A Market Microstructure Examination of Australian Treasury Bond Futures Overnight Options

by

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To my parents

&

My dear husband Max and daughter Rosie

This dissertation is completed with their love and encouragement

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ABSTRACT

The creation of the Black-Scholes-Merton options pricing model and its publication in 1973, expanded risk management financial research and practice. Concurrently, there have been many assets created in the derivative markets. In line with this, the introduction of Australian Treasury-Bond futures overnight options at the Sydney Futures Exchange (SFE) during 1993 offers a unique opportunity to examine trading behavior with a different market microstructure. This dissertation is the first study of its kind to investigate the market microstructure of the SFE overnight options market. This work explores market microstructure aspects of Australian Treasury Bond futures overnight options regarding market liquidity, transaction costs, market order flows, information asymmetry, and market volatility.

We first present an institutional overview of the Sydney Futures Exchange (SFE) and discussions about products traded at the SFE. This builds the foundation for the following empirical studies. Next, we examine trading behaviours of 3-Year and 10-Year T-Bond futures overnight options by looking at intra-night bid-ask spreads, trading volume, and volatility patterns. We observe different intra-night bid-ask spreads, trading volume, and volatility patterns compared to stocks and long dated options. Third, the impact of overnight options introduction on the underlying 3-Year and 10-Year T-Bond futures market is examined. Results indicate that the introduction of overnight options has influence on the underlying 3-Year and 10-Year T-Bond futures. Fourth, we examine information shocks on the underlying futures return volatility and present optimal time-varying models to estimate and forecast the underlying futures return volatility. The analysis undertaken allows us to recommend the most appropriate models for predicting return volatility for the underlying futures market, and hence presents a key element in the puzzle of how best to price these innovative products. Finally, implied, forecasted, and realized volatility are examined to determine information content of implied volatility when predicting future volatility. This information may be useful to traders wishing to accurately price overnight options.

Table of Content

Tables

Figures

Chapter 1 Introduction

The creation of the Black-Scholes-Merton options pricing model and its publication in 1973, expanded risk management financial research and practice. Concurrently, there have been many assets created in the derivative markets. In line with this, the introduction of Australian Treasury-Bond futures overnight options at the Sydney Futures Exchange (SFE) during 1993 offers a unique opportunity to examine trading behavior with a different market microstructure, namely the SFE overnight options market. This dissertation is the first study of its kind to investigate the market microstructure of the SFE overnight options market. This work explores market microstructure aspects of Australian Treasury Bond futures overnight options regarding market liquidity, transaction costs, market order flows, information asymmetry, and market volatility.

Market microstructure is the branch of financial economics that investigates trading and the organization of markets (Harris (2003)). It is concerned about market liquidity, transaction costs, information asymmetry, market volatility, and trade execution. In addition, a thorough understanding of market structure, trading rules and information systems, may help to improve trading strategies.

The Sydney Futures Exchange (SFE) offers derivative trading, risk management tools, clearing and settlement services to public investors, banks, funds managers and government users of the exchanged traded products in Australia, New Zealand and around the world. As one of the four major trading products at the SFE, interest rate products have been the most actively traded products in the SFE. There are three types of futures on interest rate products, namely 90-Day Bank Accepted Bill futures contracts, 3-Year Treasury-Bond (T-Bond) futures contracts and 10-Year Treasury-Bond (T-Bond) futures contracts. These products provide investors with ways to trade futures with different maturity terms and also provide tools for risk management to hedge the underlying positions for short, medium, and long-term interest rate movements.

Overnight options were first introduced on 15th November 1993; they are short dated European-Type of options based on the 3-Year and 10-Year T-Bond futures contracts. They last for one SYCOM (Sydney Computerized System)[1] session and expire after the SYCOM night session if the options are at-the-money or out-of-the-money. Those in-the-money options are exercised immediately after the SYCOM night session. Overnight options are important tools to hedge the overnight risk of their underlying futures position or the underlying Bank Bill / T-Bond positions. They also presents investors with a means to hedge event risk, e.g. a major economic information release from the US, as Australian night trading occurs while US markets are open.

Chapter 2 in this dissertation gives an institutional overview of the Sydney Futures Exchange. In Chapter 2, firstly, an historical overview of the SFE is presented. This includes the history of the exchange, and its institutional structure. Secondly, floor trading and SYCOM (Sydney Computerized Market) will be explained and compared with the other major world exchange, i.e. Chicago Mercantile Exchange (CME).

[1] This is the electronic trading platform used by the SFE.

Thirdly, there is a discussion on the products that are traded at the SFE in terms of contract specification and trading volume. Chapter 3 of this dissertation also gives detailed discussion in terms of the products that we are using for other chapters. Finally, the clearing and settlement procedure is explained.

The first objective of this dissertation is to find out intra-night trading behaviors of 3-Year and 10-Year T-Bond futures overnight options in terms of bid-ask spreads, trading volume, and volatility. Chapter 4 documents these questions by looking at intra-night patterns of bid-ask spreads, trading volume, and volatility. There is evidence that intra-day bid-ask spreads, trading volume and return volatility are not constant over time. Chan, Chung and Johnson (1995) provide a useful summary of the factors affecting intra-day bid-ask spreads. Hasbrouck (1988) proposed a theory based on information uncertainty. Ho and Stoll (1983) used the inventory of the market maker to explain the spreads and Lee, Mucklow and Ready (1993) found the intensity of trading activity was the decision factor. As a result, O'Hara (1995) concluded that there were three models to explain the trading patterns for bid-ask spreads. These are the inventory model, the asymmetric information model, and the market structure model.

Many previous researchers have found a U-shaped pattern for stock bid-ask spreads. This indicates that bid-ask spreads are wider at the open and close of the stock market. Results for options are mixed. McInish and Wood (1992), and Chan, Chung and Johnson (1995) found reverse J-shaped patterns for options. An explanation for the difference between the stock and the option markets is that the width of bid-ask spread at the market open is due to the degree of uncertainty. The wide stock bid-ask spread and the narrow option bid-ask spread is due to the differing market structure. Thus, one may expect different intra-night bid-ask spread patterns for overnight options because of the special characteristics of these securities in terms of maturity time, pricing formula, exercise style, and market structure.

It is argued that greater trading volume narrows bid-ask spreads. Greater trading volume also generates greater volatility for the market. Previous studies have found that intra-day trading volume and intra-day volatility follow U-shaped patterns similar to bid-ask spreads patterns. Thus, it is useful to conduct an intra-night analysis for trading volume and return volatility patterns to see whether previous findings hold for the overnight options market.

The second objective of this dissertation is to investigate impacts of the overnight options introduction on the underlying 3-Year and 10-Year T-Bond futures. The impact of option listing on the underlying securities has attracted great attention in academic literature. Further, any exchange would like to know the interrelationship between products traded. Thus, it is worth examining the impacts of overnight option introduction on the underlying 3-Year and 10-Year T-Bond futures that are traded at the Sydney Futures Exchange (SFE). Chapter 5 extends the analysis by looking at the impact on liquidity, the impact on order flow, the impact on volatility, and the impact on pricing error variance of 3-Year and 10-Year T-Bond futures.

Previous studies have suggested that the derivatives market may draw uninformed traders away from the underlying market, and thus decrease the liquidity of the underlying market (see Kumar, Sarin and Shastri, 1998). The liquidity of the underlying market could also be negatively affected if the introduction of the derivative on the market causes an increase in formation-based trading. It has been argued in Kumar, Sarin and Shastri (1998) that derivatives markets destabilize the cash market by encouraging arbitrate-related activities that increase short-run price swings.

On the other hand, the introduction of options could encourage greater speculative trading. Informed traders will be likely to shift from the underlying markets to options market, due to the leverage effects and lower transaction costs for trading in the options market. The migration of informed traders from the underlying markets would reduce the informational asymmetry problem faced by market makers, as suggested by the adverse selection model found in market microstructure theory. In turn, this will increase the liquidity of the underlying market. In addition, the lower speculative activities in the underlying market will result in a decrease in the volatility generated by speculators in the underlying market who create noisy trading. However, this will simultaneously decrease the trading volume in the underlying market. Thus, the theoretical arguments behind the impacts of the options listing on the underlying market are in conflict. Each market has its own characteristics and market structure, hence an empirical study on this issue for the overnight option market will be useful in order to understand the impact created on this particular market. In Chapter 5, the bid-ask spread is used as a measurement of liquidity; trading volume is used as measurements of order flow.

It is reasonable to expect that the unique nature of overnight options on T-Bond futures will result in them having different characteristics to long dated options in terms of trading behavior and market microstructure. Factors such as bid-ask spreads, trading volume patterns, and return volatility will possibly be very different from those discussed in the literature on conventional long dated options. The key input into all conventional option pricing models is volatility. Thus, the third objective of this dissertation is to determine a model which can estimate and forecast volatility for underlying futures market Chapter 6 seeks to improve the ability to price overnight options of T-Bond futures by estimating and testing a model for predicting underlying futures volatility.

How information shocks impact on return volatility is the key ingredient in modelling volatility, as information flows into a market place can have a major impact on volatility. There is ample evidence that good news has less of an impact on volatility than bad news. Linear GARCH models, which have traditionally been used for predicting future volatilities, assume that the impact of news is symmetrical and this has led to the development on asymmetrical models such as EGARCH model. Chapter 6 examines how information flows affect volatility in order to determine which of the available linear and non-linear GARCH models theoretically yields the best result. It then tests each of the models by producing parameter estimations and goodness-of-fit statistics using market data to see if the theoretical predictions prove correct. In addition, the models are applied to out of sample data to see if the results are robust. The analysis undertaken in Chapter 6 allows us to recommend the most appropriate models for predicting return volatility patterns for the underlying 3-Year and 10-Year T-Bond futures, and hence solve a key element in the puzzle of how best to price these innovative products.

The fourth objective of this dissertation is the consideration of overnight options implied volatility. It is believed by academics and market participants that implied volatility is informationally superior to other volatility measures to predict future volatility. The implied volatility is the market perception about future security volatility. If option markets are efficient, implied volatility should be an efficient forecast of future volatility, i.e. implied volatility should subsume the information contained in all other variables in the market information set in explaining future volatility. For short-dated options, i.e. the SFE overnight options, we investigate their implied volatility to determine how the market perceives the information content of overnight options volatility. Overnight option's implied volatility may give investors an idea of how the market is going to act in the next period (i.e. next SYCOM night trading session).

Chapter 7 investigates whether or not implied volatility is an unbiased and efficient forecast of future volatility. It also tests whether or not implied volatility contains information content about future volatility for 3-Year and 10-Year Australian T-Bond futures overnight call and put options. Chapter 7 also applies multiple regression models to identify an optimal model to describe the relationship between implied, forecasted and realized volatility. This gives investors an alternative way to predict overnight options volatility when pricing it.

Chapter 8 concludes and summarizes contributions of this dissertation. We conclude with future work suggestions.

Chapter 2 The Sydney Futures Exchange (SFE): An Introductory Overview

1. Introduction

The Sydney Futures Exchange (SFE) provides exchange-traded and the over-the-counter services throughout the Asia Pacific region. It is one of the largest futures exchanges in this region. The SFE offers derivative trading, risk management tools, clearing and settlement services to public investors, banks, funds managers, and government users of exchange-traded products in Australia, New Zealand and around the world. The SFE's derivative markets cover four major areas – equities, interest rates, currencies, and commodities. During 2002, on average more than 144,000 futures and options contracts were traded each day. With an annual turnover of nearly 37 million contracts the SFE is positioned as one of the major derivatives exchanges in the Asia Pacific region (The SFE 2002 Annual Report).

As one of the four major trading products at the SFE, the interest rate products have been the most actively traded products in the SFE. There are three types of futures on interest rate products, namely 90-Day Bank Accepted Bill futures contracts, 3-Year Treasury Bond (T-Bond) futures contracts and 10-Year Treasury Bond (T-Bond) futures contracts. They provide investors with ways to trade futures with different maturity terms and also provide tools for risk management to hedge the underlying positions for short, medium, and long-term interest rate movements. With the success of the interest rate futures contracts, the SFE introduced options on the 90-Day Bank Accepted Bill futures, and options on the 3-Year and 10-Year T-Bond futures. These give investors other alternatives to profit from trading and/or hedging their underlying positions.

Overnight options were first introduced on 15th November 1993, they are short dated European-Type options based on the 3-Year and 10-Year T-Bond futures contracts. They only last for one SYCOM session and are expired after the SYCOM night session if the options are at-the-money or out-of-the-money. Those in-the-money options are exercised immediately after the SYCOM night session. The overnight options are positioning themselves as important tools to hedge the overnight risk of their underlying futures position or the underlying Bank Bill / T-Bond positions. They also provide investors with a means to hedge event risk, e.g. a major economic information release from the US, as Australian night trading occurs while US markets are open. With the successful introduction of overnight options and active trading, the SFE in April 2002 introduced another short-dated option, namely an intra-day option on 3-Year and 10-Year T-Bond futures. This option was targeted on hedging the domestic event risks when major Australian economic announcements occurred during normal business hours.

Since one-session options have special characteristics, a thorough study of the overnight options markets is essential for us to identify the nature of trading for the one-session options at the Sydney Futures Exchange (SFE). Hence a comprehensive overview of the regulations, operations, participants, trading protocols of the SFE is required before we can have in-depth examinations and analysis. This chapter will provide such information on the Sydney Futures Exchange (SFE). We may consider this chapter as an introductory overview on the market structure of the Sydney Futures Exchange.

Market microstructure research (O'Hara (1995)) may cover a very wide range of topics, for example, price formation and price discovery, market structure and design, information and disclosure. These topics include the determinants of trading costs, the relationship between price formation and trading protocols, as well as market transparency (which is the ability of market participants to observe information). Market microstructure theory suggests that all necessary market elements will be converted into trades eventually. Market transparency, liquidity and volatility are influenced by these elements. The pricing of securities differs in terms of differing market microstructure.

This chapter is organized as follows. Firstly, an historical overview of the SFE will be presented. This overview will include the history of the exchange and its institutional structure. Secondly, floor trading and SYCOM (Sydney Computerised Market) will be explained and compared with the other major world exchange, i.e. Chicago Mercantile Exchange (CME). Thirdly, there is a discussion on the products that are traded at the SFE, in terms of contract specification and trading volume. Finally, the clearing and settlement procedure will be explained.

2. Overview of the SFE

2.1 Historical Perspective

Sydney Futures Exchange Corporation Limited (SFE) and its subsidiary companies provide exchange-traded and over-the-counter (OTC) financial services to institutions throughout the Asia-Pacific region and globally. In 1960, the SFE commenced its operation as The Sydney Greasy Wool Futures Exchange. In 1972, after 12 years in operation, it changed to its current name. Compared to the Chicago Board Options Exchange (CBOE) that was founded in 1973, the SFE has a long history. Prior to the year 1963, options were traded on an unstandardized basis and the principle of *fair and orderly markets* was not utilized.

The SFE's international reputation has been built on its successful operation of a futures and options market for over 40 years. In 1999, the SFE trading 'floor' and the traditional 'open-outcry' system were closed down and all trading migrated to the fully electronic system, SYCOM. This was accompanied by an expansion of the SFE's global proprietary communication network. This enables investors to trade for 24 hours (www.sfe.com.au). With a fully electronic and 24-hour trading capability, the SFE offers the financial market community trading products for investment and risk management. It also disseminates real-time and historical trading market data and provides centralized clearing, settlement and depository services. With the ability to access the major global financial markets via an open trading interface, the SFE integrates the world with a communication network hub.

There are more than 50 futures exchanges worldwide. The Sydney Futures Exchange ranks among the top 10 in the world, and the second in the region, on trading volume in year 2002. Table 2.1 below lists the top 10 world futures exchanges and the top 10 in the Asia Pacific region. The SFE has experienced a steady growth since the year 1997, Table 2.2 below illustrates the traded volumes (contracts) for the SFE Group from 1997 to 2002.

Table 2.1 Ranking of Financial Futures and Options Exchanges

World Ranking			Regional Ranking		
	Exchange	2002 Volume		Exchange	2002 Volume
1	Korea Stock Exchange	1,932,634,032	1	Korea Stock Exchange	1,932,634,032
2	Eurex	657,890,220	2	**Sydney Futures Exchange***	36,870,542
3	Chicago Mercantile Exchange	558,447,820	3	Singapore Exchange	32,887,395
4	Chicago Board of Trade	343,882,529	4	Osaka Securities Exchange	20,563,557
5	Euronext – LIFFE, UK	241,092,206	5	Korea Futures Exchange	15,073,295
6	Euronext – Paris	111,345,979	6	Tokyo Stock Exchange	14,759,690
7	BM&F – Brazil	101,615,788	7	National Stock Exchange of India	10,513,589
8	Chicago Board Options Exchange	94,408,976	8	Taiwan Futures Exchange	7,944,254
9	Tel – Aviv Stock Exchange	41,419,705	9	Hong Kong Exchange and Clearing	7,304,644
10	**Sydney Futures Exchange***	36,870,542	10	Tokyo Internal Financial Futures Exchange	4,470,763

Source: The SFE 2002 Annual Report[2].
Includes NZFOE volumes.

Table 2.2 Exchange Traded Volumes (Contracts)

SFE Group	Annual Volume[a]					
	1997	1998	1999	2000	2001	2002
Total Futures	26,458,880	28,854,604	28,008,712	29,695,870	35,086,351	34,602,798
Total Options	3,158,738	2,424,563	2,646,388	2,463,875	1,805,303	2,267,744
Total SFE Group	29,617,618	31,279,167	30,655,100	32,159,745	36,891,654	36,870,542

Source: The Sydney Futures Exchange Annual Reports.
[a] Including NZFOE volumes

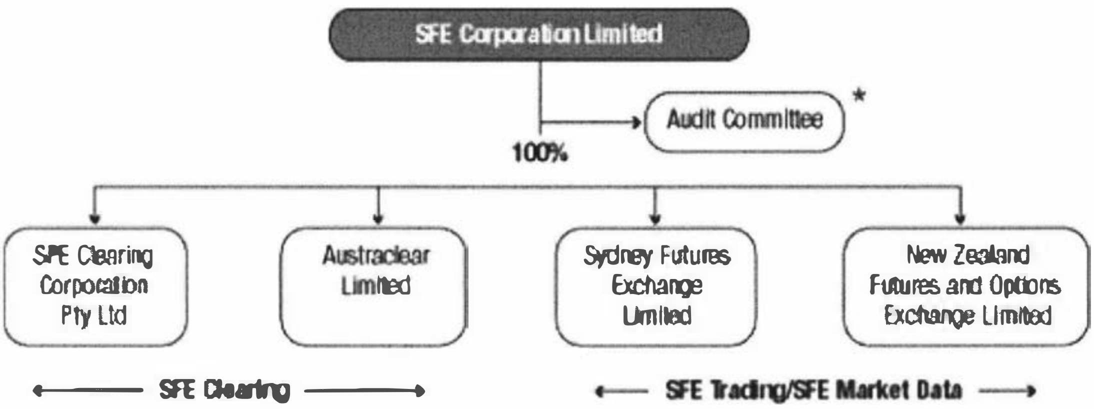
2.2 Institutional Structure

Figure 2.1 represents the corporate structure of the SFE. The SFE Corporation Limited owns SFE Clearing Corporation Pty Ltd, Austraclear Limited, Sydney Futures and Exchange Limited and New Zealand Futures and Options Exchange Limited. Known as SFE Clearing, SFE Clearing Corporation Pty Ltd and Austraclear Limited provide the SFE's clearing operations. Its customers can access a complete service from the

[2] The Stockholmsbörsen, however, had a trading volume of approximately 61 million contracts, which will be ranked ahead of the SFE.

clearing and settling of exchange-traded derivatives and OTC securities, to cash transfers, depository, registry and custodial services. This provides investors a complete service which in turn improves the liquidity of the market.

Figure 2.1: The SFE Corporate Structure



* The SFE Corporation Limited Audit Committee comprises Messrs Payne (Chairman), Wame, Wilson and Gray (a director of SFE Clearing). The CEO and other senior executives and the external auditor attend meetings by invitation.
Source: The Sydney Futures Exchange (www.sfe.com.au).

3. Floor Trading Versus SYCOM Trading

SYCOM (Sydney Computerized Market) was first introduced by the SFE in November 1989. The SFE began to gradually shift their products from floor trading to SYCOM in 1989. By 12 November 1999 all SFE products had shifted to SYCOM, and floor trading ceased. Before the introduction of the SYCOM, all trading was executed by floor trading.

3.1 SFE Floor Trading

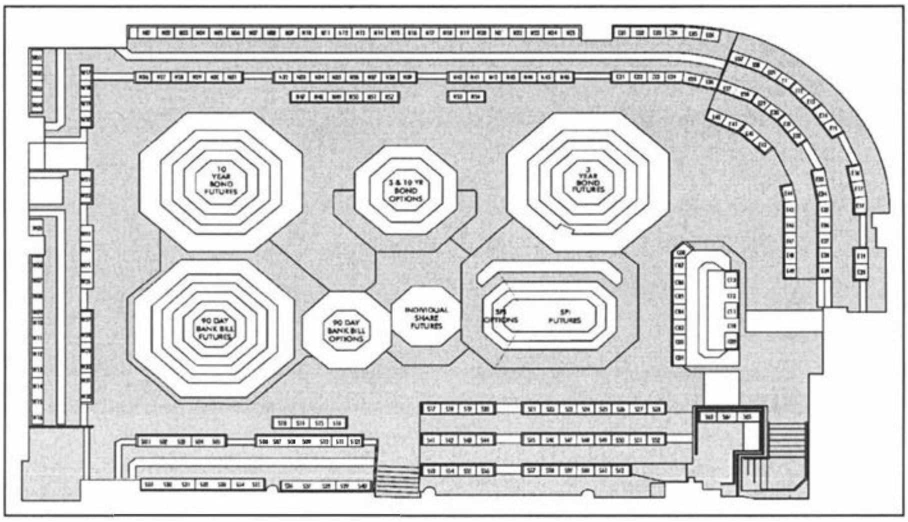
The SFE trading floor was similar to the system of trading on the Chicago Mercantile Exchange. This type of trading system is similar to hundreds of simultaneous auctions.

Traders stand in a trading pit and call out prices and quantities that indicate their willingness to buy or sell. They use hand signals to convey information, which is highly effective since it can be difficult to hear if everyone is shouting. Open outcry is an efficient means of *price discovery*, allowing buyers and sellers to arrive at the best prices given the supply and demand for a given futures or options product (www.cme.com). The open outcry system ensures that all market participants are informed of the market's activity, and thus have equal opportunities to participate in the trade. Although floor trading is an efficient means of delivering the *price discovery* function, the majority of the world's leading stock exchanges and derivatives exchanges have shifted their trading from floor to electronic trading. They have done this because electronic trading can improve market liquidity, lower transaction costs in the form of lower bid-ask spreads, allows large transactions to be executed at the same time, and more quickly executes transactions than flooring trading. Electronic trading facilities also provide investors with easy access to the market, i.e. through computers at work or at home, or through internet trading.

The SFE had eight trading pits, with each pit trading a particular product or products. Figure 2.2 illustrates the layout of the trading floor in the SFE in 1996. Pits trading Bank Accepted Bill Futures, 3-Year and 10-Year T-Bond Futures and Share Price Index Futures were more active than those trading other contracts.

A number of booths surrounded the trading floor housed member employees. A large number of phone lines were connected to the booths. This allowed investors to contact their brokers without delay.

Figure 2.2 The Sydney Futures Exchange Trading Floor



Source: The Sydney Futures Exchange

At the Chicago Mercantile Exchange the open outcry platform and trading floor systems are linked to the electronic trading platform. This allows market participants to buy and sell whether they're sitting at trading booths on the exchange's trading floors, working at offices or homes far away, for trading that occurs both during and after regular trading hours. At the SFE a catwalk was located above the trading floor where SFE staff entered trade information into the computer system. Information screens arranged around the floor would inform the traders. Figure 2.3 below shows the Catwalk and information screens at the SFE's trading floor viewed from the trading floor.

3.2 Participants of the Trading Floor

Trading floor participants were employees of the SFE, or employees of the floor members and local members. There were three categories of membership at the SFE; floor members, associate members and local members. Under the SFE Business Rules

Figure 2.3 Catwalk and Information Screens

Source: The Sydney Futures Exchange

floor members had full access to the trading floor and were permitted to trade either on their own account or for their client. Associate members did not have direct access to the trading floor. They could give advice to their clients, accept orders from their clients, and pass them on to floor members. Local members could trade on their own account, and they were permitted to execute orders for other brokers on a *give up* basis. Give up business is where a local member suspends their own principal trading and trades on behalf of others for a fee. Sometimes local members can purchase membership from an existing member. Also temporary local membership could be obtained by leasing a membership from a permanent local member. All the trading floor participants were required to wear either a lapel badge or a colour-coded jacket when on the trading floor.

3.3 Floor Trade Execution

A trade is said to be executed when a bid or an offer from one trader in the pit is accepted immediately and the trade is confirmed. The trade will only be valid if all bids or offers, and their acceptances, are made by open outcry in the relevant pit. The price quoted must be the best bid or best ask at the time when the trade is executed and the quantities, which are known as market depth, must be specified at the same time.

3.4 SYCOM Trading

SYCOM (Sydney Computerized Market) was first introduced in November 1989 and its success eventually eliminated floor trading[3]. SYCOM was the world's first after-hours electronic trading system. Its aim was to provide a platform for the trading of SFE products during the key time zone when European and North American markets were active. The first contract listed on SYCOM was the 10-Year T-Bond futures contract. This was followed by the 90-Day T-Bill futures contract on 11 January 1990. The SFE's other major contracts followed shortly thereafter. In 1995, the SFE expanded its electronic trading by providing links via SYCOM with the New York Mercantile Exchange (NYMEX) and the New Zealand Futures and Options Exchange (NZFOE) (NZFOE officially became a subsidiary of SFE on 31 December 1992). On 15 November 1999, the SFE switched to full-time electronic trading and abandoned floor trading. Now, all trades at the SFE are conducted exclusively via SYCOM[4].

3.5 SYCOM Trading Hours

Because SYCOM provides a 24-Hour trading platform, overseas investors can trade on the Australian futures market during their normal business hours. SYCOM also allows Australian investors to hedge their risk when overseas markets are open as this is when

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[3] Many large security exchanges around world have changed floor trading to electronic trading. This may improve the efficiency of the market as large numbers of transactions could be executed within a very short time period.

[4] See Appendix 1 for the chronological history of the SFE.

information flows into the local market from overseas markets. Table 2.3 lists the equivalent times for the major global financial markets when the SFE's day and night sessions are open.

