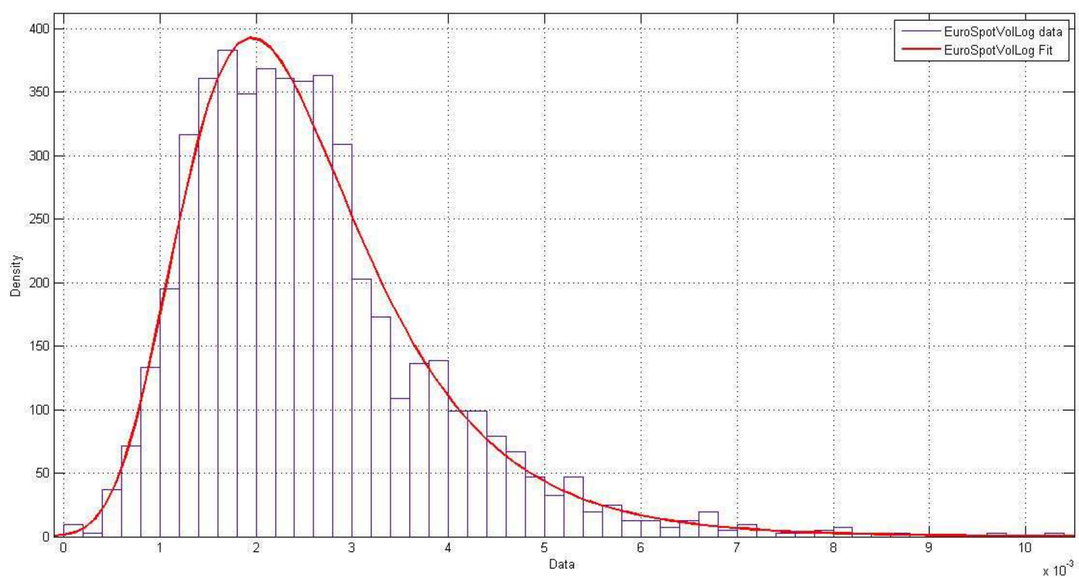

Figure 45. PDF on the EUR/USD spot for volatility.

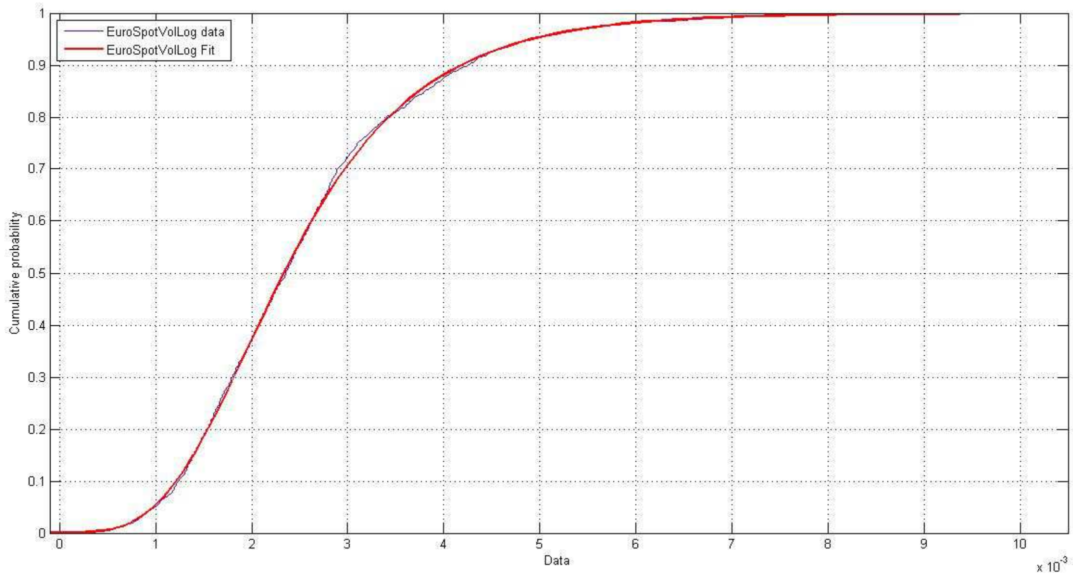

Figure 46. CDF on the EUR/USD spot for volatility.

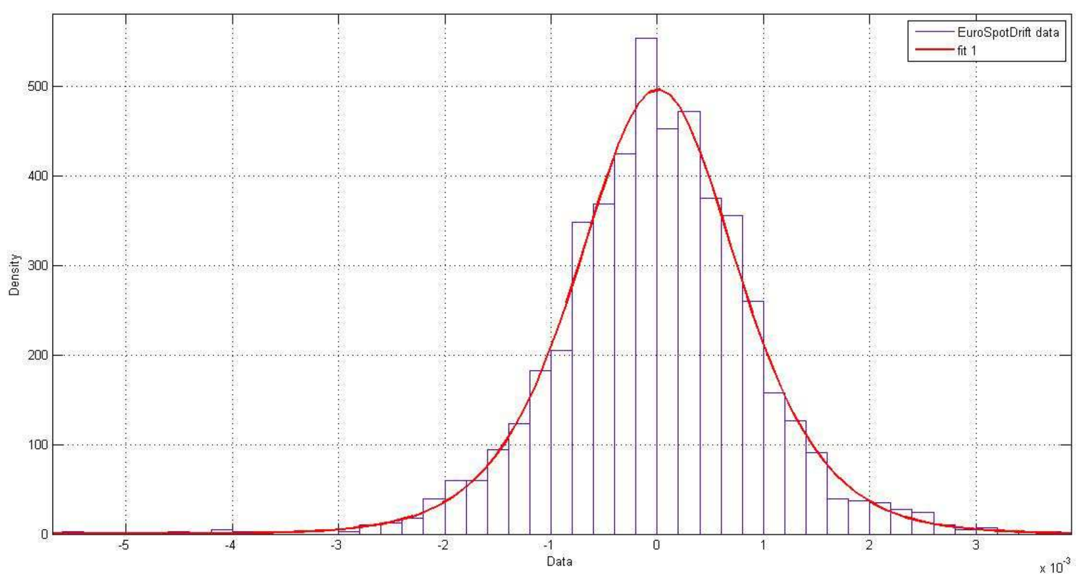

Figure 47. PDF on the EUR/USD spot for drift.

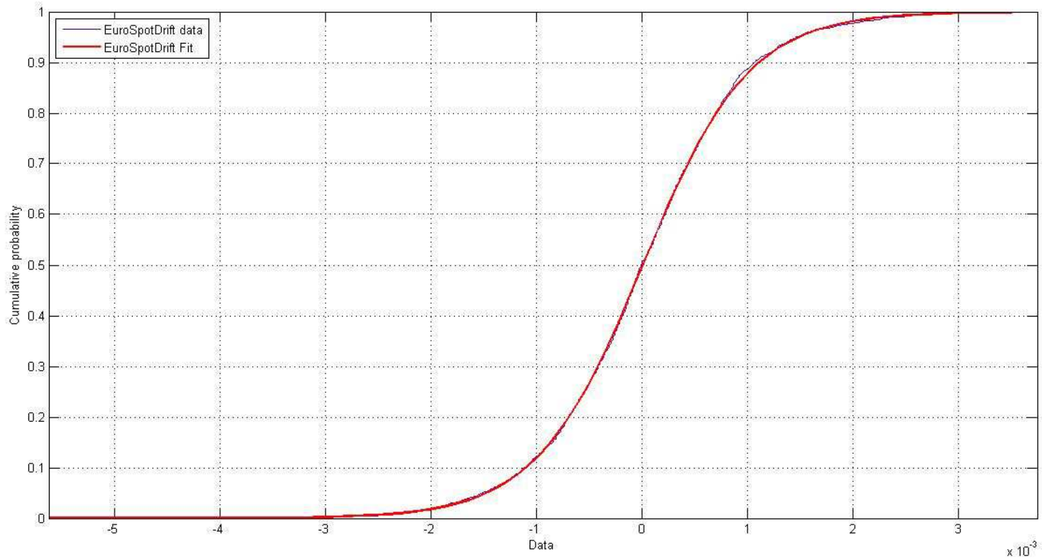

Figure 48. CDF on the EUR/USD spot for drift.

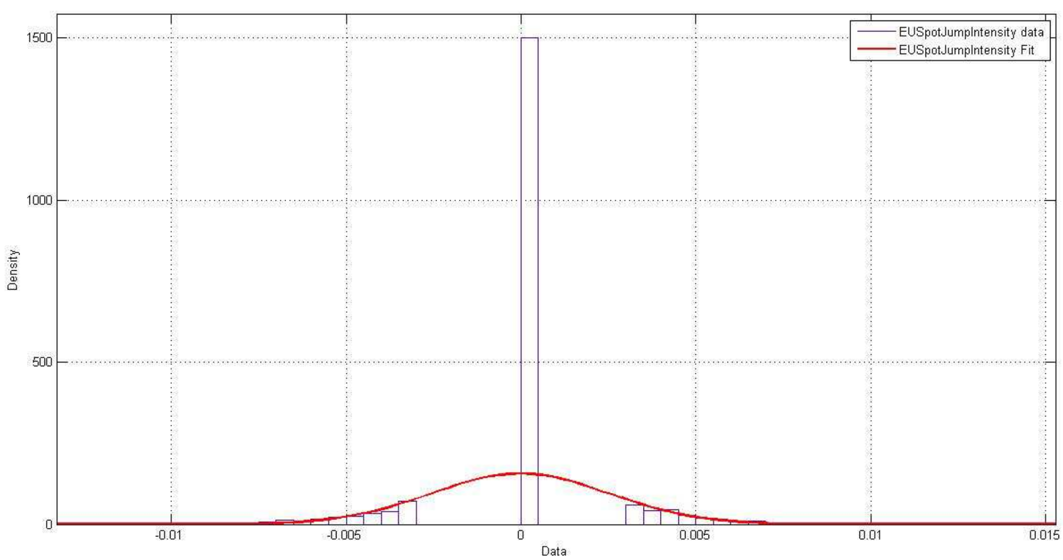

Figure 49. PDF on the EUR/USD spot for jump intensity.

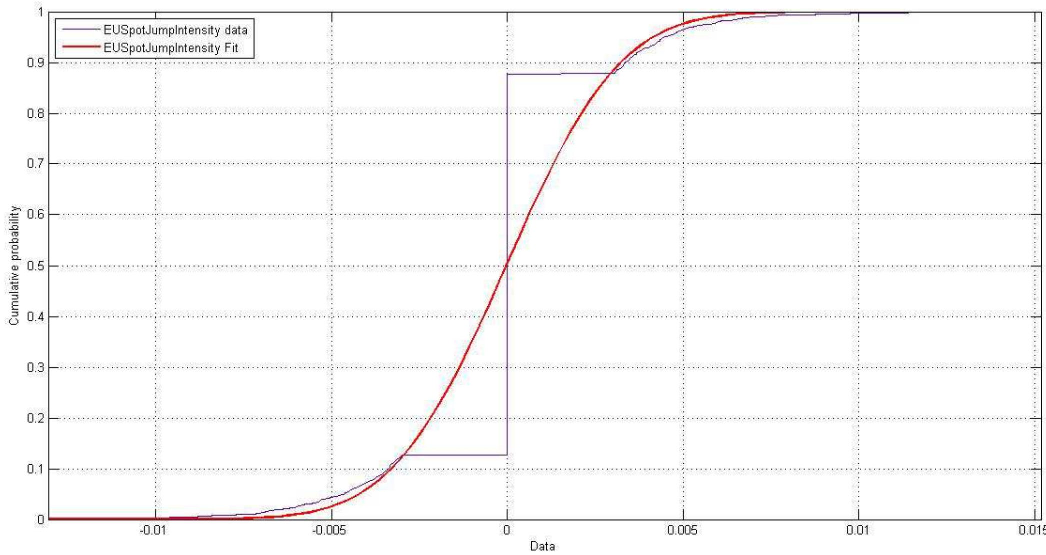

Figure 50. CDF on the EUR/USD spot for jump intensity.

Simulated Dataset Description

Shown in Figures 51 through 66 are some notable observations of the simulated market independent variable. The three dimensional graphs for the simulated market were prepared the same way as described for the previous mentioned contracts and the time span were the same as well. In Figure 51 the financial crisis of 2008 was not shown since this is simulated data independent of the actual events of the financial crisis of 2008. Extreme volatility was not exhibited, and represents a somewhat homoscedastic volatility. This homoskedastic volatility was expected for the simulation data because news events and other exogenous shocks were not within the stochastic process. Even though Figure 51 has price movement that is similar to actual historical data within this research data, the returns of those prices are quite different. The simulation data is used to see how well the different hedging methods perform in a homoskedastic environment.

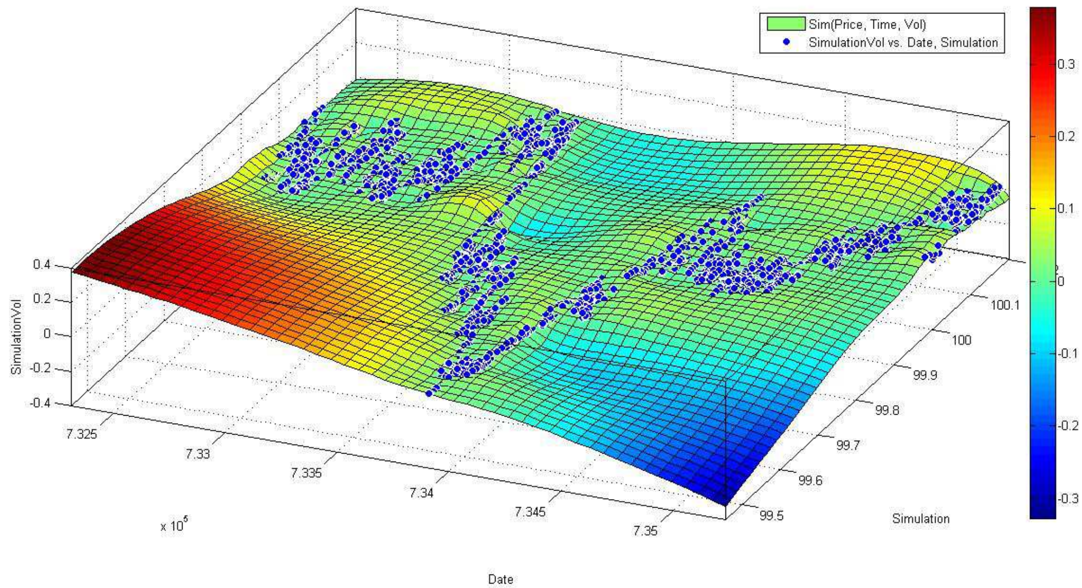

Figure 51. Simulated market for price, volatility, and time.

