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Pricing efficiency and market success of the BFP futures and options

Heidi Funk

To the Graduate Council:

I am submitting herewith a thesis written by Heidi Funk entitled "Pricing efficiency and market success of the BFP futures and options." I have examined the final electronic copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Science, with a major in Agricultural Economics.

Edward C. Jaenicke, Major Professor

We have read this thesis and recommend its acceptance:

Accepted for the Council:
Carolyn R. Hodges

Vice Provost and Dean of the Graduate School

(Original signatures are on file with official student records.)

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Interim Vice Provost and
Dean of The Graduate School

Pricing Efficiency and Market Success of the BFP Futures and Options

A Thesis
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Heidi Funk
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ABSTRACT

During the past decade, the United States dairy industry has begun a significant restructuring toward a market-driven system. This shift brings greater milk price volatility and risk to the cash market. The recent development of dairy futures and options markets on the Chicago Mercantile Exchange (CME) could prove to be an important source of price discovery and risk management for this industry in transition. This study examines the efficiency of the CME basic formula price (BFP) futures and options markets as well as the usefulness of various option pricing models in pricing these fluid milk contracts.

Several characteristics of the maturing CME BFP futures market are examined according to Black's (1986) criteria for a successful market. These characteristics include: trading volume and open interest, spot price forecasting ability, and residual risk. These characteristics together do not point conclusively to long-term market failure or indicate any market inefficiency. Rather, the characteristics indicate the potential for CME BFP futures market success.

Three alternative option pricing models are compared in this study: 1) the traditional Black model with historical 30-day volatilities; 2) the GARCH option pricing model with trading volume; and 3) the GARCH-in-mean option pricing model with trading volume. These models are compared to their performance in pricing BFP options in contrast to actual market premiums. Six option contracts are analyzed, including both in-the-money and out-of-the-money put and call options for January, April, and July 1999. The GARCH models lead to two approximations of predicted conditional volatility used in an option pricing formula. Using root mean square error as a comparison criterion, the Black model outperformed both GARCH models and their approximations in pricing most options. All models generally priced calls more accurately than puts. All models also priced out-of-the-money options more accurately than in-the-money options.

The results indicate that the BFP futures and options markets are efficient and effective risk management tools for dairy producers. The results also indicate that the traditional Black option pricing model may price a maturing market more accurately than GARCH models or their variants. Mispricing of in-the-money options is a consistent result of all models and may be related to the unique characteristics of a maturing market.

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CHAPTER I

INTRODUCTION AND OBJECTIVES

During the past decade, the United States dairy industry has begun a significant restructuring from governmental reliance through price supports and surplus purchases to a market-driven system. This shift brings greater milk price volatility and risk to the cash market. The recent introduction of dairy futures and options markets on the Chicago Mercantile Exchange (CME) and other exchanges could prove to be an important source of price discovery and risk management for this industry in transition. To educate dairy producers about the potential benefits of fluid milk options to manage price risk, the USDA introduced the Dairy Options Pilot Program (DOPP) in 1999. Established under the 1996 Farm Bill, DOPP allows participating dairy producers to buy a government-subsidized put option as a protective hedge against price risk in the cash market. However, to serve as an effective hedge, the market must be efficient in its price-forecasting ability. Thus the utility of this dairy program as a price risk management tool depends on the pricing accuracy and forecasting performance of the market. This study will examine (1) the successfulness and efficiency of the CME basic formula price (BFP) futures and options markets and (2) the usefulness of various option pricing models in pricing these fluid milk contracts.

BACKGROUND IN MILK PRICING AND POLICY

The 1996 Farm Bill has reformed the dairy industry into a more market-oriented industry. The bill intended to phase-out the dairy pricing support program by the beginning of 2000, but supports have recently been extended to December 31, 2000. The bill also called for a restructuring of the federal milk marketing orders, which affect the current pricing system. Administered by the Secretary of Agriculture, federal milk marketing orders are voluntary agreements initiated by producers in a specific geographic region and serve to establish class pricing and therefore influence the flow and production of milk within the region. Federal milk marketing orders have been consolidated from the 31 order areas into 11 federal orders.

The dairy pricing system has changed from one based on the BFP to a class pricing system. As specified under federal milk marketing orders, the BFP was the minimum price that regulated plants had to pay producers for milk used in manufacturing. The new pricing system, implemented February 1, 1999, uses Class III and Class IV manufactured milk prices to price Class I, drinking milk, and Class II, soft dairy products. The price differentials, added to the lower of the Class III or IV release price, are assigned under the federal marketing orders. Due to a change in release price timing, this new system has the advantage of reducing the lag time between the release of Class I prices relative to manufactured dairy product prices.

The new pricing system provides a greater financial reward than the more inequitable BFP pricing system to those producers whose milk is rich in protein. Over time, this incentive should benefit consumers by increasing the production of higher protein milk. Through the use of simulated prices, the Class III and IV prices appear to track the BFP within a few cents per cwt. The new pricing system does not mark a significant departure from the past pricing system as the dairy industry moves into the competitive market sector.

With the eventual elimination of government price supports and purchases, the dairy industry expects a continuation of the decade-long trend of more variable milk prices (Fortenbery, Cropp, and Zapata 1997). This increased variability led to the development of dairy futures, designed to help reduce the risk in changing milk prices and the greater variability in prices occurring in a competitive market industry. Dairy futures trading began in 1993 with the introduction of cheddar cheese and non-fat dry milk futures on the New York Board of Trade (NYBOT). Currently, dairy futures trading also includes butter and fluid milk as well as cheddar cheese and non-fat dry milk at the CME. Fluid milk futures and options began trading in 1995 at the NYBOT and in 1996 at the CME. The fluid milk contracts have the largest trading volume of any of the dairy contracts. Dairy futures and options at the CME have had significantly greater trading volume and open interest than the dairy contracts traded at the NYBOT. This lack of trader participation has led the NYBOT exchange to announce its discontinuance of all dairy futures listings as of December 2000.

Fluid milk put options provide producers with the right, but not the obligation, to sell a futures contract at a specified strike price, while call options provide the right to buy a futures contract at a specified strike price. Dairy producers are mainly interested in buying put options to hedge against decreasing milk prices. Dairy food processors, manufacturers, and retailers buy call options to hedge against increasing milk prices. As part of the 1996 Farm Bill, the Federal Agricultural Improvement and Reform Act authorized the operation of option pilot programs. Administered by USDA's Risk Management Agency, DOPP is the first options pilot program under this act. It is designed to help producers learn price risk management in the transition to an industry without governmental market intervention.

For producers who market at least 100,000 lbs of milk annually, DOPP offers them experience in options trading for a six-to-eight month period. The pilot program is run in selected counties for each phase of the program with a maximum of 100 counties participating in the three years of the program operation.[1] The Risk Management Agency pays 80 percent of the option premium and up to 30 dollars of brokerage fees per round trade. The producer is responsible for the other 20 percent of the option premium. The put option must be placed out-of-the-money, i.e., where the put's exercise price is below the future's price. The first round of the program began in January of 1999, and is continuing its expansion in 2000.

Besides serving to educate producers in the use of options for price risk management, DOPP was also established to examine the utility of the new fluid milk futures and options contracts as price risk hedging tools (Connor 1998). The usefulness of a market to manage price risk, however depends on its efficiency and price forecasting ability.

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[1] As of January 2000, producers in one Tennessee county, McMinn County, are eligible to participate in DOPP.

When examining pricing efficiency in an immature market such as the BFP (now Class III) fluid milk futures and options markets, there exist additional considerations in contrast to the study of a well-established, mature market. The efficiency of immature markets is often questioned, in part, due to the number of uninformed traders, low trading volume and open interest, and insufficient liquidity that are more prevalent in the beginning years of a market. In addition, an emerging market does not have the advantage of a long time series of data, with which to chart market trends and seasonal patterns. Contract length and number of delivery months may change with the growth of the market. Market disturbances may reflect an initial adjustment that will not occur in subsequent periods. Despite these considerations, the efficiency of an immature market can be an indicator of the potential long-term success or shortcomings of the market.

There exists an extensive body of literature on market efficiency theory and its applications to futures markets. An efficient market incorporates all available information into market price. Efficiency research grew in magnitude in the 1970s with Fama's (1970) seminal work and is still an active research area. However, there are very few published studies investigating the efficiency of the new dairy futures markets. Over the same general time frame that market efficiency theory and research were developed, and applied, derivative pricing models were also proposed and applied to these markets. Traditional option pricing models, such as Black-Scholes (1972) and Black (1976), have been developed, tested, and more recently compared to the results of newer pricing models, such as the generalized autoregressive conditional heteroskedastic (GARCH) model, developed by Bollerslev (1986), and GARCH variants, which reflect the distribution of futures price changes more accurately than the traditional models.

The efficiency and effectiveness of a market is an important issue facing all participants. The long term success and usefulness to participants depends on the market's efficiency. In the BFP futures and options markets, these participants include milk producers, milk processors, dairy product manufacturers, and retailers. By examining pricing efficiency, this study will help determine whether the BFP futures and options markets are useful to these participants as both a risk management and price discovery tool. More specifically, examining market efficiency will benefit DOPP producer participants and policymakers by giving them a clearer picture of the market. This research will also benefit policymakers by identifying unique market characteristics that may prove important in any evaluation and modification of the DOPP program.

OBJECTIVES

This research has two main objectives. The first objective is to investigate the characteristics of the BFP futures and options markets from their inception to ascertain whether the markets have the potential for "success" as defined by previous analysts (e.g., Black 1986). Various determinants of a successful market include substantial trading volume and open interest, sufficient price volatility in the cash market, and a large pool of potential hedgers and speculators. Econometric tests include examining forecasting ability and residual risk in the BFP futures market and its cross-hedge markets. Residual risk is the price risk to which a hedger is exposed as compared to the lack of risk in a perfect hedge. Regarding this first research objective, the working hypothesis is that estimated indicators will reveal that the BFP futures market has the potential to be "successful," even if a few indicators and test results suggest otherwise.

The second objective of the thesis is to assess the usefulness of various option pricing models in forecasting BFP option prices. These models include the Black model (a variant of the traditional Black-Scholes option-pricing model) and the GARCH model. The Black model is criticized for assuming futures price changes are i.d.d. normal. Excess kurtosis and time-varying volatility, two characteristics that violate this assumption, have been found in the behavior of futures price changes (Kang and Brorsen 1995, Najand and Yung 1991). The GARCH model corrects for the criticisms of the Black model by allowing for kurtosis and time-varying volatility in changes in the underlying futures price. In GARCH models, the future's price conditional volatility is a function of the past squared errors of futures price changes and their return distributions. The GARCH model can also be extended to accommodate additional factors, such as trading volume or bid-ask spreads, that might affect trading volatility. Forecasts from both the Black model and GARCH model variants will be compared to actual market premiums for BFP option contracts to determine their accuracy in pricing these contracts. Regarding this second objective, the working hypothesis is that variants of the GARCH model, particularly those that account for trading volume, will have greater predictive capabilities than the traditional Black model because they use more information to estimate market volatility, a key determinant of option premiums. Alternatively, if immature markets are characterized by misleading or inaccurate information, then the additional information, utilized by the GARCH models could be detrimental to their predictive performance.

In general, the results of both objectives will provide insight into whether the immature BFP market can be used as an efficient and effective risk management tool. Moreover, the results can also help evaluate the utility of DOPP in encouraging producers to hedge their price risk through the market. The results of the first objective, discussed in detail later in this thesis, indicate potential for market success and do not conclude inefficiency. These results support the use of the market by producers for hedging their risk through participation in DOPP or private trading. The results of the second objective, also discussed in detail later, generally support arguments in favor of pricing efficiency. The option pricing models generally yield low root mean square errors when compared with actual option market premiums. One surprising result is that the traditional Black model compares favorably to the GARCH model in its predictive ability.

The study is organized into five chapters. Chapter II contains the literature review of research pertaining to market efficiency, the dairy futures market, and option pricing models and applications. Chapter III details the sample data and methodology applied in the study including description of econometric tests and option pricing models used. Chapter IV presents the results of the models and analysis of the BFP futures and options markets. Finally, Chapter V summarizes the conclusions concerning market efficiency and applicability of option pricing models, and discusses possible further research.

CHAPTER II

LITERATURE REVIEW

Several areas of research, including those investigating market efficiency in general, the dairy market in particular, developing markets, and option pricing models, are relevant to this research. Each of these areas is addressed in turn.

REVIEW OF MARKET EFFICIENCY RESEARCH

The role of the market is resource allocation, in which firms and investors participate under the assumption that prices accurately signal the value of those resources. An inefficient market does not accurately value its resources. Market inefficiency results in misinformed prices and alters the value of transactions.

Fama (1970) defined an efficient market as one in which prices always reflect all available information. He devised three tests – weak, semi-strong, and strong -- of market efficiency involving separate information sets. These tests are applied to futures markets. The weak form test of efficiency concerns whether past price data predicts future returns. In a weak efficient market, historical prices cannot be used to forecast future prices, since all market information is incorporated into the current futures price. The semi-strong and strong tests both involve how information is incorporated into the futures price. The semi-strong test concerns whether all public information is included in the formation of the current market price. The strong test is similar, but it involves the influence of private information in the market.

Kofi (1973) developed a framework to assess the efficiency of futures markets. He examined the relationship between the spot and futures price of different commodity contracts and of the same contract at different time periods. Optimal inventory allocation and forward pricing efficiency, he concluded, are functions of three variables: (1) the nature of the commodity, including the degree of uncertainty in annual production variations, and supply and demand elasticities; (2) the quality of information about past and future economic conditions for a particular commodity, and how easily this information can be used to predict future supply and demand; and (3) the nature and extent of government intervention influencing the competitive market price. Commodities with greater certainty in production and stability in inventories, readily available information, and little governmental intervention have efficient futures markets due to the futures price being closely tied to the future spot price. These commodities included corn, soybeans, and wheat futures.

Fama (1991) conducted a follow-up survey of market efficiency theory and testing. He cited Jensen's (1978) definition of an efficient market as a market where prices reflect information to the level where the marginal benefits of acting on information are not greater than the marginal costs. This definition departs from Fama's (1970) earlier definition of market efficiency in recognizing that every market has trading and information costs. The disadvantage of this definition, as well as earlier ones, is that market efficiency cannot be tested alone, but jointly with the application of some asset-pricing model. Tests for market efficiency, therefore, have been revised to include tests for return predictability, tests of how information events are incorporated in price, and tests for private information.

Many researchers have conducted empirical efficiency studies specific to commodity markets. Kaminsky and Kumar (1990) examined excess returns in seven commodities futures markets to determine whether futures markets could be regarded as efficient. Based on long-term forecasting ability -- i.e., six– to nine-month horizons, they found the majority of futures markets studied were inefficient. In contrast, their results indicated that market efficiency was present during short-term horizons without examining the risk premium component of futures price. When one separates the risk premium component from the futures price, the remaining component should be a predictor of the future spot price.

It is this price forecasting ability that reflects the market's agility at incorporating information and defines an efficient market. Kenyon (1993) tested the price forecasting performance of corn and soybean futures contracts by examining whether changes in the grain market since 1971 (a year that reflects the introduction of floating exchange rates, wide fluctuations in crop yields and exports, and a new emphasis on market-oriented government programs) affected the ability of the futures market to forecast accurate harvest prices. Kenyon found that pre-1973 spring futures provided reasonable estimates of harvest prices, but that post-1973 spring futures were poor predictors of harvest prices. Kenyon concluded that there exists a weak relationship between futures prices and the future spot price for those particular commodity markets.

Crowder and Hamed (1993) performed a test for weak form efficiency of the oil futures market. They compared two hypotheses: (1) the arbitrage equilibrium hypothesis, which states that the expected return to speculation in the market should equal the risk-free rate of return, and (2) the simple efficiency hypothesis, which states that the futures price should be the unbiased predictor of the future spot price, and any evidence of a risk premium implies market inefficiency. They found that the oil futures market was efficient, based on the simple efficiency hypothesis, with zero return to speculation and the nonexistence of a risk premium. The arbitrage equilibrium hypothesis did noy apply because of the lack of a market risk premium. As defined by the simple efficiency hypothesis, it is this price relationship between futures price and future spot price that underlies the hedging role of futures markets.

Futures markets serve the dual purposes of facilitating price discovery for speculators and risk management for hedgers. Therefore, an efficient futures market should serve as a price leader to the cash market. When market information is not incorporated into the futures price, an inefficient futures market exists from which abnormal profits can be extracted. Garcia et al. (1988) evaluated the pricing efficiency of the live cattle futures market. They compared price forecasts from the futures market to those from several econometric models, using mean square error as the basis for comparison. In all instances they found that at least one of the models forecasted prices more accurately than the futures market. Garcia et al. cautioned that this result does not necessarily indicate market inefficiency because the model forecasts had large risk-return ratios, which were not evident in the futures market.

