Selected Research Methods

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Annotation Bibliography

Ankirchner. S. & Heyne, G. (2012). Cross hedging with stochastic correlation. *Finance Stoch*. *16*, 17-43.

Research Methodology and Findings

This is a quantitative methodology, whereby a mathematic framework was developed. The research involves risk management. The research question was: How to use cross hedging with stochastic correlation? The model utilized was assuming that correlation is not static. Since the methodology utilized an analytical framework no statistical test was performed – this was a theoretical paper. The variables in the mathematical model were the following: the dependent variable was a quadratic hedge and the independent variable was a stochastic process. The findings showed that conditions on correlations are fulfilled by a large class of dynamics and that models using constant correlation are not recommended.

Critical Assessment

To prove the mathematical framework, statistical tests should be performed to determine validity. When dynamic hedging correlations do breakdown, a model that can adjust the hedging ratio based on changing correlations might perform better. The framework in the Ankirchner and Heyne (2012) paper provides a good starting point to developing a hedging model utilizing stochastic correlation methods. One possible way to test this framework is to use historical data on assets that have high correlation but are known to breakdown in time, such as the spot price on gold and the spot price on the USD/JPY currency pair.

Cao, L. & Guo, Z. (2012). A comparison of delta hedging under two price distribution assumptions by likelihood ratio. *The International Journal of Business and Finance Research*. *6*(1), 25-34.

Research Methodology and Findings

This is a quantitative study involving risk management, specific to delta hedging. The research question was: How do net profits from delta hedging perform for European call options when assuming that underlying stock prices follows a geometric Brownian motion or variance-gamma process? The model used in this research study was a likelihood ratio. The sample size was historical data of stock prices of Google from the WRDS database. The time period considered for the historical dataset is from March 10, 2008 to September 10, 2008, which involved only daily prices. The dependent variable was mean net-profit; and the independent variables were hedging frequency and the type of process. The type of processes considered were geometric Brownian motion (GBM), difference variance-gamma (DVG), and gamma-time change Brownian motion subordinated by a gamma process (GVG). The research findings are that the mean values of net gains from higher hedging frequencies are always larger than ones with smaller frequencies. Also standard error was found to be smaller for higher hedging frequencies. Lastly, mean gains are larger for variance gamma processes for Google for the specified timeframe.

Critical Assessment

This research study is very important for dynamic hedging. It is possible to implement a hedging model utilizing a variance gamma process to reduce hedging error and increase portfolio performance. Further research needs to be conducted using variance gamma processes not only in equities but also in the futures market of commodities. In addition, a larger dataset covering a larger timeframe might capture stylistic facts on the equity investigated to understand the true standard error over a longer time horizon. In conclusion, this study might have external validity issue, which warrants further research in the process of variance-gamma in hedging models.

Fleten, S., Brathen, E., & Nissen-Meyer, S. (2010). Evaluation of static hedging strategies for the hydropower producers in the Nordic market. *The Journal of Energy Markets. 3*(4), 3-30.

Research Methodology and Findings

This was a quantitative study involving risk management through hedging the energy sector. The research question was the following: How to derive a static hedge position for hydropower producers with different risk characteristics. The hedging methods were natural hedging, static hedging and dynamic hedging. The sampling was historical data from 1998 through 2008 of weekly production volume, weekly spots prices, and historical forwards. The predicted scenarios were from January 2007 to April of 2009. All production data collected were from hydro producers and the actual prices collected from the Nord Pool. The dependent variable was optimized hedge positions. The independent variables were VaR, CVaR and standard deviation of revenue. The research findings were that optimized positions vary over time and hedging with the use of forward contracts significantly reduces the risk. The added hedged protection results in only a minor reduction in mean revenue.

Critical Assessment

The study was an excellent example of how volatile the spot price is in the electricity market and how energy producers hedge their risk. It is important to not just hedge for speculation purposes but also for hedging production risk. Optimizing through VaR and CVaR is also an interesting method to pursue for possible reduction in hedging error.

Frikha, N. & Lemaire, V. (2013). Joint modeling of gas and electricity spot prices. *Applied Mathematical Finance. 20*(1), 69-93.

Research Methodology and Findings

This quantitative study pertains to pricing assets. The research question posed was: How to model gas and electric power spot prices? The model used in this research was a mean-reverting model using cross correlation. The sampling for calibration of the model was from the French power market and the United Kingdom gas market from January 14, 2003 to August 20, 2008. The dependent variable was the de-seasonal spot price. The independent variables were Gaussian Ornstein-Uhlenbeck processes, spike component, and seasonality functions. The research findings were as follows. First, the article proposes a simple model that captures the cross-correlation, long-term dependency between gas and power, and the stylized features of each spot price. Secondly, the maximum likelihood estimator and the least squares procedured allowed for parameter estimation. Thirdly, there was no need to consider multiple price drivers for commodities considered. Lastly, the model is close to a multi-factor model that is based on jump-diffusion processes.

Critical Assessment

This research study is useful in understanding how to price high volatility energy commodities. This study also provides an understanding on the dependency or correlation between electricity and natural gas in relation to spot price. This can be used in an objective function to determine how to hedge an energy position. In terms of external validity, more research should be conducted in other electricity and gas markets, e.g. North America, Latin America and Australia.

Hassan, Syed Aun. (2011). Modeling asymmetric volatility in oil prices. *The Journal of Applied Business Research. 27*(3), 71-77.

Research Methodology and Findings

This is a quantitative study on volatility modeling. The researcher investigated how exogenous shocks affect oil prices relative to good and bad news. The models used were: GARCH (1,1), GARCH inverted-mean (1,1), and EGARCH (1,1). The data was collected from the Energy Information Administration. The time period for the dataset was from May 1, 2000 to April 30, 2010 of daily spot prices for West Texas Intermediate crude oil – totaling 2,506 usable observations. The dependent variable was persistence of a shock, whereas the independent variables were volatility models. It was found in this study that shocks are persistent because the alpha and beta terms are close to 1. In addition, bad news affects price more than good news because of the sigma term being negative.

Critical Assessment

This research proves that there are asymmetries in oil prices and that protecting for negative shocks are important. It is possible to protect from these asymmetries through dynamically hedging the oil contract. This research also provided a good example on how to conduct a volatility study using GARCH models. This research should be expanded to other high volatile commodities and currencies to strengthen external validity.

Hinnerich, M. (2013). Pricing equity swaps in an economy with jumps. *Applied Mathematical Finance. 20*(2), 94-117.

Research Methodology and Findings
This was a quantitative study that explores modeling price dynamics. The research question posed was: How to price equity swaps in a jump-diffusion dynamic? The model used in their research study was utilizing Martingale methods. There was no sampling done in this research because of the analytic nature of solving the research problem. The dependent variable was price of the equity swap and the independent variable was the type of swap. The research findings showed that by using Martingale methods and calculating convexity of correlation terms an extended general pricing model for equities can be implemented. The extension of the model also allows for international markets to be non-Gaussian.

Critical Assessment
Because time-series in the real world are not continuous researchers need to utilize jump-diffusion models for pricing and forecasting. This research paves the way to utilizing jump-diffusion models for equity swaps but more research needs to be conducted in using jump-diffusion models for high volatile commodities and currency pairs. It is possible to integrate a jump-diffusion model in a hedging strategy to reduce hedging error. Unfortunately this was only a theoretical solution to pricing equity swaps and that a statistical investigation with equity swaps needs to be conducted to support the hypothesis that this Martingale method with jump-diffusions is statistically significant.

