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SURVEY vs MARKET EXPECTATIONS

OF TREASURY BILL YIELDS

BY

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EXECUTIVE SUMMARY

The aim of the thesis to examine the accuracy, rationality and value to traders of published consensus forecasts of US Treasury bill yields.

Interest rate forecasts are important for traders in bond markets and money markets. They have implications for the conduct of monetary policy. They are of direct interest to private investors and mortgage holders. As might be expected, the quality of interest rate forecasts in the US and elsewhere has been extensively investigated over the past two decades.

The research reported in this thesis differs from previous studies in two major ways.

First, the data set that we used for survey data comes from *Blue Chip Financial Forecasts*, a well-known but under-researched US consensus forecasting service. This attracts forecasts from a number of leading financial analysts and economists. An important feature of *Blue Chip Financial Forecasts* is non-anonymity of the forecasters. This gives forecasters a reputational incentive to provide their best forecasts. This is in contrast to the more heavily researched Goldsmith-*Nagan Bond and Money Market Letter.* The *Blue Chip Financial Forecasts* also provides longer-dated interest rate forecasts, up to 15 months ahead. This is important due to the fact that exploitable inefficiencies in futures markets often occur in the more distant contracts.

Second, we look at the the value of the forecasts not only relative to the realised Treasury bill yields and Treasury bill futures prices, but also relative to the information contained in traded options on Treasury bill futures. No previous study has addressed the question of whether, for example, the dispersion of Treasury bill yield forecasts can be used to predict the volatility of future Treasury bill yields, or to devise rules for profitable trading of options on Treasury bill futures.

Our analysis focuses on the value of the mean ("consensus") forecasts from the Blue Chip panel, and the variance of individual forecasts ("dispersion") around this mean. In both cases we are interested in the accuracy of the survey data, and their value for investors and traders in futures and options markets.

With respect to the mean survey forecasts, our findings, based on directional accuracy, conventional quantitative error measures and relative predictability measures, support the notion that market-based forecasts manage to predict the Treasury bill yields as well as the professional forecasters. This is especially true for near-term interest rate predictions. However, when one compare market and survey forecasts with a random walk benchmark, the naïve no-change prediction is more accurate than either.

From a trading perspective, a relevant comparison is between the survey mean forecasts and Treasury bill futures prices. Previous studies carried out by Belongia (1987) and Hafer and Hein (1989) conclude that there is little or no information in survey forecasts additional to what is already impounded in futures prices. However, our study shows that, particularly for longer forecast horizons, the survey mean contains significant information, which can be translated into profitable futures trades. These results are inconsistent with the notion of efficiency in the Treasury bill futures market for longer dated contracts, and imply that in spite of their weak accuracy record, professional interest rate forecasts are valuable.

Measures of the dispersion of forecasts around the mean potentially indicate the degree of uncertainty about prospects for future interest rates. A market-based measure of uncertainty already exists in the form of implied volatility from options on T-bill futures. Many investors assume the best forecast of future realised volatility is today's levels of implied volatility. However, several studies such as Hill (1996) and Canina & Figlewski (1993) demonstrate that this is not the case and that realised volatility over a previous period is a better forecast of realised volatility over a future period. A commonly used naïve volatility forecast also exists in the form of "historic volatility", the variance of yields over the recent past. And more recently sophisticated time-series based GARCH models of time-varying volatility have been popular as methods for forecasting volatility.

Our research compares the survey-based measure with all these alternatives. Our results show that while implied volatility is useful in forecasting future volatility, it is not the optimal predictor, especially at long forecast horizons. Both survey variances and GARCH variances do play a significant additional role in explaining realised volatility. This suggests that implied volatility does not efficiently utilise all past information. Moreover, this inefficiency is exploitable, in the sense that 1-month straddle positions triggered by differences between survey and implied volatility are consistently profitable.

Our results are of course limited by the low frequency of the survey data, and may be sensitive to changes over time in the sophistication of investors in the Treasury Bill derivatives markets. However, they do point to the presence of information in survey responses which are not fully captured in market prices, and confirm that such surveys are potentially of value to traders and investors.

Chapter 1

INTRODUCTION

1.1 INTRODUCTION

Forecasts of financial variables such as interest rates, stock returns and exchange rates are of interest to businesses and financial institutions engaged in risk measurement, investment analysis, capital allocation, trading, pricing and hedging. In some contexts, such as trading, they are interested in predicting only the direction of change of these variables. In other contexts, they need forecasts of the expected values of the variables – for example, to determine fair prices for long-term contracts involving interest rates. In yet other applications, institutions may need forecasts of the volatility of the variables, to help calculate value at risk, or to help price options.

This thesis examines the following questions about the behaviour of the US Treasury bill market, and published forecasts of US Treasury bill yields:

- Are expert forecasts of Treasury bill yields, as revealed in survey data, more accurate than simple alternatives?
- Can they be used to make money by trading Treasury bill futures, and does this imply that the futures market is inefficient?
- Is there information in the survey data relevant to predicting the volatility of Treasury bill yields?

- How does this compare to more conventional volatility forecasts, such as those from the implied volatility in three months treasury bills futures-options; historical volatility, and time-series based volatility forecasts based on the popular GARCH (1,1) model
- Can these forecasts be used to make money by trading options on Treasury bill futures?

These questions are interesting for two reasons. First, they have obvious implications for the use of economic survey data by traders and fund managers. Second, they amount to tests of the hypothesis that the futures and futures options markets in US Treasury bills are speculatively efficient. This is a pervasive null hypothesis in finance theory.

In order to answer the above questions, we proceed as follows. Firstly we look at the data set that we are going to use (Chapter 2). Next, we examine forecast accuracy and also the profitability of various trading rules (Chapters 3 and 4). Efficiency tests are also carried out in both the futures and futures-options market (Chapters 5 and 6). Finally, we make a comparison of various estimates of volatility (Chapter 6).

In this introductory Chapter, our aim is to set the scene for the thesis, by reviewing our state of knowledge on interest rate forecasts, volatility forecasting.

Interest rate forecasts produced by professional economists and analysts are available at low cost from several sources, and a number of academic studies have tried to assess their value. In particular, there have been many studies of "consensus" forecasting services such the *Wall Street Journal's semi-annual survey* and *Blue Chip Financial Forecasts,* which pool the forecasts of large numbers of contributing forecasters. In the case of forecasts of US Treasury bill yields, the *Goldsmith-Nagan Bond and Money Market Letter* is often used. As shown by Bates and Granger (1969), by following the average "consensus" forecast, a subscriber to the service can produce a forecast which has an expected error variance lower than the great individual component forecasts.

While the relative performance of the consensus forecast vis-à-vis the individual forecasts are not in doubt, there are serious questions over the value of the whole set of interest rate forecasts. For example, Friedman (1979), Hafer and Hein (1989) and Hafer, Hein and MacDonald (1992) showed that *GoldSmith-Nagan* forecasts are significantly less accurate as predictors of future Treasury bill yields than naïve alternatives such as current Treasury bill futures price and the current Treasury bill spot yield. Other research such as Belongia (1987) and Hafer, Hein and MacDonald (1992) has shown that even the consensus is less accurate than the "random walk" forecast, which suggests that the best predictor of future spot yields is simply the current spot yield. However, some individual forecasts do outperform the consensus, and occasionally even the random walk. But Kolb and Stekler (1996) showed that the differences in accuracy across one representative group of US forecasters –

contributors to the *Wall Street Journal* surveys – are not statistically significant, so any out-performance is more likely due to chance than skill.

The value of forecasts of volatility has mainly focused on the use of implied volatilities or historical volatilities in option pricing models such as Black and Scholes (1972); Latane and Rendleman (1976); and Schmalensee and Trippi (1978). Others have investigated the relationship between implied volatility of option prices and historical volatility of the underlying asset. Some studies such as Day and Lewis (1992); Scott (1992) etc question the hypothesis that option prices offer substantial information content regarding expected volatility conditions in the underlying market. However, other works such as Beckers (1981); Chiras and Manaster (1978); Latane and Rendleman (1976) etc suggest that implied volatility may be useful in predicting subsequent movements in historical volatility of the underlying instrument's return.

Superior volatility forecasts can be turned into excess profits by trading options, since overly high volatility inflates option premia (selling opportunity), while low volatility deflates premia (buying opportunity). In addition, volatility also provides clues to possible developments in an underlying contract. When volatility is extremely low, a big move almost always follows, generally in the opposite direction of the previous trend. Implied volatility may also filters technical trading signals, confirming or negating breakouts.

In order to determine if volatility is high or low, one can simply compared recent figures to different period in the past. This task is made easier because volatility tends to be "mean reverting", that is, it usually moves from extreme high or low values back to some central level.

Although empirical returns distributions are definitely not normal it is, nevertheless, very convenient to retain normality assumptions when modelling financial risk. Normality assumptions underpin all the fundamental analysis and numerical pricing and hedging models. For a unified framework of theoretical models and empirical estimation, normal models have a natural appeal. And if returns are assumed to be normally distributed with zero-mean, then volatility estimates are all that is necessary to completely specify the returns distribution. This is one of the reasons that risk measurement has focused so much on volatility. Volatility is usually measured by the standard deviation of financial returns - expressed as an annualised percentage.

One way of retaining normality assumptions whilst allowing leptokurtic distributions is to use certain stochastic volatility models, and in particular, normal Generalised Autoregressive Conditional Heteroscedasticity (GARCH) models provide instantaneous estimates as well as term structure forecasts of both volatility and kurtosis. GARCH is a mathematical method that traders and academics use for forecasting volatility.

GARCH stands for autoregressive Conditional Heteroscedasticity: "Generalised" because it is a general class of ARCH model, 'Autoregressive' because the variances generated by ARCH models involve regression on their own past, and 'Conditionally Heteroscedastic' literally means changing variance, or 'volatility clustering' as it has become known. A time series displays conditional heteroscedasticity if it has highly volatile periods interspersed with tranquil periods. Engle (1982) introduced the first ARCH model. Tim Bollerslev (1986) developed the GARCH formulation of the model, which is used in financial markets. GARCH (1,1) specifies that the variance today depends upon three factors: a constant; yesterday's forecast variance (the GARCH term), and yesterday's news about volatility which is taken to be squared residual from yesterday. The (1,1) in GARCH (1,1) refers to one GARCH and one ARCH term.

This specification makes sense in financial setting where an agent or trader infers today's variance by forming a weighted average of a long term average or constant variance, the forecast from yesterday, and what was learned yesterday. If the asset return was large in either the upward or the downward direction, then the trader will increase the estimate of the variance for the next day. This specification of the variance incorporates the familiar phenomenon of volatility clustering which is evident in financial returns data. Large returns are more likely to be followed by large returns of either sign than by small returns.

This research is different from previous research in the sense that the data used in our study come from another well known but under-researched source, the monthly *Blue Chip financial Forecasts*[1] newsletter. From this we used the consensus forecasts of 3-month Treasury bill yields to test our hypotheses. The forecasts were made in the year between 1984-1992, for the current and four successive quarters. This yields a database that allows us to cover a longer time-period and a greater variety of forecast horizons. In addition it also enables us to remedy previous research limitations – data with short forecast horizons, which is an important consideration as the most exploitable inefficiencies in derivatives markets occur in the more distant contracts.

In addition, besides comparing survey variance with implied volatility or historical volatility, survey variance is used also to compare with various other alternative measures. If the option markets are informationally efficient, then information available at the time market prices are set cannot be used to predict actual return variance better than the variance forecast embedded in the future-option price, which represents the subjective expectation of the market. That is, the forecast error of the subjective expectation should be orthogonal to all available information. To test this orthogonality restriction, near or at-the-money call futures-options are used to derive implied volatility and compare with variance obtained from the survey, GARCH and moving average. In this study, we also extend the simplest GARCH specification to include the weekend effects. Since traders can accurately forecast weekends and holidays, it seems, a prori, to allow the GARCH model access to this information.

[1] Details and samples of the monthly Blue Chip Financial Forecasts newsletter can be seen and

1.2 CONCLUSION

Interest rate and volatility forecasts are crucial to traders, risk managers and decision-makers. They played a crucial role in decision making.

In the past a lot of research has already been done regarding the value of such forecasts. However, results shown on these studies have been mixed. This research is different in the sense that the data that we have used come from a well known but under-researched US consensus forecasting service. In addition, we also looked at the value of the forecasts not only relative to the realised Treasury bill yields and Treasury bill futures prices, but also relative to the information contained in traded options on Treasury bill futures. We also compared the forecasts not only to historical volatility and implied volatility but also to GARCH with weekend effects taking into consideration.

discussed in chapter 2.

Chapter 2

THE SOURCES & BACKGROUND OF DATA

2.1 INTRODUCTION

Firms and investors often seek readily available and accurate forecasts of interest rates and other key macro-economic variables. Often this information can be obtained through many different sources. With regard to Treasury bill rates, two alternatives market-related forecasts are generally available. First, futures market quotes and forward rates implicit in spot rates for instruments of differing maturities can be employed to generate interest rate forecasts. Second, forecasts can be obtained from surveys of professional analysts - a direct measure - such as *Blue Chip Financial Forecasts* and the *Wall Street Journal's* semi-annual survey etc. Studies carried out by Friedman (1979)[1], Belongia (1987), Hafer and Hein (1989), Hafer, Hein and MacDonald (1992), Kolb and Stekler (1996)[2] all used survey data as one of the sources for interest rate forecasts.

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1 Friedman (1979) compared Treasury bill forecasts from the *Goldsmith Nagan Bond and Money Market Letter* survey and forward rates.

2 Belongia (1987) compared survey projections from the *Wall Street Journal's* annual survey of market professionals with futures market forecasts of near-term Treasury-bill rates.
Hafer and Hein (1989) indirectly compared futures rate forecasts with the *Bond and Money Letter* survey forecasts.
Hafer, Hein and MacDonald (1992) uses *Bond and Money Letter* survey to measure relative accuracy of forecasts obtained from various other sources.
Kolb and Stekler (1996) uses *The Wall Street Journal* with interest rate forecasts made for the period 1982-90, to examine whether there is any agreement among analysts about the level of interest rates six months in the future. They also investigated whether these forecasts are of any use to prospective clients.

The first part of this chapter describes the Blue Chip survey data, and develops the two survey-based statistics - the mean expectation and standard deviation- for forecasts of Treasury bill yields. The second section describes the market in US Treasury bill futures and futures-options, and introduces market-based measures of expectation and risk - the future price and the standard deviation of future changes in yields implied by premia on the Treasury bill futures options traded on the International Monetary Market (IMM).

2.2 SURVEY-BASED MEASURES

2.2.1 Background of the Blue Chip Financial Forecasts

The *Blue Chip Financial Forecasts* is a consensus forecasting service that began in late 1982. It provides forecasts of many important financial data series such as U.S. prime rate, Federal Funds, Treasury bonds (30 Years), Real GNP, Consumer Price Index etc and includes long-run forecasts twice a year. An example of the survey can be seen on page 5, Table 2.1. Around the 23rd day of each month, the service conducts telephone survey of the interest rate forecasts of a panel of economists and financial analysts in major investment houses and US banks. The forecasts made for each variable is then tabulated and their unweighted mean - the consensus forecast - calculated. The full results - both individual forecasts and the mean value - are mailed to contributors and to subscribers on the first day of the following month.

The membership of the panel has stayed around 50 throughout the history of the service, but the composition of the panel has changed over time, and not all panelists provide forecasts in every month. All forecasts are for quarterly averages, and are made for 5 horizons i.e. surveys published in January, February and March are forecasts of averages interest rates in Q1, Q2, Q3 and Q4 of the current year, and Q1 of the following year. In this study, the period covered start from April 1984 - Dec 1992 for futures data and May 1986 - Dec 1992 for future-options data and we focus on 90-day Treasury Bill yields made at 5 horizons.

One important feature of the *Blue Chip Financial Forecasts* is non-anonymity of the forecasters. All forecasters are identified by letter codes[3]. They may choose to remain anonymous, but majority do not. The beauty of this feature is to encourage people to provide their best forecasts because forecasters can claim credit for particularly good forecast performance, and can they be held accountable for particularly bad forecasts. Some critics of survey data argue that without such accountability, forecasters may make less accurate predictions because there are fewer consequences to making poor forecasts.[4] This is clearly not the case with the Blue Chip panel, where individual

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[3] Note: From 1993 onwards, forecasters were no longer represented by codes but rather by institutions' names.

[4] Croushore (1996) in his reviewed of Inflation Forecasts also stated that people being surveyed were not very good at forecasting inflation because they had no reason to be good at doing so; their livelihoods did not depend on their inflation forecasts. An alternative view was that people did not have strong incentive to respond accurately to the surveys, because they were not paid to supply their forecasts.

Table 2.1 Example of Blue Chip Financial Forecasts Survey

First Quarter 1988

Interest Rate Forecasts | **Key Assumptions Behind Interest Rate Forecasts**

ANALYST IDENTITY CODE	1. Prime Rate	2. Fed Funds	3. Com. Paper 1-Mo.	4. T-Bills 3-Mo.	5. T-Notes 3-Yr.	6. T-Bonds 30-Yr	7. Mun. Bonds 20-B	8. Corp Aaa B (Seas)	9. A Util. (Seas)	10. Home Mtg. FHLMC	11. Mon. Base	12. Money Stock M1	13. Money Stock M2	14. Cons. Inst. (Net)	15. Com & Ind. Loans	A. Real GNP	B. GNP Defl. (Prices)	C. Cons. Price Index
	PERCENT: Short Term				Inter.	Long-Term					Money Supply: Annual rate—% (Q-Q Change)			Borrowing: Annual Rate-$bil. (Q-Q Change)				
L	10.3H	8.8H	8.8H	8.1H	9.7H	10.5H	9.5H	11.4H	12.2H	12.3H	—	6.5	10.5	5.0	—	3.9	4.5	5.5
D	9.5	8.0	8.0	7.5	8.5	9.5	9.0	10.0	10.5	11.0	—	—	9.5	—	—	4.2	5.5	4.5
A	9.2	7.7	7.6	6.9	7.4	8.0	7.0	9.2	9.2	9.6	9.6	7.5	8.2	59.2	25.6	3.2	5.3	5.1
I	9.0	7.9	8.0	7.4	8.7	9.4	8.6	10.3	10.9	11.1	7.0	8.0	7.0	8.0	12.0	3.3	4.7	5.3
R	9.0	7.5	7.5	7.0	8.5	9.5	8.5	10.3	11.0	10.5	6.0	6.0	8.0	40.0	60.0	4.0	4.5	4.0
F	8.9	7.4	7.7	7.3	8.4	8.9	7.1	9.4	10.1	10.3	5.3	6.8	5.4	4.0	44.0	2.0	4.3	4.8
CC	8.6	7.1	7.0	6.5	7.6	8.3	7.5	9.3	10.3	10.0	8.0	11.0	7.8	35.0	36.0	3.8	4.7	4.8
MM	8.2	7.1	6.9	6.3	7.3	8.6	7.0	9.3	9.7	10.0	11.1H	10.5	13.1H	13.0	35.0	3.3	5.4	6.3
J	8.1	6.5	6.3	5.9	6.9	7.7	7.2	8.9	9.4	9.8	8.4	10.0	8.2	40.0	30.0	4.2	2.6	4.8
QQ	8.0	7.5	7.5	6.5	7.7	8.7	7.0	8.5	9.1	9.1	5.0	10.0	8.0	41.0	19.0	4.0	3.0	3.0
XX	8.0	7.3	6.9	6.5	7.5	8.0	7.3	8.7	9.4	9.4	7.0	8.0	9.0	—	—	4.5	3.5	4.5
II	8.0	6.9	6.7	6.3	7.7	8.6	7.2	9.0	9.7	10.3	5.0	7.0	6.0	33.0	39.0	2.8	4.0	4.7
ZZ	8.0	6.8	6.8	6.1	7.2	8.1	7.1	8.8	9.4	9.5	7.5	7.0	8.5	70.0	60.0	3.2	4.0	4.5
JJ	8.0	6.6	6.5	6.0	6.9	7.5	6.5	8.5	9.0	9.5	—	4.5L	7.5	20.0	40.0	3.8	3.6	4.1
G	8.0	6.6	6.4	6.0	7.1	8.1	7.0	8.8	9.6	9.7	5.0	7.0	8.0	25.0	33.0	2.7	4.8	5.1
M	8.0	6.5	6.4	5.8	7.0	7.9	7.2	8.9	9.8	10.4	5.8	8.0	7.0	64.1	43.0	3.9	5.0	4.8
H	8.0	6.5	6.5	6.0	7.5	8.8	8.1	9.7	10.1	10.3	7.8	11.0	6.4	21.0	13.0	1.0	4.4	4.5
U	8.0	6.5	6.5	5.9	7.0	8.3	7.2	9.6	9.9	10.0	8.0	8.0	8.5	40.0	35.0	4.0	3.5	4.0
UU	8.0	6.5	6.0	5.3	6.7	7.5	7.4	8.3	9.5	10.8	6.0	6.0	6.0	10.0	-10.0L	-1.1L	3.8	4.0
EE	8.0	6.5	6.5	6.5	7.5	8.7	7.1	9.0	9.5	9.5	5.0	6.0	5.5	10.0	9.0	3.0	3.5	4.5
PP	8.0	6.5	6.3	5.8	7.0	8.0	7.5	9.1	9.8	10.3	7.5	8.0	8.0	35.0	30.0	3.3	3.5	4.0
V	8.0	6.4	6.5	6.0	6.9	7.8	7.0	8.6	9.5	9.3	8.0	8.5	8.0	50.0	20.0	2.4	4.8	4.4
B	8.0	6.3	6.1	5.7	6.8	7.6	6.6	8.6	9.1	9.5	4.8	6.8	5.7	28.0	30.0	3.4	3.7	4.2
TT	8.0	6.2	6.2	5.7	6.8	7.7	7.6	8.6	9.1	9.2	7.1	7.8	7.7	—	—	2.0	4.0	4.0
WW	8.0	6.2	6.3	6.2	6.9	8.0	6.8	8.7	9.0	9.3	8.1	9.1	7.9	24.0	20.0	2.2	2.5	3.7
YY	7.8	6.2	6.1	5.5	6.6	7.6	6.7	8.5	9.0	9.3	7.9	8.0	8.3	40.0	26.0	2.8	3.1	3.8
C	7.8	6.2	6.1	6.1	7.5	8.4	7.1	9.2	9.9	9.9	—	11.0	8.0	27.0	6.4	2.6	5.7	6.0
SS	7.7	6.3	6.2	5.8	6.8	7.9	7.0	8.8	9.3	9.6	8.4	8.2	8.4	10.0	64.0H	3.2	4.1	4.6
HH	7.7	6.3	6.3	6.0	7.1	8.0	6.9	8.8	9.2	9.6	—	12.3	7.4	—	—	2.8	3.0	4.9
VV	7.5	6.4	6.6	5.7	6.8	7.8	—	8.7	9.0	9.3	—	—	—	4.0	—	3.5	4.0	4.3
O	7.5	6.3	6.4	5.8	6.7	7.7	6.9	8.5	9.3	9.6	8.0	8.0	8.0	25.0	25.0	2.5	4.0	4.0
FF	7.5	6.3	6.2	5.7	7.3	8.3	7.4	9.2	9.5	10.3	10.0	6.5	8.0	75.0H	50.0	4.4	3.9	5.0
NN	7.5	6.1	5.8	5.4	6.4	7.3	6.5	8.2	8.6	8.8	9.0	10.0	8.5		10.0	1.3	2.6	3.1
AA	7.5	6.0	5.9	5.5	6.5	7.4	6.5	8.4	8.9	9.1	7.5	7.5	7.5	15.0	38.0	3.4	3.5	3.5
T	7.5	6.0	6.0	5.5	6.5	7.5	6.8	8.5	9.1	9.5	7.5	8.0	7.5	30.0	20.0	1.5	2.5	3.0
Q	7.5	6.0	6.1	5.5	6.6	7.5	6.6	8.4	9.0	9.1	8.0	8.0	6.5	4.0	10.0	3.0	4.0	4.0
DD	7.5	5.7	5.6	5.4	6.2	7.8	6.6	8.8	9.0	9.3	—	—	—	—	—	2.9	5.5	4.9
KK	7.4	5.7	5.6	5.0	5.6	6.7	6.3	7.9	8.5	8.7	9.7	6.6	—	42.0	38.0	3.1	3.0	3.5
BB	7.3	5.8	5.8	5.7	6.6	7.2	6.8	8.5	9.2	9.3	9.0	15.0H	9.0	15.0	10.0	2.5	4.5	4.5
Z	7.3	5.5	5.5	5.0	6.5	7.5	6.8	8.7	9.3	9.4	8.0	8.5	8.1	30.0	15.0	3.2	4.0	4.0
GG	7.0	6.0	5.8	5.4	6.6	7.0	6.2	7.7	8.0	8.4	10.0	10.0	8.0	45.0	15.0	3.0	2.0	2.0
W	7.0	5.7	5.4	5.2	6.6	7.3	6.5	8.3	8.8	9.3	9.0	7.0	9.0	7.0	9.0	4.3	4.3	4.8
P	7.0	5.6	5.6	4.9	6.0	7.0	6.4	8.3	8.9	8.8	6.0	8.0	7.0	20.0	20.0	3.0	3.2	3.0
N	7.0	5.5	5.3	4.8	5.7	6.3	5.3L	7.0L	7.4L	7.8L	7.0	8.0	7.0	—	—	5.3H	1.6L	1.6L
LL	7.0	5.4	5.3	5.2	6.1	7.2	6.3	8.4	9.1	9.4	7.1	8.8	7.5	25.0	30.0	3.0	4.0	3.7
K	7.0	5.3	5.2	4.8	5.7	7.0	6.2	8.0	8.3	8.6	7.0	8.2	7.0	24.0	20.0	1.2	3.9	3.9
Y	6.8	5.7	5.0	4.3L	5.2L	6.2L	5.8	7.5	8.0	8.7	8.0	9.0	7.0	15.0	20.0	2.5	3.5	3.2
E	6.7	4.9L	—	4.4	—	6.2L	5.5	8.3	—	8.1	—	—	—	—	—	3.3	3.3	3.8
OO	6.5	5.4	5.1	4.8	5.8	6.6	5.8	7.6	8.6	8.6	4.0L	8.0	5.0L	27.0	35.0	3.2	9.0H	10.0H
S	6.2L	5.0	4.8L	4.3L	5.9	6.7	6.0	7.6	8.0	8.8	—	7.0	7.0	-10.0L	50.0	2.0	2.0	2.5
APR: AVG.	7.8	6.4	6.3	5.8	6.9	7.8	7.0	8.7	9.3	9.6	7.4	8.3	7.7	27.3	27.7	3.0	3.9	4.3
TOP 10	8.9	7.6	7.6	7.0	8.2	9.1	8.1	9.9	10.5	10.7	9.4	11.1	9.4	52.6	48.8	4.3	5.5	5.8
BOT 10	6.8	5.4	5.3	4.8	5.9	6.7	6.0	7.8	8.3	8.5	5.2	6.3	6.1	5.2	8.4	1.5	2.5	2.8
MAR. AVG.	7.8	6.3	6.2	5.8	6.9	7.8	7.0	8.8	9.4	9.7	7.5	8.1	7.7	32.7	29.1	2.9	4.0	4.2
NUMBER OF FORECASTS CHANGED FROM A MONTH AGO:																		
DOWN	9	7	8	8	10	11	17	15	21	19	9	13	11	22	14	9	12	11
SAME	27	24	21	22	20	22	15	18	16	18	22	24	22	13	23	24	26	24
UP	14	19	20	20	19	17	17	17	12	13	11	11	14	8	5	17	12	15
DIFF. IND.[1]	55%	62%	62%	62%	59%	56%	50%	52%	41%	44%	54%	50%	54%	35%	40%	58%	50%	54%

[1] See bottom of p. 7 for detailed definitions and sources of data.

DIFFUSION INDEX - Indicates the percentage of components that are rising (with half of the unchanged components considered rising). Cyclical changes in diffusion indexes tend to lead the change in the averages.

forecasts are published and attributed. The list of some regular forecasters contributed to the Blue Chip Financial Forecasts can be seen in Appendix 2.1.

2.2.2 Measures:

2.2.2.1 Mean Expectation

The consensus forecast is utilised in this study. These consensus predictions are computed by simple averaging all the contributors' responses; no effort has been made to use anything other than equal weighting. This method is very accessible and inexpensive. This is consistent with Zarnowitz & Braun (1992). They argued that gains are obtained via the diversification of the forecasts that are combined e.g. group mean forecasts should be better, the more different and complementary the information embodied in their components. In addition, it has been shown by Zarnowitz & Braun (1992) and Batchelor (1993) that group mean forecasts are generally much more accurate than the majority of individual forecasts. Zarnowitz & Braun (1992) using data obtained from NBER-ASA on GNP, RGNP and IPD found that the sample forecasts have considerably smaller errors than the average individual respondents do by using conventional accuracy criterior such as mean error and root mean square error.

In order to compare these forecasts with market-based figures, it is necessary to translate these quarterly average consensus forecasts into point forecasts for the settlement dates of the IMM 90-day Treasury bill futures contracts ending March, June, September & December each year. The approach I have taken is simply to assign the quarterly averages to the mid-point of each quarter, and to make a linear interpolation between the average forecast for the quarter in which the futures contract is settled and the immediately succeeding quarter. This is consistent with Batchelor (1993) who also used Treasury-bill futures in testing his proposition.[5]

The general formula for calculating the point forecast from the monthly survey data is as follows:

$$2/3Q_n + 1/3Q_{n+1}$$

The only exception is when the contract is close to expiration i.e. one month before maturity; and on expiration month, then the following formulation are utilised respectively:

$$6/5 * Q_n + 2/5 * Act_{m-1} + 1/5 * Q_{n+1}$$

and

$$3 * Q_n - Act_{m-1} - Act_{m-2}$$

where n = target quarters

m = month

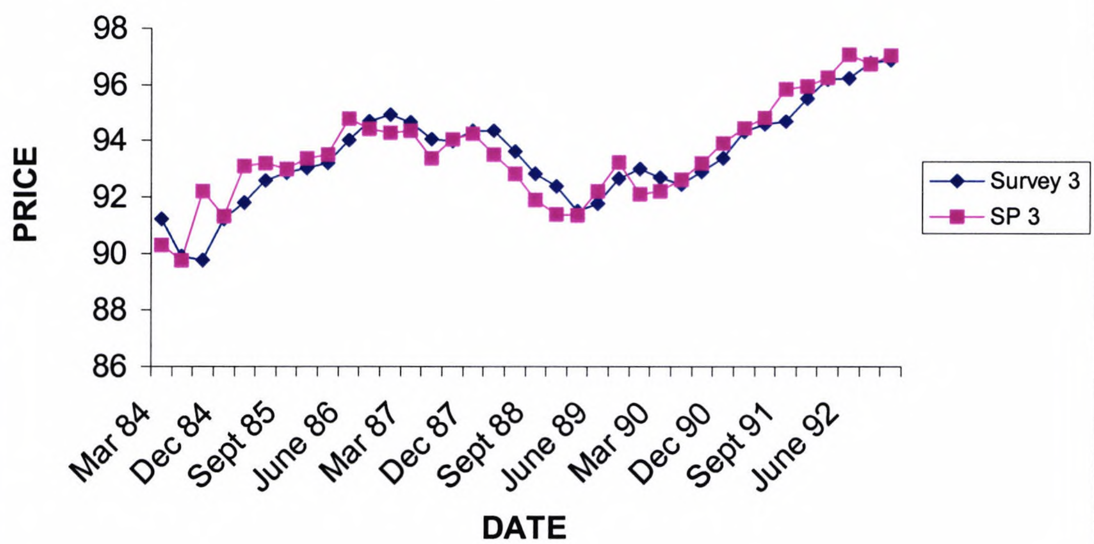
Act = Actual treasury bill rate

Q = Consensus forecast for quarterly average

[5] Batchelor (1993) also experimented with various non-linear interpolation schemes, but found no significant changes in results.

Figure 2.1 - 2.3 present the consensus forecasts obtained from the Blue Chip survey along with the actual three-month Treasury bill settlement price. Both the survey forecasts and the settlement price tend to exhibit similar patterns with forecasts lying close to the Treasury bill yields at the date the forecast was made. As the forecast horizon increases, the differences between the survey data and the settlement price tend to increase.

Figure 2.1
Survey Forecast vs Settlement Price
Forecast Horizon: 3 Months



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significant changes in results.

Figure 2.2
Survey Forecast vs Settlement Price
Forecast Horizon: 6 Months

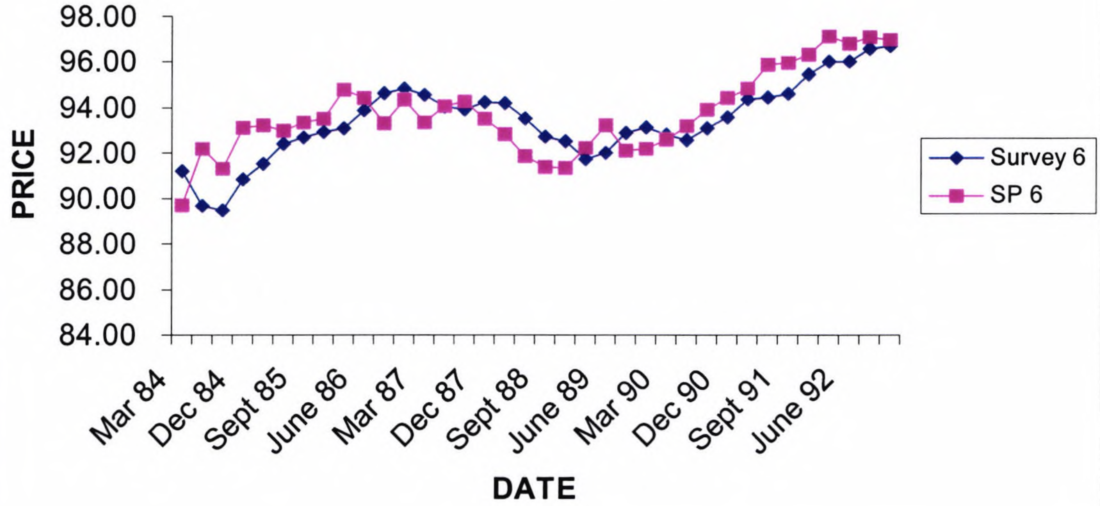
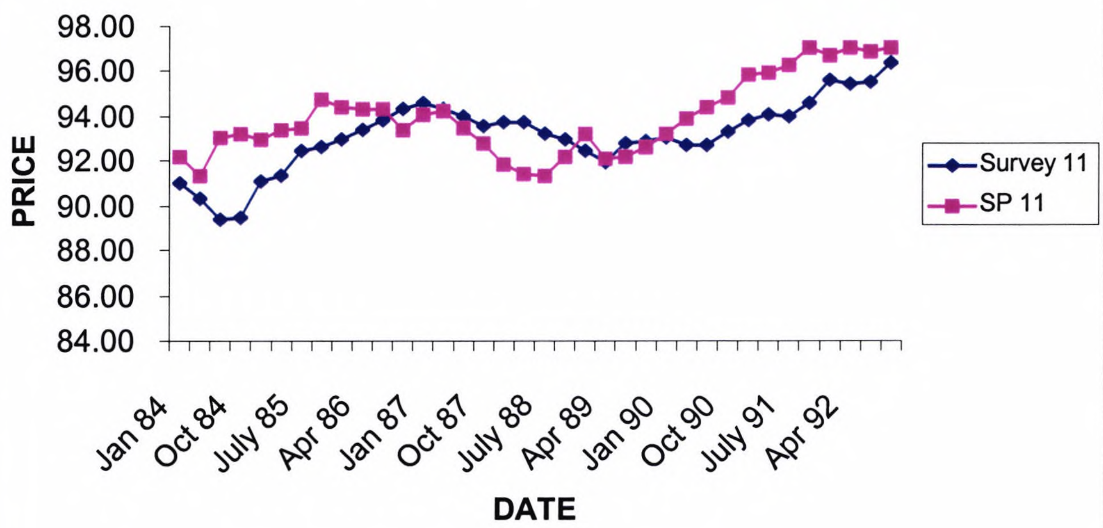


Figure 2.3
Survey Forecast vs Settlement Price
Forecast Horizon: 11 Months



2.2.2.2 Standard Deviation

The standard deviation is used to measure the variations of expectations across individual panellists. As with the mean expectation, these forecasts have to be translated into point forecasts. A simple way to approach this is to utilise the following system of formulae as illustrated from the table below:

	Contracts:	
Date/Month	Mar	June
Jan.	$(2/3*S_n+1/3*S_{n+1})^{1/2}$	$(2/3*S_n+1/3*S_{n+1})^{1/2}$
Feb.	$(4/5*S_n+1/5*S_{n+1})^{1/2}$	$(2/3*S_n+1/3*S_{n+1})^{1/2}$
Mar	$(S_n)^{1/2}$	$(2/3*S_n+1/3*S_{n+1})^{1/2}$
April		$(2/3*S_n+1/3*S_{n+1})^{1/2}$
May		$(4/5*S_n+1/5*S_{n+1})^{1/2}$
June		$(S_n)^{1/2}$

where S_n = Variance derived using quarterly consensus forecast

In words, two months before the expiration of each contract a different set of formulae is used respectively (i.e.$(4/5*S_n+1/5*S_{n+1})^{1/2}$; $(S_n)^{1/2}$). However, at any other time one has to proportion it linearly according to this formulation: $(2/3*S_n+1/3*S_{n+1})^{0.5}$. This method of linear interpolation of variance is consistent with the idea of random walk[6].