Leuthold, et al. (1989) examined the informational efficiency of the hog futures market by developing market models that incorporated all public information and by comparing the performance of those models to the behavior of the actual futures market. They found that at least one of the models consistently forecasted more accurately than the futures forecast, a necessary condition for rejecting market efficiency. Leuthold et al. then tested the sufficient condition for market inefficiency, whether the forecast methods generated risk-adjusted profits that exceed the costs of participating in the market. Using simulated market trading strategies, excessive risk-adjusted profits were found to exist. Therefore, the authors concluded that informational inefficiencies were present in the live hog futures market.

Kellard et al. (1999) used cointegration analysis to examine the relative efficiency of commodity futures markets. Their efficiency measure was derived from the ability of the futures price to forecast the future spot price compared to the forecast produced by the "best-fitting" quasi-error correction model. They examined six different commodity futures markets (corn, soybeans, wheat, sugar, live cattle, and feeder cattle) and found that in the long run an equilibrium condition existed and that the markets were efficient. However, in the short-run they found evidence of inefficiencies. They found that several markets had greater degrees of inefficiency than those of other markets. Futures markets with greater degrees of inefficiency carry greater costs to their market participants. Therefore, the authors concluded that knowing the degree of inefficiency within a market is more informative than efficiency tests alone.

REVIEW OF DAIRY MARKETS RESEARCH

The 1996 Farm Bill has reformed the dairy industry into a more market-oriented industry. The bill called for a restructuring of the federal milk marketing orders, which affect the current pricing system. Federal milk marketing orders are voluntary agreements initiated by producers in a specific geographic region and serve to establish class pricing and therefore influence the flow and production of milk within the region. Federal milk marketing orders have been consolidated from the 31 order areas into 11 federal orders. The dairy pricing system has also changed from one based on the BFP to a class pricing system. As specified under federal milk marketing orders, the BFP was the minimum price that regulated plants had to pay producers for milk used in manufacturing. Under the new pricing system, the federal orders specify a Class III or IV base price as the minimum price paid to producers for milk used in two types of manufactured milk products. The Class I, drinking milk, and Class II, soft dairy products, prices are in turn calculated by adding specified differentials to the lower of the Class III or IV base price.

With the eventual elimination of government price supports and purchases, the dairy industry expects a continuation of the decade-long trend of more variable milk prices (Fortenbery, Cropp, and Zapata, 1997). This increased variability led to the development of dairy futures, designed to help reduce the risk in changing milk prices and the greater variability in prices occurring in a competitive market industry.

Because the introduction of dairy futures and options trading is relatively recent, research in dairy financial futures is not as extensive as in other futures markets. Cheese futures trading began in 1993, followed by BFP fluid milk futures trading in 1995 at the NYBOT. BFP fluid milk futures were later added to the CME in 1996 and were followed by the addition of butter and nonfat dry milk trading to the CME.

Fortenbery and Zapata (1997) examined the price linkages between futures and cash markets for cheddar cheese. They examined to what extent futures markets are price leaders to cash markets, and the degree to which futures and cash markets are valuing the same new market information. For futures markets to be efficient, there must be a strong relationship between the futures price at contract expiration and the cash price for delivery at the same period. Fortenbery and Zapata used cointegration analysis to examine the price relationship between the cheese cash and futures markets and found no linkage between futures market and cash market price discovery or cash market and futures price discovery. Fortenbery and Zapata, therefore, concluded that cash and futures cheese markets display independence in pricing new market information. They reasoned that the degree of market infancy or the low volume traded in the futures market might account for their results. They suggested that until a strong relationship between the cash and futures markets appears, the cheese futures market might be an inefficient pricing mechanism.

Thraen (1999) conducted a follow-up study by re-examining the relationship between cheddar cheese cash and futures prices. Specifically, Thraen examined whether an equilibrium relationship had been established between cash and futures prices since Fortenbery and Zapata's study. Thraen used cointegration analysis with data from a longer time period and found that an equilibrium relationship among the futures and spot cheese markets did exist. This finding indicated that there was an information flow between the two markets. Therefore, the futures market could be used for price discovery and for risk management.

Understanding the relationship between the cash and futures prices is important in developing a hedging program for risk management. This relationship can be used to forecast cash/futures basis levels. Basis is the difference between the cash price at a specified location and the futures price for a particular delivery period. Accurate forecasts of basis levels are necessary for the use of fluid milk futures as a hedging tool. Fortenbery, Cropp, and Zapata (1997) conducted an analysis of the expected price relationships between fluid milk futures and fluid milk cash prices. The authors compared historical cash prices from 1988 to 1995 and simulated futures prices over that period. Their results suggested a possible strong relationship between the futures market and fluid milk prices in the cash markets. More importantly, their results indicated that the fluid milk futures could be used as a risk management tool under some federal milk marketing orders.

Wolf and Berwald (1999) also examined the potential of BFP milk futures contracts as risk management tools. They examined 1997 and 1998 BFP futures contracts trading on the NYBOT. The authors proposed three criteria for whether a futures contract will fail as a risk management tool: (1) if producers do not use the contract for hedging, (2) if producers use the contract for hedging but it does not offset their risk, or (3) if the futures contract is not an efficient mechanism of price discovery. To investigate criteria (1), Wolf and Berwald examined trading volume and open interest of all BFP futures contracts and found that the markets were small and illiquid. For criteria (2), they conducted a regression measuring residual risk in the BFP futures market versus cross-hedging in the cheese futures market. They found the BFP futures market to be more useful in reducing price risk than cross-hedging in the cheese market. To address criteria (3), Wolf and Berwald used a Dickey-Fuller unit root test, and found that returns for BFP futures were not predictable using past returns, thus indicating weak-form efficiency. The BFP futures contract, overall, was found to be a potentially successful risk management tool. However, the low open interest and trading volume on the NYBOT indicated a thin, illiquid market, in which hedging may not become viable. The authors reasoned that the competition from the CME dairy futures contracts was taking trading volume away from the NYBOT dairy futures contracts, and therefore, the CME was replacing the NYBOT as the exchange for dairy futures trading. Their reasoning proved correct as the NYBOT announced the discontinuance of dairy futures trading as of December 31, 2000, due to lack of participation.

DEVELOPING MARKETS

There are unique issues and challenges associated with studying an immature or developing market. These markets are typically characterized by low trading volume, illiquidity, and uninformed or misinformed participants. Black (1986) developed a set of criteria for examining the potential "success" of new futures contracts. This "success," which was found to be linked to a number of commodity and contract characteristics, translates into market efficiency. *Commodity* characteristics relating to futures success included: (1) storability, (2) homogeneity, (3) volatile cash price, (4) large number of participants in cash market, (5) unrestricted supply, and (6) breakdown of forward contracting. *Contract* characteristics that related to futures success included: (1) ability to attract hedgers, (2) ability to attract speculators, and (3) ability to prevent manipulation. Black tested these characteristics by examining the level of trading volume and open interest, residual risk of cross-hedging compared to own-hedging, and spot price forecasting ability of the contract before maturity.

As described above, Wolf and Berwald (1999) applied these criteria to their examination of the NYBOT BFP futures market and found that the BFP futures were an efficient price forecaster, but not, however, a viable hedge because of the market's thin trading volume and illiquidity.

To examine informational efficiency effects in a developing market, Kamara (1990) conducted an empirical study of the developing Treasury bill futures market. He argued that in a developing market there is increased risk sharing because of many uninformed traders, a characteristic that reduces the overall risk premia. But due to the number of uninformed traders, Kamara argued, there is also a greater tendency for misinformation effects in the market. His results demonstrated that the relative forecasting accuracy of the Treasury bill futures market did improve over the years the market matured. Kamara found a relationship between the improvement of the futures price forecasting accuracy and the increased liquidity of the market. He concluded that in an immature market, misinformation effects are higher relative to risk premia, while in a mature market, risk premia dominate misinformation effects.

REVIEW OF OPTION PRICING MODELS AND APPLICATIONS

The Black-Scholes (1972) and Black (1976) models have served as the traditional option-pricing models.[1] Black formed a model where the expected return on a perfectly hedged position in options must equal the risk-free rate of return on another financial asset. The valuation of the option is a function of its strike price, the underlying futures price and its volatility, and the time to maturity (Black). This relationship is modeled as a partial differential equation in which the equilibrium option price must equal the risk-free rate when the option is balanced with a continuously changing perfect hedge.

The Black model has been widely applied toward commodity markets. Its use, however, requires the assumption that it represents the correct option valuation model. Hauser and Liu (1992) conducted riskless hedging simulations to evaluate the performance of Black's option-pricing model, and to test the efficiency of the cattle options market. The efficiency test was based on the presence of arbitrage opportunities in the market. Although they found that profits could be earned by identifying mispriced options, there were no consistent arbitrage opportunities found using the forecast variations of Black's model. Thus inefficiency was not indicated in the live cattle futures market.

Wilson, Fung, and Hicks (1988) used Black's option-pricing model to examine option price behavior in the grain futures markets. Their study tested the influences on

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[1]Black and Black-Scholes models are quite similar, with the main difference being that Black focuses on American options instead of European options. American options can be exercised at any time from purchase to maturity. European options can only be exercised at maturity.

American actual premiums versus option premiums derived from Black's model based on European style options. American options can be exercised prior to the futures maturity or delivery month, while European options lack this early exercise privilege. They compared actual premiums from corn, soybean, and wheat futures markets to those premiums derived from the Black model. The actual premiums were found to differ significantly from the derived Black premiums. They found that actual premiums decreased relative to Black premiums as options moved into-the-money, and also when market volatility increased. Actual premiums increased relative to Black premiums as the option moved out-of-the-money, and also when time to maturity of the option lengthened.

Others have tested the Black model in relation to other option valuation techniques. Myers and Hanson (1993) studied commodity option pricing in the potential presence of excess kurtosis and time-varying volatility, two conditions that violate the underlying assumptions in the Black model. They applied the generalized autoregressive conditional heteroskedastic (GARCH) model to this option-pricing problem. Really a family of models, GARCH does not assume that proportional changes in the natural log of the underlying futures price are normally distributed, an assumption required in Black's model. Myers and Hanson tested the GARCH option-pricing model by pricing options for soybean futures and found that the GARCH model prices more accurately than the traditional Black model.

Kang and Brorsen (1995) applied Myers and Hanson's study to wheat futures and compared Black's model to several GARCH models. They found that differences between Black's model and the GARCH models increased as time to maturity increased. They also found that GARCH priced wheat options more accurately than Black's model for deep in-the-money options and deep out-of-the-money options.

A significant criticism of Black's model is that it assumes a normal distribution of the underlying logged futures price. There is contradicting evidence that changes in logged futures prices are not normally distributed. Najand and Yung (1991) found this result in examining the distributional properties of Treasury bond futures. Bakshi, Cao, and Chen (1997) reasoned that the Black lognormal distribution created pricing biases, underpricing deep out-of-the money options and overpricing deep in-the-money options. Hull and White (1987) explained that this bias also lowers implied volatility as time to maturity increases. As a result, this bias has come to be known as the volatility "smile."

A further criticism of Black's model is that it does not account for past market disturbances' impact on current volatility. For nine different commodities contracts, Anderson (1985) found that futures price volatility changes as the market moves through seasonal cycles, and also as time to maturity changes and participants are faced with uncertainty concerning the future economic situation. This would seem to be especially true for emerging markets where new traders deal with great uncertainty due to both lack of information and market illiquidity. Thus, past market volatility shocks should be incorporated into estimating current volatility.

The GARCH model, a time series model, corrects for some of the Black's model criticisms. Bollerslev (1986) composed the GARCH model, which allows the conditional variance to be a function of past conditional variances, and also allows for the presence of kurtosis in the return distribution. The GARCH model is composed of two equations: The first typically explains the mean return (in log form) as a function of a constant and an error term. The second equation typically explains conditional volatility as a function of a constant, past error terms from the mean equation, and past estimates of conditional volatility. The two equations are, therefore, linked by the error term in the mean equation. GARCH has been applied to the pricing of many financial assets because it is capable of imitating the volatility and variability found in these markets, where past price disturbances often influence current price fluctuations.

For wheat futures, Myers (1991) used a GARCH model to estimate optimal hedge ratios, the proportion of a cash position that should be covered with an opposite position in the futures market. He compared the performance of a constant conditional covariance model to the GARCH model and found that GARCH outperformed the constant conditional covariance model in hedging results. Myers concluded that GARCH was a better estimator of the optimal futures hedge than a constant conditional covariance model because it allowed for time-varying market volatility over time.

Park and Switzer (1995) estimated the optimal hedge ratios for stock index futures in a GARCH framework. They explained that recent studies have found that the application of a time-series conditional variance model improves the hedging performance in various futures contracts. However, their study was unique in considering transaction costs in their GARCH hedging method. They compared the GARCH hedging model to three other models: a naive hedging model where the hedge ratio was always one, an ordinary least squares (OLS) model, and an OLS model with cointegration between spot and futures. They found a noticeable improvement in hedging effectiveness through the GARCH model as compared to the other models even after accounting for transaction costs.

One particular variant of the standard GARCH model, the GARCH-in-mean model, may prove to be particularly useful in investigating option pricing in an emerging market. The GARCH-in-mean model allows for an explicit relationship between the risk and expected return on the asset (Engle, Lilien, and Robins, 1987). The model places the conditional variance in the mean return equation, thereby directly affecting the logged change in the futures price. This relationship between trading volume and price volatility has been increasingly well-studied. Particularly in an emerging market characterized by low trading volume, this pricing relationship can impact option price variance. Admati and Pfleiderer (1988) studied intra-day trading patterns to compose an explanation of the volume/variance relationship. They concluded that trading is clustered because both informed and amateur traders prefer to trade when volume is high. The high trading volume helps the market incorporate new information quickly into prices resulting in greater price variance.

Trading volume can be also added as a variable in the conditional variance equation of the GARCH model. Lamoureux and Lastrapes (1990) added volume into the conditional variance equation in their study of whether the GARCH effects found in derivative return data reflected the persistence of volatility shocks or simply the arrival rate of information. They used trading volume as a proxy for information flow to the market. They found that trading volume yielded a positive, significant relationship to conditional volatility and that the GARCH effects diminished. Therefore, Lamoureux and Lastrapes concluded that GARCH effects in return data relate to the rate of information arrival to the market.

Najand and Young (1991) used a GARCH model to examine the relationship between volume and price variability in the Treasury bond futures market. The authors found GARCH to be a more applicable model than other standard statistical models because it recognizes long-term memory in the variance of conditional return distributions. They cautioned that most standard models, such as Black's, tend to assume nearly continuous and log normally distributed price changes of financial assets. The authors concluded that GARCH sufficiently reflected the actual Treasury bond futures price movements.

Jacobs and Onochie (1998) extended Najand and Yung's examination of the relationship between volume and price variability in the Treasury bond futures market. The authors applied a bivariate GARCH-in-mean model, which allows for a positive or negative sign on the conditional variance and also provides a way to estimate the risk premium by placing the conditional variance in the mean return equation. Through the use of this model they found a positive, time-varying relationship existed between volume and price changes. They concluded that the bivariate GARCH model captured all the time-series effects satisfactory.

SUMMARY

Extending for more than three decades, there exists a substantial body of research on market efficiency. Fama's (1970) definitions and tests of efficiency serve as the foundation for efficiency studies specific to commodity markets. His definition of an efficient market will be the basis for this study. The research regarding developing markets is not as extensive as efficiency studies. One reason for this could possibly be the unique characteristics of immature markets, which may be difficult to incorporate into modeling and which may not persist as the market develops. Black's (1986) characteristics of potential futures market success will be applied in this thesis.

Dairy futures research is limited due to the recent development of the markets in the mid-1990s. This research will follow some of the similar tests of judging potential market success as Wolf and Berwald (1999) applied to the NYBOT BFP futures.

Option pricing models have been developed and advanced as derivatives have become an increasingly important financial tool. Both Black and GARCH models have been successfully applied to pricing commodity futures. These two option pricing models will be used in pricing CME BFP options.

CHAPTER III

DATA AND METHODOLOGY

DATA DESCRIPTION

Trading data are available for BFP fluid milk futures and options contracts from the CME and range from the creation of the market in January 1996 through January 2000. The data include opening, closing, and settlement prices, trading volume, contract year, delivery month, and trading date for futures and options contracts, as well as a call/put distinction, and open interest for option contracts. Contract size is 200,000 lbs of Grade A fluid milk. Starting in 1998, contracts trade for each calendar month and begin trading twelve months prior to maturity. Contracts are cash settled according to the USDA BFP monthly release price.

Futures prices are quoted in dollars per hundredweight (cwt.). This number is multiplied by 2,000 to get total contract cost. The minimum price tick or fluctuation is $.01 per cwt., which equals $20.00 per contract. For options, strike prices are quoted in intervals of $.25 and have the same minimum price fluctuation. Trading volume is quoted in number of contracts. Data for comparing cross-hedge efficiency include prices for NYBOT BFP fluid milk futures and options contracts with the same specifications as the CME contracts.

