A COMPARISON OF IMPLIED STANDARD DEVIATIONS AND HISTORICAL ESTIMATES OF VOLATILITY DURING AND AFTER THE PARTICIPATION OF THE BRITISH POUND IN THE ERM

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(ABSTRACT)

This thesis tests the hypothesis that the qualities of different forecasts of exchange rate volatility depend on the underlying exchange rate regime. By examining the British pound during and after its withdrawal from the European Monetary System (EMS), this analysis compares “backward-looking” historical forecasts of future volatility with the “forward-looking” forecast of volatility reflected in current option prices. Because option implied volatility contains the market’s most current expectations about future prices, theory and much previous evidence suggests this should be the superior predictor of future volatility. In contrast to previous research by findings, this study concludes that option implied volatility is not superior. During the time when the pound was in the EMS, implied volatility provided reasonably good forecasts of future volatility. However, after the pound withdrew from the EMS, various statistical measures of historical volatility are found to have greater informational content and predictive power about future actual volatility than implied volatility. In particular, a time series estimate, specifically a GARCH(1,1) model, had the most informational content and predictive power about realized pound volatility, especially in the period following sterling’s withdrawal from the EMS.
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This thesis is dedicated to my parents, Dr. Carole M.P. Neves and Antonio M. Pimenta Neves.
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CHAPTER 1

INTRODUCTION

This paper examines whether the predictability of future exchange rate volatility as forecasted by historical estimation and implied volatility is affected by a shift in an exchange rate regime. The study of volatility in markets has become critical to participants in asset markets. But the question remains unanswered as to what is the best means of predicting changes in volatility. Futures and options markets present a unique opportunity to investigate this issue because the volatility of an option may be “backed out of” the corresponding option price. According to theories of efficient capital markets, it follows that this option “implied volatility” serves as the best source from which to derive future expected volatilities.\(^1\)

So far, various studies have been performed which compare the forecasting ability of option implied volatility to more traditional historical or times series methods for estimating volatility.\(^2\) The results of these studies indicate that the option implied volatilities are indeed superior to several alternative methods. Jorion (1995), for example, showed that implied volatility is a better predictor of actual volatility than various historical measures of volatility for the Japanese yen, Swiss franc, and Deutsche mark.

Specifically, this paper applies Jorion’s analysis to the British pound prior and subsequent to the European Currency Crisis of 1992. In contrast to Jorion and others, the evidence here suggests that forward-looking measures of volatility worked reasonably well during the period in which the pound was in the European Monetary System. Afterwards, however, backward-looking historical measures of volatility are better predictors of future exchange rate volatility than implied volatility.

The organization of this paper is as follows. Chapter 2 presents background information on the structure of the European Monetary System and describes the various events that triggered the crisis along with an emphasis on the role of the British pound. Chapter 3 describes the theory underlying the various methods used in calculating the volatility of options on currency futures. Aside from option implied volatility, two historical moving average processes are used along with a time series-based conditional volatility estimator. In Chapter 4, a description of the data and statistical techniques that are utilized to compare these different approaches to volatility are provided. Chapter 5 presents and examines the results of this comparison of different volatility predictions along with other relevant statistical information. Finally, Chapter 6 concludes with some suggestions for further research.

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\(^1\) For a classic review of the concept of market efficiency, see Fama (1970, 1991).

CHAPTER 2

CRISIS IN THE EUROPEAN MONETARY SYSTEM

Prior to the crisis of 1992-3, the development of the European Monetary System was considered one of the most successful achievements of the European experiment towards unity. Before examining this crisis, however, it is first necessary to take a few steps backwards. The road towards the formation of an economic and political union in Europe has been a long and difficult one. This section begins by presenting a brief look at previous attempts to achieve monetary union in Europe that led to the development of the European Monetary System (EMS). Next, the formation and objectives of the EMS is discussed. In this section, the focus is on the establishment of the Exchange Rate Mechanism (ERM) between member nations of the EMS. The following section examines the affairs surrounding the British pound and the Italian lira, particularly, their withdrawal from the ERM. Finally, this chapter concludes by describing the effects of this tremendous volatility both on the currency markets and other financial instruments such as futures and options.

2.1 Previous Attempts

The desire to achieve economic and political union in Europe has been building since the end of the Second World War. The process of economic integration has not been a smooth one following from some functional logic nor is it the result of natural economic law enforced by Adam Smith’s “invisible hand.” Rather, it is dependent upon the political and economic dynamics of its members. Although the origins of the EMS may be traced to the issuance of the Werner Report in 1970, which proposed monetary union for the first time, several significant systems preceded the EMS. They are worth mention since the EMS adopted many of its provisions from these previous attempts.

The first significant steps towards monetary stability occurred when the major industrialized countries of the world gathered in 1944 with the objective of redesigning the international monetary system into a regime based on multilateral cooperation and free convertibility of currencies. The result was the “Bretton Woods” system. With the U.S. dollar functioning as a reserve currency, Bretton Woods operated somewhat like a gold exchange standard with most currencies linked to gold indirectly through their convertibility into U.S. dollars, which in turn was linked to gold directly. Prior to Bretton Woods, monetary conversion systems were based on the notion that currency values should be maintained at exactly their official parities to the underlying reserve asset. Bretton Woods replaced this notion with the concept of a “pegged exchange rate.” Although the system ended formally in 1971, the de facto end of the system came in 1967 when dollar convertibility into gold was first restricted due to the lack of bullion reserves.

The days of currency convertibility were over with the end of Bretton Woods, and the era of “managed floating” had begun. “Floating” refers to a monetary regime in which currencies are convertible only into other currencies and not into a reserve asset at some official rate. The

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3 See Artis and Lee (1995), p. 2. Also, this text serves as a comprehensive guide to the economic policies behind the ERM and its applications.
4 Appendix 1 is dedicated entirely to a chronological look at the European Monetary System, including a general timeline of its entire history and a detailed list of the events leading to the suspension of the pound and lira in 1992.
5 See Bulmer in Artis and Lee (1995) and Bladen-Hovell, also in Artis and Lee (1995).
6 For a good description of this process towards European economic unity, see Melvin (1985) and Walters (1990).
regime is referred to as a “managed” float because exchange rates are not entirely determined by market forces but rather, as various systems illustrate, often guided by policy resolutions.

The Smithsonian Accord represents the first of such attempts at a managed exchange rate system where nations agreed to maintain official exchange rate parities with respect to the dollar—which was in turn linked to gold but not convertible into gold—through foreign exchange (FX) market intervention. Specifically, nations agreed to maintain the market values of their currencies within 2¼% of the official parities by buying and selling currency on the FX market. When economic conditions dictated a change in official central rates, redefinitions occurred in the form of “revaluations” and “devaluations.”

Despite this flexibility, the lack of convertibility of any currency into gold made the official parities of the Smithsonian Agreement largely meaningless and, as a result, the international monetary system envisioned by the Smithsonian Agreement did not last a year.

Shortly after the ineffectiveness of the Smithsonian Agreement became apparent, the major countries of Europe decided to try to reduce intra-European currency volatility by agreeing to keep their currencies roughly in line with one another and to let all their currencies collectively float together relative to the U.S. dollar. The result was the pseudo-system known as “the Snake.” The major currencies participating in the Snake were the Deutsche mark, British pound, French franc, and Italian lira. This cooperative effort to reduce European exchange rate volatility did not last long, however, mostly due to the fact that there was no way of holding member nations to their pledges to keep the currencies in line. Furthermore, the rise of interest rates and inflation in the 1970’s made the task even more daunting. The Snake fell apart in 1973, led by the abandonment of the pound, lira, and franc. This was the last attempt at a managed exchange rate regime until the birth of the EMS in 1978. Throughout the EMS, however, it is easy to recognize various contributions from these previous regimes.

### 2.2 The European Monetary System

The EMS was officially launched in spring of 1979 by agreement of its founding members with the intention of creating monetary stability in Europe. The nine founding members were: Germany, France, the United Kingdom, the Netherlands, Belgium, Luxembourg, Italy, Denmark, and Ireland. At its inception, the EMS was greeted skeptically by many. This is perhaps due to the breakdown of the Bretton Woods system or failure of the previous Snake regime in which members attempted to stay within certain bands of currency fluctuation relative to each other by simple pledge. The goals of the EMS, however, were more encompassing than those set by previous regimes, as it represented the operational framework for monetary union among its members.

The EMS was chartered with the intention of reducing European currency volatility, enhancing intra-European trade, promoting convergence in inflation rates across EMS member nations, and providing a common European market that encouraged growth and stability. These goals were to be accomplished through several key provisions.

The cornerstone of the EMS was the Exchange Rate Mechanism (ERM), which represents an agreement by member countries to limit bilateral exchange rate fluctuations within

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7 A currency is devalued if it’s worth relative to another currency falls. Similarly, a revaluation occurs if the worth of one currency increases relative to another. For a good description of the workings of currency markets, see Grabbe (1996).

8 Many articles focus on the overall credibility of the ERM, particularly during the time period leading to the collapse of the ERM. For a good review, see Frankel (1993).
margins around central parities. In other words, European currency values would be preserved in terms of other member currencies within prescribed bands of fluctuation. This would be accomplished under the common understanding that the central parities would be adjusted to meet changing economic conditions and the relative performances of other currencies. Thus, within a rather rigid system of exchange rates known as the “central parity grid,” a currency is permitted to float between the upper and lower bands. If a currency is incapable of remaining within those limits, actions could be taken to adjust the central parity rate. These adjustments are known as realignments, and one of the principal objectives of the EMS was to keep these to a minimum.

Seven countries originally participated in this mutual obligation system with a ±2¼% band width with the exception of the Italian lira which was granted a ±6% band.9 These seven nations represented the major countries of Europe with the exception of Great Britain who joined the ERM at a much later date (October 8, 1990) despite its membership in the EMS. (This hesitancy serves as an initial indication of British skepticism with regards to the ERM.)10

Another main provision of the EMS was the creation of the European Currency Unit (ECU) which serves as a common currency of the EMS and is used primarily to settle external balances. The ECU derives its composition according to weights assigned to each particular currency in the EMS “basket.” The ECU played a tremendous role in the operational sense since the significant divergence of any currency from its central parity, either on the strong or weak side, was measured against the ECU. This “symmetry” in recognition of currency divergences represented one of the most attractive attributes of the ERM, unlike those systems that preceded it. When a significant departure from the central rate occurred, a decision was taken by the faltering country to intervene either through the foreign exchange market or by some monetary or fiscal policy to maintain the currency within its band. A country facing threats of a weakening currency could, for example, raise domestic interest rates to attract more foreign investment.11 Consistent “triggering” of the divergence threshold indicated that some more serious form of intervention was necessitated, as in some realignment of the central parity rate.