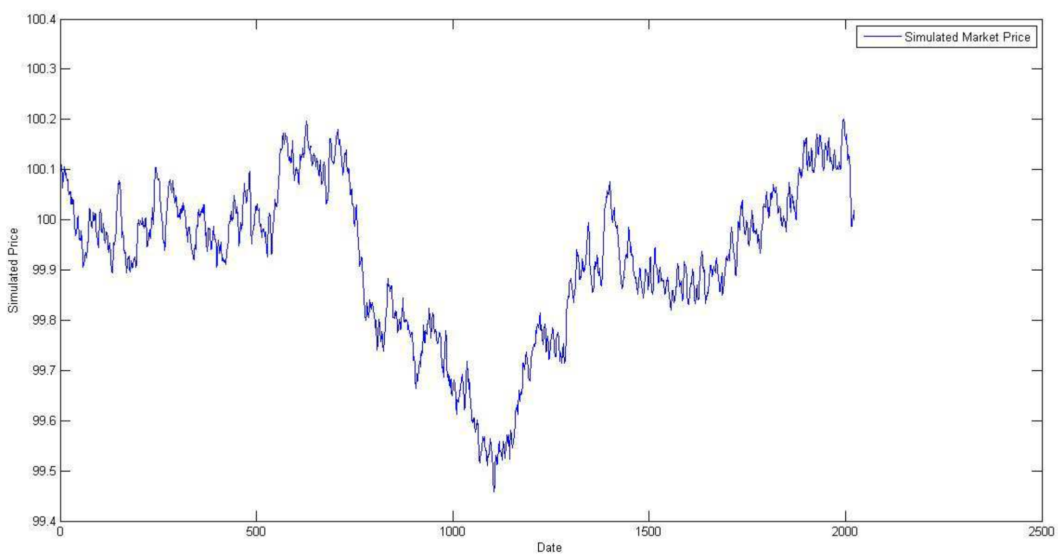

Figure 52. Simulated market for price and time.

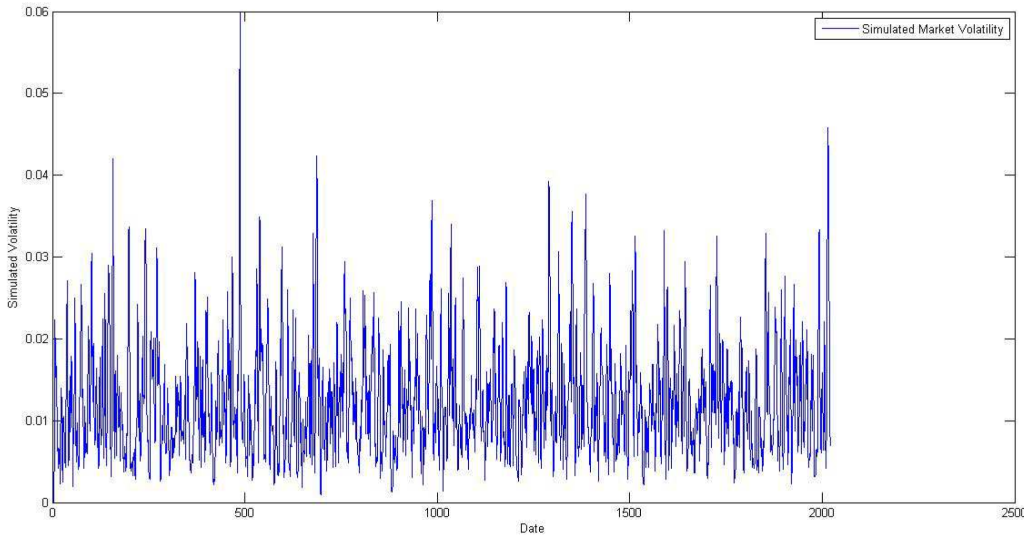

Figure 53. Simulated market for volatility and time.

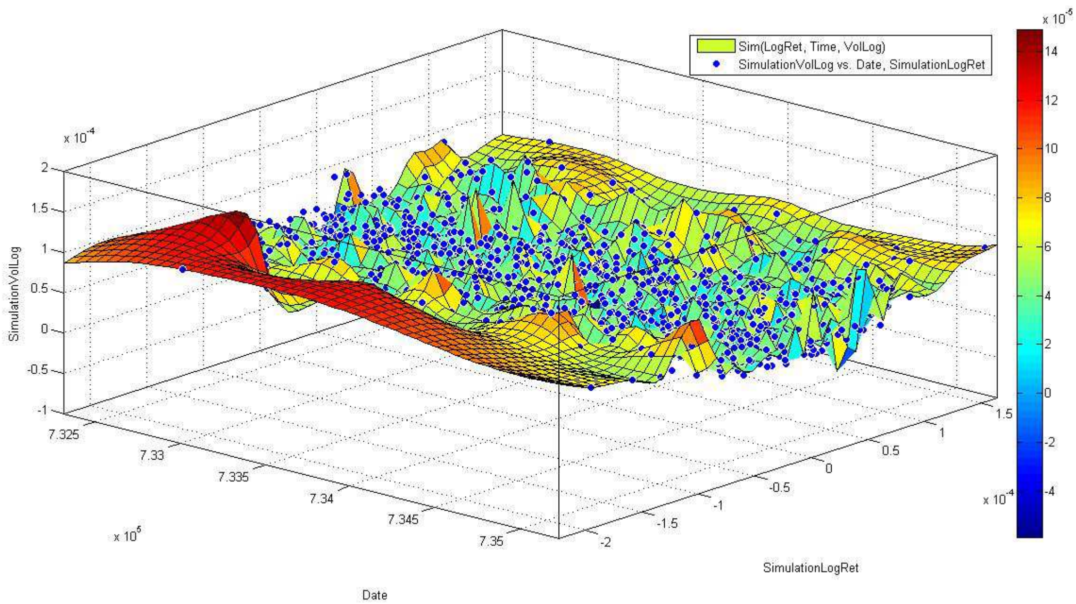

Figure 54. Simulated market for log return, volatility, and time.

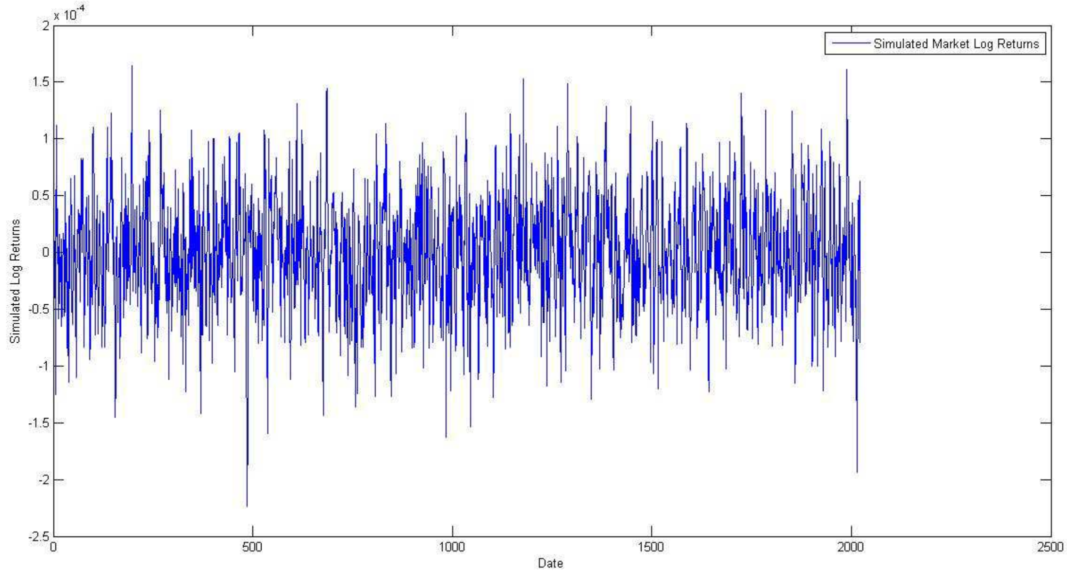

Figure 55. Simulated market for log return and time.

I represented the Levy process calculations in Figures 56 through 58 for the simulated market. As shown in Figure 56, similar characteristics to the surface shape as of Figure 38 did exist because drift was calculated from the log returns within a 5-day moving window and these log returns exhibited homoskedastic volatility. As can be seen in Figure 56, the volatility spikes were somewhat uniform. Figures 57 and 58 showed clearly the homoskedastic characteristics of the simulated market. Figure 57 can be considered the filtered signal of stress within the simulated market through the investigated 8-year period. The jump intensity for the simulated market was filtered with a 0.0055% threshold. A moving average of 30 days was used in the modified RHCSP to determine the probability of a jump and the intensity when calculating the expected price of the simulated market during the Monte Carlo simulation process.

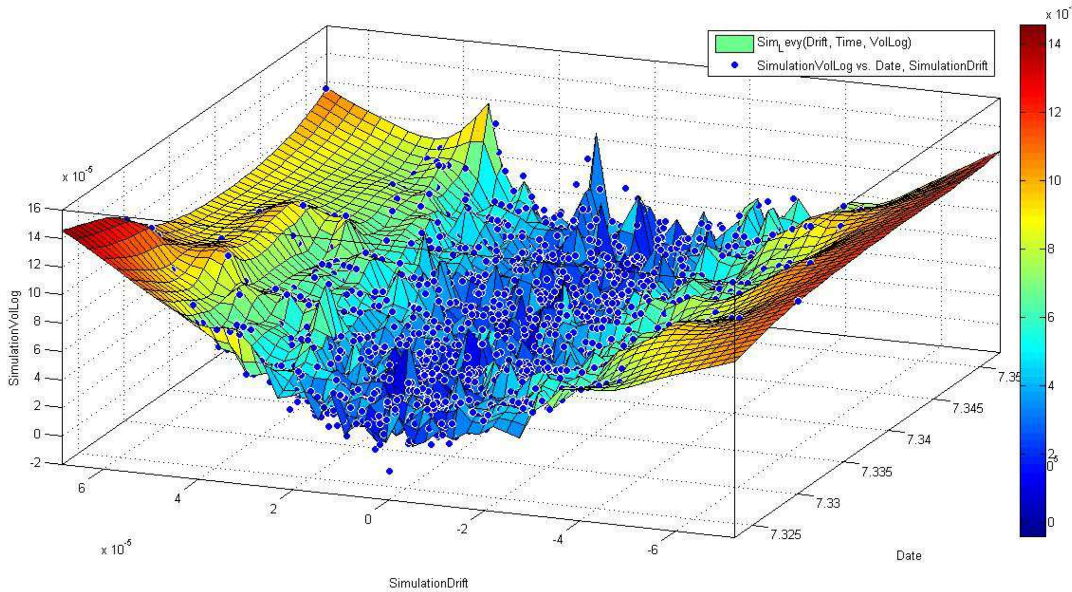

Figure 56. Levy process on the simulated market for drift, volatility, and time.

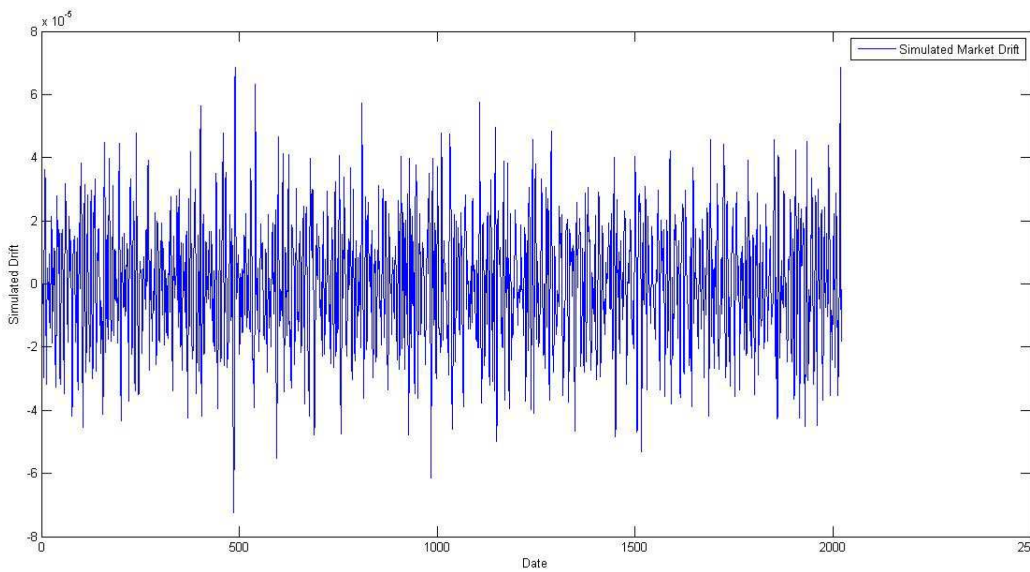

Figure 57. Levy process on the simulated market for drift and time.

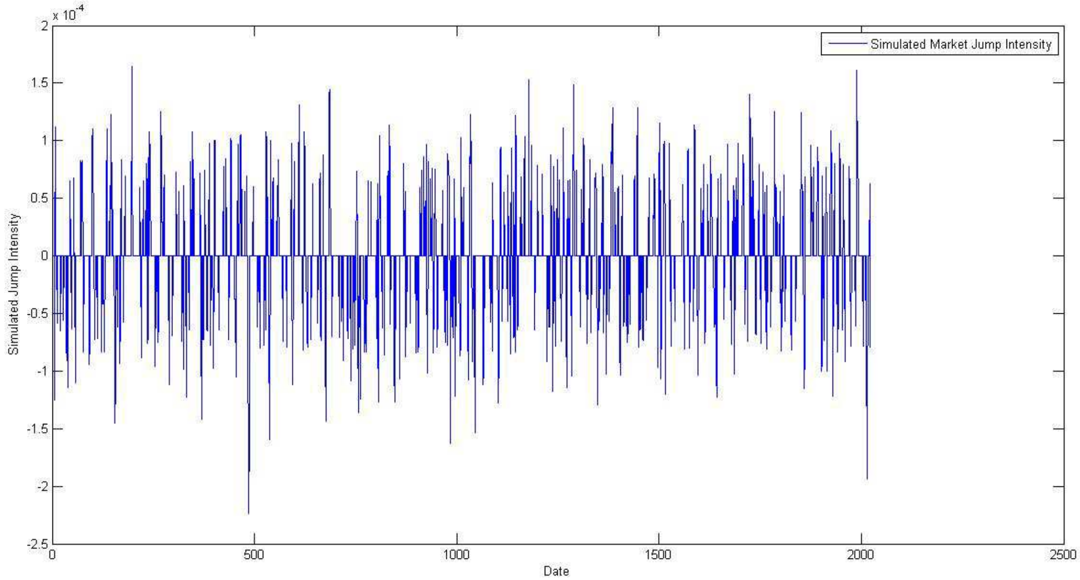

Figure 58. Levy process on the simulated market for intensity and time.

Shown in Figures 59 through 66 were the probability density functions and the cumulative distribution functions for the simulated market and its Levy process calculations. The PDF and CDF graphs showed the level of skewness, kurtosis, and the probability of a certain variable to be in the simulated market dataset. I used a random number generator to determine if a jump was activated based on the jump average count within a 30-day window. If a jump was activated then another random generator was used to determine the size of the jump. I set the intensity threshold to be around 25% of the total log return distribution to allow for enough of the signal to be in a 30-day window.