Figures 1-3 show January, April, and July 1999 BFP milk futures closing price and trading volume activity for the six months preceding contract maturity. All figures and tables are located in the appendix. For January and July contracts, the futures price generally increases toward contract maturity. Decay of the time premium as time to maturity decreases may exert downward pressure on the futures price. For the April futures contract, the futures price decreases as it approaches maturity. The increasing or decreasing trend of the futures price approaching contract maturity is dependent on market conditions. In Figures 1-3, trading volume is sporadic. There are several days of high trading volume intermittent with many days of low trading volume. In the figures, a relationship between trading volume and closing price emerges, as large changes in trading volume are matched with shifts in the market.

Figures 4-6 show January, April, and July 1999 BFP options premiums price and trading volume activity for the two months preceding contract maturity. Option premiums are highly volatile for these contracts. For all of these contracts, the option premiums generally decline in value as they approach futures maturity and the decline is particularly evident for July 1999 options. This is the normal pattern as the time premium decreases. As with the futures contracts, trading volume is sporadic. There are spikes of relatively high trading volume interspersed with many days of low or zero trading volume. As in the futures price and volume figures, an option premium/trading volume relationship is apparent, as substantial changes in trading volume are matched with shifts in option premium price.

METHODS 1: ANALYSIS OF POTENTIAL MARKET SUCCESS

Methods for testing the potential "success" of the BFP futures and options market include regressing futures prices on BFP spot prices to measure futures forecasting ability and regressing cash price changes on futures price changes to find residual risk. This residual risk regression will be applied to both CME and NYBOT BFP futures prices and the CME butter futures prices to compare the risk between similar contracts. If residual risk is greater in the NYBOT BFP or CME butter futures market than the CME BFP futures market, hedgers will prefer the less risky CME contract. Two highly visible indicators of market "success" are the level of trading volume and open interest. These two indicators will be examined for the short history of the BFP market.

In examining the price forecasting ability of the BFP futures market, the following regression is used:

(1) $$BFP\ spot\ price_t = \beta_0 + \beta_1 * BFP\ futures\ price_{t-i} + \varepsilon_t$$

where t is the time at maturity and i is the month ahead futures price of the contract at maturity t, and ε_t is assumed to be distributed normally. The futures price is regressed on the spot price using monthly intervals of data to measure how accurately the futures price can predict the spot price one month, two months, and so on, up to five months from futures contract maturity. At contract maturity, the futures contract is settled with the released BFP or spot price. If the regressions yield a high R-squared it indicates that the futures market is a good forecaster of future spot price. The further away from contract maturity that the market can forecast spot prices the better the market functions as a price discovery tool for both hedgers and speculators.

The following price forecasting regression will also be applied to the BFP spot and futures markets:

(2) $$BFP\ spot\ price_t = \beta_0 + \beta_1 * BFP\ futures\ price_{t-i} + \beta_2 * BFP\ spot\ price_{t-1} + \varepsilon_t.$$

The futures price and one-month lagged BFP spot price is regressed on the spot price at time t using the same monthly intervals of data as in the prior regression. This regression will indicate if there is an autoregressive component in the current spot price. This would reflect the incorporation of historical cash price information into current cash prices.

Price forecasting ability is an indicator that the market is efficiently incorporating available information into futures prices to predict the correct future cash price, since the cash price reflects all the supply and demand influences of the competitive market. The price forecasting ability of an immature market may be limited due to uninformed traders or asymmetric information. Separating the data into yearly intervals allows one to investigate whether the forecasting ability is improving or lessening over time. If forecasting ability is improving over time, one could conclude that the market is maturing and has increasing potential for success.

Black (1986) suggests using the concept of residual risk to measure a contract's effectiveness in managing risk. Residual risk is the price uncertainty in using futures to hedge as compared to no uncertainty under the "perfect hedge," where the futures market exactly predicts the spot market price. Dairy producers will only hedge with BFP futures if the residual risk in the CME BFP futures is less than the risk in cross hedging in another substitute contract. Applying Black's regression equation:

(3) $R_s = \beta_0 + \beta_1 * R_f + \varepsilon$,

where R_s is the return of the asset in the spot market, R_f is the return from holding the asset in the futures market during the same length of time to contract maturity, and ε is assumed to be distributed normally. Residual risk is measured by subtracting equation

(3)'s R-squared regression statistic from one, i.e., residual risk = $1-R^2$. If this is a perfect hedge, the residual risk will be zero.

If the residual risk is higher in a hedger's own market than in a market with a close substitute, the hedger will establish a cross hedge in the other market (Black 1986). This would result in lack of hedger participation in the market. Two likely cross hedges include the CME butter and former NYBOT BFP futures markets. Therefore, residual risk in the CME BFP futures will be compared to the residual risk of the two substitute futures markets. If the residual risk is higher in the NYBOT BFP futures than the CME BFP futures, this will support the lack of participation and elimination of the NYBOT BFP futures market. If the residual risk is higher in the CME BFP futures than the CME butter futures, hedgers may choose to utilize the butter futures market for price risk protection.

Relative residual risk is a measure of the risk carried when one cross hedges rather than hedges in his own market. More specifically, relative residual risk is the cross hedge residual risk of participating in the substitute market divided by the cross hedge residual risk of participating in the hedger's own market. This measure predicts whether there is sufficient need for a newly introduced contract, which may have a close substitute market. A relative residual risk coefficient of one means that there is no difference in risk-bearing between the two comparable contracts. A relative residual risk coefficient greater than one suggests that the hedger's own market serves as a more effective contract in managing risk.

METHODS 2: ANALYSIS OF OPTION PRICING MODELS

Methods for testing the usefulness of various option price forecasting models include comparing the predictive ability of several GARCH model variants against that of the Black model. Black is the traditional option pricing model and represents the closed-form solution to an arbitrage equation assuming that logged futures price changes are i.d.d. normal. Black uses a partial differential equation to solve for the equilibrium option price. GARCH is an open-form model, which does not provide a direct option price solution. However, the model relaxes the assumptions of the Black model and allows time-varying volatility to affect the distribution of futures price changes. Moreover, estimates of conditional volatility can be recovered from the GARCH model and substituted into Black's pricing formula to provide a simple GARCH approximation. The distribution of BFP futures price changes, especially as the market develops, may not be i.i.d. normal and may be better modeled by a GARCH process. In examining the immature BFP market, the applicability of either option pricing model to the market could indicate pricing forecasting efficiency and the usefulness of the market to its participants.

Black Option Pricing Model

The Black pricing model is based on the relationship between the return of the option and its underlying futures contract and the risk-free rate of return using some benchmark such as U.S. Treasury bills. This study uses the 26-week discount rate on U.S. Treasury Bills at six months prior to maturity as the benchmark risk-free rate. By adjusting the futures position continuously, the return on the option and the futures contract can be made riskless and should equal the risk-free rate. This relationship is the foundation for Black's partial differential equation for option price. The equation is a function of the futures price, option strike price, time to maturity, implied volatility, and the risk-free rate of return. Black's equation for a put option is given as:

$$(4) \qquad P_t = -\, e^{(-r \bullet t)} \bullet [U \bullet N(-x_1) - E \bullet N(-x_2)]$$

Black's equation for a call option is given as:

$$(5) \qquad P_t = e^{(-r \bullet t)} \bullet [U \bullet N(x_1) - E \bullet N(x_2)]$$

where:

$$x_1 = [ln(U/E) + (v^2 \bullet t)/2] \,/\, (v \bullet t^5)$$

$$x_2 = [ln(U/E) - (v^2 \bullet t)/2] \,/\, (v \bullet t^5)$$

where P_t equals the put premium at time t, r equals the risk-free rate of return, v is the implied volatility, U is the underlying futures price, and E is the strike price of the option.

The Black model operates under the assumption of risk neutral investors. Therefore, the option is priced at its expected value at maturity discounted to the current time at the risk-free rate of interest (Myers 1993). This valuation results in zero cost of entering a futures contract because the potential carrying cost/holding premium is only equal to the risk-free rate. Hence, the contract is risk neutral. Also, the assumption of risk neutrality restricts the current futures price to be an unbiased predictor of the future cash price at contract maturity, otherwise, arbitrage opportunities would exist (Myers 1993). For example, if the predicted futures price was significantly higher than the cash price, one could sell in the futures market, buy in the cash market, and gain excess profit beyond the risk-free rate of return.

The Black model also assumes that logged changes in the underlying futures price are normally distributed and independent of past volatility:

(6) $\Delta f_t = \mu + \varepsilon_t \qquad \varepsilon_t \sim N(0,\sigma^2)$,

where Δf_t is the logged difference of futures price changes ($\ln F_t - \ln F_{t-1}$), μ is the constant in the mean equation and reflects the average return, and σ^2 is an unchanging one-period variance. This assumption of normality must be made so futures price change behavior is predictable. Implied volatility (σ^2) is estimated with the previous 30 days variance of price changes. This implied volatility estimate is a constant that does not depend on time or past conditional variances. This assumption of time-invariant volatility satisfies the differential equation and provides a closed solution.

The major criticism of Black's model is that futures price changes do not appear to be i.d.d. normal. Excess kurtosis and time-varying volatility have been found in the behavior of futures price changes (Kang and Brorsen 1995, Najand and Yung 1991). Excess kurtosis, which involves fatter tails than the normal curve distribution implies price changes are clustered at both extremes of low and high prices. Time-varying volatility of futures price changes suggests that a derivative security's conditional variance is a function of all its past conditional volatilities. This relationship corresponds to the widely observed fact that the market tends to stay in a state of high or low volatility. It has been suggested that market volatility tends to persist because price or information shocks to the market die out slowly over time (Bollerslev 1986).

GARCH Option Pricing Model

The GARCH model corrects for some of the criticisms of the Black model. Unlike the traditional Black model, the GARCH model can allow for kurtosis and time-varying volatility in changes in the underlying futures price. It can also be extended to accommodate additional factors, such as trading volume or bid-ask spreads, that might affect trading volatility. GARCH does not provide a closed-form solution for equilibrium option price. Option prices can be simulated or derived through approximation by replacing the implied volatility in Black's model with the conditional volatility calculated in the GARCH model.

Conditional volatility is a function of the past squared errors of logged futures price changes and their return distributions. The GARCH (1,1) model uses two equation to represent futures price changes as:

(7) $\Delta f_t = \mu + \varepsilon_t$

$\varepsilon_t \sim N(0,h_t)$

$h_t = \omega + \alpha\varepsilon^2_{t-1} + \beta h_{t-1}$

where h_t is the conditional variance of futures price changes, and $N(0,h_t)$ is the normal distribution of errors with conditional variance h_t (Bollerslev 1986).[2]

Additional variables may be added to the conditional variance equation. To account for the immaturity of the BFP market, trading volume is added to the conditional variance:

[2] The GARCH (1,1) model can be generalized to GARCH (p,q) by including p lagged ε^2_{t-1} and q lagged h_{t-1} terms. To account for the possibility of excess kurtosis, some researchers have specified that ε_t follows a

(7a) $h_t = \omega + \alpha\varepsilon^2_{t-1} + \beta h_{t-1} + \theta V_t$

where V_t represents trading volume at time t.

The GARCH-in-mean model with trading volume is another GARCH variant that will be used. GARCH-in-mean allows for an explicit relationship between risk and expected return on an asset. GARCH-in-mean places the conditional variance into the mean equation, which directly affects the estimation of the logged futures price changes (Engle, Lilien, and Robins 1987). This model allows for a positive or negative sign on the conditional variance's effect on the logged return. GARCH-in-mean models futures price changes as:

(8) $\Delta f_t = \mu + \delta h_t + \varepsilon_t$

$\varepsilon_t \sim N(0,h_t)$

$h_t = \omega + \alpha\varepsilon^2_{t-1} + \beta h_{t-1} + \theta V_t.$

Each of the GARCH models allows for heteroskedasticity in the regression residuals by taking into account the variance of all past return distributions. This ability of the model makes GARCH useful in imitating the time series return on financial assets. These assets are characterized by clustered regression residuals, which are due to large market disturbances followed by other large disturbances, and small disturbances followed by other small disturbances, with intermittent stable periods. GARCH incorporates this market characteristic into the model by allowing for conditional heteroskedasticity.

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student-t rather than a normal distribution. For the empirical estimation of BFP futures prices studied here, the student-t specification introduced convergence problems for the maximum likelihood estimation of (7).

If futures price changes are accurately modeled by GARCH, then the argument for pricing options in a risk-neutral world is flawed. Under the assumption that futures price volatilities are time-varying, one cannot have a risk-free portfolio mix of options and underlying futures contracts. This is because the time-varying or random component of volatility adds a component of risk to the portfolio that cannot be hedged against (Myers and Hanson 1993). Thus if futures price changes exhibit time-varying volatilities, GARCH will likely outperform Black's model in pricing options compared to actual market premiums. However, option pricing can still be restricted to a risk-neutral world with time-varying volatilities under the assumption that many of the agents participating in the market are, in fact, risk-neutral (Myers and Hanson). In addition, the pricing formula for a non risk-neutral world would have to account for the individual risk preferences of all the participants in a market, which is unknown and infeasible.

Since there exists no closed-from solution to GARCH, simulation or closed form approximations are most often used to estimate option prices. This study uses two closed-form approximations of GARCH based on proposals by Myers and Hanson (1993). The first approximation -- GARCH approximation I -- requires taking the one-period-ahead conditional variance, h_{t+1}, estimated using data up to time period t with GARCH. Approximation I assumes that all following price changes are distributed normally with a constant variance of h_{t+1}. This conditional variance, h_{t+1}, replaces the implied volatility, σ^2, estimated from 30-day historic volatilities in Black's model and the differential equation is then evaluated for the equilibrium option price. Formally, the estimate for h_{t+1} replaces v in equations (4) and (5). Approximation I is relatively straightforward to calculate, but has one major criticism in assuming incorrectly that future volatilities after the date of estimation will be constant up to the maturity of the option.

The second closed-form GARCH approximation – GARCH Approximation II -- involves forecasting the variance of futures price changes at option maturity based only on the price information available at the current time *t*. Myers and Hanson (1993) develop a formula that provides the basis for estimating the conditional variance of logged futures price at maturity T (f_T). Myers and Hanson's formula must be extended, however, when a trading volume variable is present in the conditional variance equation. Using the theoretical results from Rubenstein (1976) and the steps outlined in Hull (2000, p.379), one can develop the following formula to estimate the j-period ahead conditional variance at maturity T, which is labeled GARCH Approximation II:

(9) $var(f_T) =$

$$\left[(\alpha + \beta)^j \bullet \left(h_t - \frac{\omega}{1-\alpha-\beta}\right)\right] + \frac{\omega}{1-\alpha-\beta} + \frac{\theta\overline{V} \bullet \left(1-(\alpha+\beta)^{j+1}\right)}{1-\alpha-\beta}$$

where $\overline{V}$ is the trading volume mean.

If the distribution of the changes in futures prices is approximately normal with the variance given by (9), the option pricing formula that follows is:

(10) $P_t = e^{r(t-T)} \bullet$

$$\left\{F_t C \bullet \left[\frac{\ln(F_t / E) + 0.5\,\mathrm{var}(f_T)}{\sqrt{\mathrm{var}(f_T)}}\right] - EC \bullet \left[\frac{\ln(F_t / E) + 0.5\,\mathrm{var}(f_T)}{\sqrt{\mathrm{var}(f_T)}}\right]\right\}$$

where F_t is the futures price at contract maturity, C is the cumulative standard normal distribution, E is the strike price on the option. In comparison with the first approximation, this approximation directly accounts for time-varying volatility. One major drawback of this second approximation, however, is the assumption that $\overline{V}$ is a good forecaster of volume, at maturity, time T.

Option Pricing Model Evaluation

Predictions from three alternative option pricing formulas are compared in this study: (1) the traditional Black formula with historical 30-day volatilities, as specified by equations (4) and (5); (2) the Black formula with the historic volatility replaced by approximations generated by the GARCH model as specified in equations (7) and (7a); and (3) the Black model with the historic volatility replaced by approximations generated by the GARCH-in-Mean model as specified in equation (8). These three predictive formulas are compared to their performance in pricing BFP options in contrast to actual market premiums. To evaluate these three sets of formulas, and hence the GARCH and Black models, relative to each other, the associated root mean square error (RMSE) is used as the distinguishing criteria. The RMSE is calculated simply as the square root of the sum of squared errors as determined by the difference between the actual and predicted option premium, calculated over the 60-day period prior to contract maturity.

CHAPTER IV

RESULTS

This chapter presents two separate types of results, one that supports the analysis of the BFP futures market regarding its potential for success, and another that supports the analysis of the predictive ability of option pricing models in the BFP futures and options markets.

ANALYSIS OF BFP FUTURES MARKET SUCCESS CHARACTERISTICS

Black (1986) identified several characteristics of a successful futures market. The factors examined include contract trading volume and open interest, role in risk management, and price forecasting ability of the market. These factors are related to the ability of the market to attract both hedgers and speculators. Hedgers or producers use the market to minimize their cash price risk, while speculators seek profit opportunities in trading. Both groups are necessary in a well-functioning, efficient market. In this study, these tests examine the CME BFP fluid milk futures.