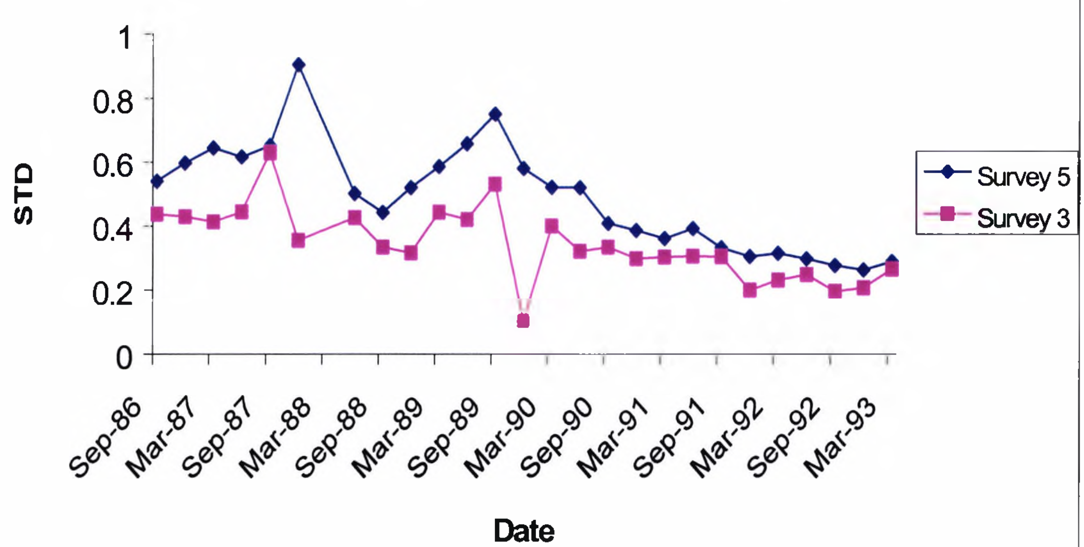
[6] The Random Walk Theory is a subset of the efficient markets hypothesis, which is an economic theory which attempts to quantify why prices move over time. The Random Walk Theory states that all prices or rates follow a totally random pattern of movement over time and are in no way

Figure 2.4 illustrates the two different levels of volatilities for two different forecast horizons based on the survey estimates. Both follow a similar behaviour, with volatility falling over time as the general level of Treasury bill yields falls. As the forecast horizon increases, the implied standard deviation is at a higher level. This is indeed expected. After all, the degree of uncertainty rises with the growth of the time span, as less information is available.

Figures 2.4

Survey Data: Standard Deviation

Forecast Horizons: 3 Months & 5 Months



2.3 MARKET-BASED MEASURES

2.3.1 Background

2.3.1.1 IMM 90-day Treasury Bill Futures

Trading in Treasury bill futures contracts[7] takes place on the International Monetary Market (IMM) of the Chicago Mercantile Exchange between the hours of 7.20 a.m. and 2 p.m. (Chicago Time) except on the last day which finishes trading at 10 a.m. Like options, the price is quoted in index points and the minimum price change is .01 (1 basis point). The future contracts traded call for delivery of $1 million of Treasury bills maturing 90 days from the delivery day of the futures contract. This means that 1 basis point has a value of $25. These contracts call for delivery four times a year[8]. Details of the contract can be seen from the table below.

The futures market[9] forecasts were gathered so that the futures market rate was taken on the same approximate date that the survey forecast was made. The settlement price

7 A futures contract is an agreement to make delivery (short position) at a later date, or to accept delivery (long position) at a later date, of a fixed amount of a specific grade or quality of a commodity at a specific price.

8 Since the introduction of T-bill futures contracts trading in IMM - 1976 Jan., the total volume for all delivery months reached the height of 738,394 in August 1982. Since December 1987, there seems to be a decline of interest in T-bill contracts. This coincides with the introduction of a Eurodollar futures contract which may be viewed as a substitute for the Treasury bill contract.

9 By providing a continuous flow of price information, futures markets perform an important economic
function - price discovery.

quoted in the Datastream is the official closing price issued by the IMM.[10]

Table 2.2

90-Day U.S. Treasury Bill Futures

Contract Specifications

	3-Months US Treasury Bill Futures
Ticker Symbol	TB
Trading Unit	TB $1,000,000
Price Quote	Index Points
Minimum Price Fluctuation (Tick)	.01 (1 Basis pt.) 1 basis point = $25 (.0001*$1,000000*90/360 =$25)
Price Limit	None
Strike Price Intervals	N.A.
Contract Mths.	Mar, Jun, Sept, Dec
Trading Time[1] (Chicago Time)	7:20 a.m. - 2:00 p.m. (Last day-10 a.m.)
Last Day of Trading	The business day immediately preceding the first delivery day
Delivery Days	Three successive business days, beginning the day after the last day of trading

1 Trading will end at 12:00 noon onthe business day before a CME holiday and on any U.S. bank holiday that the CME is open.

[10] Gemmill (1991) used closing prices of FTSE100 options to find the forecasting performance of implied volatility.

2.3.1.2 IMM 90-day Treasury Bill Futures-Options: Chicago Mercantile Exchange's stats database

Options[11] on Treasury bill futures were first introduced in the IMM in 1986. The table below shows the contract specification. This instrument is similar to a futures contract in that its premium is initially margined in short-term securities. There is therefore no opportunity cost associated with the purchase of such an option; nor is there an opportunity cost associated with the underlying futures contract. The net result is that short-term interest rates are not a factor in the pricing of futures-style options on futures contracts. As in the case of the futures contracts, trading for option contracts is on the March-June-September-December cycle. To simplify trading, prices for options are quoted in terms of index points rather than dollar values. The dollar value of a Treasury Bill option price is equal to the quoted index price times $2500. The options each cover one futures contract, and like the futures have a minimum price fluctuation of .01 index points[12]. No margin is required for put or call option buyers, but the premium must be paid in full; option sellers must meet additional margin requirements as determined by the Standard Portfolio Analysis of Risk (SPAN) margin system.

[11] An option is a derivative contract that gives the purchaser the right to buy or sell an underlying asset at certain price or before an agreed date.

Table 2.3

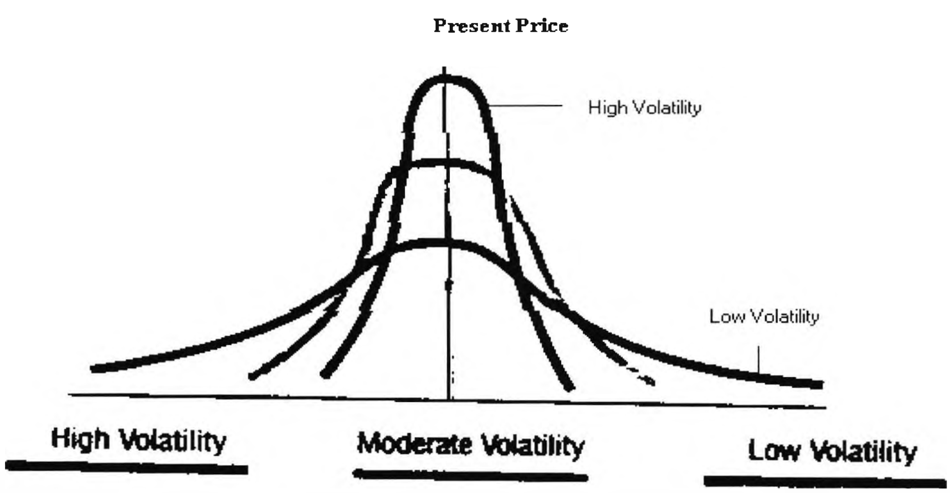
Options on Treasury Bill Futures
Contract Specifications

	Options on Treasury Bill Futures
Ticker Symbol	Calls: CQ Puts: PQ
Underlying Contract	One T-bill futures contract
Premium Quotations	U.S. $ per index point
Minimum Price Fluctuation (Tick)	.01 =$25.00 (cabinet=$12.50)
Price Limit	None
Strike Price Intervals	Below 91.00 : 50 Points Above 91.00 : 25 Points
Contract Mths.	Mar, Jun, Sept, Dec
Trading Time (Chicago Time)	7:20 a.m. - 2:00 p.m.
Last Day of Trading	Last business day of the week, preceding by at least 6 business days the first business day of contract month.
Delivery Days	Exercisable on any trading day until expiration on the last day of trading

[12] A trade may occur at a price of .0004 (=$1) if it results in position liquidation for both parties.

The price of an interest rate option is directly related to the underlying futures price, rather than to the current cash market interest rate. Option premia are affected by the relationship between the option's strike price and the underlying futures prices. The diagram below will be able to illustrate this relationship. When futures contract shows little price movement, volatility is low. High volatility generally causes options premiums to increase - sometimes very dramatically. This is because when markets

Price Distribution At Expiration



become volatile, option buyers are willing to pay larger premiums for greater protection against adverse price risk, as there is a greater likelihood of a price change in the underlying instrument. On the other hand, a greater chance for price change means more risk for the option seller. He therefore demands a larger premium in exchange for the risk. Some typical quotes for future-options and futures are given in Table 2.4, which is an extract from the Wall Street Journal. The first column lists several strike prices for the contract. In reality, the exchange lists many more strike prices, but the newspaper only displays those closest to the current future prices. Option premiums for

Table 2.4 Price Quotations

Price quotations for futures options: November 1, 1990

INTEREST RATE

FUTURES OPTIONS

T-BONDS (CBT) $100,000; points and 64ths of 100%

Strike Price	Calls—Last Dec-c	Mar-c	Jun-c	Puts—Last Dec-p	Mar-p	Jun-p
88	4-04	4-23	4-37	0-12	0-61	1-40
90	2-20	3-00	3-20	0-27	1-35	....
92	0-61	1-57	2-20	1-04	2-26	3-15
94	0-19	1-08	1-38	2-26	3-41	4-28
96	0-05	0-40	1-03	4-12	5-05	....
98	0-01	0-23	0-42	6-08	6-50	....

Est. vol. 200,000, Wed vol. 27,985 calls, 40,707 puts
Open interest Wed 393,965 calls, 476,244 puts

T-NOTES (CBT) $100,000; points and 64ths of 100%

Strike Price	Calls—Last Dec-c	Mar-c	Jun-c	Puts—Last Dec-p	Mar-p	Jun-p
94	2-24	2-46	....	0-10	0-49	....
95	1-33	2-03	....	0-17	1-04	....
96	0-53	1-31	1-51	0-37	1-31	....
97	0-22	1-02	....	1-07	2-00	....
98	0-10	0-45	....	1-57	....	....
99	0-04	0-30	....	2-51	....	....

Est. vol. 4,700, Wed vol. 488 calls, 628 puts
Open interest Wed 16,728 calls, 20,872 puts

MUNICIPAL BOND INDEX (CBT) $100,000; pts. & 64ths of 100%

Strike Price	Calls—Settle Dec-c	Mar-c	Jun-c	Puts—Settle Dec-p	Mar-p	Jun-p
87	2-28	2-36	....	0-22	1-14	....
88	1-47	....	....	0-41	....	....
89	1-10	1-34	....	1-04	2-09	....
90	0-46	1-10	....	1-39	2-47	....
91	0-27	....	....	2-20	....	....
92	0-14	....	....	....	....	....

Est. vol. 76, Wed vol. 1 calls, 0 puts
Open interest Wed 11,226 calls, 11,272 puts

5 YR TREAS NOTES (CBT) $100,000; points and 64ths of 100%

Strike Price	Calls—Last Dec-c	Mar-c	Jun-c	Puts—Last Dec-p	Mar-p	Jun-p
97	2-20	....	....	0-02	....	....
98	1-24	1-36	....	0-05	....	....
99	0-38	0-61	....	0-19	....	....
100	0-11	0-35	....	....	....	....
101	0-03	....	....	....	....	....
102	....	....	....	....	....	....

Est. vol. 770, Wed vol. 150 calls, 240 puts
Open interest Wed 8,736 calls, 5,041 puts

MORTGAGE-BACKED (CBT) $100,000; pts. and 64ths of 100%

Strike Price	Calls—Settle Nov-c	Dec-c	Jan-c	Puts—Settle Nov-p	Dec-p	Jan-p
Cpn	9.5	9.5	9.5	9.5	9.5	9.5
97	2-12	2-13	....	0-03	0-16	0-25
98	1-16	1-24	1-29	0-10	0-31	....
99	0-33	0-53	....	....	....	....
100	0-11	....	....	1-05	1-26	....
101	0-02	0-12	....	1-60	2-13	....
102	....	....	....	2-58	....	....

Est. vol. 30, Wed vol. 0 calls, 10 puts
Open interest Wed 812 calls, 1,126 puts

EURODOLLAR (IMM) $ million; pts. of 100%

Strike Price	Calls—Settle Dec-c	Mar-c	Jun-c	Puts—Settle Dec-p	Mar-p	Jun-p
9175	0.41	0.66	0.69	0.02	0.06	0.13
9200	0.20	0.46	0.50	0.06	0.10	0.19
9225	0.08	0.30	0.35	0.19	0.18	0.27
9250	0.03	0.17	0.23	0.39	0.30	0.39
9275	0.01	0.10	0.14	0.61	....	....
9300	.0004	0.06	0.09	....	....	....

Est. vol. 23,189, Wed vol. 11,272 calls, 8,579 puts
Open interest Wed 240,052 calls, 181,667 puts

EURODOLLAR (LIFFE) $1 million; pts. of 100%

Strike Price	Calls—Settle Dec-c	Mar-c	Jun-c	Puts—Settle Dec-p	Mar-p	Jun-p
9175	0.40	0.68	0.70	0.02	0.06	0.12
9200	0.19	0.48	0.52	0.06	0.11	0.19
9225	0.07	0.31	0.37	0.19	0.19	0.29
9250	0.02	0.19	0.24	0.39	0.32	0.41
9275	0.00	0.10	0.15	0.62	0.48	0.75
9300	0.00	0.06	0.08	0.87	0.69	0.75

Est. Vol. Thur, 0 Calls, 10 Puts.
Open Interest Wed 3,933, Calls, 2,427 Puts.

LONG GILT (LIFFE) £50,000; 64ths of 100%

Strike Price	Calls—Settle Dec-c	Mar-c	....	Puts—Settle Dec-p	Mar-p	....
82	2-32	3-35	....	0-12	0-53	....
83	1-45	2-56	....	0-25	1-10	....
84	1-01	2-18	....	0-45	1-36	....
85	0-36	1-50	....	1-16	2-04	....
86	0-18	1-23	....	1-62	2-41	....
87	0-09	1-00	....	2-53	3-18	....

Est. Vol. Thur, 1,575 Calls, 2,825 Puts.
Open Interest Wed 18,440, Calls, 25,782 Puts.

—OTHER INTEREST RATE OPTION—

Final or settlement prices of selected contract. Volume and open interest are totals in all contract months.

Treasury Bills (IMM) $1 million; pts. of 100%

Strike	Dec-c	Mar-c	Jun-c	Dec-p	Mar-p	Jun-p
9325	0.14	0.55	....	0.10	0.09	0.13

Est. vol. 164, Wed vol. 566, Op. int. 6,875.

CBT—Chicago Board of Trade. CME—Chicago Mercantile Exchange. FINEX—Financial Instrument Exchange, a division of the New York Cotton Exchange. IMM—International Monetary Market at Chicago Mercantile Exchange. LIFFE—London International Financial Futures Exchange.

Source: The Wall Street Journal, November 2, 1990.

Prices of T-bill futures on January 22, 1990

TREASURY BILLS (IMM)—$1 mil.; pts. of 100%

	Open	High	Low	Settle	Chg	Discount Settle	Chg	Open Interest
Mar	92.65	92.69	92.62	92.65	+ .02	7.35	− .02	32,928
June	92.76	92.82	92.76	92.79	+ .05	7.21	− .05	5,531
Sept	92.76	92.78	92.76	92.78	....	7.22	....	178

Est vol 4,477; vol Fri 6,082; open int 38,712, −787.

Source: The Wall Street Journal, January 23, 1990.

calls expiring December, January, and March appear in the next three columns. The last three columns show the same expiration months for put options. Estimated total volume appears below the columns; actual volume from the previous trading day. Actual open interest (the number of outstanding contracts) from the previous trading day appears on the same line. Exercise prices[13] are shown down the page, with maturities across the page. One can observe from these quotes that an option's value erodes as its expiration nears. Usually, the more time there is for the underlying futures to move, sellers will demand, and buyers will be willing to pay a larger premium which comprises of two components: time value[14] and intrinsic value[15].

Normally, at expiration, an option has no remaining time value, so one would only exercise any open in-the-money option contracts. However, exercise of a Treasury Bill option[16] on expiration day results in a futures position that will have two to four weeks of trading life remaining.

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[13] Exercise price, also called strike price, is the predetermined price at which a given futures contract can be bought or sold for the case of futures-options.

[14] Time value refers to its value over and above its intrinsic value. Time value reflects the possibility that an option will gain in intrinsic value and move into the money before it expires. Time value is typically greatest when an option is at the money. This is because at-the-money options have the greatest likelihood of moving into the money before expiration. In contrast, most of the time value in a deep in-the-money option is eliminated, because there is a high level of certainty that the option will not move out of the money. Similarly, a deep out-of-the-money option is unlikely to move into-the- money.

[15] It represents the amount realised by the option holder if he were to exercise his option immediately.

[16] Options on Treasury Bill futures are exercisable on any trading day until expiration on the last day of trading. Exercise is accomplished by the clearing member representing the buyer presenting an Exercise Notice to the Clearing House by 7:00p.m. on the day of exercise.

2.3.2 Measures:

2.3.2.1 Mean Expectation

The futures market price is chosen as the market-based measure of mean expectation of market participants on the assumption that the market is speculatively efficient. In this case, the collective actions of investors betting interest rates will rise above today's level (who will sell Treasury bill futures short) and investors betting that interest rates will fall (who will buy, or go long in, Treasury bill futures) will drive price towards the "market's" expectation of what interest rates will be at a specified future date. Under this (testable) hypothesis, these forecasts should reflect all available information held by market participants.

Similar to the survey-based forecast, futures prices tend to reflect what the actual settlement prices are going to be. This can be observed from figure 2.5 - 2.7. In fact, the price behaviour of these futures prices on selective dates (23rd of the preceding month, 2nd, 7th and 23rd of the current month) appear to have a closer relationship than they do with the actual settlement price (Figure 2.8).

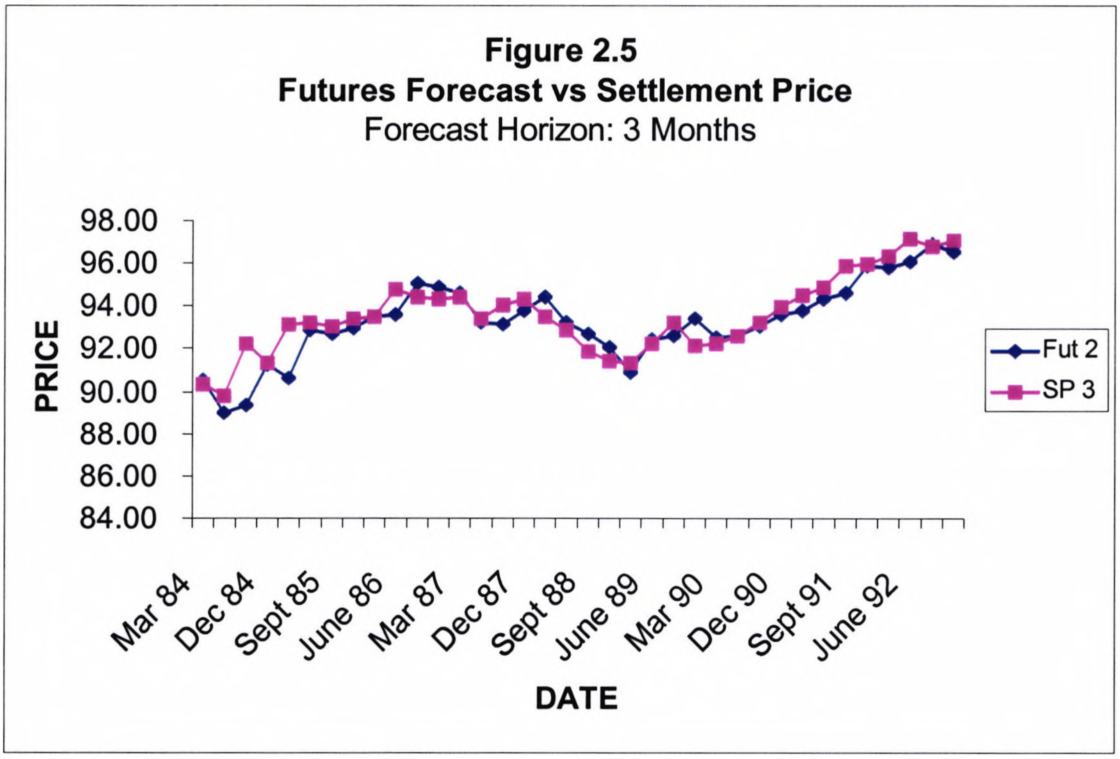
Figure 2.5
Futures Forecast vs Settlement Price
Forecast Horizon: 3 Months
98.00
96.00
94.00
92.00
90.00
88.00
86.00
84.00
PRICE
Fut 2
SP 3
Mar 84
Dec 84
Sept 85
June 86
Mar 87
Dec 87
Sept 88
June 89
Mar 90
Dec 90
Sept 91
June 92
DATE

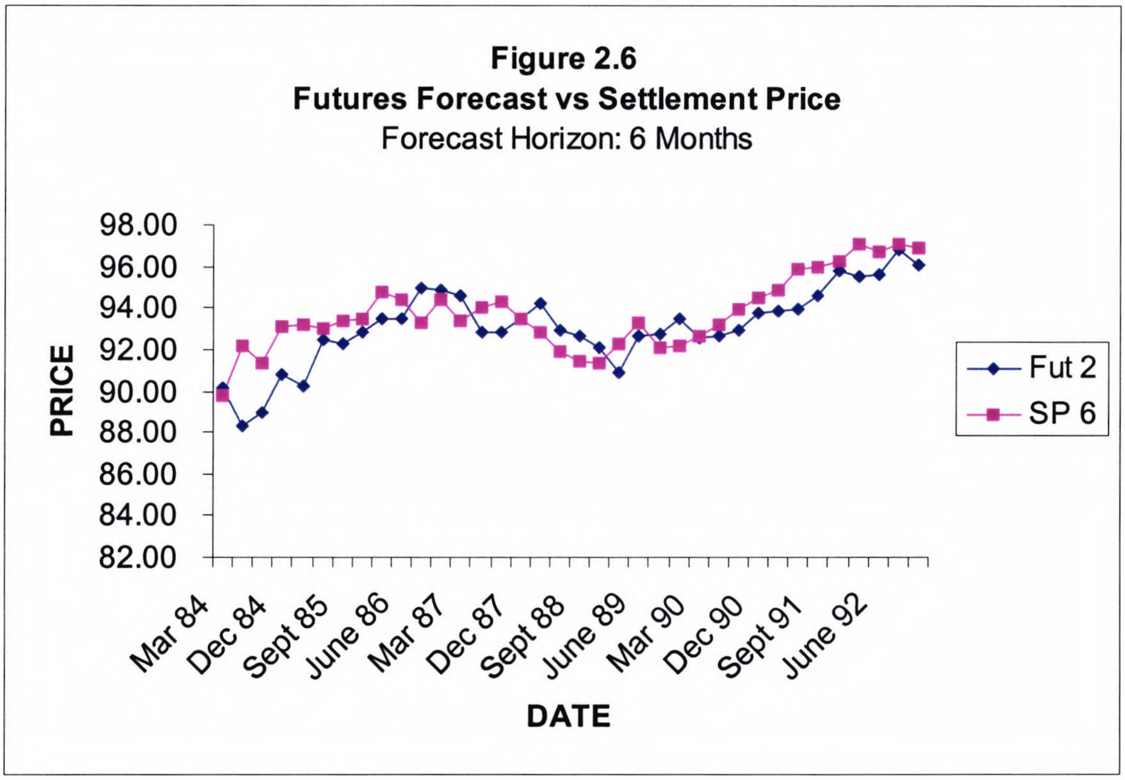
Figure 2.6
Futures Forecast vs Settlement Price
Forecast Horizon: 6 Months
98.00
96.00
94.00
92.00
90.00
88.00
86.00
84.00
82.00
PRICE
Fut 2
SP 6
Mar 84
Dec 84
Sept 85
June 86
Mar 87
Dec 87
Sept 88
June 89
Mar 90
Dec 90
Sept 91
June 92
DATE

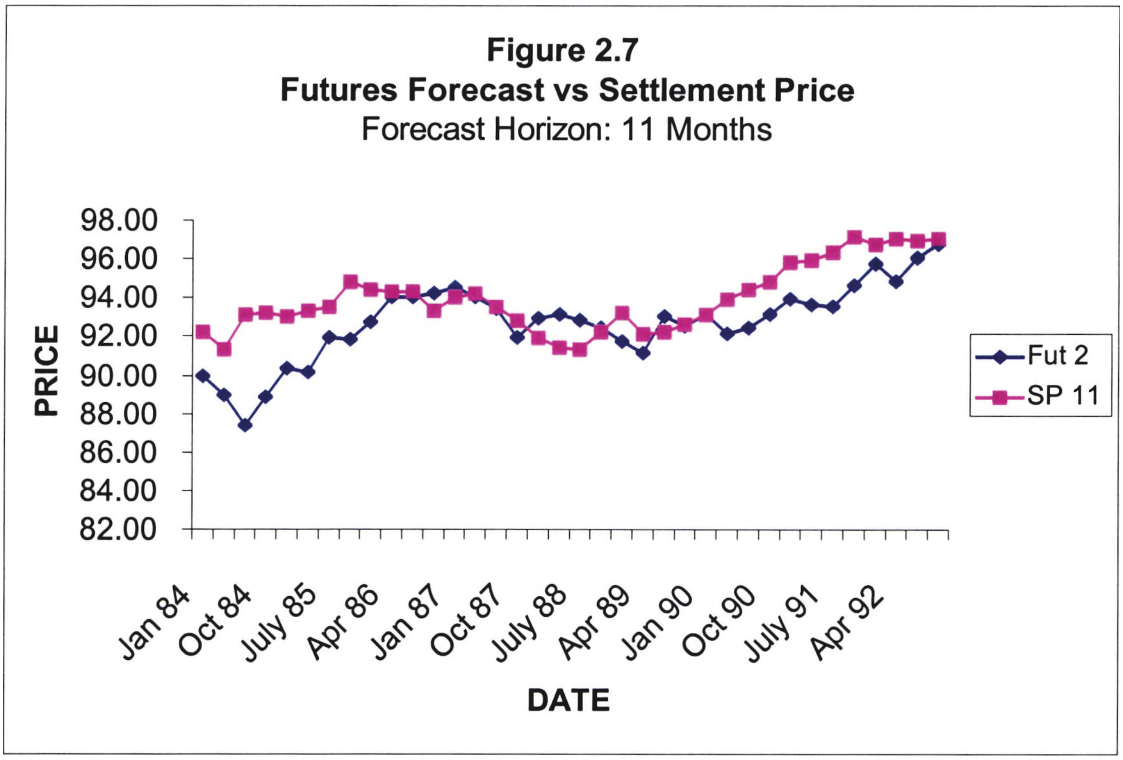
Figure 2.7
Futures Forecast vs Settlement Price
Forecast Horizon: 11 Months
98.00
96.00
94.00
92.00
90.00
88.00
86.00
84.00
82.00
PRICE
Fut 2
SP 11
Jan 84
Oct 84
July 85
Apr 86
Jan 87
Oct 87
July 88
Apr 89
Jan 90
Oct 90
July 91
Apr 92
DATE

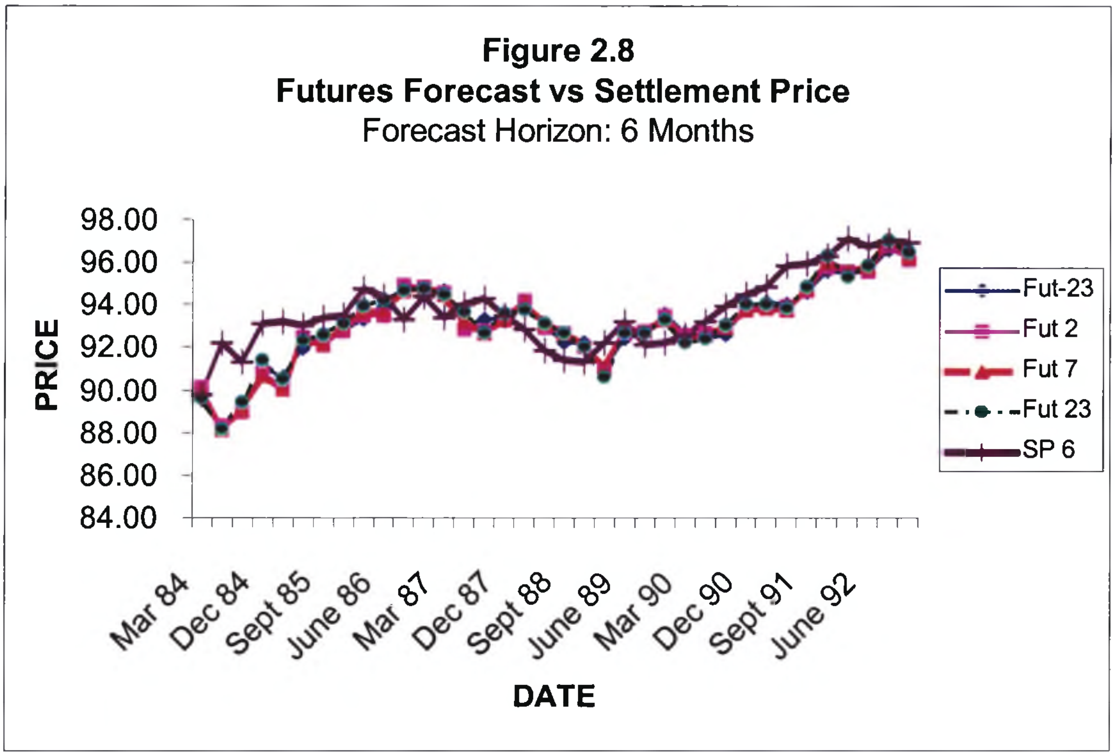
Figure 2.8
Futures Forecast vs Settlement Price
Forecast Horizon: 6 Months
98.00
96.00
94.00
92.00
90.00
88.00
86.00
84.00
PRICE
Fut-23
Fut 2
Fut 7
Fut 23
SP 6
Mar 84
Dec 84
Sept 85
June 86
Mar 87
Dec 87
Sept 88
June 89
Mar 90
Dec 90
Sept 91
June 92
DATE

The reason why these dates are selected is because on the 23rd (see chart below) of the current month, this is when the survey is completed. However the survey did not get published until the 2nd of the following month. During this period, information in the survey that is not publicly available may be used for trading.

Time	Dates	Events
t-1	23rd	Survey completed
	2nd	Survey published
	7th	2 weeks after survey completed, 5 days after survey published
t	23rd	One month after survey completed

2.3.2.2 Derivation of Implied Standard Deviation

The value of premia on options on financial assets depends in part on the expected volatility[17] in the price of the asset during the life of the option. Often changes in the premia can reflect what expectations market participants will have about the future volatility. In this case, changes in the premia of 90 days Treasury bill futures options can therefore give an insight into the expectations of market participants about the volatility of Treasury bill futures prices, and hence, since futures prices typically have the same characteristics as cash market price, into the expected volatility of Treasury bill yields.

Black (1976) published a model for use on futures options that is very close to the

[17] Volatility measures how much the underlying asset price is likely to change, regardless of direction, over a given period of time.

original Black-Scholes option model. The only difference from the original is that: the current price (in this case, the trading price of the futures contract) is replaced by the current price discounted continuously at the risk-free interest rate from the expiration of the option. The model, in simple terms, may be written in the following form:

$$c = c(F, X, T\text{-}t, \sigma)$$

$$p = p(F, X, T\text{-}t, \sigma)$$

where c is the price of a call option;

p is the price of a put option;

F is the futures price at time t;

X is the option exercise price;

σ is the standard deviation of the futures price;

T is the maturity date

t is the current calender time

If one assumes that the futures price, F, of an asset can be related to its spot price, S, by a cost-of-carry expression of the form:

$$F = Se^{r(T-t)}$$

where r, is the risk-free rate of interest less the yield on the asset. If the futures price is log-normally distributed, and if a riskless hedge may be formed between the call[18] and its underlying futures contract, then the call price, c, and the put price, p, for the futures options are therefore represented by the following equations with S replaced by F:

---

[18] A call option gives the holder the right to buy the underlying asset by (or sometimes on) a certain date at a certain price. A put option gives the holder the right to sell the underlying asset by (or

$$c = e^{-r(T-t)}[FN(d1) - XN(d2)]$$

$$p = e^{-r(T-t)}[XN(-d2) - FN(-d1)]$$

where

N(.) = cumulative normal distribution function

$$d1 = [\ln(F/X) + (\sigma^2/2)(T-t)]/[\sigma\sqrt{(T-t)}]$$

$$d2 = [\ln(F/X) - (\sigma^2/2)(T-t)]/[\sigma\sqrt{(T-t)}]$$

or

$$d2 = d1 - \sigma\sqrt{(T-t)}$$

The above call equation merely says that the current value of the call equals the present value of its expected value at expiration. At expiration, the futures option is worthless if it is out-of-the-money (i.e., if F_{T-t}, < X) and it is worth F_{T-t} - X if it is in-the-money (i.e. $F_{T-t} > X$)[19].

The expected value of the call option at maturity is therefore the expected difference between the futures price and the exercise price conditional upon the option being in-the-money times the probability that the call option will be in-the-money. This is represented by the term [FN(d1) - XN(d2)]. The term $e^{-r(T-t)}$ is the appropriate discount factor by which the expected expiration value is brought back to the present. The term

sometimes on) a certain date at a certain price.

19 An option is in the money if the exercise price is more favourable than the current market price of the underlying - that is the current market price is lower if it is a put and higher if it is a call. An option is at the money(spot) if the exercise price is equal to the market price of the underlying. And

N(d2) is the risk-neutral probability that the futures price will exceed the exercise price at option's expiration[20]. The delta factor given by the Black model [N(-d1)] shows the price changes of an option and its underlying future will relate. Afterall, the option's price and the futures' price will not move on a one to one basis.

This model assumes that both variances and interest rates are non-stochastic, "r" is only a function of time, and that the instrument cannot be exercised by expiry.

Ramaswamy and Sundaresan (1985), Schaeffer and Schwartz (1987) and Hull and White (1987) try to find the effects on option values when these assumptions mentioned above are loosened. Generally, they conclude that the effects appear to be small when options are near the money or are relatively close to expiry. Feinstein (1989), investigates the proposition that the use of Black-Scholes implied standard deviation as a forecast of future volatility is systematically biased due to the Black-Scholes formula's non-linearity. He concluded that this does not apply to implied volatility for exactly at the money options to any significant degree. At the same time, the problem of bias stemming from volatility forecasts through the non-linear pricing model is not relevant for at- and near-the-money options.

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it is out of the money if the strike price is less favourable than the current market price.

20 The term [XN(-d2) - FN(-d1)] in the valuation of put option equation means: the expected value of the put option at expiration conditional upon the option being in-the-money at expiration times the probability that the put option will finish in-the-money; N(-d2) is the probability that the futures price will be below the exercise price at maturity.

Ho and Abrahamson (1990)[21] compares the results for Treasury Bond futures options of arbitrage free rate movements or "AR" model[22] pricing with prices calculated from the Black model. They found that the results are quite similar to the closing market prices of treasury bond future options. According to Campa and Chang(1995), using daily closing quotes on foreign exchange options, stated that at-the-money options hold three key advantages. First, markets are most liquid in at-the-money or near-the-money options. Second, option premium is close to linear in volatility for at-the-money options, with deviation from linearity (as expressed by the magnitude of $d^2C/d\sigma^2$ declining for smaller values of σ and approaching zero for $\sigma \rightarrow 0$[23]. Since at-the-money options have zero intrinsic value and moreover have a zero intercept with respect to volatility. This simplifies the relationship between quoted volatilities and the option premium. Third, the pricing bias incurred in using the Black-Scholes model rather than the Hull and White (1987) stochastic volatility model is independent of the instantaneous level of volatility for at-the-money forward strike price. Harvey and Whaley (1991) states that at-the-money options are used to estimate implied volatility because they contain the most information about volatility; that is, they are the most sensitive to changes in the volatility rate.

All of the parameters of the Black model are readily observed in historical series apart

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[21] See Chapter 8 of Financial Options: From Theory to Practice. Edited by: Figlewski, Silber & Subrahmanyam

[22] Ho and Lee(1986) developed the AR model. Rather than modeling the behaviour of one or more interest rates in order to derive the future term structure, the AR model begins with the existing term structure and models how it might evolve over time.

[23] In fact, the option price is concave in volatility, but as an empirical matter, this concavity is negligible.

from σ, which market participants are assumed to estimate. There are several ways to estimate σ. For example, one can use historical data to calculate the standard deviation of futures price changes or one can use implied volatilities which is defined as the value of a stock's standard deviation of returns which, when employed in the option pricing formula, will equate an observed option price with the price calculated from the option formula. Implied volatilities reflect the market's assessment of future volatility. In order to avoid the shortcomings associated with the use of estimation of variance from the past data, implied standard deviations are used as an estimate of variance in this study. At the same time, one must bear in mind that when deriving the implied standard deviation for call options one assumption that has to be made: is that investors behave as if price options according to the Black model.

Given the information on all the other variables, time series for implied volatilities could be obtained by solving the Black Model for σ[24]. In order to minimise the possibility of getting bias in this data set, the only futures options that are selected are the ones nearest the money or at-the-money. The main reason is that at-the-money options are in general the most actively traded options, and suffer the least from measurement errors, which arise mainly from non-simultaneity in reported prices and bid-ask spread[25]. In other

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[24] This is done by using Excel Goal Seek function which utilises the Newton-Raphson algorithm. This procedure is an iterative search technique which consistently decreases the model's pricing error relative to the input market price until a convergence criteria is met. The more stringent the convergence criteria the more iterations and thus more processing time that is required before a figure is arrived at. According to Mayhew(1995) this method can achieve reasonably accurate estimates within two or three iterations. This method speeds up convergence by taking advantage of information in the function's first derivative.