Table 2.3 SYCOM Trading Hours and the Equivalent Times

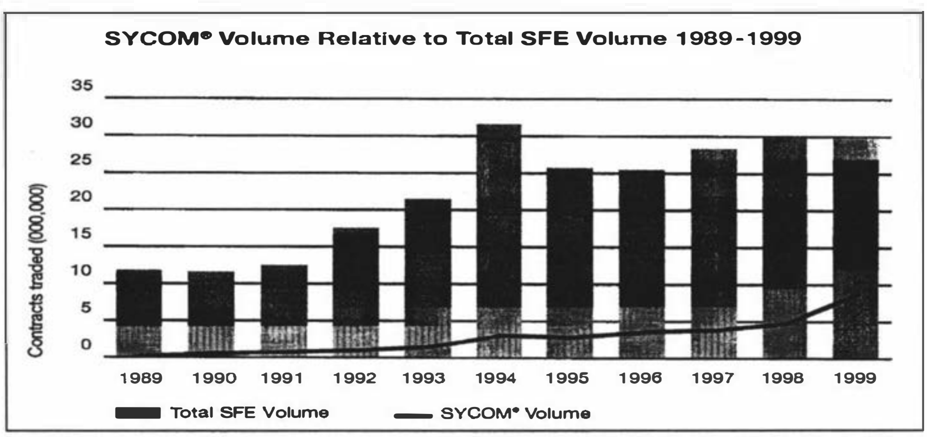
	SYCOM Trading Hours		
Time Zones	Morning Session	Afternoon Session	Night Session
Sydney	8:30am – 12:00pm	2:00pm – 4:30pm	5:10pm – 7:00am
	Equivalent Times		
Chicago	5:30pm – 9:30pm	11:00pm – 1:30am	2:10am – 4:00pm
London	11:30pm – 3:30pm	5:00am – 7:30am	8:10am – 9:00pm
New York	6:30pm – 10:30pm	0:00am – 2:30am	2:10am – 3:00pm

Source: The Sydney Futures Exchange (www.sfe.com.au).

3.6 SYCOM Trading Volume

SYCOM trading volumes have risen steadily since its inception in 1989. Figure 2.4 shows the SYCOM volume relative to total SFE volume from 1989 to 1999.

Figure 2.4 The SYCOM Volume to the Total SFE Volume

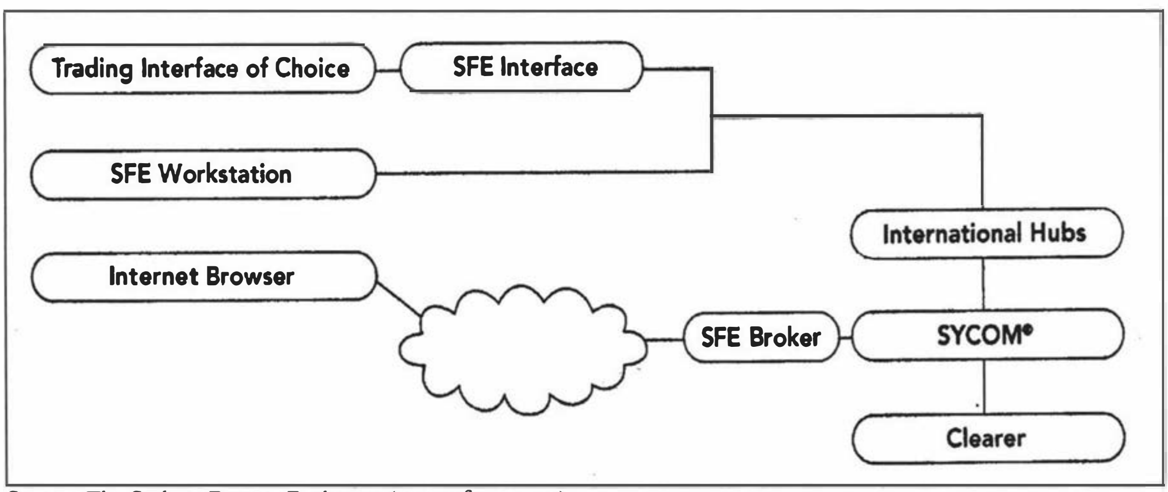


Source: The Sydney Futures Exchange (www.sfe.com.au).

3.7 SYCOM Technical Specifications

Figure 2.5 illustrates how to access SFE trading. Direct access to SYCOM is only available to SFE full participants and can be obtained by two different methods; one is the SYCOM Trader Workstation and the other is the SYCOM Trading Interface. The SYCOM Trader Workstations are computer terminals that run exclusively on the SYCOM system. This access allows full participants to manually trade all SFE contracts directly from their own offices, using their own propriety trading systems if they wish. Orders are then routed electronically, directly from the system in the full participant's office to SYCOM. The use of the trading interface is popular, contributing approximately 20% of total contract turnover (www.sfe.com.au).

Figure 2.5 Access to SYCOM Trading Interface



Source: The Sydney Futures Exchange (www.sfe.com.au).

The SFE also provides an SFE Internet trading platform that enables customers to trade via the Internet. Figure 2.6 shows the SYCOM hubs around the world. There are seven SYCOM hubs located in London, Tokyo, Hong Kong, Sydney, Melbourne, Auckland and Wellington. There are two other hubs being approved for installation in the United

States by the Commodity Futures Trading Commission[5]. Currently, anyone in the world may access the SFE at any time as the SYCOM provides 24-Hour trading[6].

Figure 2.6 Location of the Hubs

Source: The Sydney Futures Exchange (www.sfe.com.au).

3.8 SYCOM Trading Execution

3.8.1 Order Type

Usually when an investor wishes to trade on a particular product, they inform their broker and give instructions about the price and volume, as well as the way they wish their order to be handled. There are several ways an order can be executed on SYCOM. Those commonly used are: limit order, fill or kill order, market order, market if touched order, stop loss order, stop limit order, good till cancelled order, and discretionary order.

- A *limit* order is *an order to execute a transaction only at a specified price (the limit) or better.* A limit order to buy would be at the limit or lower and a limit order to sell would be at the limit or higher.

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[5] Not available at present.
[6] See Appendix 2 for the detailed SYCOM technical specifications and features.

- A *fill or kill* order is *an order that is sent for immediate execution.* If it cannot be filled immediately, it is automatically cancelled. Investors usually use this type of order to trade before the release of economic announcements, as after an announcement their orders will be cancelled from the system.
- A *market* order is *an order to buy or sell at the best offer or ask price.* This is a customer order for immediate execution at the best price available when the order reaches the marketplace.
- A *market if touched* order *is an order that is executed when the market reaches a particular level as specified in the order.* Once at that level, the order will be filled.
- A *stop loss* order is *an order placed with a broker to buy or sell when a certain price is reached.* It is designed to limit an investor's loss (or lock in profit) on a security position. This is sometimes called a *stop market* order.
- A *stop limit* order is *a specialized order in which a limit order and a stop order are combined.* Once the specified stop price has been reached or exceeded, the stop-limit order becomes a limit order. A stop-limit order differs from a stop order, which becomes a market order when the stop price has been reached or exceeded. A stop-limit order to buy must have a stop-limit price above the market price. Conversely, a stop-limit order to sell must have a stop-limit price below the security's market price.
- A *good till cancelled* order is *an order to either buy or sell a security which remains in effect until it is cancelled by the customer or until it is executed by the broker.*

- A *discretionary* order is *an order giving a broker the ability to decide when to buy/sell securities at the best possible price for the customer*. Some discretionary orders place restrictive terms to limit the amount of broker discretion. Investors usually give limited discretion to the broker in order to allow themselves to decide the time of buying/selling.

In practice, the order type does influence the market in some instances. For example, if investors use market orders the liquidity will be higher than if investors use limit orders. In chapter 4 of this study we will not distinguish the order type when we analyze the bid-ask spread. It will be left to other researchers to test the market liquidity effect of different order types. The explanation here is purely designed to give readers an idea of the different types of orders.

3.8.2 Procedures for Executing Orders on SYCOM

Whenever an order is received, it must be immediately entered into the SYCOM order book following the client's instruction. Thus a time-stamped[7] record of each order will be recorded into the SYCOM system. Once the order has been entered in the SYCOM system, the system will create an execution priority relative to all other standing orders for the same contracts. The order will stay in the queue until all orders in front of it are executed or cancelled. The system will use the following priority after executing the order: all subsequent entries at the same price; all entries at a lower price for a bid; all entries at a higher price for an offer.

[7] Orders are time-stamped within one-hundredth of a second.

Table 2.4 is a snap shot of the trader's order book window of SYCOM IV. It holds and displays a trader's complete order book. These may include active orders which have been released to the market, and orders that are not released to the market.

Table 2.4 The Trader Book Window

Contract	Code#	C-type	PriceVolume	Bid/Ask	Account
IRH1	1807	CFUT	9249100	A	09009918
IRM0	1808	CFUT	927310	B	09099918

Source: The Sydney Futures Exchange (www.sfe.com.au).

When a trade is executed, the trader will receive electronic confirmation of the trade which appears on the Confirmed Trades Screen. This screen is similar to the trader book window which displays all confirmed trades for individual traders and all shared trades for the user's firm. Depending on the functions selected for the screen, all of a firm's trades can also be displayed simultaneously.

3.8.3 Other SYCOM Features

In addition to the previously mentioned windows, SYCOM IV also provides several additional windows for the trade execution. These are[8] :

- The Market Window
- The Intra-Spread Market Window
- The Inter-Instrument Market Window
- The New Strategy Dialogue
- The Message Window

[8] See Appendix 3 for the detailed explanation of each window from the SYCOM manual.

- The Custom Market Window
- Additional Features Window

3.8.4 Summary of SYCOM Key Features

In summary, SYCOM operates 24-hours a day, providing complete coverage which allows users to take advantage of trading opportunities whenever they occur. It can provide custom market trading which allows participants to create their own trading strategies. It also provides the Intra-Commodity[9] spread trading which allows participants to perform spread trades within the same contract, and Inter-Commodity[10] spread trading which allows spread traders to trade through a dedicated spread trading window within SYCOM. For example, a strip trading order may be placed on SYCOM where four or more consecutive traded months of a futures contract are bought or sold simultaneously with the same volume for each of those traded months.

One of the significant contributions provided by SYCOM spread trading is that the SYCOM system can use this feature to generate prices in back months where there might be no bids or asks. SYCOM can also generate prices in underlying markets based on spread orders if there are no bids or offers in the underlying market for the contract month. SYCOM simply calculates the midpoint of the high-low range for the nearest month and uses this as the price for the nearest month. SYCOM then subtracts the difference from the nearest month, after confirming that this price is within the high-

[9] An intra-commodity spread trading is a trading strategy involving buying one month and selling another month for the same contract, i.e. 3-Year T-Bond futures contract.
[10] An inter-commodity spread trading is a trading strategy involving buying and selling for the different contracts in the corresponding months.

low range for the next month, then sets this as the price for the next month. This has been useful in the one-session options market, since the trading during the first couple of years in this market was thin. This trading function provides continuous data for the market.

4. Products Traded at the SFE

Products traded at the SFE cover four major areas – equities, interest rates, currencies, and commodities. During 2002, a daily average of more than 144,000 futures and options contracts were traded. The annual turnover was nearly 37 million contracts (The SFE 2002 Annual Report).

4.1 Interest Rate Products[11]

Interest rate products are the most active traded products at the SFE. These include the Australian 90-Day Bank Bill futures and options, the Australian 3-Year and 10-Year T-Bond futures, swaps, options, overnight options and intra-day options, the New Zealand 90-Day Bank Bill futures and options, the New Zealand 3-Year and 10-Year Government Stock.

4.1.1 Australian and New Zealand 3-Year and 10-Year T-Bond Futures and Options

These are the benchmark derivative products for trading and hedging medium to long-term AUD fixed interest securities and interest rate swaps. The 3-Year Bond Futures contract is ranked amongst the 10 most traded interest rate futures products in the world (www.sfe.com.au).

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[11]A more detailed presentation of the interest rate products is presented in Chapter 3.

4.1.2 SFE's 90-Day Bank Bill Futures

This is Australia's leading short-term interest rate derivative product. The 90-Day Bank Bill was the first interest rate futures contract to be listed outside the United States.

4.1.3 NZFOE 90-Day Bank Bill Futures and Options

These are New Zealand's leading short-term interest rate derivative products and the NZFOE's most actively traded contracts.

4.1.4 One-Session Options on Australian 3-Year and 10-Year TBond Futures

Overnight options and Intra-day options are also traded at the SFE during both the day session (Intra-Day Options) and night session (Overnight Options). One-Session Options could be used to profit from anticipated short-term price movements in the interest rate market or to hedge positions from event risk, i.e. economic announcements from the US.

4.2 Equities

The SFE provides benchmark equity index futures and options for Australia and New Zealand investors. The equity derivatives from the SFE provide investors with tools for hedging, arbitrage and gaining exposure to the Australian and New Zealand equity market. They provide index futures and options as well as individual share futures.

4.2.1 Index Futures and Options – SPI 200™ and NZSE-10

The SPI 200™ tracks the movement of the S&P100 and the ASX200. It is the global benchmark equity index derivatives contract for the Australian equity market.

The NZSE-10 Share Price Index Futures contract tracks the movement of the NZSE-10 Stock Index providing exposure to the New Zealand Share Market.

4.2.2 Individual Share Futures

SFE's individual share futures are futures contracts based on selected individual stocks listed on the Australian Stock Exchange. Share futures are offered on many of Australia's largest and most profitable companies including News Corporation, Telstra, BHP and National Australia Bank.

4.2.3 Equity Options

NZFOE's equity options are based on a selection of equities listed on the New Zealand Stock Exchange including Telecom NZ, Carter Holt Harvey and Fletcher Challenge.

4.3 Currency

The SFE also provides Australian dollar futures contracts. This enables both institutional and individual investors access to the world's largest financial market sector, the foreign exchange market, in an easy and cost effective way. These include the Australian Dollar/US Dollar futures and options on futures.

4.4 Commodities

The SFE provides futures contracts on a variety of commodities, for example, Australian Electricity and Wool. This provides investors with a way to hedge their exposures to the above commodities.

4.4.1 Electricity

SFE's Base Load and Peak Period New South Wales and Victorian Electricity futures contracts are risk management tools that provide certainty and transparency in an increasingly deregulated and competitive electricity market.

NZFOE's North Island Electricity futures contracts were the world's first cash settled electricity futures contracts and provide a means of hedging price risk in the volatile electricity market.

4.4.2 Wool

The wool contracts provide market participants with the tools to protect themselves against adverse price movements in the volatile physical wool market.

4.5 Trading Nominal Value and Trading Total Volume

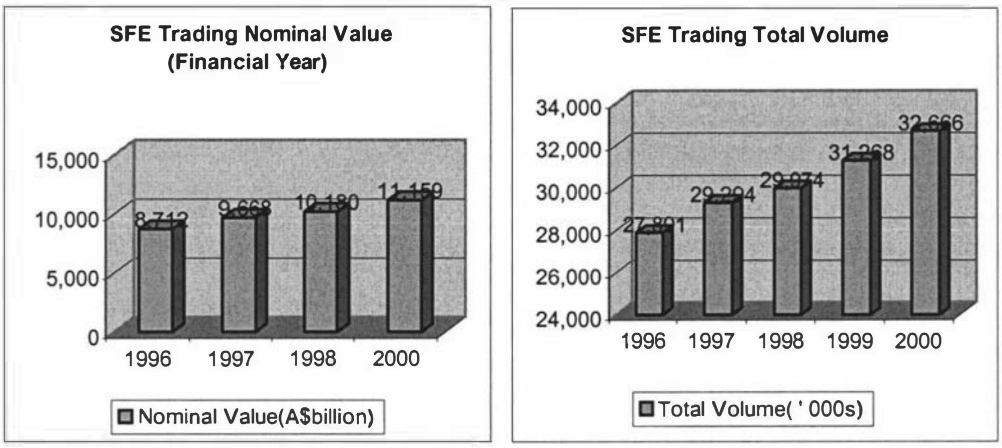
Figure 2.7 indicates the total nominal value and total volume for the years 1996 to 2000 at the SFE. As we can see from the graphs, the trading nominal value and the total trading volume gradually increased from 1996 to 2000, which indicates that the overall liquidity of the SFE's trading has improved year by year.

In 2000, there was a daily average of more than A$40.5 billion[12] worth of futures and options contracts traded on the SFE. The annual nominal value of this turnover exceeds A$11 trillion. It is 17 times larger than Australian gross domestic product[13] (www.sfe.com.au). Although the SFE is still a relatively small market compared to

[12] Assuming 275 trading days, thus we have A$11,150 Billion /275 = A$40.5 Billion
[13] The GDP for Australia in year 2000 was US$393,380,000 (Source: Datastream).

some of the world's larger derivative exchanges, it provides enough liquidity for the market.

Figure 2.7 The SFE Nominal Value and Total Volume



Data Source: The Sydney Futures Exchange (www.sfe.com.au).

5. Clearing and Settlement Procedures

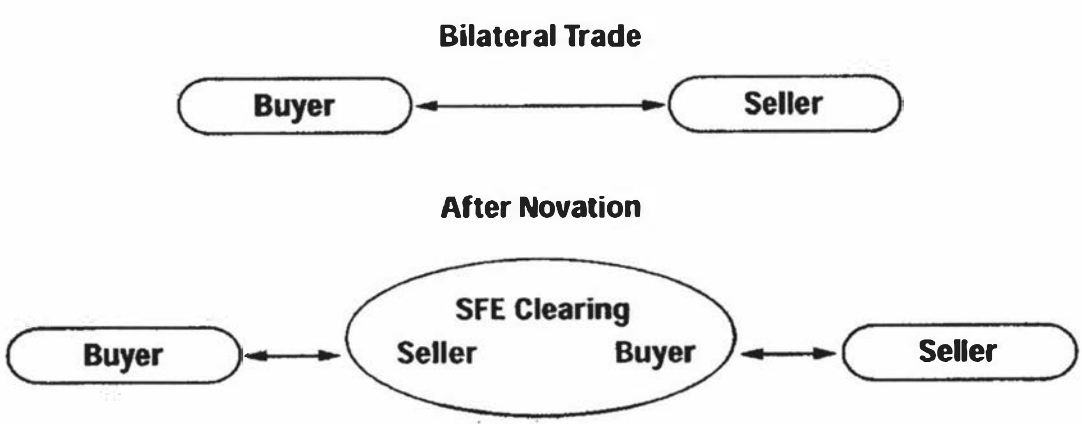
The SFE established its own clearinghouse in 1991. This clearinghouse focused on the clearing of exchange-traded instruments. In December 2000 the SFE merged its clearing operations with another Australian clearing organization, Austraclear Limited. A prerequisite for the successful operation of any financial market place is the existence of a well regulated, efficient, and financially sound clearing and settlement service. SFE Clearing is now taking a role in developing these services across all asset classes and markets in Australia, New Zealand and in the Asia-Pacific region. The clearing and settlement services provided by the SFE fall into the following four categories.

5.1 Central Counter-Party (CCP) Clearing

"Central to CCP clearing is the process of 'novation', which involves the SFE Clearing interposing itself between a buyer and a seller and becoming the central counter-party or principal to all trades" (www.sfe.com.au).

Importantly, through this process the SFE Clearing remains liable to perform against all contracts to which it is a party, even if either the buyer or seller fails to fulfill its obligations. Therefore SFE Clearing effectively guarantees performance of all other clearing participants. To enable this to happen, and to ensure the continued financial integrity of both CCP and the market, SFE Clearing imposes strict financial requirements and criteria on its participants. It ensures adequate capital, guarantees and operational safeguards are in place at all times and continually monitors these through risk management and front-line regulatory surveillance. Figure 2.8 shows Bilateral Trade before and after Novation (the involvement of the SFE Clearing during trading):

Figure 2.8 Bilateral Trade Before and After Novation



Source: The Sydney Futures Exchange (www.sfe.com.au)

The process of *novation* provides a number of benefits for users including surety of payment, margin netting, risk management and liquidity. Market users are able to deal with any market participant of their choice and are not required to revert to their original counter-party in order to negate or close-out their original transaction. It also means the participant is not required to assess the credit worthiness of other market participants. This in turn enhances market efficiency and promotes liquidity.

5.2 Delivery Versus Payment (DVP)

"The activity of Delivery versus Payment (DVP) settlement provides protection for the various parties involved in the clearing and settlement" (www.sfe.com.au). The process involves the final transfer of an asset or security to the buying party only when the transfer of cleared funds in payment for the security to the selling party is confirmed (and vice-versa).

5.3 Central Securities Depository (CSD) Services

"For a DVP operational model to work efficiently the underlying security and transfer of title should take place electronically within either a Central Securities Depository (CSD) or Registry" (www.sfe.com.au). SFE Clearing's Austraclear Limited is Australian major debt securities CSD. As such it is able to provide a wide range of services such as depository, registry, and corporate actions associated with debt instruments. So investors are able to use their comprehensive power in the debt securities market without asking anybody else if they wish.

5.4 Issuing and Paying Agency (IPA), Cash Transfer and Payments, Confirmations and Settlements

SFE Clearing also offers additional services to issuers and users of cash and derivatives products. These include:

- Issuing, registration and lodgment of short, medium and long-term debt securities.
- Payment of interest for securities with a fixed, floating or indexed rate of interest.
- Recording of transactions and payments for a wide range of securities.
- Confirming FX transactions, both A$ and cross currency, and enabling settlement of the A$ currency leg on an irrevocable funds basis.
- Matching interest rate swap confirmations and the settlement of the Australian Dollar transaction.
- Irrevocable settlement of the cash leg of transactions via real-time access to credit funds held in Exchange Settlement (ES) Accounts conducted by the RBA for banks and other approved institutions operating in Australian financial markets

(Source: www.sfe.com.au)

The integration of the SFE's clearing service with its other operations provides investors with a single solution. This improves the operation of the SFE, thus increasing liquidity in the market as well as improving the efficiency of the market. At the same time, it also lowers the transaction costs, which in turn promotes market transparency and efficiency.

6. Financial Integrity of the SFE

The regulatory framework in which the SFE Corporation Limited operates and in particular how this translates to the SFE Clearing will be discussed briefly in this section. The relationship between the SFE Trading, the SFE Clearing and associated government regulators will now be discussed in detail.

The SFE Corporation Limited acts as the ultimate regulator of market participants. This involves real-time monitoring of trading activity and enforcement of the SFE rules. This activity supplements the investigative and enforcement roles of regulatory agencies established by the state government. It provides investors with a well-regulated, fair, and orderly market. Table 2.5 below illustrates the regulatory framework in which the SFE group entities operate:

Table 2.5 Regulatory Framework at the SFE

	Exchange Trading		Clearing and Settlement	
SFE Entity	SFE Corporation Limited As operator of Sydney Futures Exchange (SFE)	New Zealand Futures and options Exchange Limited (NZFOE)	SFE Clearing Corporation Pty Ltd	Austraclear Limited
Government Regulators	ASIC (and CFTC and SEC in USA; FSA in UK; etc) Minister for Financial Services	Securities Commission (NZ) (and ASIC, CFTC, SEC, FSA, etc)	ASIC and RBA (ASIC sole regulator until commencement of Financial Service Reform Act 2001 (Cwlth) Minister for Financial Services	ASIC and RBA (no regulator until commencement of financial Service Reform Act 2001 (Cwlth) Minister for Financial Services
Relevant Law	Corporations Act 2001 (Cwlth)	Securities Amendment Act 1988 (NZ) and the Futures Industry (Client Funds) Regulations 1990 (NZ)	Corporations Act 2001 (Cwlth)	Corporations Act 2001 (Cwlth)
SFE Entity Regulation	SFE Board SFE Business Conduct Committee SFE Market Practices Committee	NZFOE Board NZFOE Business Conduct Committee	SFE Clearing Corporation Board SFE Business Conduct Committee	Austraclear Board

Source: The Sydney Futures Exchange (www.sfe.com.au).

7. Conclusion

This chapter has provided an introductory overview of the Sydney Futures Exchange with regard to its regulations, operations, participants, trading protocols, clearing and settlement procedures and the regulatory background. The elements described in this chapter have a big influence on market transparency, volatility, information transmission, the lead-leg relationship of different markets, as well as the liquidity of the market. These factors will be the focus for the following chapters.

Price formation, price discovery, market structure and design, information and disclosure are the topics which are described in market microstructure theory. These theories cover the determinants of trading costs, the relationship between price formation and trading protocols, and market transparency (the ability of market participants to observe information). All these necessary market elements will inevitably have an effect on trading. Market transparency, liquidity and volatility are influenced by these elements and the pricing of the securities is different under different market microstructures. Thus, changes in the market microstructure of the SFE will have direct impacts on trading execution. Hence, the discussion in this chapter has been designed to give reader a thorough understanding of the market microstructure of the SFE, the trading execution procedure, the price formation, the information transmission, and the market transparency.

It should also provide useful information for investors and traders wishing to enter the futures and options trading market. As we discussed earlier in this chapter, the shift to a fully electronic trading environment provides investors with more information transparency, and enables the market to execute multiple large transactions simultaneously.

Chapter 3 Interest Rate Products Traded at the Sydney Futures Exchange (SFE)

1. Introduction

Interest rate derivatives are the most actively traded products at the Sydney futures Exchange (SFE) and are offered on maturities all along the yield curve. The first interest rate product was launched on 17th of October 1979. It was the 90-Day Bank Accept Bill contract. This contract was followed by 10-Year T-Bond futures which listed on 5th of December 1984. Since then, more interest rate derivative contracts have been introduced.

The 90-Day Bank Bill futures contract is a short-term interest rate derivative product and was the first 90-Day Bank Bill interest rate futures contract to be listed outside the United States. The average daily turnover of this contract is approximately 6 times the turnover of the underlying cash market (www.sfe.com.au).

Contracts for 10-Year T-Bond Futures were listed at the SFE on 5 December 1984, and 10-Year T-Bond futures options were listed on 6 November 1985. The 3-Year T-Bond Futures and Options contracts were introduced earlier in 1988. These contracts are the benchmark derivative products for the trading and hedging of Australian dollar medium to long term fixed interest securities and interest rate swaps. They provide domestic and overseas investors with a way to gain exposure to the Australian debt markets. The 3-Year T-Bond futures contract is ranked among the top ten debt market futures contracts in the world by turnover (www.sfe.com.au). The 3-Year and 10-Year T-Bond futures contracts have a face value of A$100,000 and a coupon rate of 6%. They are cash settled against a basket of Commonwealth Government Bonds.