Trading Volume and Open Interest

Adequate trading volume and open interest is the first indicator of a successful market. A high volume of trading translates into a large number of market participants, both hedgers and speculators, and results in increased liquidity and a low bid-ask spread in the market. Black defines a market's success in terms of volume by applying *The Wall*

Street Journal's criteria for listing. Open interest must exceed 5,000 contracts daily and trading volume must be greater than 1,000 contracts daily in order to be listed. These numbers are typically reached by a contract within the first three years of its development if it is to be successful (Black 1986).

The CME BFP fluid milk futures and options contracts were developed in the beginning of 1996. The contract is not currently listed in *The Wall Street Journal*, but trading volume has grown since its inception. Table 1 shows the average daily trading volume and open interest for trading years 1996 through 1999 for BFP futures and options. For example, Table 1 shows that, in 1996, BFP futures open interest averaged over 23 contracts daily and average trading volume was 2.83 contracts daily. In the BFP options market, average open interest was just under five contracts daily and average trading volume was 0.168 contracts daily. In 1999, BFP futures average open interest grew to 401 contracts daily and average trading volume grew to approximately 16 contracts daily. In the 1999 BFP options market, average open interest was 14 contracts daily and average trading volume was approximately 0.4 contracts daily. Significant growth in trading volume has occurred through the development of the fluid milk contracts. As Table 1 shows, average futures trading volume nearly doubled from 1996 to 1997, more than tripled from 1997 to 1998, and grew by nearly 40 percent from 1998 to 1999. However, these numbers, which are not at the level of *The Wall Street Journal* listing criteria, indicate that the market is still thin and relatively illiquid.

Price Forecasting Ability

A successful and efficient market does not have predictable returns, but it does allow for price discovery (Fama 1970). It is this factor that encourages speculator participation in the market. Speculators are necessary to bear the risk offset by hedgers in the market. Price discovery is also useful to producers in predicting future cash prices and income flow. An indication of price forecasting ability is given by estimation of equation (1) using ordinary least squares.

Table 2 contains the regression coefficients and their significance levels, and the R-squared for each regression given by equation (1), for the periods 1996-1997 and 1998-1999. A high R-squared value indicates that the futures market is a good forecaster of future spot price. As Table 2 shows, 1996 and 1997 futures contracts are good price forecasters of the spot BFP price when predicting the one-month ahead price. This finding is indicated by the high R-squared of 0.8336 shown in the first row of Table 2. Contrary to the typical increasing trend of R-squared values approaching contract maturity, there is some variability in the R-squared values. The furthest forecast from maturity, five-months ahead, has an R-squared of 0.8647. Comparing the price forecasting results for the two periods, 1996-1997 and 1998-1999, yields a surprising result: The forecasting regressions for 1996-1997 contracts have higher R-squared values than the regressions for 1998-1999 contracts. The hypothesis that the price forecasting ability of an immature market may be limited due to uninformed traders or asymmetric information, therefore, is not applicable to the results found in the BFP futures contract's first two trading years. Put another way, price forecasting ability generally did not improve with the 1998 and 1999 futures contracts. Yet despite the result that the R-squared values for the 1998-1999 forecasts are generally lower than their 1996-1997 counterparts, the futures price is still a relatively good predictor of the cash price. In Table 2, the one-month ahead price forecast for the 1998-1999 contracts has an R-squared of 0.9736. The futures market still retains some forecasting ability when predicting five months ahead, as demonstrated by an R-squared of 0.7570.

Because greater price forecasting ability is an indicator that the market is behaving more efficiently in incorporating available information into prices, the results presented in Table 2 indicate that from its inception the BFP futures market has been an accurate forecaster in predicting future spot price. Therefore, these results are considered a positive indicator of potential market success.

Equation (2), which contains an autoregressive component, is also estimated over two separate time periods to investigate forecasting ability. Table 3 contains the regression coefficients and their significance levels, and the R-squared for each regression. The 1996 and 1997 futures contracts prove to be a better price forecaster when incorporating the lagged BFP price in the regression only in the four and five month estimates, further from maturity. All the monthly interval forecasts have R-squareds greater than 0.69. In Table 3, the one-month ahead forecast is the least accurate with an R-squared of 0.6947, and the five-month ahead forecast is the most accurate with an R-squared of 0.9609.

The 1998 and 1999 futures contracts prove to be a more accurate price forecaster with the inclusion of the lagged BFP price. The inclusion of the lagged BFP price parameter improves the R-squared values for all the monthly estimates with the exception of the one-month ahead forecasting regression. All the monthly interval forecasts for 1998-1999 contracts have R-squareds greater than 0.83. In Table 3, the two-month ahead forecast is the least accurate with an R-square of 0.8336, while the five-month ahead forecast is the most accurate among the 1998-1999 contracts with an R-square of 0.8647. The presence of an autoregressive component in price forecasting, which reflects the incorporation of historical cash price information into current cash prices, generally improves the forecasting accuracy, especially in the 1998-1999 contracts.

In summary, both sets of contracts, 1996-1997 and 1998-1999, accurately predict future cash price as the time to contract maturity increases. Future price forecasting ability remains strong even at five months before contract maturity. This forecasting ability of the market indicates a close relationship between the milk futures and cash markets.

Residual Risk and Risk Management

As the price forecasting ability of a contract attracts speculators to the market, the utility of the contract as a risk management tool affects hedgers' attraction to the market. Black (1986) uses the concept of residual risk to measure a contract's effectiveness in managing risk. Residual risk is the price change risk to the hedger under uncertainty as compared to no price change risk under the perfect hedge where future prices are known with certainty. Dairy producers will only hedge if the residual risk in the CME BFP futures is less than the risk in cross hedging in another substitute contract.

The residual risk is found using the R-squared value associated with the estimation of equation (3). Table 4 contains the measures of residual and relative residual risk for three comparable contracts. The cross hedge residual risk from hedging in the CME BFP futures is 0.2843. If this were a perfect hedge, the residual risk would be zero. When the NYBOT BFP contract, which has a smaller volume of BFP futures trading, is tested as a cross hedge, the residual risk is found to be 0.2961, as shown in Table 4. The CME also trades other dairy futures contracts, and one possible cross-hedge for producers is the CME butter futures contract. Table 4 shows residual risk in the CME butter futures contract is 0.1226.

Table 4 also contains the measures of relative residual risk for the three comparable contracts. The relative risk coefficient for CME BFP futures is 1.042, while the relative risk coefficient for NYBOT BFP futures is 0.9601. Because the relative residual risk coefficient is greater than one for the CME BFP futures, these contracts have a slightly lower hedging risk than the NYBOT BFP futures. However, with both of these relative residual risk coefficients being so close to one, the CME and NYBOT BFP contracts could serve as substitute contracts for hedgers. This finding could indicate that one of the markets is redundant and that only one exchange is needed in the BFP futures market. Wolf and Berwald (1999) in their study of NYBOT BFP futures efficiency indicated that the CME was gradually replacing the NYBOT for dairy futures trading.

As shown in Table 4, the relative risk coefficient for the CME butter futures is 2.319. Because it is greater than one, this result suggests that the CME butter futures have a lower hedging risk than the CME BFP futures. This could indicate that more hedgers will prefer to participate in the less risky CME butter futures as a source of price protection.

Summary of Success Indicators

Several characteristics of the maturing CME BFP futures market have been examined according to Black's criteria for a successful market. Trading volume and open interest are not as substantial as in other futures markets, but steady growth has occurred since the market's creation. The price forecasting ability of the market generally has remained accurate over time. The most recent results suggest that the market currently does predict spot price adequately even as time to maturity increases. The results also suggest that there is an autoregressive component in the release pricing equation. Finally, the measures of residual risk in the market suggests that the CME BFP futures and NYBOT BFP futures are close hedging substitutes for each other, and it is likely that only one exchange is needed in the BFP futures market. The measures of residual risk also suggest that hedging in the CME butter futures market may be less risky than hedging in the BFP futures market. Taken together these characteristics and indicators suggest the potential for long-term market success rather than market failure, although relative residual risk and insufficient volume are concerns. Moreover, the indicators do not provide any direct evidence that the CME BFP market is inefficient.

APPLICABILITY OF OPTION PRICING MODELS

This section presents, in a comparative format, the option pricing performance results of the traditional Black model and two variants of a standard GARCH option pricing model. More specifically, this section compares the results of three alternative option pricing formulas: (1) the traditional Black option pricing formula with historical 30-day volatilities as specified by equations (4) and (5); (2) the Black formula with the historic volatility replaced by two different approximations generated by the GARCH model as specified in equations (7) and (7a); and (3) the Black formula with the historic volatility again replaced by two approximations generated by the GARCH-in-mean model as specified in equation (8). The two approximations of volatility generated by the GARCH models are the one-period ahead estimate given by Myers and Hanson (1993), and the j-period ahead estimate given by equation (9). Considering all combinations of the two GARCH model variants (GARCH with volume and GARCH-in-mean with volume) and the two volatility approximations (the one-period ahead and j-period ahead approximations) yields four option pricing formulas that require econometric estimation of a GARCH model and one, the traditional Black formula that requires only historical market data. Six CME BFP option contracts are chosen to compare predictive pricing performance against actual market premiums. These contracts include both in-the-money and out-of-the-money put and call options for January, April, and July 1999.[1] The contract months represent different seasonal periods in the year. Data from 1999 are used because there are greater price and trading volume changes in the market compared to earlier years. In other words, 1997 and 1998 contracts were rejected as the focus of this study due to little trading volume and ,hence, small or zero futures price changes, which adversely affected the results of the pricing models.

Table 5 compares the 30-day historical volatility of BFP futures returns used in the traditional Black formula against the estimates of volatility using the two GARCH models and two approximation formulas. The futures return volatilities range between 0.03 and 0.26 for all models and approximations. Volatility is needed in a market to attract speculators who profit on price uncertainty because speculators accept the producers' risk from their hedge. In Table 5, the Black 30-day historic volatilities are generally higher than the conditional volatilities from the GARCH approximations. The Black volatilities range form a low of 0.08 to a high of 0.15. The first GARCH approximation produces volatilities that range from a low of 0.03 to a high of 0.26. The second GARCH approximation produces the lowest conditional volatilities, on average. These volatilities range between 0.03 and 0.21.

To calculate option premiums, the GARCH models given by equations (7), (7a), and (8) are estimated on a daily basis for two months before contract maturity. In deriving the conditional volatility, each model "run" uses data starting eight months before contract maturity and ending within a two-month window prior to maturity. This longer volatility estimation period contrasts with the 30-day Black volatility estimate. Estimation of the GARCH model proved to be highly sensitive to changes in the time length of data used to estimate the conditional variance. For example, the GARCH terms

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[1] For example, an in-the-money put option would have a strike or exercise price higher than the futures

became insignificant when applying a shorter two- or four-month estimation period for the conditional variance. Because the two GARCH models are estimated approximately 45 times each (once for each trading day in a two-month period) for January, April, and July 199 BFP futures contracts, individual GARCH estimation results are not presented with one exception. Table 6 presents the estimation results of the two GARCH models for one selected time period, chosen because it was representative of most of the GARCH results.In the GARCH model with trading volume, Table 6 shows that the "ARCH" constant (ω) is significant at the 0.01 level, and the ARCH and GARCH coefficients (α and β) are both significant at the 0.10 level. The trading volume coefficient (θ) is significant at the 0.001 level. The constant coefficient in the mean equation (μ) is not significant with a p-value of 0.54.

The GARCH-in-mean model results, also shown in Table 6, show that the conditional variance coefficient in the mean equation (δ) and the ARCH constant are both significant at the 0.05 level. The volume coefficient (θ) is highly significant at the 0.001 level. The ARCH coefficient (α) and the constant coefficient in the mean equation (μ) are both significant at the 0.10 level. The GARCH coefficient (β) is not significant, but has a p-value of 0.14.

The model estimates in Table 6 generally reflect the model estimates of other time periods. Not all time periods yield significant ARCH and GARCH coefficients at the 0.05 or 0.10 level. The significance of the GARCH-in-mean coefficients also vary from

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price, while an out-of-the-money put option would have a strike price lower than the futures price and the option would not be exercised.

below the 0.05 level to a p-value of 0.65. The significance of the constant in the mean equation also greatly varies. The volume coefficient for both GARCH and GARCH-in-mean models is typically significant at the 0.10 level in nearly all estimations run. Though all the coefficients are for the most part statistically significant, they remain small in value for all GARCH models run. The small ARCH and GARCH coefficients lead to low estimates of conditional volatility for both GARCH approximations.

Option premium prices are derived from all the models and compared to actual market premiums. Figures 7-9 show the actual market premiums compared to the Black and GARCH predicted premiums for an April 1999 in-the-money call option with a strike price of 1150 and a futures maturity price of 1180. In Figure 7, note that the Black model's predicted prices closely follow the market's actual premiums. In Figure 8, the GARCH approximation I predicted prices roughly follow, the actual market premiums, but not as closely as the Black model's predictions. Note also that the predicted prices are usually below the actual premiums. Figure 9 shows that the prices predicted by GARCH approximation II have the greatest deviation from the actual market premiums. In all three models, the largest errors occur when there are sudden, substantial market increases or decreases in option premiums.

Figures 10-12 show the actual market premiums compared to the Black and GARCH predicted premiums for an April 1999 in-the-money put option with a strike price of 1200 and a futures maturity price of 1180. While it may be hard to determine when comparing the three figures, the Black predicted prices, in Figure 10, have the smallest deviation from actual market premiums. In Figure 11, the GARCH approximation I predicted prices loosely follow actual market premiums with the largest deviation being 22 dollars. In Figure 12, (as in Figure 9 for calls), the GARCH approximation II predicted prices have the largest deviations from actual market premiums. As was true in Figures 7-9, in all three models, the largest errors occur when there are sudden, substantial market increases or decreases in option premiums.

To evaluate GARCH and Black models relative to each other more accurately, the root mean square error (RMSE) is used as the distinguishing criteria. Table 7 shows the RMSE for the Black model compared against the two alternative GARCH and GARCH-in-Mean models with trading volume added and the two volatility approximations. Figure 13-18 graphically depict the comparable RMSE's for January, April, and July 1999 put and call options in bar charts. These figures, along with Table 7, document several major results.

First, Table 7 shows that the RMSE results vary greatly with contract choice and contract distinction, i.e. call or put. For example, the RMSEs are low for January 1999 puts (ranging from about 1.3 to 3.7) and even lower (8.3E-12 to 0.37) for July 1999 puts. Alternatively, the RMSEs are higher (6.4 to 11) for April 1999 puts, and substantially higher (all at around 305) for April 1999 calls. RMSE results also vary with whether the contract's strike price is in-the-money or out-of-the-money. For example, April 1999 puts, which are in-the-money, have higher RMSEs (6.4 to 11) than January 1999 out-of-the-money puts (1.3 to 3.7).

Table 7 also shows that the Black results are comparable to the GARCH results, and even outperform them on several occasions. This result comes despite the fact that the Black results simply require historical data while the GARCH results require multiple estimations of a complicated time series model. Black has lower RMSE's than the GARCH approximations for three of the six contracts presented in Table 7. These contracts include January 1999 puts, April 1999 puts, and April 1999 calls. For example, Black's RMSE for January 1999 puts at 1.2662 is slightly lower than the RMSE for approximation II of the GARCH models at 1.2693. While no model does well in predicting April 1999 call prices, Black performs slightly best with a RMSE of 305.34. The RMSEs calculated with the use of the GARCH models and approximation II, are the lowest for three of the six contracts.

When comparing the GARCH models and the two approximations, Table 7 shows that approximation II usually improves the pricing predictive performance of the GARCH model over the simpler approximation I. This result is evident in four of the six contracts. For example, the RMSE using approximation I is low for July 1999 calls (approximately 0.04 for GARCH and 0.03 for GARCH-M), but the RMSE using approximation II is almost zero (1.3E-18 for GARCH and 7.7E-16 for GARCH-M). However, with both the April 1999 contracts, which have the highest overall RMSEs, the simpler approximation I outperforms approximation II. For example, the RMSEs for April 1999 puts with approximation I are roughly 7.7 and 7.9 for GARCH and GARCH-M respectively. The RMSEs for the same contract with approximation II are roughly 10.8 and 11 for GARCH and GARCH-M respectively. The improved predictive ability of approximation II is also evident in Figures 13, 14, 17, and 18 for various option contracts.

Finally, the use of the GARCH-M with volume model rarely improves the pricing predictive performance when compared to the slightly simpler GARCH with volume model. Table 7 shows that the GARCH-in-mean model often generates slightly higher RMSE's than the GARCH model with volume. This result is found with nearly every contract. The RMSE's for April puts provide one example: The GARCH-in-mean models' RMSEs range from 7.70E-16 to 305.43. The GARCH models RMSE's range from 1.30E-18 to 305.42. GARCH-M does outperform the simpler GARCH model in pricing July 1999 contracts in two instances.

Summary of Option Pricing Models Results

Three alternative option pricing models are compared in this study: (1) the traditional Black model with historical 30-day volatilities as specified by equations (4) and (5); (2) the Black model with the historic volatility replaced by approximations generated by the GARCH model as specified in equations (7) and (7a); and (3) the Black model with the historic volatility replaced by approximations generated by the GARCH-in-Mean model as specified in equation (8). The pricing performance -- actual vs. predicted -- is compared for several BFP option contracts in 1999.