Jiang, N. (2010). *Three essays on the foreign exchange markets.* NewYork: The City University of New York.

Research Methodology and Findings
This study was quantitative involving term structure modeling. The research question was the following: What is the profitability of using a vector error correction model (VECM) strategy? The model used to do this research study was the VECM. The data was collected from Bloomberg for daily currency rates in the spot and forward markets. The following currencies were used: AUD, CAD, CHF, DKK, EUR, GBP, JPY, NOK, NZD and SEK. The datasets are from October 28, 1996 through May 15, 2009. The dependent variable was the forecast error and the independent variables were VECM and a random walk. It was found in this study that VECM performs better than a random walk in forecasting in the foreign exchange market. VECM also shows advantages in prediction at the 1 week prediction horizon.

Critical Assessment

This research was excellent in utilizing 10 different currency pairs to show strength in external validity. But all currency pairs were compared to the USD, therefore further studies should be made on cross-currency pairs, e.g. EUR/JPY, EUR/GBP, and EUR/CHF. In terms of internal validity it seems adequate via their forecast error comparison and the simulated trading of profitability.

Kaya, H., Lee, W., & Pornrojnangkool, B. (2011). Implementable tail risk management: an empricial analysis of CVaR-optimized carry trade portfolios. *Journal of Derivatives & hedge Funds. 17*(4), 341-356.

Research Methodology and Findings

This research study on risk management was an experimental quantitative design. The research question was how to model tail risk for portfolio management? The VaR and CVaR models were implemented in this research study. The samples were drawn from weekly returns for the USD/JPY, EUR/USD, GBP/USD, AUD/USD, USD/CAD from January 1990 to August 2009. The dependent variable was statistics on returns, whereas the independent variables were the naïve portfolio, mean variance optimization, and the mean CVaR optimization. It was found that the persistence in volatilities can be filtered via GARCH models to achieve stability for fat tail and dependency modeling. Second, out-of-sample tests show that managing risk even with mean-variance may improve investment performance, but only a non-normal model with tail risk controls seems to be effective statistically in reducing drawdown magnitude and rare loss events. Thirdly, a researcher should use GJR models for inclusion of leverage effects on asset returns. Lastly, bivariate normal distributions can be inadequate in modeling joint behavior of certain currency pairs; therefore modeling marginal distributions by fitting fat-tailed distributions to the residuals of the GJR process and calibrating a t-copula to join the marginal distributions is recommended.

Critical Assessment

This research article was an excellent example on how to conduct a currency pair study related to fat-tail risk. But this study should have expanded on the number of different currency pairs, instead of just the major currencies. Some currency pairs are more volatile than others due to liquidity of the cross-pairs, e.g. AUD/SEK. Another validity issue was how this can be applied to the energy sector; therefore to improve the external validity the same sorts of investigations should be done on oil, natural gas, and electricity futures. This research about GARCH models being able to filter persistent volatility might cause problems in matching real world conditions, but the out-of-sample testing seems to show that internal validity is not compromised. More investigation needs to be conducted to understand how GARCH models can affect fat-tail and dependency modeling.

Kristensen, D. & Mele, A. (2011). Adding and subtracting Black-Scholes: a new approach to approximating derivative prices in continuous-time models. *Journal of Financial Economics. 102*, 390-415.

Research Methodology and Findings

This is a quantitative study related to pricing derivatives. The research question is how to model asset prices in a nonlinear, multifactor diffusion setting. The Taylor series approximation of the Black Scholes model with a stochastic volatility parameter was the model used in this research study. A simulation was performed and analyzed. The dependent variable was error. The independent variables were stock price using a Fourier transformation, Yang expansion, and the new model proposed. It was found that approximations models for pricing derivatives are adequate when a pricing model lacks a closed form solution.

Critical Assessment

This research provides evidence of the validity to use approximation models for pricing derivatives. Back-testing pricing models using approximation methods with actual historical data and determining pricing error would strengthen internal validity. It is possible that the simulation method used in this research study might not fully capture real world dynamics and approximation models in certain cases might be adequate.

Manzur, M., Hoque, A. & Poitras, G. (2010). Currency option pricing and realized volatility. *Banking and Finance Revie. 1*, 73-85.

Research Methodology and Findings

This study was quantitative involving option pricing. The research question was: What volatility model is best for currency option pricing? The models used in this study were: implied volatility, realized volatility, and GARCH. The sampling was from the GBP, CHF and EUR from July 22, 2002 to June 20, 2006. These sample prices were for 3 month contracts. The dependent variable was pricing error. The independent variables were: SGVPE, SIVPE, SEVPE, FGVPE, FIVPE, FRVPE models. The findings were that realized volatility outperformed implied and GARCH volatility for currency options and futures for the GBP, CHF, and EUR markets when measured with USD.

Critical Assessment

The finding that realized volatility is better to use in pricing currency options for the three major pairs investigated is important to implement in a dynamic hedging model. There is a debate on the best way to model volatility in pricing futures and options of high volatile markets, such as energy and currency. Many practitioners assume that if implied volatility is lower than historic volatility then volatility will go up and vice versa. But implied volatility is priced using the Black Scholes model and that the assumption of the model might not be appropriate to high volatile markets. It is interesting that GARCH performed worse than realized volatility modeling when pricing currency options. GARCH is a standard in volatility modeling in quantitative finance.

Menkhoff, L., Sarno, L., Schmeling, M., & Schrimpf, A. (2012). Currency momentum strategies. *Journal of Financial Economics. 106*, 660-684.

Research Methodology and Findings

This study was using quantitative methods to develop trading strategies. The research question was: What are the momentum profit dynamics in the foreign exchange markets? A model used in this study was utilizing currency excess returns. The sample size was from spot and forward markets from January 1976 to January 2010 from the Barclays Bank International and Datastream. There were 48 countries that were involved in the sample. The dependent variable was excess returns; and the independent variables were lagged excess returns, lagged forward discounts, and lagged spot rate changes. The findings in this research were the following. Momentum strategies can deliver high excess returns in the foreign exchange market, whereby currencies are hard to hedge and have high country risk. This is very similar to non-investment grade corporate bonds and high credit risk equity.

Critical Assessment

This research suggested that speculative equilibrium dynamics might be involved in momentum trading strategies, whereby once a momentum is initiated it can drift from fundamental equilibrium. This research, in conjunction with directional indicators, can improve on profitability in trading currencies, due to the strong dynamic of momentum. In terms of hedging, a momentum indicating signal might be used in an artificial intelligent trading system to determine a delta hedge position ratio - allowing for the portfolio to benefit from a realized mean reversion. What is important to note is that excess returns need to be risk adjusted to fully understand the true risk in the position being held. This study used lagged returns, lagged forward rates, and lagged spot rates to determine statistical significance to excess returns.

Moldovan, D., Moca, M., & Nitchi, S. (2011). A stock trading algorithm Model Proposal, based on technical indicators signals. *Informatic Economica. 15*(1), 183-188.

Research Methodology and Findings

This was a qualitative research study involving algorithmic trading models. This was just a proposal and had no statistical analysis or inference. The research problem was how to design a technical indicator trading system? The models proposed in this qualitative study were the MACD, ROC, and stochastic oscillation models. The trading system produces a trade signal based on trading algorithms. The proposal is to use an automated trading system using a multi indicator system that has parameters optimized that are unique to the asset traded. The use of genetic algorithms will help determine best technical indicator signals to use, whereby the parameters and best technical indicators to use might change over time.