The SFE is the first futures exchange in the world to launch overnight options. With the introduction of the world's first after hours trading system, the SYCOM (Sydney Computerized Market), the SFE introduced overnight options on the 3-Year and 10-Year T-Bond futures contracts on 15th of November 1993. These overnight options allow local investors to manage risk whenever overseas markets are open, and in particular to hedge positions when US economic announcements occur. Given the success of the overnight options' introduction, the SFE introduced intra-day options on 3-Year and 10-Year T-Bond futures in April 2002, providing investors additional tools to hedge their risk, take positions before anticipated events, and profit from speculation. One-Session options are European style options. These options are only valid for one SYCOM session and will either expire or be exercised at the end of the SYCOM session if they are out-of-the-money or in-the-money respectively. One-session options are considered cost effective since there is no margin requirement for them. They provide investors and traders with additional flexibility when trading bonds. One-session options on 3-Year and 10-Year T-Bond futures are quoted in yield percent per annum in multiples of 0.005 percent.

According to the statistical department at the SFE[14], approximately 40 percent of business transacted in 3-Year and 10-Year T-Bond Futures and Options is hedging related, while another 40 percent is attributable to speculating. The remaining 20

[14] Results from an interview with SFE staff.

percent appears to be related to arbitrage activities and financial product packaging. The customer base for the bond contracts is comprised of approximately 20 percent international institutions, 70 percent domestic institutions, and 10 percent domestic private clients and local traders. In terms of design and specification, the SFE's 3-Year and 10-Year T-Bond Futures contracts are similar to other leading debt futures contracts, such as Chicago Board of Trade's US Treasury Bond and Notes products and EUREX's Euro-Bond contracts[15].

The following sections discuss 3-Year and 10-Year T-Bond Futures, Options and One-Session Options in more detail. Specifically, contract specification, previous trading information and trading strategies will be presented. These provide a good understanding of the fundamentals needed for chapters 4, 5, 6 and 7 in which we analyze overnight options, their bid-ask spreads, volatility, and trading activity.

2. The Underlying Market

Three-Year and 10-Year Commonwealth Treasury Bonds are fixed interest securities issued by the Federal Government to satisfy its borrowing requirements. They are issued with a set term to maturity and pay interest semi-annually, which remains fixed for the life of the bond. Approximately A$90 billion of these securities are on issue with an average daily turnover in the secondary market of A$3.5 billion (www.sfe.com.au). Their dominance in the Australian fixed interest market means they are regarded as being the benchmark indicators of medium and long-term interest rates in Australia.

[15] The following section will give examples of spread trading by using SFE interest rate futures as well as futures on debt instruments from overseas markets.

3. Overview of the 3-Year and 10-Year T-Bond Futures

The 3-Year and 10-Year T-Bond futures contracts traded at the SFE are the benchmark indicators for medium to long-term interest rates in Australia since their underlying securities are the 3-Year and 10-Year Treasury Bonds. They have also been approved for trading by the US Commodities Futures Trading Commission (CFTC) and UK Financial Services Authority (FSA). The 3-Year T-Bond futures contract has been ranked among the top ten debt market futures contracts in the world by turnover (www.sfe.com.au).

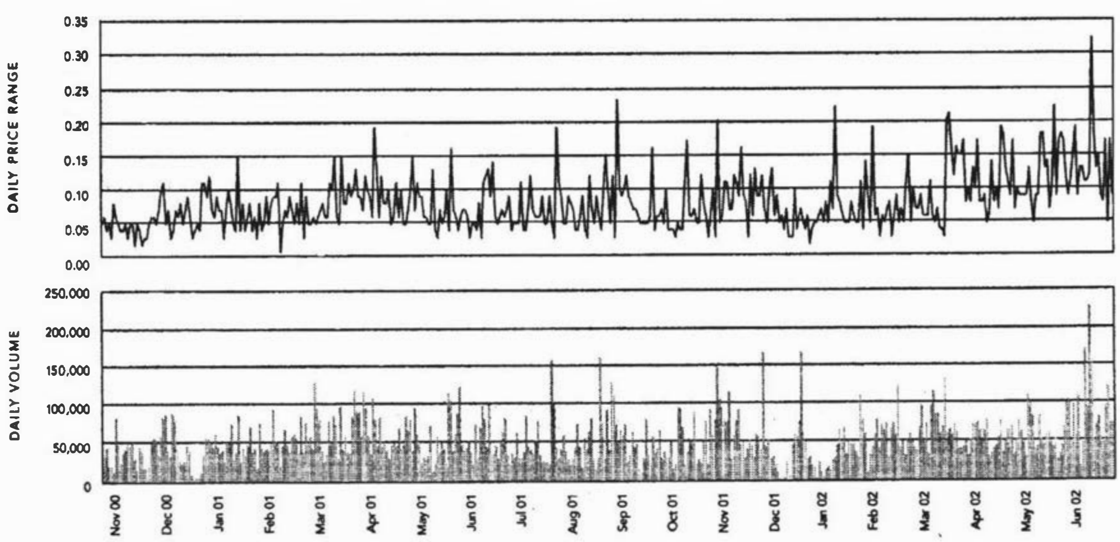
The 3-Year and 10-Year T-Bond futures contracts have a face value of A$100,000 and a coupon rate of 6%. They are cash settled against a basket of Commonwealth Government Bonds. According to the SFE contract specification, 3-Year T-Bond futures prices are quoted in yield per cent per annum in multiples of 0.01 per cent. For quotation purposes the yield is deducted from an index of 100. The minimum fluctuation of 0.01 per cent equals approximately A$28 per contract, and changes with the level of interest rates. Ten-Year T-Bond futures prices are quoted in yield per cent per annum in multiples of 0.005 per cent. For quotation purposes the yield is deducted from an index of 100. The minimum fluctuation of 0.005 percent equals approximately A$40 per contract, and changes with the level of interest rates (www.sfe.com.au).

Trading in 3-Year and 10-Year T-bond futures contracts allows investors or speculators following the medium to long-term interest rate trends to have an efficient way to gain exposure to the Australian debt markets. It also enables investors to hedge medium to long-term AUD fixed interest securities and interest rate swaps.

3.1 Price and Volume for 3-Year T-Bond Futures

As a rule, the 3-Year T-Bond futures contract has a daily trading range which fluctuates between 0.03 and 0.07 points. The strong liquidity that is a characteristic of the 3-Year T-Bond futures contract is evident on days when large intra-day price movements occur (www.sfe.com.au). Figure 3.1 shows the daily price range and volume for the 3-Year T-Bond Futures contracts from November 2000 to June 2002. Notice that the variance of the price movement for the 3-Year T-Bond futures was increased over the period, whereas the trading volume was fairly stable for the period.

Figure 3.1 Daily Price Range and Volume for 3-Year T-Bond Futures

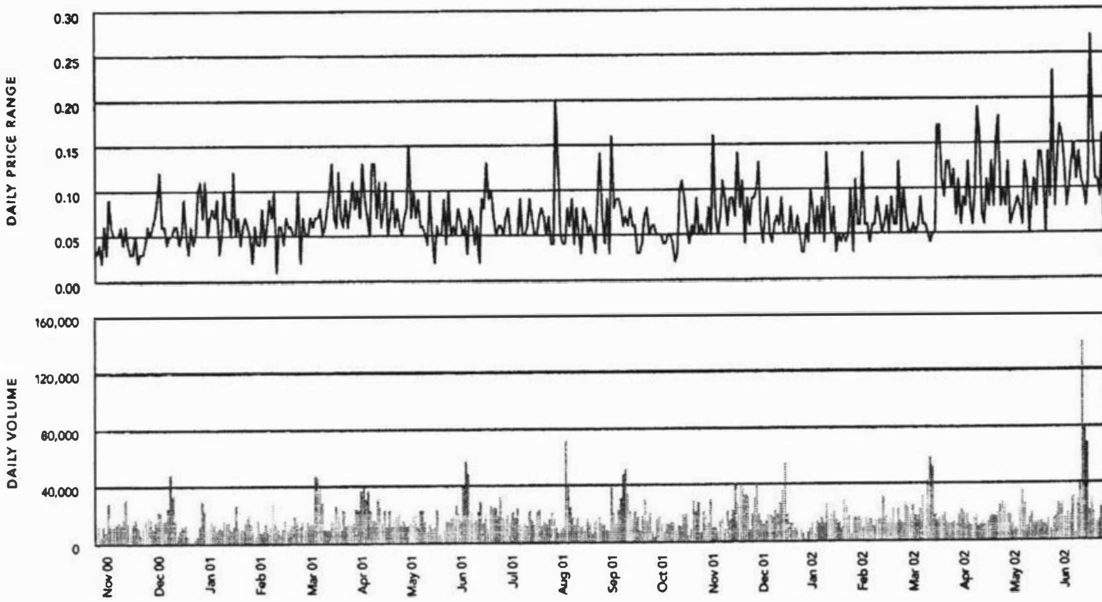


Data Source: The Sydney Futures Exchange (www.sfe.com.au).

3.2 Price and Volume for 10-Year T-Bond Futures

The 10-Year T-Bond futures contract has a trading range which fluctuates between 0.04 and 0.10 points on an average day. The following diagram shows the daily price range and volume for 10-Year T-Bond Futures contracts from November 2000 to June 2002. Notice that the variance of the price movement for 10-Year T-Bond futures increases over time, which is similar to what we found for 3-Year T-Bond futures.

Figure 3.2 Daily Price Range and Volume for 10-Year T-Bond Futures



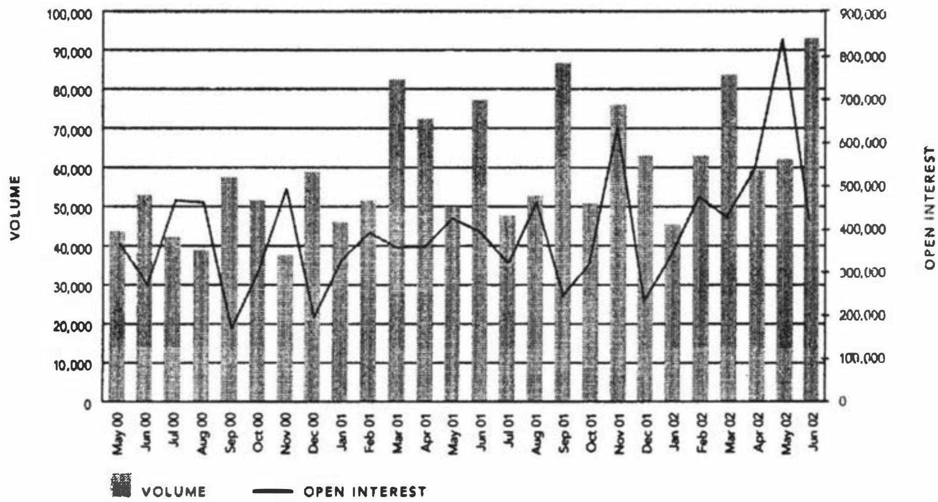
Data Source: The Sydney Futures Exchange (www.sfe.com.au).

3.3 Average Daily Volume and Open Interest for 3-Year T-Bond Futures

The SFE has a position reporting facility that requires SFE participants to supply details of all futures and options positions held. The 3-Year T-Bond futures contract shows strong volume growth. Growing levels of corporate/asset backed issuance in short/medium term assets has led to stronger volumes in this contract[16] (www.sfe.com.au). Figure 3.3 shows the average daily volume and month end open interest for the 3-Year T-Bond futures from May 2000 to June 2002. Notice that the average daily trading volume and the average open interest increased over the period.

[16] The average daily volume was about 40,000 contracts for May 2000 and was more than 90,000 contracts for June 2002.

Figure 3.3 Average Daily Volume and Open Interest for 3-Year T-Bond Futures

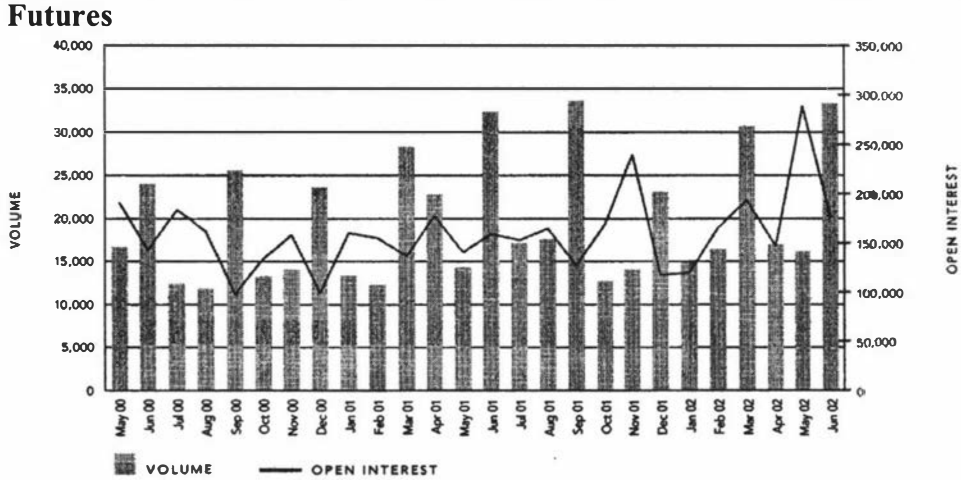


Source: The Sydney Futures Exchange (www.sfe.com.au).

3.4 Average Daily Volume and Open Interest for 10-Year T-Bond Futures

Figure 3.4 shows the average daily volume and the month end open interest for the 10-Year T-Bond futures from May 2000 to June 2002. Here it is seen that the trading volume for 10-Year T-Bond futures stayed relative stable, and that the overall trading volume for the 10-Year T-Bond futures trading volume was relative lower than the trading volume for the 3-Year T-Bond futures.

Figure 3.4 Average Daily Volume and Open Interest for the 10-Year T-Bond Futures

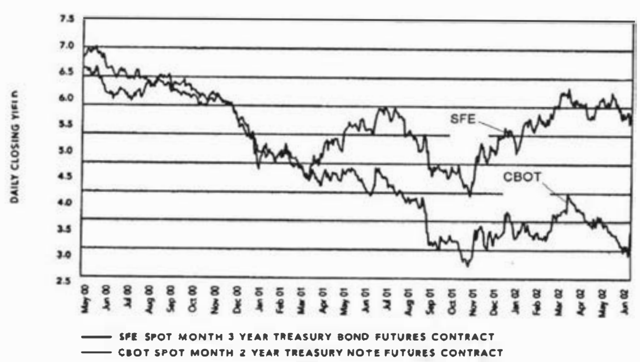


Source: The Sydney Futures Exchange (www.sfe.com.au).

3.5 Yield Comparison

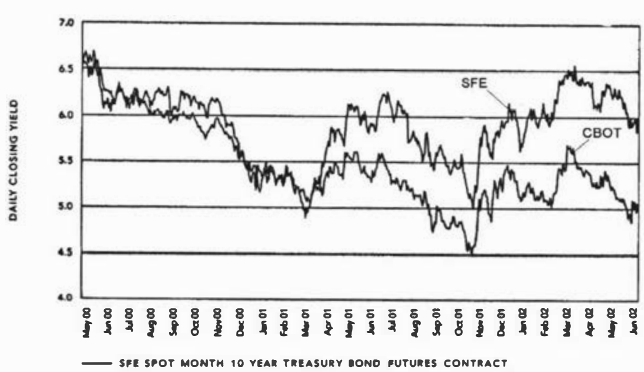
There are medium to long term trading opportunities for investors as suggested by the trends in the spreads between SFE's T-Bond futures, US debt futures and Euro-Bond futures as described in Figures 3.5, 3.6 and 3.7. These figures illustrate the spreads that exist between SFE 3-Year T-Bond futures and CBOT 2-Year Treasury Note futures in the US, between SFE 10-Year T-Bond futures and CBOT 10-Year Treasury Note futures, and between SFE 10-Year T-Bond futures and Eurex Euro-Bond futures.

Figure 3.5 SFE 3-Year T-Bond Futures Versus CBOT 2-Year Treasury Note Futures



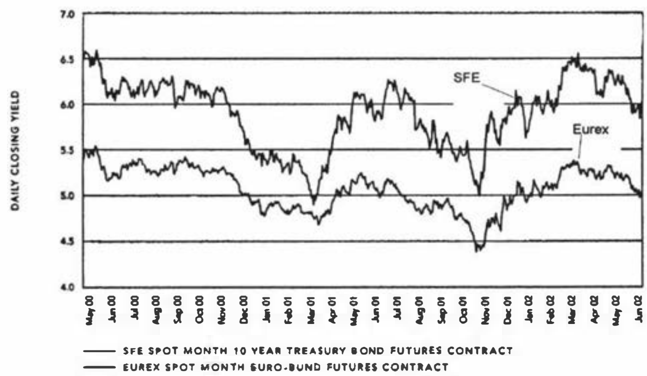
Source: The Sydney Futures Exchange (www.sfe.com.au).

Figure 3.6 SFE 10-Year T-Bond Futures Versus CBOT 10-Year Treasury Note Futures



Source: The Sydney Futures Exchange (www.sfe.com.au).

Figure 3.7 SFE 10-Year T-Bond Futures Versus Eurex Euro-Bond Futures



Source: The Sydney Futures Exchange (www.sfe.com.au).

From the above three figures it can be seen that there are yield spreads which exist between the SFE's 3-Year and 10-Year T-Bond futures and CBOT's 2-Year and 10-Year Treasury Notes futures contracts, as well as between the SFE's 10-Year T-Bond futures and the Eurex Euro-Bond futures contracts. Investors need to carefully investigate the magnitude of the spread in basis points, testing whether they are going to be economically significant after adjusting for transaction costs. We believe that if the market is efficient, an arbitrage opportunity will not last long or at least long enough for anyone to make a profit.

4. Overview of Overnight Options and Intra-Day Options

The SFE 3-Year and 10-Year T-Bond futures overnight options were introduced on 15 November 1993. Three-Year and 10-Year T-Bond futures intra-day options were launched in April 2002 as a consequence of the high market demand following the success of the overnight options. The 3-Year and 10-Year T-Bond futures overnight and intra-day options are One-Session European-style options that trade for one SYCOM session. They are quoted in yield percent per annum in multiples of 0.005

percent. Exercise prices are set at intervals of 0.01 percent per annum yield. The option exercise prices available for trading are announced prior to the opening of each session. All one-session options are automatically exercised after the SYCOM session if they are in-the-money. All at-the-money and out-of-the-money options will be left to expire after the SYCOM session. Exercise of a one-session option will result in the holder receiving a futures position at the option's strike price. Overnight and Intra-day options are considered to be low costs products, as there is no margin requirement[17] for trading in one-session options.

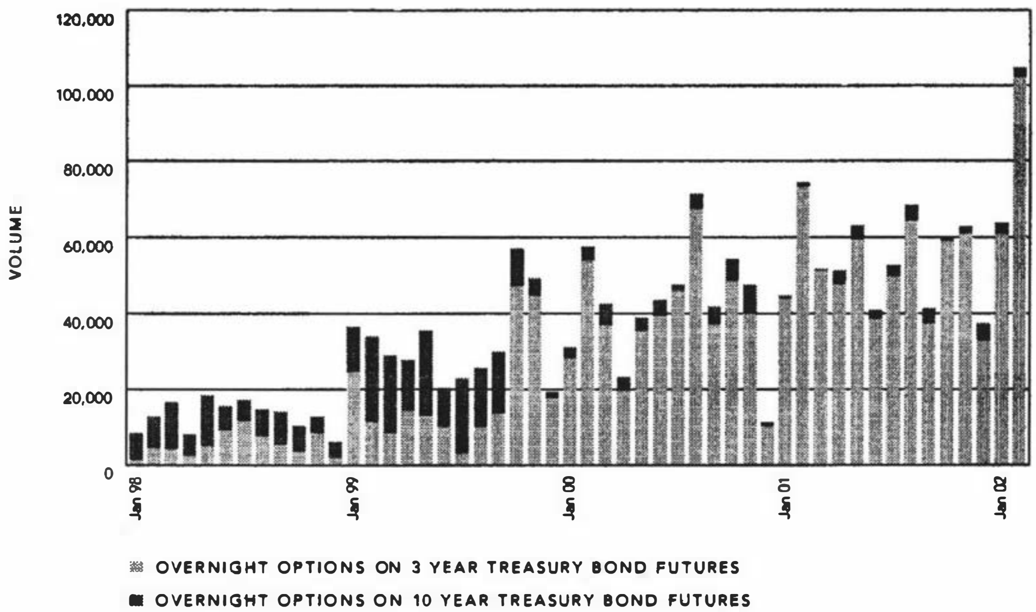
One-session option trading has been approved by the US Commodities Futures Trading Commission (CFTC) and the UK Financial Services Authority (FSA). In summary, the introduction of overnight options and intra-day options provide investors and traders with additional flexibility in the bond market as well as the bond futures market. Investors are able to manage the short-term exposure against short-term price movements. More specifically, an investor's bond positions can be protected against event risk when official cash rates are announced and economic data such as employment figures, inflation rates, and GDP figures are released domestically or in offshore markets, particularly in the US and UK. Speculators can also profit by anticipating short-term price movements in the bond market.

4.1 Trading Volumes for 3-Year and 10-Year T-Bond Futures Overnight Options

Figure 3.8 illustrates the monthly volumes for overnight options on the 3-Year and 10-Year T-Bond futures from January 1998 to January 2002.

[17] There is no margin requirement between the SFE and Brokers. However, for each individual broker, they might ask for a margin from their own clients depending on the creditworthiness of their clients.

Figure 3.8 Monthly Volumes for Overnight Options on the 3-Year and 10-Year T-Bond Futures



Data Source: The Sydney Futures Exchange (www.sfe.com.au).

As can be seen from Figure 3.8, the trading volume of the overnight options for 3-Year T-Bond futures contracts has grown substantially since the middle of 1999. We can see that trading in overnight options for 10-Year T-Bond futures was greater than that for 3-Year T-Bond futures before the year of 2000. One of the reasons is that most of the investors trading overnight options are hedging their underlying futures positions. One needs less 10-Year overnight options contracts to hedge one's underlying futures when compared with 3-Year overnight options. Thus investors are more likely to use 10-Year overnight options. However, the situation has changed dramatically since 1999[18]. The 3-Year contract now exceeds the volume of 10-Year T-Bond futures overnight options. Chapter 4 will have a detailed discussion of the reasons for this change in trading

[18] Chapter 4 will discuss this issue in detail.

volume, and analyse why 3-Year T-Bond futures overnight options have grown so substantially.

5. Contract Information

5.1 3-Year and 10-Year T-Bond Futures

5.1.1 Contract Specification[19]

Three-Year and 10-Year T-Bond futures contracts are the futures on Commonwealth Government Treasury Bonds with a face value of A$100,000, a coupon rate of 6% per annum, and a term to maturity of 3 years and 10 years respectively. The contract months are March, June, September and December. Prices are quoted in terms of yield percent per annum in multiples of 0.01 percent. The minimum fluctuation of 0.01 percent equals approximately $28 per contract for 3-Year T-Bond futures and $40 per contract for 10-Year T-Bond futures.

5.1.2 Valuation for 3-Year and 10-Year T-Bond Futures[20]

The value of SFE T-Bond futures is calculated using the Reserve Bank of Australia's bond pricing formula. The formula can be also used to calculate contract and tick values for both 3 Year and 10 Year Bond Futures contracts.

5.2 Options on the 3-Year and 10-Year T-Bond Futures

5.2.1 Contract Specification[19]

Put and call options on 3-Year and 10-Year T-Bond futures contracts are available up to 2-quarter months ahead. They are quoted in yield percent per annum in multiples of

[19] See Appendix 4 for the contract specification.
[20] See Appendix 5 for the valuation formula.

0.005 per cent. The exercise prices are set at intervals of 0.25 percent per annum. New option exercise prices are created automatically as the underlying futures contract price moves. Options may be exercised on any business day up to and including the day of expiry. In-the-money options are automatically exercised at expiry.

5.2.2 Valuation for 3-Year and 10-Year T-Bond Futures Options [20]

Three-Year and 10-Year T-Bond futures options are quoted as an annual percentage yield (i.e. 0.405%). The premium of an option is priced in terms of its yield percent per annum in multiples of 0.005 percent. For quotation purposes the premium is multiplied by 100.

5.3 One-Session Options on 3-Year and 10-Year T-Bond Futures

5.3.1 Contract Specification [19]

According to the SFE contract specification (www.sfe.com.au) one-session call and put options are available on futures contracts for the nearest quarter month ahead. The one-session options will only last for one SYCOM session. They are quoted in yield percent per annum in multiples of 0.005 percent. The exercise prices are set at intervals of 0.01 percent per annum yield. Nine option-exercise prices are available for trading, with additional strike prices listed at the discretion of the SYCOM manager or the Chief Executive of the SFE. All in-the-money options will be exercised on the business day immediately following the SYCOM session. All others will be expired after the SYCOM session. The exercise of an option will result in the holder receiving a futures position at the option's strike price. The settlement price is the weighted average of trade prices executed in the underlying contract between 8:30am and 8:40am on the business day immediately following the SYCOM session for the overnight options, and between 4:15pm and 4:25pm for the intra-day options.

5.3.2 Valuation for the One-Session Options[20]

The one-session options only last for one SYCOM session, and they are European-type of options. Thus, we may use Black's (1976) formula to value them.

5.4 Tick Value Calculation[20]

Because 3-Year and 10-Year T-Bond futures contracts are quoted in percent yield format, the dollar value of a 0.01% change in yield does not remain constant over time. Rather it varies in accordance with changes in the underlying interest rate. For a futures option with a particular exercise price, the value of a move of a certain size in the futures market will not equate exactly in dollar terms with a move of the same size in the option premium. Investors should also be cautious about implementing conversion strategies owing to the differences in tick sizes between an option strike price and the prevailing futures price. For example, it can happen that an option appears to be priced slightly below its intrinsic value in terms of the yield when in fact, in dollar terms, the pricing is correct (www.sfe.com.au).

6. Conclusion

This chapter details the interest rate products traded at the Sydney Futures Exchange in terms of past trading history, trading volume, contract specification, and valuation method. It gives us a good understanding about the product that we are going to discuss in detail in the following chapters. The interest rate products traded at the SFE are the most active traded products. These include the interest rate futures contract, the interest rate futures options contract, the interest rate futures overnight options contract, and the interest rate futures intra-day options contract. All of these products provide us with a very rich database to do empirical analysis. This is particularly so for overnight options and intra-day options as they are relative new to investors and have different market microstructure and different risk-return characteristics. Thus, we expect to observe differing patterns of bid-ask spreads, trading volume and volatility, which we will discuss in chapter 4.