[25] The implied volatility for out-of-the money options may differ from those for at-the-money options because the tail of the distribution may not be consistent with the assumption of a log-normal

words, the rationale for this approach is based on the evidence that market prices of at-the-money options have the least pricing bias vis-à-vis model prices. [Feinstein (1989); Geske and Roll (1984)]

In a few cases the implied standard deviation was impossible to calculate because the published option price falls below that which is consistent with the theory. In these instances, it may be impossible to derive reasonably good standard deviation estimates if other effects like transaction costs, taxes etc. are considered. However, in order to avoid complications, but nonetheless important considerations in computing implied standard deviations, these options are omitted from our analysis and an alternative option is used.

Figure 2.9 presents the implied standard deviation derived from 90 days Treasury bill futures options. From the figure, these implied standard deviation are derived from different dates but have the same forecast horizon, namely, three months ahead, and they portray the same general pattern. However, when one compares the implied standard deviation of different forecast horizons, the story is quite similar. The behaviour of two months ahead implied volatility appears to behave the same as five months ahead implied standard deviation (Refer to Figure 2.10). The only difference is that at five months ahead, the implied standard deviation is at a higher level than implied standard deviation obtained at 2 months.

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diffusion in the Black model.

Figure 2.9
Market Based Data: Standard Deviation
Forecast Horizon: 2 Months

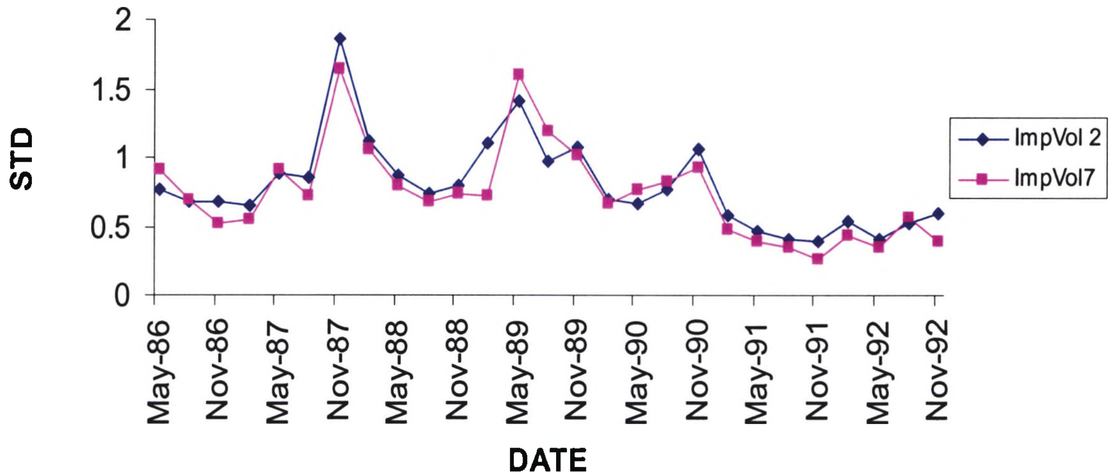
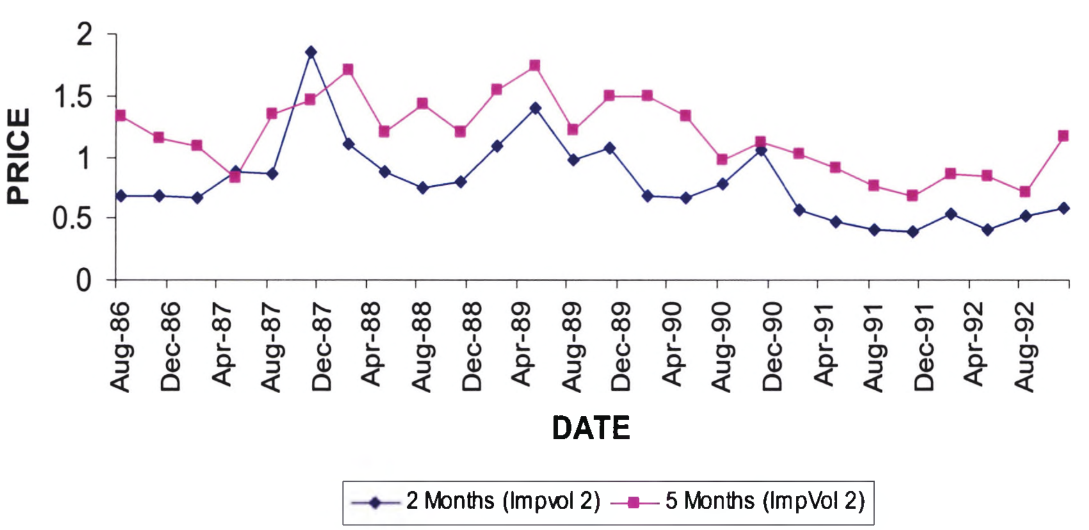


Figure 2.10
Market Based Data: Standard Deviation
Forecast Horizon: 2 Months & 5 Months



2.4 CONCLUSION

Interest Rate forecasts can be obtained from surveys of professional analysts or futures market quotes.

In this study we have chosen to use *Blue Chip Financial Forecasts* data as our main source of survey data . This is due to the following reasons: Firstly, a frequent criticism of surveys is that people did not have a strong incentive to respond accurately to the surveys, because they were not being paid to supply their forecasts, and they made their forecasts anonymously. The *Blue Chip Financial Forecasts* do not keep the forecasters' name anonymous. This will encourage forecasters to provide their best forecasts because forecasters can claim credit for particularly good forecasts.

Secondly, although this is a well-known survey, but under-researched. In the past, a lot of empirical research on U.S. Treasury bills had been based on data obtained from *GoldSmith-Nagan Bond and Money Market Letter* or *Wall Street Journal* surveys.

Thirdly, surveys such as *Goldsmith-Nagan Bond and Money Market Letter* asks contributors only for 3- and 6-month ahead interest rate forecasts, and the twice-yearly Wall Street Journal surveys of financial analysts asks for 6-month forecasts only. This could post a limitation to the study and hence results. This is due to the fact that often exploitable inefficiencies in futures markets occur in the more distant contracts. Using *Blue Chip Financial Forecasts* data will help to remedy this drawback.

Another source of market-related data is coming from futures and futures-options quotes. In this study, only at-the-money or nearest the money futures options are used. This is to ensure that our data set would not be biased in any way (Feinstein (1989); Ramaswamy and Sudaresan (1985); Schaeffer and Schwartz (1987)).

APPENDIX

Appendix 2.1 Blue Chip Financial Forecasts: Panel of Regular Forecasters

Institution	Forecaster (at 12/92)	Previous Institutions	Previous Forecasters
Standard and Poors Corporation	David M. Blitzer		
Aubrey G. Lanston & Co.	David M. Jones		
Bankers Trust, New York	Jay N. Woodworth		
Manufacturers Hanover Trust	Irwin L. Keller		
Oliver Jones and Associates	Oliver Jones		
US Trust Company NY	Thomas W. Synott III		
Metropolitan Insurance Companies	Robert H. Vatter		
Prudential Insurance Co. of America	Michael W. Keran		
Nelson Banking/ Finance Economics Inc.	Richard Nelson	Chemical Bank, SUNY, FHLB	
Moskowitz Capital Consulting Inc.	Arnold X. Moskowitz	Dean Witter Reynolds, County Natwest Bank	
FES Corporation	Herbert E. Neil	Harris Trust and Savings Bank	
DePrince and Associates	Albert E. DePrince Jr.	Marine Midland Bank	
C. J. Lawrence Inc.	Edward E. Yardeni, Deborah Johnson	Prudential Bache Securities	
First Interstate Bank	Lynn Reaser		A. James Meigs, Jerry Jordan
Sanford C. Bernstein & Co.	Giulio Martini		David A. Levine
Chase Manhattan Bank	Henry Willmore		Douglas L. Bendt, Greg Hoelscher
Valley National Bank	John Lucking		Elliott D. Pollack
Wells Fargo Bank	Gary Schossberg, Mark Green		Harold C. Nathan
National Association of Realtors	John A. Tuccillo		Jack Carlson
Merrill Lynch NY	Donald Straszheim		Robert A. Schwartz, Nancy Vanden Houten
US Chamber of Commerce	William MacReynolds		Ronald D. Utt, Grace Ortiz
First National Bank of Chicago	James E. Annable Jr.		Roy E. Moor
LaSalle National Bank	Carl R. Tannenbaum		William W. Tongue
Corestates Financial Coproration	Carol A. Leisenring	Philadelphia National Bank	A. Gilbert Heebner
First Fidelity Bankcorp	Joel L. Naroff	The Fidelity Bank	Mickey D. Levy

Chapter 3

FORECAST ACCURACY

3.1 INTRODUCTION

The user has to look ahead and act now on the basis of the best forecast available, this is the intrinsic reason for the importance of forecasts. The evaluation of past forecasting performance is an important input, since it provides a prediction of future performance. To a certain extent, this also answers the question of how much confidence one should placed in economic forecasts. Granger and Newbold (1973) point out that because typical time-series of economic levels is a near random walk, and because one random walk can appear to predict another independent random walk rather well, it is more meaningful to evaluate forecasts in terms of predicted and actual change.

The aim of this chapter is to examine forecast accuracy of market and survey data via the following methods such as directional accuracy, conventional summary measures and relative predictability.

Berstein and Silbert (1984) make a good case that professional forecasts are likely to be better than naïve predictions/random walk, especially for economic measures where market values are not directly driven by expectations. However, Armstrong (1988) points out, gaps still exist in terms of the forecast performance "desired" and that which is "produced".

Indeed a lot of other empirical evidence such as Stekler (1968), Cicarelli and Narayan (1980) etc seems to agree with Armstrong that professional forecasters add little to the forecasts generated by the simplest of models. Belongia (1987), Hafer and Hein (1989) found that survey forecasts added little to the forecasts implied by prices of nearby Treasury bill futures contracts. Kolb and Stekler (1996) show that differences in accuracy across one representative group of US forecasters – contributors to the *Wall Street Journal* surveys – are not statistically significant, so any out-performance is more likely due to chance than skill.

Other studies that compared futures rates, forward rates, and no-change forecasts of the Treasury bill rate have mixed results. Howard (1982), for example, found that for relatively short forecast horizons the no-change forecasts were more accurate than either futures or forward rates. However, for forecast horizons of 7-25 weeks, futures and forward rates are no more accurate than naïve forecast. MacDonald and Hedge (1989), using forecast horizons of 1-90 days, found that futures market quotes are generally more accurate prediction of the delivery-day Treasury bill rate.

When evaluating forecasts it is important to separate predictions for different horizons. This is crucial since, to make sense of the performance records, it is necessary to deal with homogeneous sets of information. Additionally, some methods may be relatively successful in very short-run forecasting, while others may be better in predicting further ahead.

Given time series of forecasts and outcomes, the first step is usually to provide some statistical basis for assessing the accuracy of these forecasts. Summary statistics are therefore calculated. Some conventional measures of forecasting accuracy such as the Root Mean Squared Error (RMSE) is based on the idea of quadratic-loss function in that larger errors carry proportionally greater weight than smaller ones. According to Nelson (1972), such measures reflect the view that forecast evaluation should centre on "all large disturbances" whether or not they are linked with "turning-point errors (which) are of no special interest in and of themselves". Prell (1973) finds that forecasters consistently missed turning points in the time series.[1] He suggested that this is especially important because "while the amplitude of a movement in a given direction affects the size of a potential capital gain, an error in forecasting the direction of movement can result in a capital loss. It will, therefore, be desirable to look more closely at errors in the forecasted direction of rate movement." Zarnowitz (1978) showed that turning points are among the most serious errors that a forecaster can make.

Diebold and Kilian (1997) argued that existing methodologies in measuring the predictability of forecasts might be inadequate in light of work emphasizing non-stationarities of various sorts, rich and high-dimensional information sets, non-quadratic and possibly even asymmetric loss functions, and variations in forecast accuracy across

---

1 Prell (1973) considered seven interest rates (i.e. Federal Funds, 3-month Treasury Bills, Intermediate Treasury Note, Bond Buyer Municipals, 3-Month Eurodollar, 1-Year Treasury Bills and Aaa Utility Bonds) obtained from Gold-smith-Nagan quarterly surveys. The forecast data utilized were taken from the surveys made from September 1969 to December 1972. He examined a few standard graphical and statistical measures of accuracy such as "prediction-realization" diagram, mean error of forecast and Theil's inequality coefficient, U^2. He also compared the experts' forecasts with the accuracy of alternative forecasts obtained through the use of certain "naive" mechanical methods.

horizons.

In order to provide an adequate assessment about the Blue Chip Financial Forecasts, directional accuracy, conventional summary measures, and the measure which Diebold and Kilian (1997) suggested, which is based on ratio of expected loss of a short-run forecast to the expected loss of the long-run forecast are used. The latter looks into the relative predictability between various time-series.

This chapter proceeds as follows: section 3.2 describes the various methods of assessing forecast accuracy, followed by the empirical results (Section 3.3). Section 3.4 will provide a summary and limitations.

3.2 BASIC CONCEPTS

3.2.1 Directional Accuracy

A first assessment about the accuracy of professional forecasts can be made against the criterion of the predicted direction of change. In terms of direction, forecast changes consist of increases, decreases, and small / no changes (this is possible but rarely the case for no changes). For this purpose, the current level of the Treasury bill rate is assumed to be that at the close of the 2^{nd} Day of the month – that is, the day on which the forecast was published[2].

Directional accuracy is measured by the proportion of forecasts that correctly predict the direction of change in the Treasury bill yield between the forecasts date and the futures delivery date, when spot and futures yields converge. Directional errors occur when the signs of the difference between actual "A" and current level of Treasury bill rate "R" and the deviation between predicted "F" and Spot "R" in a given period of time differ. From this definition, the determination of directional accuracy appears to be pretty straightforward. All differences between predictions and spot for Treasury bill rate can be summarily partitioned into decreases –(F-R), and increases +(F-R) where "F" represents predicted, and "R" stands for spot rate. These projections can then be compared to the differences between actual "A" and spot [-(A-R) and +(A-R)], so as to determine the number of times the predict series decreases as predicted [-(A-R)|-(F-R)], and the number of times it did not. Forecast increases can simply be calculated using the same idea. Simple summation yields the number of times of correctly predicted directional changes, [-(A-R)|(F-R)]+[+(A-R)|+(F-R)], as well as directional errors {i.e. [-(A-R)|+(F-R)]+[+(A-R)|-(F-R)]}. Finally, express these figures in terms of percentage.

The importance of using directional accuracy as a measure for forecast accuracy has been shown in various empirical researches. Wecker (1979) using quarterly seasonally adjusted GNP shows that linear least-squares prediction methods are not directly applicable to the prediction of time series "turning points." The theory of minimum

2 Batchelor (1993) carry out a similar test on Blue Chip data and used 23rd day of the month preceding the survey month as the current level of the Treasury bill rate rather than the day on

mean square error linear prediction is concerned with point estimates of future values of a time series conditional on observed values of that time series. The estimate ($xf_{n,h}$), which is restricted to be a linear function of the data, is "best" in the sense of minimising the expected squared prediction error $E(x_{n+h} - xf_{n,h})^2$. Based on this theory, he showed that such predictions are lacked of turning points which he claimed is a characteristic that seems to be inconsistent with the past behaviour.

Smith, Brocato & Dabbs (1991)[3] found that at longer horizon, the US macroeconomic variables, namely: Fed Funds rate; money growth; inflation and GNP, they find slope error growing as the dominant systematic influence, replacing bias in the forecast error. This indicates forecasters are, in general, unable to anticipate changes in direction for these variables over time. They suggested that forecasters should more closely scrutinise turning points to improve prediction accuracy. That is, directional accuracy, as measured by the proportion of forecasts, which correctly predicts the direction of change, is more important than the magnitude of the accuracy.

Cicarelli (1982) using GNP data illustrated that different measures of forecast accuracy can produce diametrically opposite conclusions about the predicative performance of a forecasting model. He argued that evaluating economic forecasts in terms of magnitude error alone is likely to give an incomplete picture of forecasting accuracy. Whereas, Leitch and Tanner (1995) suggested that the appropriate strategy that money managers

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which it was published. He found that this makes little difference to the results.

3 Smith, Brocato and Dabbs (1991) using data from the Blue Chip Financial Forecast from 1983:II through 1988:III analyses forecast precision of four major US macroeconomic variables. Theil's Mean Square Error, Root mean square error are used to measure forecast accuracy.

should undertake is "take position only if forecast change has opposite directional sign to market forecast". He explained this is due to the difficulty in forecasting the direction of interest rate changes. As interest rates are about equally likely to rise as to fall in the sense that they tend to follow a random walk, it is thought to be too risky to use a magnitude measure. His results indicate that the economists' forecasts are competitive with the simpler alternative approaches only when using the directional accuracy criteria.

Ash, Smyth and Heravi (1997) in evaluating the accuracy of OECD forecasts also calculate turning point errors. They pointed out that it might be more harmful to make smaller prediction error yet mis-forecast the direction of change than to make a larger, directionally correct error.

3.2.2 Summary Measures

Economic forecasts are typically evaluated by comparing the errors obtained when measuring the predicted values against the actual outcomes. The commonly used statistics classifying forecasts in this manner are the mean absolute error (MAE), mean squared error (MSE) and root mean squared error.

Let $F_{t,t+n}$ be the prediction made in time period "t" for "t+n", and "A_{t+n}" be the actual value in period "t+n" for the set of "T" observations. The forecast error for these forecasts is therefore given by $e_{t+n} = A_{t+n} - F_{t,t+n}$. The expressions for the mean absolute error (MAE) and the mean squared error (MSE) are as follows:

$$MAE = \Sigma|e_{t+n}|/T$$

$$MSE = \Sigma(e_{t+n})^2/T$$

The MAE – the mean of the absolute values of the errors – act as a better measure of the precision of forecasts is obtained by ignoring the signs of the forecast errors and considering only their absolute magnitudes. The MSE as its name suggests, is the mean of the squares of the forecast errors. According to the survey results of Carbone and Armstrong (1982)[4], in practice, this is the most frequently employed measure by both academicians and practitioners. However, there are suggestions that it is inappropriate to use this measure for forecast evaluation because this statistic involves averaging the squared errors over observations that have different degree of variability [Fair (1980), Jenkins (1982) and Pack (1982)].

According to Boothe and Glassman (1987), RMSE is a good measure of forecast performance *only* when the goal is to minimise the size of squared forecast errors, regardless of their direction. Whenever the direction of the forecast error is important, the RMSE criterion could be inappropriate. Whereas Joutz (1988) suggested that decision markers are faced with quadratic cost or loss function from basing decisions on forecasts. Hence, they will try to minimise the squared error. The RMSE is a good test statistic for accuracy, because it is a monotonic transform of the MSE and is expressed

[4] Carbone and Armstrong (1982) data set consists of two hundred and six responses. These responses are from the attendees of the First International Symposium on Forecasting held in Quebec City. Of

in units similar to the forecasts themselves.

Often for ease of interpretation in terms of the original units of measurement, root mean squared error (RMSE)[5] is calculated. This is calculated by taking the square root of the MSE:

$$\mathrm{RMSE} = [\Sigma(e_{t+n})^2/T]^{1/2}$$

The RMSE has the same units as the MAE. The RMSE is, by mathematical necessity, always greater than the MAE when the forecast errors are not all of the same size. Comparing Table 3.1 and Table 3.3 one can find evidence of what has just been stated. Apart from this difference in magnitude, the patterns noted for MAE's hold for the RMSE's. The real value of RMSE relative to the MAE lies not in the additional light it sheds on forecast accuracy, but rather in its more direct relationship to other useful statistics. Both measures are similar, however, using the RMSE to measure the accuracy gives a bigger penalty to larger errors than does the MAE.

Overall, these summary statistics are useful for describing the record of an operational forecasting system. However, it does not provide much direct information about whether something better might be achieved. These descriptive statistics must be compared against some standard before one can determine whether the forecasts are good. If these measures are purely on their own, they do not provide any meaningful

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the 206 responses, only 145 replies were retained; 75 practitioners and 70 academicians.

[5] Use of the RMSE is also consistent with the view that forecasters, or the consumers of forecasts, have quadratic loss functions under which the loss in welfare ascribed to a prediction error is proportional to the square of the error.

information by themselves because no unique estimate of the level of uncertainty exists. The only sensible standard of comparison is some alternative forecasting technique. Often these descriptive statistics may be compared with similar statistics obtained from a naive standard or time series regression [Moore (1969)]. The rationale for such comparisons is that forecasters should perform at least as well as the simplest models from which predictions could have been derived. This is in line with Prell (1973), where he suggested that naive forecasts provide a benchmark for assessing the value of experts' forecasting efforts - an assessment that is worthwhile because sophisticated forecasting procedures require costly resources.

3.2.3 Measure of relative predictability based on the ratio of expected loss function

At first sight the problem of how to evaluate the quality of a set of forecasts might seem to be quite simple, straightforward one. However, this is often not the case. In comparing predictability of various series we need a common numeraire as the expected losses of forecasts for the two series may be very different in magnitude or may be measured on different scales.

Granger and Newbold (1986) suggested a measure of the forecastability of covariance stationary series under squared-error loss, patterned after the familiar R^2 of linear regression:

$$R^2 = \frac{Var(\hat{y}_{t+j,t})}{Var(y_{t+j})} \equiv 1 - \frac{Var(e_{t+j,t})}{Var(y_{t+j})}$$

Where $\hat{y}_{t+j,t}$ is the optimal forecast and $e_{t+j,t} = y_{t+j} - \hat{y}_{t+j,t}$. For series that cannot be forecast, such as white noise, R^2 will be zero, but for other series R^2 will lie between zero and unity. If the series is not stationary, such as random walk, then a value of R^2 very close to one can be obtained, but this situation was specifically excluded from the above definition. The possible value of the ratio then depends on the degree of forecastability of the series. Diebold and Kilian (1997) continued to develop this measure by relaxing several constraints that limit the broad applicability of Granger-Newbold method[6]. The essence of the Granger-Newbold suggestion is that it is natural to base a measure of predictability on the difference between the conditionally expected loss of an optimal short-run forecast, $E(L(e_{t+j,t}))$, and that the optimal long-run forecast, $E(L(e_{t+k,t}))$, $j << k$. If $E(L(e_{t+j,t})) << E(L(e_{t+k,t}))$, then the series is highly predictable at horizon "j " relative to "k", and if $E(L(e_{t+j,t})) \approx E(L(e_{t+k,t}))$, the series is nearly unpredictable at horizon "j " relative to "k".

Thus, a general measure of predictability is defined as follows:

$$P(L, \Omega, j, k) = 1 - \frac{E(L(e_{t+j,t}))}{E(L(e_{t+k,t}))}$$

where the information set Ω can be univariate or multivariate. For one-step-ahead forecast horizon, the measure for predictability can be written as:

[6] Details of the advantages of relaxing the constraints that Granger-Newbold method imposed can be found in Diebold and Kilian (1997). One of the major advantages of relaxing the constraint is: it allows analysis of non-stationary and stationary series. Other advantages includes: it allows for general loss functions; predictability measure can be tailor made to specific horizons which is of economic interests; and it also allows for univariate or multivariate information sets.

$$1 - P = \frac{E(e_{t,t-1}^2)}{E(e_{t,t-k}^2)}$$

Under certain conditions, "1-P" is similar to Theil's U. The major difference is the numeraire. Theil's U compared 1-step ahead forecast with "naïve" no-change forecast, whereas P here compare 1-step accuracy relative to that of a long-horizon forecast (k-step). In the general case:

$$P(L(\cdot), \Omega, j, k) = 1 - \frac{E(L(e_{t,t-j}))}{E(L(e_{t,t-k}))}$$

Thus, $P(L(\cdot), \Omega, j, k)$ is effectively one minus the ratio of expected losses of two forecasts of the same object, y_t. One forecast, $\hat{y}_{t,t-j}$, is generally based on an information set with lots of data, while the other forecast, $\hat{y}_{t,t-k}$, is generally based on a sparse information set. The higher the values of "P", the greater the predictability of the time-series.

For the purpose of this study, several benchmarks are used to compare the performance of consensus forecasts. The naïve prediction is taken from the Federal Reserve Bulletin: auction average Treasury bill with week ending approximately around 23rd of the month – this is the day on which the survey forecast is made.

Other benchmarks are the rate implied by current futures prices for the relevant target month. In the context of the Blue Chip survey, there are two interpretations of what should count as a "current" interest rate. One possibility is to use rates on the 23rd of the month preceding the publication of the survey, or the most recent trading day before, since these rates are observable when the forecaster makes his/her prediction. The other possibility is to use rates from the 2nd day of the publication month, or the nearest trading day thereafter, since these are observable at the time a user of the Blue Chip service receives the forecast. We report results for both sets of spot and futures market rates below.

3.3 EMPIRICAL RESULTS

3.3.1 Directional Accuracy and Summary Statistics' Results

The statistics report below shows (Table 3.1), in terms of directional accuracy, the survey forecast did not outperform the futures market forecast obtained in seventh day for all the current month (Fut7) and twenty third of the current month (Fut23) at nearly all horizons. Forecasts obtained in the second day of the month (Fut2) and twenty-third of the month preceding the publication of the survey (Fut23p) in general perform worse than survey predictions. On average, the future forecasts obtained on the 7th and the 23rd of the current month get the direction of change correct 58%-60% of the time. Whereas, consensus forecast only managed to predict changes in direction of Treasury bill rates right 49% of the time. This is similar to the results obtained by Belongia (1987)[7];

[7] Belongia (1987) using the results of the professional forecasters surveyed semi-annually by the Wall Street Journal, he found they had an accuracy rate of 42% in predicting the direction of change for interest rates over a six-month horizon. The comparable rate for futures market was 55%. He did not use naive forecast in directional accuracy, since he claimed there is no meaningful way to construct a direction-of-change criterion on naive predictions.

Batchelor (1993, 1997)[8]; and Holden & Thompson (1996)[9], on the basis of direction of change, the futures market outperforms the economists surveyed. Judged by this method, Fut23 seems to be the best estimator of predicting changing directions for nearly all forecast period except 2nd and 3rd periods. The survey forecast does worst at predicting very short, one month, changes in Treasury bill yields, improves for 2-month to 6-month horizons, then deteriorates again at longer horizons. It is of no surprise that as the forecast horizons increases the accuracy of predicting changes in direction drops for both futures data and naive predictions. Survey/consensus forecasts do not seem to show any consistent pattern and is in contrast to market data and the naïve benchmark.

[8] Batchelor (1983) using 3-month Treasury bill yields obtained from Blue Chip Financial Forecasts found similar figures obtained by Belongia (1987). Details refer to Appendix 3.1. Naive benchmark follows random walk 3-month Treasury bill futures contracts are used as markets' forecast.

[9] Holden and Thompson (1996) using short sterling contract and Eurodollar contract obtained from LIFFE found that his results are similar to that of Batchelor (1994) and Belongia (1987). On average sterling futures contract correctly predicted the direction of change over 60%. For Eurodollar futures, this dropped slightly to the order of 55% (Details please refer to Appendix 3.1).

Table 3.1 Directional Accuracy of Survey & Futures Forecasts
(% correct)

Forecast Horizon	Survey	Fut23p	Fut2	Fut7	Fut23
1	0.3889	0.5000	0.5833	0.7222	0.8056
2	0.6111	0.6111	0.5833	0.7778	0.6944
3	0.6667	0.5278	0.4722	0.5833	0.6667
4	0.4722	0.4444	0.5556	0.6111	0.6389
5	0.5000	0.5278	0.6111	0.6111	0.6389
6	0.5278	0.3889	0.3889	0.5278	0.5833
7	0.3889	0.4444	0.4444	0.5278	0.5278
8	0.5000	0.4444	0.4722	0.5556	0.5556
9	0.4722	0.4167	0.4167	0.4722	0.5278
10	0.4444	0.4167	0.3889	0.5000	0.4722
11	0.4444	0.4444	0.4444	0.5278	0.5000

Key:
Fut23p = Futures market implied rates obtained on the twenty-third day of the preceding month
Fut2 = Futures market implied rates obtained on the second day of the current month
Fut7 = Futures market implied rates obtained on the seventh day of the current month
Fut23= Futures market implied rates obtained on the twenty-third day of the current month

The key summary statistics measuring the relative accuracy of the alternative forecasts are reported in Table 3.2 and 3.3. These tables compare the forecasting accuracy, as measured by MAE's and RMSE's respectively, of the professional-service forecasts and the market-based forecasts (90 days Treasury bill futures market) with the cash market price. It is indeed answering the question of how close these predicted values were to the actual values. Large variations in forecast accuracy over time have several important implications. More fundamentally, the fact that forecast accuracy varies over time poses a challenge to the constancy assumption needed to make inferences about future periods.

Table 3.2 Accuracy of Treasury bill Forecasts

Mean Absolute Errors

Forecast Horizon	Survey	Fut23p	Fut2	Fut7	Fut23	Naïve
1	0.4231	0.3808	0.3547	0.3058	0.1894	0.2619
2	0.5057	0.5661	0.5333	0.5033	0.3808	0.4092
3	0.5380	0.6006	0.6247	0.6239	0.5708	0.5370
4	0.6975	0.7258	0.6758	0.5914	0.6006	0.5383
5	0.8551	0.9583	0.8425	0.8142	0.7258	0.6773
6	1.0073	1.1319	1.1558	1.1111	0.9967	0.8243
7	1.0668	1.2519	1.2544	1.1225	1.1042	0.8520
8	1.1513	1.3914	1.3136	1.3042	1.2519	0.8870
9	1.2306	1.4925	1.5283	1.4872	1.4167	1.0064
10	1.2960	1.5822	1.5683	1.4686	1.4925	0.9544
11	1.3710	1.6486	1.5950	1.5872	1.5822	1.0770

Note: Forecast period is 1986:4-1992:12
The columns refer to the various futures forecast and survey forecast.

Table 3.3 Accuracy of Treasury bill forecasts

Root Mean Squared Errors

Forecast Horizon	Survey	Fut23P	Fut2	Fut7	Fut23	Naïve
1	0.5409	0.5027	0.4449	0.3892	0.2423	0.3291
2	0.6629	0.7531	0.7193	0.6930	0.5027	0.5404
3	0.7142	0.8295	0.8718	0.8678	0.7543	0.7181
4	0.8626	0.9714	0.9083	0.8334	0.8295	0.7159
5	1.0142	1.2588	1.1791	1.1233	0.9714	0.8482
6	1.1552	1.3557	1.3941	1.3837	1.2794	0.9870
7	1.2484	1.4764	1.4270	1.3457	1.333	1.0483
8	1.3576	1.6887	1.6253	1.5705	1.4764	1.1056
9	1.4364	1.7594	1.7785	1.7713	1.6983	1.2518
10	1.5344	1.8956	1.8458	1.7562	1.7594	1.1889
11	1.6316	2.0721	2.0171	1.9656	1.8956	1.3658

Note: Forecast period is 1986:4-1992:12

It has been widely observed, "almost all the forecasts deteriorate as the forecast horizon lengthens."[10] This result is readily apparent from the above tables i.e. Table 3.2 and 3.3, both MAE & RMSE indicate an improvement in accuracy as the horizon of the forecast declines (not surprisingly, it is harder to make accurate predictions further into the future). In addition, naive prediction has consistently outperformed the survey forecasts

[10] Carl Christ, "Judging the Performance of Econometric Models of US Economy," International Economic Review, Vol.16, No.1, February 1975.
Kolb and Stekler (1990) found that there was a significant difference among the forecast errors associated with different forecasting horizons.
Zarnowitz (1979) has also shown that subjective forecasts become more accurate as the forecast horizon is shortened.
Bernstein and Silbert (1984) using graphical analysis to examine the Blue Chip Economic Indicators similarly concluded that as forecasts approach their target date, they become more accurate.
Smith, Brocato and Dabbs (1991) showed that, except for real GNP, the rationality of these predictions, namely, Fed Funds rate, money growth and inflation, improves as the forecast horizon is shortened applying the Theil Mean Square Error.
Zarnowitz & Braun (1992) showed the absolute or squared errors tend to increase with the span of forecast for both individuals and group means, but less so for the latter.

even in longer forecast horizons. This is indeed in line with Bowlin and Martin (1975) where they found that a no-change forecast of interest rates is as accurate as other mechanical forecasts. This suggests that the best predictor of future spot yields is simply the current spot yields.

Boothe and Glassman (1987) observed that forecast errors grow as the forecast horizon extended. However, they were surprised that structural models' forecasts of exchange rates show no sign of improved rankings over the longer horizons. From these summary statistics, one cannot determine whether there is a statistically significant decline in forecast errors when the forecast horizon is reduced. The size of these statistics varies across time. As one of the crucial determinants of the size of forecast error is the forecast period; some periods are very difficult to predict while others are relatively easy. These results conform to those reported by Prell (1973) and Dua (1988). Dua (1988) using interest rates data obtained from bi-weekly Goldsmith-Nagan Bond and Money Market letter examine the accuracy of forecasts of interest rates over different horizons. The results indicate deterioration in "absolute" forecast accuracy measured by the mean absolute error and the RMSE, but no decrease in "relative" accuracy measures by Theil Coefficient with an increase in the forecast span[11].

However, Baghestani and Nelson (1994) using *ASA-NBER* survey annual data from 1983-1991 showed that although the forecast accuracy of three-month Treasury bill rate is lower than real GNP or implicit price deflator, the self-consistency of the forecasts, in general, is still similar to what common sense suggests. Furthermore, they found that consensus forecasts of this indicator are considerably better than the naive forecasts based on U-statistic.

Other studies like Hafer, Hein & Macdonald (1992), Hafer & Hein (1989), Belongia (1987)[12] established that the values of both the MAEs and the RMSEs are quite similar across forecasts. Based on MAE statistics, Belongia (1987) found there is only about 23 basis points difference between the best (naive) and worst (survey). For the full period, Hafer and Hein (1989) found that the MAE for three-month ahead forecast for the survey and futures rates is 1.18% and 1.25% respectively. They are both about the same as no change forecast (1.20%). Whereas for the six-month ahead forecast, both the futures and survey forecasts is comparable. In other words, the predictions provided by the futures market are comparable in quality to those of the experts. This provides some support for the efficient market theory, which states that all currently available information will be reflected in today's price. Hence, it is impossible to outguess the market. This is a question possibly warranting some further investigation. The results displayed in this chapter seem to be quite consistent with the other studies.

On average, the summary statistics in table 3.2 and 3.3 reveal that the accuracy of the futures and survey forecasts is comparable for all forecast horizon. The results show that the longer the forecast horizon the bigger the difference. This is indeed expected. Generally, there is little difference between the MAEs and RMSEs for the above forecast series. The MAE shows that on average the range of about 35 basis points

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[11] For details of Dua (1988) results see Appendix 3.1

[12] Details of the summary statistics for Hafer and Hein (1989) and Belongia (1987), refer to Appendix

between the best (naive) and worst (often Fut23p). The RMSE statistic, which is a measure of the dispersion of forecast errors, shows the naive, then follow by the consensus to perform best.

Basing upon these error-magnitude criteria, it seems that firms appear to waste money on buying professional economic forecasts[13] because the naive predictions always seem to outperform the rest. However, if one ignores the naive benchmark one can observe that, judging from this method, the best estimates for shorter horizons i.e. the one that produces the smallest error-magnitude is not forecast from professional services but rather futures price at 23rd of the current month. For longer forecast horizons, professional survey forecasts consistently have an edge over futures market. Both MAE and RMSE displayed the same evidence. The relative rankings of the six alternative projections are similar in terms of RMSEs and MAEs. The naive generally has the lowest RMSE and MAE, followed by the survey forecast. Next is forecasts obtained in the futures market, namely: Fut23 and Fut7. Whereas, Fut23p and Fut2 have the largest RMSEs. This ranking is in contrast to Hafer, Hein and MacDonald (1992)[14] and Prell (1973)[15] but similar to Throop (1981)[16], Belongia (1987) and Batchelor (1993). Belongia (1987) suggested an explanation for the futures prediction having the highest

3.1.

[13] Economist often puzzled as to why firms buy professional forecasts when traditional summary statistics such as RMSE and MSE often indicate that a naive model will forecast about as well. Leitch and Tanner (1991) argued that these conventional evaluation criteria might be inappropriate. This issue will be discussed in the following chapter.

[14] Hafer, Hein and MacDonald (1992) found that regardless of whether it is delivery-day observations or end-of-quarter observations are used, the relative rankings of the four alternative forecasts basing on RMSEs and MAEs are as follows: the futures rate generally has the lowest RMSE and MAE, followed by the no-change forecast. The forward rate and the survey projection have the largest RMSEs.

[15] Prell (1973) did show that with respect to short-term rates, the experts' forecasts did produce smaller RMSE's than did the no-change forecast, although the margin of improvement was not very large for the three-month forecast spans. Details refer to Appendix 3.1

RMSE is due to the method of calculation. "The RMSE will tend to be lower for forecasts that made many errors of a smaller size relative to forecasts that had smaller errors, on average, but had several very large errors. This result occurs, of course, because calculating the RMSE involves squaring the forecast errors. The effects of random variation in small samples are also a potential source of distortion. Thus, two very large futures market errors offset a record of generally accurate forecasts as indicated by other statistics".

Throop (1981)[17] consider two specific types of information that the Treasury bill market could utilise in formulating a two-quarter ahead forecast of the three-month bill rate. The first is simply an autoregressive forecast based on the past history of the bill rate. The second type of information is the average interest rate forecast made by a panel of professional analysts, and compiled by *the Goldsmith-Nagan Bond and Money Market Letter*. The forecast period is 1970-I through to 1979-III. Forward rates adjusted for "liquidity premium" are used as market's forecast. The measure of forecast accuracy, MSE and RMSE were used. Throop concluded that professional analysts' prediction of the Treasury bill rate two-quarters ahead is significantly more accurate than market predictions. This indicates that the market does not efficiently utilise all available information in making Treasury bill rate forecasts. By making use of the information contained in the analysts' forecast, an investor in Treasury bills could have improved his return. From the above, it seems that there is lack of consensus as to the best predictor of the near-term Treasury bill rate. This could be explain by the fact that due to the

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16 Details of Throop (1981) results refer to Appendix 3.1.