Critical Assessment

The strength of this research proposal it the use of a multi indicator system that is optimized uniquely to a particular traded asset. This is important because currencies and equities trade differently and might have different over-bought or over-sold parameters. In terms of weaknesses the research is just a proposal and need to be validated empirically, whereby the use of historical datasets to determine profitability of different automated strategies should provide validity. The problem with a multi indicator system for trading is there might be analysis paralysis – leading to inaction. There needs to be a balance between actionable intelligence and just system noise. Too many indicators might produce just more system noise. To reduce this system noise caused by too many indicators in a trading algorithm, the researcher can determine the optimum amount of indicators using an ANOVA analysis.

Srinivasan, P. (2011). Modeling and forecasting the stock market volatility of S&P 500 index using GARCH models. *The IUP Journal of Behavioral Finance. 7*(1), 51-69.

Research Methodology and Findings

This was a quantitative study pertaining to risk management. The research question asked was: What volatility model should be used when considering the S&P 500 index? GARCH, EGARCH, and TARCH are the compared volatility models. The dataset was from January 1, 1990 to Jan 29, 2010 of the S&P 500 returns and January 30, 2009 to January 29, 2010 for the out-of-sample testing. The control in this experimental design was the S&P 500 returns. The dependent variable was the volatility. The independent variables are the different ARCH models. The different ARCH models have a series of parameters to consider as well. The findings were that the symmetric GARCH models are found superior in forecasting variance in the S&P 500 index returns rather than asymmetric GARCH models.

Critical Assessment

This research suggests that at least in the S&P 500 during the period investigated that asymmetric dynamics do not really need to be considered in modeling volatility. This might be due to the S&P 500 index being a very liquid market which in most time periods is relatively symmetric. But returns in the S&P 500 index do exhibit high kurtosis and skewness, which suggests the need to model asymmetries. Perhaps with higher volatility assets, e.g. oil futures, asymmetric GARCH modeling should be uses.

Viebig, J. & Poddig, T. (2010). Modeling extreme returns and asymmetric dependence structures to hedge fund strategies using extreme value theory and copula theory. *The Journal of Risk. 13*(2), 23-55.

Research Methodology and Findings

This is a quantitative study involving modeling extreme returns. This research can be used in risk management and risk modeling. The research question was: How to use extreme value theory and copula theory to model multivariate daily return distributions of different hedge fund strategy indexes? The models used in the research study are from extreme value theory and copula theory. The samples were from 1,559 daily returns for each strategy index over the period of April 1, 2003 to June 8, 2009. The HFRX index was from a pool of 7,500 funds. The hedge fund strategies were calculated by the Hedge Fund Research group. The following hedge fund strategies were: (1) convertible arbitrage, distressed securities, equity hedge, equity market neutral, event driven, macro, merger arbitrage, and relative value arbitrage. In terms of the extreme value theory, the dependent variable was the probability of returns exceeding high thresholds and the independent variable was the general Pareto distributions. In terms of copula theory, the dependent variable was the joint distribution function. The independent variables for analyzing copula theory were copulas and marginal distributions. The findings suggest that dependency structures between several hedge fund strategies are often asymmetric when testing for correlation symmetry. This research also revealed that the clustering of outliers during the financial crises of 2008-2009 suggests that stress in financial markets are contagious and affect hedge funds. It was concluded that the clustering behavior was attributed to volatilities and credit spreads widening when investors see illiquidity.

Critical Assessment

This research is excellent to understand hedge fund strategies and how these hedge funds can become stressed when financial market exhibit asymmetries. This is due to the breakdown in correlations and increased volatility. Another important attribute of this research study is how to evaluate a series of hedge funds using copula and extreme value theory. It would be interesting to extend this research into the 2009 to 2013 time period to determine how hedge funds perform in a mean reverting market and to determine if hedge fund strategies remain asymmetric in terms of dependency structures.

Zha, X. (2011). *On oil futures prices and term structure*. Hong Kong:The Chinese University of Hong Kong.

Research Methodology and Findings

This was a quantitative study that involved terms structures for oil futures. The research questions were the following. What are the term structures of oil futures between 1989 through 2010? What are some of the reasons for contango and backwardation in the oil futures market? This research utilized spot premiums and risk premiums for the theoretical framework. The sample data was from 1989 through 2010 for light sweet crude traded on the NYMEX. The dependent variable was the type of term structure and the independent variable was time. The research findings suggested that backwardation in the oil futures curve is not as persistent as many previous studies have concluded for recent time periods. Secondly, the contango term structure occurs more often than in earlier years, leading to a more volatile term structure for the oil futures market.

Critical Assessment

This research is excellent for understanding the term structure dynamics of oil futures. For developing a spread trading strategy understanding the backwardation persistence is very important. Spread trading is a form of hedging risk and is very involved in the term structure and current momentum of the price action of the oil future being traded. This research method shows how to analyze term structures of the energy market. It would be interesting to understand if similar dynamics are present in the Brent crude oil futures as well or if WTI crude oil futures are unique of some reason. Future studies are needed in understanding the application of the conclusion of this research study for other products in the energy sector.

LITERATURE REVIEW ESSAY

INTRODUCTION

The purpose of this section on research methods and designs is to analyze the contemporary literature in the field of quantitative finance. Fifteen selected research articles were compared and contrasted on how to analyze hedging and price methods for financial assets. In addition, an investigation and evaluation of recent trends with research designs for the use in quantitative finance to develop and establish hedging and pricing techniques will be conducted.

The first article investigates modeling asymmetric volatility in the context of research methods explored by Hassan. The second research study involves oil future prices and term structures, whereby understanding the permanent and transitory shocks in oil futures can be accomplished via a structural vector auto-regression model by Zha. The third article of inquiry is by Cao and Guo which involved delta hedging performance methodologies. In the fourth research study, Ankirchner and Heyne suggested how to use research methods using cross hedging with stochastic correlations. In the fifth article, Srinvasan investigated stock market volatility and used different volatility models that are GARCH-types. The sixth peer-review study investigated is by Menkhoff , which involves currency momentum and the use of moving averages. The seventh research article was about how to price currency options and the methods used to determine which volatility model performed the best proposed was by Manzur, Hoque, and Poitras. The eighth scholarly study, which was authored by Jiang, involves foreign exchange markets and the use of a vector error correction model.

The ninth intellectual inquiry investigated was on tail risk management and some of the methodologies used when modeling with Value-at-Risk and conditional Value-at-Risk by Kayan, Lee, and Pornrojnangkool. The tenth article explores the hydroelectric power industry and how to incorporate a hedging strategy and test for performance by Fleten, Brathen, and Nissen-Meyer. The eleventh research study investigated was by Frikha and Lemaire involved the gas and electricity spot price using a multi-factor model that can present higher volatility markets. The twelfth scholarly article proposed was by Hinnerich which explores equity swaps and demonstrates how to incorporate a jump diffusion model to capture price dynamics. The thirteenth study relates to derivative pricing using a close-form approximation relying on series expansions by Kristensen and Mele. The fourteenth study in this section involves how to build a trading algorithm system by Moldovan, Moca, and Nitchi. The last article reviewed was by Viebig and Poddig, whereby extreme value theory and copula theory was considered as a way to model multivariate daily return distributions of hedge funds.