In the early years of the EMS, from 1979-83, a number of realignments occurred, mostly due to inflationary conditions at the time. From the period of 1983-9, however, the ERM experienced a time of relatively stable exchange rates. This encouraged the participation of other currencies such as the Greek drachma, Spanish peseta, and Portuguese escudo. Late 1989 marked the beginnings of turbulence for the ERM and for Great Britain, in particular. Concerns heightened with regards to the strength of the Deutsche mark in the ERM. The concept of symmetry that had won previous accolades by members in the ERM seemed to be replaced by the strong presence of the Bundesbank and Chancellor Helmut Kohl’s monetary policy.12 A hot public debate over the degree of Britain’s involvement in the ERM led to the resignations of Sir Alan Walters and Nigel Lawson, advisors to Margaret Thatcher.13 She resigned a year later, shortly after Britain joined the ERM at the ±6% band width.

Despite these issues surrounding Britain and a number of claims that Britain had joined the ERM at an unsuitable central parity rate, more countries had decided to participate in the ERM, although not quite as formally. Norway, Sweden, and Finland all claimed “links” to the

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9 Note that this ±2¼% band width was likely adopted from the Smithsonian Accord described above.
10 See Thatcher (1993) and Walters (1990) for thought on Britain’s preconceptions regarding the EMS.
12 See Bladen-Hovell in Artis (1995) and de Grauwe (1989) for more insight into German domination of the ERM.
13 For personal accounts of this turbulent era, see Thatcher (1993) and Walters (1990).
ERM and adopted the narrow ±2¼% band width. In late 1991, the European Council, consisting of delegates from all members of the EMS, reached an agreement on amendments to the Treaty on European Union (TEU) in the form of a timetable for the establishment of the European Monetary Union (EMU). This revised agreement became known as the Maastricht Treaty and it served as the catalyst for the crisis awaiting the ERM.

2.3 “Black Wednesday”

Despite the build-up of tensions in Europe prior to 1992, one incident in history clearly resonates as having pulled the trigger in the debacle that followed. On June 2, the Danish vote to reject the Maastricht Treaty sent waves of shock through the financial and political world. The strengthening of the Deutsche mark that resulted put considerable pressure on the sterling and the lira. Both nations faced severe recessions and their currencies continued to weaken relative to the mark. Artificial interventions by the U.S. and other nations seemed temporarily to alleviate the situation in Italy, however, fears of realignment dominated both nations. In a final attempt to prevent this from occurring, Britain borrowed money from other nations to defend its currency and Italy raised its discount rate on currencies from 1.75% to 15%. Despite all of these efforts, both currencies remained weak.

In the meanwhile, the Nordic currencies with linkages to the ERM were all suffering, as well. Sweden raised interest rates to 24%, almost 800 basis points on September 8. On the following day, the Bank of Finland declared that it would “float” the maarkha and disassociate with the ERM. This prompted Sweden to raise its interbank lending rate to 75% in order to attract more investors and discourage any speculative attacks on the currency.

On September 13, a revaluation of 3.5% occurred across all currencies in the ERM with the exception of the Italian lira which was devalued 3.5%. This was equivalent to a 7.0% devaluation of the lira. On September 16, a date that became known as “Black Wednesday,” Great Britain suspended the British pound from the ERM. Also on this date, Swedish interbank interest rates rose to an unbelievable 500%. On this following day, the Italian lira followed the pound and left the ERM. Ironically, a few days later, on September 20, the French narrowly approved the Maastricht treaty by 51%.

It would not be until late 1993 that the chaos finally settled in the ERM and the decision was made to allow all currencies to fluctuate within a ∀15% band. And, finally, on November 1, 1993, the Maastricht Treaty was approved by all members of the EMS.

The turmoil in the spot market also affected derivatives markets, in particular futures transactions (i.e., contracts for the purchase or sale of spot currency with specific delivery dates and terms) and options on futures (i.e., contracts entitling but not obligated the owner to buy or sell a currency futures contract). The value of any derivatives contract is significantly affected by any changes in the value of the underlying asset. The mechanics of currency futures and options on currencies are discussed further in Appendix 2.

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14 The TEU had last been adjusted in 1989 when a three-stage transition to economic and monetary union was proposed. These adjustments included the establishment of a Central European Bank system and the adoption of a single currency in the EMU.

15 The use of the term “Black Wednesday” for September 16, 1992, by now is well accepted nomenclature although in England, it is referred to as “White Wednesday” since it allowed the Central Bank of England to pursue a more expansionary monetary policy.
CHAPTER 3

VARIOUS MEANS OF ESTIMATING VOLATILITY

It is of great concern to financial economists to be able to monitor and model the behavior of financial time series and to understand the probable development of prices in the future.\(^{16}\) Volatility is an important element of time series analysis.\(^ {17}\)

Some measures of volatility express the volatility of a time series using only realizations of that time series to date. These volatility measures are “backward-looking” in the sense that they rely on the history of prices that have already been observed in a time series rather than on expected future prices. Unlike these historical measures, “forward-looking” measures of volatility rely on current prices which incorporate all available information about future prices. Alternatively stated, since these current prices are determined by the best and most up-to-date information, they reflect participant’s expectations about future market conditions.\(^ {18}\)

This chapter begins by describing some of the more common measures of backward-looking or “historical” volatility, moving average and ARCH processes. Then, the chapter switches to examine option implied volatility as a forward-looking measure of volatility.

3.1 Historical or “Backward-Looking” Measures of Volatility

3.1.1 Moving Average Processes

One of the simplest approaches to calculating volatility involves estimating a historical moving average.\(^ {19}\) To get a moving average estimate of volatility, the average is taken over a rolling window of historical volatility data. The order \(m\) of a moving average process is characterized by the length of the window that is chosen, hence processes are denoted by \(\text{MA}(m)\).\(^ {20}\) A longer rolling window implies a moving average process that essentially retains a longer memory of past information.

As an example of a moving average process, consider a 20-day rolling window.\(^ {21}\) The daily calculation of volatility would be the variance of daily returns over the most recent 20 days. To calculate this, assuming a zero mean daily return, the squared returns for the last 20 trading days are averaged. On the next day, a new return becomes available for the volatility calculation. To maintain a 20-day measurement window, the first observation is dropped off and the average is recomputed as the basis of the next day’s volatility estimate.

More formally, denote the daily return from time \(t-1\) to time \(t\) as \(r_t\). Assuming a zero mean daily return, the moving average volatility over a window of the last \(m\) days is calculated as follows:

\[
\nu_t^2 = \frac{1}{m} \sum_{j=1}^{m} r_{t-j}^2
\]

\(^{16}\) See Taylor (1986).
\(^{17}\) Throughout this paper, references to volatility are synonymous with references to standard deviation.
\(^{20}\) The length of the window is chosen by the user.
\(^{21}\) See Culp, Miller and Neves (1998). An MA(20) process was used by Jorion (1995) and hence used in this study.
where \( v_t \) is the daily estimate of volatility, expressed as a standard deviation.\(^{22}\)

Because moving-average volatility is calculated using equal weights for all observations in the historical time series, the calculations are very simple. The result, however, is a smoothing effect that causes sharp changes in volatility to appear as plateaus over longer periods of time, failing to capture dramatic changes in volatility. This smoothing effect becomes more severe as the rolling window gets longer. A more sophisticated means of calculating a moving average approximation is the exponentially weighted moving average (EWMA) approach. This method has been popularized by the advent of RiskMetrics\(^{\text{©}}\) in calculating Value at Risk measurements.\(^{23}\) This approach was considered for use in this study, however, and was not included for reasons explained in Appendix 3.

3.1.2 ARCH Models

Another approach for estimating backward-looking volatility involves the use of “conditional variance” time series methods. The first conditional variance model was developed by Engle in 1982 and is known as the autoregressive conditional heteroskedasticity (ARCH) model.\(^{24}\) ARCH combines an autoregressive process with a moving average estimation method so that variance still is calculated in the rolling window manner used for moving averages.

Since its introduction, ARCH has evolved into a variety of other conditional variance models, such as Generalized ARCH (GARCH), Integrated GARCH (IGARCH), and exponential GARCH (EGARCH).\(^{25}\) The predominant model for estimating volatility in currencies is a GARCH model based upon normally distributed errors, as will be described later.\(^{26}\)

Following the seminal paper by Engle (1982), the ARCH process may be described as

\[
y_t = \beta_0 + \beta_1 y_{t-1} + \epsilon_t, \tag{2}
\]

\[
\epsilon_t = z_t \sigma_t \tag{3}
\]

where \( z_t \) is i.i.d. with \( E(z_t) = 0 \) and \( \text{var}(z_t) = 1 \). Also, \( \sigma_t^2 \) is the conditional variance of \( \epsilon_t \), and is a time-varying, positive and measurable function of the time \( t-1 \).\(^{27}\) Engle also introduced the possibility to describe the conditional variance, \( \sigma_t^2 \) as a linear function of past squared values of the process or in terms of the number of lags. This process is known as the ARCH(\(q\)) model where \( q \) denotes the number of days prior to time \( t \). The essence of the ARCH model lies in the Equation (3) above where the variance of the process is identified. The first equation, known as the “mean” equation, can take various forms. For example, the above model would still be an ARCH model if the lagged dependent variable is dropped from the mean equation.

The next development in the ARCH family models was the GARCH(\(p,q\)) process presented by Bollerslev (1986). In this model, the main stochastic process or mean equation remains the same as would appear in an ARCH model. In the structure of conditional volatility, however, while \( q \) continues to indicate the lag structure in the conditional volatility itself, \( p \) denotes a dependence of the conditional variance upon lagged values of the squared residuals in

\(^{22}\) This assumption of a zero mean daily return is quite common practice in calculating volatility (see Jorion (1995)), as will be explained later in the following chapter.


\(^{24}\) See Engle (1982).

\(^{25}\) Nelson (1989) refers to ARCH models as the most important innovation in modelling volatility changes.

\(^{26}\) See Bollerslev, Engle and Nelson (1992).