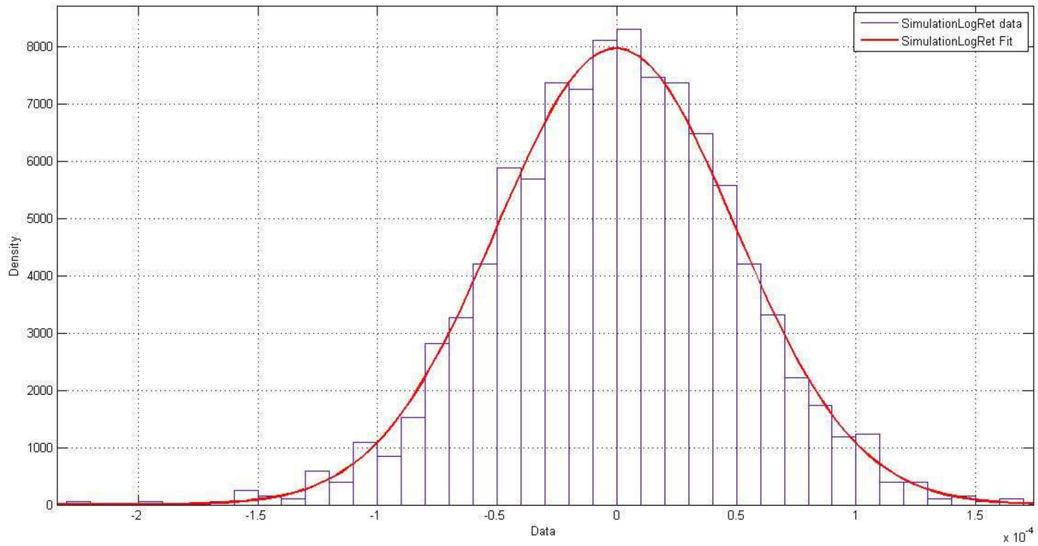

Figure 59. PDF on the simulated market for log returns.

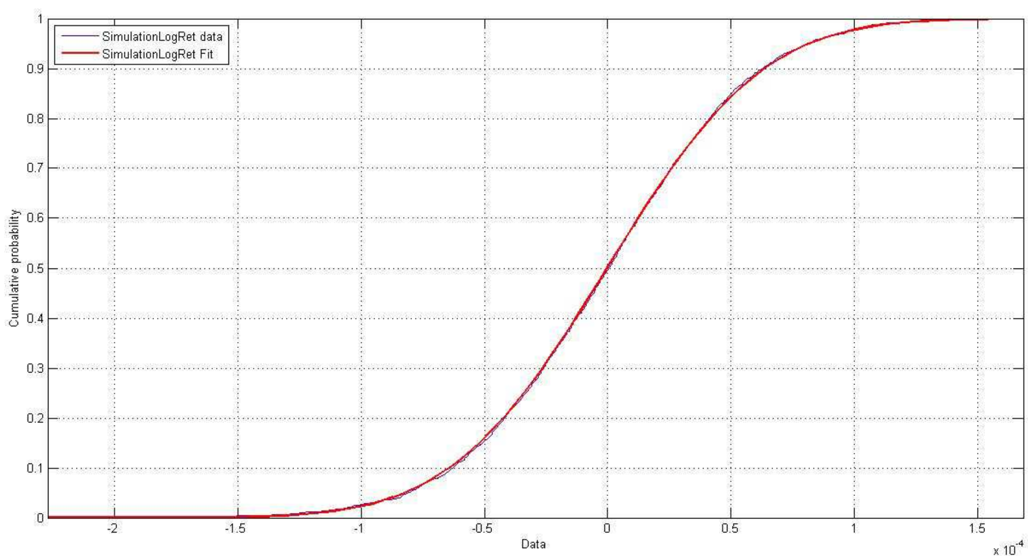

Figure 60. CDF on the simulated market for log returns.

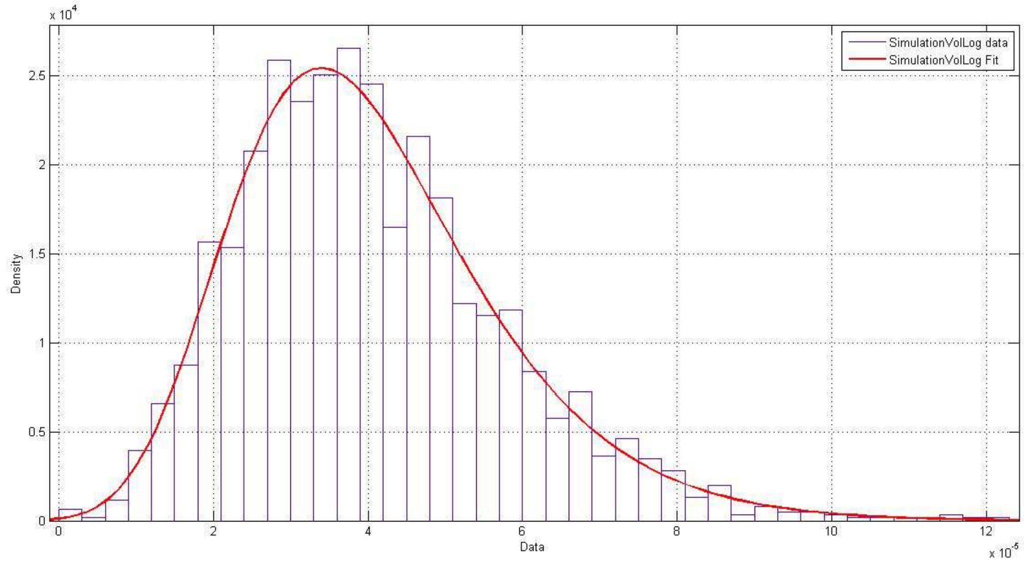

Figure 61. PDF on the simulated market for volatility.

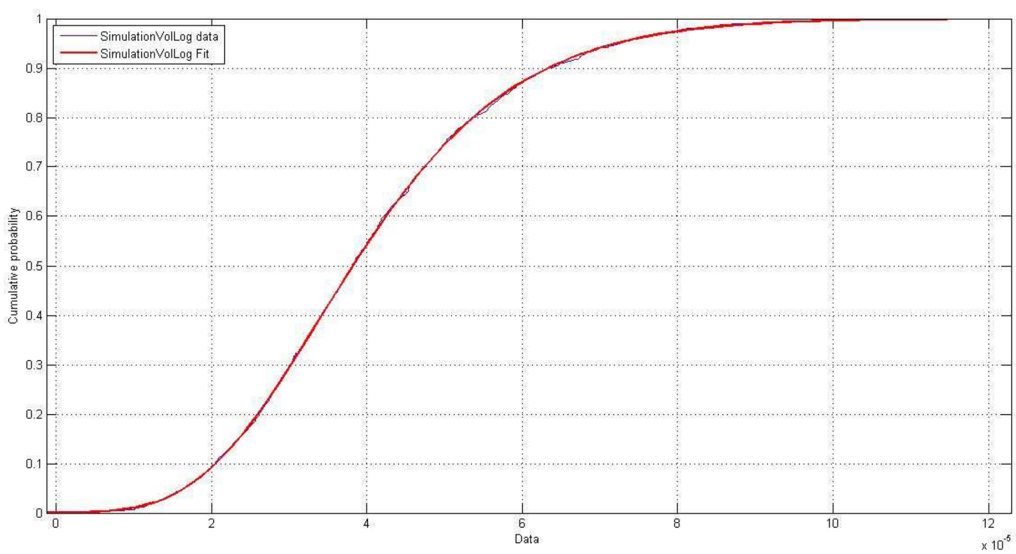

Figure 62. CDF on the simulated market for volatility.

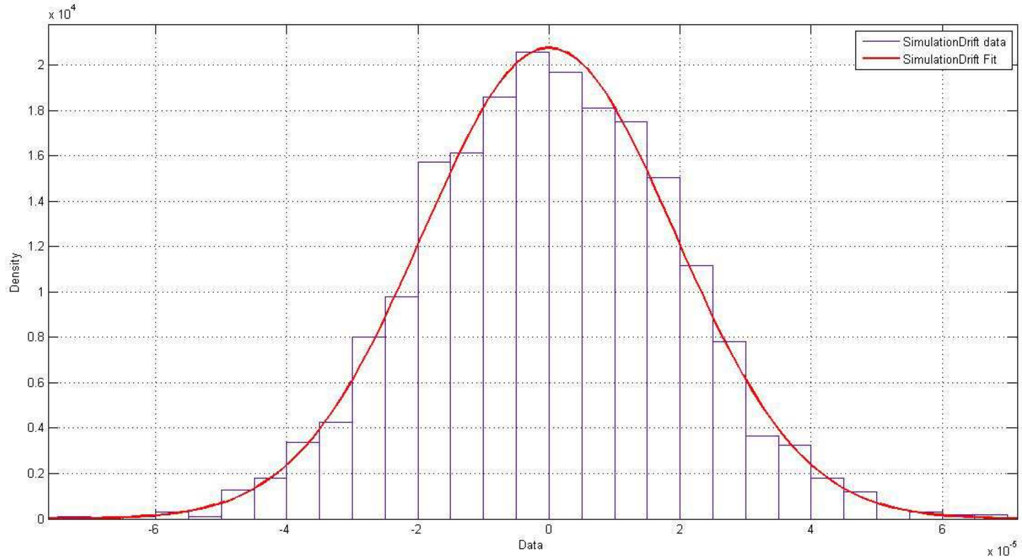

Figure 63. PDF on the simulated market for drift.

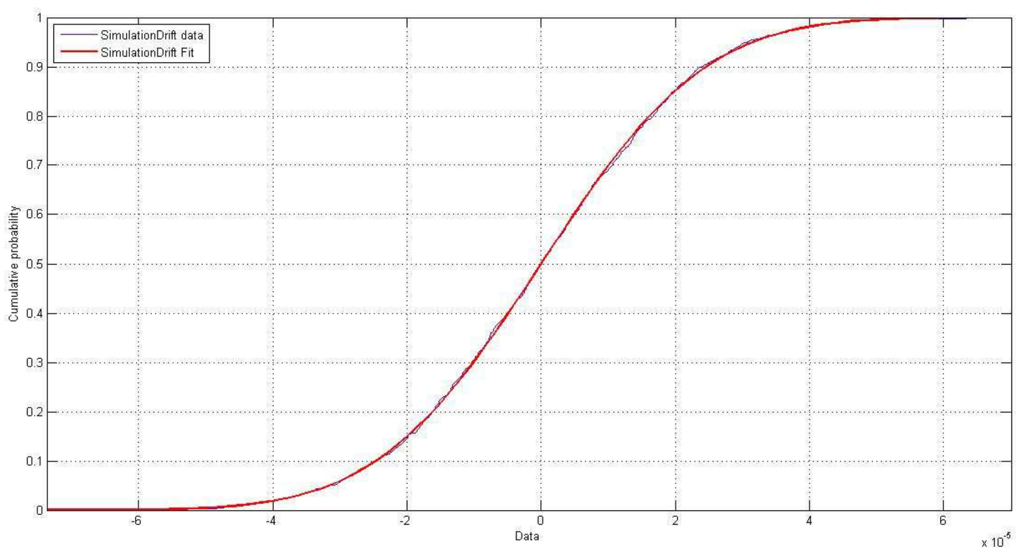

Figure 64. CDF on the simulated market for drift.

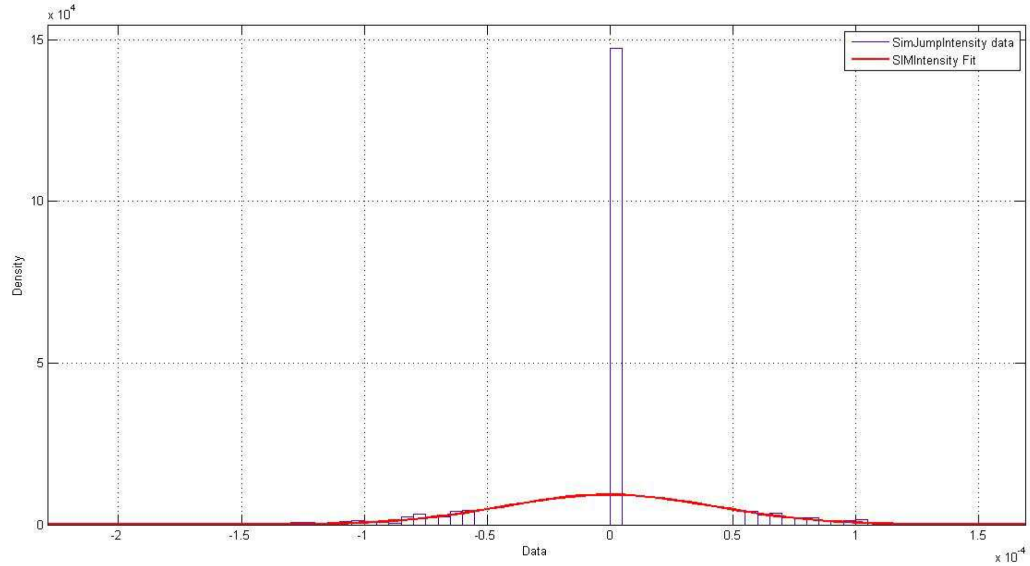

Figure 65. PDF on the simulated market for jump intensity.

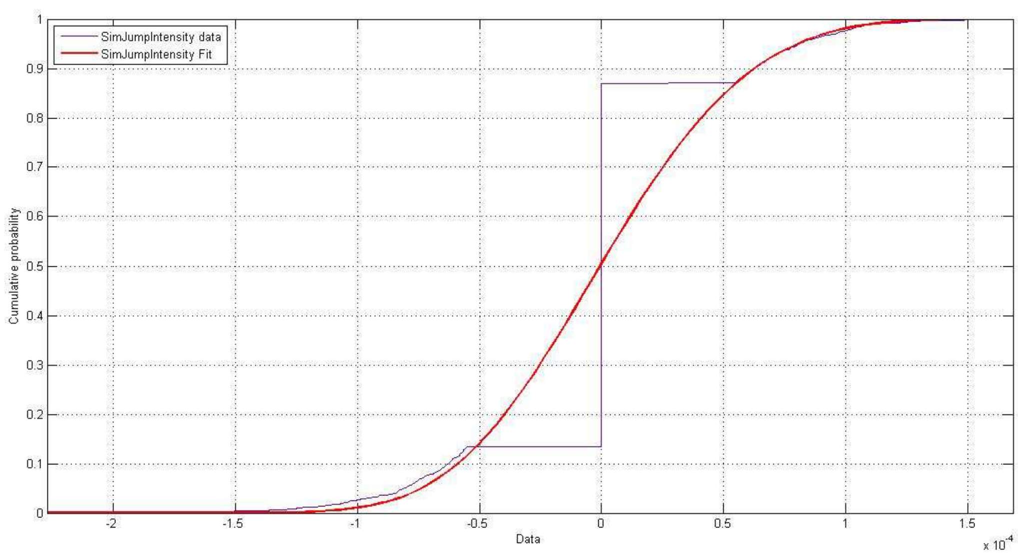

Figure 66. CDF on the simulated market for jump intensity.