In the conclusion section of this Depth component a discussion on the synthesis of the relevant research related to research design used in quantitative finance was conducted. Comments on how to approach the research design with a focus on establishing hedging and pricing strategies of financial assets was shown. The intent of this section was to explore some of the tools developed in statistical analysis that enable researchers in quantitative finance to evaluate different hedging and pricing strategies. With a better research design and the use of advanced statistical methods researchers and practitioners can evaluate their financial modeling performance more accurately.

Within the conclusion section each of the fifteen research articles mentioned above will be summarized in the framework of research methods that can promote social change. In addition to the summary of these research studies, some questions are explored to provide possible investigational paths.

Modeling Asymmetric Volatility

Understanding how shocks affect futures prices in the oil market is extremely important. GARCH models are an important modeling tool in measuring volatility in a time series. How can we test for persistence and asymmetric behavior in oil price volatility?

A possible way to analyze persistence and asymmetric behavior in time series is to test the time series with the following GARCH models: GARCH(1,1), GARCH-in-mean(1,1), and EGARCH(1,1) (Hassan, 2011, p. 72). GARCH(1,1) tests for persistence to shocks to volatility. GARCH-in-mean(1,1) also tests for persistence but has a parameter describing the relationship to expected risk and expected returns. EGARCH(1,1) models can be used to test for asymmetry to bad news.

The next step is to take a dataset of daily returns and describe the statistics of the time series. The descriptive statistics typically used are the following: mean, median, maximum, minimum, standard deviation, skewness, kurtosis, Jarque-Bera statistic, sum, sum square deviation, Ljung-Box statistic, and number of observations (Hassan, 2011, p. 74). The Ljung-

Box statistics is for serial correlation testing, whereby autocorrelation exists when $p<0.05$. The Jarque-Bera statistic is for testing normality, whereby the non-normally distributed time series exist when $p<0.05$. It is important to note that presence of fat-tails are when kurtosis is above three and that the time series is normally distributed when skewness is zero.

The third step in analyzing time series related to volatility symmetry is to perform unit root tests through the use of the Augmented Dicky-Fuller (ADF) and Phillips-Perron (PP) tests (Hassan, 2001, p. 75). A significant p-value with ADF and PP tests mean that a unit root in the time series does not exists – the time series is stationary. Unit roots of 1 mean that the time series is non-stationary. In summary it is important to test for normality, autocorrelation, and stationary characteristics of a time series.

The last procedure is to analyze the different GARCH models to determine if persistency of a shock and asymmetry of news exists in a time series of returns. In the GARCH(1,1) model the alpha and beta parameters should be summed to determine if shocks are persistent, whereby the sum of approximately to 1 means high persistence (Hassan, 2011, p. 74). Hassan (2011) also performed ARCH LM and the Ljung-Box tests on the GARCH models to determine if autocorrelation exists, whereby $p<.05$ means that autocorrelation exists (p. 74). The GARCH-in-mean (1,1) model is also tested similarly as the GARCH (1,1) model but also has the parameter that describes the expected risk, therefore testing for significance if this parameter is important is needed to determine if expected risk effects expected return. Lastly, the EGARCH (1,1) model is for asymmetry in relation to good and bad news. Hassen used EGARCH by looking at the coefficient of asymmetry and the significance of that parameter, as well as testing with ARCH LM and Ljung-Box statistics for autocorrelation.

Oil Futures Prices and Term Structures

Understanding the permanent and transitory shocks in oil futures can be accomplished via a structural vector auto-regression (VAR) model (Zha, 2011, p. 49). Zha (2011) used a two level analysis: macro and micro analysis (p. 52). Zha proposed using a two variable VAR system with gross national product (GNP) and unemployment rates for the macro analysis (p. 52). Then a regression was performed for the oil futures total return, the spot return or term structure being depended on shocks to demand, shock to supply, time-dummy terms and control variables (p. 53). Lastly, the macro level of analysis also was regressed for oil futures total return, spot returns, and term structure by the same regression function using a shock to supply or demand but replacing those shock variables with accumulative contributions to demand and supply – this provides information on how demand side growth or supply side growth affects oil futures in terms of price and term structure (p. 54).

In the micro analysis, real worldwide demand and supply data can be used to understand the components and how they influence oil prices and the term structure of the futures curve (Zha, 2011, p. 54). Zha (2011) used a regression function where the oil futures term structure was dependent on the demand of OECD and non-OECD countries with transitory and permanent demands (p. 57). Then Zha used a regression model that represents volatility in oil spot price with transitory oil demand (p. 57). An important note is the assumption that the spread between the spot price and the future price remains constant for permanent shocks and changes for transitory shocks.

For the macro analysis the real GNP and unemployment can be obtained through the central bank or a countries statistics bureau, whereas the global oil demand and supply can be obtained from the International Energy Agency (IEA) (Zha, 2011, p. 58). Zha (2011) used the following control variables: (1) U.S. oil stock data; and (2) the net long position for commercial and non-commercial traders (pp. 59-60). Through this methodology Zha found that transitory demand shocks do twist the terms structure and permanent demand shocks cause a parallel shift in the term structure (p. 88).

With the Zha (2011) study a spread trader can make a position in the market based on the type of demand shock in the news. If the demand shock is permanent a spread trader will have difficulty making a profit, but if the demand shock is transitory the twisting of the term structure presents spread trading opportunities.

Delta Hedging

Delta hedging is a very common method in hedging options, but how do we determine the delta of an option? The Black Scholes model does produce a delta for a certain option price. Delta is the first derivative of an option price relative to the spot price of the underlying. By adjusting the number of shares in the spot market you can delta hedge an option contract. Because empirical evidence shows that option prices do not really follow a geometric Brownian motion process but follow a variance-gamma process gradient estimation techniques are needed to estimate the delta (Cao and Guo, 2012, p. 26).

Simulation and gradient estimations are common practice in financial applications and that the likelihood ratio (LR) method is one such gradient estimation tool (Cao and Guo, 2012 p. 29). Gao and Guo (2012) used equation 10 to define the LR (p. 30).

$$\frac{dE[L(X)]}{d\xi} = \int_{-\infty}^{+\infty} L(x)\frac{d\ln f_x(x,\xi)}{d\xi} f_x\,(x)dx \qquad (10)$$

E[L(X)] is an objective function depending on parameter ξ and is the expectation of a sample performance measure. The variable f_x is the probability density function of X. L(X) is the performance measure of a number of random variables that are dependent on parameter ξ.

The delta estimation from the LR for a Brownian motion process to estimate delta for a European call option is shown in equation 11 (Cao and Guo, 2012, p.31).

$$e^{-rT}(x-K) \text{ X } \frac{d(\ln f(x))}{dS_0} \qquad (11)$$

The variable r risk free rate, x is the stock price at time t, K is the strike price at maturity, T is the time at expiration and S_0 is the initial spot price – f(x) remains the probability density function. Refer to Cao and Guo (2012) for the details of the probability density function used for a Brownian motion process (p. 30).