\(^{27}\) Bolleverslev, Chou, and Kroner (1992).
the mean equation. The simplest form of this application is the GARCH(1,1) process where returns are modeled as a regression on a constant:

\[ r_t = \beta_0 + \varepsilon_t \]  

(4)

where \( \varepsilon_t \) is distributed normally with mean of zero and variance of \( \sigma_t^2 \). In the GARCH(1,1) variance of an asset’s return at time \( t \) is based upon lags in both the variance and squared return as in the following structure:

\[ \sigma_t^2 = a_0 + a_1 r_{t-1}^2 + a_2 \sigma_{t-1}^2 \]

(5)

The GARCH conditional variance model thus incorporates a recursive moving average term. In the special case where \( a_0 = 0 \) and \( a_1 + a_2 = 1 \), the GARCH(1,1) model reduces exactly to the exponentially weighted moving average formulation for volatility—see Appendix 3 for this proof.28

There has been a significant amount of previous work that applies ARCH specifications to foreign exchange rate time series. Whereas stock returns are found to exhibit some degree of asymmetry in their conditional variances, foreign exchange markets tend to be more symmetrical.29 The GARCH\((p,q)\) model serves as a good candidate for modeling exchange rate dynamics.

In 1989, Hsieh found that GARCH(1,1) formulations worked well to capture most of the stochastic dependencies in the times series.\(^3^0\) Based on tests of the standardized, squared residuals, it was found that the simple GARCH(1,1) model did better at describing data than a previous ARCH(12) model also estimated by Hsieh (1988). Similar conclusions were reached by Taylor (1986), McCurdy and Morgan (1988), Kugler and Lenz (1990) and Papell and Sayers (1990).\(^3^1\) An often-noted drawback of GARCH models is their poor out-of-sample forecasting power for low-frequency data or long time horizons. For short forecasts of daily volatility data, however, the models perform reasonably well.

Overall, a tremendous theoretical appeal of ARCH and GARCH models is their correspondence to continuous-time financial valuation methods. An ARCH model is essentially a discretized stochastic difference equation. Many theoretical valuation models, such as the Black-Scholes option pricing model, rely on continuous-time stochastic differential equations based on Ito processes. Because time series are observed in discrete increments, however, stochastic differential equations cannot themselves be estimated. But Nelson (1990) has shown that ARCH and GARCH stochastic difference equations converge to Ito processes when the time increment approaches zero. Thus, ARCH and GARCH models are good candidates for estimating volatility in markets whose prices follow diffusion processes, such as floating exchange rate regimes. However, these models might not be as good at measuring volatility in managed floating exchange rate regimes in which exchange rates might not follow a simple diffusion process.

3.1.3 Adjusted GARCH (1,1) Model for Longer Time Horizon

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28 This also implies that the GARCH (1, 1) reduces to an IGARCH model, as described in Appendix 3.
29 See Bollerslev, Chou, and Kroner (1992). Also, for a fuller description of the characteristics of different time series models see Nelson (1989,1991). Also, the EGARCH model is better suited to deal with asymmetries in returns. This is useful in that EGARCH accounts for leveraged returns that are common with stocks.
30 Later, Gallant, Hsieh, and Tauchen found evidence against GARCH(1,1) for the British pound.
As mentioned in the previous section, the literature on GARCH models clearly indicates that these models, while serving as good estimators in the short term, yield poor approximations of volatility for a time period beyond several days. The model is designed, after all, to only give one-day ahead estimates of volatility and regressors. Therefore, it is unrealistic to assume that the model is capable of making predictions on a longer time horizon.

In 1994, Heynen et al. developed a method for calculating an average expected volatility from a GARCH (1,1) process for dealing with longer time horizons. Their approximation is as follows:

\[
\sigma^2_{HKV}(t, T) = \bar{\sigma}^2 + (\sigma^2_{t+1} - \bar{\sigma}^2) \frac{1 - \gamma^T}{T - 1 - \gamma}
\]  

(6)

where

\[
\bar{\sigma}^2 = \beta_0 / (1 - \beta_1 - \beta_2)
\]  

(7)

representing a fundamental level of volatility based upon the convergence of parameters yielded from the GARCH model. The \(\sigma^2_{t+1}\) term is the same as appears in a typical GARCH process, as expressed in Equation (5) and the additional terms are simply mean reversion coefficients with \(\gamma = B_1 + B_2\). This adjusted definition of variance basically allows the next-day GARCH (1,1) result to be extrapolated beyond one day by treating any deviation from the mean variance separately according to the time horizon.

The application of this method is critical when comparing GARCH models to other approximations with longer time horizons, as will be better described later.

3.2 Forward Looking Measures of Volatility

Apart from the above described methods of calculating volatility that are based on historical data, option implied volatilities can sometimes be used to calculate a forward-looking measure of volatility. The implied volatility of an option is defined as the expected future volatility of the underlying asset over the remaining life of the option that equates the fair value of the option implied by a particular model to the option’s actual market price. Many studies have concluded that measures of option-implied volatility are, indeed, the best predictor of future volatility.

Unlike time series measures of volatility that are entirely backward-looking, option implied volatility is “backed-out” of actual option prices—which, in turn, are based on actual transactions and expectations of market participants—and thus is inherently forward-looking. Recall that this measurement incorporates the most current market information and thus should reflect market expectations better than any historical measure.

Properly interpreted, the implied volatility of an option provides information about what market participants expect to happen with future asset returns. Implied volatility is the volatility implied by two things: the current market price of the option, and some model for calculating the theoretical price of the option such as Black-Scholes. To discuss implied volatility in the

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32 This GARCH (1,1) variance is referred to as \(\sigma^2_{HVT}\) since the authors of the paper are Heynen, Kemna, and Vorst.
absence of a theoretical option pricing model is meaningless. To see why, a brief review of how theoretical option prices are calculated is necessary.

3.2.1 Black Option Pricing Model

An option pricing model is an attempt to express or calculate the fair market value of an option (net of trading costs and liquidity) as a function of observable parameters, such as maturity. The theoretical price of an option is then the fair market price of an option under the assumptions made by the corresponding valuation model. The most common and well known option pricing model is the Black-Scholes model.\(^{35}\)

The original version of the model provides a closed-form solution to the problem of valuing European-style put and call options on an underlying asset. For the Black-Scholes model to yield reliable values of options, a number of assumptions must be satisfied. These include that the price of the asset underlying the option is distributed lognormally, there are no arbitrage opportunities, security trading is continuous, there are no transaction costs or taxes, and all risk free interest rates are constant over the life of the option.

The Black-Scholes model was developed to price options on equity and equity warrants, although numerous generalizations of the model extend it to the pricing of options on other assets. The basic Black-Scholes model involves options on non-dividend paying assets. For a European call with strike price \(X\), the current price of the call on a common stock is just

\[
c = SN(d_1) - Xe^{-rT}N(d_2) \tag{8}
\]

where \(c\) denotes the price of the call, \(N(d)\) denotes the cumulative normal probability distribution evaluated at \(d\), \(S\) is the stock price, \(T\) is the time to maturity of the option, and \(r\) is the riskless interest rate. In addition,

\[
d_1 = \frac{\ln(S/X) + (r + \frac{1}{2}\sigma^2)T}{\sigma\sqrt{T}} \tag{9}
\]

and \(d_2 = d_1 - \sigma T^{1/2}\), where \(\sigma\) is the volatility on the underlying stock.

Options on assets paying a constant dividend yield can be priced using a modified form of Black-Scholes. Similarly, the formula can be modified to account for options on futures contracts by simply replacing the term \(S\) in the equation above with \(F\) for the futures price and by setting the continuous dividend equal to the interest rate. The other terms in the formula must also relate to futures as the underlying asset. This variation of the Black-Scholes model was introduced by Black (1976) and is now referred to as simply the Black Model. Since this paper revolves around futures prices, all references will be to the Black model.

The one unobservable parameter in the Black model is volatility. Theoretically, the proper volatility input to the Black model is the instantaneous variance of asset returns—i.e., the variance of the underlying asset’s return over an infinitesimal time increment. Robert Merton has shown that under this interpretation, the volatility implied by the Black-Scholes model can be

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\(^{35}\) See Black and Scholes (1973) and Merton (1973). Note that Merton developed a similar representation of option pricing, hence the model is sometimes referred to as the Black-Scholes-Merton model.
interpreted as the expected future instantaneous variance of the underlying asset's return over the remaining life of the option.\textsuperscript{36}

To price an option using the Black model, we just substitute values of observed parameters and volatility into the Black equation, which provides an exact link between the inputs to the model and the theoretical option price. Suppose the valuation problem is approached from the opposite angle. Suppose a market price for a European call is observed and instead, the goal is to find that volatility, $\sigma$, which yields the quoted option price when substituted into the Black equation. In other words, suppose the strike price of the option, the current futures price and the interest rate are given. With this information and the Black model, the value of volatility, $\sigma$, which would yield the observed option price when substituted into the Black model may be calculated. The resulting value for $\sigma$ is called the Black implied volatility, because that number represents the volatility of the underlying asset that is implied by the quoted option price and the Black model.

3.2.2 Previous Work on Implied Volatility

According to efficient market hypotheses, since implied volatilities are calculated based upon today's pricing information, they contain the best information about the market. Therefore, implied volatilities are presumably the best representation of market expectations. A number of significant works in the literature have compared the ability of implied volatilities with that of more traditional historic models to forecast volatility.

Among the first papers to address the informational content of implied volatility were by Latane and Rendleman (1976) and Chiras and Manaster (1977). The former found that implied standard deviations for all options were generally a better predictor of future variability in stocks than traditional standard deviation calculations based upon historical data. The latter found the same results using a 20-day moving average calculation to represent the traditional standard deviation. Chiras and Manaster included an adjustment for dividends and also focused on developing a trading strategy that is most efficient according to the results of implied standard deviations.

Several years later, Beckers (1980) performed a similar study taking dividends into account by using the Black-Scholes formula to calculate implied volatilities of stock returns. Based upon the evidence provided in his paper, Beckers found that the most relevant information about future transactions is reflected in the price of at-the-money options. For calls and puts further in- or out-of-the-money, however, the evidence is less clear. Despite this result for these specific options, all of the previous works suggest that implied volatilities explain more variation in the future standard deviations of security returns than do historical measures of standard deviation.

The first paper to compare implied volatilities with a more sophisticated type of historical model was that of Day and Lewis (1992). This paper focused on implied volatilities derived from the S&P 100 index and compared them to GARCH and EGARCH models, both of order (1,1). Using OLS regression techniques, the authors are unable to conclude that implied volatilities contain more or less information relative to the conditional volatility estimates obtained from GARCH and EGARCH. The in-sample results point in both directions with implied volatilities looking better over the short term only. The results do provide certain evidence that GARCH models provide better forecasts than the EGARCH models in some instances.

\textsuperscript{36} See Merton (1973).
Lamoureux and Lastrapes (1993) arrived at completely different results, finding that by using all of the information available to the market through implied volatilities, forecast of variance in the market is improved. The authors used corrections to account for any bias in the statistical results. The GARCH model used in this study performed poorly due to the longer time horizon used, that of 90 to 180 calendar days. The authors concede that GARCH is not an appropriate model to use with longer term forecasts.