Results

CL Results

As shown in Figure 67, the CL contract hedging error reduced—for the most part—when hedging with the Black–Scholes method through the modified RHCSP method. The assumption was that hedging was done with reference to the CL spot price and offset with an option on a futures contract, with transaction costs of 0.3% of the spot price per contract. The CL contract was hedged discretely every five days using the BSM and Leland methods. For the Leland method the transaction cost parameter was 0.01. The Whalley and Wilmott method had a risk aversion parameter of 1.0 and a hedging upper/lower threshold of $\pm 1\text{x}10^{-10}$. The RHCSP method had a standard objective function, which included a difference threshold parameter between the predicted underlying price and the current option strike price of 0.25. The modified RHCSP method utilized the previous RHCSP objective function and parameters, but also included the utilization of the LIBOR and Levy process. The modified RHCSP had a LIBOR threshold parameter of +/- 0.000025 and used a random number generator to determine if a jump should be activated within the Levy process in conjunction with minimum and maximum jump intensity functions. See Appendix A for the Matlab code used for each of the hedging methods on the CL contract.

The sample size was 506 absolute hedging errors for the CL contract—a single sample was generated by taking the average of four daily absolute hedging errors. The descriptive statistics of the dependent variable for the CL contract are shown in Table 2.

Table 2

Descriptive Statistics of the Hedging Errors for the CL Contract

Hedging Method	*M*	*SD*	*n*
Black-Scholes	2.12188	1.34037	506
Leland	2.12663	1.35099	506
Whalley-Wilmott	2.01421	1.60341	506
RHCSP	2.06172	1.64359	506
Modified RHCSP	1.61532	1.00615	506
Total	1.98795	1.41936	2530

H_0: $\mu_{\text{(difference in hedging error)}} = 0$ for each pair of hedging methods on the CL contract, whereas H_a: $\mu_{\text{(difference in hedging error)}} \neq 0$ for each pair of hedging methods for the CL contract. Refer to Table 3 for the ANOVA table on the CL contract.

Table 3

Significance for CL Contract Hedging

Source	Sum of Squares	*Df*	*F*	Partial $\eta 2$
Hedging Method	92.169	4	11.63*	0.018
Error	5002.742	2525		

* *p* <.001

There was a significant main effect of the hedging method on the hedging error of the CL contracts, $F(4, 2525) = 11.63$, $p = .000$, partial $\eta^2 = .018$, power = 1.0. I rejected the null hypothesis and concluded that for the CL contracts there are differences in hedging error amongst different hedging methods. Furthermore, the modified RHCSP method performed significantly better than all the other hedging methods represented through the *t*–test. The largest difference in performance of hedging error was with the modified RHCSP method compared to the Leland method, $t(505) = -9.884$, $p < .05$ (two-tailed). The *t*–tests for the remaining hedging methods compared to the modified RHCSP were:

- Modified RHCSP and Black–Scholes , $t(505) = -9.860$, $p < .05$ (two-tailed)
- Modified RHCSP and Whalley and Wilmott, $t(505) = -5.511$, $p < .05$ (two-tailed)
- Modified RHCSP and RHCSP, $t(505) = -7.872$, $p < .05$ (two-tailed)

The mean differences of the Black–Scholes and Whalley and Wilmott pair, $t(505) = 1.461$, $p > .05$ (two-tailed); Black–Scholes and RHCSP pair, $t(505) = 1.022$, $p > .05$ (two-tailed) ; Leland and Whalley and Wilmott pair, $t(505) = 1.525$, $p > .05$ (two-tailed); Leland and RHCSP&P pair, $t(505) = 1.100$, $p > .05$ (two-tailed); Whalley and Wilmott and RHCSP pair, $t(505) = -.564$, $p > .05$ (two-tailed) were not significantly different. The mean differences of the Black–Scholes and Leland pair, $t(505) = -3.130$, $p < .05$ (two-tailed) was significantly different.

The post hoc Tukey test revealed that hedging error was significantly different between the modified RHCSP and the remaining hedging methods in favor of the modified RHCSP method for the CL contract between the time period investigated (all $p = .000$). The Black–Scholes, Leland, Whalley–Wilmott, and RHCSP methods were not significantly different amongst each other (with all p >.709).

Based on the results of the *F* –test, *t* –test, and the post hoc Tukey test, I rejected the null hypothesis with the modified RHCSP outperforming all the other hedging methods on the CL contract for the time period investigated. This means that incorporating a Levy process and the LIBOR in the modified RHCSP method significantly improved hedging error.

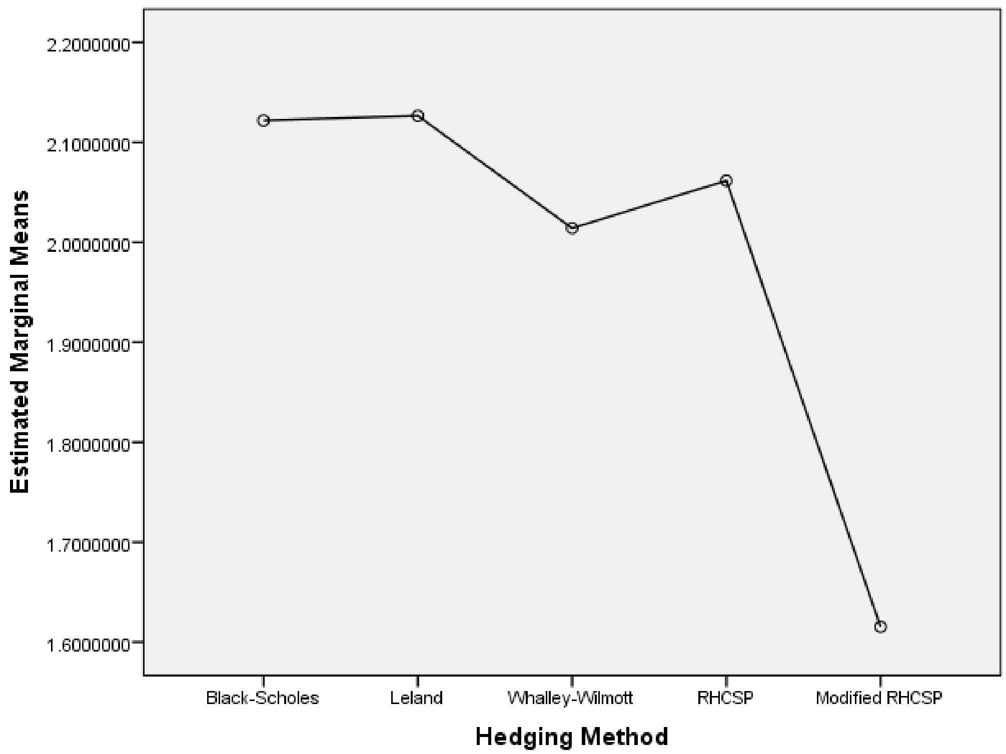

Figure 67. Profile plot of the hedging method for the CL contract.

6E Results

As shown in Figure 68, the 6E contract hedging error was reduced when hedging with the Black–Scholes method through the modified RHCSP method. The assumption was that hedging was done with reference to the 6E futures strike price and offset with a position in the EUR/USD spot market, with transaction cost of 0.0024% of the spot price per futures contract and 0.0012% per spot contract. The CL contract was hedged discretely every five days using the BSM and Leland methods. Discrete hedging pertains to a fix time when rebalancing. For the Leland method the transaction cost parameter was 0.01. The Whalley and Wilmott method had a risk aversion parameter of 1.0 and a hedging upper/lower threshold of +/- 10. The RHCSP method had a standard objective function, which included a difference threshold parameter between the predicted underlying price and the current spot price of 0.002. The modified RHCSP method utilized the previous RHCSP objective function and parameters, but also included the utilization of the LIBOR and Levy process. The modified RHCSP had a LIBOR threshold parameter of +/- 0.00135 and used a random number generator to determine if a jump should be activated within the Levy process in conjunction with minimum and maximum jump intensity functions. See Appendix B for the Matlab code used for each of the hedging methods for the 6E contract.

The sample size was 506 absolute hedging errors for the 6E contract—a single sample was generated by taking the average of four daily absolute hedging errors. The descriptive statistics of the dependent variable for the 6E contract are shown in Table 4.

Table 4

Descriptive Statistics of the Hedging Errors for the 6E Contract

Hedging Method	*M*	*SD*	*n*
Black-Scholes	.03665	.03456	506
Leland	.03664	.03455	506
Whalley-Wilmott	.01978	.02912	506
RHCSP	.00346	.00466	506
Modified RHCSP	.00753	.02126	506
Total	.02081	.03061	2530

H_0: $\mu_{\text{(difference in hedging error)}} = 0$ for each pair of hedging methods on the 6E contract, whereas H_a: $\mu_{\text{(difference in hedging error)}} \neq 0$ for each pair of hedging methods on the 6E contract. Refer to Table 5 for the ANOVA table on the 6E contract.

Table 5

Significance for 6E Contract Hedging

Source	Sum of Squares	*Df*	*F*	Paritial *η*2
Hedging Method	0.496	4	167.08*	0.209
Error	1.873	2525		

* *p* < .001

There was a significant main effect of the hedging method on the hedging error of the 6E contracts, $F(4, 2525) = 167.08$, $p = .000$, partial $\eta^2 = .209$, power = 1.0. I rejected the null hypothesis and conclude that for the 6E contracts there are differences in hedging error amongst different hedging methods. Furthermore, the RHCSP method performed significantly better than all the other hedging methods represented through the *t*–test. The largest difference in performance of hedging error was the RHCSP method compared to the Leland method, $t(505) = -21.266$, $p < .05$ (two-tailed). The *t*–tests for the remaining hedging methods compared to the RHCSP were:

- RHCSP and Black–Scholes, $t(505) = -21.265$, $p < .05$ (two-tailed)
- RHCSP and Whalley and Wilmott, $t(505) = -12.576$, $p < .05$ (two-tailed)
- RHCSP and modified RHCSP, $t(505) = -4.331$, $p < .05$ (two-tailed)

The mean differences of the Black–Scholes and Leland pair, $t(505) = .999$, $p > .05$ was not significantly different. The mean differences of the Black–Scholes and the Whalley and Wilmott pair, $t(505) = 13.191$, $p < .05$; Black–Scholes and modified RHCSP pair, $t(505) = 21.234$, $p < .05$; Leland and Whalley and Wilmott pair, $t(505) = 13.191$, $p <.05$; Leland and modified RHCSP&P pair, $t(505) = 21.235$, $p < .05$; Whalley and Wilmott and modified RHCSP pair, $t(505) = 8.555$, $p < .05$ were significantly different.

The post hoc Tukey test revealed that hedging error was significantly different between the modified RHCSP and the remaining hedging methods in favor of the modified RHCSP method for the 6E contract between the time period investigated, except for the RHCSP method (all $p = .000$, but significance was not established between modified RHCSP and RHCSP with $p = .123$)—allowing the rejection of the null hypothesis that hedging error is not significantly different amongst the different hedging methods. The hedging error was not significant between the Black–Scholes and Leland methods (with p = 1.00). The Black–Scholes and Leland methods performed worse compared to the remaining hedging methods (with p = .000). The Whalley and Wilmott method outperformed the Black–Scholes and Leland methods, but did not outperform the RHCSP or the modified RHCSP methods.

Based on the results of the F –test, t –test, and the post hoc Tukey test, I rejected the null hypothesis with the RHCSP outperforming all the other hedging methods on the CL contract for the time period investigated. This means that incorporating a Levy process and the LIBOR in the modified RHCSP method significantly improved hedging error except when comparing to the RHCSP method.

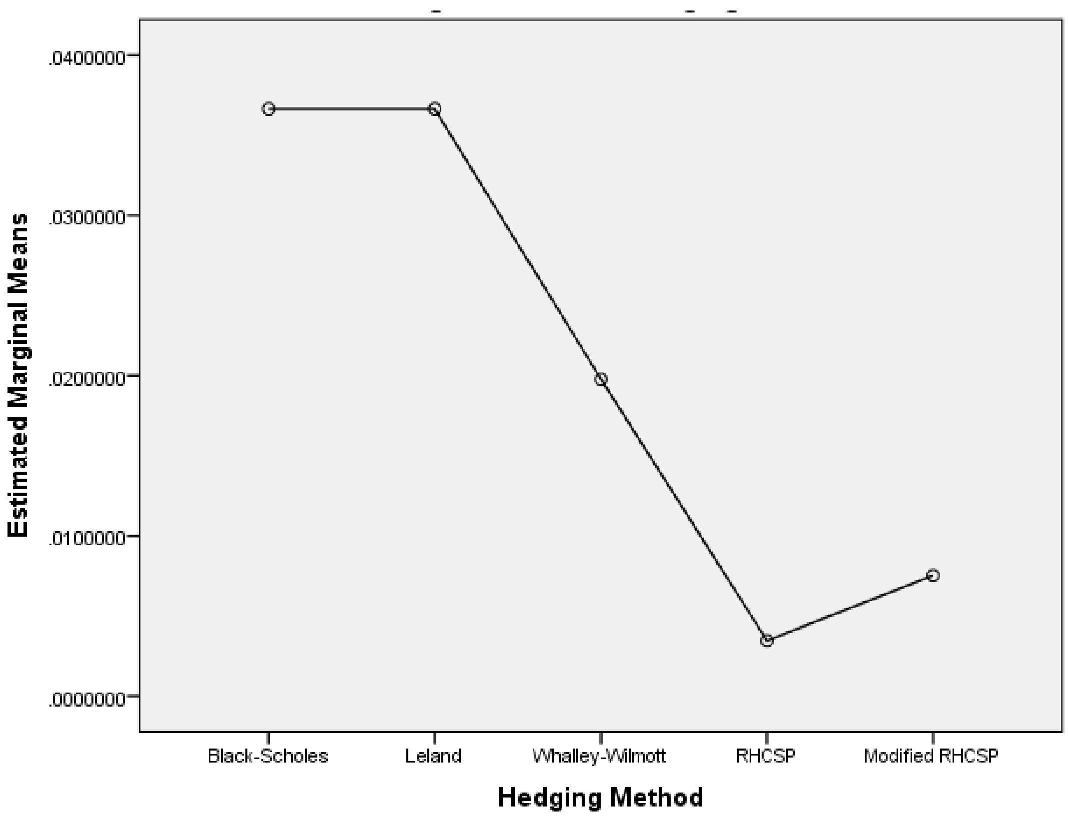

Figure 68. Profile plot of the hedging method for the 6E contract.