17 Throop (1981) did not examine the accuracy of Treasury bill futures due to the fact that 3-month

different sample period used; different combinations of forecasts and forecast horizons.

3.3.2 Predictability

Now turning to relative predictability measure in evaluating forecast accuracy, similar conclusion as directional accuracy can be drawn. Here we set the benchmark (k) to forecast horizon 11. We then assess the relative predictability of the near-term forecast horizon (j). Looking at Table 3.4 results, survey forecasts and naïve benchmark did not outperform the futures market forecast obtained on Fut7 and Fut23 at nearly all horizons (Figure 3.1 and 3.2).

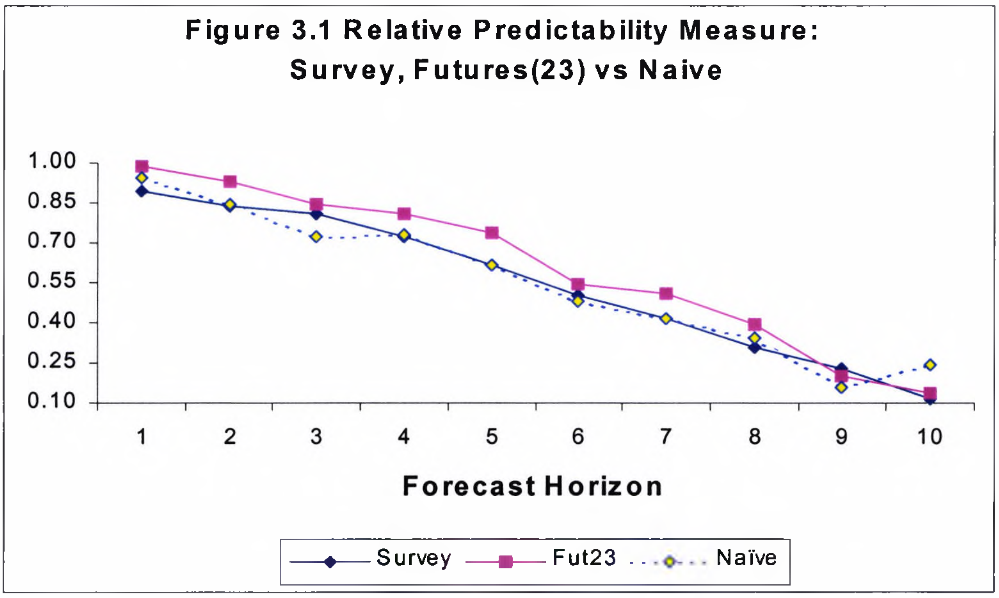
Table 3.4 Relative Predictability

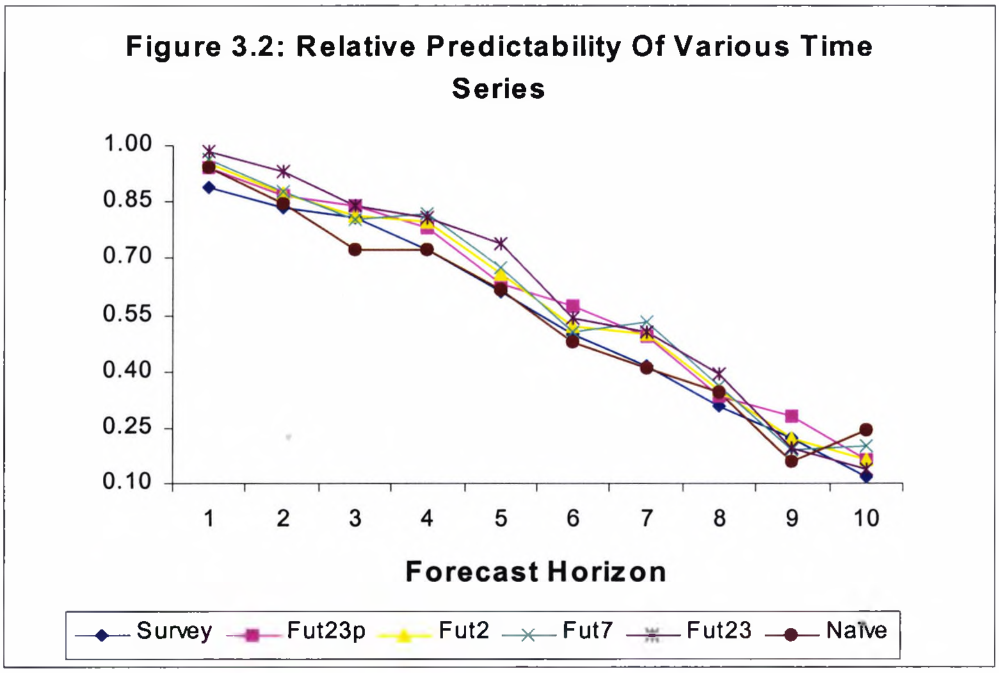
Forecast Horizon	Survey	Fut23p	Fut2	Fut7	Fut23	Naïve
1	0.8901	0.9411	0.9513	0.9608	**0.9837**	0.9419
2	0.8350	0.8679	0.8728	0.8757	**0.9297**	0.8434
3	0.8084	0.8397	0.8132	0.8051	**0.8417**	0.7236
4	0.7205	0.7802	0.7972	**0.8202**	0.8085	0.7253
5	0.6137	0.6309	0.6583	0.6734	**0.7374**	0.6143
6	0.4987	0.5719	0.5223	0.5045	**0.5444**	0.4778
7	0.4146	0.4924	0.4995	**0.5313**	0.5055	0.4109
8	0.3076	0.3358	0.3507	0.3617	**0.3934**	0.3447
9	0.2250	**0.2791**	0.2226	0.1880	0.1974	0.1600
10	0.1156	0.1631	0.1627	0.2018	0.1386	**0.2423**

Key: Results highlighted in bold showed the best predictability

Treasury bills have existed only since January 1976. Using Treasury bill futures data means reducing the number of observations by more than half.

In addition, the predictability of the various time-series exhibits the same trend: the longer forecast horizon, the less predictable the time-series (Figure 3.1 & 3.2). This is quite similar to the result showed in Diebold and Kilian (1997) where the predictability of various interest rates increases as the maturity increases i.e. from the 3-month Treasury bill rate to the 1-year and 5-year T-bond rates.





3.4 CONCLUSIONS

Accurate forecasts are important to successful enterprise. Using RMSE, MSE, directional accuracy and relative predictability measure, the accuracy of futures market and survey forecasts of three-month Treasury bill rate is compared. The test results, basing on summary statistics and relative predictability measure, generally support the notion that market-based forecasts manage to predict the Treasury rate as well as professional forecasters. This is especially true for near-term interest rate predictions where futures market constantly being more precise than the survey. However, when one compared these forecast series with the benchmark (naive), it seems that the naive prediction is more accurate than other forecast series presented in this chapter. Whereas when one use relative predictability measure, even when compare to the benchmark, market-based forecasts appeared to be more predictable than naïve.

It is difficult to draw conclusive evidence basing on just the MAEs and the RMSEs for at least one reason: there is no absolute standard against which to compare these summary statistics. Prell (1973) argued that conclusive evidence on this score cannot be offered for at least two reasons:

First, results based on a small sample forecasts may not reflect accurately the quality of the forecasts over a longer period of time; second, there is no way of judging the importance to, say, a business means of a basis point improvement in forecast accuracy. Nevertheless, there is some important information about the quality of the experts' forecasts. McNees (1995) concluded that the only relevant standard for evaluating a forecast is the accuracy of other, comparable forecasts. He claimed: "If no superior alternative exists, then a large forecast error is simply a reflection of the fact that we live in an uncertain world. This study reconfirms that both public and private forecasts are more accurate than simple rule of thumb".

In the absence of an absolute standard, various comparative procedures have been developed. The first approach is to test whether the forecast satisfies certain properties of an optimal forecast, other than that of minimum mean (This will be dealt with in Chapter 5). The second approach is to limit attention to a particularly restricted information set, namely comprising past values of the variable of interest alone, and to compare a given forecast with the 'pure time series' forecast based on this 'own-variable' information set. A third possibility is to conduct comparisons across a number of models or forecasts, and the issues that these raise, together with the possibility of combining forecasts.

APPENDICES

APPENDIX 3.1

A) Prell (1973)

Forecast Accuracy for Three-month Bills

Forecast Span	ME	MAE	RMSE	U^2 Level	U^2 Change
3-month	-8	70	83	0.02	0.79
6-month	-34	68	93	0.03	0.58

Comparison with Alternative Forecasts
(RMSE, in basis points)

Forecast Span	Survey	No-Change	1	2	3	4
3-month	83	94	117	118	93	85
6-month	93	123	131	154	119	73

Key:
1) 1 Year Moving Average Forecast
2) Extrapolative Forecast based on auto-regressive equation fitted to past data
3) Forecast based on sample period average level
4) RMSE based on optimal ex-post extrapolative equation

B) Throop (1981)

Accuracy of Forecasts for 3 month Treasury Bills (1970-1979)
RMSE (% Points)

Forecast of No Change	1.25
Market's Forecast	1.24
Analysts' Forecast	1.10
Autoregressive Forecast	0.94

C) Dua (1988)

The Accuracy of Forecasts for 3-month Treasury Bill
1972:1-1985:4

Forecast Horizon	MAE	RMSE	U
1 quarter	1.139	1.857	1.038
2 quarter	1.468	2.112	0.978

D) Belongia (1987)

Summary Statistics for Errors from Alternative Forecasts (%)
June 1982-December 1986
Forecast Horizon: Six-Months ahead

	MAE	Mean Error	RMSE
Economist Mean	1.550	-0.406	1.889
Futures Market	1.466	-1.132	2.253
Naive	1.321	-0.543	1.859

E) Hafer and Hein (1989)

Summary Forecast Statistics, Three-Month Treasury bill Rate (%)

	March 1977-October 1987		March 1980-December 1982		March 1983-October 1987	
Forecast	**MAE**	**RMSE**	**MAE**	**RMSE**	**MAE**	**RMSE**
			Three-month forecasts			
Futures	1.18	1.90	2.79	3.32	0.53	0.86
Survey	1.25	1.97	2.92	3.44	0.62	0.93
Naive	1.20	1.91	3.10	2.53	0.54	0.79
Futures	1.52	2.28	2.94	3.64	1.03	1.48
Survey	1.60	2.23	3.10	3.63	1.03	1.30
Naive	1.68	2.31	3.12	3.63	0.83	1.01

F) Hafer, Hein and MacDonald (1992)

Forecast Accuracy Comparisons: Sample Period: 1977-1988
Forecast Horizon: One-Quarter-ahead forecasts

Forecast Source	RMSE	ME	MAE	U^{Bias}
		Delivery-day Horizon		
Futures	1.90	-0.03	1.16	0.000
Survey	1.99	-0.26	1.20	0.017
No-Change	1.92	-0.21	1.16	0.011
		End-of-quarter Horizon		
Futures	1.75	0.01	1.10	0.000
Survey	1.83	-0.22	1.14	0.014
No-Change	1.77	-0.17	1.12	0.009

G) Batchelor (1993)

Forecasts Accuracy for Futures settlement Dates
RMSE (%)

	Futures Contract			
	1	**2**	**3**	**4**
Consensus	0.79	1.16	1.54	1.85
Naïve (RW)	0.73	1.04	1.38	1.65
Futures Prices				
-23	0.76	1.26	1.68	2.01
2	0.72	1.18	1.62	2.05

Directional Accuracy (% correct)

	Futures Contract			
	1	**2**	**3**	**4**
Consensus	0.33	0.39	0.47	0.50
Futures Price				
-23	0.72	0.56	0.56	0.53
2	0.75	0.64	0.61	0.58

H) Holden and Thompson (1996)

Proportion of correct Predictions of Directional Changes

Horizon Months	Short-Sterling Contract	Eurodollar Contract
1	63%	53%
2	60%	49%
3	69%	56%
6	64%	57%
12	75%	47%
18	76%	59%

I) Batchelor (1997)

RMSE of Consensus and Market Forecasts on 3 months Treasury Bill

Horizon Months	Consensus DA -23	Market Spot -23	Spot +2	Fut -23	Fut +2
1	0.14	0.09	0.06	0.06	0.06
2	0.29	0.32	0.24	0.28	0.2
3	0.48	0.5	0.44	0.58	0.5
4-6	0.85	0.75	0.74	0.74	1.01
7-9	1.71	1.44	1.42	2.19	2.15
10-12	2.57	2.28	2.28	3.43	3.35
ALL	**1.36**	**1.19**	**1.17**	**1.67**	**1.69**

Directional Accuracy of Consensus and Market Forecasts

Horizon Months	Consensus DA -23	DA+2	Market dSpot+2	Fut -23	Fut +2
1	0.47	0.33	0.83	0.69	0.78
2	0.59	0.53	0.71	0.65	0.59
3	0.61	0.58	0.72	0.69	0.56
4-6	0.5	0.53	0.62	0.62	0.59
7-9	0.42	0.46	0.55	0.5	0.49
10-12	0.46	0.49	0.53	0.49	0.53
ALL	**0.48**	**0.49**	**0.61**	**0.57**	**0.56**

Chapter 4

SURVEY FORECASTS Versus PROFITS

4.1 INTRODUCTION

The aim of this chapter is to investigate whether the value of interest rate forecasts is well measured by summary statistics on accuracy, or whether profitability provides a different benchmark.

In the past, a lot of studies such as Stekler (1968); Smyth and Ash (1975); Cicarelli and Narayan (1980)[1]; Meese and Rogoff (1983a, 1983b, 1985); Hafer and Hein (1989); Hafer, Hein and MacDonald (1992)[2] have shown that professional forecasters add little to the forecasts generated by the simplest model - random walk.

Conventional error measures such as average absolute error, the root-mean-squared error or mean-squared error rarely reveal major differences between professional forecasting services and a simple naive approach of no change in the variable being forecast.[3] Indeed, the results obtained in previous chapter seems to point to the same conclusion i.e.

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1 Stekler (1968) concluded that the results suggest that econometric models have not been entirely successful in forecasting economic activity. Whereby Smyth and Ash(1975) found that forecasts are in no way superior than those generated by naive models. Cicarelli and Narayan(1980) have a similar conclusion: that accuracy of the forecasting models was distinctly inferior to that of the ARIMA models.

2 Hafer and Hein(1989); Hafer, Hein and MacDonald(1992) show that the Goldsmith-Nagan consensus forecasts are significantly less accurate as predictors of future Treasury bill yields than virtually costless naive alternatives, such as the current Treasury bill futures price and the current Treasury bill spot yield.

3 For evidence refer to Leitch and Tanner (1991).

naive predictions have the smallest-error magnitude when compared with both market-based forecasts and professional forecasts.

Leitch and Tanner (1991,1995), suggested that this conclusion is mistaken because the conventional error criteria may not capture why forecasts are made or how they are used. Traditional error criteria, such as mean squared error measures, shows only how closely the model fits a time series by averaging the sum of the squared deviations of the two series. It does not differentiate between deviations resulting from a failure to predict a change in trend of the series or the cyclical component. This is consistent with Boothe and Glassman (1987); Satchell and Timmermann (1992) findings that squared errors (SE) and profits based forecasters can differ significantly. Empirical results from Boothe and Glassman show that simple time-series models for foreign exchange market such as random walk rank highest in forecast accuracy. In terms of profitability rankings, the results are quite different from the accuracy results especially in Canadian/US dollar. One explanation according to Wecker (1979)[4] might be that the SE criterion is of poor use to build efficient forecasts of turning points, which is a necessary condition for profitability. Thus, a more appropriate test of forecast accuracy is profitability, and not the size of the forecast error or its squared value. One would assume that firms use forecasts because they add to profits. In addition, traders are only interested in forecasting changes in the underlying trend of the financial prices rather than forecasting the level of the price series. A trader will take a long position in the

[4] In Wecker's (1979) paper the linear least squares technique is extended to allow computation of the distribution of the turning points of a time series, conditional on past observations. The method is illustrated using quarterly seasonally adjusted GNP

market in anticipation of a price rise, without attempting to forecast level. Hence, it seems natural to examine profits directly than to examine a proxy that is at best indirectly related to profits.

Indeed, the above mentioned proposition is strongly supported by Boothe and Glassman (1987) and Leitch and Tanner (1991,1995). Boothe and Glassman (1987) compare the rankings of alternative exchange rate forecasting models[5] using two different evaluation criteria: forecast accuracy and profitability in forward market speculation. They calculated profitability in the following way. First, a forecast was generated and compared to the current forward rate. If the forecast price of foreign exchange was greater (less) than the forward rate, then a forward contract was bought (sold). If the size of the realized future spot rate was greater than the forward rate, then the forward purchase (sale) was profitable (unprofitable). If the forward rate was greater than the future spot rate, then the forward sale (purchase) was profitable (unprofitable). The profit (loss) from each forward contract expressed in units of domestic currency per U.S. dollar is:

$$\text{Profit} = [s_{t+1} - f_t]z_t$$

where s_{t+1} is the realised spot rate, f_t is the forward rate, z_t=1 if a forward contract was purchased and z_t= -1 if a forward contract was sold.

[5] Boothe and Glassman (1987) use both time-series and static and dynamic structural models to construct forecasts for the Canadian dollar/U.S. dollar and German mark/U.S. dollar exchange rates over the period 1976:12-1984:9. The in-sample estimation procedure was ordinary least squares for the time-series models (Unconstrained first-order autoregressive model and random walk model) and the dynamic structural models : namely, unrestricted distributed lag with one lag of all variables; and a restricted version of the distributed lag model, in which the constraint of long-run proportionality between the exchange rate and relative money supplies is imposed. The static structural models were estimated by an iterative Cochrane-Orcutt procedure to account for the first order autocorrelation

Leitch and Tanner(1991,1995)[6] using interest rate forecasts to trade the Treasury debt market find that there is no significant correlations between the root mean square errors of six methods of forecasting US Treasury bill yields i.e. one to nine months ahead, and the profits from futures trades based on the following trading rules:

1) Forecast rates to rise, short futures contract; forecast rates to fall, buy futures contract;
2) Assumes a position only if interest rates are expected to change. If the forecast is for no change in rates, then the action is not to take a position;
3) Take position only if forecast change has opposite directional sign to market forecast. A rule which Leitch and Tanner claimed to be most likely used by professionals.[7]
4) Forecast rates to be above implied forecast of futures, go short; forecast rates to be below implied forecast of futures, go long.

Leith and Tanner (1991, 1995) also found that directional accuracy was strongly

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caused by dynamic mis-specification.

[6] Leitch and Tanner (1991) employed seven different forecasting systems for the sample period from 1982 January through December 1987. The first forecasting system was based upon the professional service : Money Rate report. Other forecasting systems include ARIMA model.

For the forward rate, end -of-month in the *Wall Street Journal*. The implicit rate up to nine months ahead for the three-month Treasury-bill rate was estimated from the Treasury-bill yield curve's bid price using the appropriate maturity dates up to one year ahead.

The future rate forecasts were derived from the historical prices of the four nearest Treasury-bill future contracts.

The other forecasting systems include naive no-change model whereby all future rates will equal the current spot rate; and constant rate growth i.e. the change in interest rates over the next x months is compounded from the most recent one-month change. Thus, rising interest rates are expected to continue to rise, while falling rates are expected to continue to fall.

[7] According to Leitch and Tanner(1994), the rationale behind this rule is because of the difficulty in predicting the direction of interest rate changes. Hence, it is thought to be too risky to use a magnitude

correlated with profits but there is no systematic relationship between the size of the forecast error and the profitability of the forecast. This may be due to the fact the profits may not be linearly related to the size of the error.

These results are rejected by Batchelor (1993, 1998) who shows significant positive correlations between profitability ranks and root mean square error ranks except in pre-release period. According to Batchelor (1993, 1998), a possible explanation for this characteristic lies in the small number of forecasts studied by Leitch and Tanner (1991), and their inclusion of a consensus forecast and a naive no-change forecast in the testing.

In the past, a lot of research had been done on comparing individual forecaster's prediction with futures prices. In this chapter, we extend previous work by looking at the profitability of trading on the standard deviation, as well as the mean, of consensus forecasts. This research is unique in the sense that survey standard deviation and not individual forecaster standard deviation is compared with implied volatility derived from using 90-day treasury bill futures-options.

This chapter is organised as follows: Section one describes the data; section two describes the various trading rules used. In section three, evidence is presented and compared the relative performance between consensus mean and naive alternatives; whereby survey standard deviation is compared to historical volatility. In the last section, summary of this chapter.

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measure.

4.2 DATA

The survey forecast used in this study are all those published in the Blue Chip Financial Forecasts for the period beginning from April 1986 and ending in December 1992[8]. This period is chosen due to the fact that options on Treasury bill futures were only first introduced in the IMM in April 1986. The naive prediction for mean trading is taken from the Federal Reserve Bulletin: auction average 90-day Treasury bill with week ending approximately around 23rd of the month - this is the day on which the survey forecast is made. This will ensure both the naive and consensus mean are comparable. Historical volatility were used. This is measured by a 100 day simple moving average.

4.3 PROFIT MEASURES Of USING An INTEREST RATE FORECAST

There are many ways to trade on an interest rate forecast. Our first profit calculation is simple, but takes the market-based forecast explicitly into account. This assumes that, if the forecast for the contract is below the yield implied by the current future prices, one will long the contract i.e. buy a future. Conversely, if rates are expected to be above the rate implied by the future contract, one will short the contract, i.e. sell a future. If the forecast is correct, the futures price will fall or rise to converge on the forecast cash market yield at settlement. After this position is taken, profits are then calculated, measured by basis points per trade (BP). The rule that we have used here is similar to

[8] Details about the data are found in Chapter 2 : "The Sources and Background of Data".

Leitch and Tanner's (1991,1995) and Batchelor's (1993, 1998).

A parallel trading strategy for volatility is utilised in this chapter. Here, one is following a filter rule. In other words, one only take a position i.e. buy/sell straddle[9] (a call and a put) if the forecast yield differs from the yield implied by the futures-option price by more than some minimum amount. In this case the threshold is set to be the average of +/- 2 and +/- 4 bps for each forecast horizon.

The combination of buying a call and a put is normally used when investors/speculators believe that asset prices will either move significantly in one direction or the other (but are uncertain as to which direction). It is a strategy to profit from volatility in the price of the underlying asset. The call makes money if the price of the underlying asset goes up strongly and the put makes money if is goes down strongly. Both options lose their time value by expiration date, so the standstill return is negative. This is a speculative position, but because it involves buying options, its risks are limited. The payoff from a straddle is calculated in Table 4.1 below:

[9] Buy a call and a put with the same exercise price and expiration date is called straddle.

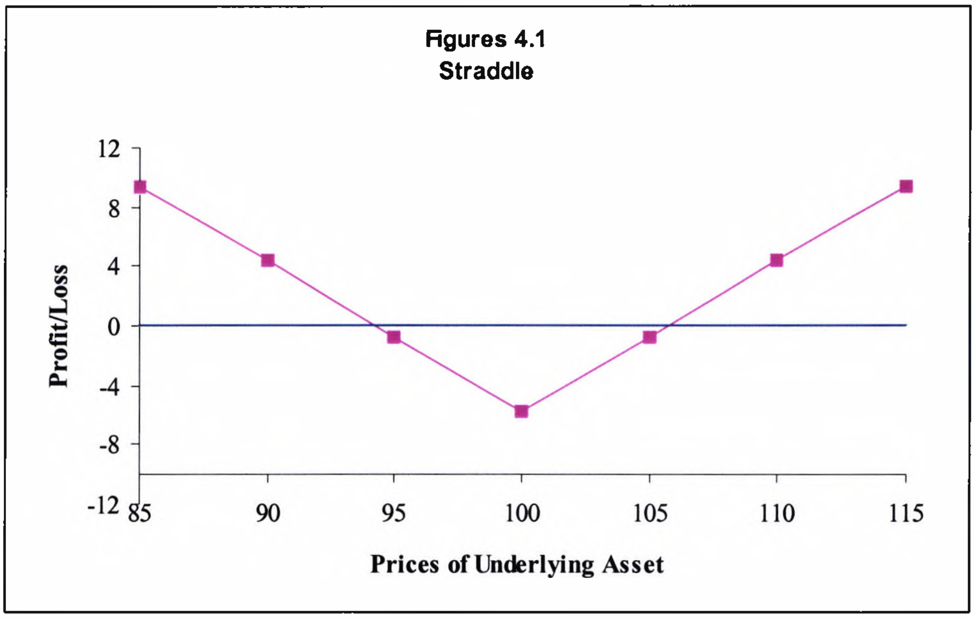
Table 4.1

Payoff From a Straddle

Range of Price	Payoff From Call	Payoff From Put	Total Payoff
$S_T \leq X$	0	$X - S_T$	$X - S_T$
$S_T > X$	$S_T - X$	0	$S_T - X$

Where: X = Strike Price; S_T = Underlying Price

The position will lose money unless the stock price moves far enough from the strike price that one of the options is in-the-money by more than their combined initial cost. To the extent that the gain on the profitable option exceeds the total premium cost of establishing such a position, there will be a net profit. The potential profit on this position is unlimited: a substantial change in prices will result in large profits. The maximum loss is the cost of the total premium paid of purchasing a call and a put. Figures 4.1 illustrates the profit and loss profile of buying a straddle. The figure below is sometimes referred to as a "bottom straddle" or " straddle purchase".



Another trading strategy that one can use: is to create a synthetic futures position. This is created by combining two option positions, such that the resulting payoff diagram is the same (or nearly the same) as that of an outright futures position. Synthetic futures positions may be more attractive than outright futures positions because they are less costly or have margining advantages.

Combining long call options with short put positions having the same strike price creates synthetic long futures positions. The reverse is true for creating a synthetic short futures position. A synthetic short futures position increase in value when prices decline and decreases in value when prices increase. Figure 4.2 below illustrates the payoff profile of a synthetic long futures position. If Treasury bill futures prices rise prior to expiration, the gain on the call option will be similar to the gain that would occur on a long futures contract; if futures prices fall, the loss on the short option position will match the loss that would occur on the long futures position.

Figure 4.2
Synthetic Long Futures

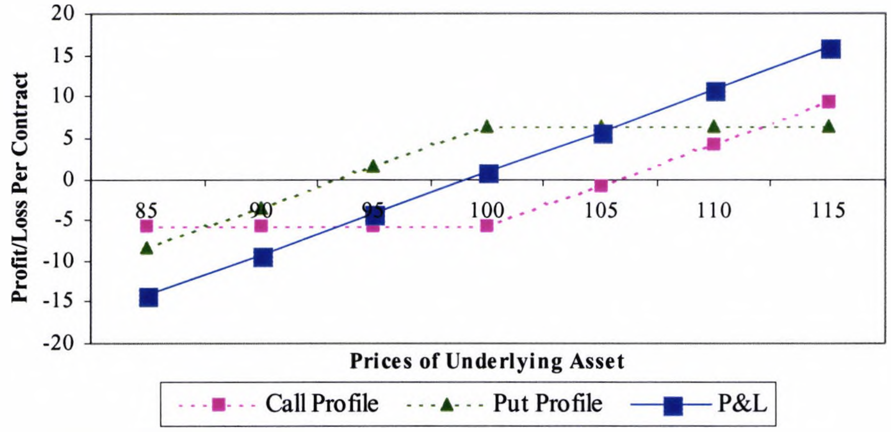
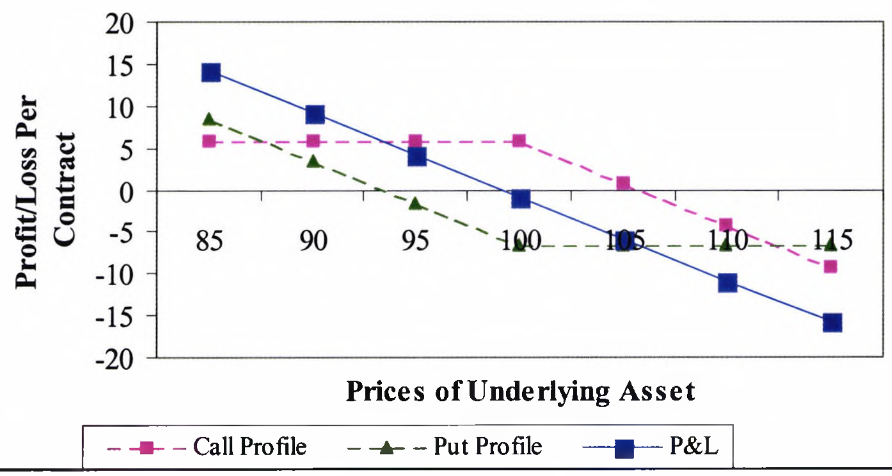


Figure 4.3 illustrates the payoff profile of a synthetic short futures position.

Figure 4.3
Synthetic Short Futures Position



In general, the cost of establishing either synthetic futures position is the difference between the respective calls and put premiums. In summary:

Synthetic Long Futures = Long Call + Short Put

Synthetic Short Futures = Long Put + Short Call

What trading strategies that one adopts depend on expectations of future market outlook. If one expects a bullish price outlook with uncertain volatility, a synthetic long futures position can be created so as to benefit as prices rise. However, if investors/speculators expects a bearish outlook, it will be beneficial to establish a synthetic short futures position.

Before making calculations of the profit, certain assumptions have to be made with respect to the size of the contract, what price, and when a position is taken and when it is unwound. We assume that the size of the position is always one contract[10]; all transactions are made at the closing price[11]. Given the timing of the Blue Chip forecasts, one possible date for taking a futures position is the 2nd day of the survey month, or the nearest trading day thereafter. This is the earliest date on which the results of the survey will be received by subscribers and could be acted on. This position will be evaluated roughly at the 23rd of the survey month. Profits will be made over this horizon if the futures price rapidly converges on the published forecast. In this sense, profits achieved before settlement depend on the influence of the forecasts on the

10 Boothe and Glassman (1987) also assumed the size of the forward contract to be one US dollar. Thus the amount speculated did not vary with the size of the predicted payoff.
Leitch and Tanner (1991) also assumes the position is always one unit.

11 Leitch and Tanner (1991) assumes all transactions were executed at closing price at the end of the month. They claimed that for most traders, placing a buy or sell "on close" order would not have any appreciable effect on price. Given their assumption of one contract, it is very unlikely that their profit calculation would be materially affected by the effect such an order would have on this relatively fluid market. In fact, their broker Shearson says that there is a 99% probability of a fill at this price as several thousand contracts were traded on a typical day during the sample period used. Thus, the assumption that fills are done on closing prices gives the most accurate *ex post* prices available.

futures-options market. We also examine the profitability of these trades under a shorter holding period assumption: roughly a week i.e. after five trading days.

The Blue Chip Financial forecasting service provides a prediction of the three-month Treasury bill rate for each of the next twelve months, and theoretically one can estimate profits for each of the twelve forecast horizons. However, since we are comparing three-month Treasury bill survey data with Treasury bill futures-option data, we used only the forecasts up to six months ahead. This is because of the availability of the data in the futures-options market for longer forecast horizons only started trading in 1986. There are not enough data to test how profitable our trading strategies will be.

4.4 EMPIRICAL EVIDENCE

The following tables below will present the profits, measured in basis points per trade made during two different holding periods, namely: weekly interval (wk) and one-month interval for six different forecast horizons for both volatility trading and mean trading.

Table 4.2

Profitability of futures-options trades for volatility (BP per trade)

	VOLATILITY(SURVEY)					
	AVERAGE		*0.02*		*0.04*	
Horizons	**WK**	**Month**	**WK**	**Month**	**WK**	**Month**
1	84		36		76	
2	-19	1	-24	-20	-15	-6
3	22	92	35	99	35	61
4	-18	98	-7	62	10	78
5	-18	49	-14	54	-16	48
6	20	77	9	91	15	73

The evidence presented here (Table 4.2) indicated that for monthly holding period and for longer forecast horizon, the profits are all positive when using volatility as an indicator. However, for shorter holding periods, the results have been inconclusive. In general, majority of the case seems to imply profits can be made except in 2nd and 5th forecast horizons.

This exercise is repeated using historical volatility (Table 4.3). Evidently, from the table below performance of volatility trading using historical volatility when compared to survey standard deviation seems to obtain a better result for shorter holding periods in majority of the forecast horizons. However, for longer holding periods, the result is completely the opposite for majority of the case.

Table 4.3

Profitability of futures-options trades for historical volatility (BP per trade)

	HISTORICAL VOLATILITY					
	AVERAGE		*0.02*		*0.04*	
Horizons	**WK**	Month	**WK**	**Month**	**WK**	**Month**
1	48	-	48	-	107	-
2	-7	59	-11	-32	-13	11
3	36	34	36	34	37	20
4	-4	-32	-1	-22	0	-36
5	-10	67	-15	77	-11	87
6	9	63	7	38	7	38

For mean trading, consensus forecast is compared to futures price, and take either a long or short position in 90 days Treasury bill futures for two different holding periods (weekly and monthly interval). Results have been relatively consistent (See Table 4.4).

Table 4.4

Profitability of futures trades for mean (BP per trade)

	Survey		Naïve	
Horizons	**WK**	**Month**	**Wk**	**Month**
1	76	106	218	464
2	157	115	63	359
3	59	216	167	438
4	97	-34	181	118
5	138	112	184	176
6	66	129	172	330

In general, there seems to be profit-making opportunities. However, when this exercise is being repeated using naive predictions rather than survey means, the result seems to indicate that consensus forecast is inferior to naive alternative. The difference in terms of profitability is huge particularly in monthly holding periods. Naïve predictions appeared to earn, on average, 60% more than consensus survey forecasts (for monthly holding periods). In fact, the outcome using naive forecast are all positive with no losses for all horizons. This result is similar to Batchelor (1993) who found that for one-month holding period, the naive seems to performed much better than consensus with the former outcomes being all positive. Leitch and Tanner (1991), also found that when using naive no-change forecast, six-year average for the nine forecast horizons produces no profits or losses. However, when survey forecasts are used, losses were made ($-3262). Whereas, Boothe and Glassman (1987) using time series data obtained from foreign exchange market (1976-1984) also indicates that the German mark profitability rankings are relatively close to the accuracy rankings and suggest that the structural models are inferior to the random walk by both criteria. They also found that the structural models' forecasts do not improve as the forecast horizon lengthens. This seems to reaffirm the hypothesis that naive forecast seems to perform as well, if not better, then survey forecast. It seems that firms appear to waste money on buying professional forecast.

However, when we use synthetic futures position as our trading strategy, the result seems to be very different from above. Table 4.5 illustrates the profitability of this trading strategy.

Table 4.5

Profitability of Using Synthetic Futures (BP per trade)

	Survey		Naïve	
Horizons	**WK**	**Month**	**Wk**	**Month**
1	-69	na	-121	na
2	-153	-131	-57	-339
3	-22	-134	-130	-398
4	-89	62	-153	-84
5	-144	-127	-218	-129
6	-49	-153	-127	-295

There appeared to be several interesting features of the above results. Firstly, the profit performance of the consensus forecast in terms of profitability is rather worse both short-term and longer-term holding periods.

Secondly, the performance of using this trading rule based on naïve/random walk forecasts is very much worse than their accuracy suggests. Indeed, it does not appear to be better than survey forecasts both in terms of shorter-term holding period and longer-term holding period. This result is consistent with Batchelor (1998) findings and appeared to be more consistent with the expectations theory of future yields, which suggests that the spot rate converges on the futures rather than vice versa.

The evidence above has not taken transaction costs, or risks involved into account when calculating profits. This is consistent with other studies such as Boothe and Glassman (1987)[12] and Batchelor (1993, 1998). Trading in IMM 90-day Treasury bill

[12] Boothe and Glassman (1987) suggested the reasons why they have omitted transaction costs from their studies. They argued that there are no direct measures of transaction costs in interbank currency markets. In addition, these costs are low because forward transactions are highly

contract, round-trip broker's fees would range from about \$10 each to about \$75, depending on the services offered by the broker, and the size of the client. One basis point on the Treasury bill contract is worth \$25. This would reduce profit by around 2-3 basis points. The only difference between trading in futures and futures-options contract is: for the latter no margin is required for put or call option buyers, but the premium must be paid in full. Hence, no opportunity loss on initial margin over the holding period of the contract. Examining at the figures above, taken into account of transaction costs, for longer holding period and forecast horizons, significant profits can still be made.

4.5 CONCLUSION

Economists often puzzled why firms buy/invest on forecasts. From the evidence presented here, significant profits can be made for longer holding period and forecast horizon than shorter holding period for volatility trading. Historical volatility have the edge for shorter holding period. However, no consistent relationship can be established when consensus forecasts are used when compare with current futures prices. Indeed, a user would make a significant higher amount of expected profit by simply using naive forecast, rather than following the consensus if a simple trading rule is use. This seems to imply that summary statistics are related to profitability, since from previous chapter, our results indicate, naive forecasts do have the smallest

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leveraged.

error. However, basing on these evidence, no conclusion can be made on how strongly or marginally related these forecast-error-magnitude criteria are in relation to profitability.

However, if one look at the result presented in Table 4.5, this seems to indicate that naïve/random walk forecasts actually performed worse than survey forecasts.

Chapter 5

EFFICIENCY OF 3 MONTHS TREASURY-BILLS FUTURES

Vs

SURVEY FORECASTS

5.1 INTRODUCTION

Given the popular attention that forecasts of interest rates generally command it is interesting to find out the reliability of survey forecasts and answer the question (in this case): "Does the Treasury-bill futures price provides a better forecast of the final settlement price of T-bill futures contracts than do survey forecasts?" In addition, since theories of financial market efficiency (according to Fama - 1970) suggest that financial asset prices should include all available information, a related question is: "Could one improve upon the price of Treasury-bill futures forecasts using the information contained in the survey projections?"