Canina and Figlewski (1993), through use of S&P 100 index options like Day and Lewis (1992), determine that implied volatility is a poor forecast of subsequent realized volatility when compared to historical measures. Unlike the previous works mentioned here, the authors calculate implied volatilities from a binomial model that adjusts for dividends and captures the value of early exercise. The historical measure of volatility used in this study is a 60-day moving average process. The authors offer good conclusions to support their unconventional results, in particular, the belief that option prices impound many extraneous factors regarding the supply and demand of the option that are unexplained by the pricing model. This may be confirmed by the strict assumptions, such as a frictionless market, upon which option pricing models are derived.

Finally, Day and Lewis (1993) produced another paper comparing option implied volatility with the conditional volatility from GARCH and EGARCH models but rather than focus on traditional stock returns, the authors examined crude oil futures. As they concluded in their previous study, Day and Lewis preferred the GARCH model to the EGARCH in response to changes in futures prices. The authors concluded that the implied volatilities had significant in-sample explanatory power. Neither the GARCH models nor historical estimates added much explanatory power to predictions of near-term volatility based on implied volatilities.

Therefore, the common trend in the literature points to implied volatilities as having superior informational content over historical estimates of both traditional and conditional volatility. All of the work reviewed so far, however, examines only price series in the equity or commodity markets. The most significant work on foreign exchange series was done by Jorion in 1995 and serves as the basis for this thesis.
CHAPTER 4

EXPLAINING VOLATILITY DURING AND AFTER THE ERM

There continues to be significant, ongoing debate over whether historical measures of volatility or forward looking measures of volatility serve as better predictors of actual volatility. As mentioned in the previous chapter, one significant work focusing on this comparison of historical and implied volatility in foreign exchange markets is Jorion (1995). He attempts to analyze whether forward-looking measures of volatility are better at explaining actual volatility than historical volatility measures. To do this, he runs two regressions: a regression of realized daily volatility on implied volatility and two historical volatility measures, a 20-day moving average volatility and a GARCH volatility, which he calls “informational content regressions”; and a regression of future volatility over the remaining life of an option on the same historical and implied volatility measures, which he refers to as “predictability regressions.” Analyzing daily Swiss franc, Japanese yen, and Deutsche mark returns from 1985 to February 1992, Jorion concludes that implied volatility outperforms all historical volatility measures as a predictor of future return variability.

This paper generalizes Jorion (1995) in two ways. First, Jorion’s paper used only short-memory measures of volatility as measures of backward-looking volatility. In other words, both his MA(20) and GARCH(1,1) measures capture only very recent volatility in the historical time series. Along with repeating these historical measurements, this paper also includes a MA(100) historical volatility measure. In other words, the short-memory MA(20) and GARCH(1,1) volatility measures are supplemented here with a longer memory measure.

This study then goes one step forward by comparing the results from separate regressions run during and after the crisis in the European Monetary System in 1992. By using British pound data before and after the European Currency Crisis, the specific hypothesis is examined that the ability of different volatility measures to predict future volatility depends on the exchange rate regime.

Before describing the regressions run here, a description of the raw data and the cleansing of that data into appropriate time series are provided. The following section describes some descriptive statistics performed on the data along with some preliminary summary statistics on the models. The last two sections focus on the main regressions themselves.

4.1 Description of the Data

Several distinct sources of data were used in this study to arrive at the various estimates for historical and forward-looking volatility. In order to calculate actual and historical estimate of volatility, a daily time series of settlement prices for all British pound futures, as traded on the Chicago Mercantile Exchange, were acquired from Futures Industry Institute. This time series is displayed in Figure 1.

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37 Another similar paper that focuses on forecasting volatility in crude oil futures is by Day and Lewis (1993).
38 Day and Lewis (1993) find similar results.
39 Futures Industry Institute (FII) is located at 2001 Pennsylvania Avenue NW, Washington DC. FII acquires this data from the CME directly.
A time series of daily implied standard deviations (ISDs) for options on CME British pound futures was available from Bridge/Knight Ridder. These ISDs are calculated by averaging the option implied volatilities resulting from the two nearest at-the-money calls and the two nearest to at-the-money puts for each option contract. Additionally, this series was modified to represent information pertaining only to the front month option for that day. The term “front month” refers to the option that is closest to expiration on a particular day. Also, it is important to note that the volatilities were converted so as to be expressed in annual fractions rather than as a percentage (i.e., 19.35% annualized was re-written as 0.1935.)

The timing of observations and the issue of matching daily observations from these two separate data files were of critical importance in this process. Since this study focuses on the performance of this data during and after the participation of the British pound in the Exchange Rate Mechanism of the EMS, the dates in use were chosen according to this event. The “ERM” period ranges from October 10, 1990, to September 15, 1992. The “post-ERM” period ranges from September 16, 1992, through March 6, 1996. Based upon this division of sub-periods, the data was formatted according to the available dates of the ISD data set. For each available date in the ISD series, the price of the option was matched according to the date and the “front month” so that each date lists a corresponding pair of ISD and underlying futures price for that particular option. For any day on which the series did not coincide, that date was deleted from the time series. Furthermore, it was important to keep track of the number of remaining days until expiration of each option series for the purpose of calculating the two regressands.

4.2 Measuring Volatility

After forming a reliable, clean, front-month series of futures prices that coincided with the ISD series, it was possible to proceed with calculating the regressands and regressors to be used in the informational content and predictability tests. It was necessary to calculate several different measures of volatility based on both backward and forward looking daily returns. Since it is assumed that futures prices are lognormally distributed, returns are calculated according to their log differences in prices and are hence continuously compounded. Therefore, a one-day behind return is calculated as

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40 Bridge/Knight Ridder is located in Philadelphia, PA. This series is known as the “Volatility Footprint.”
41 Solving for the option implied standard deviation for a single option is described in detail in the previous section.
42 A front-month series was constructed by using the option with the closest time to expiration for each date. When a particular option disappears from the ISD data, it is assumed to expire and the option with the next to closest expiration is rolled into this front month series.
43 Options on currency futures trade based upon a monthly cycle so at any point in time, there can be as many as twelve option contracts trading on any particular day, depending upon their liquidity.
44 The pound actually joined the ERM on October 8, 1990.
45 September 16, 1992 is “Black Wednesday” or the date that the pound left the ERM.
46 A front month for the futures price series was calculated in the same manner as for the ISD series. Special attention was paid, however, to the expiration of the option contract that corresponds to the current futures contract. This was an important detail since futures contracts trade on a March quarterly cycle and options contracts trade on a monthly basis. So, for example, when the March 1993 options contract rolls into the April 1993 contract, the futures contract is rolled on the same date from the March 1993 futures contract to the June 1993 contract. (Quarterly options always expire earlier in the month than the corresponding futures contract. Therefore, January, February, and March options all expire into the March futures contract whereas April, May and June all expire into the June futures contract, and so on.)
47 In particular, for calculating the actual future volatility, as explained in Section 4.4.
48 This is common practice in dealing with return series. See Hsieh (1989) and Jorion (1995).
\[ R_{t-1,t} = \ln P_t - \ln P_{t-1} \]  

(10)

where \( P_t \) denotes the futures settlement price at time \( t \). Similarly, the one-day ahead return is calculated as

\[ R_{t,t+1} = \ln P_{t+1} - \ln P_t \]  

(11).

At time \( t \), the one-day ahead return is not yet observable. In the later regressions, this measure squared will serve as a measure of actual volatility to be compared with volatility forecasts that are available at time \( t \).

Both of these daily return series were then squared to serve as a basis for either input in a measurement technique or as a measure of volatility. These series, along with any other measures of volatility that are used in the main regressions, are annualized by multiplying by the square root of 252, assuming a 252-day trading year. The resulting volatilities are expressed as standard deviations. Furthermore, it is always assumed that the mean of the return series is equal to zero so that the daily variance is explained simply by the squared returns.\(^{49}\)

The one-day behind return series was used to calculate all of the historical or backward looking measures of volatility such as MA(20), MA(100), and GARCH. These are shown in Figure 2. In the GARCH application, as demonstrated in the previous chapter, both the previous day’s return and variance are regressors in determining the conditional volatility whereas the moving average processes are simply a function of the one-day behind squared returns. All of the historical estimates were arrived at in the manner described in the previous chapter. It is important to note, however, that the available data in each final historical volatility series was truncated by the order of the moving average processes and the GARCH specifications.

The one-day ahead return series was used to calculate the regressands in the information content and predictability regressions. The one-day ahead return series, when squared, represents the actual daily volatility of the futures settlement prices. This squared one-day ahead return was the dependent variable in the information content regressions. The return series was also used to calculate the future volatility used as the dependent variable in the predictability regressions and is defined as the forward looking volatility over the remaining life of the option used to compute the ISD. The procedure for calculating this process was more complicated in that it was necessary to keep track of the lifetime of the option.\(^{50}\) So, for example, if there are fifteen days remaining in the lifetime of an option, the volatility of the futures contract is determined by averaging the squared returns over those fifteen days. The square root of this average multiplied by the square root of 252 yields the actual future volatility on an annualized basis. On the next day, the previous day’s return would be dropped from the measurement since only fourteen days remain to expiration and the procedure for calculating the volatility was

\(^{49}\) This is true even in the unusual case where returns are summed over a number of days as in the future volatility calculation. According to the basic definition for variance (\( \sigma^2 \)), \[ \sigma^2 = \frac{1}{(\nu-1)} \sum (r_i - \bar{r})^2 \] summed from 1 to \( \nu \) where \( \bar{r} \) represents the average return. The assumption that the average return is equal to zero is common practice since it is believed that daily foreign exchange returns are revert to zero. Furthermore, given the frequency of daily data, it is unlikely that the average return would be significant enough to cause any bias in the results.

\(^{50}\) A dummy variable was used to mark the lifetime of the option so that at every contract expiration the dummy variable changed indicating a new option contract was “rolled” over.
repeated. This is the method is adopted from Jorion (1995) and raises several difficulties.\textsuperscript{51} Figure 3 shows the time series of volatility implied by option prices and the actual future volatility.

The concept of calculating a daily future volatility over the remaining life of the option is controversial when used in a time series. Because of the recursive nature, the consecutive future volatilities contain a significant amount of redundant information about the return series. For example, the measure of future volatility on a day for which the corresponding option has 15 days to maturity is the average of the next 15 days’ actual one-day ahead squared returns. On the next day, the future volatility is the average of the next 14 days’ one-day ahead squared returns. Because those fourteen days also were included in the prior day’s future volatility measure, the dependent variables in these predictability regressions are overlapping variables. This topic will be more thoroughly addressed in a later section with statistical evidence.