Using RMSE as a comparison criterion, the Black model performed comparably well to both GARCH models in pricing most options. GARCH approximation II generally outperformed approximation I. The GARCH with volume added model often outperformed the GARCH-in-mean with volume added model. All models generally priced calls more accurately than puts. All models also priced out-of-the-money options more accurately than in-the-money options.

CHAPTER V

CONCLUSIONS

The two objectives of this study are (1) examining the potential success and efficiency of the BFP futures market, and (2) evaluating the performance of several option pricing models in predicting actual market premiums. The conclusions indicate the potential for market success as well as market efficiency. The option pricing formulas are found to generally price BFP options accurately. These findings are relevant to the participants and stakeholders in the BFP futures and options markets.

POTENTIAL SUCCESS OF BFP FUTURES MARKET

Black's criteria for testing the success of a futures market include examining level of trading volume and open interest, spot price forecasting performance, and degree of residual risk inherent in the market. These criteria as applied to the BFP futures market indicate the potential for market success, but not necessarily the achievement of market success.

Trading volume and open interest continue to grow annually at a steady rate. However, these numbers are still low enough to indicate lack of liquidity in the market. Illiquidity is problematic when examining the pricing accuracy of the market. An illiquid market may also discourage participation because of the inability to enter and exit the market quickly. Low volume and open interest in the BFP market led to small changes in the daily futures price and, consequently, low measure of market volatility. Low market volatility, in turn, limits the market return to participants. As shown in Table 5, market volatility does fluctuate in the BFP market, ranging from 7.7 percent to 14.7 percent, as calculated by the 30-day historic volatility used in the Black model. However, these estimates are well below the volatility values for a typical stock, which generally range from 20 percent to 40 percent a year (Hull 2000).

These measures of trading volume and open interest do not show the number of producers (sellers) compared to the number of processors or retailers (buyers) in the market. Therefore, the growth of volume may be one-sided in the market if dairy producers are not participating in great numbers. A one-sided market could produce abnormally high returns for one group of participants, who could also use the market to manipulate futures pricing by their volume of trades. Indicators reflecting the growth in trading volume and open interest alone, important for long-term market success, will not uncover this potential drawback.

The BFP futures market's forecasting ability in predicting the BFP spot release price is highly accurate close to contract maturity. The futures price converges with the spot price as maturity approaches. This forecasting ability has some variability in the months further from contract maturity. However, the market's forecasting ability should still attract hedgers to the market. The BFP monthly release price formula is composed of several dairy pricing components such as butterfat price, manufactured milk price surveys, and soft dairy products prices. These components are published monthly prior to the BFP release and could affect the market's ability in predicting the BFP spot price. This price predictability would decrease trading volume in the month of maturity when trading volume is typically heaviest. Nonetheless market's forecasting ability does indicate potential for market success.

The measure of residual risk may influence hedger participation in the market. As measured in this study, it appears that hedgers would prefer to place a cross-hedge in the less risky butter futures market. This measure may change as the BFP futures market matures and liquidity increases. If the level of comparative risk remains constant, however, hedgers would have little incentive to participate in the BFP futures market. Nonetheless, the measure of comparative risk is not substantially greater for BFP futures and, therefore, not so great as to indicate market failure.

MARKET EFFICIENCY

An efficient market is one in which all available information is contained in the market price. If all available information is incorporated in the futures price, it should accurately predict the spot price. This prediction ability is apparent in the BFP futures market. Despite low trading volume, liquidity, and level of risk, the futures price converges at maturity with the BFP release price. Thus, the market contains some informed traders to achieve this price convergence. Informed traders are an indicator of market maturity and efficiency. Since market information is incorporated into futures price, there is no direct evidence for market inefficiency.

UTILITY OF THE DOPP PROGRAM

The efficiency of the BFP futures market provides support for the usefulness of the market as a hedging tool. Since the futures market accurately forecasts the spot release price and the two markets converge in price at contract maturity, dairy producers can use the futures market to hedge their price risk in the cash market. With informed traders, the futures market follows the trends occurring in the cash market. Thus, in a declining cash market, dairy producers will be protected from losses by holding an opposite position in the milk futures market. Dairy producers can benefit from participation in the market.

DOPP is designed to encourage producer participation in the fluid milk futures market. DOPP is a risk management tool for producers faced with a volatile cash market as dairy support prices are eliminated. Support prices were intended for removal after December 31, 1999, but they have been extended through 2000. Their future for 2001 is unsure. The removal of support prices would create a greater producer need and demand for the fluid milk futures and options markets.

Several restrictions DOPP placed on participants may limit producer participation in the markets. The producer is required to buy a put option substantially out-of-the money six months in advance of maturity. The option strike price is often so much lower than the settled futures price that it goes unexercised by the producer. Hence, the dairy producer cannot gain any risk protection benefit from his position in the options market.

DOPP is useful as an educational tool in exposing dairy producers to the use of financial options as a risk management tool. The government subsidized program encourages producer participation in the market by guaranteeing producers little financial exposure. Since results indicate that the futures market is an accurate forecaster of the cash price, the futures market is useful by producers for risk management. DOPP, despite its limitations, encourages producer participation.

APPLICABILITY OF OPTION PRICING MODELS

The hypothesis of this study was that the GARCH option pricing model would outperform the traditional Black option pricing model when additional variables such as trading volume are added to the GARCH model to account for the BFP futures market's immaturity. The results contradict this hypothesis in that both models performed similarly, with the Black model pricing options slightly more accurately as evidenced by lower RMSEs than the GARCH approximations with trading volume added. This result could be due to the time sensitivity of the GARCH model, the small parameter coefficients of the GARCH model, and the predictive power of the market's historic volatility. Each of these possible explanations are discussed in turn.

The GARCH models are sensitive to the length of time used in estimating the conditional volatility. The GARCH models in the study start with estimating the conditional volatility eight months before contract maturity. This conditional volatility estimate is used to estimate GARCH models beginning two months prior to maturity and continuing to the contract maturity date. GARCH models starting less than eight months before contract maturity (e.g., two to six months prior), had insignificant GARCH and ARCH parameter estimates. The results indicate that in this particular market, GARCH is only applicable with a long time period for conditional volatility estimation. Black, in comparison, uses a 30-day length of price change data to estimate historic volatility.

In the maturing BFP futures market, the heaviest trading volume occurs in the two months prior to contract maturity. The months further removed from maturity have little trading volume. As a result, futures price changes are small or stagnant in the months removed from contract maturity. Because the conditional volatility estimate and the

GARCH parameter estimates depend on the logged futures returns, over an eight-month period, the long estimation could adversely effect the model's estimate of conditional volatility. In other words, the additional information used by the GARCH model may be detrimental rather than beneficial if in fact the additional data are misleading due to market inactivity.

Similarly, using an estimation period in which many of the daily futures price changes are zero could result in the small GARCH coefficients derived in this study. Compared to Myers and Hanson's (1993) study of soybean futures, the GARCH and ARCH parameters estimated here are as much as ten times smaller than Myers and Hanson's parameter estimates. The small GARCH coefficients generate a lower average volatility estimate than Black's 30-day historic volatility estimate.

As applied in the Black model, the use of historic market returns may be the most accurate volatility estimate in a maturing market. Due to the unique characteristics of a maturing market such as low trading volume, misinformation, or illiquidity, using past volatility to predict current volatility would incorporate any actual market irregularities or trends. To test this conclusion, 15- and 45-day historic volatility estimates were also substituted in the Black model with little variation in the RMSE results. Historic volatility estimates appear to be more applicable in pricing the BFP options market.

For the contracts studied, all of the models generally price call options more accurately than put options. Since, call options are typically purchased by a dairy manufacturer or retailer this result could indicate that more information (or more useful information) is present on the buyers' side of the market. These participants are interested in hedging their risk in purchasing milk from the producer or processor. If the market is one-sided with many large industry participants, call options would tend to have greater trading volume and greater liquidity. The market may price call options more accurately because more information is incorporated into price.

Put options are typically purchased by a dairy producer. If there are few producer or seller participants, put options would have less liquidity and lower volume. The market could be mispricing put options due to the small number of producer participants or uninformed producers creating information effects.

For the contracts studied, all of the models price out-of-the-money options more accurately than in-the-money options. This could be due to the attributes of a maturing market. The models accurately predict an extremely low price or zero price for out-of-the-money options, which is comparable to the actual market premiums. However, the models yield much higher predicted option prices for in-the-money options than the actual market premiums. This result is consistent with the observed volatility "smiles" associated with deep in-the-money or deep out-of-the-money options.

This last result could be related to either market mispricing or model mispricing. On one hand, the market may be mispricing options by depressing market premiums to ensure liquidity in a market characterized by low trading volume. In other words, participants may not be willing to pay high premium prices to enter the market. The market may also be mispricing these valuable options because it does not have sufficiently informed traders. Traders may not understand the movements in the cash or futures markets and therefore undervalue these options.

On the other hand, it may be the models rather than the market that are mispricing the options. In other words, while the market may be pricing the options accurately by incorporating all available information into price, a characteristic of a maturing market or a unique characteristic of the BFP market may not be accounted for in the models. Trading volume is added to the GARCH models in this study to account for market immaturity. Another variable such as open interest or a liquidity factor may be needed in the models. Variables that are particular to the market such as a trend or seasonal variable may be needed. The milk pricing system and its components and the timing release of governmental prices could be additional factors considered in building adequate pricing models.

IMPACT ON PRODUCERS AND OTHER STAKEHOLDERS

The BFP market serves as a viable risk management tool for dairy industry participants. The indications that the market has the potential for success and is efficient have significant impacts on dairy producers, processors, manufacturers, retailers, and other parties involved in the market. With every indication of potential market success, sellers and buyers may participate in the market knowing that trading volume, liquidity, and volatility will continue to increase. The market is actively growing in stakeholder interest and participation. With the ability to hedge their risk effectively in a market that closely follows the cash market, both sellers and buyers benefit from an efficient market. Participants know that the market price is an informed price, and that the market price has forecasting ability in predicting the future spot price. Thus, the market is a viable hedging tool.

For dairy industry participants the BFP futures market serves as effective price discovery tool. Traders are interested in option pricing models that can accurately predict option prices. This study indicates that the options market is able to conform to traditional pricing models, like Black's model, and market participants should be sufficiently able to predict option prices and forecast future trends in the market by applying option pricing techniques. Through their own use of option pricing models, traders will be attracted to the price predictability power of the market.

EXTENSION OF RESULTS

The results of the study can be extended to practical application and further modeling. Testing the accuracy of spot price predictability can be performed on the new Class III and Class IV milk futures contracts to analyze if the milk pricing system changes are being incorporated into the futures price. The predictive capabilities of the market could be compared to the regression results from the BFP futures market to analyze any changes. Finally, the level of risk in the Class III and IV contracts could be compared to the former BFP futures market and the other existing dairy futures markets. These results would impact the use of the market by producers for hedging.

Informational issues could also be investigated. For example, determining who the participants are in the market (i.e. the number of sellers versus buyers) would address the question of a one-sided or private-information-dominated market. Without adequate producer participation, the market may misprice options because of lack of information.

Further modeling could compare other maturing markets for similar phenomenon found in this study. Other studies of other new financial markets could concentrate on the pricing ability for calls versus puts or in-the-money versus out-of-the money options.

If these results are consistent for other new markets, one could hypothesize what unique characteristics of a maturing market contribute to this result.

SUMMARY

This study examines the pricing efficiency of the BFP futures and options markets. The two objectives include examining the characteristics of the futures market for potential success and analyzing the accuracy of several option pricing models to determine market efficiency and usefulness.

The results of the first objective do not indicate any market inefficiency. Furthermore, the characteristics of the maturing BFP futures market indicate potential success. Since by all indicators the market is a viable hedging tool, there is every reason to expect that the DOPP program is useful in encouraging producer participation in the market.

The results of the second objective show that, contrary to the initial hypothesis, GARCH models typically do not price BFP options more accurately than the traditional Black model. Another surprising result is that the models also price call and out-of-the money options more accurately then put and in-the-money options.

It would be straightforward to extend these objectives and results to examine the individual pricing efficiency characteristics of other new futures markets or the unique characteristics particular to the fluid milk futures market.

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APPENDIX

Table 1: Average Daily Trading Volume and Open Interest in CME BFP Futures and Options
(measured in contracts)

	BFP Futures		BFP Options	
Trading Year	**Open Interest**	**Trading Volume**	**Open Interest**	**Trading Volume**
1996	23.4	2.83	4.72	0.168
1997	48.4	3.76	19.3	0.667
1998	176	11.8	13.1	0.505
1999	401	16.4	14.3	0.397

Table 2: Forecasting Regression Results

1996-1997 BFP Futures Contracts

Dependent Variable: Cash Price Parameter Estimates	**Intercept**	**Futures Price**	**R-squared**
1 month till expiration	2.924	0.1681	0.8336
	(-3.784)*	(-0.7787)	
2 months till expiration	11.30	0.1293	0.8309
	(8.453)	(.5644)	
3 months till expiration	19.00	-0.0498	0.8451
	(9.006)	(.6351)	
4 months till expiration	20.67	-0.0536	0.848
	(6.805)	(.4861)	
5 months till expiration	27.03	-1.061	0.8647
	(11.36)	(.0871)	

1998-1999 BFP Futures Contracts

	Intercept	**Futures Price**	**R-squared**
1month till expiration	10.22	1.059	0.9736
	(.4198)	(.1006)	
2 months till expiration	-2.318	1.370	0.5684
	(8.362)	(.6893)	
3 months till expiration	-5.333	1.596	0.7058
	(7.321)	(.5948)	
4 months till expiration	-49.04	5.163	0.6783
	(25.17)	(2.053)	
5 months till expiration	-49.92	5.225	0.7570
	(20.00)	(1.709)	

*Standard Errors

Table 3: Lagged Forecasting Regression Results

1996-1997 BFP Futures Contracts Dependent Variable: Cash Price Parameter Estimates	Intercept	Futures Price	BFP Lag Price	R-squared
1month till expiration	1.526	-0.5515	1.488	0.6947
	(6.477)*	(0.6412)	(0.8093)	
2 months till expiration	3.169	-0.4369	1.227	0.7152
	(6.675)	(0.4516)	(0.5542)	
3 months till expiration	7.620	-0.5915	1.034	0.8275
	(6.305)	(0.3506)	(0.3615)	
4 months till expiration	8.266	-0.5619	0.9458	0.8984
	(4.765)	(0.2250)	(0.2729)	
5 months till expiration	15.04	-1.137	0.9618	0.9609
	(3.971)	(0.2582)	(0.1694)	

1998-1999 BFP Futures Contracts	Intercept	Futures Price	BFP Lag Price	R-squared
1month till expiration	2.924	0.1681	0.6881	0.8336
	(3.784)	(0.7787)	(0.7173)	
2 months till expiration	2.538	0.1012	0.7911	0.8309
	(6.979)	(0.6893)	(0.4491)	
3 months till expiration	0.1528	0.4476	0.6489	0.8451
	(7.685)	(1.006)	(0.4839)	
4 months till expiration	-12.52	1.474	0.6561	0.8480
	(32.35)	(3.013)	(0.4392)	
5 months till expiration	76.50	-7.122	1.902	0.8647
	(102.0)	(9.906)	(1.507)	

* Standard Errors

Table 4: Residual Risk Results from Hedging BFP Spot Price

1998-1999	Cross Hedge Residual Risk	Relative Residual Risk
CME BFP Futures	0.2843	1.042
NYBOT BFP Futures	0.2961	0.9601
CME Butter Futures	0.1226	2.319

Table 5: April 1999 Estimates of Put Option Return Volatility

Trading Date	Black	GARCH* Approx I**	GARCH Approx II	GARCH-M Approx I	GARCH-M Approx II
04/05/99	0.146424	0.097423	0.058524	0.095156	0.046301
04/06/99	0.147276	0.092716	0.056920	0.088887	0.044692
04/07/99	0.145635	0.105703	0.056730	0.103915	0.044387
04/08/99	0.142962	0.071609	0.055844	0.069778	0.044028
04/09/99	0.137310	0.068481	0.054716	0.066849	0.042763
04/12/99	0.137296	0.149485	0.059924	0.151782	0.049457
04/13/99	0.140262	0.215987	0.060948	0.215779	0.051149
04/14/99	0.102878	0.111170	0.060741	0.101865	0.050715
04/15/99	0.104351	0.061648	0.060953	0.058288	0.050896
04/16/99	0.095165	0.100678	0.059457	0.094249	0.049146
04/19/99	0.095515	0.071394	0.057807	0.068234	0.047547
04/20/99	0.095921	0.053827	0.056004	0.053295	0.045735
04/21/99	0.095827	0.068803	0.053408	0.066380	0.042804
04/22/99	0.095079	0.029707	0.052823	0.033380	0.042484
04/23/99	0.084935	0.056596	0.050150	0.055790	0.039528
04/26/99	0.083822	0.053162	0.047734	0.053101	0.037143
04/27/99	0.084054	0.111719	0.045950	0.105403	0.034545
04/28/99	0.080499	0.085294	0.042838	0.081062	0.030457
04/29/99	0.077231	0.136554	0.048718	0.126382	0.036707
04/30/99	0.079649	0.068789	0.042777	0.066905	0.029229
05/03/99	0.079839	0.250237	0.113546	0.263872	0.105052
05/04/99	0.088726	0.164194	0.216011	0.163388	0.230615

* Here GARCH refers to the GARCH model with trading volume and GARCH-M refers to the GARCH-in-mean model with trading volume.
** Approximation I refers to the one-period ahead estimate of the conditional variance and Approximation II refers to the j-period ahead estimate.