Chapter 4[21] Intra-Night Trading Behavior of the Australian Treasury-Bond Futures Overnight Options

1. Introduction

Research into the trading behavior of options has been a popular topic for researchers. Previous work has focused on standard options primarily traded on large markets with available data in the US and UK. Conclusions indicated that time, volatility, maturity effects, and differing market microstructure make it difficult for market participants to conduct price discovery in the face of new information. In line with the emerging research area, the introduction of overnight options on T-Bond futures contracts at the Sydney Futures Exchange (SFE) offers a unique opportunity to study trading behavior with a different market microstructure, namely the SFE overnight options market.

As we discussed in chapter 3, overnight options (One-session options) are European-style options that are only valid for the duration of the SYCOM session in which they are traded. Since there are no margin requirements for trading overnight options, overnight options are low cost products. They provide investors and traders with additional flexibility in the bond market. They can also be used to manage short term exposure (i.e. overnight exposure), to hedge positions from event risk (i.e. investors often take their position before the US markets open particularly for those days with economic announcements), to profit by anticipating short term price movements in the bond market, to take positions on events, and to place the equivalent of a stop loss

[21] A paper based on Chapters 4 & 5 was accepted and presented at the FMA (Financial Management Association) 2003 Annual Conference held on 8th October in Denver, the US (Zou, Rose and Pinfold, 2002, 2003a).

order. Thus, a comprehensive analysis of overnight options trading behavior will give investors a good understanding of how to best execute trading in this market.

Most previous research has found a U-shaped pattern for stock bid-ask spreads. This indicates that bid-ask spreads are wider at the open and close of the stock market. Results for options are mixed. McInish and Wood (1992) for the stock market, and Chan, Chung and Johnson (1995) found reverse J-shaped patterns for options. An explanation for the difference between the stock and the option markets is that the width of bid-ask spread at the market open is due to the degree of uncertainty. Thus the wide stock bid-ask spread and the narrow option bid-ask spread is due to differing market structure. Thus, one may expect different intra-night bid-ask spread patterns for overnight options because of the special characteristics of these securities in terms of maturity time, pricing formula, exercise style, and market structure. In this chapter we are going to analyze intra-night bid-ask spread patterns for 3-Year and 10-Year T-Bond futures overnight call and put options. By examining the intra-night patterns for the overnight options, we can see whether or not there are significant variations across time intervals during the trading night, and whether or not there are significant variations at the market open or close.

It is argued that greater trading volume narrows bid-ask spreads. Greater trading volume also generates greater volatility for the market. Previous studies have found that intra-day trading volume and intra-day volatility follow U-shaped patterns similar to bid-ask spreads patterns. Thus, it is useful to conduct an intra-night analysis for trading volume and volatility patterns to see whether previous findings hold for the overnight options market. As the overnight options market is operating with competing market makers, all positions in the overnight options are automatically exercised at the end of the night trading. This will affect the theoretical models that attempt to explain patterns in bid-ask spreads, volume, and volatility.

The structure of this chapter is as follows. Firstly, we are going to explore the market microstructure of the overnight options market in relation to patterns of bid-ask spreads, trading volume, and volatility. More specially, intra-night patterns of bid-ask spreads, trading volume, and volatility will be examined. Then, we will test if there are significant differences across time intervals during the trading night, and if there are significant differences during the market open and close from other intervals. Finally, we use t-test to examine impacts on intra-night trading behaviour with US macroeconomic news releases.

2. Literature Review

The intra-day trading behavior of the bid-ask spreads, trading volume, and return volatility has been extensively studied on different financial markets. The issue is influenced by the market microstructure. Trading patterns have been observed to be dependent on market microstructure. Market microstructure theory suggests that intra-day trading behavior is related to the trading behavior of intra-day bid-ask spreads, intra-day trading volume, and intra-day volatility. There is evidence that intra-day bid-ask spreads, trading volume and return volatility are not constant over time. Chan, Chung and Johnson (1995) provide a useful summary of the factors affecting intra-day bid-ask spreads. Hasbrouck (1988) proposed a theory based on information uncertainty. Ho and Stoll (1983) used the inventory of the market maker to explain the spreads and

Lee, Mucklow and Ready (1993) found the intensity of trading activity was the decision factor.

2.1 Patterns of Bid-Ask Spreads and Its Determinants

The intra-day behavior of bid-ask spreads has a significant impact on how and when trades are executed within a marketplace. The concept has been studied in most financial markets using a range of differing financial instruments: McInish and Wood (1992) for stocks on the NYSE; Wang et al. (1994) for S & P 500 index futures; Chan, Christie and Schultz (1995) for NASDAQ; Chan, Chung and Johnson (1995) for CBOE options and their underlying NYSE stocks; Gwilym, Buckle and Thomas (1997, 1998) for LIFFE stock index options; Duffy (1999) for Australian futures markets; Tse (1999) for the FTSE index futures; Pinder (2000) for Australian options. Most of the results report intra-day U-shape or reverse J-shape patterns for bid-ask spreads over the periods from the market opening to its close (see also Vijh, 1990, George and Longstaff, 1993, Guilym and Buckle, 1996, and Cyree and Winters, 2001).

Demsetz (1968) was one of the first to theoretically address bid-ask spreads. He placed the bid and the ask price in a demand and supply framework. This modelled the spread as a transaction cost paid by a trader for the opportunity to trade immediately. Since the bid-ask spread represents the difference between the price of buying and the price of selling for a particular trade, it is an important element in any financial market. Market microstructure theory (O'Hara, 1995), puts forward several explanations for the behaviour and determinants of the bid-ask spread. These are the inventory model, the asymmetric information model, and the differing market structure theory.

2.1.1 The Inventory Model

The inventory model of bid-ask spread considers the costs faced by dealers who are forced to either take a long or short position in the security. Market makers are rewarded by bid-ask spreads for bearing the risk of holding inventory that deviates from an equilibrium position. Under this framework, in order to maximize the expected average profit per unit of time, a dealer would set the bid-ask spread as a mechanism to keep inventory at the desired level. Alternatively, the dealer can be viewed as an investor who would like to diversify holdings and has preferences regarding the risk-return profile of a portfolio (Coughenour and Shastri, 1999).

Amihud and Mendlson (1980) developed a model for specialists whereby spreads are widened as inventory imbalances accumulate. The bid-ask spread could be characterised as a means of assessing the liquidity in the market that is being supplied by the dealer. Market microstructure theory suggests that one of the main elements of supplying liquidity to the market is the cost of holding inventory and processing orders. Coughenour and Shastri (1999) pointed out that a wider spread represents a lower liquidity level. The requirements of providing liquidity in the market forces the market maker to hold portfolios that are sub-optimal. Therefore, the dealer sets the bid-ask spread such that the utility gained from the dollar compensation paid offsets the loss in utility from the extra risk borne by holding a sub-optimal portfolio. The inventory models suggest that bid-ask spreads increase with price and the risk of the security, and decrease with trading volume and the number of market makers.

2.1.2 The Asymmetry Information Model

The asymmetry information model is based on the theory that the bid-ask spread is a purely informational phenomenon. This model (Copeland and Galai, 1983, Kyle, 1985, Easley and O'Hara, 1987, and Madhavan, 1992) focuses on adverse information selection between market makers, informed traders, and the liquidity traders. Under this framework, informed traders have informational advantages, while liquidity traders who must trade at a given time during the day regardless of costs will not be trading on the basis of information. Thus, the market makers must set the bid-ask spread wide enough so that the losses from trading with informed traders will be offset by the gains from trading with the liquidity traders. The model suggests that in periods of high price volatility informed traders win by picking off those traders wishing immediacy (liquidity traders). Thus the asymmetric information model suggests that the bid-ask spreads will increase with the increase of security price volatility.

2.1.3 Differing Market Structure Theory

The intra-day pattern of the bid-ask spread has significant influence on when and how trades are executed in the market. There are theoretical and empirical distinctions that exist between the intra-day behaviour of bid-ask spread in markets with a monopolistic specialist (e.g., NYSE) versus those with competing market makers [e.g. National Association of Securities Dealers Automated Quotation (NASDAQ)]. Brock and Kleidon (1992) developed a model where a single specialist has monopolistic power and is faced with inelastic demand at the open and close of trading, due to information accumulation over the night prior to opening, and the immediacy of the non-trading period after the close. Brock and Kleidon (1992), and Chan, Chung and Johnson (1995) show that the bid-ask spread at the NYSE follows a U-shape pattern throughout the day. However, they found that the bid-ask spread on the CBOE narrows near the close. Similar results are reported by Kleidon and Werner (1993) for the London Stock Exchange, and by Chan, Christie, and Schultz (1995) for NASDAQ. Also Tse (1999) found that spreads are stable over the day, but decline sharply at the close of FTSE-100 index futures trading on LIFFE (London International Financial Futures and Options Exchange).

2.2 Patterns of Trading Volume

The trading volume patterns were found to follow a U-Shaped pattern in the earlier studies. For example, Jain and Joh (1986, 1988) examined hourly data for the total trading volume on the NYSE and found a U-Shaped curve for the stock trading volume. Similar results were also found by McInish and Wood (1989), and Foster and Viswanathan (1990). Sometimes examining the trading volume on its own cannot explain the whole picture of the intra-day trading activities, as a greater number of trades may occur during a particular time period. This was found by McInish and Wood (1991) using NYSE stocks. They found that the greatest number of trades occurred in the first hour.

The options market exhibits a different pattern of trading volume to the stock market because of its different market microstructure. Stephan and Whaley (1990) found that the options market started at a lower trading level and gradually increased to a higher level of activity about 45 minutes after market opening. However, Chan, Chung and Johnson (1995) found that trading volume is low for the first 5 minutes on the CBOE options market because of the differing market microstructure between CBOE and NYSE. Chan, Chung and Johnson (1995) also found that the trading volume of call options decreased in the last ten minutes at CBOE when the underlying stock market closed, and the trading volume of put options increased in the last ten minutes. Berkman (1993) found similar trading volume patterns for equity call options traded at the European Options Exchange (EOE). On the other hand, Berkman (1993) found that trading volume was low for the opening half-hour, increased for the next two hours, and then fell before eventually going up later in the session.

2.3 Patterns of Volatility

Wood, McInish and Ord (1985) reported that the variance of price changes and the variance of returns follow a U-shaped pattern on the NYSE (see also McInish and Wood (1990)). This generates several questions: 1. Why are returns more volatile for some time periods during the day? 2. Do the periods with higher trading volumes tend to have higher return variability? 3. Why does the trading occur more in one particular time period rather than in other periods during the day?

Option markets may have different return volatility patterns to equity markets. Chan, Chung and Johnson (1995) examined intra-day patterns for standardized volatility for CBOE options. They found that volatility patterns for CBOE options follow a U-Shaped pattern with a decrease during the last ten minutes of trading when the underlying market is closed.

2.4 Impacts on Intra Day/Night Patterns with Macroeconomic News Releases

As we discussed in earlier chapters, one of the important motivation for trading into overnight options market is to hedge the position when there are US macroeconomic information releases. As in Ederington and Lee (1993), many market participants believe that scheduled macroeconomic news releases such as the employment report, the consumer price index (CPI), and the producer price index (PPI), have a major impact on financial markets (Also see Fleming and Remolona (1999), Ederington and Lee (1995), and Frino and Hill (2001)). The SYCOM trading session spans these releases, we are going to examine whether US macroeconomic releases can explain the intra-night patterns in bid-ask spreads, trading volume, and volatility.

3. Data and Methodology

3.1 Data

The Security Industry Research Centre of Asia-Pacific (SIRCA) and Reuters provided the research data.

3.1.1 Data Sample

Three-Year and 10-Year T-Bond Futures and their overnight options intra-night data starting from November 15 1993 to August 2000 are used to study the trading behaviour of overnight options in terms of bid-ask spreads, trading volume, and return volatility. Intra-night data consists of the time-stamped raw data for each quoted bid and ask to the nearest second. The trade data contains the time of the trade, the trading price, and the trading volume.

3.1.2 Database Construction

From the time-stamped quote data, we eliminate all the quotations with either bid or ask equal to zero. Then we delete all quotations with negative bid-ask spreads[22]. We

[22] We keep the quote where bid equals quote, although the spread is zero.

also split the data into calls and puts for both 3-Year and 10-Year T-Bond futures overnight options. We choose the best bid-ask spread for each particular time. Then intra-night time-weighted average relative bid-ask spreads are generated for a particular time interval. For the actual trade data, we split trades into overnight calls and puts in order to calculate the trading volume for each time interval during the trading night.

3.2 Methodology

We followed the method as suggested by McInish and Wood (1992) to calculate the intra-night time-weighted average standardized relative bid-ask spreads for a particular time interval. These were calculated by using selected time intervals during the night. Trading volume was calculated for each time interval. Volatility was calculated from bid-ask midpoints. Then, we regress standardized intra-night bid-ask spreads, intra-night trading volume, and intra-night volatility on dummy variables which represent the different time intervals during the trading night, to test whether there is any difference between time intervals. Finally, we use US macroeconomic information release dummy variables to test whether there are differences in terms of bid-ask spreads, trading volume, and volatility for different time intervals during the trading night.

3.2.1 Calculation of standardized Relative Bid-Ask Spreads

Because there are nine different exercise prices for overnight options, we therefore need to adjust the variable to the standardized variable. Following the method as adopted by Chan, Chung and Johnason (1995), the standardized relative bid-ask spreads are defined as $(X_{it} - \mu_{it})/\sigma$, where X_{it} is the relative bid-ask spread variable as calculated $X_{it} = [(ask - bid)/(ask + bid)/2]$, μ_{it} is the mean for the night , and σ is the standard deviation for the night.

3.2.2 Calculation of Time-Weighted Average Standardized Relative Bid-Ask Spreads

McInish and Wood (1992) is one of the classic articles which describe time weighted bid-ask spreads. In this chapter we use a similar method to calculate time-weighted average standardized relative bid-ask spreads for the 3-Year and 10-Year T-Bond futures overnight options. Suppose that in the time interval (T, T') there are N quotation updates, occurring at times t_i, i= 1, ….., N, with spreads BAS_i, where $t_0 = T$ and $T_{N+1} = T'$. Thus time-weighted average standardized relative bid-ask spreads will be calculated as follows for the first quote of the night:

$$\sum_{i=1}^{N} \frac{BAS_i (t_{i+1} - t_i)}{T' - t_1}$$

where BAS_i is the standardized relative bid-ask spreads for each time second, $(t_{i+1} - t_i)$ is the time interval between quotations. So the first interval is time t_1 to T'. But the subsequent intervals in the day will be t_0 to T', which we will use the following formula:

$$\sum_{i=0}^{N} \frac{BAS_i (t_{i+1} - t_i)}{T' - T}$$

3.2.3 Calculation of Standardized Trading Volume

Intra-night trading volume is calculated as the time weighted-average standardized trading volume for a particular time interval. The calculation of the standardized trading volume is the same as the standardized bid-ask spreads described in section

3.2.1. The first time interval is a half-hour interval from 16:30:00 to17:00:00. One-hour intervals were used from 17:00:00 onwards.

3.2.4 Calculation of Volatility

Intra-night volatility patterns were examined using volatilities calculated from standardized quoted bid-ask midpoints. We use the midpoint of bid and ask quotes instead of transaction prices as suggested by McInish and Wood (1992). This avoids a bid-ask bounce problem. We first calculate the standardized volatility using the method suggested by Chan, Chung and Johnson (1995). The standardized bid-ask midpoint volatility is defined as $(x_t-\mu_t)/S_t$, where x_t is the bid-ask midpoint for each time second, μ_t is the mean for the day, and S_t is the standard deviation for the day. Then, we calculate the standard deviation of the standardized bid-ask midpoint to get the intra-night mid-point volatility for different time intervals. The standardized volatility is the absolute value of the bid ask midpoint return. The first time interval is a half-hour interval from 16:30:00 to17:00:00. One-hour intervals were used from 17:00:00 onwards.

3.2.5 F-Statistics for Intra-Night Bid-Ask Spreads, Trading Volume, and Return Volatility Patterns

We regress standardized intra-night bid-ask spreads, trading volume, and volatility on dummy variables which represent different time intervals during the trading night plus an intercept to generate F-statistics. F-statistics examine differences in intra-night bid-ask spreads, trading volume, and volatility across eight time intervals during the first half of the trading night.

3.2.6 Impact of US Macroeconomic New Releases

As in Ederington and Lee (1993), many market participants believe that scheduled macroeconomic news releases such as the employment report, the consumer price index (CPI), and the producer price index (PPI), have a major impact on financial markets (Also see Fleming and Remolona (1999), Ederington and Lee (1995), and Frino and Hill (2001)). Thus, in order to examine the impact of US macroeconomic news releases on intra-night bid-ask spreads patterns, intra-night trading volume patterns, and intra-night price volatility patterns, we partitioned our data based on days with scheduled US macroeconomic news releases[23], and days without US macroeconomic news releases. We choose the first two time intervals[24] and use the t-test to examine the significance of the difference in mean bid-ask spreads, trading volume, and volatility between US macroeconomic releases and non-releases days.

4. Analysis

We analyse the trading behaviour of 3-Year and 10-Year T-Bond futures overnight options by testing the intra-night patterns for quoted standardized bid-ask spreads, trading volumes, and volatility. Regressing intra-night bid-ask spreads, intra-night trading volume, and intra-night volatility on an intercept and dummy variables will be used to calculate the F-statistics. This gives a statistical test of whether or not the intra-night patterns for the three variables are statistically significant across different time intervals. Finally, we use the t-test to examine the impact of US macroeconomic releases on intra-night patterns.

[23] We use days with employment rate, CPI, and PPI releases.

[24] We found that most quotes and trades are occurred within the first two time intervals.

4.1 Trading Behavior of the 3-Year and 10-Year T-Bond Futures Overnight Options

A description of the number of quotations and trading volumes for 3-Year and 10-Year T-Bond futures overnight call and put options are presented for the period of November 15 1993 to August 31 2000. Table 4.1 below shows the intra-night number of bids, asks, and trades at one-hour intervals for 3-Year and 10-Year T-Bond Futures overnight calls and puts options over the period November 15 1993 to August 2000. The first time interval is the half hour starting from 16:30:00. One-hour intervals were used from 17:00:00[25]. This is also illustrated by Figure 4.1.

Table 4.1 Number of Quotes and Trades for 3-Year and 10-Year T-Bond Futures Overnight Options[26]

Number of bids, asks and trades are presented in this table for the period from November 15, 1993 to August 31, 2000. Bid refers to how many bids are quoted in a particular one-hour time interval. Ask refers to how many asks are quoted in a particular one-hour time interval. And trade refers to how many actual trades occurred in a particular one-hour time interval.

Time Interval[27]	3-Year TBond Futures						10-Year TBond Futures					
	Calls			Puts			Calls			Puts		
	Bid	Ask	Trade	Bid	Ask	Trade	Bid	Ask	Trade	Bid	Ask	Trade
16:30:00-17:00:00	2236	2360	339	2149	2275	502	11078	11640	1708	10971	11591	1780
17:00:00-18:00:00	4636	4778	1342	3989	4186	1332	11860	12484	2277	11209	11956	2425
18:00:00-19:00:00	1084	1130	298	910	959	322	3637	3830	668	3626	3833	617
19:00:00-20:00:00	495	510	143	471	491	172	1884	1987	321	1648	1742	350
20:00:00-21:00:00	269	270	95	280	303	89	1065	1130	197	919	1000	194
21:00:00-22:00:00	228	243	48	187	198	73	593	636	110	562	601	125
22:00:00-23:00:00	102	119	15	99	102	30	277	288	66	264	292	63
23:00:00-24:00:00	32	38	4	37	37	6	130	140	36	89	93	22
24:00:00-01:00:00	14	13	9	8	8	3	41	50	14	32	39	11
01:00:00-02:00:00	3	3	1	1	1	1	12	13	6	15	16	6
02:00:00-03:00:00	-	-	2	2	3	1	15	21	8	14	15	4
03:00:00-04:00:00	1	1	-	2	5	-	9	13	5	9	9	3
04:00:00-05:00:00	1	1	-	4	5	2	12	12	1	15	15	5
05:00:00-06:00:00	9	9	7	1	1	-	9	9	6	6	6	7
06:00:00-07:00:00	1	1	-	-	-	-	-	1	3	-	2	1

[25] One-hour intervals were used in order to obtain enough observations in each time segment.
[26] The numbers of bids and asks are not matched, as we are counting the raw bids and asks, not in pairs.
[27] The overnight options start to trade from 4:30:00pm and cease at 7:00:00am the next day.

From table 4.1, we observe that most of the quotes and trades occur during the first half of the night, particularly in the first two hours. This may be explained by the special nature of overnight options. Overnight options appear to be used for hedging or speculating against price sensitive information originating in the US market. Market participants take positions before the US market opens or before US economic announcements occur, and then hold these positions[28]. Overnight options only last for one night, and if they are in-the-money, exercise will be automatic at the end of the night session, while all other options will expire worthless. So we would expect to see more quotes and trades at the beginning of the night session, where adequate liquidity exists to enable participants to hedge or speculate.

From Table 4.1 we also observe that the trading of overnight puts for both the 3-Year and 10-Year T-Bond futures contracts are greater than overnight calls. That indicates investors are more often pessimistic than optimistic about the market, and expect the market to fall more often than to rise, leading to more puts than calls being traded. We may then conclude that market participants are using the market primarily for hedging against a fall in the underlying futures market.

Table 4.1 also illustrates that numbers of quotations at each time-interval for the 10-Year T-Bond futures overnight call and put options are greater than for the 3-Year issues. This may indicate that the 10-Year T-Bond futures overnight options market is more efficient than the 3-Year T-Bond futures overnight options market. This phenomenon is also contributed to the fact that traders have been using 10-Year T-Bond

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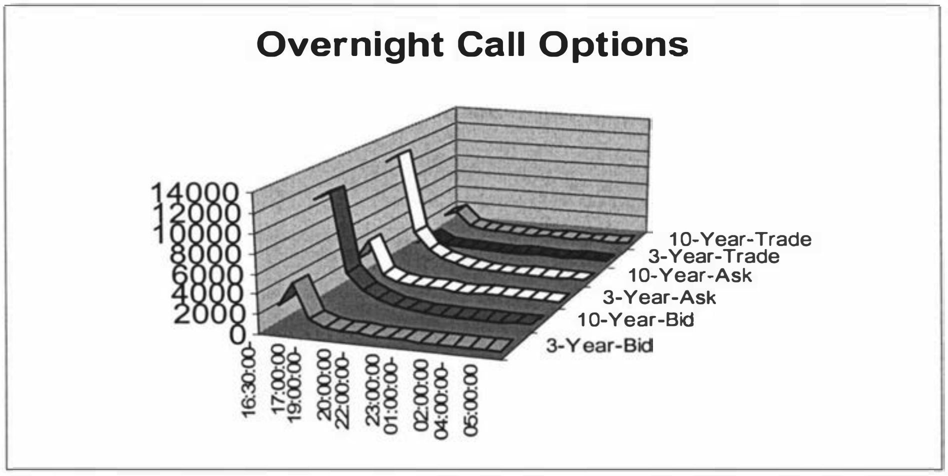
[28] Source: Interviews with overnight options traders and SFE staff.

futures overnight options in the first couple of years, since trading in 10-Year contracts is cost effective[29] as discussed in chapter 3.

Figures 4.1 and 4.2 graphically illustrate the results from Table 4.1. Figure 4.1 is the intra-night numbers of bids, asks and trades for the 3-Year and 10-Year T-Bond futures overnight call options. Figure 4.2 is the intra-night numbers of bids, asks and trades for the 3-Year and 10-Year T-Bond futures overnight put options. It is obvious that the number of bids, asks and trades for both the 10-Year T-Bond futures overnight call and put options are greater than for the 3-Year T-Bond futures overnight call and put options respectively.

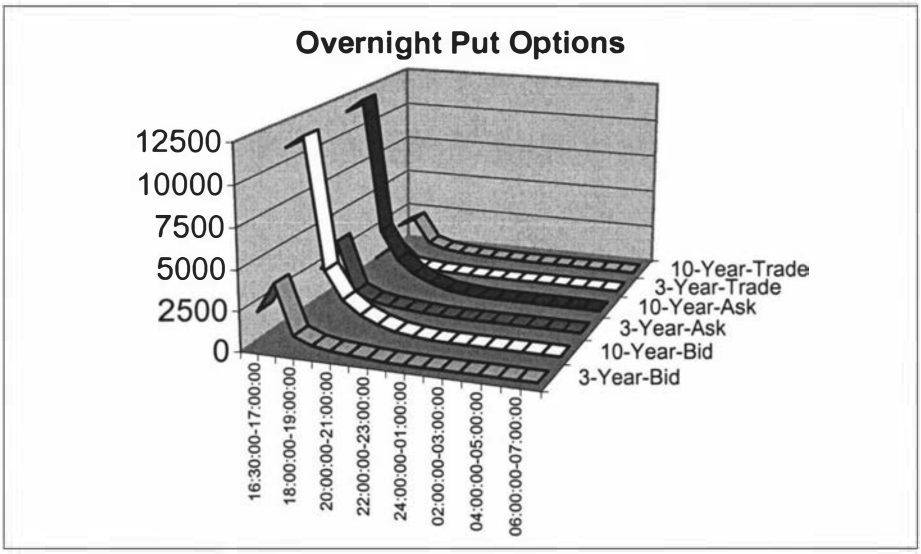
Figure 4.1 Intra-Night Numbers of Bids, Asks and Trades for 3-Year and 10-Year T-Bond Futures Overnight Call Options

Results from Table 4.1 above are used to compare the number of bid, asks and trades for the 3-Year and 10-Year T-Bond futures overnight call options. The x-axis in the graph is the intra-night time interval, the first time-interval is half an hour starting from 16:30:30. One-hour intervals are used thereafter. The y-axis gives the number of bids, asks and trades in a particular time interval.



[29] It has a greater tick size than for the 3-Year contract. See Appendix 5 for tick value calculation.

Figure 4.2 Intra-Night Numbers of Bids, Asks and Trades for 3-Year and 10-Year T-Bond Futures Overnight Put Options
Results from Table 4.1 above are used to compare the number of bid, asks and trades for the 3-Year and 10-Year T-Bond futures overnight put options. The x-axis in the graph is the intra-night time interval, the first time-interval is half an hour starting from 16:30:30. One-hour intervals are used thereafter. The y-axis gives the numbers of bids, asks and trades in a particular time interval.



4.2 Changes in Quoted Bid-Ask Spreads, Trading Volume and Trading Frequency

To test if there are changes regarding the bid-ask spread, trading volume, and trading frequency, overnight options data was segmented by year starting from their introduction on November 15 1993 up to August 31 2000. Table 4.2 reports the daily mean and median time-weighted average relative bid-ask spread, trading volume, and trading frequency. The quoted time-weighted average relative bid-ask spreads narrowed over time for most of the overnight calls and puts for both 3-Year and 10-Year T-Bond futures contracts. Over the period of the study, trading volume of the overnight calls and puts continually increases for the 3-year overnight options, however for 10-Year overnight options the trading volume fell over time.