To achieve the above objective, this study will compare the 3 months Treasury bill futures price of various contracts traded on the IMM between April 1986 to Dec 1992 with the price implied by the *Blue Chip Financial Forecasts* survey of 3 months Treasury bill rates. First, this chapter will consider rationality of survey data i.e. unbiasedness and orthogonality. This is essential because the value of a forecast depends not only on its accuracy but also unbiasedness. Second, this chapter will investigate whether information in the survey forecast will help to reduce the forecast error by using solely the Treasury bill futures market prediction. Such a comparison is desirable because it is essentially a comparison of information sets that forecasters posses.

Studies by Friedman (1979) and Throop (1981) and other reveal that survey forecasts often are more accurate than the forecasts from implicit forward rates. However, previous researchers such as McDonald and Hein (1989) have also shown that Treasury bill futures rates are better predictors of the future Treasury bill rate than implied forward rates. Fama (1984) for example finds that the one-month forward rates has a power to predict the spot rate one month ahead, but little evidence that two- to five-month forward rates can predict future spot rates. He conjectures that weakness of the forecast power stems from model misspecification or measurement error. That is, since forward spread (implied forward rate net of spot interest rate) incorporates both a forecast of future spot rate changes and a premium for risk, failure to control for this risk premium in predictive regression models of future spot rate changes on the forward spread could lead to specification bias.

5.2 BASIC CONCEPTS

Rationality of expectations implies that the market's subjective probability distribution of any variable is identical to the objective probability distribution of that variable conditional on available information at the time the forecast is made. A relevant empirical test involves explicitly whether forecast was an orthogonal to (uncorrelated with) known variables.

The application of rational expectations to financial markets has meant that prices in such markets are expected to react only to the unexpected components of macroeconomic announcements.

Many empirical studies have examined survey data on expectations in terms of such statistical properties as unbiasedness and orthogonality. A common finding is that these data are inconsistent with the restrictions implied by the theory of rational expectations e.g. Figlewski and Watchel (1981); Holden et al. (1985); Lovell (1986); Pearce (1987); Simon (1989); Croushore (1996). The use of survey data in testing for the expectational rationality has for example been criticised on the grounds that: firstly, a respondent asked to complete a survey questionnaire has no economic incentive to make accurate forecasts. Choosing a set of survey data to test for rational expectations is a crucial issue. If the forecasters' responses do not reflect their true expectations, then our tests of rationality will not be valid and we would not learn much from them. Zarnowitz (1985) and Keane and Runkle (1990) suggest that this limitation can be overcome by using data provided by the professional economic forecasters whose livelihood depends on their ability to forecast financial prices e.g. Blue Chip Financial Forecasters, ASA-NBER etc.

Secondly, in general previous studies used either inappropriate data or incorrect statistical methods e.g. Figlewski and Wachtel (1981) and Zarnowitz (1985). Both of these studies used OLS regression for testing rationality. Figlewski and Watchel (1981) assume that forecast errors are independent across forecasters. Since aggregate shocks affect the price level, this assumption is certainly not true. Falsely assuming independent errors creates a severe downward bias in estimated standard errors, tending to cause false rejection of the rational expectations hypothesis.

Thirdly, most tests compare survey forecasts to revise rather than initial data. These data revisions introduce a systematic bias that may invalidate tests of unbiasedness.

A necessary condition for rationality is that a variable's forecast is an unbiased estimate of the realised value (A_{t+n}). This relationship can be expressed as:

$$E_t(A_{t+n} - F_{t,t+n}|I_t)=0$$

where "A_{t+n}" denotes the realised value of a given variable, and "$F_{t,t+n}$" the consensus forecast made in the forecast month "t", the value of which will be known in the month "t+n". "I_t" is the information available at time "t", and "E_t" is the objective expectation operator as of period "t", i.e. conditional on the information set available at time "t".

The information set can be rewritten as $I_t = \{x_t\}$, where "x_t" denotes a vector of variables known to the forecasters at the time they made the forecast. Over a span of time, information cannot diminish, relevant material in determining the variable "A_{t+n}" is added to the existing body of knowledge. Therefore it follows that the information set at time "t" is contained in all subsequent periods, so:

$$I_{t+k} \geq I_t, \text{ where } k>0 \text{ for all } t$$

This is a particularly useful result. It seems reasonable to consider the possibility that forecasters expectations are, in fact, optimal forecasts, if their predictions are based on a wide enough information set. This set need not consist merely of past and present numerical data but could also include subjective information.

Now look at a series of forecasts of "A_{t+n}" made at different times but for the same forecast horizon/target dates. Consider two such forecasts: "$F_{t,t+n}$" and "$F_{t+1,t+n}$". If the forecasts are rational:

$$E_t\,(A_{t+n} - F_{t,t+n}|I_t)=0$$

and also

$$E_{t+1}\,(A_{t+n} - F_{t+1,t+n}|I_{t+1})=0$$

What these two equations imply is that: they should exhibit all the properties of rationality and, in particular, both should be an unbiased estimate of "A_{t+n}" (Given that $I_{t+1} \supseteq I_t$). In addition, since "$I_{t+1,t+n}$" contains all the information in set "I_t", logically speaking "$F_{t+1,t+n}$" should provide a "better" estimate than "$F_{t,t+n}$".

The results of most surveys are published in a form of a consensus forecast, and most rationality tests are based on the properties of that consensus. The frequent release of relevant information and the monthly Blue Chip forecasts that are made repeatedly for target dates, rather than for a fixed forecast horizon, make it possible to test the properties of rationality, which are as follows:

- Unbiasedness: $E\,(e_{t,t+n}|I_{t,t+n}) = 0$
- Orthogonality: $E\,(e_{t,t+n}x_{t,t+n}|I_{t+n}) = 0$

where $e_{t,t+n} = A_{t+n} - F_{t+n}$.

These two conditions require errors from rational forecasts to have zero mean white noise - that is, the forecasts should equally overshoot and undershoot the actual data - constant variance and successive forecast errors are uncorrelated with each other and with the information set used at the time the forecast is made. The second property of forecast errors - orthogonality[1] - requires forecast errors not only have a zero expected value but should also be uncorrelated with any information that is available to economic actors. Thus price changes must be unpredictable in this version of the efficient markets hypothesis. If this were not the case it would be possible to improve the forecast by incorporating this correlation into the forecast. To put it simply, an indication of a good forecast is that any subsequent forecast errors should be inherently unpredictable and hence unrelated to any information available at the time the forecast is formulated.

[1] Shiller (1978) discusses the importance of orthogonality.

5.2.1 Tests of Unbiasedness

A simple test of unbiasedness is to calculate the sample mean forecast error and compare it to its standard error. Many studies, instead or in addition, estimate the realisation-forecast regression :

$$A_{t+n} = \alpha + \beta F_{t,t+n} + u_{t,t+n}$$

which is equivalent to:

$$(A_{t+n} - F_{t,t+n}) = \alpha + (\beta\text{-}1)F_{t,t+n} + u_{t,t+n}$$

where A_{t+n} and $F_{t,t+n}$ denote the actual value at t+n and the forecast made at t for t+n respectively, and test the joint hypothesis $\alpha=0$ and $\beta=1$ under the assumption that $u_{t,t+n}$, the random disturbances, are independent and identically distributed with $u_{t,t+n} \sim N(0,\sigma^2)$. In particular, they are serially uncorrelated[2]. The assumption that no serial correlation exists means that watching linear patterns in past forecast errors will not improve future forecasting performance. While this is often interpreted as a test of unbiasedness, since if $\alpha=0$ and $\beta=1$ the forecasts are unbiased, it is in fact a stricter test, and was originally presented as a test of efficiency by Mincer and Zarnowitz (1969). In effect, this is a test of hypothesis that the forecasts "$F_{t,t+n}$" are the most efficient in the class of possible predictors ($\alpha + \beta F_{t,t+n}$). The rejection of the null hypothesis implies that the forecasts can be easily been improved. For example, if α is not zero, it can mean that the forecasts are consistently biased, in which case the addition of an appropriate constant to

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2 The statement that errors must be serially uncorrelated strictly applies to one-period-ahead expectations only.

each forecast will remove the problem.

Unfortunately, the class of predictors considered under the Mincer-Zarnowitz efficiency is very narrow. The concept of efficiency underlying this realisation-forecast regression is a relatively weak one. Granger and Newbold (1977) argue that $\alpha=0$ and $\beta=1$ 'constitutes a necessary condition for forecast efficiency, but according to any acceptable interpretation of that word it cannot be regarded as a sufficient condition'. Hence, forecaster should not be complacent because his or her predictions appeared to be unbiased / Mincer-Zarnowitz efficient. They could still be substantially poorer than other easily obtained projections.

The test of unbiasedness will then be constructed within the framework of the linear model:

$$A_T = \alpha_h + \beta_h F_{T-h,T} + u_{T-h} \quad h=1,...,T-1 \text{ ------ } (5.1a)$$

And

$$(A_T - F_{T-h,T}) = \alpha + (\beta-1)F_{T-h,T} + u_{T-h} \quad h=1,\ldots,T-1 \text{ ------ } (5.1b)$$

where "A_T" is the settlement price of the futures market and "$F_{T-h,T}$" is the Blue Chip consensus price forecast implied by the 3 months Treasury Bill rate[3]. The unbiasedness

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[3] Survey forecasts of 3-month Treasury bills (Auction Average) are for bond equivalent yield. In order to deduce the price for treasury bill futures implied by the yield the following formula has been used:

TBF = 100 -[(360*TBI/365+91*TBI)]

where TBF = Treasury Bill futures

TBI = Consensus forecast of the Treasury Bill Interest Rates property is examined by the null hypothesis: H_0: $(\alpha,\beta) = (0,1)$ for equation 5.1a and H_0: $(\alpha,\beta\text{-}1) = (0,0)$ for equation 5.1b. If the regression analysis of this equation leads to rejection of the joint hypothesis: $(\alpha,\beta) = (0,1)$ or $(\alpha,\beta\text{-}1) = (0,0)$, then we reject the hypothesis of unbiasedness, and infer that the consensus forecasts made by the experts are not partly (nor, of course, completely) rational. However, one must remember that the irrationality of survey forecasts does not in itself imply that the market forecasts are also irrational. As Mishkin suggested "not all market participants have to be rational in order for the market to display rational expectations." The behaviour of a market is not necessarily the same as the behaviour of the average person. As long as the arbitrage condition is eliminated by some participants in a market, then the market will behave as though expectations are rational despite irrational participants in that market.[4]

5.2.2 Test of Orthogonality

A key property of a rational forecast is that it must fully reflect all freely available relevant information at the time the forecast is made, and any information fully incorporated in this sense will be uncorrelated with the errors associated with rational expectations[5]. In this study, this implies if the professional forecasts are behaving rationally, prediction errors should show no significant relation to prior futures price on the 23rd of the month preceding the survey (F23P).

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4 For more details, please refer to Mishkin (1978).

5 Friedman (1979) discussed the importance of the error orthogonality property of rational expectations in the context of macroeconomic policy models.

The test regresses settlement price of the futures contract on the consensus forecasts and futures price on the 23rd of the month preceding the survey. This can be written as:

$$A_T = \alpha_h + \beta_1 F_{T-h,T} + \beta_2 F23P + u_{T-h} \quad h=1,\ldots,T-1 \text{ ------ } (5.2a)$$

And

$$(A_T - F_{T-h,T}) = \alpha_h + (\beta_1 - 1)FT_{-h,T} + \beta_2 F23P + u_{T-h} \quad h=1,\ldots,T-1 \text{ ------ } (5.2b)$$

where "F23P" is the futures price on the 23rd of the month preceding the survey. The orthogonality property is examined by the null hypothesis: H_0: $(\alpha,\beta_1,\beta_2) = (0,1,0)$ for equation 5.2a and H_0: $(\alpha,\beta_1-1,\beta_2) = (0,0,0)$. A chi-square χ^2 test with a 5% significance level is used to measure whether the coefficients in a regression differ in any significant way from what they are expected to be. Rejection of these hypotheses implies that the survey participants do not fully utilise the freely available information on other relevant variables in the forecasting process. They could have improved the survey predictions by better exploiting the information contained in the futures market (in this case). Indeed, this is also a joint test on Mincer-Zarnowitz efficiency and conditional efficiency introduced by Granger and Newbold (1973, 1986)[6].

5.3 ECONOMETRIC PROBLEMS

[6] One set of forecasts is said to be conditionally efficient with respect to another if combining the second set with the first produces no gain in mean squared error compared with using the first set alone.

There are numerous problems with the above approach of testing rational expectations hypothesis. One of the problems is that the stationarity assumption for the variables under consideration can be in doubt, at least in finite samples.

In principle it is hard to argue that interest rates are truly nonstationary variables. They are bounded below by zero, and also have a fuzzy upper bound in the sense that their maximum value is unlikely to rise much above the inflation rate plus some maximal value for the real interest rate (say, the highest likely long run growth of the economy). In theoretical models of interest rates used, for example in option pricing models, interest rates are more ususally assumed to follow some stable mean-reverting structure.

However, in finite samples they may have characteristics similar to a random walk, and standard tests of stationarity may find it hard to reject the null of a unit root in the process driving rates. A mechanical approach to our data, which we implement below, involves testing actual and forecast series for unit roots, by using a test such as Augmented Dickey-Fuller. If the problem is identified, the original data is tested and differenced again. In this way, we are able to identify the order of the integrated process for each data series. Once all data series have completed this process, they are regressed together and tested for cointegration relationship by using the Johanssen Approach. As there are more than 2 variables involved in the regression model, the direction of causality may not be clear, or one-sided. The basis of this approach is to estimate by maximum likelihood methods of the following general form:

$$\Delta X_t = \Pi X_{t-1} + \Sigma \Gamma \Delta X_{t-i} + \varepsilon_t$$

where the value of "i" determines the number of lags specified.

Secondly, and separate from the issue of stationarity, estimation of the above regression requires some assumptions about the probability structure of the residuals. Typically, it is assumed that the disturbances are serially uncorrelated and the ordinary least squares (OLS) technique is applied. This assumption is unlikely to be met under multi-period forecasts issued at monthly intervals. The reason to expect serial dependence is that economists will have no knowledge of errors in forecasts already made but not yet realised. Forecast errors are realised "h" months later, so the error in a forecast constructed at "t" will be correlated with errors in forecasts in the subsequent "h" months. In other words, since their forecast errors are not part of the available information set, we cannot rule out the possibility that the covariances of these error terms will be non-zero, thus violating one of the OLS assumption. The usual estimated covariance matrix generated with OLS is inconsistent, even if the coefficients will be unbiased.

One possible solution is to use some kind of generalised least squares (GLS) estimator if efficiency is to be achieved. For one-period ahead expectations where data of the same frequency is available, the error term is white noise and independent of the regressors in OLS therefore provides a BLUE - best linear unbiased efficient. Unfortunately, this is usually not an effective solution to the serial correlation problem especially when the survey data on expectations is assumed to be measured with error. As Brown and Maital (1981) point out, when the regressors are not strictly exogenous, GLS is likely to distort the orthogonality conditions and introduce inconsistent estimates[7]. The reason is that in effect GLS transforms the model to eliminate the autocorrelation in the disturbances. However, the transformed disturbances for some particular period will be linear combinations of the original disturbances with their lagged values. These in turn are most probably correlated with the transformed data for the same period, since these include current values of the variables in the information set. Following their suggestions, the tests for rationality requires the use of OLS but "corrects" the covariance matrix to take account of serially correlated errors by employing the particular form of Hansen (1982) generalised method of moments estimator[8] (GMM: this also facilitates a non-parametric correction for heteroskedasticity) first proposed by Hansen and Hodrick (1980). By using this methodology, this will allow us to use GMM standard errors that will take into account the moving average process and generate efficient standard errors, which allow us to make correct inferences about the coefficients.

In addition to Brown and Maital (1981), other studies like MacDonald and Macmillan (1994), Baghestani and Kianian (1993), Baghestani (1992), Schroeter and Smith (1986), Bryan and Gavin (1986), Swidler and Ketcher (1990), and Batchelor and Dua (1991); Sobiechowski (1996) also use the GMM procedures. In other studies where serial correlation was not considered, coefficient standard errors are liable to be biased downward and r^2 values biased upward. The loss of efficiency - underestimation of

[7] Hansen (1979) discusses the inconsistency of GLS.

[8] The GMM estimator assumes that the exogenous variables are stationary, ergodic, continuously measurable, and that the relevant matrices are full rank. For more details refer to Hansen (1982).

sampling variances of the regression coefficients - may in some cases invalidate the results of these tests and making it likely that the rationality hypothesis will be incorrectly rejected - type I error.

Another problem is the residuals are likely to be heteroskedastic because the forecast error variance decreases with the forecast horizon, and some periods are very difficult to predict while others may be relatively easy to forecast. It is well known that the existence of heteroskedasticity in the residuals leads to consistent but inefficient parameter estimates and inconsistent covariance matrix estimates. In order to eliminate this difficulty, previous studies like Figlewski and Watchel (1981) and Pearce (1984) take account of heteroskedasticity, by employing weighted least squares based on squared residuals from the OLS regression. This method will only be efficient provided you know the form of heteroskedasticity. However, in general, it may not always be clear what form it is.

With both the presence of heteroskedasticity and serial correlation in the residuals, the solution is to utilise the GMM covariance estimator as some of the studies cited above which is consistent under heteroskedasticity, and under the more complex higher-order serial correlation expected in the Blue Chip errors. To describe this procedure, consider the following general model:

$$Y = \beta X + u$$

where "Y" is the (T x 1) vector of all observations on "A_{t+n}", "X" is the (T x k) matrix of observations on "k" explanatory variables, and "u" is the (T x 1) vector of disturbances.

For the OLS estimator to provide a consistent estimator for β, the standard assumption is that the residuals satisfy:

$$V = E(uu') = \sigma^2 I$$

In the case of heteroskedasticity, where it may not always be clear what form V should take, although least squares may still provide consistent estimates of the coefficients,

$$s^2 X'X^{-1}$$

is not a consistent estimate of the variance of the coefficient estimates. Hansen (1982) and White (1980) and others show that it is possible to compute consistent estimators for the covariance estimators in a wide range of situations using a procedure that imposes little structure upon the matrix V. The estimators for least squares[9] is:

$$V = (X'X)^{-1} \mathrm{mcov}(X,u)(X'X)^{-1}$$

where

$$\mathrm{mcov}(X,u) = \sum\sum u_t X'_t X_{t-k} u_{t-k}$$

$$u_t = \text{residual at time t}$$

This test follows a χ^2 distribution[10] under the null hypothesis and is expected to be significantly large under the alternative hypothesis.

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9 Serial Correlation in X'u is handled by making lag(s) non-zero. This corrects the covariance matrix for serial correlation in the form of moving average (not autoregressive) of order L.
In some circumstances, the proper value of L is known from theory. Otherwise, it has to be set to catch most of the serial correlation.

10 χ^2 tests rather than F tests are used because the forecast errors would have to be normally distributed

5.4 EMPIRICAL RESULTS

5.4.1 Test of Unit Root and Cointegration

Appendix 5.1 shows the result of the unit root tests of actual and survey mean. The Augmented Dickey-Fuller (ADF) test indicates that in no case is the hypothesis of unit root rejected for these 2 series under 5% critical value when using price level data. However when this is repeated using first difference, ADF tests showed that the hypothesis of unit root could be rejected. Our tests seem to indicate that these variables all appeared to be I(1) in the relatively small samples examined in this study.

Next we test the existence of cointegration. Based on Likelihood Ratio Test of 5% significance level, results in Appendix 5.2 show that actual and survey mean are cointegrated at all horizons, with a cointegration factor very close to one. We can be reassured therefore that the dependent variables in test equations 5.1b and 5.2b – the differences between actual and forecast rates - are stationary, and the apparent I(1) character of the levels series will not bias the coefficients or lead to spurious correlation in any of the test equations.

5.4.2 Test of Unbiasedness and Orthogonality

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for the F tests to be valid. The χ^2 tests are asymptotically valid.

The first test of rationality requires the survey forecast of 3-months Treasury bill be an unbiased estimate of the actual settlement price of the futures market. Appendix (5.3) reports estimates of equation (5.1a&b) including the estimated α and β values with their corresponding corrected standard errors using the GMM technique[11], where the asymptotically appropriate test statistic for the joint hypothesis that the coefficient α should be zero and β should be unity is distributed $\chi^2(2)$. The sample runs from the April survey of 1984 through the December survey of 1992. Each forecast horizons has an equal sample size of 36 observations. Similar to other studies like Hafer, Hein & MacDonald (1993), and Hafer & Hein (1989), the null hypothesis of unbiasedness are accepted based on 5% significance level for the survey forecasts of three-months Treasury Bill for all horizons except 11th months ahead forecasts. However, there seems to be some evidence of a bias at 10% level of significance for longer forecast horizons namely from 9th months ahead forecast onwards. Overall, in majority of the cases, individual t-ratio indicates that the intercept is not significantly different from zero but positive and that the slope coefficient is not significantly less than one. The R^2, seems to become larger and the standard error of estimates becomes smaller as the forecasting horizon gets shorter. This result is indeed as expected.

When this is repeated using equation 5.1b, similar conclusions can be drawn. The coefficients on the cointegrating vector are not significantly different from 0 and 1 except for 11 months ahead forecast where the null hypothesis can be rejected at all significance level.

[11] Before using GMM, OLS has been used on the same sample set. It indicates the presence of both

Since the unbiasedness test is not rejected, one must test the further implication of rational expectations that forecast error should be orthogonal to any relevant and costlessly available information set, that is, if an improvement in predictions showed up as a result of the added variable (F23P), forecast rationality can be refuted. For each of the forecast horizons, the estimated coefficients would be significantly different from those values suggested by the null hypothesis at 5 percent level if the $\chi^2(3)$- statistic were to exceed 7.81. The evidence is quite conclusive. In general, the results seem to suggest that the survey predictions of Treasury bills yields appear to be rational in the sense of efficiently incorporating information contained in the futures market. There is no significant evidence against the null hypothesis that the forecasts are not Mincer-Zarnowitz efficient and conditionally efficient with respect to the futures price forecasts. The coefficients for α and β_2 are not significantly different from zero and β_1=1, the value of the χ^2-statistic is low enough to indicate that knowledge of "Fut23P" cannot be used to help to predict the settlement price except in the 1st, and the 11th horizons. The result obtained in the last forecast horizon is indeed expected since the hypothesis of unbiasedness is refuted to start of with. In general, it seems that the survey predictions of the price implied by the 3-months Treasury bill yield is rational in the sense of informational efficiency in all forecast horizons. This is good news because if a set of forecasts turns out not to be conditionally efficient with respect to some other forecasts, this indicates that some modification is required. The following table will provide a quick summary of how well these professional consensus mean forecasts have

heteroskedasticity and autocorrelation.

performed in terms of passing tests of rationality. Accordingly, the survey forecasts from the panel of professional economic forecasts (who have an incentive to provide accurate forecasts) accept the null hypothesis of unbiasedness and pass orthogonality test except in the first and last forecast horizons.

Table 5.1

Summary of Rationality Tests: 1984:4-1992:12

Forecast Horizon	Unbiasedness	Orthogonality
1	Pass	Fail
2	Pass	Pass
3	Pass	Pass
4	Pass	Pass
5	Pass	Pass
6	Pass	Pass
7	Pass	Pass
8	Pass	Pass
9	Pass	Pass
10	Pass	Pass
11	Fail	Fail

(Based on Equation 5.1a & 5.2a)

This exercise is repeated once again using equation 5.2b - to test whether the forecast error from the survey is orthogonal to "known" futures price FUT23P and to later futures prices FUT2, FUT7 and FUT23. Results shown in Appendices 5.4 for FUT23p seems to imply that the cointegrating vector cannot be expanded to involve futures prices. The only exception appeared to be in first forecast horizon where the null hypothesis can be rejected at all signficance level. When Fut2 is used as the additional information set, the results are similar to Fut23p, namely, there seems to be no improvement in predictions as a result of this added variable (Appendix 5.5). However, if this additional information comes from Fut23 (Appendix 5.7), the result is completely the opposite of Fut2. If this postulate is tested under yet another different information set i.e. Fut7 (Appendix 5.6), the result is mixed. Majority of the time, the null hypothesis is not rejected.

A similar test which is both Mincer-Zarnowitz efficient and conditional efficient is used to test what happens if some other variable is added.

The survey forecasts are both Mincer-Zarnowitz efficient and conditional efficient, if and only if the estimated coefficients $\alpha=0$, $\beta_1=1$, and $\beta_2=0$. It is required then to test the null hypothesis

$$H_0: \alpha=0, \beta_1=1, \beta_2=0$$

This is achieved through fitting by least squares the regression equation as in 5.2a&b. The null hypothesis is rejected if the statistic is bigger than 7.81 under χ^2 of 5% significance level. The result varies pending on the information set added to test for this hypothesis. When Fut2 is used as the additional information set, the results are similar to Fut23p, namely, there seems to be no improvement in predictions as a result of this added variable. The coefficients for α and β_2 are not significantly different from zero and β_1 =1 except for the first and the last forecast horizons. What this implies is the presence of Fut2 cannot help to predict the settlement price except in the first and the last forecast horizons. However, if this additional information comes from Fut23, the result is completely the opposite of Fut2. Except for the 8th and 9th forecast horizons, this joint hypothesis can be rejected. If this postulate is tested under yet another different information set i.e. Fut7, the result is mixed. Majority of the time, the null hypothesis is not rejected. The following table will provide a quick overall view of the results (Details of the result see Appendix 5.4-5.7).

Table 5.2

Mincer-Zarnowitz efficient and conditional efficient,

where H_0: $\alpha=0, \beta_1=1, \beta_2=0$

	Futures Price (Date)		
Forecast Horizon	2nd	7th	23rd
1	XXX	XXX	XXX
2	Pass	Pass	XXX
3	Pass	Pass	X
4	Pass	XXX	XXX
5	Pass	Pass	XXX
6	Pass	Pass	XXX
7	Pass	X	XXX
8	Pass	Pass	Pass
9	Pass	Pass	Pass
10	Pass	Pass	X
11	X	X	X

where X = Reject H_0 at 5% level of significance
XXX = Reject H_0 at all level of significance

5.5 EFFICIENCY of 3-MONTH TREASURY BILL FUTURES MARKET

The result so far hardly tells us anything about the efficiency of the Treasury bill futures with respect to survey forecast. The efficient markets literature asserts that financial markets use all available information to remove any known profitable opportunities in the market. In the case of risk-free fixed-income securities, such as Treasury bills, the relevant information consists of expectations about the future course of interest rates. And if the market is efficient, there should be no more accurate forecast of future security prices than the forecasts already implied by current spot rates or prices in the interest rate futures markets. This model states that the expected interest rate, at some specified future point in time, given all information presently available, is equal to the interest rate plus whatever change in interest rate is suggested by currently available information[12].

The futures market offers an interesting perspective on forecasts. At a given point in time, individuals may enter into agreements to buy or sell interest-sensitive assets, such as Treasury-bills, at a date as much as two years into the future. The futures market reflects all available information held by market participants and these participants have a compelling reason to forecast accurately. If they are wrong, money is lost.

A number of studies have conducted comparisons between various subsets of the Treasury bill rate forecasts. Often, Treasury bill future rate is compared with an arbitrageable alternative rate, such as forward rate; e.g., Poole (1978), Vignola and Dale (1980), Rendleman and Carabini (1979), and Kawaller and Koch (1984). These studies

[12] The efficient markets model applied to interest rate determination can be expressed as:

$$E(i_{t+1}|\Omega_t) = i_t(1+E(i_{t+1} - i_t|\Omega_t))$$

primarily compare futures and forward rates as a means of testing futures market efficiency. If these two rates are found to be statistically different from one another, then one or both markets is said to be inefficient. Many such studies, but not all, conclude that the Treasury-bill futures market is inefficient.

To investigate the proposition of efficiency of the Treasury-bill futures, one can adopt a similar model as suggested by Footnote 12 which is one of the popular methods used; or alternatively use what Throop (1981)[13] has proposed: a test to determine whether knowledge of the survey forecast of Treasury bill rates could reduce the forecast error made by the futures market. In general, evidence seems to indicate that survey forecasts added little to the forecasts derived from futures market quotes.[14]

This study will examine efficiency of the Treasury bills futures market under the following framework:

$$A_T = \alpha + \beta_1 F_{T-h,T} + \beta_2 FN_z + u_{T-h} \quad h=1,\ldots,T-1 \quad \text{----} \quad (5.3a)$$

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where E is the expectations operator and Ω_t is the information available to agents at the time forecasts are made. For more detail, see Fama and Miller (1972) or Mishkin (1983).

13 Throop (1981) use this approach and compared 6-month-ahead Treasury bill rate forecasts from the Bond and Money Market Letter survey and the forward rate. He found evidence of inefficiencies in the forward market and concluded that the treasury-bill market is inefficient. Kamara and Lawerence (1986) and MacDonald and Hein (1989) use this approach and find that Treasury-bill futures rates are more accurate forecasts when compared with the forward rates.

14 MacDonald and Hein (1989) indirectly compared futures rate forecasts with the Bond and Money Market Letter survey forecasts for both 1- and 2-quarters ahead and found the survey added little to the forecasts derived from futures market quotes. Belongia (1987) found survey projections from the Wall Street Journal's annual survey of market professionals to be statistically inferior to futures market forecasts of near-term Treasury-bill rates.

where "FN_z" = the Future Price at a specified date and subscript "z" represents 23rd of the preceding month; 2nd day of the current month - first day of trading after the survey has just been published; 7th day of the current month - approximately 5 trading days after survey published; or 23rd of the current month - time when survey is made; in subsequent regressions. These future market dates are chosen according to this criterion: the day when the experts' forecasts were published and those for other trading days. Specifically, this involves the testing to see whether α and β_1 differs from zero and whether β_2 differ from one. The imposition of these restrictions indicates that, if the null hypothesis is true, information in the survey forecasts is already incorporated in the futures market projection. The presence of the survey mean will not help to predict the Treasury-bill settlement price (recall that the forecasts are useful to the market only if they add to the existing pool of market information). Rejection of the null hypothesis implies there is a difference in the body of knowledge incorporated in the survey price forecasts implied by the three months Treasury bill yield and the futures price. By making use of the information contained in the analysts' forecast, an investor could have improved his/her return. This will be inconsistent with the notion that market participants efficiently utilise all available information.

5.5.1 RESULTS

Estimates of equation (5.3a&b) including the estimated values of α, β_1, β_2 with their corresponding corrected standard errors in parenthesis using the GMM technique to test the efficiency of the three-month-ahead Treasury bill futures market forecasts are reported in Appendix 5.5-5.7. The results for all the chosen dates indicates that, majority of the time, especially for longer forecast horizons, the null hypothesis can be rejected at the 5% level of significance under $\chi^2(3)$. The absolute values of the regression intercepts $|\alpha|$ often increase with the predictive horizon, whereas the signs of these estimates tend to be positive. For shorter forecast horizons, there seems to be no conclusive evidence. The results tend to vary depending on the horizons and the chosen future dates that are used together with the survey price forecasts.

The violation of the imposed restrictions on the estimated equation in longer forecast horizons, suggested that the sole presence of the futures price variable is not going to be sufficient. In other words, futures price is no longer an efficient predictor. The survey mean is required in order to improve the prediction for the settlement price. These results are inconsistent with the notion of efficiency, as an investor can always make use of forecasts to improve his / her returns. The following table below will give a quick review of the results.

Table 5.3

Summary of the Efficiency Tests: 1984:4 - 1992:12

$$A_T = \alpha + \beta_1 F_{T-h,T} + \beta_2 FN_z + u_{T-h}$$

Test: (0,0,1)

	Futures Price (Date)			
Forecast Horizon	**23P**	**2nd**	**7th**	**23rd**
1	Pass	Pass	Pass	Pass
2	X	X	Pass	Pass
3	X	XXX	XXX	X
4	Pass	Pass	Pass	Pass
5	XXX	X	Pass	Pass
6	XXX	XXX	XXX	XXX
7	XXX	XXX	X	XXX
8	XXX	XXX	XXX	XXX
9	XXX	XXX	XXX	XXX
10	XXX	XXX	XXX	XXX
11	XXX	XXX	XXX	XXX

where X = Reject H_0 at 5% level of significance
XXX = Reject H_0 at all level of significance

The above results is in contrary to previous studies carried out by Belongia (1987)[15], Hafer and Hein (1989) where they conclude that no or little information in the survey forecast could reliably improve upon the prediction for settlement price. And hence, suggests that the forecast provided in the futures market is as efficient as those produced by the professional forecasters.

[15] Belongia (1987) runs a similar test and find that the experts' forecast announcement has no effect on Treasury bill rates. He concluded that the Treasury bill market had already incorporated information underlying these forecasts prior to release.

5.6 SUMMARY and CONCLUSIONS

This version of rational expectations hypothesis has been examined using the mean survey forecast. By and large, our test results generally support the perception that the survey forecasts are unbiased predictors of future Treasury bill rates, at the same time the null hypothesis of orthogonality is not rejected in both longer and shorter forecast horizons. This is indeed is not a surprising result, because to reject analysts' rationality suggests that analysts repeatedly and systematically make costly mistakes and do not learn from them. Such seemingly non-rational behaviour is within the realm of possibility, but it seems unlikely for professionals whose livelihood depends on rational forecasts. These results substantiate that these forecasts are the best available, given current knowledge. Because they are rational, the forecasts can be considered trustworthy as inputs into formulating policies. Evidence also suggests that information in the survey forecasts could reliably improve upon the futures rate prediction.

This conclusion about market efficiency contrasts sharply with previous studies cited above. Results indicate that Treasury bill futures price does not incorporate all of the information contained in the survey considered here. Daily price quotes in the futures market cannot provide a valuable benchmark of what the market's expectation of what the future settlement price is going to be. From this, it seems the value of these professional forecasts to an investor is immense. Investors could improve his/her return by utilising the survey data.