Simulated Market Results

As shown in Figure 69, the simulated contract hedging error increased when hedging with the Black–Scholes method through the modified RHCSP method. The assumption was that hedging was done with reference to the simulated spot price and offset with an option on a futures contract, with transaction cost of 0.3% of the spot price per contract. The simulated contract was hedged discretely every five days using the Black–Scholes and Leland methods. For the Leland method the transaction cost parameter was 0.01. The Whalley and Wilmott method had a risk aversion parameter of 1.0 and a hedging upper/lower threshold of +/- 16.2. The RHCSP method had a standard objective function, which included a difference threshold parameter between the predicted underlying price and the current option strike price of 0.04. The modified RHCSP method utilized the previous RHCSP objective function and parameters, but also included the utilization of the LIBOR and Levy process. The modified RHCSP method had a LIBOR threshold parameter of +/- $1x10^{-9}$ and used a random number generator to determine if a jump should be activated within the Levy process in conjunction with minimum and maximum jump intensity functions. See Appendix C for the Matlab code used for each of the hedging methods for the simulated contract.

The sample size was 506 absolute hedging errors for the simulated contract; this sample was generated by taking the average of four daily absolute hedging errors. The descriptive statistics of the dependent variable for the simulated contract are shown in Table 6.

Table 6

Descriptive Statistics of the Hedging Errors for the Simulated Contract

Hedging Method	*M*	*SD*	*n*
Black-Scholes	.18071	.04602	506
Leland	.18071	.04602	506
Whalley-Wilmott	.36456	.26942	506
RHCSP	.28827	.19617	506
Modified RHCSP	.50352	.14577	506
Total	.30356	.20518	2530

H_0: $\mu_{\text{(difference in hedging error)}} = 0$ for each pair of hedging methods for the simulated contract, whereas H_a: $\mu_{\text{(difference in hedging error)}} \neq 0$ for each pair of hedging methods for the simulated contract. Refer to Table 7 for the ANOVA table on the simulated contract.

Table 7

Significance for Simulated Contract Hedging

Source	Sum of Squares	*Df*	*F*	Paritial $\eta 2$
Hedging Method	37.505	4	343.31*	0.352
Error	68.960	2525		

*$p < .001$

There was a significant main effect of the hedging method on the hedging error of the simulated contracts, $F(4, 2525) = 343.31$, $p = .000$, partial $\eta^2 = .352$, power = 1.0. I rejected the null hypothesis and concluded that for the simulated contracts there were differences in hedging error amongst different hedging methods. Furthermore, the Black–Scholes and Leland methods performed significantly better than all the other hedging methods represented through the *t*–test. The largest difference in performance of hedging error was the Leland method compared to the modified RHCSP method, $t(505) = -47.026$, $p < .05$ (two-tailed). The *t*–tests for the remaining hedging methods compared to the Leland method were:

- Leland and Black–Scholes, $t(505) = -1.00$, $p > .05$ (two-tailed), not significant
- Leland and Whalley and Wilmott, $t(505) = -16.027$, $p < .05$ (two-tailed)
- Leland and RHCSP, $t(505) = -10.660$, $p < .05$ (two-tailed)

The mean differences of the Black–Scholes and Whalley and Wilmott pair, $t(505) = -16.027$, $p < .05$; Black–Scholes and RHCSP pair, $t(505) = -10.660$, $p < .05$; Black–Scholes and modified RHCSP, $t(505) = -47.026$, $p < .05$; Whalley and Wilmott and RHCSP pair, $t(505) = 4.706$, $p < .05$; Whalley and Wilmott and modified RHCSP pair, $t(505) = -10.011$, $p < .05$; RHCSP and modified RHCSP pair, $t(505) = -26.042$, $p < .05$ were significantly different.

The post hoc Tukey test revealed that hedging error was significantly different between the Black–Scholes and the Leland methods compared to the remaining hedging methods in favor of the Black–Scholes and Leland methods for the simulated contracts between the time period investigated (all $p = .000$). The Black–Scholes and Leland methods were not statistically different amongst each other, (with $p = 1.00$). The Whalley and Wilmott method performed statistically better in terms of hedging error compared to the modified RHCSP method, but the Whalley and Wilmott method did statistically worse relative to RHCSP. The use of the LIBOR and the Levy process did not help reduce hedging error in the simulated market investigated, nor did threshold parameters used in the RHCSP objective function or in the Whalley and Wilmott method. Since the characteristics of the simulated market were more homoskedastic and had price swings that were lower compared to the currency and oil markets, using a discrete hedging method like the Black–Scholes or the Leland method outperformed the hedging methods investigated.

Based on the results of the F–test, t–test, and the post hoc Tukey test, I rejected the null hypothesis with the Black–Scholes and Leland methods outperforming all the other hedging methods on the simulated contract for the time period investigated. This means that incorporating a Levy process and the LIBOR in the modified RHCSP method did not significantly improve hedging error.

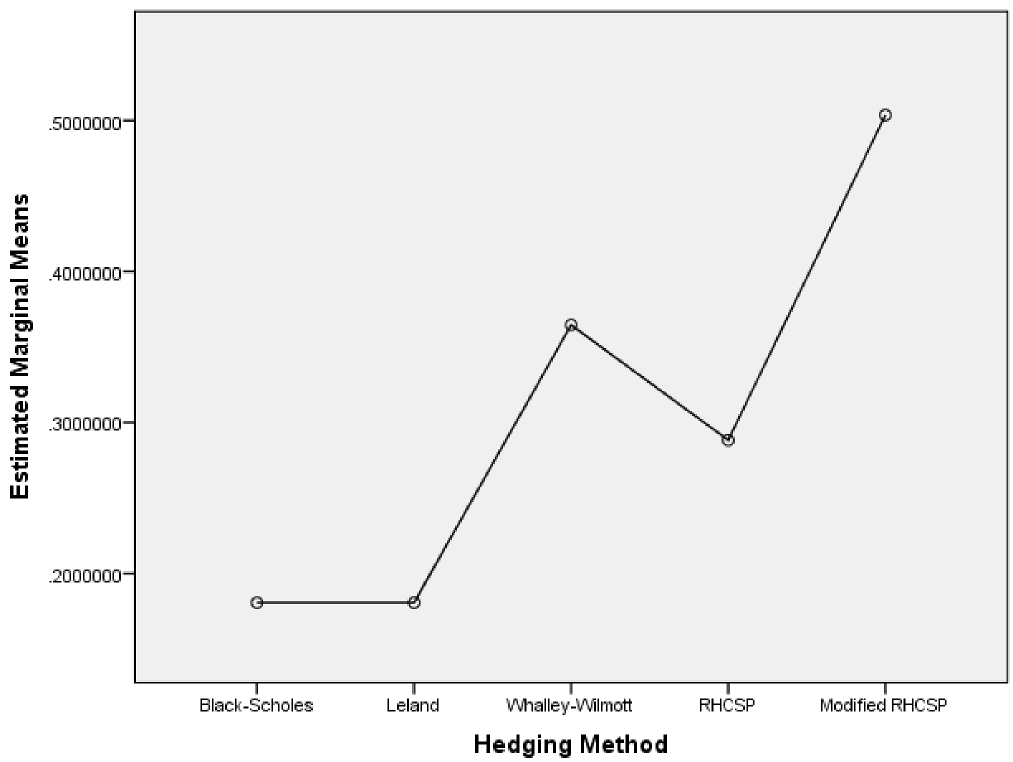

Figure 69. Profile plot of the hedging method for the simulated contract.

The following are the answers to the research questions and conclusions relative to the hypotheses. Can the RHCSP hedging method improve hedging error compared to the Black–Scholes, Leland, and Whalley and Wilmott methods when applied to a simulated market, oil futures market, and currency futures market? This depends on the type of market investigated. The RHCSP hedging method was shown to outperform in the 6E market relative to the Black–Scholes, Leland , and Whalley and Wilmott methods—whereas the RHCSP method was not statistically different from the Black–Scholes, Leland, and Whalley and Wilmott methods for the CL market. The RHCSP hedging method did not outperform for the simulated market investigated, except when compared to the Whalley and Wilmott method.

Can a modified RHCSP method significantly reduce hedging error under extreme market illiquidity conditions when applied to a simulated market, oil futures market, and currency futures market? The modified RHCSP hedging method did outperform in the CL and 6E markets, which included the extreme market illiquidity conditions of the 2008 financial crisis. The modified RHCSP did not outperform compared to the other hedging methods for the simulated market.

For the CL market I rejected the null hypothesis because there were significant differences in hedging error amongst the different methods resulting in the modified RHCSP outperforming. For the 6E market I could also reject the null hypothesis because there were significant differences in hedging error amongst the different methods resulting in the RHCSP and modified RHCSP outperforming. Lastly, for the simulated market I rejected the null hypothesis because there were significant differences in hedging error amongst the different methods resulting in the Black–Scholes and Leland methods outperforming.

Summary

It has been shown that the hedging methods perform statistically different depending on the type of market used, when considering the time period between January 1, 2005 and December 31, 2012. For the CL market, hedging error was shown to be significantly reduced by using the modified RHCSP method. The 6E market revealed that either the RHCSP or the modified RHCSP method performed statistically better compared to the other methods considered. These results match the results found for the CL contract because of the heteroskedastic characteristics of this financial asset. Lastly, the simulated market revealed that hedging with the Black–Scholes or the Leland outperformed significantly better than all other hedging methods investigated in this research. The superior performance of the BSM and the Leland methods in the simulated market is due to the homoskedastic behavior of the log returns. In addition, the simulated market did not fluctuate wildly around its starting point compared to the CL contract.

Can the RHCSP hedging method improve hedging error compared to the Black–Scholes, Leland, and Whalley and Wilmott methods when applied to a simulated market, oil futures market, and currency futures market? This depends on the type of market investigated. The RHCSP hedging method was shown to outperform in the 6E market relative to the Black–Scholes, Leland , and Whalley and Wilmott methods—whereas the RHCSP method was not statistically different from the Black–Scholes, Leland, and

Whalley and Wilmott methods for the CL market. RHCSP hedging methods do not outperform for the simulated market investigated, except when compared to the Whalley and Wilmott method.

Can a modified RHCSP method significantly reduce hedging error under extreme market illiquidity conditions when applied to a simulated market, oil futures market, and currency futures market? The modified RHCSP hedging method did outperform in the CL and 6E markets, which included the extreme market illiquidity conditions of the 2008 financial crisis. The modified RHCSP did not outperform compared to the other hedging methods for the simulated market.

For the CL market I rejected the null hypothesis because there are significant differences in hedging error amongst the different methods resulting in the modified RHCSP outperforming. For the 6E market I can also reject the null hypothesis because there are significant differences in hedging error amongst the different methods resulting in the RHCSP and modified RHCSP outperforming. Lastly, for the simulated market I rejected the null hypothesis because there were significant differences in hedging error amongst the different methods resulting in the Black–Scholes and Leland methods outperforming.

I showed that hedging error amongst the hedging methods are significantly different, therefore rejecting the null hypothesis. The modified RHCSP did outperform for the CL and 6E markets, but not the simulated market. In Chapter 5, I explained the results, provided conclusions, and put forth recommendations on how to use the modified

RHCSP in oil and currency markets, as well as exploring possible future research on the modified RHCSP method.

Chapter 5: Discussions, Conclusions, and Recommendations

The purpose of this research was to address a gap in the literature concerning how to utilize and improve the performance of the receding horizontal control and stochastic programming (RHCSP) method pertaining to the oil and currency markets. This research study considered the following time periods for the oil and currency market: (a) precrisis, (b) during the global financial crisis of 2008, and (c) postcrisis. This research also contributed to the body of knowledge by improving on a dynamic hedging strategy used in illiquid markets.

The nature of this study was quantitative utilizing an experimental research design. This research study was intended to compare different hedging methods by using a hedging error metric, and to improve on the RHCSP method by utilizing the London interbank offered rate (LIBOR) and the Levy process to perform better in illiquid markets. The study followed two basic precepts: that it is important to understand the volatility of the oil and currency market because they are very important financial sectors for the global economy, and that by understanding these dynamics better predictions of inflation or deflationary conditions can be obtained, potentially leading to increased performance of hedging strategies.

Key Findings

My research findings showed that the hedging methods performed statistically different depending on the type of market used over a time period from January 1, 2005 and December 31, 2012. For the CL market, using the modified RHCSP method significantly reduced hedging errors. For the 6E market either the RHCSP or the modified RHCSP method performed statistically better compared to Black–Scholes, Leland, and Whalley and Wilmott. These results match the results found for the CL contract because of the heteroskedastic characteristics of this financial asset. The simulated market results indicated that hedging with the Black–Scholes or the Leland methods significantly outperformed each of the other hedging methods investigated in this study. The superior performance of the Black–Scholes and the Leland methods in the simulated market was due to the homoskedastic behavior of the log returns. In addition, the simulated market did not fluctuate wildly around its starting point compared to the CL contract.

Interpretation of Findings

Modified RHCSP

These findings suggest that volatility of the oil and currency markets can be tamed by using the modified RHCSP method proposed in this research study. When investing in oil and currency future markets, dynamic hedging can help reduce return volatility and reduce contingency claim risk. Contingency claim risk is when someone is obligated to purchase or sell a certain amount of assets at a certain time. Due to the unknown price of assets at the time of asset transfer, individuals need to hedge their futures contracts to cap their risk exposure. One way to cap this risk exposure is through a dynamic hedging strategy utilizing the modified RHCSP method. This research showed that modified RHCSP can cap risk exposure in the CL and 6E contract for the time period investigated.

The results showed that coupling principles of dynamic hedging and the modified RHCSP method reduces hedging error. This reduction in hedging error provides portfolio managers, investors, and risk managers with an additional means of stabilizing returns in periods of illiquidity. For example, if a portfolio manager started to see returns declining rapidly they could initiate a dynamic hedging strategy using the modified RHCSP. This dynamic hedging activation will help to reduce further return declines. Utilizing a hedging method that has minimum hedging error improves the performance of dynamic hedges.

These findings showed that heteroskedastic markets such as CL and 6E contracts are well suited for the use of more sophisticated dynamic hedging strategies utilizing the modified RHCSP. The modified RHCSP method employs the Levy process and the LIBOR to predict where the price is in a future time period; the results show that this combination helps hedge against price changes. The performance of those price predictions was due to calculating hedging error. These findings also suggest that hedging methods like RHCSP and modified RHCSP do not perform better than standard methods in very low volatility markets that have homoskedastic characteristics. In short, volatile market can be tamed using the modified RHCSP method, but do not perform as well in tranquil markets.

The following are some observations to consider regarding dynamic hedging of energy and currency futures. For the CL contract, the modified RHCSP performed significantly better than all the other hedging methods considered in this research. This indicates that when a contingency claim is based on the CL spot and risk is hedged with options on a future contract, using the LIBOR and the Levy parameters with the modified RHCSP hedging method results in significantly lower hedging error compared to the Black–Scholes, Leland, Whalley and Wilmott, and RHCSP methods.

For the 6E contract, RHCSP and modified RHCSP performed significantly better than other hedging methods investigated in this research. This indicates that when hedging a futures strike price based on the 6E contract and risk is hedged with a currency spot contract using the LIBOR and Levy parameters with the modified RHCSP method, the hedging error was significantly lower compared to the Black–Scholes, Leland, and Whalley and Wilmott. Hedging performance was not significantly different between RHCSP and modified RHCSP, representing that either RHCSP method would be adequate for dynamically hedging the 6E contract.