As discussed earlier, though the 10- Year options were cost effective, the underlying market did not provide as much liquidity relative to the 3-Year options[30]. Thus investors adjusted their trading strategies and moved to the most liquid market. The trading frequency pattern reflects this by showing an increasing volume for the 3-Year contracts over time. It appears that the 3-Year T-Bond futures overnight options market became more efficient overtime, as its use by market participants increased. On the other hand, the 10-Year T-Bond futures overnight options market became less efficient with decreasing trading volume and trading frequency, although the bid-ask spread did shrink. This indicates investors choose to trade the derivative securities with the most liquid underlying market despite higher transaction costs.

Table 4.2 Mean and Median Relative Bid-Ask Spreads, Trading Volume, Trading Frequency Over Time

RBAS is the daily mean and median relative time-weighted average bid-ask spreads. Volume is daily mean and median total trading volume during one night. Frequency is the daily mean and median average number of transactions during one night. We use the time period between November 1993 to August 2000.

Year	3-Year TBond Futures						10-Year TBond Futures					
	Calls			Puts			Calls			Puts		
	BAS	Vol	Freq	BAS	Vol	Freq	BAS	Vol	Freq	BAS	Vol	Freq
93-94	0.60[31]	63	1.30	0.49	97	1.40	0.68	99	2.60	0.64	88	2.30
	0.61[32]	50	1.00	0.39	100	1.00	0.68	60	2.00	0.64	73	2.00
94-95	0.65	106	1.70	0.74	154	1.90	0.75	132	2.90	0.73	130	2.20
	0.60	63	1.00	0.60	100	1.00	0.73	100	2.00	0.67	100	2.00
95-96	0.57	218	2.80	0.49	260	3.40	0.64	311	6.10	0.59	281	5.90
	0.60	150	2.00	0.48	150	2.00	0.65	250	5.00	0.59	200	4.00
96-97	0.36	176	2.10	0.30	282	3.50	0.51	353	6.20	0.48	369	6.60
	0.18	150	2.00	0.17	170	3.00	0.55	258	5.00	0.51	250	5.00
97-98	0.19	302	2.90	0.13	339	3.20	0.25	235	4.50	0.21	211	4.20
	0.00	275	2.00	0.00	231	2.00	0.08	157	4.00	0.05	150	3.00
98-99	0.37	658	4.00	0.33	650	4.30	0.32	336	5.90	0.37	416	7.00
	0.29	400	3.00	0.24	500	3.00	0.37	230	5.00	0.31	311	6.00
99-00	0.34	1076	6.20	0.39	1931	10.10	0.40	166	2.80	0.39	173	2.90
	0.28	940	5.00	0.33	1600	9.50	0.34	110	2.00	0.34	150	2.00

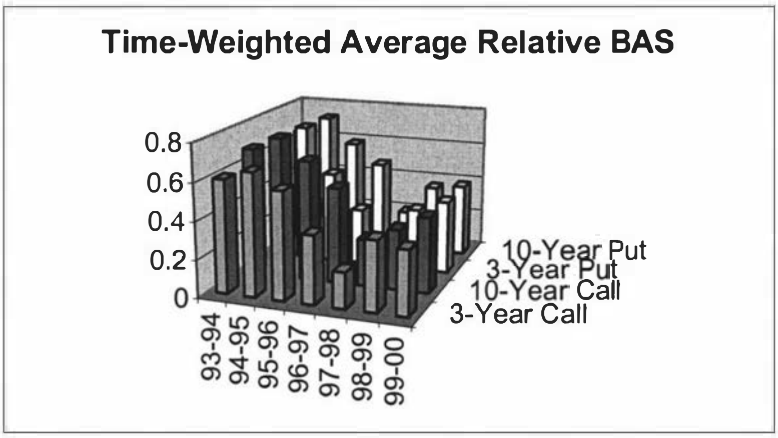
[30] It may be useful to divide the sample into sub-sample for both 3-Year and 10-Year T-Bond futures overnight options to examine possible reasons for changing usage of the contracts.

[31] Mean value.

[32] Median value.

Figure 4.3 below illustrates the time-weighted average relative bid-ask spreads over time by using the mean value from Table 4.3. We found that the time-weighted average relative bid-ask spreads for 10-Year T-Bond futures overnight options (both calls and puts) are greater than that for the 3-Year options.

Figure 4.3 Time-Weighted Average Relative BAS for 3-Year and 10-Year Overnight Options Over Time



4.3 Intra-Night Trading Patterns

This section presents the intra-night patterns of standardized relative bid-ask spreads, trading volume, and volatility.

4.3.1 Intra-Night Bid-Ask Spreads Patterns

Figure 4.4, Panels A, B, and C, illustrate quoted standardized intra-night bid-ask spreads for the 3-Year T-Bond futures and its overnight call and put options. Figure 4.5, Panels A, B, and C, illustrate quoted standardized intra-night bid-ask spreads for the 10-Year T-Bond futures and its overnight call and options. Time-weighted average standardized relative bid-ask spreads for one-hour intervals are calculated following the methodology of McInish and Wood (1992). The first time interval is the half hour starting from 16:30:00. A one-hour interval was used from 17:00:00[33] onwards[34].

Most previous studies have observed U-Shaped or reversed J-Shaped bid-ask spread patterns. In contrast, this study found that bid-ask spreads for the underlying 3-Year and 10-Year T-Bond futures are the lowest when the night SYCOM session starts trading, then, gradually go up during the rest of the trading night and decrease at the end of the night SYCOM session. It was not surprising to see a lower bid-ask spreads at the beginning of the night session, as the night SYCOM session starts just after the closing of the day SYCOM session. Thus, we would not expect to see a typical higher bid-ask spreads in the beginning of the trading night.

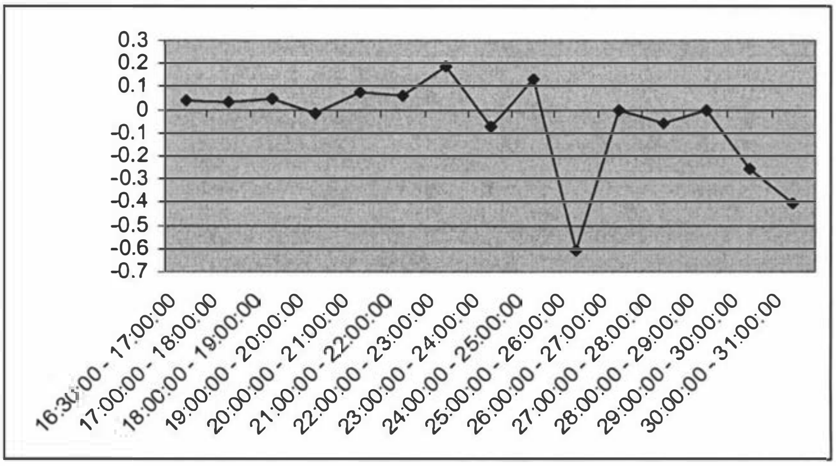
For 3-Year T-Bond futures overnight call and put options, bid-ask spreads patterns are relatively flat during the first half of the trading night. However, after 22:00 and particularly after 24:00, bid-ask spread patterns fluctuate, and the number of quotes thins during the second half of the night[35] . As the overnight option only lives for one night, it was designed for investors to hedge or speculate when the US market opens. Thus investors who want to hedge or speculate against risk, while US markets are open or when US economic announcements are scheduled, would take their position before the US market opened, i.e. during the first half of the night session.

[33] One-hour intervals were used in order to obtain enough observations in each time segment.
[34] We treat as the missing value for intervals which had no quotes.
[35] From table4.1 we observe the quotes and trades after 22:00 decreased substantially, although the patterns in Figures 4.1 & 4.2 are relative flat up till 24:00 for the 3-Year contracts and 26:00 for the 10-Year contracts.

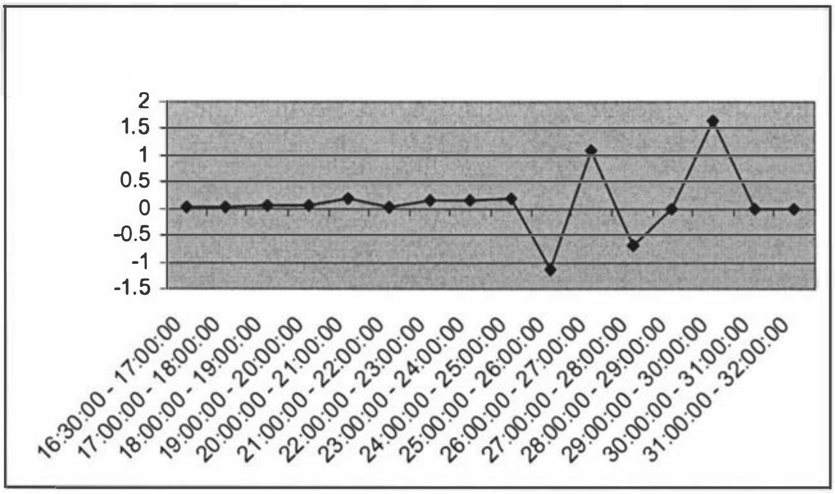
Figure 4.4 Intra-Night Time-Weighted Average Standardized Relative Bid-Ask Spreads Patterns for 3-Year T-Bond Futures and its Overnight Options

The time-weighted average standardized relative bid-ask spreads for one-hour intervals are calculated using the method suggested by McInish and Wood (1992), and Chan, Chung, and Johnson (1995) for 3-Year T-Bond futures, its overnight call and put options. The standardized relative bid-ask spreads are defined as $(X_{it} - \mu_{it})/\sigma$, where X_{it} is the relative bid-ask spread variable as calculated RBAS $=\left[(ask - bid)/(ask + bid)/2\right]$, μ_{it} is the mean for the day/night , and σ is the standard deviation for the night. The first time interval is the half hour starting at 16:30:00. A one-hour interval was used from 17:00:00 onwards. No adjustment needed for the first half-hour interval in terms of standardized bid-ask spreads.

Panel A Overnight Calls



Panel B Overnight Puts



Panel C 3-Year T-Bond Futures SRBAS

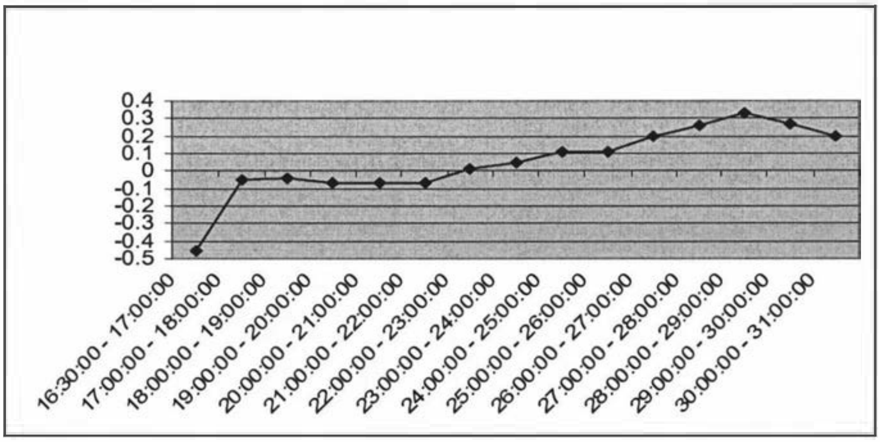
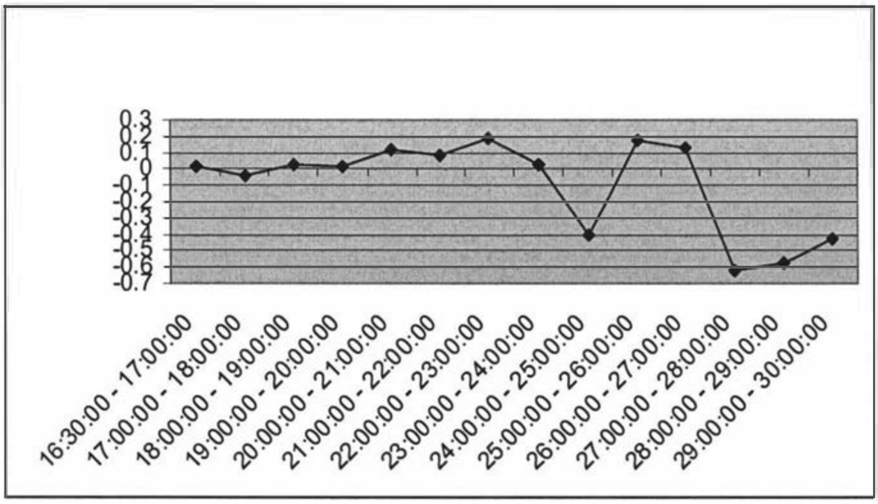


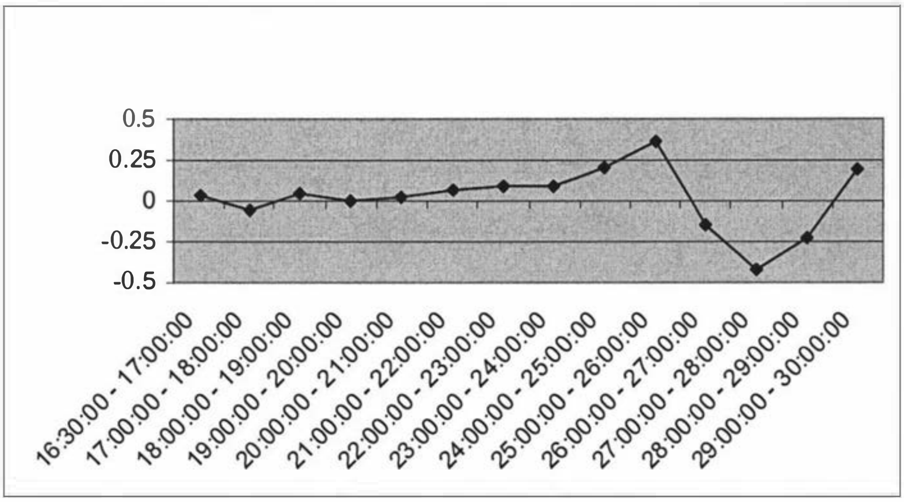
Figure4.5 Intra-Night Time-Weighted Average Standardized Relative Bid-Ask Spreads Patterns for 10-Year T-Bond Futures Overnight Call and Put Options

The time-weighted average standardized relative bid-ask spreads for one-hour intervals are calculated using the method suggested by McInish and Wood (1992), and Chan, Chung, and Johnson (1995). The standardized relative bid-ask spreads are defined as $(X_{it} - \mu_{it})/\sigma$, where X_{it} is the relative bid-ask spread variable as calculated RBAS $= [(ask - bid)/(ask + bid)/2]$, μ_{it} is the mean for the day/night , and σ is the standard deviation for the night. The first time interval is the half hour starting at 16:30:00. A one-hour interval was used from 17:00:00 onwards. No adjustment needed for the first half-hour interval in terms of standardized bid-ask spreads.

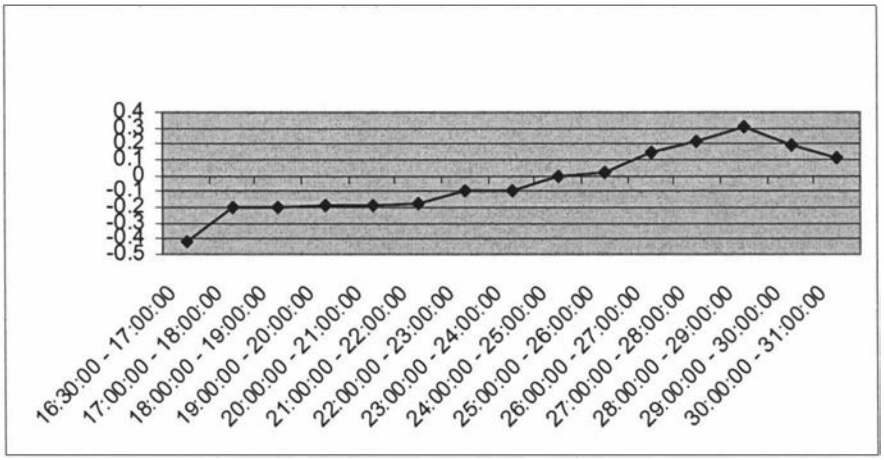
Panel A Overnight Calls



Panel B Overnight Put Options



Panel C 10-Year T-Bond Futures



4.3.2 Intra-Night Patterns of Trading Volume

Figure 4.6, Panels A, B, and C illustrate the standardized intra-night trading volume for the 3-Year T-Bond futures, its overnight call options, and put options. Figure 4.7, Panels A, B, and C illustrates the intra-night trading volume for the 10-Year T-Bond futures, its overnight call options, and put options. The standardized intra-night trading volume is calculated for the one-hour time interval. The first time interval is the half hour starting from 16:30:00. A one-hour interval was used from 17:00:00[36] onwards.

As the results in Table 4.1 suggest that most quotes and trades happened in the first half of the trading night, we will focus on the analysis of the first half of the night. Most previous studies observed U-Shaped intra-day trading volume patterns. We found similar trading volume patterns for the underlying 3-Year and 10-Year T-Bond futures, which the standardized trading volume are higher in the beginning and at the end of the night SYCOM session for both the 3-Year and 10-Year T-Bond futures.

For the T-Bond futures overnight options, we found that the standardized trading volume patterns for the 3-Year T-Bond futures overnight call options starts higher when the market opens, and gradually decreased for the first half of the trading night. It fluctuates for the rest of the trading night. For the 3-Year T-Bond futures overnight put options, we found a U-Shaped trading volume patterns for the first half of the trading night, it then fluctuates for the rest of the night. We found a similar U-Shaped trading volume patterns for the 10-Year T-Bond futures overnight call options for the first half of the night. But for the 10-Year T-Bond futures put options, the trading volume is higher in the beginning, then decreases and fluctuates through the rest of the night.

The resulting intra-night trading volume patterns support the argument that investors take their positions during the first couple of hours, when the overnight trading starts,

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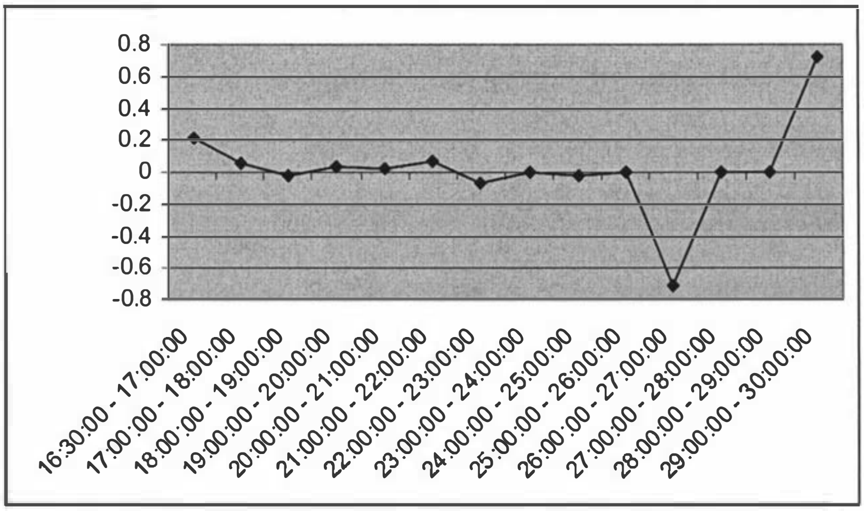
[36] One-hour intervals were used in order to obtain enough observations in each time segment.

and before the US markets open. For overnight options, positions that are taken for hedging purposes may conform the pattern: hedgers open a "buy-and-hold" position early in the night which is automatically exercised at the end of the trading night. Thus, there is no need to trade to close out positions at the end, and hence this will lead to lower volumes at the end of the night. This may be an explanation for the observed patterns in bid-ask spreads and in trading volumes. Again, positions that are taken for speculating purposes may conform the pattern: speculators take positions just before the US market opens or US macroeconomic news releases which is approximately during midnight, and hold it till the end. There is also no need to close out their positions at the end, and hence this will lead to a relative higher volume during midnight.

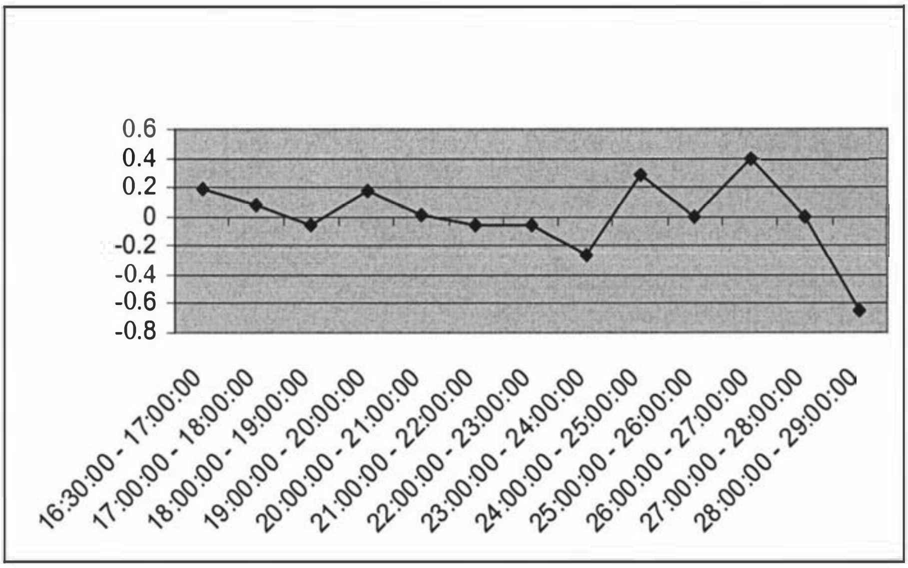
Figure 4.6 Intra-Night Patterns of Standardized Trading Volume for 3-Year T-Bond Futures Overnight Options and the Underlying Futures

The standardized trading volume is defined as $(X_{it} - \mu_{it})/\sigma$, where X_{it} is the raw trading volume at a particular time, μ_{it} is the mean for the trading night , and σ is the standard deviation for the night. The first time interval is the half hour starting from 16:30:00. A one-hour interval was used from 17:00:00 onwards. We adjust the trading volume by multiplying two for the first time interval.

Panel A Overnight Calls Standardized Intra-Night Trading Volume Patterns



Panel B Overnight Puts Standardized Intra-Night Trading Volume Patterns



Panel C 3-Year T-Bond Futures Standardized Intra-Night Trading Volume Patterns

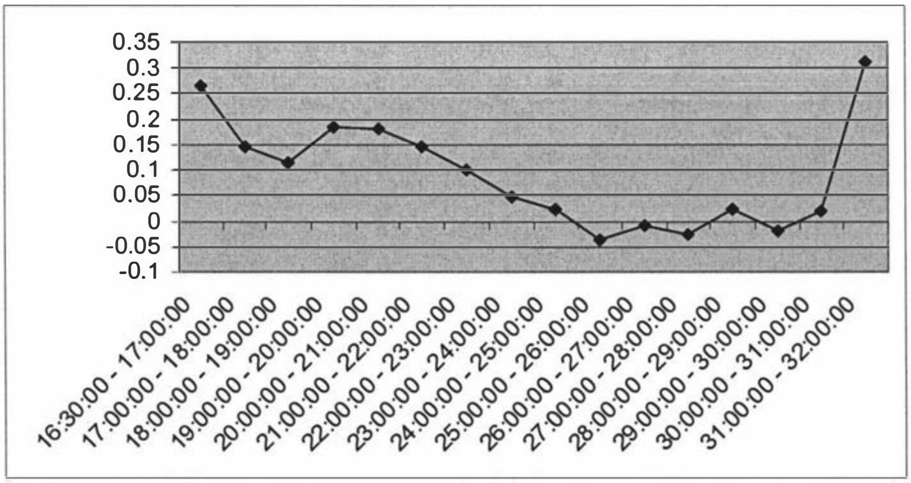
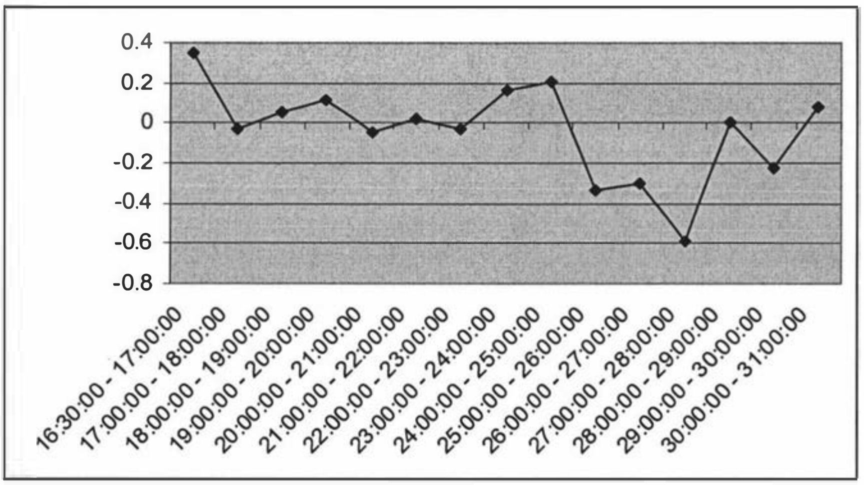


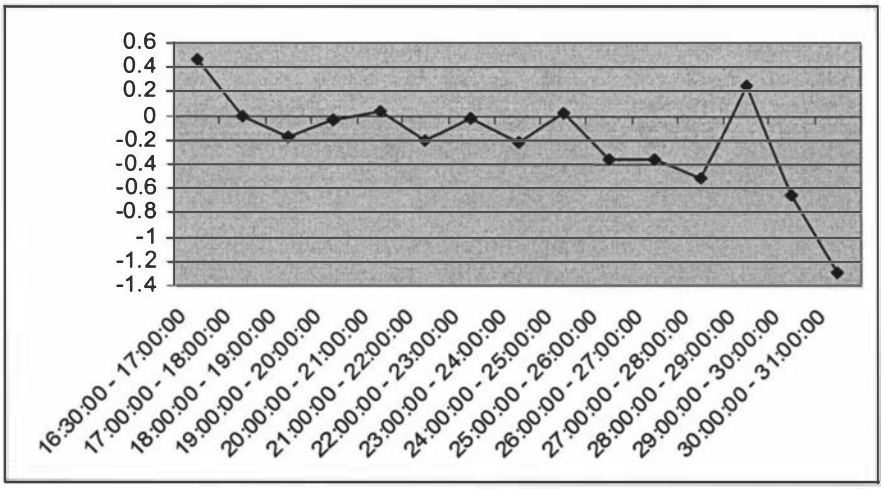
Figure 4.7 Intra-Night Patterns of Standardized Trading Volume for 10-Year T-Bond Futures Overnight Options and the Underlying Futures

The standardized trading volume is defined as $(X_{it} - \mu_{it})/\sigma$, where X_{it} is the raw trading volume at a particular time, μ_{it} is the mean for the trading night , and σ is the standard deviation for the night. The first time interval is the half hour starting from 16:30:00. A one-hour interval was used from 17:00:00 onwards. We adjust the trading volume by multiplying two for the first time interval.