APPENDICES

Appendix 5.1

Test of Stationarity Assumption on Survey Mean and Actual

	Horizon	Level ADF*	1st Difference
		Level	Difference
Survey Mean	1	-1.4306	-3.9273
	2	-0.9750	-3.7228
	3	-2.2948	-4.2522
	4	-1.5701	-4.2421
	5	-1.4064	-4.0877
	6	-2.4194	-4.3886
	7	-1.7664	-4.5187
	8	-1.1262	-4.2987
	9	-2.5341	-4.3844
	10	-1.9828	-4.4591
	11	-1.2479	-4.1457
Actual		-1.0476	-3.9324

KEY

* Augumented Dickey Fuller Test for stationarity with 5% critical value =-2.95

Appendix 5.2

Test of Cointegration

	Likelihood	Cointegrating Vector:	
Horizon	Ratio*	Constant	Survey Mean
1	26.0452	3.4620	0.9625
2	23.6771	2.1532	0.9775
3	24.9452	-2.5295	1.0282
4	44.2263	1.4853	0.9859
5	53.2942	2.6639	0.9746
6	41.0549	-4.4427	1.0515
7	29.1146	-1.2024	1.0179
8	23.2083	2.8430	0.9757
9	29.7287	-17.9681	1.1991
10	23.7782	-17.2733	1.1925
11	17.7501	6.2192	0.9255

KEY

* Tests for zero cointegrating vectors with 5% critical value = 15.41

Appendix 5.3

Rationality of Survey Forecasts

A) Equation 5.1a

Horizon	Unbiasedness Coefficients: Constant	SURVEY MEAN	Chi-Square (0,1)
1	4.0047	0.9564	2.30
	(5.21)	(0.06)	
2	4.8817	0.9478	0.38
	(8.03)	(0.086)	
3	4.8377	0.9491	0.50
	(8.31)	(0.088)	
4	7.8682	0.9172	0.79
	(10.41)	(0.11)	
5	11.4585	0.8799	1.65
	(13.05)	(0.14)	
6	16.2379	0.8295	2.40
	(15.79)	(0.17)	
7	18.0822	0.810538	2.90
	(16.65)	(0.18)	
8	20.6195	0.7843	3.51
	(19.50)	(0.21)	
9	24.9353	0.7395	4.68**
	(20.97)	(0.23)	
10	28.5290	0.7014	5.82**
	(21.58)	(0.23)	
11	30.9111	0.6766	7.01*
	(23.27)	(0.25)	

Key:

Standard Errors are represented in parentheses

*** = Reject Null Hypothesis at all significance levels

** = Reject Null Hypothesis at 10% significance levels

* = Reject Null Hypothesis at 5% significance levels

B) Equation 5.1b

Horizon	Coefficients: Constant	Survey Mean	Chi-Square (0,0)
1	3.9999	-0.0436	1.71
	(-4.30)	(-0.01)	
2	4.856	-0.0518	0.45
	(7.23)	(0.08)	
3	4.8378	-0.0509	0.43
	(9.09)	(0.10)	
4	7.8682	-0.0828	0.85
	(10.35)	(0.11)	
5	11.458	-0.1201	1.86
	(12.71)	(0.14)	
6	16.2379	-0.1705	2.11
	(16.12)	(0.17)	
7	18.0822	-0.1895	2.84
	(16.28)	(0.17)	
8	20.6195	-0.2157	3.82
	(18.33)	(0.20)	
9	24.9353	-0.2605	6.40*
	(17.67)	(0.19)	
10	28.5290	-0.2986	7.67*
	(18.33)	(0.2)	
11	30.9111	-0.3234	9.22***
	(19.83)	(0.21)	

KEY:

*** = Reject Null Hypothesis at all significance levels

** = Reject Null Hypothesis at 10% significance levels

* = Reject Null Hypothesis at 5% significance levels

Standard Errors are in parenthesis

Appendix 5.4

Orthogonality

A) Equation 5.2a

Horizon	Orthogonality Coefficients: Constant	Survey Mean	Future Price Fut23p	Chi-Square (0,1,0)	Chi-Square (0,0,1)
1	3.6237	0.1308	0.8303	15.31***	1.27
	(4.83)	(0.23)	(0.22)		
2	4.8358	0.9574	-0.0091	0.39	9.73*
	(8.55)	(0.43)	(0.39)		
3	5.6235	0.7953	0.1457	0.91	8.42*
	(8.22)	(0.35)	(0.34)		
4	8.4855	0.7781	0.1327	1.27	5.56
	(10.02)	(0.43)	(0.43)		
5	7.2134	1.3420	-0.4179	2.36	15.74***
	(13.88)	(0.52)	(0.45)		
6	16.9027	0.7397	0.0830	3.03	23.64***
	(14.58)	(0.41)	(0.32)		
7	18.8118	0.8060	0.0041	3.16	20.07***
	(18.21)	(0.53)	(0.40)		
8	18.8367	0.9281	-0.1252	6.47**	43.92***
	(24.04)	(0.67)	(0.44)		
9	26.9014	0.5484	0.1707	4.56	23.02***
	(23.23)	(0.52)	(0.35)		
10	28.6426	0.6899	0.0103	5.94	15.76***
	(24.03)	(0.73)	(0.56)		
11	31.6662	0.6241	0.0447	8.11*	19.34***
	(29.31)	(0.81)	(0.55)		

Key:

Standard Errors are represented in parentheses

*** = Reject Null Hypothesis at all significance levels

** = Reject Null Hypothesis at 10% significance levels

* = Reject Null Hypothesis at 5% significance levels

B) Equation 5.2b

Horizon	Coefficients: Constant	Survey Mean	Future Price Fut23p	Chi-Square (0,0, 0)
1	3.6237	-0.8703	0.8314	26.09***
	(4.97)	(0.18)	(0.17)	
2	4.7936	-0.0404	-0.0107	0.46
	(7.71)	(0.44)	(0.41)	
3	5.6242	-0.2047	0.1457	1.09
	(9.02)	(0.29)	(0.28)	
4	8.4855	-0.2218	0.1327	1.75
	(9.99)	(0.38)	(0.39)	
5	7.2134	0.3420	-0.4178	3.08
	(13.03)	(0.46)	(0.39)	
6	16.9027	-0.2603	0.0830	2.65
	(15.85)	(0.44)	(0.41)	
7	18.1177	-0.1940	0.0042	2.84
	(16.96)	(0.56)	(0.48)	
8	18.3670	-0.0719	-0.1252	4.76
	(22.10)	(0.66)	(0.47)	
9	26.9014	-0.4516	0.1707	6.48**
	(19.54)	(0.48)	(0.34)	
10	28.6426	-0.3101	0.0103	7.69**
	(20.53)	(0.70)	(0.57)	
11	31.6662	-0.3759	0.0447	9.64*
	(25.09)	(0.75)	(0.54)	

KEY:

*** = Reject Null Hypothesis at all significance levels

** = Reject Null Hypothesis at 10% significance levels

* = Reject Null Hypothesis at 5% significance levels

Standard Errors are in parenthesis

Appendix 5.5

Efficiency of 3-Months Treasury bills Futures Market

Horizon	Coefficients Constant	Survey Mean	Future Price FUT2	Chi-Square (0,1,0)	Chi-Square (0,0,1)
1	3.4382	0.0667	0.8965	15.80***	1.53
	(3.91)	(0.27)	(0.25)		
2	8.0879	0.5147	0.3993	2.3853	9.88*
	(8.32)	(0.31)	(0.27)		
3	4.9176	0.9293	0.0190	0.6215	17.16***
	(8.03)	(0.24)	(0.25)		
4	9.6446	0.3942	0.5047	6.46**	5.79
	(9.98)	(0.25)	(0.25)		
5	14.3225	0.6321	0.2175	3.1347	9.23*
	(13.40)	(0.39)	(0.33)		
6	15.8981	0.8777	-0.0447	3.2457	39.40***
	(13.66)	(0.28)	(0.22)		
7	20.6990	0.4295	0.3541	4.2261	54.07***
	(17.06)	(0.29)	(0.19)		
8	25.2407	0.4809	0.2547	3.5795	26.14***
	(24.56)	(0.62)	(0.39)		
9	25.4851	0.6849	0.0489	4.7172	34.04***
	(22.14)	(0.41)	(0.25)		
10	30.0865	0.5153	0.1702	5.5694	17.85***
	(23.20)	(0.62)	(0.48)		
11	39.7458	0.1786	0.4051	9.14*	17.82***
	(30.51)	(0.87)	(0.62)		

Key

Standard Errors are represented in parentheses

*** = Reject Null Hypothesis at all significance levels

** = Reject Null Hypothesis at 10% significance levels

* = Reject Null Hypothesis at 5% significance levels

For equation 5.2b

Horizon	Coefficients: Constant	Survey Mean	Future Price Fut2	Chi-Square (0,0, 0)
1	3.4389	-0.9338	0.8969	31.85***
	(4.59)	(0.26)	(0.23)	
2	8.0537	-0.4833	0.3976	2.13
	(8.44)	(0.34)	(0.28)	
3	4.9176	-0.0706	0.0189	0.80
	(8.62)	(0.21)	(0.23)	
4	9.6446	-0.6057	0.5047	10.24*
	(10.44)	(0.20)	(0.22)	
5	14.3225	-0.3679	0.2175	4.29
	(12.98)	(0.34)	(0.29)	
6	15.8981	-0.1223	-0.0447	2.42
	(15.28)	(0.27)	(0.27)	
7	20.6990	-0.5705	0.3541	3.62
	(16.44)	(0.37)	(0.31)	
8	25.2407	-0.5191	0.2547	3.95
	(22.61)	(0.62)	(0.43)	
9	25.4851	-0.3151	0.0489	6.61
	(18.70)	(0.39)	(0.27)	
10	30.0865	-0.4847	0.1702	7.58
	(19.66)	(0.55)	(0.43)	
11	39.7458	-0.8214	0.4051	11.20*
	(25.99)	(0.77)	(0.56)	

KEY:

*** = Reject Null Hypothesis at all significance levels

** = Reject Null Hypothesis at 10% significance levels

* = Reject Null Hypothesis at 5% significance levels

Standard Errors are in parenthesis

Appendix 5.6

Efficiency of 3-Months Treasury bills Futures Market

Horizon	Coefficients Constant	Survey Mean	Future Price FUT7	Chi-Square (0,1,0)	Chi-Square (0,0,1)
1	4.2846	-0.1067	1.0610	27.46***	1.69
	(3.41)	(0.23)	(0.22)		
2	7.5419	0.4640	0.4555	2.4352	6.13
	(7.97)	(0.34)	(0.31)		
3	5.7007	0.7998	0.1404	1.2181	15.97***
	(8.05)	(0.24)	(0.23)		
4	12.1018	-0.0207	0.8939	24.00***	3.52
	(9.13)	(0.22)	(0.23)		
5	15.0429	0.5115	0.3303	3.6451	7.43
	(13.14)	(0.39)	(0.33)		
6	17.5290	0.6847	0.1313	3.1754	34.80***
	(13.83)	(0.26)	(0.19)		
7	24.1451	-0.0042	0.7516	8.30*	10.51*
	(14.55)	(0.40)	(0.33)		
8	25.3836	0.4376	0.2962	3.8325	17.84***
	(22.48)	(0.54)	(0.36)		
9	27.6064	0.5210	0.1907	4.4275	25.72***
	(22.78)	(0.45)	(0.29)		
10	37.6974	-0.2399	0.8465	7.05**	12.53***
	(22.74)	(0.58)	(0.48)		
11	38.2106	0.2310	0.3687	8.10*	16.66***
	(29.36)	(0.89)	(0.66)		

Key

Standard Errors are represented in parentheses

*** = Reject Null Hypothesis at all significance levels

** = Reject Null Hypothesis at 10% significance levels

* = Reject Null Hypothesis at 5% significance levels

For equation 5.2b

Horizon	Coefficients: Constant	Survey Mean	Future Price Fut7	Chi-Square (0,0, 0)
1	4.2863	-1.1069	1.0622	45.89***
	(4.00)	(0.23)	(0.21)	
2	7.5138	-0.5342	0.4539	3.39
	(7.54)	(0.29)	(0.26)	
3	5.7006	-0.2002	0.1404	2.02
	(8.63)	(0.18)	(0.20)	
4	12.1018	-1.0207	0.8939	30.04***
	(10.19)	(0.20)	(0.22)	
5	15.0429	-0.4885	0.3303	5.25
	(12.85)	(0.29)	(0.25)	
6	17.5290	-0.3153	0.1313	4.36
	(15.28)	(0.25)	(0.25)	
7	24.1451	-1.0042	0.7516	9.80
	(15.75)	(0.41)	(0.39)	
8	25.3836	-0.5624	0.2962	4.31
	(20.80)	(0.53)	(0.38)	
9	27.6064	-0.4790	0.1907	6.24
	(19.28)	(0.43)	(0.29)	
10	37.6874	-1.2399	0.8465	9.23*
	(19.17)	(0.54)	(0.44)	
11	38.2106	-0.7690	0.3687	10.36*
	(24.99)	(0.77)	(0.57)	

KEY:

*** = Reject Null Hypothesis at all significance levels

** = Reject Null Hypothesis at 10% significance levels

* = Reject Null Hypothesis at 5% significance levels

Standard Errors are in parenthesis

Appendix 5.7

Efficiency of 3-Months Treasury bills Futures Market

Horizon	Coefficients Constant	Survey Mean	Future Price FUT23	Chi-Square (0,1,0)	Chi-Square (0,0,1)
1	2.4863	-0.1547	1.1282	87.41***	2.13
	(2.47)	(0.13)	(0.13)		
2	5.2627	-0.3974	1.3410	29.60***	1.98
	(5.03)	(0.31)	(0.28)		
3	7.0895	0.4467	0.4788	10.20*	7.91*
	(6.93)	(0.21)	(0.20)		
4	9.8347	0.2097	0.6875	22.49***	4.76
	(8.62)	(0.19)	(0.19)		
5	15.0288	-0.0958	0.9382	19.32***	4.43
	(11.00)	(0.30)	(0.30)		
6	20.2494	0.3261	0.4614	13.65***	36.79***
	(13.92)	(0.26)	(0.14)		
7	21.9454	0.1572	0.6134	11.24*	44.17***
	(14.23)	(0.30)	(0.24)		
8	25.6241	0.1237	0.6083	7.29**	16.39***
	(19.81)	(0.42)	(0.27)		
9	29.9621	0.2687	0.4185	6.65**	19.04***
	(22.50)	(0.41)	(0.25)		
10	33.9568	0.0896	0.5557	8.49*	16.39***
	(22.52)	(0.40)	(0.27)		
11	36.2939	0.1194	0.5014	8.81*	14.82***
	(24.83)	(0.59)	(0.43)		

Key

Standard Errors are represented in parentheses

*** = Reject Null Hypothesis at all significance levels

** = Reject Null Hypothesis at 10% significance levels

* = Reject Null Hypothesis at 5% significance levels

For equation 5.2b

Horizon	Coefficients: Constant	Survey Mean	Future Price Fut23	Chi-Square (0,0, 0)
1	2.4874	-1.1546	1.1281	89.63***
	(2.45)	(0.13)	(0.13)	
2	5.2678	-1.3958	1.3394	43.90***
	(5.60)	(0.26)	(0.22)	
3	7.0890	-0.5533	0.4788	13.14***
	(8.36)	(0.17)	(0.16)	
4	9.8347	-0.7903	0.6875	23.85***
	(9.94)	(0.18)	(0.18)	
5	15.0288	-1.0957	0.9382	23.39***
	(12.00)	(0.27)	(0.27)	
6	20.2494	-0.6739	0.4614	11.11*
	(15.51)	(0.29)	(0.25)	
7	21.9454	-0.8428	0.6134	13.44***
	(15.93)	(0.32)	(0.31)	
8	25.6241	-0.8763	0.6083	6.79**
	(18.57)	(0.47)	(0.37)	
9	29.9621	-0.7313	0.4518	8.14*
	(18.56)	(0.38)	(0.25)	
10	33.9568	-0.9104	0.5557	10.52*
	(18.65)	(0.37)	(0.27)	
11	36.2939	-0.8806	0.5014	11.36***
	(20.85)	(0.52)	(0.39)	

KEY:

*** = Reject Null Hypothesis at all significance levels

** = Reject Null Hypothesis at 10% significance levels

* = Reject Null Hypothesis at 5% significance levels

Standard Errors are in parenthesis

Chapter 6

Information Content of Survey Data

In Three Months Treasury Bills Futures-Options

6.1 INTRODUCTION

It is widely believed that the implied volatility in option prices derived using Black's model (1976) for bond and interest rate options is the market's best estimate of future volatility.

The objective of this chapter is to examine the information content and predictive power of survey data in three-months Treasury bills and compare it with various other measures, namely: implied volatility (IV) in three-months Treasury bills futures-options - based on the Black model (1976); historical volatility measured by using simple moving average estimated over 100 day window; and time-series based volatility forecast: ARCH/GARCH which explicitly accounts for the time series behaviour of volatility, that is clusters[1], mean reversion[2], spikes and decay.

Indeed, volatility clustering is one of the oldest noted characteristics of financial data. This clustering could represent the arrival of information in clusters, or delays in the

[1] See Mandelbrot (1963) where he observed "...large changes tend to follow large changes.. of either signs" in prices of many financial instruments. McNess (1979) agreed with Mandelbrot and suggests that "the inherent uncertainty of randomness associated with different forecast periods seems to vary widely overtime."

[2] Stein (1989); Porteba and summers (1986) recognise that while volatility is probably mean reverting, the reversion occurs at a hyperbolic rate (Ballie et al., 1993; Bollerslev and Mikkelson, 1993).

market adjustment process as traders try to gauge its content. News that induces volatility spikes can happen at any time, and sharp volatility reaction to news may depend on the current volatility level. The market seems to be vulnerable to a spike in volatility when volatility is low. As Engle et al. (1990) point out, if information arrives in clusters, than the asset returns or prices may exhibit ARCH (Autoregressive Conditional Heteroskedasticity) behaviour even if the market instantaneously adjusts to the news. The name ARCH refers to a particular type of heteroskedastic (non-constant variance) error term in a regression model; "autoregressive conditional" heteroskedasticity means that a large past variance induces a large current variance for the error term. In other words, volatility follows clear patterns: today's depends on yesterday's and the "shock" in the price of the asset yesterday. Importantly, the links between these do not themselves change over time. The implication of this is that, knowing yesterday's or last week's volatility, one can predict how volatility should change in the future. In particular, GARCH model shows that volatility should regress back to its long-run average, indicating whether volatility now is abnormally high or low. In the alternative, even if the market takes time to resolve expectational differences, it is still informationally efficient in the sense of being unbiased.

Modelling volatility clustering in interest rate data goes back at least to Fama (1976). The first explicit ARCH formulation is given in Weiss (1984), who estimates ARCH model on a set of sixteen different macroeconomic time-series. Very significant ARCH effects are evident. These findings have been confirmed in many subsequent studies, and as for stock returns the actual parameter estimates obtained from many of these models are indicative of high persistence in the volatility shocks, or Integrated GARCH (IGARCH) behaviour[3] i.e. where the multi-step forecasts of the variance do not approach the unconditional variance. A necessary condition for the GARCH (p,q) process to be integrated in variance is that the α_i's and β_i's (sum of the coefficients on lag squared errors and lag squared variances) sum to one. For instance, Hong (1988), using monthly data from April 1959 to December 1985, on estimating a GARCH (1,1) model on excess return of three-month Treasury bills over one-month Treasury Bills. Similar results are reported in Engle, Lilien, and Robins (1987). The data starts from 1960 through 1984. They found that ARCH was clearly present in the forecast errors of bond holding yields indicating substantial variation in the degree of uncertainty over time. This measure of uncertainty proved very significant in explaining the expected returns in both three-month and six-month Treasury bills. Interestingly, with the exception of the yield spread, variables, which had previously been found successful in forecasting excess returns generally, are no longer significant when a function of the conditional variance is included as a regressor. The final model, which they have used, is ARCH-M (12)[4] specification on quarterly data for the excess holding yield of six-month Treasury bills over three-month Treasury bills. On average the term premium is only 0.14 quarterly percent, but it varies in a systematic way through the sample.

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[3] The empirical plausibility of integrated GARCH models has already been established by the findings in Engle, Lilien and Robins (1987) and Bollerslev, Engle and Woodridge (1988) that ARCH and GARCH models for interest rates typically exhibit parameters which are not in the stationary region.

[4] Backus, Gregory, and Zin (1989) have challenged the usefulness of the ARCH-M model for providing a good measure of risk on more theoretical grounds. Mehra and Prescott (1985) showed that ARCH effects are more closely related to forecast errors than to the risk premium. Backus and Gregory (1993) found that there need to be no relationship between risk premium and conditional variances in their theoretical economy.

Kuberek (1992) using monthly U.S. Treasury yield changes from 1946-1991, found strong evidence of ARCH disturbances and suggested that the best conditional predictions of interest rate volatility are obtained with a variant of the first order ARCH model that incorporates a twelve-month moving average variance as an estimate of the prior period's variance.

The simple ARCH models with conditionally normal errors have been inadequate in capturing all the excess kurtosis for stock return and foreign exchange rates, less evidence along these lines is currently available for interest rates[5]. However, most studies involving interest rates have adopted linear GARCH (p,q) specifications[6].

In the past, a lot of research has focused on the use of implied volatilities or historical volatilities in option pricing models such as Black and Scholes (1972); Latane and Rendleman (1976); and Schmalensee and Trippi (1978). Others have investigated the relationship between implied volatility of option prices and historical volatility of the underlying asset. Some studies question the hypothesis that option prices offer substantial information content regarding expected volatility conditions in the underlying market [Wilson and Fung (1990); Brace and Hodgson (1991); Lamoureux and LaStrapes (1993); Day and Lewis (1992); Scott (1992); Canina and Figlewski (1993)[7]]. However, other work suggests that implied volatility may be useful in predicting subsequent movements in historical volatility of the underlying instrument's

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[5] Studies by Lee and Tse (1991) and McCulloch (1985) disagree with this idea.

[6] See the survey by Bollerslev, Chou and Kroner (1992) for evidence.

[7] Day and Lewis; Lamoureux and Lastrapes; Scott etc find that volatilities implied by options prices do

return, for example, regress future volatility on the weighted implied volatility across a broad sample of Chicago Board Options Exchange (CBOE) stocks.[8] [Heaton (1986); Beckers (1981)[9]; Chiras and Manaster (1978)[10]; Latane and Rendleman (1976)[11], Gemmill (1986)[12]].

Park and Sears (1985) lend support to the usage of implied volatility as a measure of ex-ante volatility. Whereas Brace and Hodgson (1991) established that "...implied volatility may be a highly relevant indicator of impending large or unusual volatility." Scott and Tucker (1989), using currency options data, found implied volatility performed well and that adding historical volatility does not improve predictive accuracy. Xu and Taylor (1993) extended the approach adopted by Day and Lewis (1992) to account for the term structure of volatility and found that for three out of four foreign exchange options, implied volatility is the best one-period predictor and that historical data add no additional explanatory power. Generally, if implied volatility is a good proxy for ex-ante volatility (i.e. what rational investors actually perceive about future volatility), then implied volatility will be related to observe historical return data in a Bayesian sense.

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not capture all available information about the future volatility of the underlying asset.

[8] The slope coefficients, however, were generally around 0.5, instead of unity.

[9] Beckers have shown that future volatility is more closely related to the implied volatility derived from the Black-Scholes option pricing model than to estimate volatility using historical data.

[10] Chiras and Manaster (1978) found that weighted implied standard deviations (WISDs) were better than past standard deviations as predictors of future volatility were.

[11] Latane and Rendleman (1976) derived standard deviations implied in actual call option prices on the assumption that investors price options according to Black-Scholes model. They found that the ISD's were highly correlated (0.827) with the actual standard deviation over a two-year period starting with their first observation date.

[12] Gemmill (1986) using London Prices found that implied volatility provided a better forecast than the historic volatility. He also found that nearest –the-money measure contains the most information about future volatility.

Early studies by Latane and Rendleman (1976) made no adjustments for dividend payout. Chiras and Manaster (1978) corrected this mistake by using Merton's continuous-payout European call formula. Beckers (1981) recognising the problem posed by the possibility of early exercise, adopted an ad hoc adjustment to the European formula, all use the basic Black-Scholes European option model or a variant of it to find implied volatilities for American calls on dividend paying stocks. Obviously, using the wrong model will cause the computed implied volatility to differ from the market's real volatility forecast.

More recently, research has turned to the analysis of volatility in a time-series framework. Akgiray (1989) compares the estimates of the standard deviation using GARCH methodology, developed by Bollerslev (1986), with an estimate based on historical returns series. Among various ARCH and GARCH specification with historical estimate, he finds GARCH (1,1) performs the best and provides a better estimate of future volatility than the historical estimate. However, Tse (1991) and Tse and Tung (1992) questioned the superiority of the GARCH model in the Japanese and Singaporean markets, respectively.

Day and Lewis (1992)[13] analyse options on the S&P 100 Index from 1983 to 1989. They added the implied volatility to GARCH and EGARCH models as an exogenous variable; the within-sample incremental information content of implied volatilities is

[13] Day and Lewis (1992) use likelihood ratio tests to compare the information content of the volatility

then examined using a likelihood ratio test of several nested models for conditional volatility. Out-of-sample predictive content of these models is then examined by regressing ex-post volatility on the implied volatility and the forecasts of GARCH and EGARCH models. They found that the implied standard deviation (ISD) has significant information content for weekly volatility, although not necessarily higher than that of time-series models. This approach, however, ignores the term structure of volatility since the return horizon is not matched with the life of the option.

To solve the problem, Canina and Figlewski (1993)[14] using data S&P 100 index options regress the volatility over the remaining contract life against the implied volatility of S&P 100 Index options over 1983 to 1986. They report that ISDs have little predictive power for future volatility, and are significantly biased forecasts. Furthermore, option volatilities appear to be even worse than simple historical measures.

Finally, Lamoureux and LaStrapes (1993) focus on daily individual stock options, measuring prices and matching the forecast horizon, and find that historical time-series contain predictive information over and above that of implied volatilities. They view their result as a rejection of joint hypotheses of market efficiency and the Black-Scholes (BS) class of option pricing models.

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estimates. They have included the implied volatility in their modified GARCH models.

[14] Canina and Figlewski (1993) derived the implied volatilities from a binomial model that adjusts for dividends and captures the value of early exercise.

This chapter is different from previous research in the sense that survey variance[15] is used to compare with various alternative measures and not only just with implied volatility or historical volatility. If the option markets are informationally efficient, then information available at the time market prices are set cannot be used to predict actual return variance better than the variance forecast embedded in the future-option price, which represents the subjective expectation of the market. That is, the forecast error of the subjective expectation should be orthogonal to all available information.

To test this orthogonality restriction, near or at-the-money call futures-options are used[16] to derive implied volatility and compare with variance obtained from the survey, GARCH and moving average. Also in this study we extend the simplest GARCH specification to include the weekend effects[17]. As traders can accurately forecast weekends and holidays, it seems, a priori, to allow the GARCH model access to this information. Indeed, Gibbons and Hess (1981) using T-bills with maturities ranging from about 25 to 30 days report that returns on an index of T-bills are lower on Monday

[15] Variance is used due to Cauchy-Schwarz Inequality. More details see Appendix 6.1.

[16] Latane and Rendleman (1976) noticed that not all options are equally sensitive to an exact specification of the standard deviation: at-the-money options with relatively long life are most sensitive, whereas in the money options close to maturity are hardly affected by a large change in the standard deviation.
Kroner, Kneafsey, and Claessens (1995) also noted that the difference in the ISDs from the at-the-money option and the near-the-money option is likely to be very small. They also suggested that contract price should be the most sensitive to volatility, it should therefore return most accurate measure of volatility. Second, the value added by the American feature is the smallest for at-the-money options (Ramaswamy and Sundaresan (1985)). Third, at-the-money options have the smallest bias when volatility is not constant. The Black model is (approximately) linear in volatility for at-the-money options, which implies that the at-the-money implied volatility estimates will result in only a small bias when volatility is stochastic (Hull and White (1987)).

[17] French (1980), Gibbons and Hess (1981), and Keim and Stambaugh (1984) have documented that the average return on Friday is abnormally high, and the average return on Monday is abnormally low. This what has come to known as the "weekend" or "day-of-the-week" effect. The difference between the terms "weekend" and "day-of-the-week" effects stems from Rogalski's (1984) findings, which indicate that much of the decline in prices occurs over the weekend as opposed to on Monday.

than on other days of the week; Wednesday's return on average is higher than other days of the week. Flannery and Protopapadakis (1988) using a variety of US Treasury data from 1977 to 1984, discovered that Monday's mean Treasury returns are smaller than any other day's for all maturities and that Monday returns become more negative for securities with longer maturities. However, Johnston, Kracaw, and McConnell using T-bill futures from Jan 1976 to Dec 1988 found there is no significant seasonal patterns in returns on T-bill contracts. Average returns on T-bill contracts are not significantly different from zero for any of their samples tested. In addition there exits a relatively small empirical literature testing the information content of survey data with regards to Treasury-Bills and compared it with time series based forecast.

The rest of the chapter is organised as follows: The next section describe the various volatility forecasting method. This is followed by the methodologies. The fourth section discusses the data, results are presented in the fifth section, and the final section concludes the study.

6.2 EXISTING FORECASTS

6.2.1 Realised Forecast

In order to provide an answer to the question of whether variance obtained from the Blue Chip Financial Services rather than implied volatility is a superior forecaster of actual volatility, one has to estimate the actual/realised volatility[18].

For a series of prices $\{P_0, P_1, ..., P_t\}$ - in this case daily prices is used, the realised forecast is defined as the annualised standard deviation of the continuously compounded returns, $\{R_1, R_2, ..., R_t\}$, where $R_t \equiv \ln(P_t/P_{t-1})$, is the sample mean of the "Rt", and "K" is the number of observation intervals in a year which in this case is one. "T" is the total number of returns. The realised variance is therefore calculated as follows:

$$\sigma^2 = \frac{K}{T-1} \sum_{t=1}^{T} (R_t - \bar{R})^2$$

In order to find the annualised standard deviation, multiply σ^2 by 260 (the number of trading days in a year) and take a square root of this value to get to the annualised standard deviation[19]. According to Canina and Figlewski (1993) "..this is widely used as a consistent estimator of volatility, but while the expression in the large parentheses yields an unbiased estimate of the variance, taking the square root to obtain the volatility is a non-linear transformation that introduces a small bias in a finite sample by Jensen's inequality. It is common practice to treat this bias as negligible". This annualised volatility will be realised over the remaining lifetime of the future-options. This is by far the most popular measured used in practice.

[18] The derivation of actual/realised volatility is similar to Canina and Figlewski (1993); Heynen and Kat (1994).

[19] Unlike rates of return, which increase proportionately with time, standard deviations increase with the square root of time.

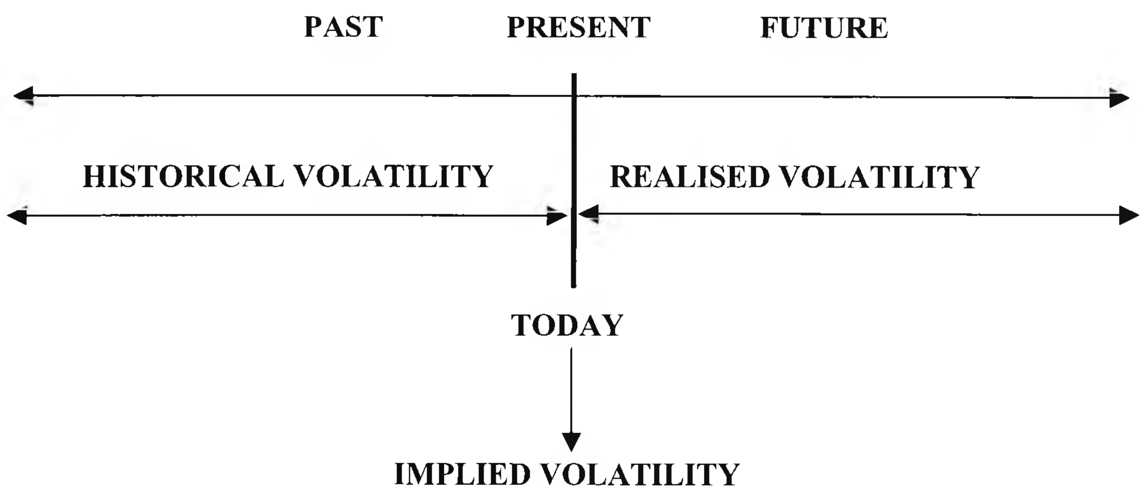
6.2.2 Historical Volatility

Historical volatility is a statistical measure based on past price variability. It is usually expressed as the annualised standard deviation of the percentage daily changes of price or yield. This is useful because a normal distribution may be fully defined by reference to its mean and standard deviation. In addition, historical volatility is independent of any one pricing methodology, but instead relies on the natural occurrences of the market to generate the required variances.

Both historical and realized volatilities are measures of observed futures price variability, however, their difference lies in time reference. Historical volatility covers the past and provides a guide to how volatile the underlying futures market is likely to be. Realized volatility covers the future. It determines in part how profitable an option trade proves to be (See figure 6.1 below for comparison between historical, implied and realised volatility).

Figure 6.1

Three Types of Volatility



If volatility is stationary through time, historical volatility is a reasonably good indicator of subsequent volatility. Unfortunately, and especially over a short measurement intervals, nonrecurring events or conditions often cause volatility to shift up or down temporarily, so that historical volatility will over or underestimate subsequent volatility. There are several ways to calculate historical measures such as the standard deviation of futures price returns based on closing prices; the standard deviation of future price returns from close to open and from open to close or the high/low range of the futures price. The most widely used is the first - typically daily percentage price changes based on closing exchange prices- due to its simplicity of calculation and ease of use. Measurement may be taken over any time frame. In this case, a 100 day simple moving average is used which is annualised. This is due to the fact that the volatility of the daily price/yield changes has a slight bias towards lower prices/yields. However, even using this method of calculating historical volatility, it still cannot model slumps and are very slow to adjust to shocks in the time series.

In addition, although historical and implied volatility generally correlate over time, short-term discrepancies are not uncommon, and long-term divergences can sometimes occur.

6.2.3 Implied Standard Deviation

If option markets are efficient - which means investors' expectations of future volatility is embodied in option prices. It should be the best volatility forecast available, and the pricing model is valid, given the current price of a specific option contract along with the model's other parameters, the model can be solved backwards for the value of the volatility parameter implied by the current price of the option - option price is a monotonically increasing function of expected volatility - using Newton-Raphson Method[20] which is a numerical approximation technique. This is often refer as "market-based" forecast because it should be based entirely on the expectations of participants in the options market (given a particular option pricing model). This figure amounts to an estimate of how variable the market would have to be to justify the "pit" price. If the current implied volatility is historically high, or high relative to the recent volatility of the underlying futures contract, the premium levels are high (a selling opportunity); if the implied volatility is unusually low, premium levels are low (a buying opportunity).

[20] For more details on the derivation of implied volatility, refer to Chapter 2: "The Sources and

These pricing reflects option traders' sense of risk inherent in the market at the moment. If the market is likely to surprise them, or they fear it might, they charge more for an option. If they think they quite certain what may happen in the next few days or weeks, their prices do not need to include much risk factor. That is the same as saying they do not expect much price movement. Long dated options will generally be less sensitive to the recent level of volatility than shorter expiries. Where volatility on options with shorter expiration is low (high), long dated options will generally trade at higher (lower) implied volatility.

The major conceptual advantage of the ISD over the traditional time-series estimates is that it is an ex-ante estimate based on the most recent observable data, it is a forward-looking measure of likely future volatility conditions. Implied volatility presumably contains some information about the market's expectations of future volatility. It provides an index of what "the market" thinks. Hence, in the academic finance profession, ISD is almost assumed to be the "market's" volatility forecast[21] and it is widely believed to be informationally superior to historical volatility. Indeed, Latane and Rendleman (1976), Schmalensee and Trippi (1978), Chiras and Manaster (1978), Beckers (1981), Scott and Tucker (1989), Xu and Taylor (1993), and several others all found that implied volatility is better than historical standard deviation at forecasting future realized volatility.

Background of Data".

[21] See Patell and Wolfson (1979,1981) or Poterba and Summers (1986) for examples of the use of implied volatility as a proxy for the market's risk assessment. Stein's (1989) used implied volatility as

Latene and Rendleman found this result using 39 weekly observations for options on 24 stocks from October 1973 to June 1974. Schmalensee and Trippi used 56 weekly observations for options on six stocks from April 1974 to May 1975. Besides finding no significant relationship between historical volatility and implied volatility, they also found that implied volatility seems to decline following price increases and that implied volatilities are positively correlated across stocks. Chiras and Manaster, using a sample of 23 monthly observations from June 1973 to April 1975, accounted for dividends by converting realized dividends to a continuous rate. They found that during the first nine months of their sample, implied volatility was not significantly better than historical standard deviation at forecasting volatility. That result, however, is reversed in the remainder of the sample, leading the authors to conclude that the market took some time after the opening of the CBOE in 1973 before beginning to incorporate volatility forecasts into option prices. Heaton (1986) using data from 1973-1981 came to a similar conclusion that implied volatility incorporates all the relevant information in past prices.

There are several problems inherent in these market-based forecasts. According to Kroner et al. (1995), one of the most important problems is the trading of options with maturities exceeding six months is often so thin that long horizon forecasts of volatility using ISDs are potentially unreliable. Also, most option-pricing models assume that volatility is constant, so when forecasts are extracted from these models in a world of dynamic volatility, it is not clear what is really being forecast. Finally, it is possible that

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a proxy for the true instanteous price volatility of the underlying asset.

the option-pricing formulas are incorrect and/or the options market is not efficient, as evidenced by the different ISDs that are extracted from different exercise prices. All these suggest that the forecasts extracted from option-pricing models might not be the best available forecasts. However, Bartunek and Mustafa (1994) find that for the stocks they used, historic volatility outperformed both ISD-based forecasts and GARCH-based forecasts for long horizons (80 and 120 days). This result seems to contradict much of the extant literature.

6.2.4 Survey Volatility

The use of cross sectional dispersion from survey data to estimate the variance of the underlying time series has been advocated by a number of researchers. Zarnowitz and Lambros (1987) discuss a number of these studies with macroeconomic variables[22]. However, survey measures only provide an indicator of the heterogeneity in expectations, which may not be a good approximation of the fundamental underlying certainty depending on the homogeneity of expectations. Rich, Raymond and Butler (1992) only find a weak correlation between the dispersion across the forecasts for inflation and an ARCH based estimate for the conditional variance of inflation.

6.2.5 Time-series Forecasting

Another method that has been proposed to forecast volatility involves time-series

[22] For more examples see Bollerslev et al. (1992).

modelling of the variances. Many assets are characterised by time-varying variance[23] such as Bera and Higgins (1993) present three typical data on price changes - weekly rate of return on the U.S. dollar/British pound exchange rate; changes in three-months Treasury bill rate and growth rate of the NYSE (New York Stock Exchange) monthly composite index. They observed that the common features of all three series are: while the means are constant, the variances change over time. Consequently require dynamic models of volatility. ARCH which produces a distribution with fatter tails than normal, is a modelling technique that particularly fits the distributional properties noted above, is first introduced by Robert Engle (1982) and generalised to GARCH by Tim Bollerslev in 1986[24], which provides a parsimonious parameterization for the conditional variance, and its various extensions.

The essence of ARCH-type models is that they show how a spike or jump in volatility persists, and gradually decaying over time. It has the advantages of rendering a better description of stochastic volatility because it accounts directly for clusters, mean reversion, spikes and decay. Indeed, Weiss (1984), Milhoj (1987) and also Bollerslev (1986) have studied the statistical properties of this class of processes. The empirical distribution of variables generated by these processes is heavy tailed, compared to the normal distribution. Due to the characteristics just mentioned, one could easily recognised what is the major drawback of using classical linear regression model - its

[23] See Mandelbrot (1963, 1966), Fama (1963, 1965) recognized that uncertainty of speculative prices, as measured by the variances and covariances, is changing through time, and Blattberg and Gonedes (1974) for evidence.

[24] The GARCH model was also independently proposed by Taylor (1986), who used a different acronym.

inability to cope with the heteroskedastic bias when the magnitude or pattern of the error terms fluctuates overtime. ARCH-type models deal directly with nonlinearity of these data series - spikes followed by slow decays.

In many applications with the linear ARCH (q) model with a long lag length q is called for. Bollerslev (1986) therefore extends the ARCH process to GARCH, which allows for a more flexible lag structure. The underlying regression is the usual one that is:

$$y_t = \beta' x_t + \varepsilon_t$$

Conditioned on an information set at time "t", denoted by Ω_{t-1}, the distribution of the disturbance so is assumed to be:

$$\varepsilon_t \mid \Omega_{t-1} \sim N(0, h_t)$$

The variance equation is:

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j}$$

where $\alpha_i, \ldots, \alpha_q$, $\beta_j, \ldots, \beta_p$, and α_0 are constant parameters, with $\alpha_0 > 0$, $\alpha_i \geq 0$, $\beta_j \geq 0$. These restrictions will ensure that the conditional variance is strictly positive. The unconditional mean and variance of a GARCH process are constant. For a GARCH (1,1) process, it follows that ε_t is covariance stationary if and only if $\alpha_1+\beta_1<1$; when this is the case, the unconditional, long run, variance is given by $\alpha_0/(1-\alpha_1-\beta_1)$. An ARCH process is a special case of GARCH process. Simple substitution reveals that GARCH model is an infinite order ARCH model with exponentially decaying weights for larger lags. Thus, a low order GARCH model may have properties similar to high order

ARCH models without the problems of estimating many parameters subject to non-negativity constraints. The ARCH models estimated by Engle (1983), Engle and Kraft (1983), and Engle, Lilien and Robins (1987), impose linearly declining weights in the α_i's so that the only free parameters are q and the sum of the weights. Thus, the GARCH model appears to be a natural and simple generalization of the ARCH model, and the empirical evidence suggests that it fits as well or even better than the ARCH model with linearly declining weights with roughly the same mean lag. (See Bollerslev (1985a) for more details).