4.3 Descriptive Statistics

Some basic summary statistics were run on the available return and volatility series over the entire sample period as shown in Table 1.\textsuperscript{52} These consisted of calculations of the mean and standard deviation of each time series, autocorrelations, and Dickey-Fuller test statistics. From the estimates of the means and standard deviations shown in the table, all measures of volatility are comparable.\textsuperscript{53} The Dickey-Fuller test is one of the principal methodologies used in testing for the presence of unit roots in time series. In all of the time series examined in Table 1, the test statistic is clearly insignificant, thus we can reject the null hypothesis of a unit root in favor of the alternative that all the series are stationary processes.\textsuperscript{54}

In addition, Table 2 provides the Portmanteau statistics for the return series and the squared return series (as a proxy for volatility.)\textsuperscript{55} All of the series examined in this table are demeaned so that the table reports the statistics for the residuals when a regression is run of daily returns or volatilities on a constant. This comparison has been used by Hsieh (1989) and others as a test for conditional heteroskedasticity in currency returns.\textsuperscript{56} In general, if the Portmanteau statistics are not statistically significant for returns but are statistically significant for squared returns, the series is heteroskedastic. As may be seen in Table 2, the Q statistics are always strongly significant in the variance series, almost double those for the returns. As a result, GARCH estimation methods may be appropriate.\textsuperscript{57} The autocorrelations in Table 1 provide further evidence of time varying volatility.\textsuperscript{58}

\textsuperscript{51} The concept of using the trading days remaining over the lifetime of the option for the purposes of averaging rather than the calendar days is credited to French (1984).

\textsuperscript{52} All of the regressions and other statistical analysis in this study were performed using RATS Version 4.1.

\textsuperscript{53} An EGARCH(1, 1) model was also estimated, however the lack of comparability in the summary statistics against other measures mandated that the estimation be eliminated from further regressions.

\textsuperscript{54} See Mills (1993) and Maddala (1992).

\textsuperscript{55} Portmanteau statistics are tests for “white noise” and indicate whether there is autocorrelation between higher order lags of residuals.

\textsuperscript{56} See Hsieh (1989).

\textsuperscript{57} GARCH (1,1) is not the only specification for a GARCH model, as discussed in Chapter 3. It is the specification most used in FX applications and the model used by Jorion (1995), hence its choice here. For an alternative interpretation, see Gallant, Hsieh, and Tauchen (1989). Also, see Footnote 47.

\textsuperscript{58} Autocorrelations are reported in Table 1 lags of one through five and ten days in each series. Those not shown are not substantially different and follow a similar pattern to those displayed here.
Finally, Table 3 reports the maximum likelihood estimates resulting from the GARCH (1,1) estimation.\textsuperscript{59} The statistical significance of the parameters further attests to the presence of time variation in volatility.\textsuperscript{60}

Now that preliminary statistics have been run on the time series, it is possible to proceed with confidence in the series used for input in the main regressions. The next sections focus on these two regressions and present a discussion of their results.

4.4 Informational Content Regressions

As stated previously, the informational content regressions were designed by Jorion (1995) to compare the abilities of several estimated measures of volatility to explain actual volatility. Daily actual volatility is calculated by squaring the one-day ahead returns then annualizing the resulting variance. This number is used as the regressand in all of the informational content regressions. The various measures of volatility serve as the regressors in this ordinary least squares regression.

A typical informational content regression is as follows:

\[
\sqrt{R^2_{t,t+1}} = \beta_0 + \beta_1 \sigma_t + \epsilon_{t+1}
\]  

(12)

The estimated volatility forecast may include four separate volatility measures: the ISD from option prices, MA(20), MA(100), or the GARCH (1,1) model.

Two types of informational content regressions were run. The first set consists of four simple OLS regressions of daily actual volatility run separately on each of the four volatility measures. The second set of OLS regressions are multiple regressions of daily actual volatility on various combinations of volatility forecasts. As the sole measure of forward-looking volatility, the ISD is included in all multiple regressions. Three of the multiple regressions include the ISD and one of each of the three backward-looking volatility forecasts. The remaining two multiple regressions include the ISD and several historical volatility measures. The results from these regressions are presented in Tables 5 and 6. All regressions were run first for the ERM period from October 10, 1990, through September 15, 1992, and next for the post-ERM period from September 16, 1992, through March 6, 1996. Chow tests showing any significant difference in coefficient estimates across these two sub-periods are also reported in Tables 5 and 6.

In choosing the regressors for the multiple regressions with more than one historical volatility measure, the correlations across regressors served as a guide. Shown in Table 4, the correlations suggest that including the two short-memory historical volatility measures, (GARCH and MA(20)) in the same regression could create serious multicollinearity problems. So, these measures are never included in the same regression.

4.5 Predictability Regressions

The predictability regressions, also presented by Jorion (1995) were designed to compare the abilities of several measures of estimated measures of volatility in determining the future volatility over the remaining life of the option used for the ISD regressor. In order to do so, a time series of future volatility had to be created. This was done by calculating the average daily

\textsuperscript{59} All of the EGARCH (1,1) parameter estimates were insignificant thus providing further reason to not include the model in further regressions.

\textsuperscript{60} It is important to note that simply because the significance of the parameters suggest that the series is heteroskedastic and that GARCH-type methods may be appropriate, this does not necessarily mean that GARCH (1,1) is that best specific model. Statistical methods for determining the “optimal” GARCH specification are controversial. Instead of using such tests, GARCH (1,1) is employed to keep consistent with most empirical work examining GARCH models for currencies. See Jorion (1995) and Hsieh (1989).
return over the remaining life of the option, as described in Section 4.2 above. This daily future volatility series is denoted by $\nu_{t,T}$ where $t$ represents the current date and $T$ represents the future date of option expiration.

A typical predictability regression is an ordinary least squares regression that may be expressed as:

$$\nu_{t,T} = \beta_0 + \beta_1 \sigma_i + \epsilon_{t+1}$$

where the estimated volatility forecast, $\sigma_i$, may again include the ISD from option prices, MA(20), MA(100), or the GARCH (1,1) model.

The same regressions were run to test predictability that were run to test the informational content of volatility forecasts with one exception. Rather than using the results from the traditional GARCH (1,1) calculation, the adjusted GARCH (1,1) methodology was used in order to account for the number of days remaining until option expiration. Table 7 shows the results from the four simple regressions of future volatility on the ISD against the three historical volatility measures, and Table 8 presents the results of the multiple regressions. The regressors used in the multiple regressions are the same as those used in the information content regressions. As before, the regressions were all run separately for the ERM sub-period and the post-ERM sub-period, and Chow tests for the equivalence of parameter estimates in each sub-period are given.

As is evident from the extremely low Durbin-Watson statistics in Tables 7 and 8, the residuals in the predictability regressions are strongly positively autocorrelated. This autocorrelation is due to the overlaps in the future volatility dependent variable. To account for this autocorrelation, the standard errors in all the predictability regressions were corrected using the method of White (1980) and Newey and West (1987). Over the full data sample, the average time to expiration for the options used is 11.15 days, which means the average number of one-day ahead squared returns in the future volatility variable is about 11 days. Thus, the lag length used for the Newey-West standard error correction was 11.

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62 These methods serve as corrections for heteroskedasticity.
CHAPTER 5
DISCUSSION OF RESULTS

This chapter presents a discussion of the results obtained from the informational content and predictability regressions described in Chapter 4. The chapter also addresses these results in light of other statistical information reflected in the previous tables and the work done by Jorion (1995). Recall that Jorion ran the same types of regressions, except where noted, for three currency futures: the Japanese yen, the German mark, and the Swiss franc.

5.1 Informational Content Regressions

5.1.1 Simple Informational Content Regressions

This discussion may begin by analyzing the results of the Simple Informational Content Regressions on Table 5. Recall that these are simple OLS regressions designed to determine the ability of the various volatility estimates to predict actual volatility. This section begins by addressing each regression separately. For now, the Chow F-Statistic results may be ignored, as they will be defined later. Also, the Durbin-Watson statistics reveal a lack of serial correlation in all of the regressions on this table but otherwise are not discussed below.

From Regression number 1, it is evident that the ISDs serve as a good predictor of actual volatility during both of the ERM sub-periods. Both coefficients are statistically significant at the level of 1%. The coefficients on the ISDs are of high magnitude, 0.516 during ERM and 0.634 post-ERM. For the post-ERM period, this means that a 10% change in the ISDs leads to a 6.34% change in the actual volatility, thus the ISDs are quite influential. These magnitudes are a bit lower than those reported by Jorion that range from 0.783 for the Japanese yen to 0.854 for the Swiss franc. It is interesting to note, however, that the adjusted $R^2$ statistics are low particularly during the ERM sample period, 0.0123, and increase in the post-ERM period to 0.0767, indicating an improvement in the “goodness of fit.” Jorion’s reported $R^2$ statistics for each simple regression of ISDs on actual volatility yielded $R^2$ statistics ranging from 0.035 to 0.0515, lower than those reported for the post-ERM period in this study.

Regression number 2 uses the MA(20) estimate to fit actual volatility. The coefficients indicate that the MA(20) served as a better predictor post the ERM crisis. This conclusion may be drawn based upon several factors. First, the during-ERM coefficient of 0.32 is significant only at the 5% significance level while the coefficient of 0.53 for the post-ERM period is significant at the 1% level. These coefficients are all comparable with those arrived at by Jorion for the MA(20) simple regression. Again, the coefficients revealed by the post-ERM regression are a bit higher than those of Jorion that average to about 0.37. Second, the improvement in coefficients in this study is accompanied by a noticeable improvement in the adjusted $R^2$ statistics from 0.011 to 0.095, indicating a dramatic improvement in the explanatory power of the regressor. The post-ERM statistic is much higher than Jorion’s reported statistic, similar to what may be seen in the ISD simple regression.

The third simple regression involves the MA(100) estimation. This is our first interesting result in that the resulting statistics for the during-ERM phase are quite different than for the post-ERM phase. During the ERM, the coefficient is very low and insignificant. The reported adjusted $R^2$ statistic is also extremely low. It is possible to have a negative $R^2$ statistic as a result of the adjustment for the number of degrees of freedom.