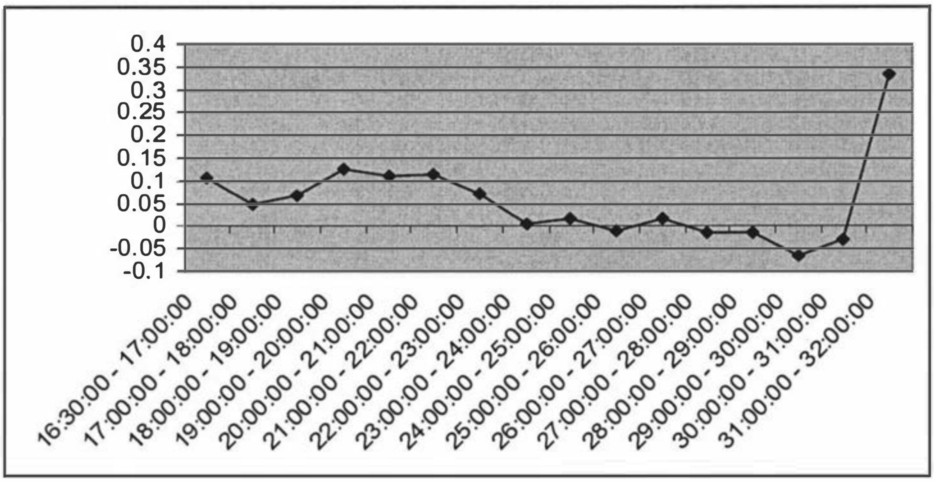
Panel A Overnight Calls



Panel B Overnight Puts



Panel C 10-Year T-Bond Futures



4.3.3 Intra-Night Volatility Patterns

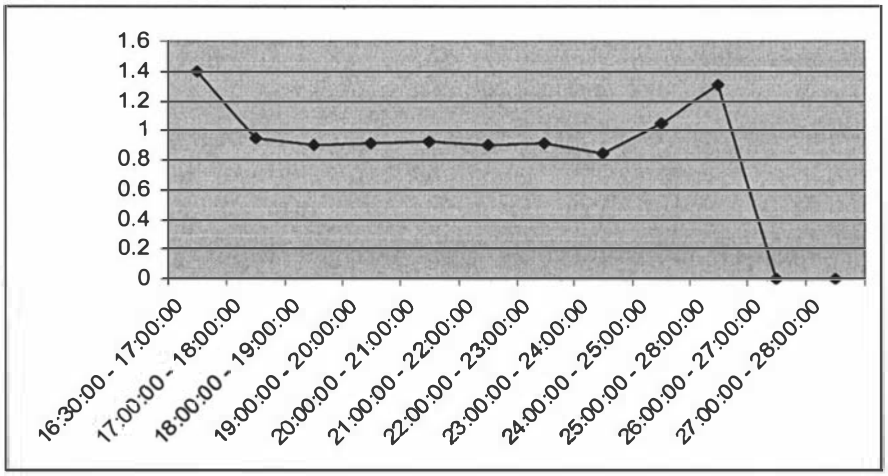
Figure 4.8, Panels A, B, and C, illustrate the intra-night volatility patterns for the 3-Year T-Bond futures, its overnight call options, and put options. Figure 4.9, Panels A, B, and C, illustrate the intra-night volatility patterns for the 10-Year T-Bond futures, its overnight call options, and put options. Intra-night volatility patterns are examined using the price volatility of standardized quoted bid-ask midpoints. Specifically, we calculated the standardized price volatility using the method suggested by Chan, Chung and Johnson (1995). The standardized price volatility is defined as $(x_t-\mu_t)/S_t$, where x_t is the bid-ask mid-point, μ_t is the mean for the day, and S_t is the standard deviation for the day. We then adopt the McInish and Wood (1992) methodology to calculate time-weighted average bid-ask midpoints for each one-hour time interval. Using the standardized midpoint of bid and ask quotes instead of transaction prices, as suggested by McInish and Wood (1992), avoids the bid-ask bounce problem. The first time interval is the half-hour interval from 16:30:00 to17:00:00, one-hour intervals were used from 17:00:00 onwards.

Like most previous studies which found U-shaped intra-day volatility patterns for longer-dated options, we found a similar pattern for both 3-Year and 10-Year T-Bond futures overnight call and put options for the first half of the trading night. The intra-night volatility patterns also showed a U-Shaped pattern for the underlying 3-Year and 10-Year T-Bond futures.

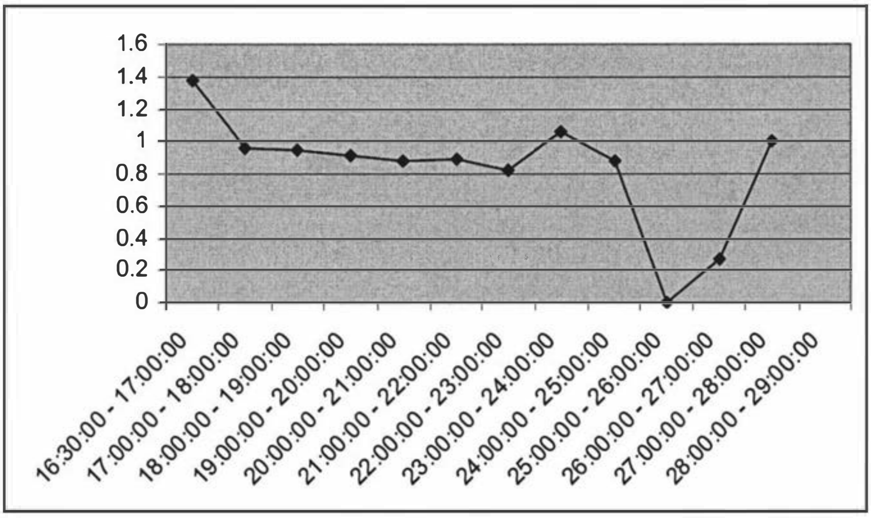
Figure 4.8 3-Year T-Bond Futures and Its Overnight Options Intra-Night Volatility Patterns

Intra-Night volatility pattern is examined using the volatility of bid-ask quote midpoints. Using the midpoint of bid and ask quotes instead of transaction prices, as suggested by McInish and Wood (1992), avoids a bid-ask bounce problem. We calculated the standardized price volatility using the method suggested by Chan, Chung and Johnson (1995). The standardized price volatility is defined as $(x_t-\mu_t)/S_t$, where x_t is the relative bid-ask mid-point, μ_t is the mean for the day, and S_t is the standard deviation for the day. We then calculated the time-weighted average standardized bid-ask midpoint for each one hour time interval. The first time interval is half-hour interval from 16:30:00 to17:00:00, one-hour intervals were used from 17:00:00 onwards. We adjust the volatility by multiplying square root of two for the first time interval.

Panel A Overnight Call Options



Panel B Overnight Put Options



Panel C 3-Year T-Bond Futures

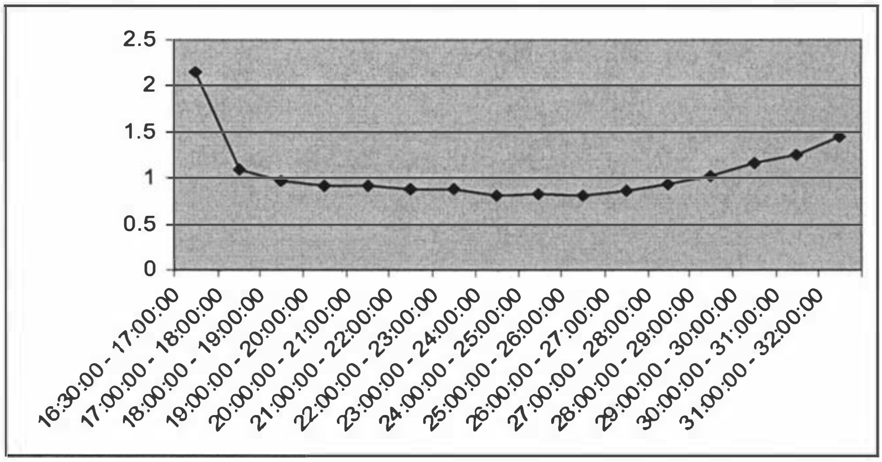
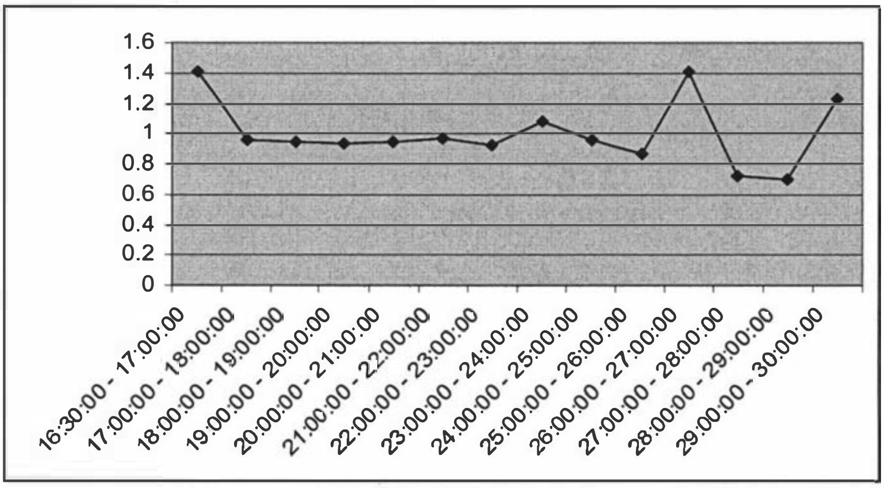


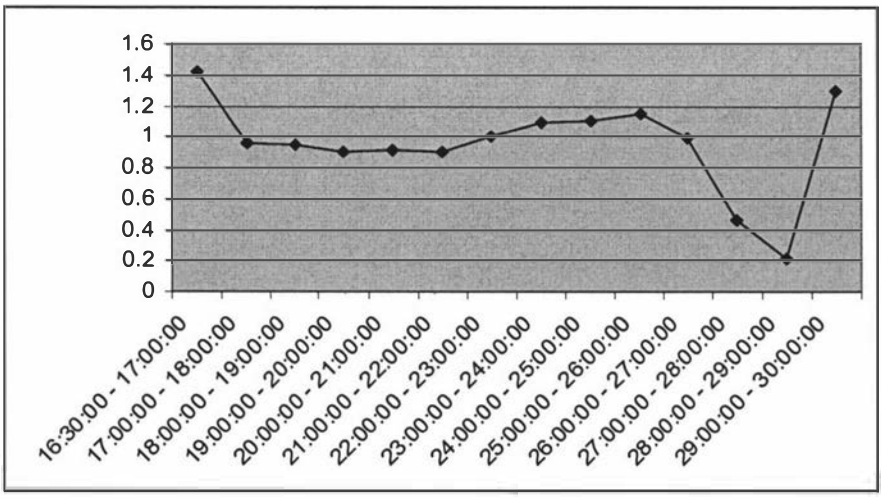
Figure 4.9 10-Year T-Bond Futures and Its Overnight Options Intra-Night Volatility Patterns

Intra-Night volatility pattern is examined using the volatility of bid-ask quote midpoints. Using the midpoint of bid and ask quotes instead of transaction prices, as suggested by McInish and Wood (1992), avoids a bid-ask bounce problem. We calculated the standardized price volatility using the method suggested by Chan, Chung and Johnson (1995). The standardized price volatility is defined as $(x_t-\mu_t)/S_t$, where x_t is the relative bid-ask mid-point, μ_t is the mean for the day, and S_t is the standard deviation for the day. We then calculated the time-weighted average standardized bid-ask midpoint for each one hour time interval. The first time interval is half-hour interval from 16:30:00 to17:00:00, one-hour intervals were used from 17:00:00 onwards. We adjust the volatility by multiplying square root of two for the first time interval.

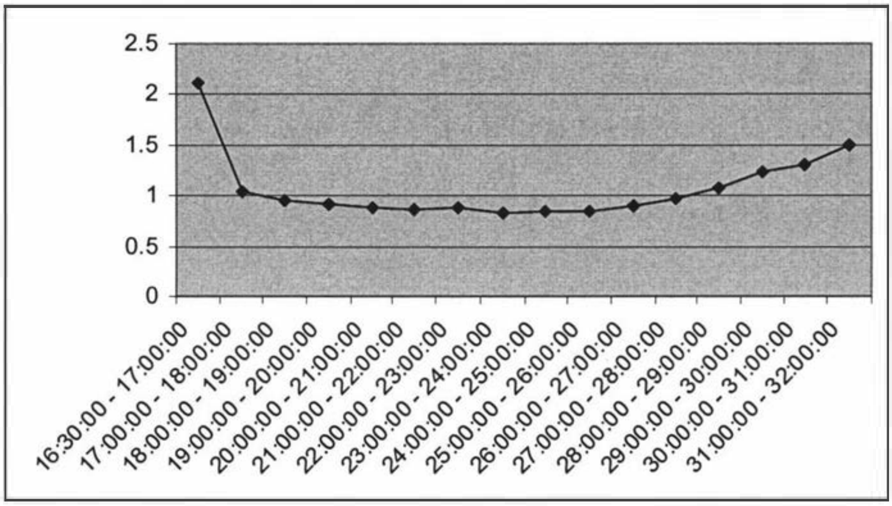
Panel A Overnight Call Options



Panel B Overnight Put Options



Panel C 10-Year T-Bond Futures



4.4 F-Statistics for Intra-Night Standardized Relative Bid-Ask Spreads, Standardized Trading Volume, and Standardized Return Volatility Patterns for Overnight Options

The intra-night bid-ask spreads, trading volume, and return volatility patterns illustrated in Figures 4.4, 4.5, 4.6, 4.7, 4.8, and 4.9 cannot explain whether bid-ask spreads, trading volume, and volatility are statistically significant across different time intervals during the trading night. As we discussed earlier in Chapter 3 and in Table 4.1, we found that most trades and quotes happened during the first half of the trading night. Therefore, we will only use time intervals that fall into the first half of the night to run the regression. Because quotes and trades are thin in the second half of the trading night, including data from this period in our regressions may distort our results.

We use F-Statistics from a regression to test whether bid-ask spreads, trading volume, and return volatility are statistically different across all time intervals during the first half of the trading night; whether bid-ask spreads, trading volume, and return volatility are statistically different between the first two intervals and the rest of the night; and whether bid-ask spread, trading volume, and volatility are statistically different between the last time interval of the first half night and the rest of the night.

Table 4.3, Panels A, B and C, report the relevant F-statistics from the regression for bid-ask spreads, trading volume, and volatility respectively. Results from Panel A suggest that the standardized relative bid-ask spreads are statistically significant at the 1% level across all time intervals for the 10-Year T-Bond futures overnight call and put options, but are insignificant for the 3-Year T-Bond futures overnight call and put options. F-statistics for the first two time intervals are statistically significant at the 1% level for 10-Year T-Bond futures overnight call and put options. However, F-statistics from the last time interval for the first half night are not statistically different from other intervals for both the 3-Year and 10-Year T-Bond futures overnight call and put options.

Results from Panel B suggest that trading volume are statistically significant at the 1% level across all time intervals for 10-Year T-Bond futures overnight call and put options. F-statistics for the first two time intervals are statistically significant at the 1% level for 10-Year T-Bond futures overnight call and put options. F-statistics from the last time interval for the first half night are not statistically different from other intervals for both 3-Year and 10-Year T-Bond futures overnight call and put options.

F-statistics for intra-night volatility from panel C are statistically significant at the 1% level for both 3-Year and 10-Year T-Bond futures overnight options (except for 3-Year overnight call options which significant at nearly 5% level). For the first two time intervals, F-statistics are statistically significant at the 1% level for 3-Year and 10-Year T-Bond futures overnight call and put options (except for 3-Year overnight calls which significant at 5% level). This indicates that return volatility patterns are quite volatile during the first half of the trading night for both the 3-Year and 10-Year T-Bond futures overnight call and put options.

4.5 The Impact of US Macroeconomic News Releases on Intra-Night Patterns

In order to examine the impact of US macroeconomic news releases on intra-night bid-ask spreads patterns, intra-night trading volume patterns, and intra-night price volatility patterns, our sample is partitioned based on days with scheduled US macroeconomic news releases, and days without US macroeconomic news releases. We choose the first two time intervals[37] to examine the significance of the difference in mean bid-ask spreads, trading volume, and volatility for each time interval between US macroeconomic releases and non-releases days using t-test.

Table 4.4 presents the t-test for the mean standardized relative bid-ask spreads, trading volume, and volatility for the two time intervals for both 3-Year and 10-Year T-Bond futures overnight call and put options. Table 4.4 reports that volatility is significantly wider on days with US macroeconomic news releases for both 3-Year and 10-Year T-Bond futures overnight call and put options, whereas trading volume is significantly greater on days with US macroeconomic news releases only for 10-Year T-Bond

[37]We observed most quotes and trades occurred within the first two time intervals.

Table 4.3 F-Statistics for Standardized Intra-Night Bid-Ask Spreads, Trading Volume and Volatility Patterns

The F-statistics for intra-night bid-ask spreads, trading volume, and return volatility patterns are generated by regressing bid-ask spreads, trading volume and return volatility on an intercept and dummy variables that represents each individual time-interval during the trading night. The first time interval is half-hour interval from 16:30:00 to17:00:00, a one-hour intervals were used from 17:00:00 onwards.

Panel A F-Statistics for Bid-Ask Spreads Regression

F-Statistics	3-Year Overnight Calls	3-Year Overnight Puts	10-Year Overnight Calls	10-Year Overnight Puts
$F_{1\text{-}8}$[a]	0.9019(0.5137)	0.8574(0.5520)	5.3523(0.0000)***	6.1147(0.0000)***
F_{open}[b]	1.7026(0.1823)	1.4720(0.1691)	14.8691(0.0000)***	22.9707(0.0000)***
F_8[c]	0.0127(0.9103)	0.9824(0.3217)	1.3439(0.2464)	0.6432(0.4227)

Panel B F-Statistics for Trading Volume Regression

F-Statistics	3-Year Overnight Calls	3-Year Overnight Puts	10-Year Overnight Calls	10-Year Overnight Puts
$F_{1\text{-}8}$[a]	0.8496(0.5461)	1.4328(0.1775)	5.20980.0000)***	8.7692(0.0000)***
F_{open}[b]	0.8519(0.4268)	1.0932(0.3353)	17.5549(0.0000)***	31.5380(0.0000)***
F_8[c]	0.0753(0.7838)	0.1128(0.7370)	0.7878(0.3748)	0.7205(0.3960)

Table 4.3 Continued

Panel C F-Statistics for Volatility Regression

F-Statistics	3-Year Overnight Calls	3-Year Overnight Puts	10-Year Overnight Calls	10-Year Overnight Puts
$F_{1\text{-}8}{}^{a}$	1.8991(0.0557)*	5.3478(0.0000)***	3.7599(0.0002)***	5.4167(0.0000)***
$F_{open}{}^{b}$	4.5813(0.0103)**	13.5308(0.0000)***	11.7290(0.0000)***	17.3884(0.0000)***
$F_{8}{}^{c}$	1.4774(0.2242)	0.1466(0.7018)	0.2647(0.6069)	0.2012(0.6538)

* Significant at the 10% level.
**Significant at the 5% level.
*** Significant at the 1% level.
a $F_{1\text{-}8}$ is the F-statistics testing differences across 8 time intervals during the first half of the trading night.
b F_{open} is the F-statistics testing differences of the first and the second time-interval from intervals 3 to 8.
c F_8 is the F-statistics testing differences of the 8^{th} time interval from intervals 1 to 7.
Note: Because quotations and trades are thin in the second half of the trading night, we will only use time intervals that fall into the first half of the trading night to test if there are any significant differences across each time interval; whether there is significant difference during the opening; and whether there are any significant differences during the last interval for the first half of the night.

futures overnight call and put options (significant at the 10% level for 3-Year T-Bond futures put options for the first time interval). However, there is no evidence of any significant difference for the mean bid-ask spreads for both 3-Year and 10-Year T-Bond futures overnight options. Thus, this may imply that US macroeconomic news releases may cause greater volatility and higher trading volume in intra-night trading behaviour of the Australian T-Bond futures overnight options market.

Table 4.4 T-Test for Mean Spreads, Trading Volume, and Volatility With and Without US Macroeconomic News Releases

Time-weighted average standardized relative bid-ask spread, trading volume, and bid-ask midpoint volatility are calculated for the first time intervals on days with no US macroeconomic news releases (NR) and days with US macroeconomic news releases (R). We use the employment rate, CPI, and PPI as indicators of announcement days. Independent sample t-statistic is used to compare the mean spreads, trading volume, volatility on days with and without US news releases. The figures for t-statistics are the P value.

	Spreads			Volume			Volatility		
	NR	R	t – Statistic[a]	NR	R	t-Statistic[a]	NR	R	t-Statistic[a]
3-Year Overnight Call Options:									
16:30 – 17:00	0.1057	0.1784	0.3820	125.8600	127.9100	0.9120	0.0030	0.0052	0.0040***
17:00 – 18:00	0.0399	0.0715	0.5664	132.5000	123.9700	0.4580	0.0034	0.0055	0.0005***
3-Year Overnight Put Options:									
16:30 – 17:00	0.0425	0.0047	0.7374	116.1300	149.4300	0.0980*	0.0026	0.0038	0.0150**
17:00 – 18:00	-0.0278	0.0011	0.6923	131.6400	135.2700	0.7330	0.0036	0.0047	0.0221**
10-Year Overnight Call Options:									
16:30 – 17:00	0.0300	-0.0082	0.5197	62.9100	72.9500	0.0350**	0.0000	0.0100	0.0000***
17:00 – 18:00	-0.0503	-0.0141	0.4915	51.8000	66.2900	0.0000***	0.0039	0.0058	0.0000***
10-Year Overnight Put Options:									
16:30 – 17:00	0.0610	0.0408	0.3164	63.6100	71.8300	0.0840*	0.0040	0.0060	0.0000***
17:00 – 18:00	-0.0815	-0.0063	0.1467	52.7600	60.9000	0.0200**	0.0039	0.0055	0.0000***

a This is the P value of the t-Statistic.
*Significance at the 10% level.
**Significance at the 5% level.
***Significance at the 1% level.

5. Conclusions

The introduction of overnight options at the Sydney Futures Exchange (SFE) offers a unique opportunity to study trading behavior on a market with a different market microstructure. One-session options (i.e. overnight options) can be used to manage short term exposure, hedge positions to event risk, or to profit by anticipating short term price movements in the bond market by taking a position on events or by putting the equivalent of a stop loss order in place. Thus, this chapter gives us a comprehensive analysis of intra-night trading behaviors of bid-ask spreads, trading volume, and return volatility for 3-Year and 10-Year T-Bond futures overnight options. This may give investors a better understanding of this market and provide knowledge of how to execute trading in this market.

We find most quotes and trades happen in the first half of the trading night. The number of quotes and trades are thin during the second half of the night. One explanation may be related to the special nature of overnight options. As the overnight option only lasts for one night, it was designed to match the time zone for investors wanting to hedge the US market risk. Anyone wishing to use the overnight option as a hedging tool will want to trade the overnight option at the beginning of the night.

Results also indicated that over time the quoted bid-ask spread narrowed for both the 3-Year and 10-Year T-Bond futures overnight calls and puts, while trading volume and trading frequency increased for the 3-Year contracts. Trading volume and trading frequency fell for the 10-Year contracts. One reason for this result may be that the underlying 3-Year T-Bond futures market provides more liquidity than the 10-Year market, although in early years investors were using 10-Year contracts because of their larger tick size. This suggests that 3-Year T-Bond futures overnight options are becoming more efficient as the underlying futures market provides more liquidity. Like most of the options traded on world exchanges, quoted bid-ask spreads of overnight options appear to be explained by the transaction price, the trading volume, and the volatility. Specifically, the quoted bid-ask spreads increase with higher transaction prices and increased return volatility, while quoted bid-ask spreads fall as trading volume increases.

We observe there are no significant differences across different time intervals for intra-night bid-ask spreads for 3-Year T-Bond futures overnight call and put options. We also find there are significant differences between the first two time intervals and other intervals for 3-Year T-Bond futures overnight options. However, for 10-Year T-Bond futures overnight options, there are significant differences across all time interval during the first half night for 10-Year T-Bond futures overnight call and put options. We observe similar results for intra-night trading volume. It is found that there are significant differences across different time intervals, and for the first two intervals, from other intervals for 10-Year T-Bond futures overnight call and put options. However, for 3-Year T-Bond futures overnight options, there is no significant difference across different time intervals during the first half night. Results for intra-night volatility indicate that there are significant differences across different time intervals during the first half of the trading night for both 3-Year and 10-Year T-Bond futures overnight call and put options.

In order to access the impact of the US macroeconomic news releases, mean bid-ask spreads, trading volume, and volatility for the first two time intervals are examined using t-test. We report that volatility are significantly wider on days with US macroeconomic news releases for both 3-Year and 10-Year T-Bond futures overnight call and put options, whereas trading volume are significantly greater on days with US macroeconomic news releases only for 10-Year T-Bond futures overnight call and put options . There is no evidence there is any significant difference of the mean bid-ask spreads for both 3-Year and 10-Year T-Bond futures overnight options. Thus, this may imply that intra-night trading behaviour of Australian T-Bond futures overnight options market reflect US macroeconomic news releases with greater volatility and higher trading volume.

Chapter 5 Influence of Overnight Options Introduction on Underlying Markets

1. Introduction

As discussed in Chapter 4, the introduction of overnight options on the 3-Year and 10-Year T-Bond futures market offers us a unique opportunity to study the microstructure of this new market, in terms of bid-ask spreads, trading volume, and volatility. We found differing intra-night trading behaviour for the overnight options market. The impact of option listing on underlying securities has attracted great attention in the academic literature. As the overnight option market has different intra-night trading patterns, the impact of its introduction may behave differently, thus, it is worth studying the impacts of overnight option introduction on the underlying 3-Year and 10-Year T-Bond futures that are traded at the Sydney Futures Exchange (SFE).