For the simulated contract, modified RHCSP performed the worst in terms of hedging error compared to all other hedging methods investigated in this study. This indicates that when a contingency claim is based on the simulated spot price and risk is hedged with option contracts by using either the Black–Scholes or the Leland method, the hedging error is significantly lower than that obtained through the Whalley and Wilmott, RHCSP, or the modified RHCSP methods. For homoskedastic markets it is better to utilize the standard hedging methods, such as Black–Scholes method.

These research findings and observations show that modified RHCSP utilizing the Levy process and the LIBOR can significantly reduce hedging error and reduce return volatility in heteroskedastic markets. The Levy process is important in improving the price prediction one time period out because the Levy process captures the price curve dynamics of a 5-day moving window; this allows for new endogenous information to influence the price prediction for future time periods. The LIBOR process data showed that banking stress was a strong indicator for the financial crisis of 2008. By using the LIBOR in the modified RHCSP method, I was able to get banking stress signals to improve dynamic hedging rebalancing, which was found to improve hedging error. Using a modified RHCSP method an investor can improve hedging performance in the oil and currency market.

It is my recommendation to investors to implement a modified RHCSP hedging strategy in heteroskedastic markets when utilizing the Levy process and the LIBOR in the RHCSP objective function. By using this type of hedging method portfolios can reduce the return volatility. The sophisticated investors and professional investment managers need access to better risk management tools, such as dynamic hedging, to mitigate market corrections or crashes. These investors can better risk manage their portfolios by utilizing the modified RHCSP method.

Benefits of Modified RHCSP

This research addresses a research gaps on extending the RHCSP method using endogenous and exogenous variables. This study used these variables to improve on hedging error in the context of a dynamically hedging strategy by specifically utilizing a Levy process and LIBOR. I extended the RHCSP method by using the Levy process and the LIBOR rate as signals to improve on hedging error, which had not been done before using the RHCSP method. This research also expands the body of knowledge on how the EUR/USD and oil crude future contracts perform using a RHCSP and modified RHCSP method. A strength of this study was that it focused on a specific timeframe spanning from January 1, 2005 to December 31, 2012, a period encompassing the boom-bust-recovery cycle of the financial crisis of 2008. By specifically focusing on this timeframe, I was able to establish how dynamically hedging with the modified RHCSP performs in extreme illiquid conditions. This research constitutes a major contribution to the body of literature regarding financial risk management.

The findings of this study confirm what other researchers have found about dynamic hedging. Meindl (2006) showed that the RHCSP method can reduce hedging error in certain types of simulated markets, and this research confirmed those findings for heteroskedastic markets. Kennedy (2007) showed the use of a Levy process could help with regime switching events. In the context of this research study, a Levy process indeed helped with controlling hedging error within the modified RHCSP method for the CL and 6E contracts. Fleten et al. (2010) showed that due to the high volatility of energy commodities, such as hydroelectric power, controlled dynamic hedging could be advantageous. This study also confirms the conclusion from Fleten et al. that energy commodities can be dynamically hedged to reduce price volatility.

The theoretical framework of this research was from chaos theory and emergence. The findings suggest that the financial markets are not rational and exhibit inefficiencies, especially in illiquid conditions. These illiquid conditions are the result of herd behavior of investors. It is important to be able to reduce volatility and exposure to the buildup of internal and external risk factors. Within chaos theory there are unsuspected changes in nonlinear systems, such as financial markets moving into speculative bubbles or crashes.

With the understanding that chaotic systems can behave erratically, I need means to maintain control of this nonlinear system. The RHCSP and modified RHCSP methods in this research study did show that volatility could be reduced and improved hedging performance results could be achieved. Even though hedging error is not completely eliminated using dynamic hedging, at least the chaotic system is tamed to the degree of the hedging method used. In this case, the modified RHCSP on oil and currency markets for the timeframe investigated can control disequilibrium of chaotic systems.

Limitations of the Study

Generalizability, Validity, and Reliability

For generalization of the findings in this study, I can comment on a few items. Since this study looked at three financial markets, (i.e., simulated, energy, and currency markets), and found similar results; therefore, I can conclude that the modified RHCSP method can improve on hedging error in different markets that are heteroskedastic. In addition, the modified RHCSP can also be used in different illiquidity periods as well. Since the price dynamics are similar in the CL and 6E markets, the modified RHCSP method performed similarly with reduced hedging error. Since the objective function can be easily adapted to specific needs, expanded usage of the modified RHCSP for different assets is possible and this is mentioned in the further research section. The major limitation of this study relative to generalization is that other assets and a wider time period should be investigated.

With any comprehensive research study I must consider the internal and external validity of the findings. The internal validity of this research study was relatively strong because of the use of both simulated and real market data for evaluating hedging error for each of the five categorical variables representing the different hedging methods. External validity was demonstrated by the testing of hedging performance for different time periods and within different markets. In this research study I established similar hedging performance in different markets over an 8-year timeframe. A limitation of this study regarding external validity was how the hedging error would perform in periods other than January 1, 2005 to December 31, 2012 in different asset markets, such as bonds and credit default swaps. But it might be safe to assume that similar price dynamics would result in similar hedging error performance for the five different hedging methods investigated.

How reliable are the finding in this research study? Reliability can be established by showing how often measurements can be repeated. I conducted this study with three different markets and five different hedging methods as independent variables with the dependent variable being the calculated 4-day average absolute hedging error. This study showed similar hedging error characteristics for each of the different hedging methods when applied to the heteroskedastic financial markets. In addition, the total sample size was 506 hedging error calculations, which allowed a power of 1.0 and permitting a strong probability of reducing type II error. By reducing type II error I lowered the probability of failure in rejecting that there was no significant differencing in hedging methods when testing in a simulated, currency, or oil market. I relatively controlled for generalization, validity, and reliability within this research study; and any resulting limitations of the study are addressed with additional investigations, which were suggested in the further research section of this chapter.

Recommendations

Future Research

The use of a modified RHCSP or just a simple RHCSP dynamically hedging strategy is vast. But further research needs to be conducted in many areas to improve on the external validity and to expand on the positive social change potential. In terms of improving on the external validity, the modified RHCSP needs to be investigated in the bond markets, natural gas, and additional currency pairs.

The potential research in the bond market using the modified RHCSP dynamic hedging method is with a concentration on spread trading. For example, can a modified RHCSP with an adjusted objective function decrease a bond portfolio's volatility to interest rate risk via dynamic hedging in the futures market? In this case the portfolio might be bonds that are in the front of the yield curve, (e.g., 2-year treasuries), while the other part of the portfolio has bonds from the end of the yield curve, (e.g., 30-year treasuries.) As interest rates increase in this proposed bond portfolio the 2-year treasuries will affect the different components of the bond portfolio. In this case the 2-year bonds will lower in price faster than the 30-year bonds. Therefore, when interest rate changes are a significant factor to the portfolio one might want to dynamically hedge the risk using the modified RHCSP. Development in how to hedge bond portfolios would be a very significant improvement in the use of the RHCSP strategy.

By expanding the use of the modified RHCSP method to the natural gas market it could help gas producers and industrial consumers to hedge the volatility of the spot price. This future research could be setup similar to the oil futures study conducted in this research, but natural gas has a tendency to exhibit more volatility. Part of the reason for increased volatility in natural gas prices is due to the difficulty of storage compared to crude oil. In addition to natural gas future research, one could improve the external validity of the findings in this research study by exploring other important currency pairs, (e.g., GBP/USD, USD/YEN, and GBP/YEN.)

Other research could be focused on expanding the time frame of the study to cover multiple boom-to-bust cycles, (i.e., 30 years.) Another valuable area of research is exploring ways to expand the objective function used in the RHCSP to allow for pattern recognition. This pattern recognition could possibly augment or supersede the modified RHCSP proposed in this research study. Other potential investigations could include a large portfolio of assets to see if there are any unique aspects to dynamically hedging such portfolios with a modified RHCSP strategy.

It is technically possible for central banks to use the modified RHCSP for implementing their quantitative easing regimes. Even though a central bank does not need to hedge their balance sheet they do need to intervene in the financial markets to set monetary policy. This is usually in the bond markets, whereby the central bank buys bonds to inject money into the financial system or sell bonds to soak up money out of the financial system. One possible way to improve effectiveness of quantitative easing is to use the RHCSP method with a specialized objective function, whereby a central bank's intervention into the markets is automatic. Lastly, improved visualization techniques to understand the RHCSP dynamics could be helpful to risk managers and dynamic hedgers. These improved visualization tools might be neural network diagrams showing when to rebalance a portfolio or how systemic risk is building up in the financial system, whereby an automatic dynamic hedging trigger is initiated.

Implications

Positive Social Change

This research provides the potential for several positive social changes. Firstly, it has been shown that dynamic hedging using the modified RHCSP method in the oil and currency market can reduce hedging error. This means that individual portfolios can reduce volatility and have more stable returns over time, especially through illiquid periods. The average investor might not be able to directly utilize the findings in this research study, but professional portfolio managers, risk managers at investment firms, and software developers do have the means to utilize these research findings.

In terms of portfolio managers, they can implement in their investment strategy dynamic hedging to reduce certain types of risk using the modified RHCSP method, either with using the LIBOR and Levy process or an updated objective function to determine when to rebalance the hedging strategy. For risk managers at an investment firm, they could utilize the research findings to help reduce risk with their trading floor. As certain trading positions start to build up in the currency or energy parts of their portfolio they could employ the modified RHCSP method to reduce any unwanted risk. Another way that risk managers could use the modified RHCSP findings in this research is to build an endogenous and exogenous risk signal from the LIBOR and Levy process. This risk signal not only could be used for rebalancing the dynamic hedging position, but could be used to curtail other trading and counterparty risk activities to reduce overall market risk exposure for the firm.

Another major positive social change that the modified RHCSP method can be used for is in software development which specializes in financial trading. Retail trading platforms can utilize the modified RHCSP method, so individual investors can trade with an automatic dynamic hedging strategy. The individual retail investor might not fully understand the mechanics of the modified RHCSP method, but can still benefit from the lower volatility in asset returns in their portfolio. Coupled with additional research in expanding the potential of RHCSP in portfolio management, these software developers can reduce the need for professional investment managers and allow for retail investors and corporations to use automatic stabilizers to reduce return volatility.

Why does reduced return volatility provide positive social change at the individual or societal level by using the modified RHCSP method? If the majority of investors do not reduce volatility in their portfolios during a crisis period of a market correction then the time to recover the losses will be extended. In the theory of behavioral finance, there is a herd effect—investors are exiting out of their position in tandem, which leads to further asset price decline. Depending on the counterparty risk, the fragility of the economy, and the severity of the herd effect these factors will determine the level of the price decline and intensity of the contagion. By using the modified RHCSP method I can reduce risk and increase the recovery time because less intensive shocks to the portfolio would be realized. This would help the individual investor because the total assets would be relatively stable and would help the overall economy, because less draconian measures would be taken by corporations, (e.g., excessive personnel reductions, and lower capital investment). By reducing the contagion of a financial crisis less damage to the overall economy results, allowing for relatively more stable employment and GDP.

Lastly, a central bank can make use of the modified RHCSP method proposed in this research study or a derivative of it to improve on the efficacy of certain monetary policy. Instead of using a series of macroeconomic indicators and surveys of different industries to understand the health of the overall economy, the modified RHCSP method could be used to automatically stabilize the monetary base when using a certain target, such as inflation targeting of two percent. Again the use of the Levy process for endogenous risks and the use of the LIBOR for exogenous risk could be signals, which are coupled with other macroeconomic indicators to adjust central bank intervention into the financial market, (i.e., the bond markets.) In theory, the use of the modified RHCSP method for monetary policy could reduce inflationary swings, which erodes the value of savings and creates financial instability. As can be seen, the modified RHCSP method has broad implication for positive social change.

Conclusion

The Message

Since the financial crisis of 2008 was so devastating to the global economy there must be ways to better risk manage financial assets. A simple buy and hold strategy does not seem to work for many investors, since market corrections are very turbulent. With the power of algorithms and the computational power of computers, tracking systems can add some stability to an investor's portfolio. The research in this study showed that the use of the modified RHCSP method for oil and currency markets can help reduce return volatility through reduced hedging error of a dynamic hedging process.

The research in this study helped fill some gaps in the literature. For example, this study was the first to demonstrate the use of the Levy process and the LIBOR rate as endogenous and exogenous risk signals respectively and implemented in a RHCSP method. Secondly, this study also demonstrated that high volatile markets, such as currency and energy markets, can be stabilized using RHCSP methods.

Since the RHCSP method is relatively easy to adapt through the design of the objective function, it is quite versatile. This versatility allows for many applications in the field of finance, especially in targeting certain financial goals—as demonstrated with reduced hedging error. Not only can the RHCSP be hard coded to accomplish certain financial objectives—but as shown with the modified RHCSP—artificial intelligence can be allowed to search for signals and adjust the dynamic hedging timing periods to adapt to illiquid market conditions. Investors now have tools to reduce portfolio return volatility via the use of the modified RHCSP method.