Table 6: GARCH Models Results for April Futures Contracts
September 1, 1998, through March 1, 1999

GARCH with Volume

$\Delta f_t = \mu + \varepsilon_t \quad \varepsilon_t \sim N(0,h_t)$

$h_t = \omega + \alpha\varepsilon^2_{t-1} + \beta h_{t-1} + \theta V_t$

Variable	Coefficient	Standard Error	T-Statistic	Significance Level
μ	0.0223	0.0362	0.6146	0.5388
ω	0.0197	0.0062	3.178	0.0015
α	0.3461	0.1946	1.778	0.0754
β	0.1573	0.0873	1.801	0.0717
θ	0.0187	0.0040	4.643	0.0000

GARCH-in-Mean with Volume

$\Delta f_t = \mu + \delta h_t + \varepsilon_t \quad \varepsilon_t \sim N(0,h_t)$

$h_t = \omega + \alpha\varepsilon^2_{t-1} + \beta h_{t-1} + \theta V_t$

Variable	Coefficient	Standard Error	T-Statistic	Significance Level
μ	0.0670	0.0404	1.684	0.0922
δ	-0.3398	0.1537	-2.211	0.0270
ω	0.0282	0.0103	2.728	0.0064
α	0.3691	0.1945	1.898	0.0577
β	0.1105	0.0747	1.479	0.1392
θ	0.01604	0.0039	4.142	0.0000

Table 7: RMSE Results

Put Options	Out-of-the-Money January 1999	In-the-Money April 1999	Out-of-the-Money July 1999
Black	1.2662	6.3600	0.37104
GARCH w/ volume			
Approximation I	2.3281	7.7388	0.58658
Approximation II	1.2693	10.753	1.40E-11
GARCH-M w/ volume			
Approximation I	3.6616	7.8859	0.70599
Approximation II	1.2693	10.957	8.30E-12

Call Options			
Black	2.60E-05	305.34	0.01966
GARCH w/ volume			
Approximation I	0.32140	305.36	0.04137
Approximation II	1.20E-07	305.42	1.30E-18
GARCH-M w/ volume			
Approximation I	0.94228	305.37	0.02507
Approximation II	2.30E-07	305.43	7.70E-16

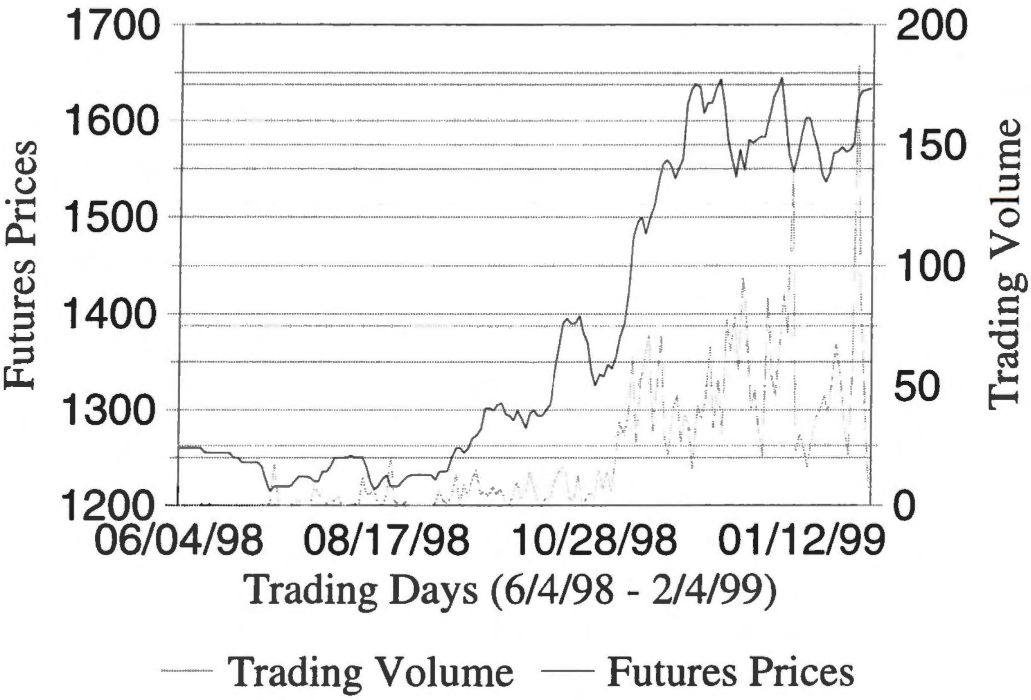


Figure 1: January 1999 BFP Futures Prices and Trading Volume Activity

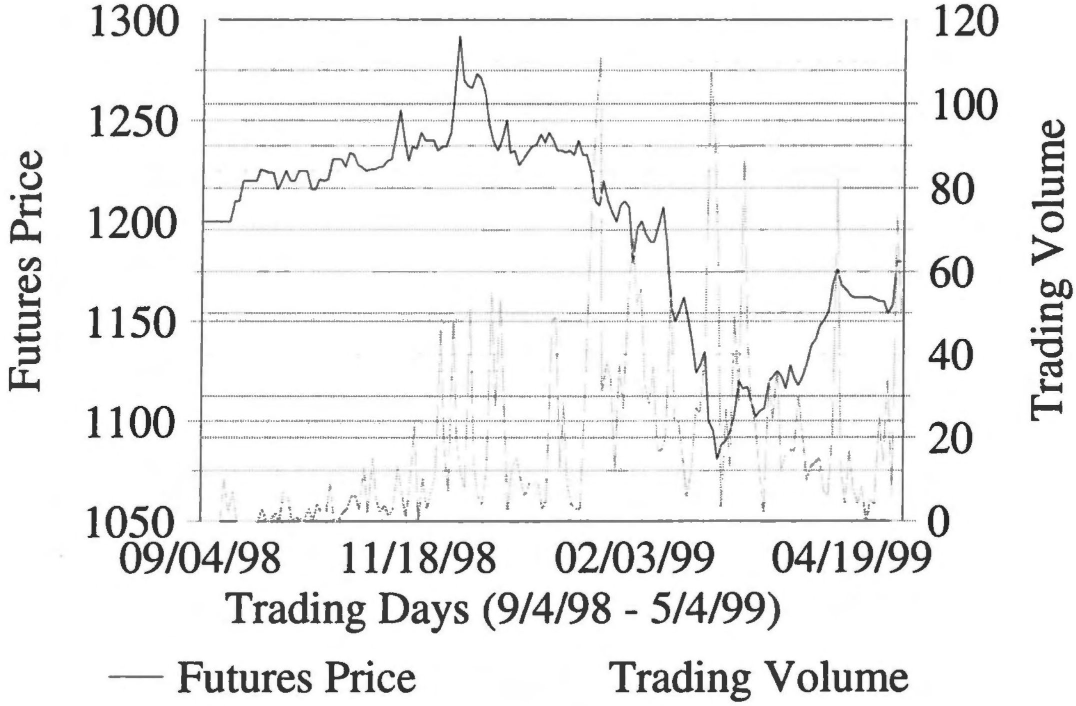


Figure 2: April 1999 BFP Futures Price and Trading Volume Activity

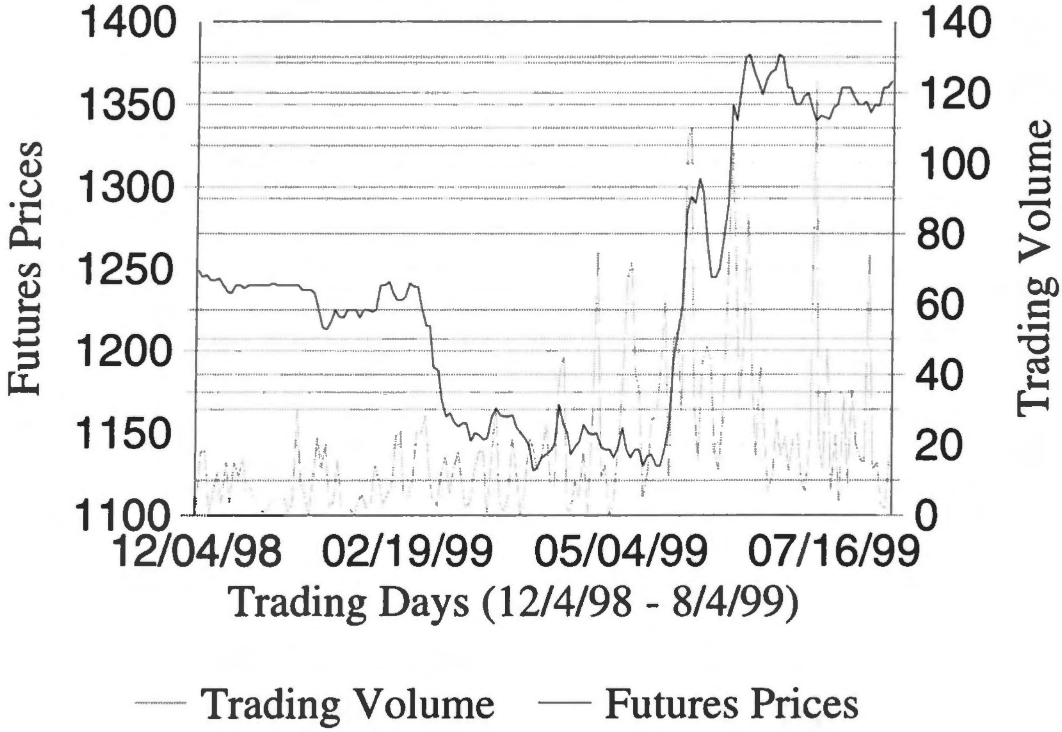
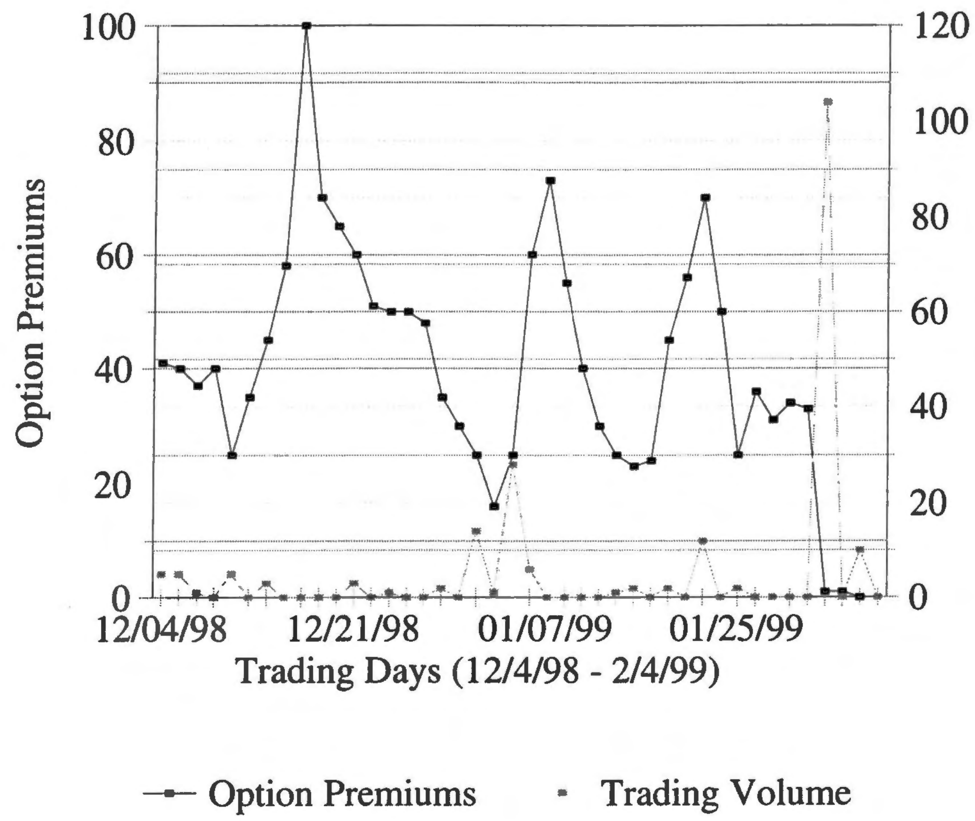
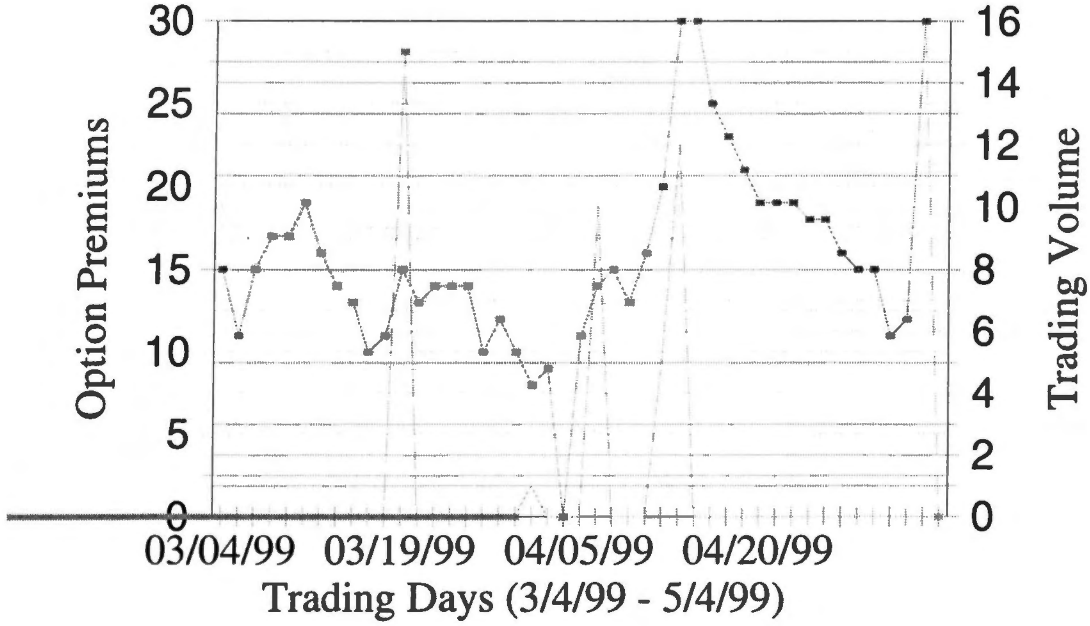


Figure 3: July 1999 BFP Futures Price and Trading Volume Activity



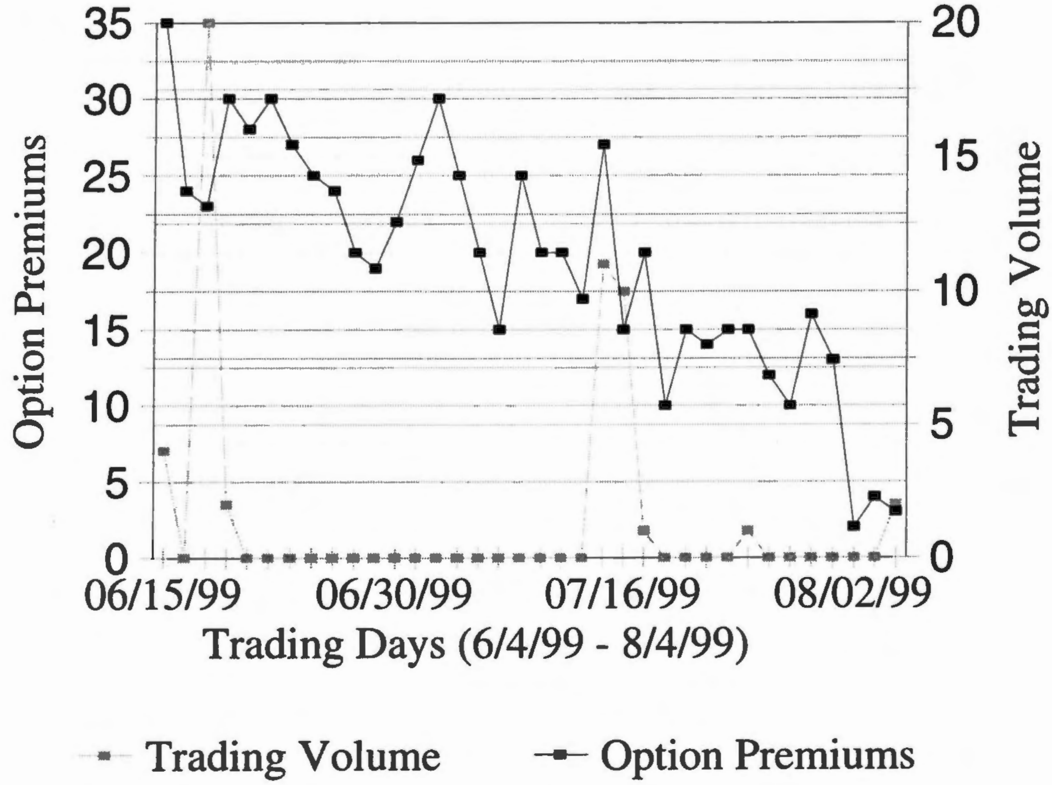
Put strike price is 1600. Price at maturity is 1634.