Market microstructure theory suggests the quoted bid-ask spreads could be used as a proxy to measure market liquidity. Many previous studies have suggested that the derivative markets may draw uninformed traders away from the underlying market, so the liquidity of the underlying market may fall. On the other hand, due to leverage effects and lower transaction costs in the derivative market, informed traders may shift from the underlying markets to the derivative market. Thus, the migration of informed traders from the underlying markets would reduce the information asymmetry problem faced by market makers, as suggested by the adverse selection model in market microstructure theory. This in turn will increase the liquidity of the underlying market.

Therefore, we will test whether or not liquidity is affected for the underlying 3-Year and 10-Year T-Bond futures after overnight options are introduced.

On the other hand, the introduction of overnight options may encourage greater speculative option trading. Informed traders may be likely to shift from the underlying markets to the options market, due to leverage effects and lower transaction costs for trading in the options market. The migration of informed traders from the underlying markets would reduce the informational asymmetry problem faced by market makers, as suggested by the adverse selection model found in market microstructure theory. In turn, this will increase the liquidity of the underlying market. In addition, the lower speculative activities in the underlying market may result in a decrease in the volatility generated by speculators who create noisy trading in the underlying market. However, this will simultaneously decrease the trading volume in the underlying market. Thus, the theoretical arguments behind the impacts of options listing on the underlying market are in conflict. Each market has its own characteristics and market structure, hence an empirical study on this issue will be useful in order to understand the impact of this particular instrument.

In this chapter we will analyze the impact of overnight options introduction on the 3-Year and 10-Year T-Bond futures, in order to examine changes in liquidity, trading volume, and volatility. We will use bid-ask spreads as a measurement of liquidity, trading volume as a measurement of order flow, and bid-ask midpoint for calculating return volatility. We also examine changes in pricing error variance for both 3-Year and 10-Year T-Bond futures before and after the overnight options introduction.

2. Literature Review

There is extensive debate among investors, practitioners, and academics on whether or not derivative trading is beneficial to the operation of financial markets. Market participants would like to know the impact of the derivative instrument on the underlying security risk and return, as risk and return are the fundamental characteristics in any financial decision.

2.1 Theoretical Literature

There are three closely related ways in which derivative markets improve underlying markets. Ross (1976), Breeden and Litzenberger (1978), Hakansson (1978) and Arditti and John (1980) provide a detailed examination of the subject. First, derivative securities have a role in making underlying markets more complete. These authors suggest that the introduction of options expands the opportunity set faced by investors, thus making markets more complete. Second, derivative securities make the operation of underlying markets more efficient. As option trading allows investors to use leverage, short-selling and transaction costs are relatively low. So any anomalies may be exploited, making the market's operation more efficient. Third, derivative securities increase the underlying markets informational efficiency. The existence of an options market gives investors an effective means to trade and profit on information changes and expectations.

Choi and Subrahmanyam (1994), Gorton and Pennacchi (1993), and Harris (1990), and among others have suggested that the derivatives market may draw uninformed traders away from the underlying market, and thus decrease the liquidity of the underlying market (also see Kumar, Sarin and Shastri, 1998). The liquidity of the underlying market could also be negatively affected if the introduction of the derivative on the market causes an increase in formation-based trading. It has been argued in Kumar, Sarin and Shastri (1998) that derivatives markets destabilize the cash market by encouraging arbitrage-related activities that increase short-run price swings. Thus, we may conclude that an options market may also have negative impacts on the underlying market. Firstly, as we discussed in the introduction, investors may shift away from the underlying market, which may decrease the liquidity of the underlying market. Secondly, because option markets are ideally suited for speculation, trading tends to be noisy and this noise may transmit to the underlying market. This will increase the volatility of the underlying market. Thirdly, futures or options trading can be used to generate either a long or a short position in underlying securities. This may increase noisy trading in the underlying market.

2.2 Empirical Literature

There are many empirical studies about the impacts of option listings on the underlying market. Branch and Finnerty (1981), Conrad (1989), and Deptemple and Jorion (1990) studied the impact of introducing options on US stock returns. The overall results are mixed. There was some evidence that stocks showed excess returns when call options on the stocks were listed, and that negative returns occurred when put options were listed. The negative returns on stock with the put options listing may be attributed to the selling pressure faced by the underlying stock.

There are also previous studies about the impact of option listings on the underlying stock's risk. For example, Whiteside, Dukes and Dunne (1983), Ma and Rao (1988), Skinner (1989), and Mckenzie, Brailsford and Faff (2001) examined the risk of the underlying security in association with the futures listing in the US markets. They found that the stock market volatility is lower after the introduction of options.

Skinner (1989), Damodaran and Lim (1991), and Fedenia and Grammatikos (1992) also examine the microstructure impacts of option listing in the US markets. These studies examine the impacts of option introduction on bid-ask spreads and trading volume of the underlying security. Overall results suggest that spreads are lower after the introduction. But results for trading volume are mixed. Overall, there are no significant effects of option listings on the trading volume of the underlying stock.

Kumar, Sarin and Shastri (1998) claim that options listings may have a beneficial impact on the quality of the underlying asset market. They give several reasons. First, as suggested by Ross (1976) and Hakansson (1982), options improve the efficiency of incomplete asset markets by expanding the opportunity set facing investors. This in turn suggests that option listings reduce underlying stock volatility. Sahlstrom (2001) investigates the impact of stock option introduction on the return and risk characteristics of underlying stocks in Finland. Results suggest that volatility and bid-ask spread levels are lower after the option listing. Kumar, Sarin and Shastri (1998) found that option listings are associated with a decrease in the pricing error variance, a decrease in the adverse selection component of the spread, and an increase in the relative weight placed by the specialist on public information when revising prices for underlying stocks. They also reported a decrease in the spread and increase in quoted depth, trading volume, trading frequency, and transaction size after option listings.

Second, option listings may cause informed traders to migrate to the options market. Informed traders migrate to options markets on the option's listings because they view options as superior speculative vehicles. This superiority stems from an option's leverage and the fact that investors may use options to avoid short sale restrictions on stocks. The reduction in the proportion of informed traders in the underlying market lowers the market maker's adverse selection costs, thereby lowering the spread and improving market liquidity.

Third, options may improve the efficiency of the underlying market by increasing the level of public information in the market. Specifically, the marginal benefit of becoming informed after the introduction of options is greater given the option's superiority as a speculative vehicle. This increase in marginal benefit results in a greater information symmetry, lowers the spread, improves liquidity, and reduces pricing error variance, thereby making the underlying market more efficient.

3. Data and Methodology

3.1 Data

The data used in this chapter includes intra-day data for 90-Day Bank-Bill futures, 3-Year and 10-Year T-Bond futures between November 15 1992 and November 15 1994. This consists of the time-stamped raw data for each quoted bid and ask, timed in seconds. The trade data contains the time of the trade, the trading price, and the trading volume.

3.2 Methodology

Market microstructure theory suggests that the quoted relative bid-ask spreads can be used as a proxy to measure market liquidity, and thus, market quality. Trading volume and return volatility can also be used to measure market quality. So we calculate the time-weighted average relative bid-ask spreads, trading volume and return volatility (using bid-ask midpoint) before and after the overnight options introduction for 3-Year and 10-Year T-Bond futures, in order to examine changes in market liquidity, order flow, and return volatility.

As the overnight options were introduced in November 15, 1993, we use this date as our event date. More specifically, we will look at changes in bid-ask spreads, changes in trading volume, and changes in volatility for underlying 3-Year and 10-Year T-Bond futures before and after November 15, 1993. In order to control for the market trend, it is necessary to use a variable to adjust for the overall market trend. The 90-Day Bank Bill futures is a short-term debt instrument, which has similar characteristics (in terms of trading protocol, trading execution procedures, market structure) to the 3-Year and 10-Year T-Bond futures. To make sure this adjustment is clean we ensure there were no major events occurred for 90-Day Bank Bill futures during the 3-Year and 10-Year T-Bond overnight options introduction period. So we use the time-weighted average relative bid-ask spreads, trading volume, and return volatility for the 90-Day Bank Bill futures as a control variable when we calculate the impact of introduction for the 3-Year and 10-Year T-Bond futures.

3.2.1 Impacts on Liquidity

The method adopted by Mcinish and Wood (1992), Skinner (1989), and Kumar, Sarin and Shastri (1998) is used to calculate time-weighted average relative bid-ask spreads for the 3-Year and 10-Year T-Bond futures.

A relative bid-ask spread (BAS) is calculated for each quotation as: BAS $=[(ask-bid)/(ask+bid)/2]$. Suppose that in the time interval (T, T') there are N quotation updates, occurring at times t_i, i= 1, ..., N, with spreads BAS_i, where $t_0 = T$ and $T_{N+1} = T'$. Thus time-weighted average standardized relative bid-ask spreads will be calculated as follows for the first quote of the night:

$$\sum_{i=1}^{N} \frac{BAS_i(t_{i+1}-t_i)}{T'-t_1}$$

where BAS_i is the standardized relative bid-ask spreads for each time second, $(t_{i+1} - t_i)$ is the time interval between quotations. So the first interval is time t_1 to T'. But the subsequent intervals in the day will be t_0 to T', which we will use the following formula:

$$\sum_{i=0}^{N} \frac{BAS_i(t_{i+1}-t_i)}{T'-T}$$

More specifically, the time-weighted quoted relative bid-ask spreads for the 3-Year and 10-Year T-Bond futures will be obtained 100 days before the listing date of the overnight options (day –110 to day –11 relative to the listing date) and 100 days after the listing date (day 11 to day 110 relative to the listing date). We adjust for the 90-Day Bank Bill futures time-weighted average relative bid-ask spreads both before and after the introduction. We then define the bid-ask spread ratios as the daily time-weighted average relative bid-ask spreads for the post-introduction period (adjusted for 90-Day

Bank Bill futures), divided by the daily time-weighted average relative bid-ask spreads for the pre-introduction period (adjusted for 90-Day Bank Bill futures). The Binominal Sign test, the Wilcoxon Signed Rank Test, and the Van der Waerden (normal scores) tests are used to determine if there are significant decreases in bid-ask spreads after the overnight options introduction.

3.2.2 Impacts on Order Flows

As we discussed earlier in this chapter, the introduction of the derivative product may encourage greater speculative trading. Investors may shift from the underlying markets to derivative markets, thus, a decrease in trading volume normally occurs in the underlying market following the introduction of a derivative product. Thus, we may expect a decrease in trading volume of the underlying 3-Year and 10-Year T-Bond Futures.

As was the case when the impacts on liquidity were analysed, the daily trading volume for the 3-Year and 10-Year T-Bond futures will be obtained 100 days before the listing date of the overnight options (day –110 to day –11 relative to the listing date) and 100 days after the listing date (day 11 to day 110 relative to the listing date). Again, as for the bid-ask spreads, we adjust the pre and post introduction trading volume using 90-Day Bank Bill futures trading volume. We then define the trading volume ratios as the daily trading volume (adjusted) for the post-introduction period, divided by the daily trading volume (adjusted) for the pre-introduction period. The Binominal Sign Test, the Wilcoxon Signed Rank Test, and the Van der Waerden Tests are used to see if there are significant decreases in trading volume after the overnight options introduction.

3.2.3 Impacts on Volatility

As we discussed earlier, the introduction of the derivative market will draw both informed and uninformed traders away from the underlying market, thus, lower the speculative activities in the underlying market. This may result in a decrease in the volatility generated by speculators in the underlying market who create noisy trading. Thus, we use the bid-ask midpoint to calculate the return volatility before and after the overnight options introduction (adjusted for 90-Day Bank Bill futures), in order to test if there is any decrease in volatility for the underlying 3-Year and 10-Year T-Bond futures. We use the daily standard deviation of the bid-ask midpoint return as the daily volatility.

3.2.4 Binomial Sign Test, Wilcoxon Signed Ranks Test and Van der Waerden (normal scores) Test

We use the Binominal Sign Test, the Wilcoxon Signed Ranks Test, and the Van der Waerden Test as suggested by Conover (1980) and Sheskin (1997) to test the time-weighted relative bid-ask spreads, trading volume and volatility ratios, as defined before, for both the 3-Year and 10-Year T-Bond futures.

Conover (1980) and Sheskin (1997) describe the null hypothesis test which determines if the median of a series X is equal to a specified value y, against the two-sided alternative that is not equal to y. They use three statistics which are rank-basked nonparametric test statistics, reported as the Binomial Sign Test, the Wilcoxon signed ranks test, and the Van der Waerden (normal scores) test. According to Conover (1980) and Sheskin (1997), the Binomial sign test is based on the idea that if the sample is drawn randomly from a binomial distribution, the sample proportion above and below the median should be equal. The Wilcoxon signed ranks test is based on the idea that the sum of the ranks for the samples above and below the median should be equal. The Van der Waerden (normal scores) test is similar to the Wilcoxon signed ranks test, but the ranks are smoothed converting them to quantiles of the normal distribution (normal scores).

3.2.5 Variance of Pricing Error

Hasbrouck (1993) suggests a method for measuring the deviations between actual transaction prices and implicit efficient prices, whereby security transaction prices are decomposed into random-walk and stationary components. The random-walk component may be identified with the efficient price. The stationary component is defined as the pricing error, measured by using the difference between the efficient price and the actual transaction price. Thus, the quality of a security market may be tested by examining its pricing error variance. A lower pricing error variance would be evidence of greater pricing efficiency. In this study, the pricing error variances for the 3-Year and 10-Year T-Bond futures contracts before and after the overnight option introduction are compared. A decrease in pricing error variance after the overnight options introduction would suggest an improvement of market quality.

Hasbrouck (1991) used a Vector Autoregression (VAR) representation of the price revision and trade process to analyse the market quality. He incorporated a signed trade variable in the analysis, and the sign of this variable is determined by comparing the actual trade price to the quoted bid ask midpoint. As in Hasbrouck (1991), transaction price p_t is defined as the sum of the efficient price m_t and a term that embodies microstructure imperfections which could be seen as an error term s_t, so we have:

$$p_t = m_t + s_t \qquad (5.1)$$

Since the efficient price is a random-walk, m_t could be defined as

$$m_t = m_{t-1} + \nu_t \qquad (5.2)$$

where $E\nu_t = 0$, $E\nu_t^2 = \sigma_v^2$, $E\ \nu_t \nu_T = 0$, for $t \neq T$. The variance of the pricing error σ_s^2 is used to measure market quality.

Hasbrouck (1993) uses a VAR model by involving trades and price changes to measure the variance of the pricing error. Thus, we define our VAR model as follows:

$$r_t = a_1 r_{t-1} + a_2 r_{t-2} + \ldots\ldots + b_0 x_t + b_1 x_{t-1} + \ldots\ldots + \nu_{1,t} \qquad (5.3)$$

$$x_t = c_1 r_{t-1} + c_2 r_{t-2} + \ldots\ldots + d_1 x_{t-1} + d_2 x_{t-2} + \ldots\ldots + \nu_{2,t} \qquad (5.4)$$

where $r_t = p_t - p_{t-1}$, the term x_t is the signed trade variable. More generally it is a column vector of trade attributes. As in Hasbrouck (1991), the inclusion of the contemporaneous trade x_t in the transaction-revision r_t specification imposes a recursive structure that reflects the ordering at time t of the trade. In order to get the trade attributes x_t, we use the technique (see Lee and Ready, 1991) which defined x_t as +Square Root (Trade Volume) if the transaction price is above the quoted midpoint of the bid and ask prices, or – Square Root (Trade Volume) if the transaction price is below the quoted midpoint of the bid and ask prices. The error terms in equations 5.3 and 5.4 are mean zero and serially uncorrelated with $Var(\nu_{1,t}) = \sigma_1^2$, $Var(\nu_{2,t}) = \Omega$, and $E(\nu_{1,t}\ \nu_{2,t}) = 0$.

The corresponding Vector Moving Average (VAM) representation from our VAR model will be as follows:

$$r_t = a_0^* v_{1,t} + a_2^* v_{1,t-1} + \ldots\ldots + b_0^* v_{2,t} + b_1^* v_{2,t-1} + \ldots\ldots \quad (5.5)$$

$$x_t = c_1^* v_{1,t} + c_2^* v_{1,t-1} + \ldots\ldots + d_0^* v_{2,t} + d_1^* v_{2,t-1} + \ldots\ldots \quad (5.6)$$

Thus, the variance of the pricing error will be:

$$\sigma_s^2 = \sum_{j=0}^{\infty} (a_j^2 \sigma_1^2 + b_j \Omega b_j')$$

where $a_j = - \sum_{k=j+1}^{\infty} a_k^*$ and $b_j = - \sum_{k=j+1}^{\infty} b_j^*$

We are going to use 3 lags in the VAR model and 5 lags[38] in the VAM representation. The variance of pricing error will be calculated for the 3-Year and 10-Year T-Bond futures data one-month before and one-month after the introduction of the overnight option. We hypothesize that the introduction of the overnight options improves the pricing efficiency in the underlying 3-Year and 10-Year T-Bond futures market, so we expect to see a decrease in the variance of the pricing error in the post-introduction period.

4. Analysis

4.1 Liquidity Impacts

Figure 5.1 Panels A and B illustrate the mean relative time-weighted average bid-ask spreads (adjusted for 90-Day Bank-Bill futures relative bid-ask spreads) for different time intervals during the trading night for 3-Year and 10-Year T-Bond futures. From Panel A in Figure 5.1, we observed that the mean time-weighted average relative bid-ask spreads for the post overnight options introduction period is lower than that for the pre period for most of the intervals during the trading night, particularly for the first half

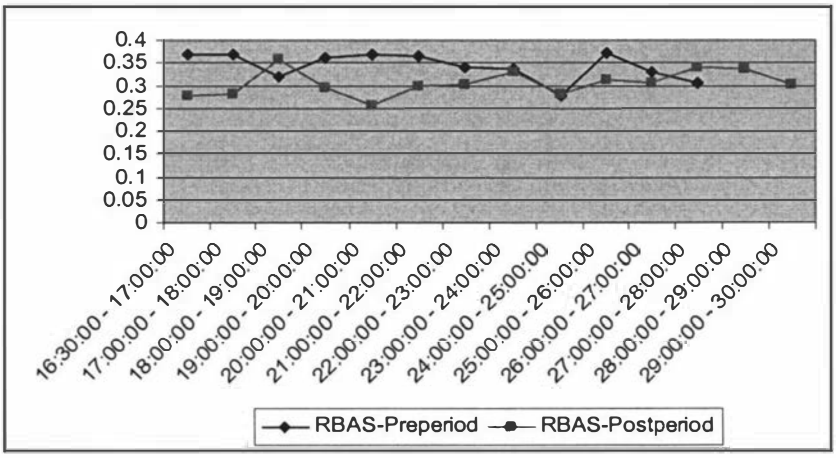
[38] We use different lag values in order to avoid error term autocorrelation. The lags are selected by using the Akaike Information Criteria (AIC).

of the trading night. This indicates that the introduction of the overnight option may increase the liquidity of the underlying futures market for 3-Year T-Bond future.

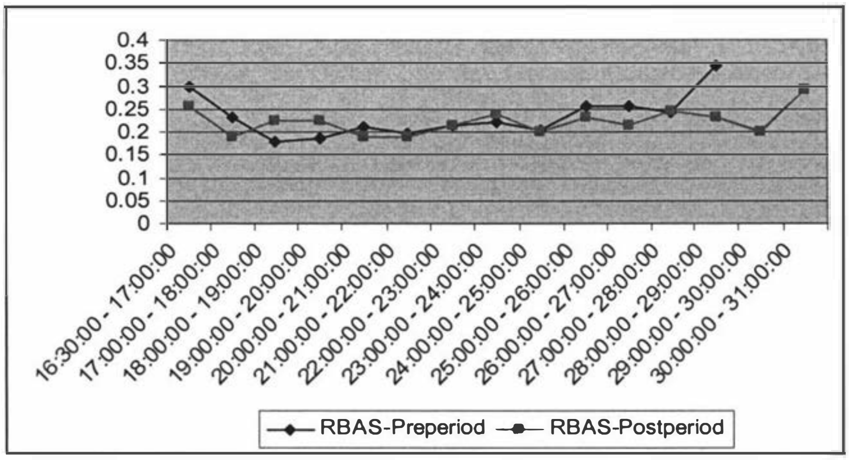
Figure 5.1 Mean Relative Bid-Ask Spreads Before and After the Overnight Option Introduction

Mean relative bid-ask spreads are calculated by using the time-weighted average relative bid-ask spreads for different time interval after adjusting for 90-Day Bank Bill futures time-weighted relative bid-ask spreads. The first time interval is half-hour interval from 16:30:00 to17:00:00, one-hour intervals were used from 17:00:00 onwards.

Panel A 3-Year T-Bond Futures



Panel B 10-Year T-Bond Futures



In Figure 5.1 Panel B, however, we observed that the mean time-weighted average relative bid-ask spreads for the post overnight options introduction period is greater than that for the pre period for most of the intervals during the trading night. This indicates that the introduction of the overnight option may not increase the liquidity of the underlying futures market for the 10-Year T-Bond future. In order to test if this result is statistically significant, we use the Binomial Sign Test, the Wilcoxon One-Tailed Signed Ranks Test, and the Van der Waerden (normal scores) tests to formally test whether the liquidity of the underlying futures market has been improved for the 3-Year and 10-Year T-Bond futures.

Table 5.1 reports the daily time-weighted average relative bid-ask spread ratios for the underlying 3-Year and 10-Year T-Bond futures. The results suggest that for the 3-Year T-Bond futures, bid-ask spreads decreased after the introduction period, as the daily median time-weighted average relative bid-ask spread ratio is less than one and we observe a 52% of the sample with bid-ask spreads ratio less than one. The Binominal Sign Test indicates that the result is not statistically significant. However, the Wilcoxon Signed Rank Test indicates that the result is statistically significant at the 10% level as the p value is 0.0978, and the Van der Waerden (normal scores) tests is statistically significant at the 5% level, indicating that the improvement of the liquidity with the introduction of overnight options for the 3-Year T-Bond futures is statistically significant. For the 10-Year T-Bond futures, we observe that 52% of the sample median daily relative bid-ask spread ratios are greater than one. The Binominal Sign Test is not statistically significant. But the Wilcoxon Signed Rank Test is statistically significant at the 5% level, and the Van der Waerden Test is statistically significant at the 1% level, indicating a significant increase of bid-ask spreads after the overnight options introduction occurred. Overall, there is no evidence of market quality improvement when using bid-ask spreads as a measurement of liquidity for the underlying 10-Year T-Bond futures market after the overnight options' introduction and there may have a deterioration.

Table 5.1 Relative Bid-Ask Spread Ratios for 3-Year and 10-Year T-Bond Futures
Bid-ask spreads for futures are calculated as the daily time-weighted average relative bid-ask spreads. Bid-ask spread ratio is the daily time-weighted average relative bid-ask spreads in the post-introduction period, divided by the daily time-weighted average relative bid-ask spreads in the pre-introduction period, all relative bid-ask spreads are adjusted by the control variable (the 90-Day Bank-Bill time-weighted relative bid-ask spreads).

Futures	Median BAS Ratios	Median Ratio[39] (Obs<1:Obs>1)	Binominal Sign Test	Wilcoxon Signed Ranks Test	Van der Waerden Test
3-Year T-Bond	0.9331	52:48	0.7664	0.0978*	0.0153**
10-Year T-Bond	1.0328	48:52	0.7664	0.0244**	0.0033***

*Significance at the 10% level.
**Significance at the 5% level.
***Significance at the 1% level.

4.2 Order Flows Impacts

Market microstructure theory suggests that the migration of traders from the underlying markets would decrease the trading volume in the underlying market. Thus, one may expect a decreased trading volume in the underlying 3-Year and 10-Year T-Bond futures. Here, median trading volume ratios are used to measure the order flow changes.

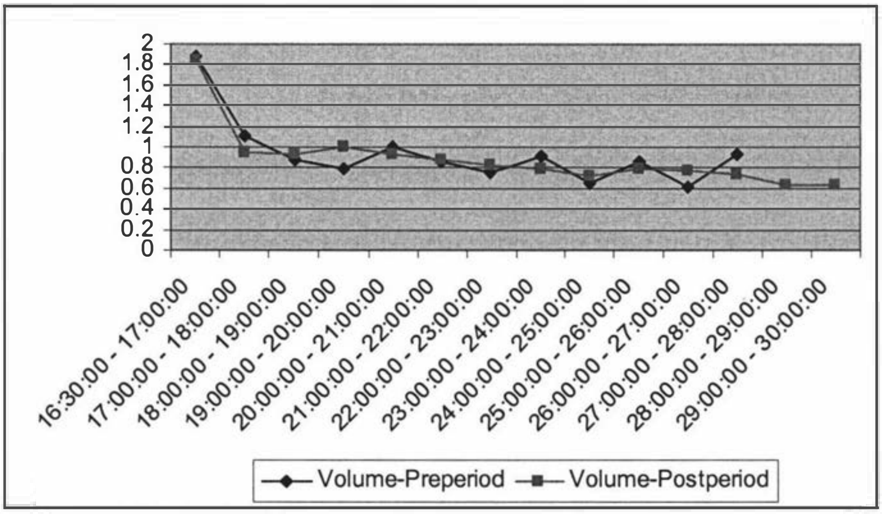
First, we graphically illustrate the difference between the mean trading volume for the different time interval during the trading night before and after the overnight options introduction, for both 3-Year and 10-Year T-Bond futures. Figure 5.2 Panels A and B illustrates the mean volume (adjusted for 90-Day Bank-Bill futures volume) for different time interval during the trading night for 3-Year and 10-Year T-Bond futures.

[39] This is the proportion with post-period to pre-period relative bid-ask spreads ratios less than 1, to the proportion with post-period to pre-period relative bid-ask spreads ratios greater than 1.

From Panels A and B in Figure 5.2, we observed that the mean time-weighted average trading volume for the post overnight options introduction period is lower than that for the pre period for most of the intervals during the trading night. This indicates that the introduction of the overnight option decreases the order flow of the underlying 3-Year and 10-Year T-Bond futures.

Figure 5.2 Mean Volume Before and After the Overnight Option Introduction
Mean trading volume are calculated by using the time-weighted average trading volume for different time interval after adjusting for 90-Day Bank Bill futures time-weighted trading volume. The first time interval is half-hour interval from 16:30:00 to17:00:00, one-hour intervals were used from 17:00:00 onwards.