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Appendix A: Code for Modeling an Oil Market

OilBSMdelta_calculate.m

```
for x = 1:5:2022


y=black_scholes_delta_hedging(CL(x,1),OptionStrike(x,1),riskfree(x,1),C
LVolLog(x,1),Expiration(x,1))

delta(x,1)= y.call;
delta(x,2)= Date(x);
end
```

black_scholes_delta_heding.m

```
function BS_delta_time =
black_scholes_delta_hedging(u,k,r,v,expiration)

%function BS_delta_time =
black_scholes_delta_hedging(u,k,r,v,expiration)
% This function is the Black Scholes Delta Hedging model from
% Meindl, P.(2006). Portfolio Optimization and Dynamic Hedging with
% Receding Horizontal COntrol, Stochastic Programming and Monte Carlo
% Simulation. This function calculates the delta(t) - the number of
shares
% of the underlying.

% u= Current underlying price S(t)
% k= Strike price of the option price
% r= Risk free rate
% v= volatility (standard deviation of returns)
% T= Time of expiration of the option
% t= current time

% A normal cumulative distribution is assumed (Mu=0, Sigma=1)for
pricing
% option.

    %d1=(log(u./k)+((r+(v^2)/2)*(T-t))./(v*sqrt(T-t)));

    d1=(log(u./k)+((r+(v^2)/2)*(expiration))./(v*sqrt(expiration)));
    BS_delta_time.call= normcdf(d1,0,1);
    %BS_delta_time.put=BS_delta_time.call-1;

 end
```

leland_delta_hedging.m

```
function leland_delta_time =leland_delta_hedging (u,k,r,v,expiration,g)


%function leland_delta_time =leland_delta_hedging (u,k,r,v,T,t,g,i)
% This function is the Leland Delta Hedging model from
% Meindl, P.(2006). Portfolio Optimization and Dynamic Hedging with
% Receding Horizontal Control, Stochatic Programming and Monte Carlo
% Simulation. This function calculates the delta(t)by using the Black
% Scholes Delta Hedging model with a new calculation of volatility that
% incorporates a transacation cost.

% u= Current underlying price S(t)
% k= Stike price of the option price
% r= Risk free rate
% v= volatility (standard deviation of returns)
% T= Time of expiration of the option
% t= current time
% g= transaction cost proportion
% i= interval of time step

% A normal cumulative distribution is assumed (Mu=0, Sigma=1)for
pricing
% option.

% v_hat = the Leland volatility, which incorporates transaction costs.
% used .083333 for eurfutures
%Used .25 for Oil Futures and simulated


    %v_hat= v*((1+ ((g/v)*(sqrt((g/(pi*i*t))))))^.5);
    v_hat= v*((1+ ((g/v)*(sqrt((g/(pi*.25))))))^.5);
    leland_delta_time=black_scholes_delta_hedging
(u,k,r,v_hat,expiration);


end
```

OilFutLelanddelta_calculate.m

```
for x = 1:5:2022


y=leland_delta_hedging
(Cl(x,1),OptionStrike(x,1),riskfree(x,1),CLVolLog(x,1),Expiration(x,1),
.01)
```

```
delta(x,1)= y.call;
delta(x,2)= Date(x);
end
```

OilWilmottdelta_calculate.m

```
for x = 1:2022
    g=.01;
    u=CL(x,1);
    expiration=Expiration(x,1);
    k=OptionStrike(x,1);
    v=CLVolLog(x,1);
    r=riskfree(x,1);
    drift = CLDrift(x,1);

    d1=(log(u./k)+((r+(v^2)/2)*(expiration))./(v*sqrt(expiration)));
    gamma = normpdf(d1,0,1)./(u*v*sqrt(expiration));

    ww_delta_time.plus = nthroot(((3*g*u*exp(-r*(expiration))*(gamma-
((exp(-r*(expiration))*(drift-r))/(1*u^2*v^2)))^2)/(2*1)),3);
    ww_delta_time.negative = -1*ww_delta_time.plus;

    upper(x,1) = ww_delta_time.plus;
    lower(x,1) = ww_delta_time.negative;

end
```

OilFutRHCSPdelta_calculate.m

```
for x = 1:2022

y = Balance(x,1);

if y==1

    [RHCSP_sim, hedge,underlying] =
RHCSP_hedging(CL(x,1),OptionStrike(x,1),riskfree(x,1),CLVolLog(x,1),CLD
rift(x,1),Expiration(x,1));

    delta(x,1)=hedge.call;
    delta(x,2)=Date(x);

    spothedge(x,1)=underlying;
```

```
    difference=abs(underlying-OptionStrike(x,1));


       if difference<.25

           delta(x,1)=hedge.call;

       else
           delta(x,1)=0;


       end

end

if y==2

    [RHCSP_sim, hedge,underlying] =
RHCSP_hedging(CL(x,1),OptionStrike(x,1),riskfree(x,1),CLVolLog(x,1),CLD
rift(x,1),Expiration(x,1));

    delta(x,1)=hedge.call;
    delta(x,2)=Date(x);

    spothedge(x,1)=underlying;
    difference=abs(underlying-OptionStrike(x,1))


end

end
```

RHCSP_hedging.m

```
function [RHCSP_simulation, RHCSP_hedge,underlying_asset] =
RHCSP_hedging(initial_price,k,r,v,drift,expiration)
% This function is the RHC&SP Hedging model from
% Meindl, P.(2006). Portfolio Optimization and Dynamic Hedging with
% Receding Horizontal Control, Stochastic Programming and Monte Carlo
% Simulation. This function calculates the amount to hedge at each
horizon
% period.

% RHCSP_hedge = call or put delta hedge.
% deltaT = the difference between time periods
% RHCSP_simulation = the price curve
% deltaW = the difference in the Weiner process
```

```
% k = strike price of option


% Create 200 Monte Carlo Simulations
    mu=drift;
    sigma=v;
    deltaT=1;
    RHCSP_simulation = zeros(200,2022);
    deltaW= sqrt(deltaT)*randn(200,2022);




    for x = 1:200
      time=1;
      price = zeros(2022,1);
      delta_price=zeros(2022,1);
      price(1)=initial_price;  % initial price is 30
      RHCSP_simulation(x,1)=price(1);
        for time= 2:2022

            delta_price(time)= mu*price(time-1)+sigma*deltaW(x,time);
            price(time)=delta_price(time)+price(time-1);
            RHCSP_simulation(x,time)=price(time);
        end
    end


%Determining the bin heights and price points
%maxCone(1)-bin(1,1) is the first bin
%bin(1,1)-bin(1,2)is second bin
%bin(1,2)-minCone(1) is the third bin

    maxCone(1) = max(RHCSP_simulation(:,2));
    maxCone(2) = max(RHCSP_simulation(:,3));
    minCone(1) = min(RHCSP_simulation(:,2));
    minCone(2) = min(RHCSP_simulation(:,3));

    distance_cone(1) = maxCone(1)-minCone(1);
    distance_cone(2) = maxCone(2)-minCone(2);

    division(1) = distance_cone(1)/3;
    division(2) = distance_cone(2)/5;

    bin(1,1) = maxCone(1)-division(1);
    bin(1,2) = bin(1,1)-division(1);
    bin(2,1) = maxCone(2)-division(2);
    bin(2,2) = bin(2,1)-division(2);
    bin(2,3) = bin(2,2)-division(2);
    bin(2,4) = bin(2,3)-division(2);
```

```
% Determining the probability of crossing into a bin.

    %determine the count number for each path into a certain bin.
    count_bin1 =0;
    count_bin2 =0;
    count_bin3 =0;
    count_bin4 =0;
    count_bin5 =0;
    count_bin6 =0;
    count_bin7 =0;
    count_bin8 =0;

    for x = 1:200;


        if RHCSP_simulation(x,2) > bin(1,1)
           count_bin1 = count_bin1 + 1;
        elseif bin(1,2) <= RHCSP_simulation(x,2) &&
RHCSP_simulation(x,2)<= bin(1,1)
                count_bin2 = count_bin2 + 1;
            else
                count_bin3 = count_bin3 + 1;

        end

        if RHCSP_simulation(x,3) > bin(2,1)
            count_bin4 = count_bin4 + 1;
        elseif bin(2,2) < RHCSP_simulation(x,3) &&
RHCSP_simulation(x,3) <= bin(2,1)
                count_bin5 = count_bin5 + 1;
        elseif bin(2,3) < RHCSP_simulation(x,3) &&
RHCSP_simulation(x,3) <= bin(2,2)
                    count_bin6 = count_bin6 + 1;
        elseif bin(2,4) < RHCSP_simulation(x,3) &&
RHCSP_simulation(x,3) <= bin(2,3)
                        count_bin7 = count_bin7 + 1;
             else
                 count_bin8 = count_bin8+1;



        end


    end

    % calculating probability
```

```
    probability(1)= count_bin1/200;
    probability(2)= count_bin2/200;
    probability(3)= 1-probability(1)-probability(2);
    probability(4)= count_bin4/200;
    probability(5)= count_bin5/200;
    probability(6)= count_bin6/200;
    probability(7)= count_bin7/200;
    probability(8)= 1-probability(4)- probability(5)-probability(6)-
probability(7);

% pick highest probability
    highest_probability_time1=0;
    highest_probability_time2=0;

    %pick highest probability for time 1 (bin 1-3)

    if (probability(1) >= probability(2))&& (probability(1) >=
probability(3))
        highest_probability_time1 = 1;
    elseif (probability(2)>= probability(1)) && (probability(2)>=
probability(3))
        highest_probability_time1 = 2;
    elseif (probability(3) >= probability(1)) && (probability(3) >=
probability(2))
        highest_probability_time1 = 3;
    end

    %pick highest probability for time 2 (bin 4-8)

       if (probability(4) >= probability(5))&& (probability(4) >=
probability(6))&& (probability(4) >= probability(7)) && (probability(4)
>= probability(8))
        highest_probability_time2 = 4;
       elseif (probability(5) >= probability(4))&& (probability(5) >=
probability(6))&& (probability(5) >= probability(7)) && (probability(5)
>= probability(8))
        highest_probability_time2 = 5;
       elseif (probability(6) >= probability(4))&& (probability(6) >=
probability(5))&& (probability(6) >= probability(7)) && (probability(6)
>= probability(8))
        highest_probability_time2 = 6;
       elseif (probability(7) >= probability(4))&& (probability(7) >=
probability(5))&& (probability(7) >= probability(6)) && (probability(7)
>= probability(8))
        highest_probability_time2 = 7;
       elseif (probability(8) >= probability(4))&& (probability(8) >=
probability(5))&& (probability(8) >= probability(6)) && (probability(8)
>= probability(7))
        highest_probability_time2 = 8;
       end

% calculating the hedge (assumes longing reference leg)
```

```
    % u= Current underlying price S(t)
    % k= Strike price of the option price
    % r= Risk free rate
    % v= volatility (standard deviation of returns)
    % T= Time of expiration of the option
    % t= current time
    long_leg=1; % 1 equals long, 0 equals short reference leg

 if long_leg==1
     [underlying_asset] = long(highest_probability_time2, bin,
maxCone);
 elseif long_leg==0
     [underlying_asset] = short(highest_probability_time2, bin,
minCone);
 end

        RHCSP_hedge =
black_scholes_delta_hedging(underlying_asset,k,r,v,expiration);


% Plot Monte Carlo Simulation

   %% for z = 1:200

     %%   plot(RHCSP_simulation(z,:));
       %% hold on;
    %%end


% nested functions

 function [underlying]= long(highest_probability_time2, bin, maxCone)
  % hedging from top of bin

   underlying=0;
    if (highest_probability_time2==4)
       underlying=maxCone(2);
    elseif highest_probability_time2==5
        underlying=bin(2,1);
    elseif highest_probability_time2==6
        underlying=bin(2,2);
    elseif highest_probability_time2==7
        underlying=bin(2,3);
    elseif highest_probability_time2==8
        underlying=bin(2,4);
    end

 end
```

```
function [underlying] = short(highest_probability_time2, bin, minCone)
    % hedging from bottom of bin
         underlying=0;
         if(highest_probability_time2==4)
                underlying=bin(2,1);
         elseif highest_probability_time2==5
                underlying=bin(2,2);
         elseif highest_probability_time2==6
                underlying=bin(2,3);
         elseif highest_probability_time2==7
                underlying=bin(2,4);
         elseif highest_probability_time2==8
                underlying=minCone(2);
         end


 end

end
```

ModifiedOilFutRHCSPdelta_calculate.m

```
jumpfilter=CLJumpIntensity;
  jumpcount=0;



for j = 1:2022

y = Balance(j,1);
%jump activation
      if j<31
            jump(j,1)=0;
      end

      if j<1992
        if jumpfilter(j,1)~=0
          jumpcount=sum(CLJumpFrequency(j:j+30)~=0);
        end
      end

        if j>1992

            jumpcount=sum(CLJumpFrequency(1993:2022)~=0);
        end

        jumpaverage=jumpcount/30;
```

```
        if j>30

            if .44*randn(1,1)> jumpaverage
                if CLDrift(j,1)<0
                   if j<=1992

                   jump(j,1)=rand()*min(CLJumpIntensity(j:j+30,1));
                   end
                   if j>1992
                   jump(j,1)=rand()*min(CLJumpIntensity(1993:2022,1));
                   end

                else
                    if j<=1992

jump(j,1)=rand()*max(CLJumpIntensity(j:j+30,1));
                    else

jump(j,1)=rand()*max(CLJumpIntensity(1993:2022,1));
                    end
                end




            else jump(j,1)=0;
            end
        end

% libor activation
          if (LIBORLogRet(j,1)<-.000025 || LIBORLogRet(j,1)>.000025)
             y=2;
             libortest(j,1)=y;
          end




if y==2||y==1

    [RHCSP_sim, hedge,underlying] =
Modified_RHCSP_hedging(CL(j,1),OptionStrike(j,1),riskfree(j,1),CLVolLog
(j,1),CLDrift(j,1),Expiration(j,1),jump(j,1));

    delta(j,1)=hedge.call;
    delta(j,2)=Date(j);

    spothedge(j,1)=underlying;
    difference=abs(underlying-OptionStrike(j,1));

if y==1
```

```
    if difference<.25

           delta(j,1)=hedge.call;

       else
           delta(j,1)=0;


       end
end

if y==2
    delta(j,1)=1;

end


end


end
```