The delta estimation from the LR for a variance gamma process, which is a Levy process of independent and stationary increments, for a European call option is shown in equation 12 (Cao and Guo, 2012, p. 32).

$$e^{-rT}(s-K) \text{ X } \frac{d(\ln f_{S_T(s)})}{dS_0} \qquad (12)$$

The variables in equation 12 are defined similarly as equation 11 but s is the stock price at time t and $fST(s)$ is the probability density function of the stock price at time t. Refer to Cao and Guo (2012) for the details to the probability density function used for a variance gamma process (p. 32). The key point is that even though equation 11 and 12 are basically the same formula the probability density function for a Brownian motion process and a variance gamma process are much different. Cao and Cuo estimated the parameters of the Brownian motion and variance gamma processes with the maximum likelihood estimation method (p. 32).

Cross Hedging With Stochastic Correlation

Hedging correlations does change over time, even when the underlying asset of the future or option is the same product, e.g. S&P 500 future with the S&P 500 index spot price. Basis risk is the non-hedgeable risk in a hedged position. The non-hedgeable risk exists due to hedging instruments not being perfectly correlated (Ankirchner and Heyne, 2012, p. 17). Ankirchner and Heyne (2012) proposed that there are two types of optimal hedging criteria: (1) utility based which uses maximum exponential utility of terminal wealth minus the hedging cost, and (2) quadratic approach which focuses on reducing the quadratic hedging error (p. 18). Ankirchner and Heyne used the quadratic approach with basis risk and stochastic correlation (p. 18). Stochastic correlation was implemented to model the seemingly random behavior of correlation of hedging instruments to underlying assets.

Optimal hedging is equal to the asset hedge ratio multiplied by the asset delta plus the correlation hedge ratio multiplied by the correlation delta (Ankirchner and Heyne, 2012, p. 19). Ankirchner and Heyne (2012) defined the asset hedge ratio as the index volatility divided by the asset volatility and this quantity multiplied by the correlation process (p. 19). Ankirchner and Heyne defined the correlation hedge ratio as the correlation volatility divided by asset volatility and this quantity is multiplied by the correlation between the asset and the correlation process (p. 19). The local risk minimizing strategy, as a function of the amount of shares held and the amount of units in a money market, can be determined by the function shown in equation 13 (p. 24).

$$A_t=A(t,I_t,X_t,p_t) \qquad (12)$$

A_t is the amount of shares held at time t, which is a function of time t, I_t as the variable discounted value of the untradeable asset, X_t as the variable of the discounted value of the tradable asset, and p_t representing the correlation process. See Ankirchner and Heyne (2012) for the detailed formula for the number of shares to be held in the tradable asset to reach the local risk minimizing strategy.

The key take away from the research method from Ankirchner and Heyne (2012) was that correlations between the tradable asset and the untradeable underlying can and usually do breakdown. When hedging correlations breakdown there is need to manage and monitor the position properly. One possible method is to use the optimal hedge as defined in this section. The researcher should be methodical in defining the asset delta and the correlation delta.

Stock Market Volatility

When modeling and forecasting the volatility of the S&P 500 index GARCH models can be utilized (Srinivasan, 2011, p. 51). Srinivasan (2011) used GARCH, exponential GARCH (EGARCH), and threshold GARCH (TGARCH) to determine which volatility model best describes the volatility of the S&P 500 index by using the Ljung-Box Q statistic and the ARCH-LM test (p. 56). A researcher should start by constructing a dataset of S&P 500 index returns and develop a descriptive and diagnostic table that includes the following: mean, standard deviation, skewness, kurtosis, Jarque-Bera, Q Statistic, Augmented Dickey-Fuller (ADF), Phillips-Peron (PP), and sample size. Jarque-Bera tests for normality and the Q statistic test for autocorrelation the return and squared return series of the S&P 500 index. In the Srinivasan study the Q statistic used a 12 lag parameter (p. 59).

For the ADF and PP tests should include the following: (1) intercept; (2) intercept and trend; and (3) no intercept and no trend (Srinivasan, 2011, p. 59). ADF and PP statistics are to determine if the return series is stationary. To determine if the use of GARCH-type models are justifiable for modeling and forecasting Srinivasan (2011) used the following criteria: unconditional leptokurtic distribution, volatility clustering, and the presents of significant ARCH effects (p. 58).

The next step is to estimate each of the GARCH-type models from the S&P 500 index dataset. The statistics that should be used for each of the GARCH-type models are the Q statistics, ARCH-LM test, Akaike information criteria (AIC), Schwarz information criteria (SIC), and the log likelihood (LL) (Srinivasan, 2011, p. 59). Srinivasan (2011) used the Q statistics for each GARCH-type model to test for any remaining autocorrelation in the standardized residuals and squared standardized residuals, which should not be significant if the GARCH-type model is specified properly and successful at modeling the serial correlation structure in the conditional means and conditional variances (p. 62). In addition, the ARCH-LM test also for any autocorrelation effects left in the standardized residuals to determine if each of the GARCH-type models were properly defined. By comparing AIC, SIC and LL values a determination can be reached for which GARCH-type model performs best in modeling the volatility of the S&P 500 index. A researcher should use the minimum AIC, SIC and the maximum LL for the selection criteria of best GARCH-type model.

Lastly, out-of-sample forecasts can also evaluate GARCH-type model performance. This model performance can be accomplished by comparing the root mean error, mean absolute error, mean absolute percent error, and the Theil inequality coefficient between the actual prices minus the forecast (Srinivasan, 2011, p. 59). This research study is an excellent example of how to statistically test the following: a dataset, GARCH-type model after parameterization, and forecast performance.

Currency Momentum

Foreign exchange markets are excellent for studying momentum returns due to their depth of liquidity, size of transitions, and low transaction costs (Menkoff, Sarno, Schmeling, and Schrimpf, 2012, p. 661). A researcher can study momentum by first collecting spot and one-month foreign exchange rates which cover a large sample period. Menkoff, Sarno, Scjmeling, and Schrimpf (2012) studied 48 countries over a 34 year period (p. 664). Menkoff et al. charted momentum returns and spot rate changes using two criteria: (1) holding period measured in months, and (2) lagged returns over the previous month (p. 666). Menkoff et al. constructed the portfolio by taking the lagged returns over the previous months, e.g. 1,3,6,9,12, at the end of each month (p. 665). Monthly returns should be used over the entire sample period and statistical tests should be based on t-statistics but sharp ratios should be annualized (p. 666). The portfolios should be constructed by taking all available currencies in a given month and segregate them into equal bins ranging from lowest lagged returns to highest lagged returns (p. 665). In the case of the Menkoff's study, the number of portfolios was 6 (p. 665).

When analyzing moving averages and momentum the following descriptive statistics on each of the moving average rules should be performed: mean, Sharpe ratio, standard deviation, skewness, and kurtosis (Menkoff, Sarno, Schmeling, and Schrimpf, 2012, p. 670). Menkoff, Sarno, Schmeling, and Schrimpf (2012) used the following moving average rules for the formations and holding periods respectively: (1,20), (5, 20), (1,200) (p. 670). All lags and holding periods are in months. A regression analysis of the momentum returns for each moving average rule should be performed. The momentum strategies used in the Menkoff et al. study were with a formation lag of 1, 6, and 12 all with a one month holding period (p. 670).

The basic methodology from Menkoff et al. can be applied to future commodity markets but the researcher needs to keep in mind that future markets have higher transaction costs which might mitigate the strength of the momentum strategy. When looking at this phenomenon from a behavioral finance perspective, momentum strategies fit well with the theory of speculative and fundamental equilibrium. Usually a liquid asset is in speculative equilibrium, therefore momentum traders can profit with such strategy.