By contrast, the post-ERM coefficient is higher and
is significant at the 1% level. Since Jorion did not run any regressions on an MA(100) estimator, no comparison to Jorion may be drawn. These results, both in terms of coefficients and $R^2$ statistic are, however, along the same lines of the previous regressions described above, with the exception of the during-ERM insignificant result. This indicates an estimate of historical volatility with a “long memory” such as an MA(100) is not a good choice.64

Simple regression number 4 employs the GARCH(1,1) model estimates for comparison with actual volatility. In both sub-periods, this estimate is statistically significant at the 1% level and the coefficients are both of decent magnitude, 0.624 and 0.795, respectively. As is common to all of the regressions, the adjusted $R^2$ statistic improved in the post-ERM phase indicating that the GARCH model has better explanatory power in the post-ERM period. When compared with Jorion’s estimates ranging from 0.560 to 0.672, the coefficient reported for the post-ERM period seems much higher, thus indicating that the GARCH model suits the pound better during this sample period over the other foreign exchange time series used by Jorion. The adjusted $R^2$ statistic of 0.105 in the post-ERM period is also much higher than those reported by Jorion, indicating a better “goodness of fit” in our regression.

It is now possible to compare the coefficients across all four of these regressions. First, during the ERM, it is clear that the ISDs and the GARCH model performed better than the simple historical estimates. The coefficients for the GARCH model, 0.624, were slightly higher than those of the ISDs at 0.516, with a slightly better adjusted $R^2$ statistic in the GARCH regression. Second, in the post-ERM period, all estimates of volatility performed well. The highest coefficient is yielded by the GARCH (1,1) model of 0.795, followed by the MA(100), ISD, and MA(20). From these simple regressions, it is obvious that the post-ERM period appears to be much more straightforward to model.

As for the reported Chow F-Statistics, all four regressions reject the null hypothesis that the coefficient estimates are statistically indistinguishable across all sub-periods at the 1% level of statistical significance.65

5.1.2 Multiple Informational Content Regressions

Table 6 displays the results for the Informational Content Regressions involving multiple regressors. All of the regressions include the ISD as one of the regressors. The first set of these regressions, labeled number 1 through 3, involve only one of the other regressors (MA(20), MA(100), and GARCH (1,1)) along with ISD while regressions 4 and 5 involve some combination of those regressions. Again, the Chow test results will be discussed after addressing each individual regression.

Starting with regression number 1, the only coefficient of any significance is that of the MA(20) regression in the post-ERM period with a value of 0.422. None of the coefficients for the ISD are statistically significant. It is therefore impossible to comment on the magnitude of the coefficients since a statistically insignificant coefficient is no different than zero. The adjusted $R^2$ statistic indicates a better goodness of fit in the post-ERM period where the MA(20) seems to perform well. Now, let us compare these results with those of Jorion. Jorion found the MA(20) results to be insignificant at the 5% level and thus no different than zero. He also found

64 Unfortunately, this result may be biased in that the degrees of freedom are lowest for this estimate. The regressions were designed, however, to target the extremes in terms of the available memory of a historical estimate. 
65 In order to calculate the Chow tests, it was necessary to conduct summary statistics for the full sample. These statistics are available upon request from the author. Furthermore, all statistical tests and regressions run in this thesis were performed over the entire sample.
that the ISDs were statistically significant with coefficients ranging from 0.687 to 0.840. These results are completely opposite of those found in this study.

In the second regression, the ISD significantly outperforms the MA(100) during the ERM phase. The coefficient on the ISD is high at 0.713, and it is statistically significant at the 1% level whereas it is impossible to comment on the MA(100) since it is completely insignificant. In the post-ERM period, however, the MA(100) improves dramatically as an estimation method. This coefficient is of decent magnitude at 0.523 and is statistically significant at the 1% level. The ISD coefficient also displays this level of significance, however, its coefficient is about half in magnitude of that of the MA(100), 0.248. The adjusted $R^2$ statistics yield conclusions similar to those reported in previous results.

The third regression utilizes the GARCH (1,1) model along with the ISDs. When combined with the GARCH (1,1) model, the ISDs demonstrate no statistical significance, behavior previously seen in regression 1 of this table. The GARCH (1,1) model is weakly significant during the ERM and strongly significant at the 1% level, with coefficients of good magnitude, 0.767, in the post-ERM period. The adjusted $R^2$ statistics again indicate a better goodness of fit in the post-ERM period with a level of 0.105. When compared with Jorion, these results are opposite. Jorion never found the GARCH estimates to be statistically significant and found the ISDs to be significant in the case of each currency. The adjusted $R^2$ statistic reported in the post-ERM period is over double that reported by Jorion in his multiple ISD and GARCH regressions. Overall, this result mimics the comparative information found in the multiple regression involving ISD and MA(20).

It is interesting to note, in comparing regressions 1 through 3 of Table 6, that the ISD only performs well when pitted against the MA(100) during the period when the MA(100) performed the worst, i.e., during the ERM period, as may be seen in the simple regression on Table 5. Contrary to Jorion’s results, the ISDs are noticeably outperformed by all historical estimates in the post-ERM period. Within this study, this implies that the pound’s departure from the ERM allowed for much more informational content in historical volatility forecasts than when the pound was in the ERM. Beyond this study, in comparison to Jorion’s results, this indicates that the British pound behaved quite differently from the other currencies measured by Jorion.66

The last two regressions in Table 6 are different from any regressions ran by Jorion since they include three regressors. Again, ISDs are always used but now the MA(100) estimates are common to both regressions, as well. The motivation for these two regressions was to determine whether the ISDs performed any better against the MA(20) and GARCH(1,1) estimations when the MA(100) estimates were also included.

In regression 4, the ISDs continued to perform well against the MA(20) and MA(100) during the pound’s involvement in the ERM. In fact, it was the only coefficient that was statistically significant and with a relatively good coefficient of 0.582. The adjusted $R^2$ statistic is a bit low during this phase, but still acceptable by comparison with Jorion’s overall results. In the post-ERM period, however, the ISDs are not statistically significant. Both the MA(20) and the MA(100) are, however, significant at the 5% and 1% levels, respectively. The coefficient for the MA(100) model is slightly higher than that for the 20-day moving average process at 0.368 and 0.261, respectively. In the post-ERM period, the adjusted $R^2$ statistic increases indicating a better goodness of fit. This result is interesting in that the MA(100) continues to perform better than the MA(20) in the post-ERM period, a result that is consistent with the previous multiple

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66 Recall that Jorion also used a much longer time series, approximately 7 years worth.
regressions involving two regressor in Table 6. Again, this result is an interesting one, suggesting that the futures series exhibited more longer-term stationarity after it left the ERM.

In regression 5, the ISDs completely failed to be significant at any level in both periods when regressed against actual volatility with MA(100) and GARCH (1,1). This is an interesting result because it had previously outperformed the MA(100) estimate in regression 2. The MA(100) coefficient is also statistically insignificant during the ERM and the GARCH (1,1) parameter is significant only at the 10% level, with a coefficient of magnitude 0.64. This magnitude is a bit higher than it was in the regression number 3, involving only the ISD and GARCH(1,1). The adjusted $R^2$ statistic is low, although comparable to previous results for this sample period. In the post-ERM period, the only change is an increase in significance for the GARCH (1,1) coefficient to a 5% level with a coefficient of 0.531. The magnitude of the coefficient, however, dropped slightly from regression 3. The adjusted $R^2$ statistic increased to 0.105, among the highest in these regressions, indicating a better goodness of fit in the post-ERM period, as had been seen throughout these regressions.

The results of the Chow tests in these multiple regressions are slightly different than in the simple regressions. Recall that significance in a Chow test indicates a rejection of the null hypothesis that coefficient estimates are statistically indistinguishable across sub-periods. The Chow test are statistically significant in each individual regressions but at different levels. Regressions 1, 4, and 5 are significant only at the 5% level while regression 3 is significant only at the 10% level. Regression 2, involving the ISDs and the MA(100) is the only test that is strongly significant at the 1% level. The conclusions that may be drawn from these results is that combinations of estimators affect the statistical characteristics of the time series in different ways during and after the ERM.

It is necessary to add that there is a high degree of correlation between the MA(100) and GARCH (1,1) estimation series, as high as 95.9%, as shown in Tables 4a and 4b. Despite this high level of correlation, multicollinearity is not an issue in this regression. This is because the regression still yields a statistically significant variable. This implies that the presence of high correlation is not so dominant so as to render the regression meaningless by resulting in parameters that are indistinguishable from zero. Also, diagnostic tests for multicollinearity, such as dropping and adding regressors, did not change the $R^2$ much and thus further suggests that multicollinearity is not a major problem.67

5.1.3 Conclusions from Informational Content Regressions

There are several key conclusions that may be drawn from these informational content regressions. First, the tables indicate, with a high degree of confidence, that the departure of the pound from the ERM led to much more informational content in volatility forecasts than had been present when the sterling was in the ERM. Next, in contrast to Jorion, the historical volatility forecasts seem to consistently perform better than the ISDs. The only exception is in the case of the MA(100) in the during ERM-period, reasons for which are mentioned above. Further reason for this lack of information may be explained by the choice of option pricing model or the options, themselves, from which the ISDs are derived. See Appendix 4 for more information.

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67 The reason for running regressions 4 and 5 separately was to minimize the multicollinearity problems that resulted when all historical variables were included in the same regression.
5.2 Predictability Regressions

Recall that the Predictability Regressions are designed to see which estimate of volatility best captures the futures volatility that is reflected in the remaining life of the option. The Predictability Regressions are structured in the same format as the Informational Content Regressions with simple tests involving each variable and a series of multiple tests, all involving the ISDs. The exception in the Predictability Regressions is the use of the Adjusted GARCH (1,1) model in order based upon the approximation of Heynen et al. to account for remaining days to option expiration. The results for these regressions appear in Tables 7 and 8.

5.2.1 Simple Predictability Regressions

Table 7 displays the results for four simple regressions involving each of the estimators. Starting with the first regression involving the ISDs, the ISD coefficients are significant only in the post-ERM period with a coefficient of 0.834. This coefficient is higher than those arrived at by Jorion in his Predictability Regressions, which ranged from 0.496 to 0.547. The adjusted $R^2$ statistic of 0.372 in this post-ERM period nearly doubled the $R^2$ statistic reported by Jorion, as well. It is also interesting to compare these results with the Informational Content regressions where the ISDs were significant in both periods.

In the remaining regressions, the same pattern continued to emerge with the coefficient being significant only in the post-ERM period and with similar adjusted $R^2$ statistics. Therefore, the remaining focus will be on the post-ERM period. Across all regressions, the Adjusted GARCH model yielded the highest estimate of 1.18—actually implying that GARCH overforecasts volatility—followed by 0.96 from MA(100), 0.834 from the ISDs, and 0.696 from MA(20). This pattern is the same as that followed in the informational content regressions. When compared with Jorion’s Predictability Regressions, however, the results for the MA(20) are surprising since Jorion found this coefficient to be insignificant across all of his regressions. Also, similar to the results shown in Table 7, Jorion found the coefficients resulting from the Adjusted GARCH model to be higher than those resulting from the ISDs in two out of three of the currencies.