Modified_RHCSP_hedging.m

```
function [RHCSP_simulation, RHCSP_hedge,underlying_asset] =
Modified_RHCSP_hedging(initial_price,k,r,v,drift,expiration,jump)
% This function is the RHC&SP Hedging model from
% Meindl, P.(2006). Portfolio Optimization and Dynamic Hedging with
% Receding Horizontal Control, Stochastic Programming and Monte Carlo
% Simulation. This function calculates the amount to hedge at each
horizon
% period.

% RHCSP_hedge = call or put delta hedge.
% deltaT = the difference between time periods
% RHCSP_simulation = the price curve
% deltaW = the difference in the Weiner process
% k = strike price of option


% Create 200 Monte Carlo Simulations
    mu=drift;
    sigma=v;
    deltaT=1;
    RHCSP_simulation = zeros(200,2022);
    deltaW= sqrt(deltaT)*randn(200,2022);
```

```
    for x = 1:200
      time=1;
      price = zeros(2022,1);
      delta_price=zeros(2022,1);
      price(1)=initial_price;  % initial price is 30
      RHCSP_simulation(x,1)=price(1);
        for time= 2:2022

            delta_price(time)= mu*price(time-
1)+sigma*deltaW(x,time)+jump;
            price(time)=delta_price(time)+price(time-1);
            RHCSP_simulation(x,time)=price(time);



        end
    end


%Determining the bin heights and price points
%maxCone(1)-bin(1,1) is the first bin
%bin(1,1)-bin(1,2)is second bin
%bin(1,2)-minCone(1) is the third bin

    maxCone(1) = max(RHCSP_simulation(:,2));
    maxCone(2) = max(RHCSP_simulation(:,3));
    minCone(1) = min(RHCSP_simulation(:,2));
    minCone(2) = min(RHCSP_simulation(:,3));

    distance_cone(1) = maxCone(1)-minCone(1);
    distance_cone(2) = maxCone(2)-minCone(2);

    division(1) = distance_cone(1)/3;
    division(2) = distance_cone(2)/5;

    bin(1,1) = maxCone(1)-division(1);
    bin(1,2) = bin(1,1)-division(1);
    bin(2,1) = maxCone(2)-division(2);
    bin(2,2) = bin(2,1)-division(2);
    bin(2,3) = bin(2,2)-division(2);
    bin(2,4) = bin(2,3)-division(2);


% Determining the probability of crossing into a bin.

    %determine the count number for each path into a certain bin.
    count_bin1 =0;
```

```
    count_bin2 =0;
    count_bin3 =0;
    count_bin4 =0;
    count_bin5 =0;
    count_bin6 =0;
    count_bin7 =0;
    count_bin8 =0;

    for x = 1:200;


        if RHCSP_simulation(x,2) > bin(1,1)
           count_bin1 = count_bin1 + 1;
        elseif bin(1,2) <= RHCSP_simulation(x,2) &&
RHCSP_simulation(x,2)<= bin(1,1)
                count_bin2 = count_bin2 + 1;
            else
                count_bin3 = count_bin3 + 1;

        end

        if RHCSP_simulation(x,3) > bin(2,1)
            count_bin4 = count_bin4 + 1;
        elseif bin(2,2) < RHCSP_simulation(x,3) &&
RHCSP_simulation(x,3) <= bin(2,1)
                count_bin5 = count_bin5 + 1;
        elseif bin(2,3) < RHCSP_simulation(x,3) &&
RHCSP_simulation(x,3) <= bin(2,2)
                    count_bin6 = count_bin6 + 1;
        elseif bin(2,4) < RHCSP_simulation(x,3) &&
RHCSP_simulation(x,3) <= bin(2,3)
                        count_bin7 = count_bin7 + 1;
             else
                 count_bin8 = count_bin8+1;



        end


    end

    % calculating probability

    probability(1)= count_bin1/200;
    probability(2)= count_bin2/200;
    probability(3)= 1-probability(1)-probability(2);
    probability(4)= count_bin4/200;
    probability(5)= count_bin5/200;
    probability(6)= count_bin6/200;
    probability(7)= count_bin7/200;
```

```
    probability(8)= 1-probability(4)- probability(5)-probability(6)-
probability(7);

% pick highest probability
    highest_probability_time1=0;
    highest_probability_time2=0;

    %pick highest probability for time 1 (bin 1-3)

    if (probability(1) >= probability(2))&& (probability(1) >=
probability(3))
        highest_probability_time1 = 1;
    elseif (probability(2)>= probability(1)) && (probability(2)>=
probability(3))
        highest_probability_time1 = 2;
    elseif (probability(3) >= probability(1)) && (probability(3) >=
probability(2))
        highest_probability_time1 = 3;
    end

    %pick highest probaility for time 2 (bin 4-8)

       if (probability(4) >= probability(5))&& (probability(4) >=
probability(6))&& (probability(4) >= probability(7)) && (probability(4)
>= probability(8))
        highest_probability_time2 = 4;
       elseif (probability(5) >= probability(4))&& (probability(5) >=
probability(6))&& (probability(5) >= probability(7)) && (probability(5)
>= probability(8))
        highest_probability_time2 = 5;
       elseif (probability(6) >= probability(4))&& (probability(6) >=
probability(5))&& (probability(6) >= probability(7)) && (probability(6)
>= probability(8))
        highest_probability_time2 = 6;
       elseif (probability(7) >= probability(4))&& (probability(7) >=
probability(5))&& (probability(7) >= probability(6)) && (probability(7)
>= probability(8))
        highest_probability_time2 = 7;
       elseif (probability(8) >= probability(4))&& (probability(8) >=
probability(5))&& (probability(8) >= probability(6)) && (probability(8)
>= probability(7))
        highest_probability_time2 = 8;
       end

% calculating the hedge (assumes longing reference leg)
    % u= Current underlying price S(t)
    % k= Strike price of the option price
    % r= Risk free rate
    % v= volatility (standard deviation of returns)
    % T= Time of expiration of the option
    % t= current time
    long_leg=1; % 1 equals long, 0 equals short reference leg
```

```
 if long_leg==1
     [underlying_asset] = long(highest_probability_time2, bin,
maxCone);
 elseif long_leg==0
     [underlying_asset] = short(highest_probability_time2, bin,
minCone);
 end

        RHCSP_hedge =
black_scholes_delta_hedging(underlying_asset,k,r,v,expiration);


% Plot Monte Carlo Simulation

  % for z = 1:200

    %    plot(RHCSP_simulation(z,:));
      %  hold on;
   % end



% nested functions

 function [underlying]= long(highest_probability_time2, bin, maxCone)
  % hedging from top of bin

   underlying=0;
    if (highest_probability_time2==4)
       underlying=maxCone(2);
    elseif highest_probability_time2==5
        underlying=bin(2,1);
    elseif highest_probability_time2==6
        underlying=bin(2,2);
    elseif highest_probability_time2==7
        underlying=bin(2,3);
    elseif highest_probability_time2==8
        underlying=bin(2,4);
    end

 end


function [underlying] = short(highest_probability_time2, bin, minCone)
    % hedging from bottom of bin
         underlying=0;
         if(highest_probability_time2==4)
                underlying=bin(2,1);
         elseif highest_probability_time2==5
                underlying=bin(2,2);
```

```
        elseif highest_probability_time2==6
               underlying=bin(2,3);
        elseif highest_probability_time2==7
               underlying=bin(2,4);
        elseif highest_probability_time2==8
               underlying=minCone(2);
        end


 end


end
```

Appendix B: Code for Modeling a Currency Market

EUFutBSMdelta_calculate.m

```
for x = 1:5:2022


y=black_scholes_delta_hedging(EuroSpot(x,1),EUFutStrike(x,1),riskfree(x
,1),EuroSpotVolLog(x,1),Expiration(x,1))

delta(x,1)= y.call;
delta(x,2)= Date(x);
end
```

EUFutLelanddelta_calculate.m

```
for x = 1:5:2022



y=leland_delta_hedging
(EuroSpot(x,1),EuFutStrike(x,1),riskfree(x,1),EuroSpotVolLog(x,1),Expir
ation(x,1),.01)


delta(x,1)= y.call;
delta(x,2)= Date(x);
end
```

EUFutWilmott_calculate.m

```
for x = 1:2022
    g=.01;
    u=EuroSpot(x,1);
    expiration=Expiration(x,1);
    k=EUFutStrike(x,1);
    v=EuroSpotVolLog(x,1);
    r=riskfree(x,1);
    drift = EuroSpotDrift(x,1);

    d1=(log(u./k)+((r+(v^2)/2)*(expiration))./(v*sqrt(expiration)));
    gamma = normpdf(d1,0,1)./(u*v*sqrt(expiration));
```

```
    ww_delta_time.plus = nthroot(((3*g*u*exp(-r*(expiration))*(gamma-
((exp(-r*(expiration))*(drift-r))/(1*u^2*v^2)))^2)/(2*1)),3);
    ww_delta_time.negative = -1*ww_delta_time.plus;

    upper(x,1) = ww_delta_time.plus;
    lower(x,1) = ww_delta_time.negative;


end
```

EUFutRHCSPdelta_calculate.m

```
for x = 1:2022

y = Balance(x,1);

if y==1

    [RHCSP_sim, hedge,underlying] =
RHCSP_hedging(EuFutStrike(x,1),EuFutStrike(x,1),riskfree(x,1),EuroSpotV
olLog(x,1),EuroSpotDrift(x,1),Expiration(x,1));

    delta(x,1)=hedge.call;
    delta(x,2)=Date(x);

    spothedge(x,1)=underlying;
    difference=abs(underlying-EuroSpot(x,1));


       if difference<.0020

           delta(x,1)=hedge.call;

       else
           delta(x,1)=0;


       end

end

if y==2
```

```
    [RHCSP_sim, hedge,underlying] =
RHCSP_hedging(EuFutStrike(x,1),EuFutStrike(x,1),riskfree(x,1),EUFutVolL
og(x,1),EuroSpotDrift(x,1),Expiration(x,1));

    delta(x,1)=hedge.call;
    delta(x,2)=Date(x);

    spothedge(x,1)=underlying;
    difference=abs(underlying-EuroSpot(x,1));




end

end
```

Modified_EUFutRHCSPdelta_calculate.m

```
jumpfilter=EUSpotJumpIntensity;
  jumpcount=0;



for x = 1:2022

y = Balance(x,1);
%jump activation
      if x<30
            jump(x,1)=0;
      end

      if x<1992
        if jumpfilter(x,1)~=0
          jumpcount=sum(EUSpotJumpFrequency(x:x+30)~=0);
        end
      end

        if x>1992

            jumpcount=sum(EUSpotJumpFrequency(1993:2022)~=0);
        end

        jumpaverage=jumpcount/30;
```

```
        if x>30
            if .44*randn(1,1)> jumpaverage
                if EuroSpotDrift(x,1)<0
                   if x<=1992

                   jump(x,1)=rand()*min(EUSpotJumpIntensity(x:x+30,1));
                   end
                   if x>1992

jump(x,1)=rand()*min(EUSpotJumpIntensity(1993:2022,1));
                   end

                else
                    if x<=1992

jump(x,1)=rand()*max(EUSpotJumpIntensity(x:x+30,1));
                    else

jump(x,1)=rand()*max(EUSpotJumpIntensity(1993:2022,1));
                    end
                end




            else jump(x,1)=0;
            end
        end

% libor activation
          if (LIBORLogRet(x,1)<-.00135 || LIBORLogRet(x,1)>.00135)
             y=2;
          end

if y==2

    [RHCSP_sim, hedge,underlying] =
Modified_RHCSP_hedging(EuFutStrike(x,1),EuFutStrike(x,1),riskfree(x,1),
EuroSpotVolLog(x,1),EuroSpotDrift(x,1),Expiration(x,1),jump(x,1));

    delta(x,1)=hedge.call;
    delta(x,2)=Date(x);

    spothedge(x,1)=underlying;
    difference=abs(underlying-EuroSpot(x,1));

 end
 end
```

Appendix C: Code for Modeling a Simulated Market

SimBSMdelta_calculate.m

```
for x = 1:5:2022


y=black_scholes_delta_hedging(Simulation(x,1),OptionStrike(x,1),riskfre
e(x,1),SimulationVolLog(x,1),Expiration(x,1))

delta(x,1)= y.call;
delta(x,2)= Date(x);
end
```

SimLelanddelta_calculate.m

```
for x = 1:5:2022




y=leland_delta_hedging
(Simulation(x,1),OptionStrike(x,1),riskfree(x,1),SimulationVolLog(x,1),
Expiration(x,1),.01)


delta(x,1)= y.call;
delta(x,2)= Date(x);
end
```

SimWilmottdelta_calculate.m

```
for x = 1:2022
    g=.01;
    u=Simulation(x,1);
    expiration=Expiration(x,1);
    k=OptionStrike(x,1);
    v=SimulationVolLog(x,1);
    r=riskfree(x,1);
    drift = SimulationDrift(x,1);

    d1=(log(u./k)+((r+(v^2)/2)*(expiration))./(v*sqrt(expiration)));
    gamma = normpdf(d1,0,1)./(u*v*sqrt(expiration));
```

```
    ww_delta_time.plus = nthroot(((3*g*u*exp(-r*(expiration))*(gamma-
((exp(-r*(expiration))*(drift-r))/(1*u^2*v^2)))^2)/(2*1)),3);
    ww_delta_time.negative = -1*ww_delta_time.plus;

    upper(x,1) = ww_delta_time.plus;
    lower(x,1) = ww_delta_time.negative;

End
```

SimRHCSPdelta_calculate.m

```
for x = 1:2022

y = Balance(x,1);

if y==1

    [RHCSP_sim, hedge,underlying] =
RHCSP_hedging(Simulation(x,1),OptionStrike(x,1),riskfree(x,1),Simulatio
nVolLog(x,1),SimulationDrift(x,1),Expiration(x,1));

    delta(x,1)=hedge.call;
    delta(x,2)=Date(x);

    spothedge(x,1)=underlying;
    difference=abs(underlying-OptionStrike(x,1));


       if difference<.04


           delta(x,1)=hedge.call;

       else
           delta(x,1)=0;


       end

end

if y==2

    [RHCSP_sim, hedge,underlying] =
RHCSP_hedging(Simulation(x,1),OptionStrike(x,1),riskfree(x,1),Simulatio
nVolLog(x,1),SimulationDrift(x,1),Expiration(x,1));
```

```
    delta(x,1)=hedge.call;
    delta(x,2)=Date(x);

    spothedge(x,1)=underlying;
    difference=abs(underlying-OptionStrike(x,1));


end

end
```

Modified_SimRHCSPdelta_calculate.m

```
jumpfilter=SimJumpIntensity;
 jumpcount=0;


for j = 1:2022

y = Balance(j,1);
%jump activation
      if j<31
            jump(j,1)=0;
      end

      if j<1992
        if jumpfilter(j,1)~=0
          jumpcount=sum(SimJumpFrequency(j:j+30)~=0);
        end
      end

        if j>1992

            jumpcount=sum(SimJumpFrequency(1993:2022)~=0);
        end

        jumpaverage=jumpcount/30;


        if j>30

            if .44*randn(1,1)> jumpaverage
                if SimulationDrift(j,1)<0
                   if j<=1992

                   jump(j,1)=rand()*min(SimJumpIntensity(j:j+30,1));
```

```
                    end
                    if j>1992
                    jump(j,1)=rand()*min(SimJumpIntensity(1993:2022,1));
                    end

                 else
                     if j<=1992

jump(j,1)=rand()*max(SimJumpIntensity(j:j+30,1));
                     else

jump(j,1)=rand()*max(SimJumpIntensity(1993:2022,1));
                     end
                 end



               else jump(j,1)=0;
               end
           end

% libor activation
          if (LIBORLogRet(j,1)<-.000000001 ||
LIBORLogRet(j,1)>.000000001)
             y=2;
             libortest(j,1)=y;
          end



if y==2||y==1

    [RHCSP_sim, hedge,underlying] =
Modified_RHCSP_hedging(Simulation(j,1),OptionStrike(j,1),riskfree(j,1),
SimulationVolLog(j,1),SimulationDrift(j,1),Expiration(j,1),jump(j,1));

    delta(j,1)=hedge.call;
    delta(j,2)=Date(j);

    spothedge(j,1)=underlying;
    difference=abs(underlying-OptionStrike(j,1));

if y==1
    if difference<.04

           delta(j,1)=hedge.call;

       else
           delta(j,1)=0;
```

```
       end
end

if y==2
    delta(j,1)=1;

end


end


end
```

Curriculum Vitae

Paul Cottrell

EDUCATION

M.B.A. 2008 Wayne State University (Finance)

B.Sc. 2007 Wayne State University (Management)

WORK EXPERIENCE

Associate Director of Business Planning**.** Catholic Charities of the Archdiocese of New York, Feb. 2010-present.

Founder. The Studio – Reykjavik, Mar. 2009-present

Sr. Financial Analyst. Tiffany & Co., Aug. 2008-Dec. 2008

Sr. Product Engineer. Visteon Corporation, Inc., May 2006-Apr. 2008

Co-Founder, Accountant & Financial Analyst. Lang Studios, Inc. Apr. 2004-Jul. 2008

Nissan Senior Product Engineer. Vehma International of America, Apr. 2002-Apr. 2006

Engineering Manager. Hella-Behr Vehicle Systems, Inc., Apr. 1999-Feb.2002

Contract Product Designer / SDRC. Tool and Engineering, Inc., May 1998-Apr. 1999

Co-Founder and Managing Director . Cam & Cut, LLC., Apr. 1994-May1998

CNC Programmer and Tool Designer . Crucam, Inc. Jul. 1992-Apr. 1994

Design Engineer. Molded Materials, Inc., Apr. 1991-Jul.1992

PUBLICATIONS

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