Currency Option Pricing

Volatility is a very important parameter for option pricing and researchers and practitioners need to know which methods are best for estimating this parameter. The common methods for inputs for volatility into the Black-Scholes option pricing model are implied volatility, realized volatility, and GARACH-type models. It is very possible that certain asset types should be modeled differently for specifying volatility. It was found that realized volatility outperformed other volatility specifying methods when considering GBP, CHF, and EUR currencies (Manzur, Hoque, and Poitras, 2010, p. 84).

The first step is to determine a pricing model for the option, which usually is some Black-Scholes derivation (Manzur, Hoque, and Poitras, 2010, p. 74). Manzur, Hoque, and Poitras (2010) used spot and futures prices in the Black-Scholes model (p. 74). The next step is to start determining the implied volatility, realized volatility, and the GARCH-type volatility see Manzur, Hoque, and Poitras (2010) for exact procedure to each of these methods. For Manzure et al. each volatility model is exposed with spot and future prices with in-sample and out-of-sample data (p. 77).

That statistics for determining performance should be the following: (1) mean squared error, (2) mean absolute error, and (3) mean absolute percentage error (Manzur, Hoque, and Poitras, 2010, p. 77). Manzur, Hoque, and Poitras (2010) used the difference between the observed at-the-money option price and the model-predicted price for determining pricing errors for each model (p. 77).

After the GARCH-type model is parameterized for each dataset then a comparison can be conducted. The goal is to determine which volatility model has less error in the spot and futures market. Manzure Hoque, and Potras (2010) used the following comparisons to determine statistical significance of pricing error differences using the Diebold-Mariano Equality Test for each currency: (1) implied volatility and GARCH volatility; (2) realized volatility and implied volatility; and (3) realized volatility and GARCH volatility (p. 80). By using the prescribed procedure a researcher or practitioner can determine which volatility model should be used for pricing a particular option.

Foreign Exchange Markets

It is important to understand macroeconomic news shocks to foreign exchange markets. Foreign exchange markets are event risk driven and understanding how much a news shock can propagate into the currency market can perhaps help hedge news event risk. One method to explain and predict foreign exchange rates is the vector error correction model (VECM) on the term structure of forward exchange premium (Jiang, 2010, p. 2). Jiang (2010) used 27 macroeconomic news announcements to define dynamic factors, and then fitted spot rates and forward rates on extracted factors to obtain parameters for the VECM. Lastly, an out-of-sample prediction with the VECM method is generated and prediction errors are calculated (p. 4).

To obtain macroeconomic announcements a researcher can go to Money Market Services (MMS) (Jiang, 2010, p. 8). Jiang (2010) suggested the use of the Kalman filter to extract news factors to filter out noise from other news announcements (p. 11). Refer to Jiang (2010) for a detailed method of how to utilize a Kalman filter. Jiang then reported for each macroeconomic announcement the factor loading matrix, whereby growth and inflation effects are measured (p. 18). A t-statistic was also reported for each macroeconomic announcement with error, variance, and forecast percentage variance (p. 18). By reporting the t-statistic the estimated factors of growth and inflation can be determined if statistically significant; but a researcher should also compare if the error calculated is less than the variance of the original macroeconomic variable, as well as if the forecast percentage variance is close to 90%. If the t-statistic is significant, the error is less than the original variance, and forecast percentage variance is also close to 90% then the loading matrix is reliable (p. 19).

VECM was then used to calculate the first difference of the vector which included the spot and forward rates by utilizing the extracted dynamic factors from the macroeconomic variables, the lagged vectors of the spot and forward rates, and the matrix defined product of the number of co-integrating relations and vector of the spot and forward price (Jiang, 2010, p. 21). Jiang (2010) described the VECM method as requiring the first difference-of-vector, which represented the spot and forward rate, to be stationary and that the number of lags needs to be determined (p. 22). Jiang used the Akaike's Information Criterion (AIC) to determine the best lag parameter to use for the VECM, whereby a lower AIC value determined a goodness of fit (p. 22). Next was the likelihood ratio to verify the lag check (p. 22). Next is to test for unit roots using the augmented Dickey-Fuller (ADF) test, whereby the spot and forward rate should be non-stationary and the first difference vector of the spot and forward rate should be stationary for currencies (p. 23). The ADF test can be confirmed with the Phillips-Perron method. To test for co-integration the Johansen test should be implemented before utilizing the VECM method (p. 24). Lastly, root mean square error and mean absolute error were used for measuring accuracy between the following three methods for each currency pair: (1) VECM, (2) VECM with news factors, and (3) vector auto-regression random walks (p. 47).

Tail Risk Management

Modeling risk behavior of assets is important for investors, portfolio managers, and counterparty risk departments. The practice in the financial industry is to use the Value-at-Risk (VaR) to calculate minimum potential loss at a certain confidence interval. But VaR can actually underestimate the true risk in the fat tail of the curve. Another method is to use conditional Value-at-Risk (CVaR), which incorporates probability and expected magnitude of the loss.

Understanding volatility is essential to understanding potential risks and assessing those volatilities depends on the volatility model used. There are many GARCH models but a common model to capture asymmetric effects is the GJR-GARCH model (Kaya, Lee, and Pornrojnangkool, 2011, p. 344). Kayan, Lee, and Pornrojnangkool (2011) used four different charts to describe volatility characteristics in currency pairs: (1) excess return through time, (2) annualized volatility through time using a GJR-GARCH model, (3) excess return autocorrelation relative to lags, and (4) autocorrelation of absolute returns with GJR-GARCH filter (p. 346). By charting the volatility characteristics a researcher or investor can understand if returns are correlated to previous returns and if this correlation is persistent. Kayan, Lee, and Pornrojnangkool used GJR-GARCH filtering to determine if the autocorrelation was captured per a predetermined interval for rejection of autocorrelation (p. 346). If the autocorrelation is within the predetermined interval then the GARCH-type model does capture the autocorrelation process.

To better visualize fat tail characteristics it is important first to determine the skewness and kurtosis. Then the GJR-GARCH filtering of a currency pair return should be used to remove the volatility clustering and make plots of the cumulative distribution functions for Gaussian, empirical, and Pareto distributions of the filtered returns. Then a QQ plot should be utilized comparing filtered return quantiles as the y-axis with Gaussian distribution quantiles and Pareto distribution quantiles on the x-axis (Kaya, Lee, and Pornrojnangkool, 2011, p. 348). The more the tail behavior matches a linear line on the QQ plot the more successful the distribution approximation is in capturing the return behavior of an asset.

Being able to approximate the distribution behavior of a financial time series is important for modeling the fat tail characteristics. By using the QQ plot technique in conjunction with verifying that a GARCH-type model actual captures the volatility characteristics of the asset can help risk managers and researchers understand potential counterparty risks and loss of portfolio values.

Hydroelectric Power

Electric power is a volatile business and producers need to hedge risks due to supply and demand dynamics. To understand the volatile characteristics for the production of hydropower one can graph years on the x-axis and GWH/year on the y-axis; whereby GWH stands for gigawatt hour (Fleten, Brathen, and Nissen-Meyer, 2010, p. 8). Fleten, Brathen, and Nissen-Meyer (2010) also graphed the annual spot price for Nordic hydroelectric production measured in NOK/MWh; whereby MWH stands for megawatt hour (p. 9). Fleten, Brathen, and Nissen-Meyer calculated spot revenue from annual production and annual spot price. Then a researcher should build a descriptive statistic table that expresses production, spot price, and spot revenue for a certain time period on the following metrics: (1) mean, (2) standard deviation, (3) skewness, (4) kurtosis, (5) minimum, (6) maximum, and (7) correlation (p. 9). Due to the changing correlation of price to production volume, a correlation chart should be built representing certain chunks of time.