Figure 4: January 1999 BFP Option Premium and Trading Volume Activity



Call strike price is 1150. Price at maturity is 1180.

Figure 5: April 1999 BFP Option Premium and Trading Volume Activity



Put strike price is 1350. Price at maturity is 1364.

Figure 6: July 1999 BFP Option Premium and Trading Volume Activity

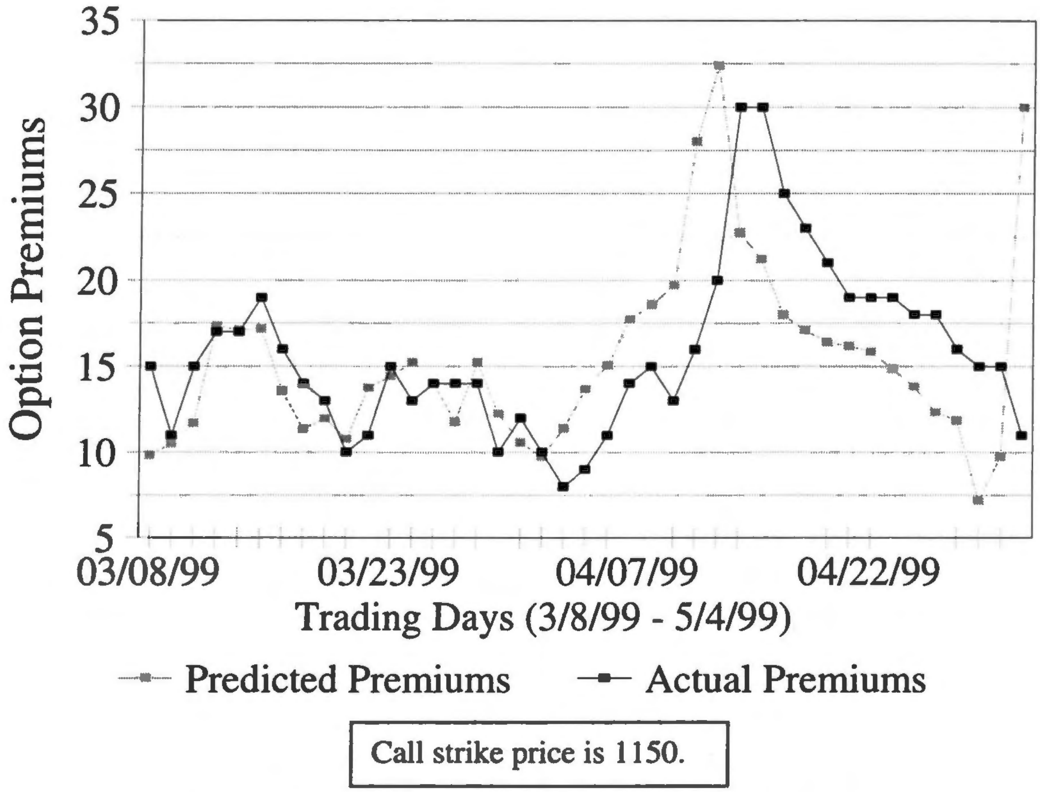


Figure 7: April 1999 Black Predicted & Actual Call Option Prices

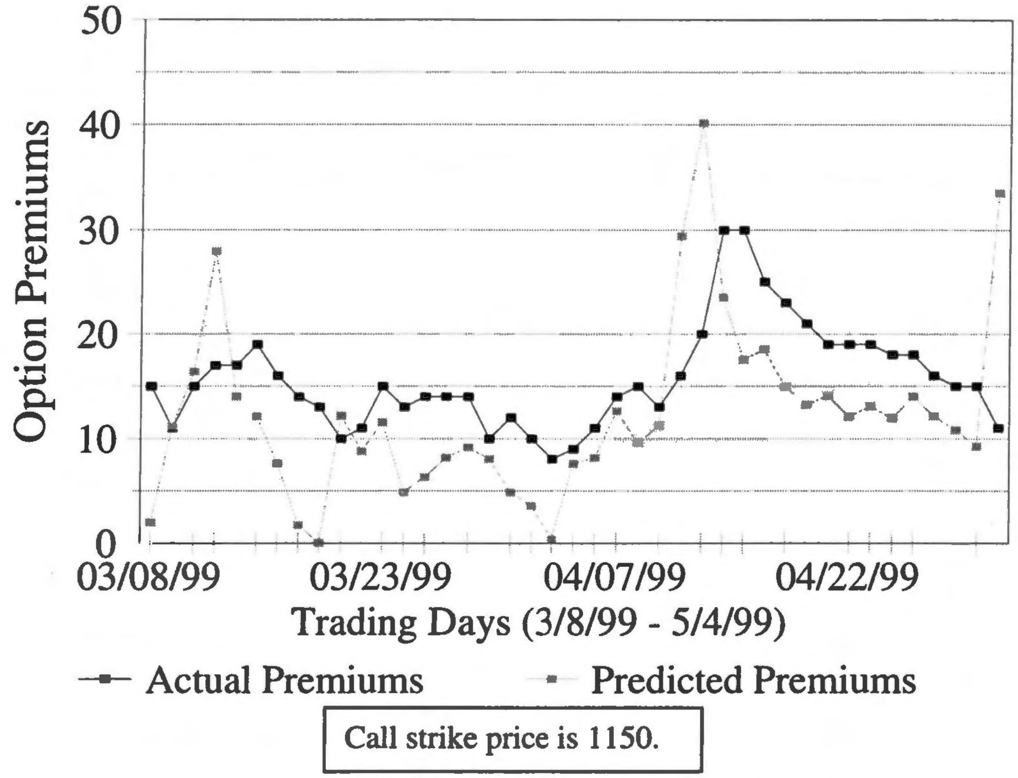
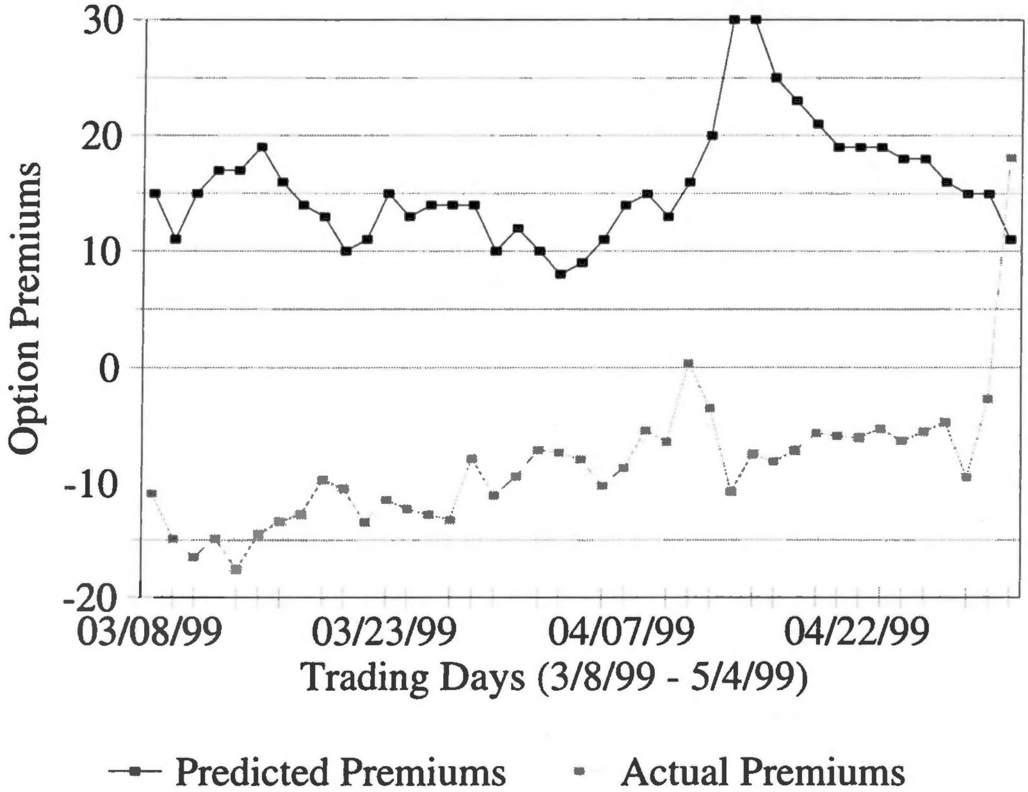


Figure 8: April 1999 GARCH Approx I Predicted & Actual Option Prices



Call strike price is 1150.