The conditional variance is defined by an ARMA (p,q) process in the innovation ε_t^2. The difference here is that the mean of the random variable of interest y_t is described completely by heteroskedastic, but otherwise ordinary regression model. The conditional variance, however, evolves over time in what might be a completed manner, depending on the parameter values of "p" and "q". The fact that conditional variances are allowed to depend on past realized variances is particularly consistent with the actual volatility pattern of the securities market where there are both stable and unstable periods. Brock, Hsieh and Lebaron (1991) show that if ε_t^2 is a linear in the sense of Priestly (1981), the GARCH (p,q) representation may be seen as a parsimonious approximation to the possibly infinite Wold representation for ε_t^2. Wold's decomposition theorem states that any stationary series can be represented as the sum of two parts, a self-deterministic component and a moving average of possibly infinite orders.

If one then take out the deterministic component by assuming it takes a particular form, such as constant. This leaves a potentially infinite-order, square-summable component. If the coefficients of this component are very small beyond a certain lag, then it may be convenient to approximate the indeterministic component by a finite-order moving average process. Alternatively, it may be better to approximate the process by an ARMA process of finite orders. Empirically, the family of GARCH models have been very successful. Of these models, the GARCH (1,1) where the effect of a return shock on current volatility declines geometrically over time is preferred in most cases [See Akgiray (1989)[25], the survey by Bollerslev, Chou and Kroner (1992), and Bera and Higgins (1993)].

The stationarity conditions are important in this context to ensure the moments of the normal distribution are finite. The reason is that higher moments of the normal distribution are finite powers of the variance.

Estimation and testing in the GARCH model is easily accomplished using standard maximum likelihood theory. Assuming conditional normality the log-likelihood is given by:

$$logL = -\frac{T}{2}\log(2\pi - \frac{1}{2}\sum_{t=1}^{T}[\log\sigma_t^2 + \varepsilon_t^2/\sigma_t^2]$$

[25] Akgiray (1989) using daily stock returns found that a reasonable return-generating process is empirically shown to be first-order autoregressive process with conditionally heteroskedastic innovations. In particular, generalized autoregressive conditional heteroskedastic GARCH (1,1) processes fit to data satisfactorily. Various out-of-sample forecasts of monthly return variances are generated and compared statistically. Forecasts based on the GARCH model are found to be superior.

Bollerslev describes a method of estimation based on BHHH (Berndt-Hall-Hall-Hausman) algorithm. The weighting matrix used in the algorithm is the BHHH estimator of the asymptotic covariance matrix of the parameters based on the current estimates. The estimations are recursive.

In order to construct the GARCH forecast, which is time-series based, we need to estimate the GARCH model. The following GARCH (1,1)[26] model is utilised to generate the volatility of three-month Treasury bills.[27] This is consistent with the results of Akgiray (1989), Day and Lewis (1992), Lamoureux and LaStrapes (1992) who finds that, within a class of GARCH processes for market volatility, the GARCH (1,1) specification provides the best fit using a likelihood ratio test.

Kroner, Kneafsey and Classens (1995) also adopted a GARCH (1,1) model to generate time-series based forecasts in Commodity Prices. A differenced version of yield is considered, in order to achieve stationarity.[28] As Fama (1976) has noted, the nominal

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[26] In order to determine the adequacy of the model specification, other models such as ARCH(q) for q=1...12 and GARCH(p,q) for q=1-2 and p=1-2 were also tried. For ARCH models, it was found that large lag q, up to 12, was required in the conditional variance function. Where as for GARCH model, when q or p is equal to 2, non-convergence or at least one coefficient could not be estimated due to singularity of the data. Details see Appendix 6.2.

[27] Connolly (1989) and Najand and Yung (1994) pointed out that previous researchers such as French (1980), Gibbons and Hess (1981), Keim and Stambaugh(1984), Jaffe and Westerfield (1985) use OLS regression with the assumption that regression errors are homoskedastic, serially uncorrelated and normally distributed, with (0,1) dummies representing days of the week in order to test the null hypothesis that the daily mean returns are not different from each other. However, conclusions based on such tests should be viewed with caution given the numerous recent findings that the distribution of asset returns is leptokurtic and the variance is time varying. Both Connolly and Najand and Yung used GARCH model to test for the above hypothesis for S&P500 Index and S&P500 Index Futures respectively. Alexander and Riyait (1992) using GARCH (1,1) extend the analysis to volatility on daily exchanges rates.

[28] Gibbons and Hess (1981) used a differenced version to test for the day of the week effects on Treasury bills.

interest rate resembles a random walk; therefore, the return series is not likely to be stationary. The proposed model below is similar to the one used by Alexander and Riyait (1992) where they used a GARCH model to analyse the volatility of daily exchange rates, taking into account of the possibility of day-of-the-week effects from the return of Treasury bills yields.

$$y_t = \alpha_0 + \delta_{1t} M_t + \delta_{2t} T_t + \delta_{3t} W_t + \delta_{4t} F_t + \delta_{5t} H_t + \delta_{6t} DIF_t + \varepsilon_t$$
$$\varepsilon_t \sim N(0,h_t)$$

$$h_t = \alpha_0 + \theta_1 M_t + \theta_2 T_t + \theta_3 W_t + \theta_4 F_t + \theta_5 H_t + \theta_6 DIF_t + \alpha_1 \varepsilon_t^2 + \beta_1 h_{t-1}$$

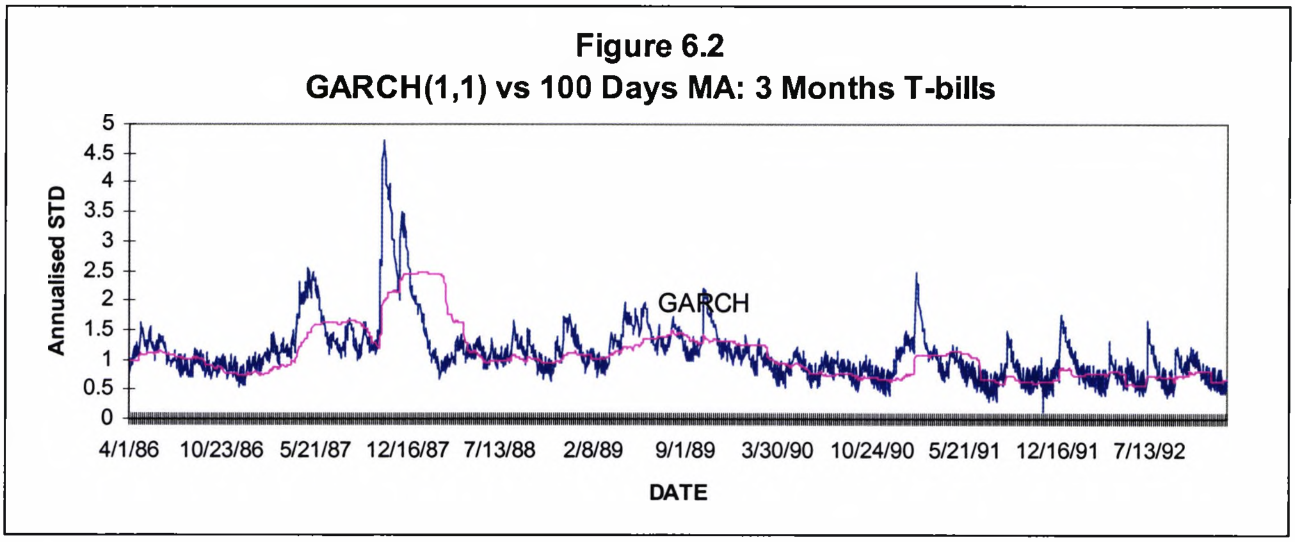
Where "y_t" is changes in the yield of the daily spot three-month Treasury-bills on day t (from t-1 to day t) and ε_t is the random error. M_t, T_t, W_t, F_t, are (zero-one) daily dummy variables identifying Monday, Tuesday, Wednesday, and Friday observations respectively. In other words, where $\delta_{1t} = 1$ if day t is a Monday and $\delta_{1t} = 0$ otherwise; $\delta_{2t} = 1$ if t is a Tuesday etc. The intercept in the above equation contains the effect of the return generated on Thursday. Thus the coefficients on dummy variables (δ_{1t}...δ_{6t}) for the remaining days of the week measure the marginal effect of each day relative to Thursday. This represents the difference between the expected return for Thursday and the expected return for each of the other days of the week if the expected return is the same for each day of the week, the estimates of δ_{1t} through δ_{6t} will be close to zero and an F-statistic measuring the joint significance of the dummy variables should be insignificant.

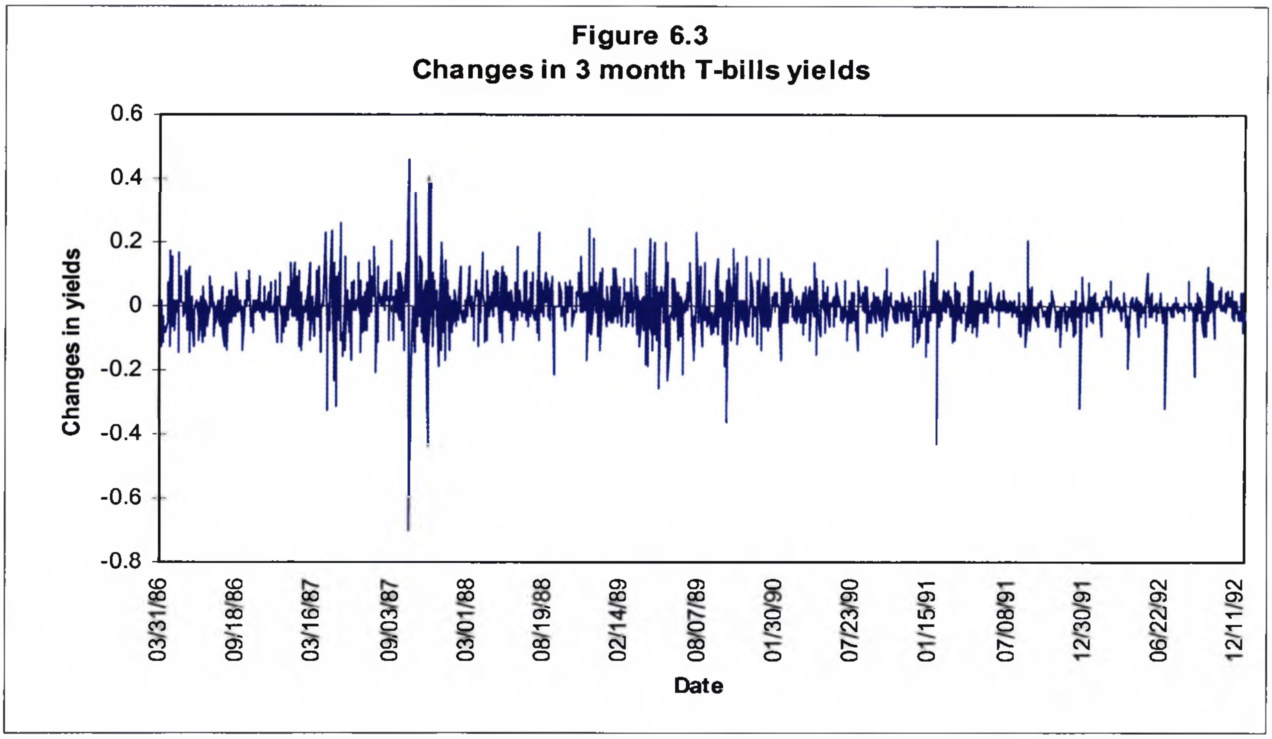
An alternative specification would be to suppress the intercept and include the dummies for each of the five trading days of the week; however, this specification will introduce bias into the coefficient estimates if the true mean return is nonzero. "Holiday" returns, which are earned over a non-trading period, are also distinguished from regular returns by utilising a dummy variable H_t. In this model, DIF_t represents the number of calendar days that have elapsed since the previous closing price. Thus, DIF_t is normally 1, but on Monday it is 3, and on a Tuesday that follows a holiday weekend it is 4. θ denotes the coefficients for the series of volatility.

Numerical maximisation of log-likelihood functions is carried out using TSP[29] package. Numerical stability and rapid convergence to the optimum is obtained in all cases. The standard errors of the point estimates are calculated using the Hessian matrix at optimum variation over time. Comparing the plot of changes in yields in Figure 6.3 with the plot of conditional variances in Figure 6.2, it is clear that a clustering of large deviations, of either sign, in the returns is associated with the rise in the conditional variance.

[29] Pre-sample values of h_t are estimated simultaneously with the other coefficients in TSP. This makes GARCH estimates less sensitive to the initial observations in the sample period. Studies on truncated infinite lag distributions (see Maddala on summary) indicate that estimating these initial conditions

Figure 6.2 attached shows the plot of the estimated of the conditional variances, h_t,





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improves the small-sample distribution of the other estimates.

6.3 METHODOLOGY

6.3.1 The Unbiasedness Test

This is the same as previous chapter i.e. to test the unbiasedness of survey volatility (SV), implied volatility (IV) and time-series based volatility forecasts, the following model based on Muth's (1961) study was used:

$$\sigma^2 = \alpha_0 + \beta_1 F_1(\phi) + \varepsilon_t \qquad (2)$$

where "$F_1(\varphi)$" is the forecast of σ^2 based on the information set "φ" and "ε_t" represents the forecast error with $\alpha_0 = 0$, and $\beta_1 = 1$ and $E(\varepsilon_t) = 0$ if the forecasts are unbiased. As in Muth (1961), ε_t must be uncorrelated with $F_1(\varphi)$. Moreover, the error series ε_t should be characterised by no significant serial correlation. If any of these conditions is not satisfied, then the hypothesis of unbiasedness is rejected.

This methodology for comparison of forecasts is similar to that in previous study, such as Latane and Rendleman (1976), Beckers (1981), Chiras and Manaster (1978), Day and Lewis (1993), Philip Jorion (1995), and Bartunek and Chowdhury (1995). This is estimated by OLS as long as the regressors and residuals are uncorrelated with one another. Where there is heteroskedasticity, White (1980) correction for heteroskedasticity is utilised.[30] The Wald test[31] is used to examine the joint null

[30] Day and Lewis (1992) use the same methodology to test the predictive power of alternative stock

hypothesis that $(\alpha_0, \beta_1) = (0,1)$.[32] This represents an efficient forecast. Hence, the closer α_0 is to zero and β_1 to 1 the better the forecast. The test statistic is distributed asymptotically as a chi-square with two degrees of freedom. The only exception is when survey variance is used. Here the appropriate test statistic is to use the t-ratio. In addition, we also compared the adjusted R^2 from the regressions over the sample period for each of the seven forecasts. The R-squared statistic measures the percentage of the total variation of the dependent variable explained by the variation in the independent variable. Thus the higher the R-squared the better the estimate.

6.3.2 Accuracy of Survey/ISD Forecasts or Encompassing Tests: The relative predictive power of alternative forecasts

While it has been observed that generally survey data and implied volatility forecasts perform better than forecasts obtained from historical volatility and forecasts obtained from autoregressive models, this chapter also investigates whether the accuracy of implied volatility/survey forecasts can be improved. In other words, one is trying to examine whether forecasts from GARCH model or moving average contains information that differs from the information in the forecasts from implied volatility and survey forecast. Lupoletti and Webb (1986) improved relative forecasting accuracy of survey forecasts by combining them with forecasts from autoregressive model. Granger

volatility forecasts.

[31] Day and Lewis (1993) also use Wald test. Details of the test please refer to Appendix 6.3.

[32] Rich, Raymond and Butler (1992) use Wald Test to test for unbiasedness for survey data.

and Ramanathan (1984), Hafer and Hein (1985,1990) recommend that it is best develop forecasts that account for information embedded in each model.[33] In the regression method, the following regression is estimated:

$$\sigma^2 = \alpha_0 + \beta_1 F_1(\phi) + \beta_2 F_2(\phi) + \varepsilon_t \quad (3)$$

where σ^2 is the realised value. The estimated β_i coefficients provide the marginal contribution for each forecast. The slope coefficient of β_1 should be unity and the less informed forecast should have $\beta_2 = 0$. Analysing the relative information content of two different forecasts by means of a regression like the above is known as an "encompassing regression" test. Fair and Shiller (1990) discuss the approach in detail and use it to evaluate the forecasting performance of different macroeconomic models.

The above equation is estimated using OLS. Where there is a presence of heteroskedasticity, White's Consistent Estimate of the coefficient covariance matrix is used. The Wald test is used to test the restrictions that $(\alpha_1, \beta_1, \beta_2) = (0,1,0)$ except when β_1 is representing survey variance. Rejection of the null hypothesis can imply the following:

a) If the estimated β_2 coefficient is significant, it indicated that $F_2(\varphi)$ provide some information concerning the actual realized values. It would also suggest that $F_1(\varphi)$ did not efficiently utilise all past information.

b) If both β's are significant, then each contributes to the explanation of the actual value.

c) If both β's are insignificant, then each forecast contains similar information.

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[33] This type of test was originally suggested by Bates and Granger (1969) to obtain weighted combinations

Another way to test the orthogonality restriction is to run the following multiple regression:

$$\sigma^2 - IMP_t = \alpha_0 + \beta_1 IMP_t + \beta_2 SV + \beta_3 SSM + \beta_4 FN_t + \varepsilon_t$$

Or

$$\sigma^2 - IMP_t = \alpha_0 + \beta_1 SV + \beta_3 GAR2/MAV + \varepsilon_t$$

where SV = Survey Variance
IMP_t = Implied Volatility
σ^2 = Realised Volatility
GAR2 = Garch Volatility
MAV = Moving Average Volatility
SSM = Mean of the survey forecast
FN_t = Future Price at Specify Date

The regression is specified in such a way that the testing of the following hypothesis:(σ^2 - IMP_t = 0) should not be significantly different from zero if the market is efficient.

The idea behind the market efficiency test is that if the options market is efficient then the ISD backed out from a properly specified options-pricing model should capture all the volatility of the spot prices that can be predicted based on current information set. The implication is that all coefficients in the equation should be zero except for the coefficient on the ISD term. If either α or β remains significant upon inclusion of the ISD term, then there is information in the past time series of volatility which is not incorporated into the market's expectations of future volatility, but is relevant in

of forecasts.

predicting future volatility. This could imply that the options are mis-priced either because the options market is inefficient or because the incorrect options pricing formula is used, and data on past volatility data can be used to take advantage of the mis-pricing.

6.4 DATA

The GARCH, MA (100 days "rolling window" moving average) standard deviation forecasts of three-month Treasury bills require spot price/yield data, which was obtained from Data Resources, Inc. The time span covered from January 1980 to December 1992, with a total of 3251 observations. To ensure that forecast comparisons are compatible, GARCH and MA forecasts are annualised i.e. variances are multiply by the total number of trading days, which is 260 days. The ISD-based forecasts require data on futures prices, interest rates, and options prices. The futures data is the settlement price quoted in the Datastream, which is the official closing price issued by the IMM (International Monetary Market). The future options price data is obtained from Chicago Mercantile Exchange's stats database[34].

6.5 EMPIRICAL ANALYSIS

We begin the empirical analysis by examining which GARCH (1,1) model shall we

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[34] For more details about the data mentioned please refer to previous chapter on "The Sources and

choose to generate volatility for three months T-bills. Appendix 6.2 gives the parameter estimates and t-statistics (in Italics) computed using numerical derivatives in the method of maximum likelihood. From the mean equation, it is obvious that there is no negative Monday effect and statistically zero at the 0.05 level of significance. Additionally, average returns are positive on Tuesday and are statistically different from zero at 5% level. However, returns on Thursday are negative. Whereas for the variance equation, the evidence reveals that volatility of three-month treasury bills tends to increase on days following holidays and for the rest of the week volatility seems to be less volatile particularly on Tuesday. The only exception is on Thursday, which seems to have the highest volatility. The GARCH coefficient β_1 is highly significant with a t-statistic of 196.119. The estimate of β_1 is always markedly greater than α_1, and the sum of $\alpha_1 + \beta_1$ is very close to but smaller than unity. This indicates that changes in market volatility tend to be persistent. The fact that $\alpha_1 + \beta_1$ is close to one[35], however, is useful for purposes of forecasting conditional variances. This result is consistent with Najand and Yung (1994), and Akgiray (1989). It implies that a significant part of the current volatility can be explained by past volatility, and that the past volatility tends to persist over time. According to Engle and Bollerslev (1986), if the sum $\alpha_1 + \beta_1$ is close to one in the GARCH (1,1) process, then the model is known as integrated GARCH (IGARCH) which implies persistence of the conditional variance over all future horizons i.e. shocks remain important determinants of the variance forecasts long after the shock occur. There is no mean-reversion in the variance. The IGARCH model has

Background of Data".

[35] The presence of near-integrated GARCH, or $\alpha_1 + \beta_1$ being close to but slightly less than unity, has been found by Bollerslev (1987), McCurdy and Morgan (1987), Ballie and Bollerslev (1989), and French, Schwert and Stambaugh (1987) for a number of financial market series.

been examined extensively by Nelson (1990a, 1990b). He shows that, even though this model does not have finite variances or covariances, it is strictly stationary and ergodic.

The following model was selected after likelihood ratio test was perform with 5% significance level and with insignificant variables being dropped :

$$y_t = \alpha_0 + \delta_{2t} T_t + \delta_{6t} DIF_t + \varepsilon_t$$
$$\varepsilon_t \sim N(0,h_t)$$

$$h_t = \alpha_0 + \theta_2 T_t + \theta_3 W_t + \theta_5 H_t + \theta_6 DIF_t + \alpha_1 \varepsilon_t^2 + \beta_1 h_{t-1}$$

6.5.1 Unbiasedness Test

To test the predictive power of implied volatility, equation (2) was fitted separately for each of the six forecast horizons that are from one month to six month ahead. The period examined began in April 1986 and lasts until December 1992. This procedure provides an intuitively appealing test of whether implied volatility, survey variance, GARCH, or simple moving average estimated over 100-day window is a superior forecaster of actual volatility.

Four simple linear regressions are performed - one in which the independent variable is the implied volatility (IMP_t) and the dependent variable is the actual volatility (σ^2) in the subsequent period, and the others in which the independent variables are survey variance, GARCH and Moving Average:

$$\sigma^2 = \alpha + \beta_1 IMP_t + \varepsilon_t \tag{4a}$$

$$\sigma^2 = \alpha + \beta_1 SV_t + \varepsilon_t \tag{4b}$$

$$\sigma^2 = \alpha + \beta_1 MV_t + \varepsilon_t \tag{4c}$$

$$\sigma^2 = \alpha + \beta_1 GAR2_t + \varepsilon_t \tag{4d}$$

These equations are estimated by OLS as long as the regressors and residuals are uncorrelated with one another, where the appropriate test statistic for the joint hypothesis that the coefficient α should be zero and β_1 should be unity is distributed $\chi^2(2)$. The only exception is for equation 4b. The table below presents a quick guide of the results: (Details are set out in appendix 6.4).

Table 6.1

Realised volatility over the remaining life the three month T-bill futures-options regressed on implied volatility, survey variance, GARCH and Moving Average :

$$\sigma^2 = \alpha + \beta_1 F(\varphi) + \varepsilon_t$$
Where $H_0: (\alpha, \beta_1) = (0,1)$

Horizon	IMP23P	IMP2	IMP7	IMP23	SV*	GAR2	MA
1	Pass	Pass	Pass	N/A	NS	Fail	Pass
2	Pass	Pass	Pass	Fail	NS	Pass	Fail
3	Pass	Pass	Pass	Pass	NS	Fail	Fail
4	Pass	Pass	Pass	Pass	S	Pass	Fail
5	Pass	Pass	Pass	Pass	S	Fail	Fail
6	Pass	Pass	Pass	Pass	S	Fail	Fail

Key: * = In survey variance, we looking at t-ratio of β_1 and not the restriction of β_1=1
Where
NS=not significant t-statistic
S = Significant t-statistic

The table above supplies evident that, majority of the time, implied volatility pass the unbiasedness test, with increasing R^2 as the forecast horizon increases. The intercept and the slope coefficient are not significantly different from zero and one respectively at the 5 percent significance level. Thus implied volatility is an unbiased forecast of future realised volatility. This result is consistent with Day and Lewis (1993) which shows that implied volatility are unbiased predictors for crude oil futures prices. This is different from Canina and Figlewski (1993) where it demonstrates that "in most cases, implied volatility has no statistically significant correlation with realized volatility at all".

However, for survey volatility the estimates of β_1 are significantly different from zero (indicated by t-statistics) for longer forecast horizon but not for shorter forecast horizon.

The same approach is repeated for historical volatility measured by simple moving average and conditional variance generated by GARCH (1,1). The table reveals that unlike implied volatility, both conditional variance (GAR2) and simple moving average forecasts are significantly different from zero at 5% level. This suggests the forecasts are biased. It is evident from the table that the rejection of the null hypothesis for simple moving average forecast and GAR2 is due to both the estimated constant term being less than zero and the estimated slope coefficients being significantly more than one for longer forecast horizon. This implies both GAR2 and simple moving average generated forecast of conditional volatility has a tendency to over-predict the realised (actual) value. This result is consistent with Bartunek and Chowdhury (1995) where they found that all estimates including GARCH and implied volatility are statistically different from efficient forecasts in all forecast horizons. Their results showed no superiority of one forecast over any of the others. In fact, in statistical sense, they found that there is no difference between the historical estimates predictive ability and either the Black-Scholes implied volatility forecasts or the GARCH forecasts. This is in contrary to the study presented by Day and Lewis (1992)[36], and Pagan and Schwert (1990) where they found that GARCH forecasts are unbiased.

6.5.2 Encompassing Tests:

Tables below report comparisons of forecasts of the monthly variance of three-month Treasury bill yields between implied volatilities and various forecasts (For further details please refer to Appendix 6.5). It is estimated using OLS by the following regression to test the restrictions that $(\alpha_0, \beta_1, \beta_2) = (0,1,0)$:

$$\sigma^2 = \alpha_0 + \beta_1 IMP_t + \beta_2 F_2(\varphi) + \varepsilon_1$$

Where

IMP_t represents implied volatility derived from 90 Days Treasury bill futures-options at time t

$F_2(\varphi)$ represents either survey variance, GARCH or simple moving average

[36] Day and Lewis (1992) compares implied volatility from option pricing models with GARCH models

Where there is a presence of heteroskedasticity, White's Consistent Estimate of the coefficient covariance matrix is used.

It is evident that the estimated coefficient on survey variance (see appendix for details) is not significantly greater than zero and the coefficient on implied volatility is nowhere significantly different from one in shorter forecast horizons. Both implied volatility and survey variance are not significant, implying, in shorter forecast horizons, they contained the same body of information. However, in longer forecast horizon the null hypothesis has to be rejected in majority of the cases. Survey variances do play a significant role in explaining the actual realized values. It also suggests that implied volatility did not efficiently utilise all past information in longer forecast horizon.

Table 6.2

Realised Volatility over the remaining life of the three-month T-bill futures-options regressed on implied volatility and survey variance for $F_2(\varphi) = SV$ where H_o: $(\alpha_0, \beta_1, \beta_2) = (0,1,0)$

Horizon	IMP23p	IMP2	IMP7	IMP23
1	Pass	Pass	Pass	N/A
2	Pass	Pass	Pass	Fail
3	Pass	Pass	Pass	Pass
4	Fail	Fail	Fail	Fail
5	Pass	Fail	Fail	Pass
6	Fail	Fail	Fail	Fail

using weekly data on stock indices.

This framework is extended to both historical and time-series based forecasts. The following regression is estimated using both implied volatility/survey variance and GARCH/MAV model forecasts:

$$\sigma^2 = \alpha_0 + \beta_1 IMP_2 + B_2 GAR2/MAV + \varepsilon_t$$

$$\sigma^2 = \alpha_0 + \beta_1 SV + B_2 GAR2/MAV + \varepsilon_t$$

The table below reports comparisons of forecasts of the monthly variance of three-month Treasury bill returns (For details see Appendix 6.6). The evidence presented here seems to indicate that at near term forecast horizon, GARCH estimates is a subset of the information contained in implied volatilities i.e. there is no difference between the body

Table 6.3

Volatility over the remaining life of the three-month T-bill futures-options regressed on implied volatility and GAR2 or MAV Where H_o: $(\alpha_0, \beta_1, \beta_2) = (0,1,0)$

Horizons	GAR2	MAV
1	Pass	Pass
2	Pass	Fail
3	Pass	Pass
4	Pass	Fail
5	Fail	Pass
6	Fail	Fail

of information contained, since the null hypothesis cannot be rejected at 5% significance level with $\chi^2(3)$. However, for longer forecast horizon, namely fifth and sixth, the result is completely different. It suggests that there is a difference in the body of knowledge incorporated in the GARCH estimate and the implied volatility. Hence, to improve the prediction for actual volatility, GARCH estimate is required. This is inconsistent with the notion of efficiency. The result presented here seems to be consistent with Day and Lewis (1992, 1993) where they found that although both implied volatilities and GARCH forecasts are individually significant in explaining the out-of-sample variation in conditional volatility, neither of the estimated coefficients reported is statistically significant (weekly data). Day and Lewis (1993) using crude oil derivatives found that for near-term horizon, neither GARCH models nor historic volatility add much explanatory power to predictions of near-term volatility based on implied volatility. The above result suggest market professionals interested in forecasting near-term volatility (up to 2 months in the future) may wish to avoid complex time series model for volatility and restrict their attention to the forecasts implicit in option prices.

Lamoureux and LaStrapes (1993), however, found for both the in-sample tests and the out-of-sample encompassing tests that while implied volatility helps predict future volatility, the orthogonality restriction of the joint null hypothesis is rejected for 10 individual stocks with publicly traded options on the CBOE (daily data). Kroner, Kneafsey, and Classens (1995), using commodity data, found that both the GARCH parameters and the ISD parameters are significant. This implies the ISDs contain information about future volatility that is not captured by the GARCH model, and the time series of volatility contains information about future volatility that is not incorporated into option price. However, when a simple moving average is used to compare it with implied volatility, no conclusive evidence can be drawn.

This test is then repeated using survey variance in place of implied volatility. Majority of the case, the results seem to point to the direction that the presence GARCH or simple moving average forecasts will not help to predict actual realised value. The only exception is in the sixth forecast horizon.

Another method to test the orthogonality restriction is to run the following multiple regression:

$$\sigma^2 - Imp_t = \alpha_0 + \beta_1 Imp_t + \beta_2 SV + \beta_3 SSM + \beta_4 FN_t + \varepsilon_t$$

Where

SSM represents mean of the survey forecast

FN_t represents the future price at a specify date

The regression is specified in such a manner so as to allow the testing of the following hypothesis: (α_0, β_1, β_2, β_3, β_4) should not be significantly different from zero if the market is efficient. Further information such as data obtained from the Blue Chip Financial Survey or futures price should not be able to add any predictive power.

The result of the regression analysis for the above hypothesis is presented in Table 6.4. The evidence seems to indicate that: no other factors can improve the forecast of future actual volatility except in the longer forecast horizons. The factor that is crucial in

Table 6.4

$$\sigma^2 - IMP_t = \alpha_0 + \beta_1 IMP_t + \beta_2 SV + \beta_3 SSM + \beta_4 FN_t + \varepsilon_t$$

Where H_0: (σ^2 - IMP_t = 0)

Horizon	IMP23p	IMP2	IMP7	IMP23
1	Pass	Pass	Pass	N/A
2	Pass	Pass	Pass	Fail
3	Pass	Pass	Pass	Pass
4	Fail	Fail	Fail	Fail
5	Pass	Fail	Fail	Pass
6	Fail	Fail	Fail	Fail

improving the predictive power is survey variance (as suggested by t-statistic). This result is consistent with the previous one displayed in table 6.3.

The same approach is also used for historical and time-series based forecasts. The results are presented below: (For details, refer to Appendix 6.8)

Table 6.5 LL

$$\sigma^2 - IMP_t = \alpha_0 + \beta_1 SV + \beta_2 GAR2/MAV + \varepsilon_t$$

where H_0: (σ^2 - $IMP_t = 0$)

Horizon	GAR2	MAV
1	Pass	Pass
2	Pass	Pass
3	Pass	Pass
4	Fail	Fail
5	Fail	Fail
6	Fail	Fail

Similar to the results obtain above, the evidence seems to point out that for shorter forecast horizon, the addition of further information will not be able to add any predictive power. However, for longer forecast horizon this is not the case. Survey variance seems to play a crucial role in increasing predictive power of realized volatility. Indeed, the R^2 seems to support this.

6.6 CONCLUSION

It is possible that implied volatility computed from futures-options prices may reflect the market expectations of future realised volatility. The results of the empirical studies suggest that implied volatility derived from Black model are useful for forecasting future volatility, but implied volatility alone in some occasions especially in longer forecast horizon are not optimal predictors. A combination of implied volatility and other factors such as survey variance may be useful in forecasting future realised volatility.

Appendices

Appendix 6.1

Cauchy-Schwarz Inequality

$$(x,y) \leq \sqrt{(x,x)}\sqrt{(y,y)}$$

The theorem follows from:

$$0 \leq (\alpha x + \beta y, \alpha x + \beta y) = \alpha^2(x,x) + 2\alpha\beta(x,y) + \beta^2(y,y)$$

by setting $\alpha = \sqrt{(y,y)}$ and $\beta = -\sqrt{(x,x)}$

From an inner product a norm can be defined as $\sqrt{(x,x)}$, often denoted as $|x|$. It satisfies the conditions

$$|x| \geq 0, \quad |x| > 0 \text{ if } x \neq 0,$$

$$|\alpha x| = |\alpha|\ |x|, \quad |x+y| \leq |x| + |y|.$$

The last inequality follows from the Cauchy-Schwarz inequality by

$$|x+y|^2 = |x|^2 + |y|^2 + 2(x,y) \leq |x|^2 + |y|^2 + 2|x|.|y| = (|x|+|y|)^2$$

Then $|x-y|$ is defined as the distance between x and y and is called the metric of the space.

A sequence $\{x^{(n)}\}$ is said to be a Cauchy sequence if

$$\lim_{n\to\infty,\ m\to\infty} |x^{(n)}-x^{(m)}| = 0$$

An element x is the limit of a sequence $\{x^{(n)}\}$ if

$$\lim_{n\to\infty} |x_{(n)}-x| = 0$$

A normed linear vector space is complete if there exits a limit in the space to every Cauchy sequence.

If $x^{(n)} \to x$ and $y^{(n)} \to y$ as $n \to \infty$, then

$$(x^{(n)},y^{(n)}) \rightarrow (x,y)$$

We have

$$|(x^{(n)},y^{(n)}) - (x,y)| = |(x^{(n)}-x,y^{(n)}-y) + (x,y^{(n)}-y) + (x^{(n)}-x,y)|$$

$$\leq |(x^{(n)} - x,y^{(n)}-y)| + |(x,y^{(n)}-y)| + |(x^{(n)}-x,y)|$$

$$\leq |x^{(n)}-x|.|y^{(n)}-y| + |x|.|y^{(n)}-y| + |x^{(n)}-x|.|y|$$

by the Cauchy-Schwarz inequality, and the right-hand side of the above equation converges to 0.

Appendix 6.2

	GARCH (1,1)	GARCH (1,1)*
CON	-0.0131	-0.0164
	-2.5093	*-6.8783*
$\delta_{1t}M_t$	0.484E-02	
	0.5318	
$\delta_{2t}T_t$	0.858E-02	0.897E-02
	2.1905	3.2989
$\delta_{3t}W_t$	-0.291E-02	
	-0.7998	
$\delta_{4t}F_t$	-0.126E-02	
	-0.2865	
$\delta_{5t}H_t$	-0.320E-03	
	-0.0303	
$\delta_{6t}DIF_t$	0.652E-02	0.875E-02
	1.5407	*6.9955*
α_0	0.218E-02	0.219E-02
	10.9639	*12.6615*
α_1	0.1010	0.1008
	17.8871	*18.0924*
α_2		
α_3		
α_4		
α_5		
α_6		
α_7		
α_8		
α_9		
α_{10}		

α_{11}		
α_{12}		
β_1	0.8984	0.8992
	192.449	*196.116*
β_2		
$\theta_1 M_t$	-0.149E-03	
	-0.5364	
$\theta_2 T_t$	-0.720E-03	-0.708E-03
	-3.0585	*-3.4422*
$\theta_3 W_t$	-0.152E-02	-0.151E-02
	-6.4171	*-6.9837*
$\theta_4 F_t$	0.219E-03	
	0.9593	
$\theta_5 H_t$	0.203E-02	0.199E-02
	6.2023	*7.4246*
$\theta_6 DIF_t$	-0.119E-02	-0.119E-02
	-7.4075	*-11.2785*
LLH	2969.72	2968.21
Likelihood Ratio		3.2

KEY:
LLH = Log of Likelihood Function
Likelihood Ratio Test with 5% Critical Value = 11.41

Appendix 6.3

Wald Test

The Wald test (W), which was suggests by Abraham Wald in 1943, allow one to compute Wald statistics for testing r independent linear or non-linear independent restrictions on the parameters of the regression model Θ. It is based on the Maximum Likelihood method. The Wald approach starts at the alternative hypothesis and considers movement towards the null.

Let the r restrictions on Θ be given by:

$$(\Theta) = 0 \quad (a)$$

where (.) is a rx1 first-order differentiable function of the unknown parameters of the regression model (both deterministic and the stochastic parts), and denote the estimator of the (asymptotic) variance matrix of Θ by $\sigma^2 V(\Theta)$. Then the Wald statistic for testing the r restrictions in (a) is given by:

$$W = '[V(\Theta)']^{-1}/\sigma^2$$

where W is a χ^2-distribution with r degree of freedom. However, before calculating the W statistic, one has to check whether the rank condition on is full rank or not. Calculation can only proceed if [] is full rank i.e. Rank [] = r

There is an interesting relationship that is valid for linear regression models between Wald test (W), Likelihood Ratio test (LR) which compares the two hypothesis directly, and Langrangian Multiplier test (LM) which starts at the null and asks whether movement toward the alternative would be an improvement. This is:

$$W \geq LR \geq LM$$

What this suggests is that a hypothesis can be rejected by the W test but not rejected by the LM test.[37]

[37] There is a lot of literature on the W, LR, and LM tests. For a survey, refer to R.F. Engle, "Wald, Likelihood Ratio, and Lagranger Multiplier Tests in Econometrics." in Z. Griliches and M.D. Intrilligator (eds.), Handbook of Econometrics, Vol2 (North Holland Publishing Co., 1984).