To determine if a certain hedging strategy works a researcher can decide first on which hedging strategies to test and then compare the revenues, CVaR, VaR, and standard deviation. CVaR tends to be a better estimator of value-at-risk because it combines expected shortfall and VaR into the calculation. The comparisons can be based on certain time frames and average revenue, whereby results can be tabulated to determine best possible hedging strategy.

Testing of hedging strategies can be conducted on yearly, quarterly, or monthly contracts in the hydroelectric power market to determine if hedging should occur and at what frequency. It was found that hydroelectric producers prefer quarterly contracts due to risk premiums and high load uncertainty compared to yearly contracts (Fleten, Brathen, and Nissen-Meyer, 2010, p. 28).

Gas and Electricity Spot Price

Due to many energy markets being deregulated, understanding and modeling the price behavior of these markets are very important to hedge risk correctly (Frikha and Lemaire, 2013, p. 69). Frikha and Lemaire (2013) suggested that many spot market prices follow an Ornstein process, whereby a classical mean reversion is assumed (p. 70). Frikha and Lemaire also suggested that a multi-factor model that models the high volatility markets are needed for electricity and gas markets (p. 71). The first step is to model seasonality of the spot prices for gas and electricity with a log function and determine the p-values of each parameter of the log function used – utilizing only the statistically significant parameters for the calculation (p. 72). To determine normality we can graph the deseasonalized data in a histogram, in which the deseasonalized data is obtain by subtracting the log of the spot price from the seasonal spot price (p. 73).

To test for mean reversion and stationarity of gas and electric spot prices, the Augmented Dickey-Fuller and Phillips-Perron tests should be used on logarithm of spot prices and logarithm of deseasonalized spot prices – with statistical significance representing mean-reversion (Frikha and Lemaire, 2013, p. 75). Frikha and Lemaire (2013) used auto-correlation functions (ACF) and cross-correlation functions (CCF) to determine how gas and electricity are correlated (p. 76). Frikha and Lemaire proposed two classes of cross-commodity multi-factor models, which were geometric and arithmetic classes (p. 81).

The basic calibration steps for the multi-factor models are as follows: (1) deseasonalizing spot prices; (2) derive the ACF and CCF; and (3) estimate the parameters of the spike components (Frikha and Lemaire, 2013, p. 83). This method is good for situations when two commodities are related in a process, e.g. power generation or downstream refining. A key feature of this method by Frikha and Lemaire was the use of ACF and CCF to understand the correlations among two commodities.

Equity Swaps

Since markets behave in a discontinuous manner using classical Brownian motion models do not fully capture price dynamics, therefore a jump-diffusion model should be utilized (Hinnerich, 2013, p. 95). Hinnerich (2013) used a convexity correction method to calculate the expected value of the payoffs of an equity swap (p. 96). Hinnerich showed that the convexity correction can be calculated explicitly instead of the standard approximation method (pp. 96-97). Next the economy needs to be modeled. Hinnerich modeled stock prices, bond prices, money markets, and exchange rates for a domestic market and three foreign markets (p. 98). This economic modeling starts with considering the international markets residing in a filtered probability space, whereby a n-dimensional Wiener process and a general marked point process with predictable intensity levels (p. 98). Please refer to Hinnerich (2013) for the modeling details to describe an economy.

The next step is to define an equity swap, whereby the model captures the counterparties' exchange of cash flows (Hinnerich, 2013, p. 100). Hinnerich (2013) considered two different types of equity swaps to price: vanilla swaps and quanto swaps (pp. 103-112). A vanilla swap is where a swap is made between two counterparties, whereby one counterparty received a cash flow based on price of a certain type of equity and the other part receives a cash flow based on a floating rate or fix rate. A quanto swap is a swap between two counterparties where cash flows are determined based on the movement of two different countries' interest rates for the swap holder and the other counterparty pays a float or fixed rate.

The method that models equity swaps with jumps in the economy is a more realistic way to represent swap pricing dynamics. A researcher can use Hinnerich's methods to determine the price of the swap and the different cash flows that result from the contract. Since swaps are a non-exchange traded asset, future pricing is model based; therefore models that do not approximate or assume Gaussian distributions are more accurate. Since the banking industry uses swaps as risk management tools as standard practice, a large amount of swaps do accumulate and can produce counterparty risk if certain negative dynamics result in the financial markets. This was the case in the financial crisis of 2007-2008. Therefore proper swap pricing and counterparty risk monitoring are very important.

Derivative Pricing

To model prices that are not in closed-form a researcher or practitioner can use partial differential equations derived through finite difference, Fourier-inversion, and tree methods. But a researcher or practitioner can also use numerical methods derived through Monte Carlo methods (Kristensen and Mele, 2011, pp. 390-391). Kristensen and Mele (2011) used a closed-form approximation relying on series expansions of conditional expectations, whereby the expansion focuses on pricing errors between the true price and the auxiliary pricing function chosen in the approximation model instead of applying directly to the payoff function (p. 391). Kristensen and Mele derived the asset price approximation by series expansion (p. 394). Refer to Kristensen and Mele for further mathematical proofs and the asset price approximation function.

Two other asset price expansion methods are the Yang's expansion and the perturbation method (Kristensen and Mele, 2011, pp. 395-396). Kristensen and Mele (2011) is similar to the Yang's expansion because of the unknown solution to the model can be expressed in residuals and a base model (p. 395). Kristensen and Mele describe the perturbation method as an expansion of the unknown pricing function based on model parameters (p. 396). The next step is to compare the different models to determine if the Kristensen and Mele method performs better.

Comparisons were done under two different settings: (1) option pricing in models with constant elasticity of variance and stochastic volatility; and (2) in the term structures of interest rates (Kristensen and Mele, 2011, p. 397). Kristensen and Mele (2011) compared the following for option pricing: (a) Fourier transformation, (b) Yang expansion, (3) Monte Carlo, and (4) Kristensen and Mele method (pp. 400-401). Kristensen and Mele also compared the Monte Carlo methods to their approximation method for term structures of interest rates (p. 408). It was concluded that the Kristensen and Mele method can provide accurate results with less computation time compared to other pricing methods (p. 410).

Trading Algorithms

Technical analysis for trading has become very popular and is based on technical indicators, such as moving averages and relative strength indexes. Another strong force is algorithmic trading, which is using a preset of instructions to determine if a position should be held or sold off, whereby the computer automatically decides and executes the trade. What is the methodology for a trading algorithm system?

First market data needs to be in real time and piped into an integration subsystem (Moldovan, Moca, and Nitchi, 2011, p.185). The Moldovan, Moca, and Nitchi (2011) proposed that the trading algorithm in the integration subsystem has four inputs and one output, whereby three signals and one execution represent the inputs and the trade order is the output determined by the trading algorithm (p. 185). Moldovan, Moca, and Nitchi then completes the trading algorithm system with bi-directional feedback between the stock exchange and the integration subsystem (p. 185).