One immediate conclusion that may be drawn across these four regressions is that there is no appropriate forecasting variable to use during the ERM period. All of the candidates are insignificant. Further, the adjusted $R^2$ statistics are extremely low for all regressions ran during this time period. In the post-ERM period, however, since all regressions were significant, it may be concluded that any one of the estimators may be used in modeling future volatility with the Adjusted GARCH performing the best.

As for the reported Chow F-Statistics, the null hypothesis is rejected across all sub-periods in all regressions. This means that the two sub-periods are statistically different from one another, as would be expected with the lack of significance for any coefficients during the ERM phase.

5.2.2 Multiple Predictability Regressions

Five multiple regressions were run similar to those run for the Informational Content tests. The results of these regressions appear in Table 8. Beginning with regression number 1, involving the ISDs and the MA(20) estimation, the only significant coefficient is the MA(20) in the post-ERM regime with a coefficient of 0.544. The ISDs failed to be significant in either period. These results are similar to those yielded by the parallel Informational Content regression in Table 6. The adjusted $R^2$ statistics follow the pattern established by the simple
Predictability Regressions, with low values during the ERM and much higher values, near or over 0.40 in the post-ERM regime. As for a comparison with Jorion’s results, those shown in Table 8 are contradictory. Jorion found the ISDs to be significant with a coefficient of 0.669 and the MA(20) to be insignificant – the opposite of these results.

In the regression involving the MA(100), the ISD was significant with a coefficient of 0.597 during the ERM but insignificant afterwards. The MA(100) was backwards in that it was insignificant during the ERM but significant with a large coefficient of 0.809. Recall that this means that a 10% increase in the MA(100) volatility forecast implies an 8.9% increase in future volatility. These results are very similar to those exhibited in regression number 2 in Table 6. It is impossible to draw any comparisons with Jorion since he did not use MA(100) as an estimator.

The third regression uses the Adjusted GARCH (1,1) estimate and the ISDs. During the ERM, the Adjusted GARCH regressor is significant at the 10% level with a coefficient of 0.611 but the ISD is not. In the post ERM period, however, the Adjusted GARCH (1,1) coefficient of 1.31 is significant at the 1% level. The high magnitude of the Adjusted GARCH regressor indicates that it is actually over-predicting volatility. This post-ERM result is similar to what was found in the Informational Content Regression in that the Normal GARCH also displayed some significance during the ERM in those regressions. As was the case with the multiple regression involving MA(20) and ISDs, Jorion found the Adjusted GARCH model to be completely insignificant and the ISDs to be significant when he ran a similar regression – again, completely opposite of the results cited here.68

The fourth and fifth regressions are modeled just like those in Table 6 of the Informational Content Regressions with the Adjusted GARCH model substituted for the normal. In fact, they also yielded results quite similar to those prior regressions. The only occasion where the ISDs were significant was when pitted against the MA(20) and MA(100) in the period during the ERM. The ISDs were significant at a level of 10% with a coefficient of 0.493. In this particular regression, since no other estimates were significant, the ISDs are obviously the better fit to future volatility. In the post-ERM period, the ISDs were insignificant while the MA(20) was significant at the 5% level with a coefficient of 0.248 and the MA(100) was significant at the 1% level with a coefficient of 0.682. These post-ERM period results are the same as was found in the Informational Content Regressions.

The fifth regression used the Adjusted GARCH (1,1), MA(100), and the ISDs. The only significant coefficient during the ERM phase the Adjusted GARCH regressor, but it is weakly significant. Afterwards, however, the Adjusted GARCH(1,1) model coefficient was highly significant with a magnitude of 0.97. In comparison with the similar regression in Table 6, the coefficients for the MA(100) were much improved. This indicates that the Adjusted GARCH (1,1) model worked significantly better in accounting for a longer time horizon than the Normal GARCH.

The results of the Chow tests in these multiple regressions are extremely similar to those in the simple regressions with very large numbers. Thus, it may be concluded that the sub-periods are statistically distinguishable in every regression performed. Multicollinearity is again not an issue, for reasons explained above.

5.2.3 Conclusions from Predictability Regressions

There are several key conclusions that may be drawn from these predictability regressions. First, the tables indicate, with a high level of confidence, that the departure of the

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68 Jorion also ran an adjusted version of the GARCH (1,1) model but his exact technique is unclear.
pound from the ERM increased the predictability in volatility forecasts than had been present when the sterling was in the ERM. Next, *in contrast to Jorion*, the conclusions are the same as those drawn in the Informational Content Regressions. The historical volatility forecasts, especially the Adjusted GARCH model, seem to consistently perform better than the ISDs. Some thoughts as to why this result exists are considered in Chapter 6.
CHAPTER 6

CONCLUSIONS

It is widely believed that implied standard deviations are the best available forecast of future market volatility. This result has been confirmed by a number of academic works, most recently Jorion (1995). This study follows the structure of Jorion’s work.

The results presented in this study provide new and interesting results comparing the ability of historical time series methods and implied standard deviations (ISDs) to estimate the actual volatility of futures prices during an economic regime shift involving the British pound’s departure from the ERM. Overall, contrary to prior results found by Jorion, historical, backward-looking estimates of volatility outperformed forward-looking ISDs in both the Informational Content and Predictability Regressions during and post-ERM.

The only occasion in which ISDs did better than a historical estimate was when pitted against the MA(100) estimate during the ERM, whereas, all other estimates of historical volatility were significant. This shows that in order to model this period during the ERM, a short-term estimator is required. In the post-ERM regime, however, all of the historical estimates performed well, particularly the normal and Adjusted GARCH (1,1) models, in both the Informational Content and Predictability Regressions. This shows that the pound’s departure from the ERM led to increased informational content and predictability than when the sterling was in the ERM, an effect which is best captured through historical modeling.

There may be several reasons for these results. First, it is possible that the ISDs used in this study lack all of the information that they are presumed to hold. Recall that ISDs are a function of the option pricing model that is chosen to solve for them, in this case, Black’s model. It is likely that the strong assumptions underlying this model are not realistic within the market. This is information that may only be captured by examining the volatility smile for these options and focusing on those options that are further in- or out-of-the-money.

Second, these results obviously reflect the fact while the pound was in the ERM, there was little informational content in the market. During this “managed floating” regime, there were many external factors controlling the markets, represented most clearly by the high number of central bank interventions during this period. When the pound returned to floating, these problems in the market became much more transparent, at least through historical estimation. The ISDs continued to be a poor estimator, more evidence indicating that the ISDs used in this model lack information.
REFERENCES


APPENDIX 1
ERM

CHRONOLOGY DEVELOPMENTS IN THE EMS
(Source: Wall Street Journal Europe)

1978
December
Formal Agreement to establish the European Monetary System (EMS). Founding Members were Germany, France, the United Kingdom, the Netherlands, Belgium, Luxembourg, Italy, Denmark, and Ireland.

1979
March 13
EMS launched. Originally, all currencies in ERM are permitted to float within a +/- 2.25% band width with the exception of the Italian Lira which was granted a +/- 6% band width.

September 24
First realignment of currency parities consists of a 2.0% revaluation of the Deutsche mark (DM) and a 2.9% devaluation of the Danish kroner (DKK).

November 30
Political uncertainty in wake of elections puts pressure on DKK which is again devalued about 4.8%.

1981
May
Mitterand is elected as President of France.

October 5
DM and Dutch Guilder (NLG) are revalued 5.5% while the French franc (FFR) and Italian Lira (ITL) are devalued 3%.

1982
February 22
Belgian franc (BEF) is devalued 8.5% and the DKK is devalued 3%.

June 14
The following re- and devaluations occur: DM revalued 4.25%, FFR devalued 5.75%, ITL devalued 2.75%, and the NLG revalued 4.25%.

1983
March 22
All EMS currencies are realigned. DM is revalued 5.5%, Irish punt (IRL) and NLG are revalued 3.5%, BEF revalued 1.5%, and FFR, ITL, & DKK are devalued 2.5%.
1984  
September  
The ECU basket of currencies is revised to include the Greek drachma (GRD) and to adjust the weight of other currencies.

1985  
July 22  
All currencies in the EMS are revalued 2.0% except for the ITL which is devalued 6.0%.

1987  
January 12  
DM at highest levels against dollar since 1980. FFR falls to lower intervention level against DM.  
September  
The “Basle/Nyborg” Agreement among EMS central banks strengthens the ERM by liberalizing the financing of intramarginal exchange rate interventions.  
October  
Worldwide collapse of international stock markets.

1988  
June 28  
Hanover Summit where the ERM leaders meet to establish the Committee for the Study of Economic and Monetary Union (Delors Committee) to propose steps to achieve European monetary union. Britain rejects proposal for a European Central Bank and currency.

1989  
April  
The Delors Committee completes its report on monetary union where it proposes a three stage transition plan to monetary union. Stage 1 consists of liberalizing capital movements and enlarging ERM membership. In Stage 2, exchange rate bands would be narrowed and realignments would be permitted only in extreme circumstances. In Stage 3, the exchange rate bands would be irrevocably locked and the European Central Bank would be established. The adoption of a single currency would complete the EMU.  
June 19  
Spain joins the ERM with a fluctuation band of +/- 6%.  
June 27  
The European Council decides to embark on Stage 1 of the Delors Plan.  
September 21  
The ECU basket is revised to include the Portuguese Escudo (PTE) and the Spanish Peseta (ESP). The weights of other currencies are adjusted accordingly.  
October 26  
Nigel Lawson and Sir Alan Walters, advisors to Margaret Thatcher resign.  
November  
Berlin Wall falls.
December

*Strasbourg Summit* takes place.

**1990**

January 8

ITL is devalued 3.64% and moves to the narrow +/-2.25% band for currency fluctuations.

February 6

Chancellor Kohl is in favor of rapid movements towards German monetary union.

March

French ministers announce that there will be no further devaluation of the FFR.

April

Germany agrees on monetary union within Germany.

May 18

Treaty to unify both Germanies is signed

June

Belgium decides, as a main policy target, to link the BEF to the DEM.

October 8

The UK joins the ERM with a 6% band for currency fluctuations but pledges to adopt the narrower band after a period of adjustment.

October 22

Norway links the Norwegian kroner (NOK) to the ECU, adopting the narrow +/-2.25% band.

October 27

The European Council meets in Rome and agrees that Stage Two of the EMU should start in 1994 though the UK disagrees.