Figure 9: April 1999 GARCH Approx II Predicted & Actual Call Option Prices

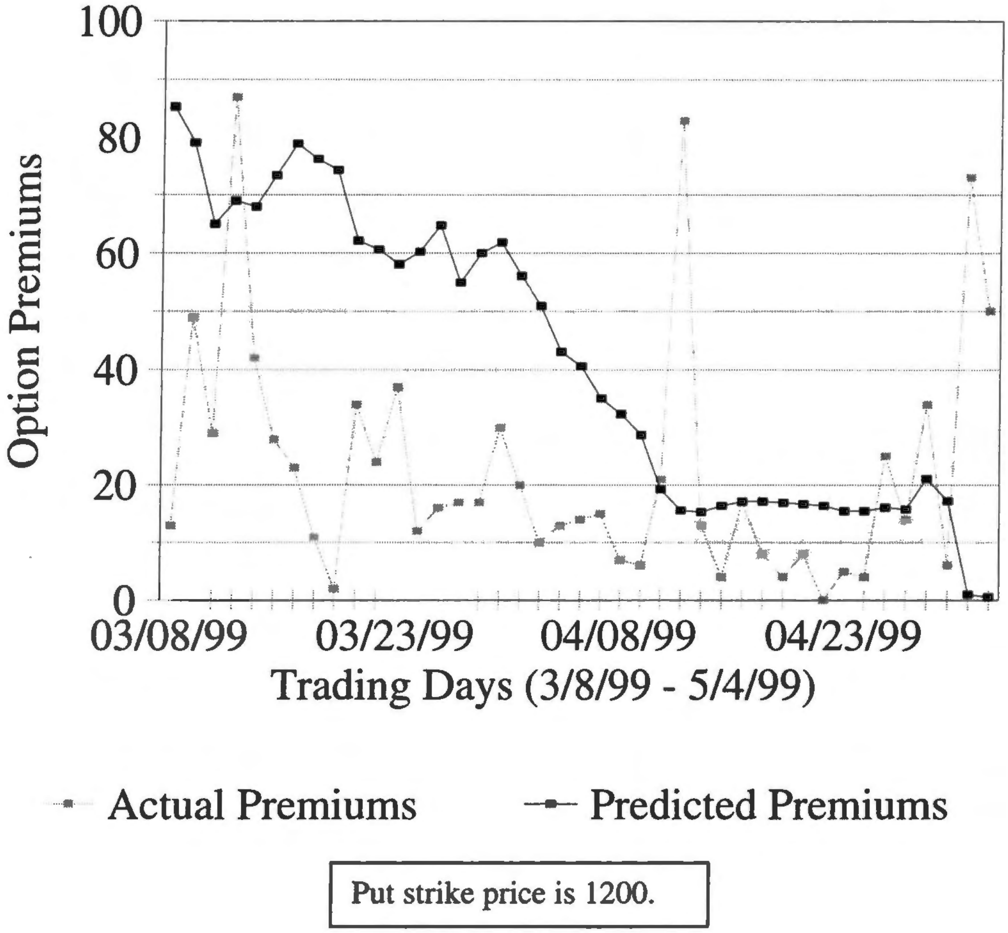


Figure 10: April 1999 Black Predicted & Actual Put Option Prices

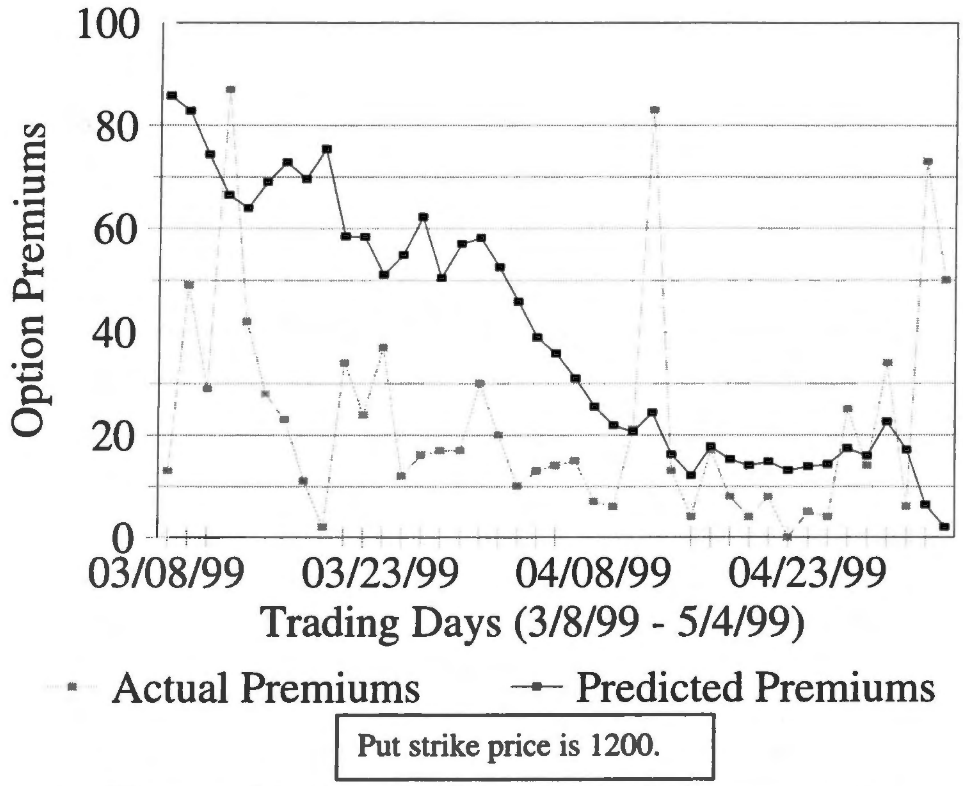


Figure 11: April 1999 GARCH Approx I Predicted & Actual Put Option Prices

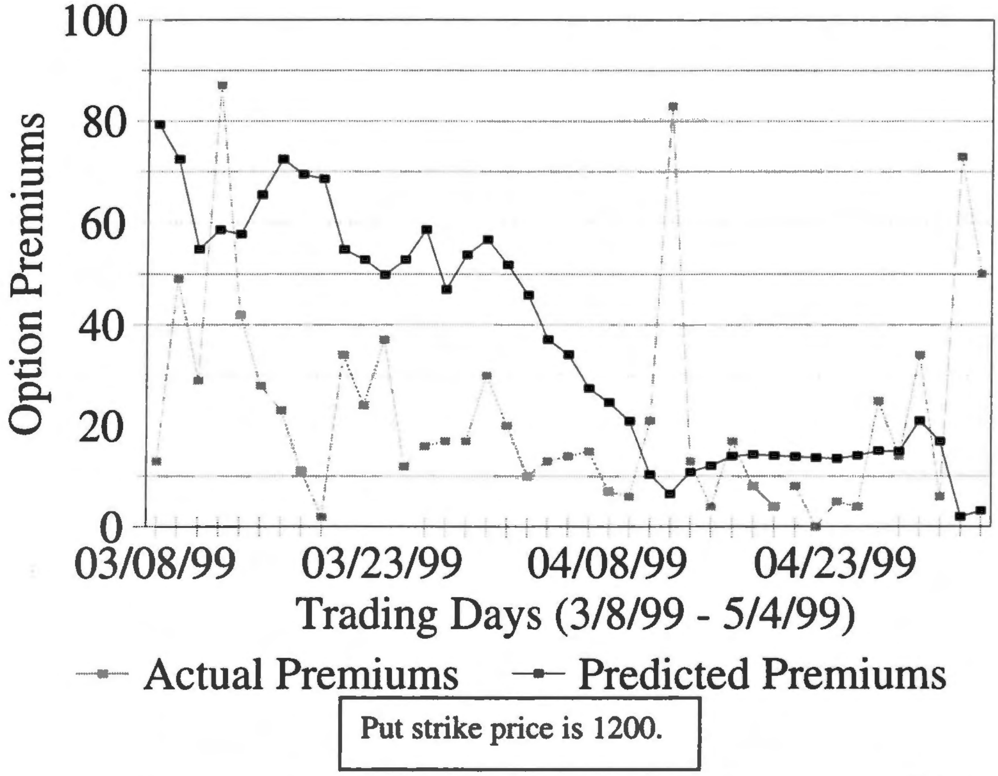


Figure 12: April 1999 GARCH Approx II Predicted & Actual Put Option Prices

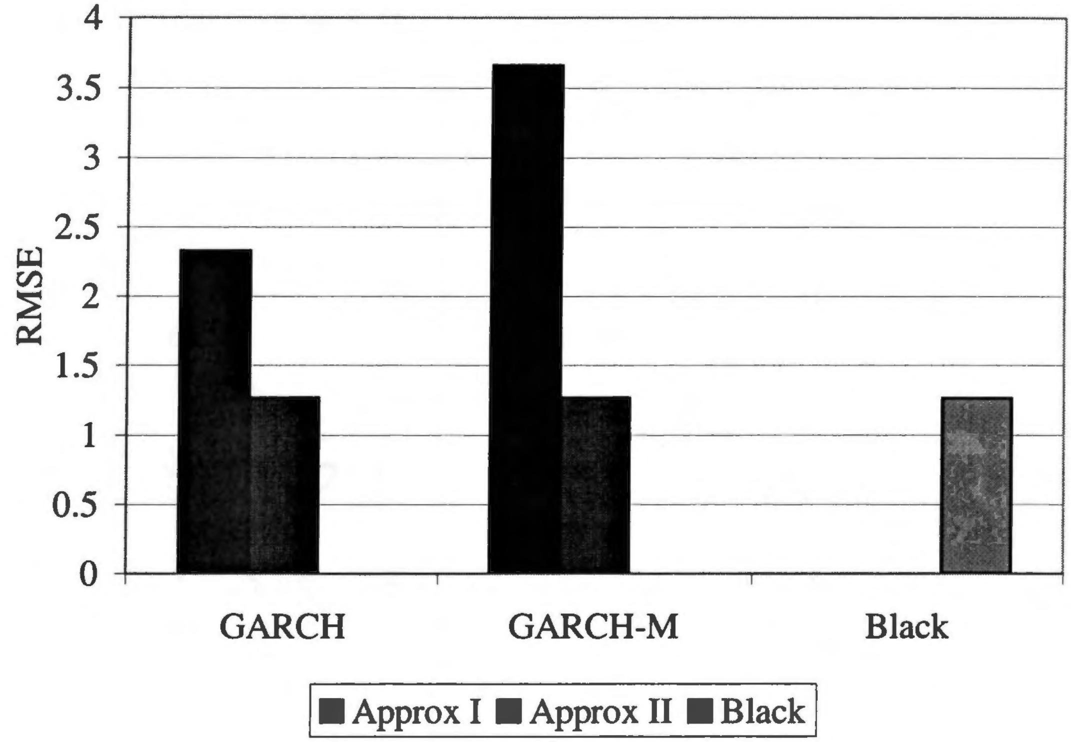
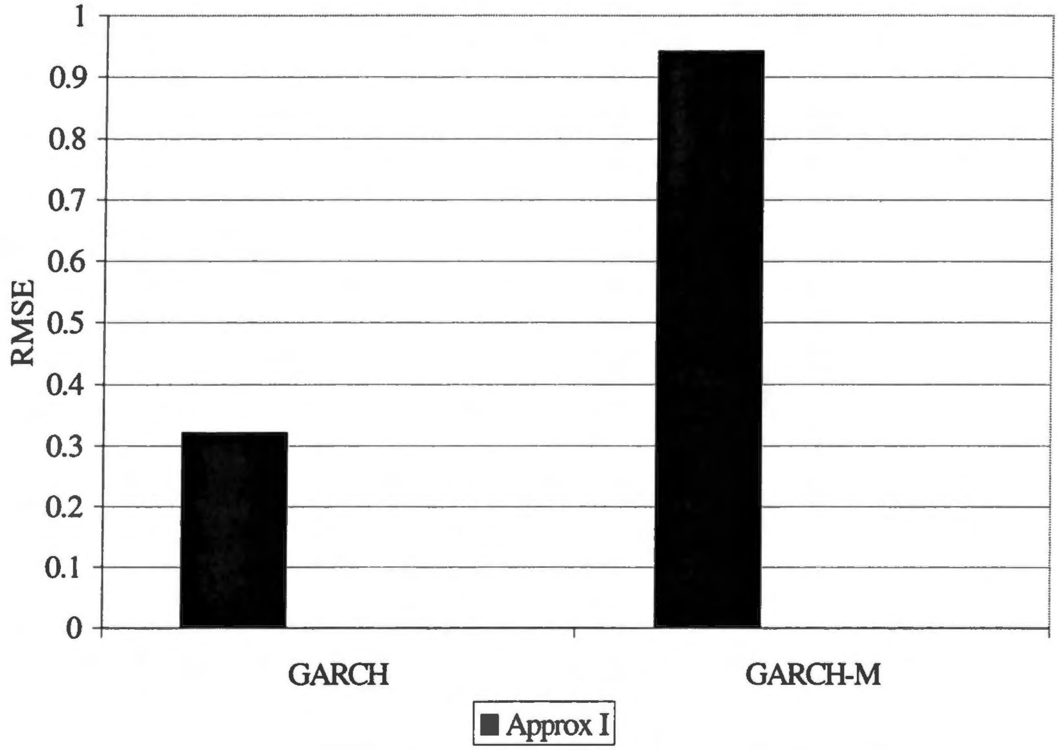


Figure 13: RMSE Results
For January 1999 Put Option Contracts



*Approx II and Black errors are extremely close to zero.

Figure 14: RMSE Results
For January 1999 Call Option Contracts

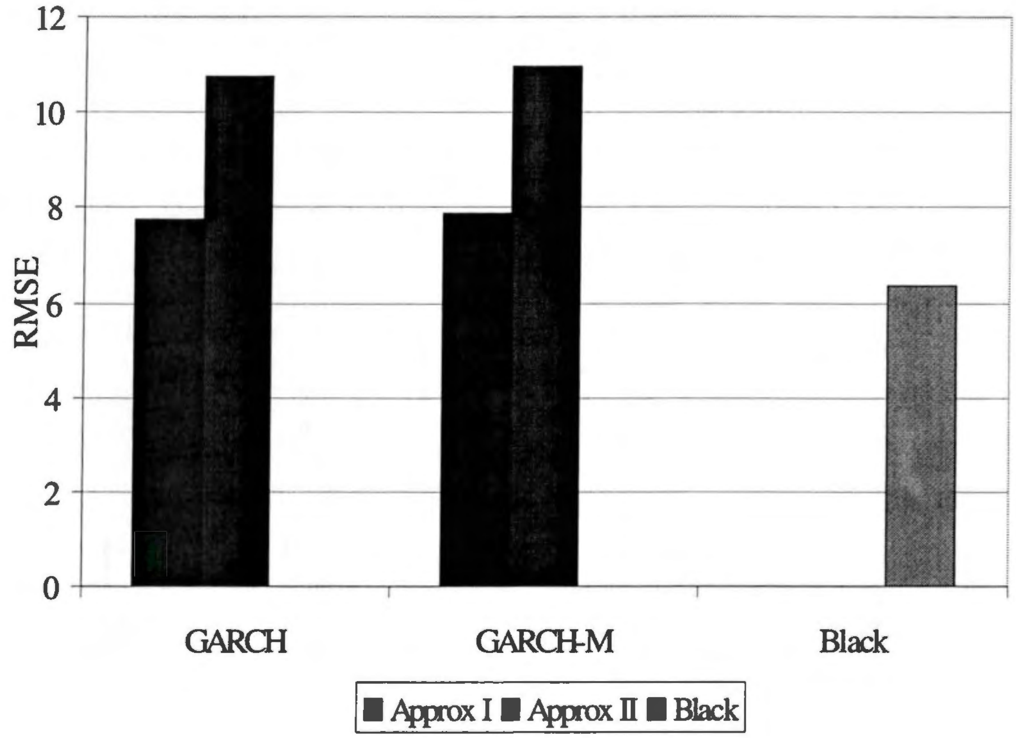


Figure 15: RMSE Results
For April 1999 Put Option Contracts

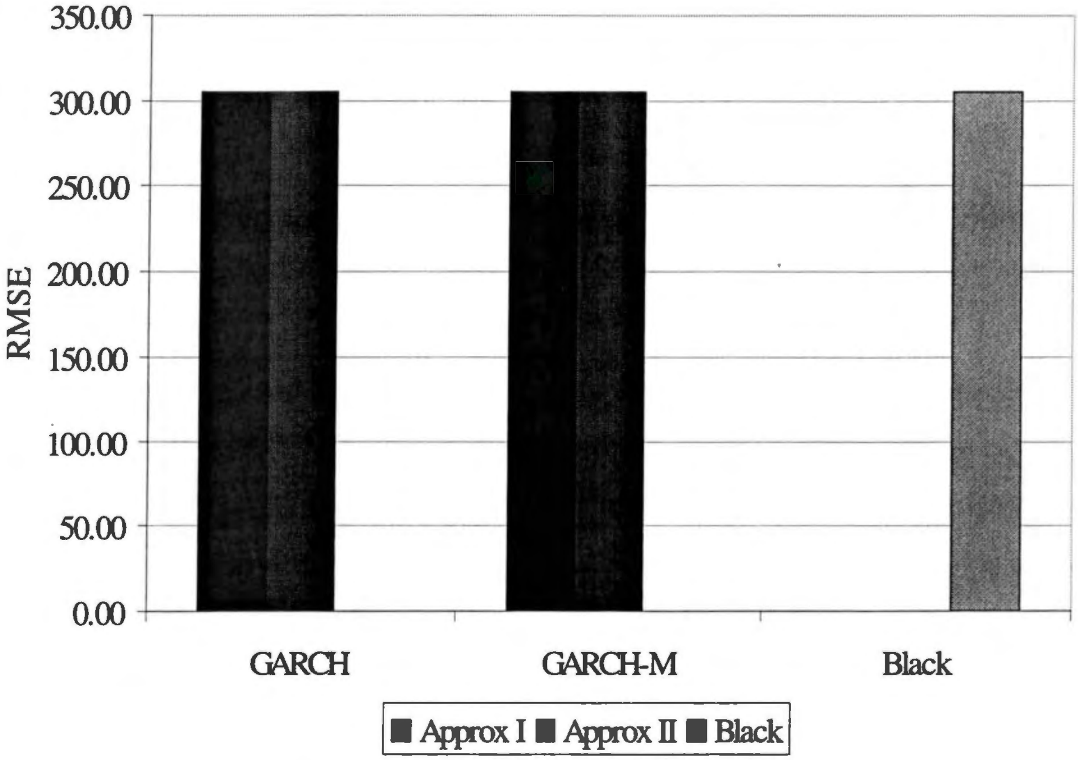
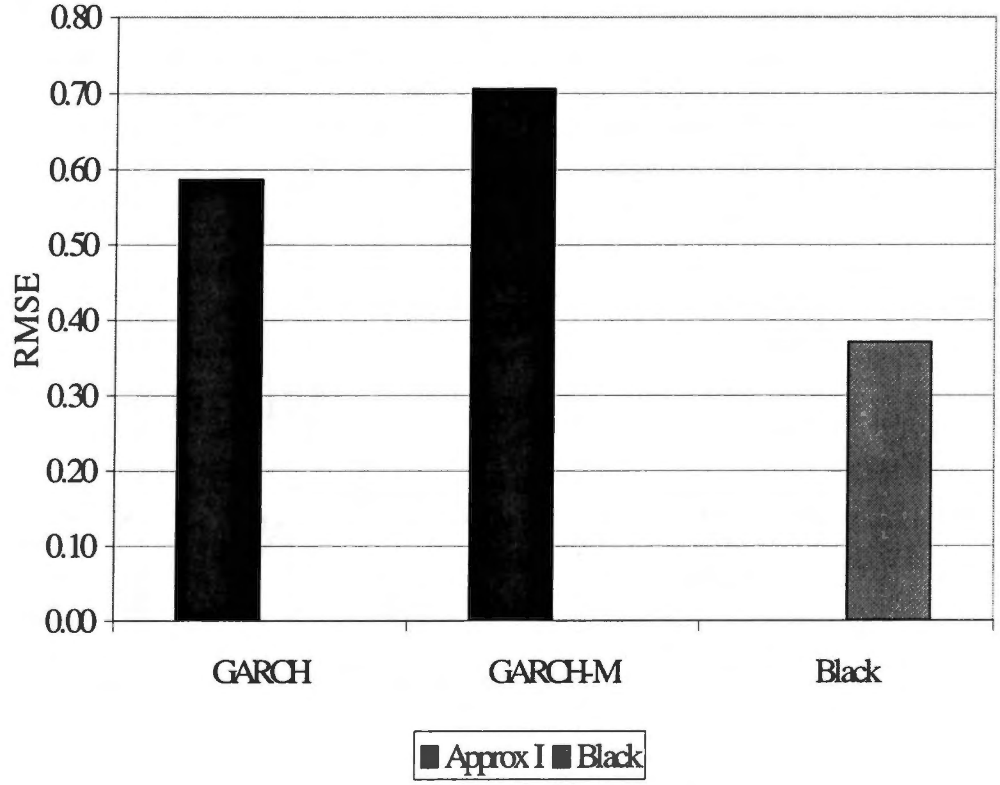
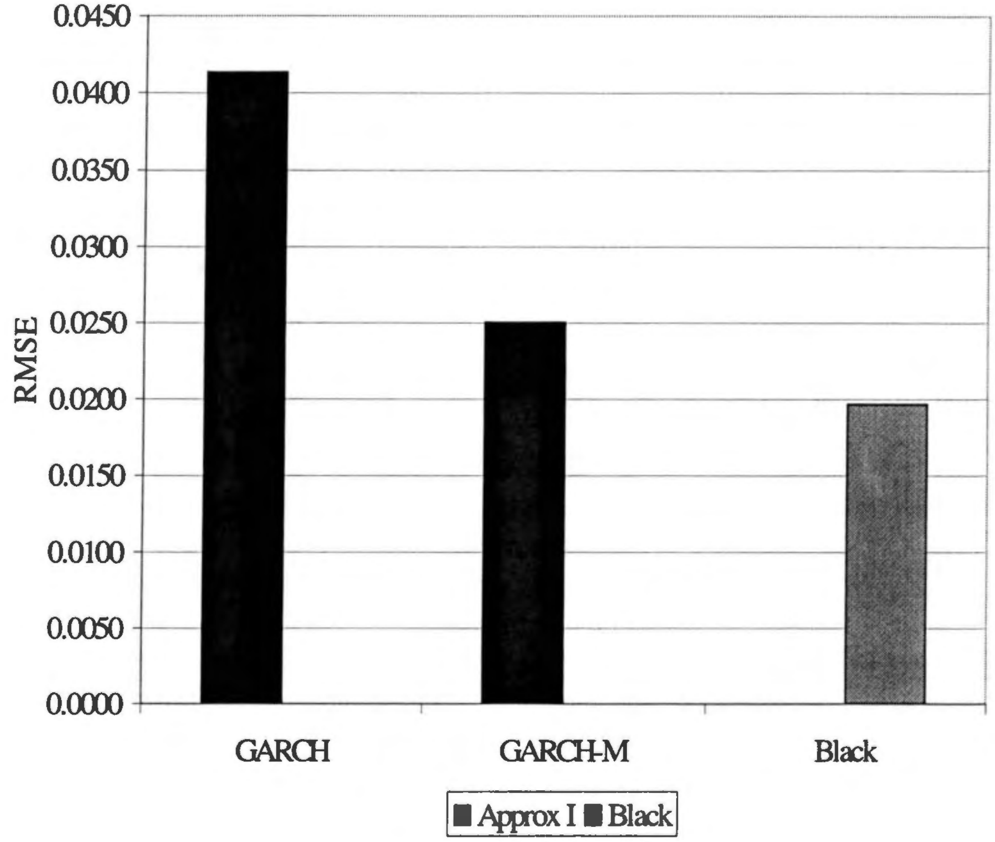


Figure 16: RMSE Results
For April 1999 Call Option Contracts



*Approx II errors are extremely close to zero.

Figure 17: RMSE Results
For July 1999 Put Option Contracts



*Approx II errors are extremely close to zero.

Figure 18: RMSE Results
For July Call Option Contracts

VITA

The author, Heidi Funk, holds her B.A. in Political Science from Carson-Newman College. She has served as a Research Assistant for the Department of Agricultural Economics at the University of Tennessee, Knoxville during her graduate work. Heidi has presided over the departmental Graduate Student Organization. She is a member of the American Association of Agricultural Economists and other honor organizations. Her career interests are in the fields of finance, and economic and statistical analysis.

Heidi enjoys time with her mother, sister, niece, chocolate lab, and soon-to-be husband. She is grateful for all their patience and support.