The next step is to further detail the functionality of the technical indicator and the risk management function. In terms of functionality of the technical indicator the following steps are proposed (Moldovan, Moca, and Nitchi, 2011, p. 186).

- Indicator computation determines if there is a buy/sell signal
- If buy/sell signal then determine if position is already open
- If no position exists then enter order, else check for exposure risk to enter another position and cycle back to indicator computation.

- If exposure risk is exceeded then cycle back to indicator computation without new order, else enter order and cycle back to indicator computation

In terms of risk management Moldovan, Moca, and Nitchi (2011) suggested profit and loss calculations needed to be performed and to determine if the loss or profit limits have been exceeded (p. 186). If profit or loss limits have been exceeded then enter closing position order. These processes are the basis of any algorithmic trading system and can be enhanced with forecasting functions coupled with technical indicators.

Extreme Value Theory and Copula Theory

To model multivariate daily return distributions of hedge funds extreme value theory and copula theory can be used (Viebig and Poddig, 2010, p. 23). Viebig and Poddig (2010) used extreme value theory and copula theory for daily return distributions because of the fat-tail and asymmetric dependency structures in the empirical data (p 24). Viebig and Poddig used generalized Pareto distributions to model tail dynamics of hedge fund indexes and copulas to model the dependency structures between hedge fund strategies (p. 24).

Five popular copulas that model distribution and dependency structures are the following: (1) Gaussian, Student-*t*, Gumbel, Clayton, and Frank copulas (Viebig and Poddig, 2010, p. 29). To determine fat-tail behavior of hedge fund strategies ARCH tests and Ljung-Box tests on residuals are needed to verify if autocorrelation exists. Viebig and Poddig (2010) tested eight hedge fund index strategies with the ARCH and Ljung-Box tests (p. 33-34). If autocorrelation exists then a filtering method is utilized and ARCH and Ljung-Box tests are redone to verify no autocorrelation.

To risk assess copula performance for each hedge fund strategy pair a generalized Pareto distribution copula approach is used, whereby a table is created to reflect the estimated errors for each of the five copulas mentioned earlier in this section (Viebig and Poddig, 2010, p. 50). Viebig and Poddig (2010) calculated estimated error by dividing the difference between estimated VaR and empirical VaR by empirical VaR (p. 50). Please refer to Viebig and Poddig on how to utilize each of the five copulas. To model fat-tails of the returns on hedge funds exceeding a certain threshold generalized Pareto distributions are good approximations to modeling such distributions (p. 51).

Conclusion

In the conclusion section of this Depth component a discussion on the synthesis of the relevant research related to research design used in quantitative finance is conducted. Comments on how to approach the research design with a focus on establishing hedging and pricing strategies of financial assets is established. The intent of this section is to explore some of the tools developed in statistical analysis that enable researchers in quantitative finance to evaluate different hedging and pricing strategies. With a better research design and the use of advanced statistical methods researchers and practitioners can evaluate their financial modeling performance more accurately.

It was shown by Hassan (2011) that to analyze persistence and asymmetric behavior in time series GARCH models can be used for persistence testing to shock and EGARCH models can be used to test for asymmetric behavior to bad news. Zha (2011) proposed a macro and micro analysis to understand the permanent and transitory shocks in the oil futures market. This macro and micro analysis used a two variable VAR system with GNP and unemployment rates. The micro analysis was real worldwide demand. Supply data was used to understand the oil price dynamics and terms structure in the futures curve. The use of a variance-gamma process by Cao and Guo (2012) can help price opinions allowing for better forecasting and delta hedging. Cao and Guo estimated the parameters of the Brownian motion and variance gamma processes with the maximum likelihood estimation method.

Ankirchner and Heyne (2012) used the quadratic approach with basis risk and stochastic correlation to determine optimal hedging. Is there a way to model changing volatility in a research design? Srinivan (2011) used GARCH-type models to determine which volatility models performed the best with the volatility of the S&P 500 index. A key tool to use is GARCH-type models to measure and forecast volatility. Volatility changes can sometimes cause correlations between assets to change. Therefore monitoring changes in volatility and correlation are extremely important. Currency momentum can be a predictor of future returns and a possible tool to determine position entry or size. Menkoff, Sarno, Schmeling, and Schrimpf (2012) studied currency momentums by using regression analysis of momentum returns of different moving averages and formation lags. Manzur, Hopue, and Poitras (2010) also investigated currencies through the option market and tested for performance of different volatility measures: implied, realized, and GARCH-type volatility. It is important for a researcher to realize that not all volatility measurements are the same and that certain assets might need to be measured with a certain type of volatility model.

The foreign exchange market is a very large and important asset for a portfolio. Participating in the foreign exchange market can help hedge for currency risk exposure. Jiang (2010) studied dynamic factors that explain and predict forward exchange premiums using a vector error correction model. Kaya, Lee, and Pornrojnangkool (2011) showed how to use QQ plots and GARCH-type models to capture volatility characteristics in assets. Another volatile market is the hydroelectric power market and therefore participants in this market might need to hedge risk exposure. Fleten, Brthen, and Nissen-Meyer (2010) determined that producers of hydroelectricity prefer quarterly contracts. So a research should consider testing for supplier or consumer risk preferences when developing hedging models. Frikha and Lemaire (2013) used a multi-factor model that models the higher volatility in the electricity and gas markets, in which they showed how to use season and deseasonlized datasets.

Hinnerich (2013) showed that modeling equity swaps can be modeled explicitly instead of the standard approximation method. There is a debate as to the proper balance between accuracy and speed of calculation. But a researcher should also keep-in-mind that many non-linear systems have to be approximated because there is no closed-form function. Derivative pricing is another asset type that is difficult to price. Kristensen and Mele (2011) used a closed-form approximation relying on series expansion. Many researchers also use Monte Carlo methods but this method does take a considerable amount of computational time.

Building trading algorithms and trading systems are becoming an important industry in finance. How to best develop a trading system? Moldovan, Moca, and Nitchi (2011) outlined and mapped out the process of a trading system and how to integrate the trading algorithm into the decision making process.

The use of risk management tools is also very important to studying hedging. Viebig and Poddig (2010) studied the use of extreme value theory and copula theory to model multivariate daily return distributions of hedge funds. There are five major copula types: Gaussian, Student-*t*, Gumbel, Clayton, and Frank copulas. The Viebig and Poddig research study showed how to use copulas to model distributions and dependency structures. As a researcher in risk management, there should be considerations on how to model dependency structures when modeling contagion and counterparty dynamics.

It has been shown in the Depth component that the uses of certain statistical methods are critical in determining autocorrelation, normality, stationarity, and volatility. It was also established in this Depth component that VaR and CVaR can be important in determining tail risk. Researchers need to also consider dependency structures by using copulas. Correlation and volatility can breakdown when constructing a portfolio and those researchers should be considering methods in establishing models that account for these potential breakdowns. Estimating a moving average of volatility using a GARCH-type method is common practice, but realized volatility might actually be a better choice for certain asset classes. Therefore, a researcher should consider the unique characteristics of the particular asset class being investigated.

In the Application component a study will be conceived for using research methods to establish hedging and pricing performance in financial markets. This section will synthesize the knowledge obtained from the Breadth, Depth, and the research findings on research design in the context of hedging and pricing financial assets. Further commentary will be presented on implementing different research designs to establish hedging and pricing performance for financial markets. Recommendations will be put forward that model a possible research design framework for establishing hedging and pricing performance of financial assets.

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