Appendix 6.4
Results of Regressions
For Table 6.1

$$\sigma^2 = \alpha + \beta_1 IMP_t + u_t$$

where H_o: $(\alpha, \beta_1) = (0,1)$

For β_1 = IMP23P

Horizon	Variables		Statistics		
	α	β_1	R^2	DW	$\chi^2(0,1)$
1	0.7158	0.5931	0.1186	1.9590	2.3574
	1.3898	*2.0567*			
2*	0.1434	1.0672	0.2730	1.6600	0.7693
	0.2259	*1.6078*			
3	0.6670	0.7612	0.0798	2.4815	0.8560
	0.8698	*1.7798*			
4	0.1934	1.1773	0.1284	2.2283	1.4587
	0.1973	*2.0231*			
5	0.0586	1.2110	0.2932	1.9007	1.8788
	0.0781	*2.9801*			
6*	-0.3845	1.4627	0.4907	1.9534	3.0171
	-0.7427	*3.5075*			

Key

* = Adjusted White's Heteroscedasticity-Consistent Standard Error is used
R^2 statistic reported here is Adjusted R_2
T-ratios are in Italic

For β_1 = IMP2

Horizon	Variables		Statistics		
	α	β_1	R^2	DW	$\chi^2(0,1)$
1	0.6251	1.0442	0.0892	1.9088	2.8396
	1.0695	*1.8302*			
2*	-0.0853	1.3181	0.4454	1.7915	2.6932
	-0.1683	*2.2636*			
3	0.8498	0.6340	0.0429	2.3573	1.1846
	1.0810	*1.4563*			
4	0.1179	1.3183	0.1596	2.1047	2.4349
	0.1266	*2.2331*			
5	0.3971	0.9961	0.1899	1.9478	1.2713
	0.4972	*2.3351*			
6*	-0.5670	1.5628	0.5153	1.8759	3.6763
	-0.9558	*3.4775*			

Key

* = Adjusted White's Heteroscedasticity-Consistent Standard Error is used
R^2 statistic reported here is Adjusted R_2 . T-ratios are in Italic

For β_1 = IMP7

Horizon	Variables		Statistics		
	α	β_1	R^2	DW	$\chi^2(0,1)$
1	0.5797	1.1951	0.1141	2.0290	3.5585
	1.0224	*2.0223*			
2*	0.2823	1.1071	0.2640	1.8678	2.2969
	0.5277	*1.6341*			
3	0.6110	0.8327	0.1062	2.5111	0.9686
	0.8373	*1.9927*			
4	-0.1350	1.5250	0.1690	2.0972	3.0115
	-0.1336	*2.2956*			
5	0.3723	1.0412	0.1871	1.9928	1.6159
	0.4578	*2.3180*			
6	-0.3494	1.4235	0.4604	1.9080	2.4616
	-0.4275	*3.7147*			

Key

* = Adjusted White's Heteroscedasticity-Consistent Standard Error is used
R^2 statistic reported here is Adjusted R_2
T-ratios are in Italic

For β_1 = IMP23

Horizon	Variables		Statistics		
	α	β_1	R^2	DW	$\chi^2(0,1)$
2*	-0.0154	1.5827	0.6454	1.7414	1.7414
	-0.0498	*3.5104*			
3	0.2153	1.2320	0.1461	2.5696	1.8377
	0.2682	*2.2975*			
4	-0.1120	1.5715	0.2519	2.0754	4.2374
	-0.1347	*2.8411*			
5	0.4187	1.0466	0.1522	2.4518	1.9423
	0.4836	*2.1003*			
6*	-0.1981	1.4261	0.3272	2.0033	2.3999
	-0.3069	*2.5971*			

Key

* = Adjusted White's Heteroscedasticity-Consistent Standard Error is used
R^2 statistic reported here is Adjusted R_2
T-ratios are in Italic

$$\sigma^2 = \alpha + \beta_1 SV_t + u_t$$
where H_o: $(\alpha, \beta_1) = (0,1)$

Horizon	Variables		Statistics	
	α	β_1	R^2	DW
1	0.5245	9.1522	0.0735	2.0307
	0.7985	*1.7044*		
2	0.6943	6.0419	0.0820	1.4443
	1.2587	*1.7220*		
3	0.3920	8.6877	0.0732	2.2876
	0.4244	*1.7250*		
4*	-0.3150	8.8668	0.6576	2.5325
	-0.8421	*4.5545*		
5	0.6207	4.1578	0.3179	2.4685
	1.1036	*3.1391*		
6*	-0.5143	6.9103	0.7003	2.5796
	-1.2993	*4.5201*		

Key

* = Adjusted White's Heteroscedasticity-Consistent Standard Error is used
R^2 statistic reported here is Adjusted R_2
T-ratios are in Italic

$$\sigma^2 = \alpha + \beta_1 GAR2/MAV + u_t$$
where H_o: $(\alpha, \beta_1) = (0,1)$
For β_1=MAV

Horizon	Variables		Statistics		
	α	$\beta 1$	R^2	DW	$\chi^2(0,1)$
1	0.9438	0.6107	0.0042	1.9618	4.2677
	1.1524	*1.0492*			
2	1.1958	0.221	0.0338	1.6091	9.3736
	2.5603	*0.8577*			
3	1.2352	0.446	0.0168	2.2681	3.648
	1.9078	*1.1951*			
4*	-0.934	2.7469	0.5935	1.7436	24.5876
	-1.4827	*3.7693*			
5*	0.1557	1.6128	0.3663	2.581	10.0964
	0.2124	*1.9792*			
6*	-0.632	2.5992	0.7222	1.8832	33.6775
	-1.2833	*6.3242*			

Key

* = Adjusted White's Heteroscedasticity-Consistent Standard Error is used
R^2 statistic reported here is Adjusted R_2. T-ratios are in Italic
T-ratios are in Italic

For β_1 = GAR2

Horizons	Variables		Statistics		
	α	$\beta 1$	R^2	DW	$\chi^2(0,1)$
1	0.9901	0.2268	0.0517	1.8726	28.2453
	2.024	*1.5194*			
2	1.1623	0.2843	-0.0223	1.5824	4.3974
	2.0904	*0.7206*			
3	1.677	0.0852	-0.0333	1.9918	22.6264
	3.1138	*0.4403*			
4	0.4817	1.2876	0.1762	2.3302	4.7675
	0.6365	*2.3436*			
5*	0.0662	1.9668	0.3834	2.3033	15.2877
	0.1066	*2.5405*			
6	0.2121	1.5614	0.7989	1.6996	26.4165
	0.6709	*7.783*			

KEY

* = Adjusted White's Heteroscedasticity-Consistent Standard Error is used
R^2 statistic reported here is Adjusted R_2
T-ratios are in Italic

Appendix 6.5

For Table 6.2

$\sigma^2 = \alpha + \beta_1 IMP_t + \beta_2 SV + ut$
where H_o: $(\alpha, \beta_1, \beta_2) = (0, 1, 0)$

For β_1 = IMP23p

Horizon	Variables			Statistics		
	α	β_1	β_2	R^2	DW	$\chi^2(0,1,0)$
1	0.8151	0.7180	-2.5310	0.0804	1.9255	2.3036
	1.1524	*1.0826*	*-0.2101*			
2*	0.0253	0.9515	2.3849	0.2539	1.5643	1.2122
	-0.0466	*1.2851*	*0.7423*			
3	0.2668	0.4848	4.9918	0.0627	2.5239	1.4017
	0.2836	*0.8538*	*0.7492*			
4	-0.0639	-0.2592	9.4314	0.6456	2.4329	33.7818
	-0.1019	*-0.5711*	*5.4949*			
5	-0.3534	0.8290	2.9932	0.4198	2.5495	7.2164
	-0.5012	*2.0400*	*2.2198*			
6*	-0.9591	0.6201	5.3106	0.7415	2.4683	20.5228
	-2.0442	*1.6885*	*3.1785*			

Key
* = Adjusted White's Heteroscedasticity-Consistent Standard Error is used
R^2 statistic reported here is Adjusted R_2
T-ratios are in Italic

For β_1 = IMP2

Horizon	Variables			Statistics		
	α	β_1	β_2	R^2	DW	$\chi^2(0,1,0)$
1	0.5463	0.7771	2.8833	0.0508	1.9533	2.7960
	0.8207	*0.6709*	*0.2667*			
2*	-0.2286	1.2433	1.7203	0.4270	1.6956	2.9338
	-0.5106	*1.9087*	*0.7979*			
3	0.2603	0.3141	6.5759	0.0475	2.4613	2.3067
	0.2705	*0.5934*	*1.0566*			
4	-0.0204	-0.3569	9.6931	0.6493	2.4154	34.7569
	-0.0338	*-0.7247*	*5.3780*			
5	-0.2237	0.6561	3.4085	0.3777	2.6652	8.0869
	-0.3017	*1.6521*	*2.5361*			
6*	-1.1066	0.7383	5.1552	0.7646	2.4134	23.4021
	-2.3357	*2.1677*	*3.5844*			

Key: * = Adjusted White's Heteroscedasticity-Consistent Standard Error is used
R^2 statistic reported here is Adjusted R_2
T-ratios are in Italic

For β_1 = IMP7

Horizon	Variables			Statistics		
	α	β_1	β_2	R^2	DW	$\chi^2(0,1,0)$
1	0.5480	1.1020	0.9933	0.0742	2.0355	3.4158
	0.8340	*1.0085*	*0.1023*			
2*	-0.0096	0.9778	3.2825	0.2629	1.6993	3.2624
	-0.0196	*1.3867*	*1.3207*			
3	0.2866	0.6166	3.8906	0.0810	2.5586	1.2838
	0.3099	*1.0968*	*0.5847*			
4	-0.0988	-0.2443	9.3504	0.6433	2.4768	34.6041
	-0.1492	*-0.4439*	*5.2525*			
5	-0.1778	0.6536	3.3816	0.3652	2.6650	8.1202
	-0.2362	*1.5305*	*2.4599*			
6	-0.9391	0.5655	5.4696	0.7315	2.4250	20.0793
	-1.7360	*1.6208*	*3.8901*			

Key: * = Adjusted White's Heteroscedasticity-Consistent Standard Error is used.
R^2 statistic reported here is Adjusted R_2
T-ratios are in Italic

For β_1 = IMP23

Horizon	Variables			Statistics		
	α	β_1	β_2	R^2	DW	$\chi^2(0,1,0)$
2*	-0.0060	1.5883	-0.1116	0.6277	1.7462	13.2863
	-0.0238	*3.0223*	*-0.0627*			
3	-0.0524	1.0150	3.3573	0.1208	2.6420	2.0943
	-0.0554	*1.5164*	*0.5563*			
4*	-0.5410	0.2846	8.2646	0.6466	2.5400	32.2985
	-0.8435	*0.3486*	*2.6567*			
5	0.2867	0.3419	3.5642	0.2932	2.7229	6.9192
	0.3617	*0.6090*	*2.1423*			
6*	-1.0035	0.5347	5.9366	0.7211	2.4460	26.5555
	-1.8298	*1.1895*	*3.4457*			

Key: * = Adjusted White's Heteroscedasticity-Consistent Standard Error is used.
R^2 statistic reported here is Adjusted R_2. T-ratios are in Italics.

Appendix 6.6

For Table 6.3
$\sigma^2 = \alpha + \beta_1 IMP23 + \beta_2 GAR23/MAV + u_t$
where H_o: $(\alpha,\beta_1,\beta_2) = (0,1,0)$
For β_2 = GAR23

Horizon	Variables			Statistics		
	α	β_1	β_2	R^2	DW	$\chi^2(0,1,0)$
2*	-0.0385	1.5277	0.0532	0.6282	1.7330	13.3310
	-0.1066	*3.3569*	*0.2219*			
3*	0.2582	1.9616	-0.7919	0.1631	2.4797	3.3603
	0.3935	*1.6545*	*-1.0480*			
4	-0.1719	1.5324	0.0951	0.2133	2.1031	4.0487
	-0.1797	*2.4183*	*0.1384*			
5	0.3841	1.4512	-0.4345	0.1369	2.1921	2.5884
	0.4393	*2.0662*	*-0.8250*			
6*	-0.2862	1.3631	0.1508	0.2796	1.9990	2.3168
	-0.4155	2.3950	0.7635			

Key: * = Adjusted White's Heteroskedasticity-Consistent Standard Error is used.
R^2 Statistic reported here is Adjusted R^2
T-ratios are in Italic

For β_2 = MA

Horizon	Variables			Statistics		
	α	β_1	β_2	R^2	DW	$\chi^2(0,1,0)$
2*	0.1962	1.9161	-0.3951	0.7143	1.8727	23.3839
	0.7518	*3.8593*	*-2.2886*			
3	-0.0408	2.1293	-0.7009	0.1558	2.3842	3.1339
	-0.0491	*2.2251*	*-1.1292*			
4*	-1.0681	0.2425	2.5669	0.5768	1.7659	23.8392
	-2.0333	*0.3880*	*2.1920*			
5*	-0.0730	0.2732	1.4413	0.3390	2.6913	8.5758
	-0.1338	*0.4124*	*1.2410*			
6	-0.5736	-0.0951	2.6889	0.7017	1.8634	23.9911
	-0.9721	*-0.1969*	*4.3102*			

Key * = Adjusted White's Heteroskedasticity-Consistent Standard Error is used.
R^2 Statistic reported here is Adjusted R^2
T-ratios a Italic

$$\sigma^2 = \alpha + \beta_1 IMP2 + \beta_2 GAR2 + u_t$$

Where H_o: $(\alpha, \beta_1, \beta_2) = (0,1,0)$

For β_2 = GAR2

Horizon	Variables			Statistics		
	α	β_1	β_2	R^2	DW	$\chi^2(0,1,0)$
1	0.6219	1.0607	-0.0050	0.0478	1.9089	2.7165
	0.9958	*0.9515*	*-0.0173*			
2*	0.1656	1.5803	-0.4873	0.4751	1.7703	5.0362
	0.3600	*2.6531*	*-1.0310*			
3	0.3240	1.4036	-0.4038	0.0671	2.0671	2.8382
	0.3686	*1.8932*	*-1.2739*			
4	0.0052	0.7143	0.8261	0.1670	2.3144	3.6366
	0.0056	*0.8829*	*1.0862*			
5*	-0.5067	0.5382	1.6390	0.4101	2.4037	9.4655
	-0.8885	*1.3985*	*1.8338*			
6	0.2781	-0.0753	1.6129	0.7838	1.7076	26.6398
	0.5362	*-0.1642*	*4.2890*			

Key * = Adjusted White's Heteroskedasticity-Consistent Standard Error is used.
R^2 Statistic reported here is Adjusted R^2
T-ratios are in Italic

For β_2 = MAV

Horizon	Variables			Statistics		
	α_0	β_1	β_2	R^2	DW	$\chi^2(0,1,0)$
1	0.6490	1.1025	-0.0483	0.0484	1.9065	2.7315
	1.0281	*1.4380*	*-0.1171*			
2*	-0.0620	2.0070	-0.6329	0.5815	1.7731	11.4027
	-0.1766	*3.1727*	*-2.1140*			
3	0.8520	0.6222	0.0121	0.0013	2.3599	1.1356
	1.0487	*0.7918*	*0.0182*			
4*	-0.8052	-0.2020	2.8968	0.5753	1.7127	25.3925
	-1.3227	*-0.3913*	*3.1743*			
5*	-0.2019	0.4042	1.3406	0.3591	2.5587	7.3594
	-0.3577	*0.8717*	*1.2477*			
6	-0.9054	0.4690	2.0996	0.7262	1.8919	18.2901
	-1.6496	*1.0965*	*3.4325*			

Key * = Adjusted White's Heteroskedasticity-Consistent Standard Error is used.
R^2 Statistic reported here is Adjusted R^2
T-ratios are in Italic

$$\sigma^2 = \alpha + \beta_1 SV + \beta_2 GAR23/MA + u_t$$

For β_2 = GAR23

Horizon	Variables			Statistics	
	A	β_1	β_2	R^2	DW
1	0.5678	10.7954	-0.1317	0.0360	2.0471
	0.83078	*1.4409*	*-0.3215*		
2*	-0.0412	1.8959	0.9051	0.3821	1.3075
	-0.1033	*0.7157*	*1.8956*		
3	0.4086	9.2743	-0.0901	0.0340	2.2590
	0.4306	*1.4609*	*-0.1575*		
4*	-0.4537	8.7330	0.1467	0.6417	2.5648
	-0.8798	4.0617	0.3185		
5	0.7753	4.5309	-0.2044	0.2895	2.2313
	1.2040	2.9726	-0.5298		
6*	-0.3741	7.2504	-0.2138	0.6853	2.4938
	-1.0393	*3.8200*	*-0.7621*		

KEY: * = Adjusted White's Heteroskedasticity-Consistent Standard Error is used.
R^2 Statistic reported here is Adjusted R^2
T-ratios are in Italic

$$\sigma^2 = \alpha + \beta_1 SV + \beta_2 GAR2/MAV + u_t$$

For β_2 = GAR2

Horizon	Variables			Statistics	
	A	β_1	β_2	R^2	DW
1	0.5744	7.8062	0.0432	0.0324	2.0127
	0.7650	*0.7355*	*0.1482*		
2	0.6875	5.9982	0.0109	0.0361	1.4441
	1.1000	*1.5081*	*0.0257*		
3	0.3040	10.3245	-0.1129	0.0440	2.1124
	0.3189	*1.7149*	*-0.5156*		
4*	-0.3476	8.7549	0.0523	0.6398	2.5651
	-0.7025	*3.5366*	*0.0887*		
5	-0.0310	2.0374	1.3637	0.3984	2.4648
	-0.0488	*1.2033*	*1.8461*		
6	-0.2795	2.8697	1.0715	0.8344	1.9318
	-0.7403	*2.0022*	*3.5136*		

KEY: * = Adjusted White's Heteroskedasticity-Consistent Standard Error is used.
R^2 Statistic reported here is Adjusted R^2
T-ratios are in Italic

$$\sigma^2 = \alpha + \beta_1 SV + \beta_2 GAR2/MA + u_t$$

For β_2 = MA

Horizon	**Variables**			**Statistics**	
	A	β_1	β_2	R^2	**DW**
1	0.4645	8.2760	0.1032	0.0350	2.0288
	0.6609	*1.3168*	*0.2848*		
2*	0.1962	1.9161	-0.3951	0.7143	1.8727
	0.7518	*3.8593*	*-2.2886*		
3	0.3967	7.7012	0.1210	0.0359	2.3681
	0.4209	*1.2143*	*0.2652*		
4*	-1.0592	5.7875	1.4486	0.7381	2.4596
	-2.1238	*2.8029*	*1.9903*		
5*	-0.2300	2.6639	1.1531	0.4550	2.8400
	-0.3650	*1.4051*	*1.3489*		
6	-0.9543	3.7812	1.5471	0.8096	1.9802
	-2.2481	*2.7258*	*3.0070*		

KEY: * = Adjusted White's Heteroskedasticity-Consistent Standard Error is used.
R^2 Statistic reported here is Adjusted R^2
T-ratios are in Italic

Appendix 6.7

For Table 6.4

$$\sigma^2\text{-IMP}_t = \alpha + \beta_1 \text{IMP}_t + \beta_2 \text{SSD} + \beta_3 \text{SSM} + \text{B}_4 \text{FN}_t + \text{ut}$$

where H_o: (σ^2 - $\text{IMP}_t = 0$)

For β_1, β_4 = IMP23p, FN23P

Horizon	Variables					Statistics		
	α	β_1	β_2	β_3	β_4	R^2	DW	χ^2
1	-333.7802	-0.2711	-0.7331	3.2052	3.3468	0.0640	2.0358	6.0174
	-1.4826	*-0.4207*	*-0.0592*	*-1.6135*	*1.4792*			
2	-180.8313	0.1073	3.3383	1.8595	1.8000	0.0499	2.1588	5.9643
	-1.5303	*0.2084*	*0.9919*	*1.7828*	*1.5172*			
3	123.4703	-0.7978	5.2797	-0.9569	-1.2448	-0.1119	2.4647	1.9878
	0.7280	*-1.1734*	*0.7562*	*-0.6283*	*-0.7301*			
4	-54.9310	-1.2761	9.5779	0.4964	0.5513	0.5306	2.4455	30.7743
	-0.4432	*-2.2661*	*5.1963*	*0.4281*	*0.4429*			
5*	-62.6547	0.0561	3.3280	0.4282	0.6302	0.0682	2.4610	7.1862
	-0.4896	*0.0827*	*2.1844*	*0.3291*	*0.4923*			
6	57.0234	-0.0535	6.0470	-0.9167	-0.5674	0.6050	2.4710	30.5667
	0.7227	*-0.0985*	*3.6670*	*-1.2299*	*-0.7155*			

* = Adjusted White's Heteroscedasticity-Consistent Standard Error is used
R^2 statistic reported here is Adjusted R_2
T-ratios are in Italic

For β_1, β_4 = IMP2, FN2

Horizon	Variables					Statistics		
	α	β_1	β^2	β^3	β_4	R^2	DW	χ^2
1	-60.2928	-0.4358	3.5344	0.7655	0.5978	-0.1390	2.0769	3.6660
	-0.4232	*-0.3615*	*0.3106*	*0.5992*	*0.4175*			
2*	78.5899	0.0223	0.9265	-0.5621	-0.7977	-0.0684	1.5259	4.0893
	0.6430	*0.0290*	*0.3310*	*-0.4630*	*-0.6521*			
3*	226.6146	-1.2664	6.8482	-1.7829	-2.2849	0.0303	2.3911	5.2806
	0.8867	*-2.0565*	*1.6459*	*-0.8096*	*-2.2849*			
4*	-46.2949	-1.3034	9.7339	0.4196	0.4639	0.5271	2.4597	32.0942
	-0.4576	*-2.2197*	*3.2725*	*0.4345*	*0.4579*			
5*	-286.5035	-0.1008	5.1036	2.6343	2.8617	0.3909	2.2049	18.3947
	-2.4269	*2.4309*	*2.2449*	*2.2770*	*-0.2260*			
6*	36.7856	0.0334	5.9298	-0.7116	-0.3664	0.6384	2.4954	34.256
	0.5867	*0.0655*	*4.0019*	*-1.1989*	*-0.5823*			

* = Adjusted White's Heteroscedasticity-Consistent Standard Error is used
R^2 statistic reported here is Adjusted R_2
T-ratios are in Italic

For β_1, β_4 = IMP7, FN7

Horizon	Variables					Statistics		
	α	β_1	β_2	β_3	β_4	R^2	DW	χ^2
1	66.9864	0.1046	-1.0166	-0.4303	-0.6768	-0.1568	2.1268	3.8439
	0.3922	*0.0732*	*-0.0822*	*-0.2670*	*-0.3955*			
2	-151.6244	-0.3015	4.0698	1.6685	1.5042	0.0598	2.3708	7.8558
	-1.4630	*-0.7073*	*1.2476*	*1.7246*	*1.4485*			
3*	228.8079	-0.7440	2.1023	-1.8911	-2.3005	0.0340	2.4611	5.7465
	1.0079	*-1.1749*	*0.5920*	*-0.9224*	*-1.0103*			
4	-42.6024	-1.2153	9.5487	0.3769	0.4267	0.5181	2.5588	31.6156
	-0.4824	*-1.3370*	*4.9531*	*0.4560*	*0.4811*			
5*	240.6406	-0.5600	4.7421	2.3738	2.3985	0.2906	2.5230	14.1753
	-2.1153	*-1.2146*	*2.0242*	*2.0075*	*2.1172*			
6*	26.9863	0.1399	6.0582	-0.7375	-0.2630	0.5908	2.2571	28.6428
	0.4738	*0.3052*	*3.3080*	*-1.1015*	*-0.4630*			

* = Adjusted White's Heteroscedasticity-Consistent Standard Error is used
R^2 statistic reported here is Adjusted R_2
T-ratios are in Italic

For β_1, β_4 = IMP23, FN23

Horizon	Variables					Statistics		
	α	β_1	β_2	β_3	β_4	R^2	DW	χ^2
2*	-85.9849	0.4124	0.8725	0.8505	0.8592	0.1068	1.7805	14.4064
	-1.1963	*0.6546*	*0.5422*	*1.2015*	*1.1949*			
3*	181.5592	-0.1427	1.5561	-1.5882	-1.8233	-0.0311	2.4917	4.9017
	0.9600	*-0.1610*	*0.4139*	*-0.8703*	*-0.1610*			
4*	22.7186	-0.2785	8.2393	-0.4552	-0.2785	0.5092	2.4308	32.2254
	0.3563	*-0.2720*	*2.7342*	*-0.7809*	*-0.2720*			
5*	-94.0183	-1.0506	4.2450	1.0937	0.9354	0.1109	2.5955	8.6646
	-1.7322	*-1.8791*	*1.3095*	*1.7337*	*1.7323*			
6*	-3.6208	0.1965	6.8582	-0.4664	0.1965	0.6251	2.5037	33.5188
	-0.0798	*0.3009*	*3.7820*	*-0.7603*	*0.0937*			

* = Adjusted White's Heteroscedasticity-Consistent Standard Error is used
R^2 statistic reported here is Adjusted R_2
T-ratios are in Italic

Appendix 6.8

For Table 6.5 LL

$$\sigma^2\text{-IMP2} = \alpha + \beta_1 SV + \beta_2 GAR2 + u_t$$

where H_o: $(\alpha, \beta_1, \beta_2) = 0$

For β_2 = GAR2

Horizon	Variables			Statistics		
	α	β_1	β_2	R^2	DW	$\chi^2(\sigma^2\text{-IMP2}=0)$
1	0.4783	3.0931	-0.0644	-0.0865	1.9569	2.8104
	0.6433	*0.2943*	*-0.2232*			
2	0.2037	4.1429	-0.3928	0.0184	1.6590	4.0425
	0.4328	*1.3831*	*-1.2307*			
3	0.0971	6.3687	-0.6763	-0.0184	2.5994	2.0242
	0.1025	*1.0046*	*-1.1844*			
4*	-0.8881	7.4180	-0.4051	0.4157	2.3205	20.7398
	-1.5184	*2.6851*	*-0.6247*			
5*	-1.0781	1.6757	0.8619	0.2162	2.3780	8.9514
	-1.6251	*0.7578*	*1.1613*			
6	-1.2524	3.4309	0.2923	0.5517	1.8066	23.5136
	-2.7863	*2.0106*	*0.8050*			

= Adjusted White's Heteroskedasticity-Consistent Standard Error is used.
R^2 Statistic reported here is Adjusted R^2
T-ratios are in Italic

For β_2 = MAV

Horizon	Variables			Statistics		
	α_0	β_1	β_2	R^2	DW	$\chi^2(\sigma^2\text{-IMP}_2=0)$
1	0.5856	1.5674	-0.0568	-0.0877	1.9315	2.7824
	0.8399	*0.2514*	*-0.1579*			
2	0.1614	4.1363	-0.3077	0.0572	1.6559	5.0309
	0.3689	*1.4562*	*-1.5488*			
3	-0.0469	6.1189	-0.5095	-0.0252	2.4687	1.8569
	-0.0496	*0.9620*	*-1.1134*			
4*	-1.6662	4.3767	1.0230	0.4560	2.2121	23.6808
	-2.4739	*1.6857*	*1.1750*			
5*	-1.0643	2.3166	0.5397	0.2040	2.4852	8.5546
	-1.3671	*1.2459*	*0.7057*			
6	-1.4938	3.2716	0.6237	0.5705	1.7646	25.1083
	-3.2382	*2.1701*	*1.1154*			

* = Adjusted White's Heteroskedasticity-Consistent Standard Error is used.
R^2 Statistic reported here is Adjusted R^2
T-ratios are in Italic

σ^2-IMP23 = $\alpha + \beta_1 SV + \beta_2 GAR23/MAV + u_t$

where H_o: $(\alpha, \beta_1, \beta_2) = 0$

For β_2 = GAR23

Horizon	**Variables**			**Statistics**		
	α	β_1	β_2	**R^2**	**DW**	**χ^2(σ-IMP23=0)**
2*	-0.0316	0.5613	0.3507	0.0622	1.6048	10.8636
	-0.1075	*0.3288*	*0.9432*			
3	0.0633	7.2998	-0.5934	-0.0095	2.4995	3.4544
	0.0718	*1.2376*	*-1.1167*			
4*	-0.9251	6.9290	-0.1943	0.4753	2.2424	27.0458
	-1.5476	*2.4798*	*-0.4254*			
5*	0.1071	3.5389	-0.6120	0.1802	2.4183	8.6655
	0.1945	*1.3106*	*-1.6555*			
6	-1.1487	5.7700	-0.4281	0.5768	2.0907	26.4348
	-2.1488	*4.6418*	*-1.2261*			

* = Adjusted White's Heteroskedasticity-Consistent Standard Error is used.

R^2 Statistic reported here is Adjusted R^2

T-ratios are in Italic

For β_2 = MA

Horizon	**Variables**			**Statistics**		
	α	β_1	β_2	**R^2**	**DW**	**χ^2(σ-IMP23=0)**
2	0.3714	3.0720	-0.1772	-0.0103	1.5832	8.6493
	0.9348	*1.1914*	*-0.9827*			
3	-0.0598	6.3898	-0.3623	-0.0323	2.4377	2.8713
	-0.0674	*1.0712*	*-0.8442*			
4*	-1.5900	4.7606	0.9368	0.5251	2.0006	31.8749
	-2.3388	*1.9674*	*1.5690*			
5*	-0.8945	1.4751	0.7307	0.1379	3.0352	7.4049
	-1.1097	*0.7138*	*0.8720*			
6	-1.5850	3.9820	0.5473	0.5529	1.8470	24.3291
	-2.9967	*2.3037*	*0.8538*			

* = Adjusted White's Heteroskedasticity-Consistent Standard Error is used.

R^2 Statistic reported here is Adjusted R^2. T-Ratios are in Italic

Chapter 7

CONCLUSIONS

7.1 SUMMARY

Interest rate forecasts and volatility forecasts are often of interest to businesses and financial institutions with the ultimate aim to enhance profits. These forecasts are often used in risk measurement, investment analysis, capital allocation, trading, pricing and hedging. Investors who trade options will find their returns are sensitive to the relationship between implied volatility they pay or receive today, and the actual realised volatility that occurs over the remaining life of the option. Hence the focus on the relationship of implied volatility with future realised volatility.

The aim of this study is to examine the rationality, accuracy and the value of published consensus forecasts of US Treasury bill yields vs market related data such as futures and futures-options.

This research differs from previous study in several ways:

First, we have chosen to use *Blue Chip Financial Forecasts* data as our main source of survey data. One of the unique features of this forecasting service is that they do not keep the forecasters' name anonymous. This will encourage forecasters to provide their best forecasts because forecasters can claim credit for particularly good forecasts. In addition, although this is a well-known survey, but under-researched.

In the past, a lot of empirical research on U.S. Treasury bills had been based on data obtained from *GoldSmith-Nagan Bond and Money Market Letter* or *Wall Street Journal* surveys which only asked for 3 and 6-month ahead interest rate forecasts. This could post a limitation to the study and hence results as very often, exploitable inefficiencies in futures markets occur in the more distant contracts. Using *Blue Chip Financial Forecasts* data will help to remedy this drawback.

Second, for market-related data, not only do we used information coming from futures market, we also use data obtained from futures-options market. No previous study has examined whether the dispersion of Treasury bill yield forecasts can be used to predict the volatility of future Treasury bill yields, or devise rules for trading options on Treasury bill futures.

Third, survey variance is used not only to compare with implied volatility and historical volatility but also with time-series based forecast.

We examine the proposition of whether expert forecasts of Treasury bill yields, as revealed in survey data, are more accurate than simple alternatives by using various accuracy measures such as summary statistics, directional accuracy and relative predictability measure. The evidence, basing on summary statistics and relative predictability measure, generally support the notion that market-based forecasts manage to predict the Treasury rate as well as professional forecasters. This is especially true for near-term interest rate predictions where futures market constantly being more precise than the survey. However, when one compared these forecast series with the benchmark (naïve), it seems that the naïve prediction is more accurate than other forecast series presented in this chapter. Whereas when one use relative predictability measure, even when compare to the benchmark, market-based forecasts appeared to be more predictable than naïve.

Economists often puzzled why firms buy/invest on forecasts. From the result presented in this thesis, it appeared that profits are sensitive to what trading rules are used. Significant profits can be made for longer holding period and longer forecast horizon than shorter holding period for volatility trading. Historical volatility has the edge for shorter holding period. Whereas for mean trading, although there seems to be some profit making opportunities when one use consensus forecast, but it still significantly under-performed, when compared with naïve forecast in terms of profit. This seems to imply that summary statistics are related to profitability, since our results indicate naïve forecasts do have the smallest error. However, based on this evidence, no conclusion can be made on how strongly or marginally related these forecast-error-magnitude criteria are in relation to profitability.

Rational expectations hypothesis has also been examined using the mean survey forecast. By and large, our test results generally support the perception that the survey forecasts are unbiased predictors of future Treasury bill rates; at the same time the null hypothesis of orthogonality is not rejected in both longer and shorter forecast horizons. This is indeed is not a surprising result, because to reject analysts' rationality suggests that analysts repeatedly and systematically make costly mistakes and do not learn from them. Such seemingly non-rational behaviour is within the realm of possibility, but it seems unlikely for professionals whose livelihood depends on rational forecasts. These results substantiate that these forecasts are the best available, given current knowledge. Because they are rational, the forecasts can be considered trustworthy as inputs into formulating policies. Evidence also suggests that information in the survey forecasts could reliably improve upon the futures rate prediction.

This conclusion about market efficiency contrasts sharply with previous studies (as mentioned in previous chapters). Results indicate that Treasury bill futures price does not incorporate all of the information contained in the survey considered here. Daily price quotes in the futures market cannot provide a valuable benchmark of what the market's expectation of what the future settlement price is going to be. From this, it seems the value of these professional forecasts to an investor is immense. Investors could improve his/her return by utilising the survey data.

Investors also need to know whether they can predict future realised volatility to be able to understand whether there is value in option volatility from this standpoint. Many investors and academics naturally assumed that the best forecast of future realised volatility is implied volatility. It is possible that implied volatility computed from futures-options prices might reflect market expectations of future realised volatility. The results of the empirical studies suggest that implied volatility derived from Black model are useful for forecasting future volatility, but implied volatility alone in some occasions especially in longer forecast horizon are not optimal predictors. A combination of implied volatility and other factors such as survey variance or Garch may be useful in forecasting future realised volatility.

7.2 LIMITATIONS

One of the beauties of using *Blue Chip Financial Forecasts'* data is the fact that one can extract longer-dated interest rate forecasts than other survey. However, there is still a drawback that these forecasts are "infrequent", only monthly updates. It is impossible to get a daily time-series due to the nature of the service and data type. Sample size is therefore limited. In order to compensate the shortfall, perhaps for future research one can use data that have more frequent updates such as trader surveys, which is published on a weekly basis by S&P/MMS.

A lot of time has lapsed since we first started on this topic. One could argue that the result could be different, if we attempt to extend the time-series to include recent data. In addition, overtime the volume and liquidity of Treasury bill futures market have declined with the introduction of Eurodollar futures market. One might therefore be able to exploit inefficiencies in the market. With the above in mind, one has to overcome several difficulties:

First, the make up of the panel for survey forecasts do change over time. This would make comparison of consensus forecasts with other alternative measures difficult.

Second, structure of the economy often changed due to changes in monetary and fiscal policy applied in other to combat various business cycles. Whether restrictive monetary policy or easing of monetary policy being adopted, will have an impact on both the short rates and long rates. This will have an impact on Treasury bill market.

7.3 DIRECTIONS FOR FURTHER RESEARCH

Consensus forecasts are the main source of our survey data used in this research. However, if time allowed, one can examine similar hypothesis by using individual forecasts. Perhaps this can provide a better insight with respect to the relationship between accuracy and profits, and at the same time answer the question of how correlated are these variables. Is individual forecasts more valuable than consensus /naïve forecasts?

Volatility is a key variable in the pricing of derivative products and calculation of risk exposures. But choosing and maintaining information on volatility is challenging, since these variables are not readily observable in the market. Professionals have to use statistical models to estimate this variable.

A key problem is that many of these models used assume that the population of market returns exhibits certain statistical properties such as assuming normally distributed data or independent and identically distributed data. Unfortunately, for most products, market volatility seems not to abide to these assumptions. Volatility has properties that make this assumption of normality difficult to support. For many markets, volatility is stable and then jumps suddenly for a period of time before settling down. This period of clustering of large volatility movements implies that the volatility level for a day may be influenced by the volatility level of the previous day.

Since we have started the research, a lot of time has lapsed. Although we did introduce the use of GARCH to take into consideration of volatility clustering, with the advancement of computational power, more advanced GARCH techniques were developed. One perhaps could take this into consideration for further studies.

In many financial markets, volatility is higher when the market is falling compared to when it is rising. The standard normal GARCH model because of its linear variance term cannot capture such features. More advanced GARCH implementations can deal with this asymmetry. Asymmetric GARCH can capture volatility response that is not symmetrical. In this model, a negative shock in the market, results in a larger estimate for conditional variance than when there is positive shock to the market.

Nelson (1991) suggested exponential GARCH model. This is appealing since it ensures that the conditional variance is always positive without the need to impose any constraints on the coefficients. This model is non-linear in variance, adding an element of asymmetry to the response and persistent components. The predictions of Asymmetric GARCH and Exponential GARCH models were seem in the recent Russian bond market default, where a larger implied volatility was observed following the significant negative market shock.

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