November

EC Committee of Central Bank Governors issue a draft statute for a proposed central bank.

November 22

Margaret Thatcher resigns.

**1991**

April

Sweden links with ECU.

May 16

Bundesbank president resigns.

June

Finland links with ECU.

December

*Maasrcht Treaty* is agreed upon.

**1992**

April 6

Portugues Escudo enters ERM with a +/-6% fluctuation band.
June 2
Danish rejection of Maastricht Treaty

June 5
Bank of Italy raises key interest rates in order to defend the ITL.

June 8
US Fed intervenes by selling DM for ITL.

June 17
ITL exchange rate plunges, Bank of Italy denies rumors of possible intervention.

June 18
Ireland ratifies Maastricht Treaty.

July 2
Italian economic ministers announce the goal of stabilizing the ITL.

July 3
Bank of Italy props up the ITL against the DEM to remain within the 2.25% band width.

July 6
Bank of Portugal lowers interest rates to support PTE which is dragged down by ITL.

July 10
GBP slides against DEM making it impossible to move to lower band width. The GBP is now the weakest currency in the ERM followed by the ITL.

July 22
DM withstands latest intervention despite US banks selling DM in market.

July 30
Resignation of Italian Minister of Finance.

August 3
Bank of Italy drastically cuts discount rate. An opinion poll released in France indicates that there is a block of undecided voters on the Maastricht Treaty.

August 21
British figures are released indicating that 1991 marks the worst recession that Britain has ever experienced; statistics show that British economy shrank 2.4% last year.

August 26
ITL sets another low record against DEM and the ESP is strong thus requiring intervention by Bank of Spain.

August 27
Chancellor of Exchange Assets in Britain announces that “there will be no further devaluation of the pound and Britain will not leave the EMS.” Bank of England supports this statement by buying marks for pounds for the first time since Britain had joined ERM. Despite this effort, Bundesbank announces that ITL and GBP will likely have to devalue their currencies.

August 28
Intervention by Bank of Italy to sell DM as ITL closes at the bottom of its band.

September 3
Britain props up the pound by buying in excess of $14 billion in other currencies.

September 4
Bank of Italy again raises discount rate to “help sagging currency.”
September 5
ERM Finance Ministers agree to resist realignment, regardless of cost.

September 8
Sweden raises interbank interest rates 800 basis point to 24%.

September 9
Bank of Finland announces that it will float the maarkha. Bundesbank takes action to drain excess DM from market after attempts to defend the ITL.

September 10
Sweden triples its interbank lending rate to 75%.

September 13
ITL is devalued 3.5% while all other currencies in ERM are revalued 3.5%. This results in an effective 7% devaluation of the ITL.

September 14
Bundesbank cut interest rates in order to allow other currencies to gain against DM.

September 16
“Black Wednesday” where the British pound is suspended from the ERM. Swedish banks raise interest rates from 75% to 500%.
Finland continues to devalue the maarkha – an effective 27%.

September 17
ITL is suspended from ERM.

September 20
France narrowly approves the Maastricht Treaty by a vote of 51%.

September 21
Sweden lowers interbank rates from 500% to 50%.

November 19
Sweden floats the SEK.

November 20
ESP and PTE are devalued 6%.

December 10
Norway floats the NOK.

1993
January 3
The GBP will not rejoin the ERM in 1993.

January 30
IRL is devalued by 10%.

May 15
ESP and PTE are devalued 6.5%.

May 18
Danes ratify Maastricht Treaty.

July
The permitted band within which the FFR can fluctuate is increased +/- 15%.

August
EC officials meet and decide to permit all currencies to fluctuate within the +/-15% band

November 1
Maastricht Treaty is approved.
APPENDIX 2

DEFINITIONS OF FUTURES AND OPTIONS

A futures contract is an agreement to buy or sell a specific amount of currency at a specified price on a particular future date. Futures contracts are exchange-traded instruments and are therefore highly standardized. Futures contracts are also unique in that they are marked to market daily.

Options are instruments that give the holder the right to buy or sell the underlying currency by a certain date for a certain price. An option merely gives the right to buy or sell but does not obligate the holder in the same manner as a forward or a futures contract. Unlike futures and forward contracts, however, an investor must pay a certain amount or premium to buy or sell an option. American options are those that may be exercised prior to the expiration date and European options may only be exercised at expiration.

Options on currency futures are traded on futures exchanges, whereas options on cash foreign exchange (called just currency options) may be exchange-traded or negotiated over-the-counter.
APPENDIX 3
EWMA and GARCH

As mentioned in the text, another historical approach often used to estimating volatility in time series is an Exponentially Weighted Moving Average (EWMA) process. Popularized by the advent of J.P. Morgan’s RiskMetrics©, it is a procedure commonly used to calculate Value at Risk measurements.\(^6\) Initial consideration was given to using an EWMA process in this study. However, there was also great need to include a GARCH (1,1) process since it is so predominant in the literature, as cited throughout. Based upon the GARCH (1,1) process for estimating conditional volatility, these two approaches are mutually exclusive. This is because there is a high level of correlation (98%) that, when added to the regression causes all explanatory variables in the regression to be insignificant including those that were previously significant, \textit{i.e.}, multicollinearity. The following proof provides an explanation through algebraic means.

An EWMA of volatility can be defined as

\[
\sigma_t^2 = (1 - \lambda) \sum_{i=0}^{\infty} \lambda^i r_{t-i-1}^2
\]  

(1)

where \(\lambda\) is the weighting factor. Expanding the summand, the right hand side of equation (1) can be re-written as

\[
\sigma_t^2 = (1 - \lambda)(r_{t-1}^2 + \lambda r_{t-2}^2 + \lambda^2 r_{t-3}^2 + ...)
\]

(2)

or

\[
\sigma_t^2 = (1 - \lambda)(1 - \lambda)(r_{t-2}^2 + \lambda r_{t-3}^2 + ...)
\]

(3)

Substituting equation (2) (lagged one period) into the last term of equation (3), the EWMA becomes

\[
\sigma_t^2 = \lambda \sigma_{t-1} + (1-\lambda)r_{t-1}^2
\]

(4)

The variance portion of a GARCH(1,1) model, in turn, can be defined as

\[
\sigma_t^2 = \alpha_0 + \alpha_1 \sigma_{t-1}^2 + \alpha_2 r_{t-1}^2
\]

(5)

In the special case where \(\alpha_0\) and where \(\alpha_1 + \alpha_2 = 1\), equation (5) can be re-written as

\[
\sigma_t^2 = \alpha_1 \sigma_{t-1}^2 + (1-\alpha_1)r_{t-1}^2
\]

(6)

Clearly, equation (6) is equal to equation (4) where \(\alpha_1 = \lambda\). So, the EWMA process is equivalent to a GARCH(1,1) process when the GARCH intercept term is zero and when the two GARCH slope coefficients sum to unity. This process is also known as IGARCH.

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APPENDIX 4
VOLATILITY SMILES

A “volatility smile” represents the relation between the implied volatility of an option and its strike price or its time to maturity. In the Black-Scholes world, underlying asset returns are distributed normally with constant variance. In such a world, an option’s implied volatility thus does not depend on the time to expiration or strike price of the option. In a Black-Scholes world, therefore, a graph showing option strike prices on the abscissa and the ISD on the ordinate would be a flat line. No matter how far in or out of the money the option is, the Black-Scholes assumptions imply a constant volatility, which translates into a constant implied volatility. Similarly, a graph of option-implied volatilities over time should be flat if returns are normally distributed and variance is constant.

Now suppose we do not live in a Black-Scholes world. Specifically, suppose that returns on the asset underlying the option are not normally distributed over time. Suppose, specifically, that returns have negative skewness and fat tails, as is empirically the case for U.S. equity prices. Because Black-Scholes assumes constant volatility and normality of returns, the implied Black-Scholes volatility will reflect differences in the true probability distribution of asset prices relative to the normal distribution. Specifically, if the Black-Scholes model prices out-of-the-money calls and puts symmetrically but market participants do not view probabilities in the same way that the Black-Scholes model assumes, the Black-Scholes implied volatility indicates this.

As a general rule of thumb, the Black-Scholes model underprices all options when the tails of the underlying asset’s return distribution are fatter than the tails of a normal return distribution (i.e., when more probability is associated with extreme positive and negative returns than in the normal distribution). When only price declines have a higher probability than in the Black-Scholes world, Black-Scholes tends to underprice out-of-the-money puts and in-the-money calls. Conversely, when only price increases have a higher probability than in the Black-Scholes world, Black-Scholes tends to underprice out-of-the-money calls and in-the-money puts.

These rules of thumb provide a quick and useful way for us to infer implications about the underlying asset price distribution. A traditional volatility “smile” occurs when implied volatilities for out-of-the-money calls and puts and in-the-money calls and puts are higher than the Black-Scholes at-the-money implied volatility. In that case, moreover, the implied volatilities typically rise at a faster rate as the option exercise price gets further away from the current spot price.
VITA

Andrea M.P. Neves was born in Sao Paulo Brasil on December 9, 1970. She has resided near Washington D.C. for the majority of her life. Ms. Neves attended Mary Washington College in Fredericksburg, Va. In 1992, she completed her Bachelors degree with a major in physics and an emphasis in economics. While in this physics program, she carried out research concerning the development of a multidetector array system designed to distinguish between surface densities under the supervision of Dr. George King, III. In 1995, Ms. Neves completed a Masters of Science degree in atomic physics. Her thesis, entitled “Atomic Cross Sections for Composite Projectile Reactions,” was performed under the supervision of Dr. John F. Reading. In the fall of 1995, Ms. Neves enrolled in the graduate economic program at the Northern Virginia campus of Virginia Polytechnic and State University. Her research efforts have been supervised by Dr. Robert J. Mackay.

While completing this degree, Ms. Neves was employed as a Research Associate in a private litigation consulting firm. Her work focused on determining the economic conditions surrounding derivatives related losses. In 1997, Ms. Neves shifted her career focus towards risk management consulting. She is currently employed by a firm in Chicago where her major clients have included institutional investors, large pension plans, and financial exchanges.

Her publications in the field of finance include Value at Risk: Uses and Abuses (Journal of Corporate Finance, Vol. 10, No. 4, 1998) with Merton Miller and Christopher L. Culp and Risk Management by Securities Settlement Agents (Journal of Corporate Finance, Vol. 10, No. 3, 1998) with Christopher L. Culp. She also has several publications in the field of physics.

Aside from her studies and work, Ms. Neves enjoys the competitive equestrian sports and travelling. She speaks four languages including her native Portuguese, French, and Spanish. The author may currently be reached at:

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