Panel A 3-Year T-Bond Futures



Panel B 10-Year T-Bond Futures

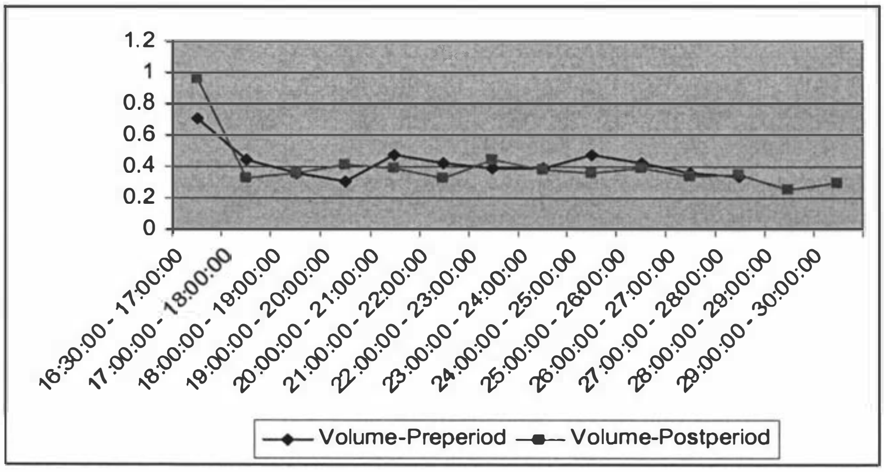


Table 5.2 Panels A and B summarizes the formal test results for the trading volume ratios. The trading volume ratios are defined as the post-introduction period daily median trading volume, divided by the pre-introduction period trading volume. A ratio greater than one indicates an improvement in the order flow. Results show that the trading volume fell at the time of the overnight option's introduction for both the 3-Year and 10-Year T-Bond futures trading during the night. We observed 57% of the sample trading volume ratios are less than 1 for the 3-Year T-Bond futures, and 58% of the sample trading volume ratios are less than 1 for the 10-Year T-Bond futures. But the Binominal Sign Test, the Wilcoxon Signed Rank Tests, and the Van der Waerden Tests are statistically insignificant. But the fall in trading volume is consistent with the market microstructure theory that traders may shift from the underlying market to the overnight options market because of its lower transaction costs and speculative power.

Table 5.2 Trading Volume Ratios for 3-Year and 10-Year T-Bond Futures

The trading volume ratios are defined as the post-introduction period trading volume divided by the pre-introduction period trading volume. Daily trading volume is calculated as the time-weighted average trading volume in a day.

Futures	Mean Volume Ratios	Median Ratio[40] (Obs<1:Obs>1)	Binominal Sign Test	Wilcoxon Signed Ranks Test	Van der Waerden Test
3-Year T-Bond	0.9333	57:43	0.1933	0.9383	0.4938
10-Year T-Bond	0.8603	58:42	0.1332	0.6661	0.7928

4.3 Volatility Impacts

As we discussed earlier, the introduction of the derivative market would shift both informed and uninformed traders away from the underlying market, which lower the speculative activities in the underlying market. This may result in a decrease in the volatility generated by speculators in the underlying market who create noisy trading.

[40] This is the proportion with post-period to pre-period trading volume ratios less than 1, to the proportion with post-period to pre-period trading volume ratios greater than 1.

To examine this issue, we calculate the daily standard deviation of the bid-ask midpoint return as the volatility for the 3-Year and 10-Year T-Bond futures (adjusted for 90-Day Bank Bill futures bid-ask midpoint standard deviation). Then, we test if there are any changes of volatility before and after the overnight options introduction.

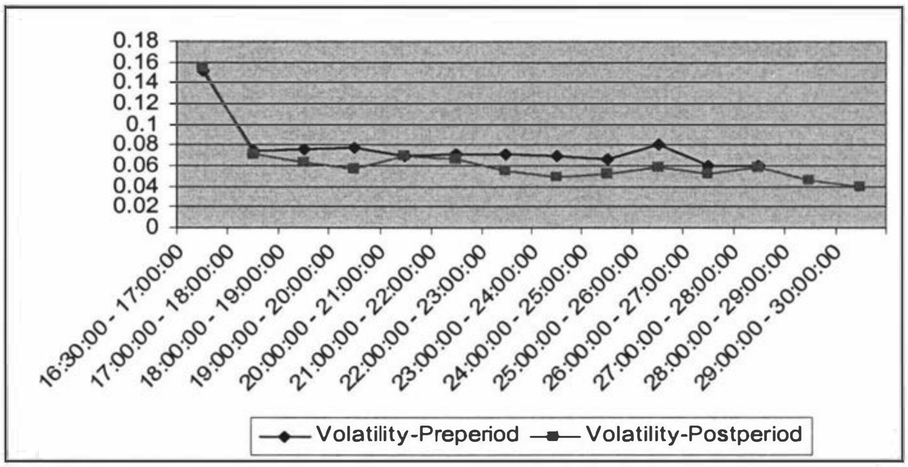
First, we graphically illustrate the difference between the standard deviation different time interval during the trading night before and after the overnight options introduction, for both 3-Year and 10-Year T-Bond futures. Figure 5.3 Panels A and B illustrates the mean volume (adjusted for 90-Day Bank-Bill futures volume) for different time interval during the trading night for 3-Year and 10-Year T-Bond futures. From Panels A and B in Figure 5.2, we observed that the return volatility for the post overnight options introduction period is lower than that for the pre period for most of the intervals during the trading night. This indicates that the introduction of the overnight option decreases the volatility of the underlying 3-Year and 10-Year T-Bond futures.

Table 5.3 Panels A and B summarizes the formal test results for volatility ratios. The volatility ratios are defined as the post-introduction period daily return standard deviation, divided by the pre-introduction period return standard deviation. A ratio less than one indicates lower volatility after the overnight options introduction. Results indicate that volatility became lower at the time of the overnight option's introduction for both the 3-Year and 10-Year T-Bond futures. There was a 62% decrease in volatility for the 3-Year T-Bond futures, and a 59% decrease in volatility for the 10-Year T-Bond futures. The Binominal Sign Test is significant at the 5% level for the 3-Year T-Bond futures, and at the 10% significant level for the 10-Year T-Bond futures. The Van der

Waerden Tests are significant at the 10% level for 3-Year T-Bond futures, and significant at the 5% level for the 10-Year T-Bond futures. The Wilcoxon Signed Test is not significant for both the 3-Year and 10-Year T-Bond futures.

Figure 5.3 Volatility Before and After the Overnight Options Introduction
Standard deviation of bid-ask midpoint return for different time interval after adjusting for 90-Day Bank Bill futures were calculated for both 3-Year and 10-Year T-Bond futures. The first time interval is half-hour interval from 16:30:00 to17:00:00, one-hour intervals were used from 17:00:00 onwards.

Panel A 3-Year T-Bond Futures



Panel B 10-Year T-Bond Futures

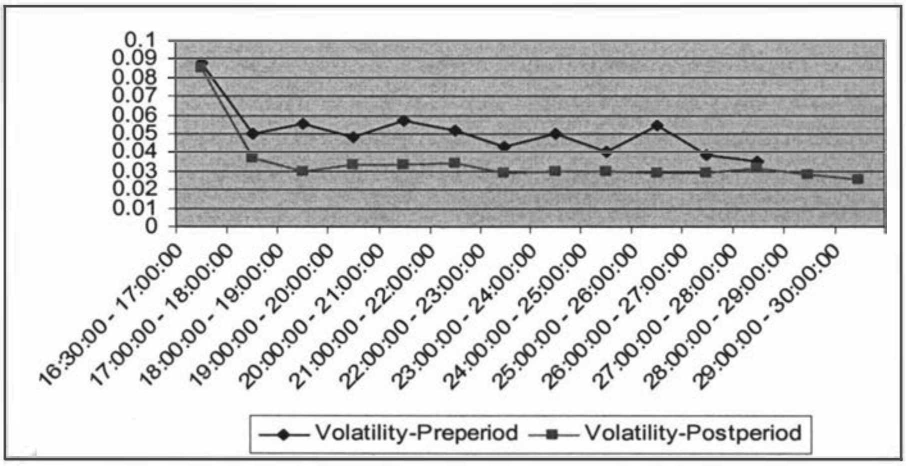


Table 5.3 Volatility Ratios for 3-Year and 10-Year T-Bond Futures
The volatility ratios are defined as the post-introduction period standard deviation of bid-ask midpoint return, divided by the pre-introduction period standard deviation of bid-ask midpoint return. The volatility has been adjusted for the standard deviation of bid-ask midpoint return from the 90-Day Bank Bill futures.

Futures	Volatility Ratios	Median Ratio[41] (Obs<1:Obs>1)	Binominal Sign Test	Wilcoxon Signed Ranks Test	Van der Waerden Test
3-Year T-Bond	0.4834	62:38	0.0210*	0.5214	0.0938*
10-Year T-Bond	0.7160	59:41	0.0886*	0.1674	0.0222**

*Significance at the 10% level.
**Significance at the 5% level.

The results above suggested that the bid-ask spreads for the 3-Year T-Bond futures narrowed after the overnight options introduction, indicating a relatively higher liquidity for the market according to market microstructure theory. But for the 10-Year T-Bond futures, the bid-ask spreads became larger after the introduction, suggesting lower liquidity after the introduction. The results from the order flow and volatility impacts suggested that the trading volume and volatility decreased after the introduction for both the 3-Year and 10-Year T-Bond futures. This may suggest that investors do shift away from the underlying futures market to the overnight options, which will result a lower order flow and a lower volatility. But liquidity results were not consistent, an apparent anomaly which warrants further attention in further studies considering the underlying futures market. But this issue is beyond the scope of this dissertation.

4.4 Variance of the Pricing Error

Hasbrouck (1993) suggested a method for measuring the deviations between actual transaction prices and implicit efficient prices, whereby security transaction prices are decomposed into random-walk and stationary components. The random-walk

[41] This is the proportion with post-period to pre-period volatility ratios less than 1, to the proportion with post-period to pre-period volatility ratios greater than 1.

component may be defined as the efficient price, and the stationary component is defined as the pricing error measured by using the difference between the efficient price and actual transaction price. Thus, the quality of a security market is tested in terms of the variance of the pricing error. In this study, the pricing error variances for the 3-Year and 10-Year T-Bond futures before and after the overnight options introduction are compared. A decrease in pricing error variance after the overnight option introduction would suggest an improvement of market quality.

Vector Autoregressive Regression and Vector Moving Average analysis, as suggested in the methodology section, are used to test the pricing error variance for the underlying 3-Year and 10-Year T-Bond futures one month[42] before and after the overnight options introduction. Results are reported in Table 5.4 and Table 5.5.

Since we have the variance of the pricing error defined as $\sigma_s^2 = \sum_{j=0}^{\infty} (a_j^2\sigma_1^2 + b_j\Omega b_j')$

where $a_j = -\sum_{k=j+1}^{\infty} a_k^*$ and $b_j = -\sum_{k=j+1}^{\infty} b_j^*$, the variance of the pricing error for 3-Year T-Bond Futures are $\sigma_s^2 = 0.1000$ and $\sigma_s^2 = 0.1730$ for the pre and post introduction periods respectively. The variance of the pricing error for 10-Year T-Bond futures are $\sigma_s^2 = 0.2353$ and $\sigma_s^2 = 0.1218$ for the pre and post introduction periods respectively.

Since the pricing error for 10-Year T-Bond futures contracts decreases after the introduction of the overnight options, it indicates that the underlying 10-Year T-Bond

[42] One-month intra-day data in seconds will be used to obtain sufficient observations for the VAR and VAM analysis. This resulted in 10,575 observations before introduction and 10,837 after for the 3-Year contracts, and 14,404 observations before introduction and 17,206 after for the 10-Year contracts.

futures market became more efficient. However, the pricing error for the 3-Year T-Bond futures contract increased after the introduction of the overnight options. Thus, pricing error analysis does not give us any extra insight into whether or not market quality has improved.

Table 5.4 Coefficients of VAR for Pre and Post Introduction Period

The following VAR equations are used for the pre and the post introduction period:

$$r_t = a_1 r_{t-1} + a_2 r_{t-2} + \ldots\ldots + b_0 x_t + b_1 x_{t-1} + \ldots\ldots + v_{1,t}$$

$$x_t = c_1 r_{t-1} + c_2 r_{t-2} + \ldots\ldots + d_1 x_{t-1} + d_2 x_{t-2} + \ldots. + v_{2,t}$$

Where $r_t = p_t - p_{t-1}$, the term x_t is defined as +SquareRoot(TradeVolume) if the transaction price is above the quoted midpoint of the bid and ask prices, or – SquareRoot(TradeVolume) if the transaction price is below the quoted midpoint of the bid and ask prices. The error terms in equations 3 and 4 are mean zero and serially uncorrelated with $Var(v_{1,t}) = \sigma_1^2$, $Var(v_{2,t}) = \Omega$, and $E(v_{1,t}\ v_{2,t}) = 0$.

Panel A VAR for 3-Year T-Bond Futures Contracts

	VAR- Equation (3)		VAR- Equation (4)	
	Pre-Period	Post-Period	Pre-Period	Post-Period
Variables	Coefficients (P)	Coefficients (P)	Coefficients (P)	Coefficients (P)
r_{t-1}	-0.6353(0.00)[43]	-0.1632(0.00)	-296.46(0.21)	-532.07(0.00)
r_{t-2}	-0.4238(0.00)	-0.0732(0.00)	-332.66(0.21)	-257.97(0.33)
r_{t-3}	-0.3093(0.00)	-0.0118(0.17)	-166.84(0.48)	2306.71(0.05)
x_t	-	-	-	-
x_{t-1}	-	-	0.3980(0.00)	0.3600(0.00)
x_{t-2}	-	-	0.2530(0.00)	0.1300(0.00)
x_{t-3}	-	-	0.2260(0.00)	0.0600(0.00)
$Var(v_{1,t}) = \sigma_1^2$	2.3005E-08	1.3069E-09	-	-
$Var(v_{2,t}) = \Omega$			11.4216	24.2936

Panel B VAR for 10-Year T-Bond Futures Contracts

	VAR- Equation (3)		VAR- Equation (4)	
	Pre-Period	Post-Period	Pre-Period	Post-Period
Variables	Coefficients (P)	Coefficients (P)	Coefficients (P)	Coefficients (P)
r_{t-1}	-0.8979(0.00)	-0.0944(0.00)	-4538.56(0.00)	-394.21(0.00)
r_{t-2}	-0.0296(0.00)	0.0003(0.01)	17.25(0.98)	-2.95(0.01)
r_{t-3}	-0.0042(0.53)	-0.0001(0.45)	929.12(0.15)	-5.16(0.00)
x_t	-	-	-	-
x_{t-1}	-	-	0.39(0.00)	0.38(0.00)
x_{t-2}	-	-	0.19(0.00)	0.18(0.00)
x_{t-3}	-	-	0.09(0.00)	0.09(0.00)
$Var(v_{1,t}) = \sigma_1^2$	9.55E-10	1.01E-09	-	-
$Var(v_{2,t}) = \Omega$			6.2571	6.8816

[43] The number in the bracket following each coefficient is the P value.

Table 5.5Coefficients of VAM for Pre and Post Introduction Period

The corresponding Vector Moving Average (VAM) representation from our VAR model will be as follows:

$$r_t = a_0^* v_{1,t} + a_2^* v_{1,t-1} + \ldots\ldots + b_0^* v_{2,t} + b_1^* v_{2,t-1} + \ldots\ldots$$

$$x_t = c_1^* v_{1,t} + c_2^* v_{1,t-1} + \ldots\ldots + d_0^* v_{2,t} + d_1^* v_{2,t-1} + \ldots\ldots$$

$v_{1,t}$ and $v_{2,t}$ are the residuals from the VAR.

For pre-introduction and post-introduction periods, the corresponding VAM (with 5 lags) are shown.

Panel A VAM for 3-Year T-Bond Futures Contracts

	VAM- Equation (5)		VAM- Equation (6)	
Variables	Pre-Period Coefficients(P)	Post-Period Coefficients(P)	Pre-Period Coefficients(P)	Post-Period Coefficients(P)
$v_{1,t}$	0.9980(0.00)	1.0007(0.00)	228.08(0.33)	199.22(0.06)
$v_{1,t-1}$	-0.6348(0.00)	-0.1362(0.00)	-194.93(0.41)	-8291.28(0.00)
$v_{1,t-2}$	-0.0200(0.00)	-0.0611(0.00)	-145.85(0.53)	-2847.59(0.00)
$v_{1,t-3}$	-0.0257(0.00)	-0.0104(0.00)	-57.99(0.80)	824.98(0.00)
$v_{1,t-4}$	0.2171(0.00)	0.0032(0.00)	61.40(0.79)	-824.12(0.00)
$v_{1,t-5}$	-0.1237(0.00)	-0.0008(0.04)	-140.09(0.55)	-566.45(0.00)
$v_{2,t}$	-	-	1.19(0.00)	1.00(0.00)
$v_{2,t-1}$	-	-	0.57(0.00)	0.39(0.00)
$v_{2,t-2}$	-	-	0.58(0.00)	0.27(0.00)
$v_{2,t-3}$	-	-	0.61(0.00)	0.19(0.00)
$v_{2,t-4}$	-	-	0.46(0.00)	0.12(0.00)
$v_{2,t-5}$	-	-	0.42(0.00)	0.09(0.00)

Panel B VAM for 10-Year T-Bond Futures Contracts

	VAM- Equation (5)		VAM- Equation (6)	
Variables	Pre-Period Coefficients(P)	Post-Period Coefficients(P)	Pre-Period Coefficients(P)	Post-Period Coefficients(P)
$v_{1,t}$	-0.9997(0.00)	0.9998(0.00)	-142.71(0.33)	-103.39(0.37)
$v_{1,t-1}$	-0.0745(0.00)	-0.0776(0.00)	-4642.59(0.00)	-5408.34(0.00)
$v_{1,t-2}$	-0.0307(0.00)	-0.0025(0.00)	-1408.97(0.00)	-1694.17(0.00)
$v_{1,t-3}$	0.0019(0.00)	-0.0044(0.00)	-305.87(0.04)	-1510.41(0.00)
$v_{1,t-4}$	-0.0003(0.00)	-0.0023(0.32)	-848.93(0.00)	-1326.27(0.00)
$v_{1,t-5}$	-0.0014(0.00)	-0.0025(0.00)	-514.53(0.00)	-938.14(0.05)
$v_{2,t}$	-	-	1.02(0.00)	1.01(0.00)
$v_{2,t-1}$	-	-	0.42(0.00)	0.41(0.00)
$v_{2,t-2}$	-	-	0.36(0.00)	0.33(0.00)
$v_{2,t-3}$	-	-	0.30(0.00)	0.29(0.00)
$v_{2,t-4}$	-	-	0.22(0.00)	0.20(0.00)
$v_{2,t-5}$	-	-	0.17(0.00)	0.15(0.00)

5. Conclusions

Typically, new product introduction, particularly in derivative markets, will impact underlying markets. The impact of the introduction of overnight options on the underlying Australian T-Bond futures was tested in this study. Changes in quoted bid-ask spread, trading volume, bid-ask midpoint return volatility, and the pricing error variance for the underlying 3-Year and 10-Year T-Bond futures, before and after the introduction of the overnight options were examined to assess the impacts of the overnight options introduction to the underlying 3-Year and 10-Year T-Bond futures.

It was found that the liquidity as measured by the quoted bid-ask spreads increased after the overnight options introduction for the 3-Year T-Bond futures, as the bid-ask spreads became smaller. But the liquidity for the 10-Year T-Bond futures decreased after the overnight options introduction, as the bid-ask spreads became larger. Order flows and return volatility fell after the overnight options introduction for both the 3-Year and 10-Year T-Bond futures. This indicated that the overnight options introduction may encourage greater speculative trading activities which may shift both informed and uninformed traders away from the underlying futures market. Lower speculative activities in the underlying market will result in a decrease in the volatility generated by speculators in the underlying market who create noisy trading. This in turn simultaneously decreases the trading volume (order flow) in the underlying market. Thus, results for order flows and return volatility are consistent with previous findings and market microstructure theory.

As 3-Year and 10-Year T-Bond futures are derived from the 3-Year and 10-Year physical T-Bond, it might be useful to analyse the physical T-Bond markets to see if there is any improvements of quality[44] in this market. Also, an analysis of the volatility of the underlying 3-Year and 10-Year T-Bond futures would be useful to more fully explain how information transmitted across the markets, and how volatility reacts to positive and negative information shocks. Chapter 6 will discuss how return volatility behaved as information shocks occur.

[44] Data is not available at present.

Chapter 6 Information Shocks, Volatility Patterns and the Choice of an Optimal Time-Varying Model

1. Introduction

There have been many assets created in the derivative markets since the advent of the Black-Scholes-Merton options pricing model. One of the more recent innovations is the overnight options market created by the Sydney Futures Exchange (SFE) in 1993. T-Bonds are the most important Australian Government bonds traded on the Australian market and the ability to hedge the risk associated with changes in the interest rates of these instruments is of paramount importance to investors. Futures contracts are one of the primary means of hedging this risk during normal trading hours. However, significant movements in interest rates can occur outside normal trading hours; for example, announcements that affect US interest rates can have a major impact on Australian interest rates. The instruments of choice for hedging interest rate risk in the overnight market are 3-Year and 10-Year T-Bond futures overnight options.

It is reasonable to expect that the unique nature of these overnight options on T-Bond futures will result in them having different characteristics to long dated options in terms of trading behaviour and market microstructure. Factors such as bid-ask spreads, trading volume patterns, and return volatility will possibly be very different from those discussed in the literature on conventional long dated options. The key input into all conventional option pricing models is volatility. Interviews with traders in the Australian overnight options market revealed that they do indeed use the underlying futures volatility of the previous night's session as a key factor in their pricing decisions. This chapter seeks to improve the ability to price overnight options of T-Bond futures by creating and testing a model for predicting the underlying futures volatility, which is the most important component when pricing options.

How information shocks impact on return volatility is the key ingredient in modelling volatility, as how information flows into a market place can have a major impact on volatility. As will be explained later, there is ample evidence that good news has less of an impact on volatility than bad news. Linear GARCH models, which have traditionally been used for predicting future volatilities, assume that the impact of news is symmetrical and this has led to the development of asymmetrical models such as EGARCH models.

In this chapter we first examine how information flows affect volatility in order to determine which of the available linear and non-linear GARCH models will theoretically yield the best result. We then test each of the models by producing parameter estimations and goodness-of-fit statistics using market data to see if our theoretical predictions prove correct. Then, the models are applied to out of sample data to see if the results are robust. The analysis undertaken allows us to recommend the most appropriate models for predicting return volatility patterns for the underlying 3-Year and 10-Year T-Bond futures and hence solve a key element in the puzzle of how best to price overnight options.

The structure of this chapter is as follows. Firstly, the previous literatures in regarding GARCH models are reviewed. Secondly, we explain the data and the methodology we are going to use. Thirdly, descriptive statistics for return volatilities are presented. We then apply linear and non-linear GARCH models to estimate return volatility. Fourthly, out-of-sample forecasts are performed to test the forecasting powers of our models. Finally, return volatility *news impact curves* from non-linear GARCH models are also presented to describe the information impacts on return volatility.

2. Literature Review

Fama (1965), among others, reported that stock returns have significantly non-normal distributions. It has been noted that the kurtosis of stock returns is larger than the kurtosis of the normal distribution, so stock returns are leptokurtic. The distribution of stock returns may also be skewed, either to the right (positive skewness) or to the left (negative skewness). So, if a traditional model, like OLS which assumes normal distribution of the time series, is used to estimate volatility it will yield biased results. Thus, an alternative estimation model is required.

2.1 Linear Models

Security return variance and covariance has been used to proxy volatility measurement for decades (Engle, 1982, Lamoureus and Lastrapes, 1990, Glosten, Jagannathan and Runkle, 1993, Sentana, 1995, Lee and Brorsen, 1997 and Lee, Chen and Rui, 2001). Besides having a skewed distribution, the return series of most financial securities also exhibit non-constant variance. Non-constant variance is considered to be uncertainty or risk, and this uncertainty is particularly important to investors who wish to minimize risks. In order to cope with these problems, Engle (1982) first estimated conditional variance by introducing the Autoregressive Conditional Heteroskedasticity (ARCH) model. The ARCH model introduced by Engle (1982) takes into account changing variance over time. ARCH models impose an autoregressive structure on the conditional variance, allowing volatility changes over time. The linear ARCH(q) model usually requires a large lag value of q in order to obtain a normal distribution of the error term. Although we may obtain a normally distributed residual by using a large lag value for the endogenous variable, residuals may still contain non-constant variance. Thus, shortly after Engle (1982) derived the ARCH model, Bollerslev (1986) generalized the ARCH model to the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model by placing a moving average term in the ARCH model. This new term improves the model because it becomes unnecessary to use large lag values. This is consistent with the efficient market theory which suggests that past information will have no (or at least less) influence on current market activity. So, the smaller the value of q, the more efficient the market appears. Usually the GARCH (1,1) model is sufficient to model the behavior of the non-constant variance error term. For example, French *et al.* (1987) and Franses and Van Dijk (1996) indicated that a small lag (i.e. GARCH(1,1)) is sufficient to model variance changes over time.

2.2 Non-Linear Models

The ARCH and GARCH models suggested by Engle (1982) and Bollerslev (1986) are linear models. While linear GARCH models address excess kurtosis in market returns, they are silent on the skewness of the return distribution. For financial time series, it is usual that downward movements in the market are followed by higher volatilities than upward movements of the same magnitude. This phenomenon could be described as the impact of asymmetric responses to good and bad news. Thus, the forecast of linear GARCH models may be biased for skewed time series. In order to deal with this problem, non-linear GARCH models are introduced which take into account skewed distributions. For examples, see the Exponential GARCH (EGARCH) model by Nelson

(1991); the Quadratic GARCH (QGARCH) model by Engle and Ng (1993) and Sentana (1995); and the GJR model by Glosten, Jagannathan, and Rankle (1993).

The Exponential GARCH (EGARCH) introduced by Nelson (1991) surmised that most of the previous research using linear GARCH has at least three major drawbacks. First, researchers beginning with Black (1975) reported a negative correlation between current returns and future returns volatility. This indicates that volatility tends to rise in response to bad news and falls in response to good news. This suggests that a model of volatility which responds asymmetrically to positive and negative shocks may be preferable. However, linear GARCH models rule this out by assuming responses are symmetric.

Second, the linear GARCH model imposes parameter restrictions that are often violated by estimated coefficients which may unduly restrict the dynamics of the conditional variance process. More specifically, linear GARCH models put nonnegative constraints on the estimated coefficients which may create difficulties in estimating GARCH models properly.

Third, interpreting whether shocks to conditional variance persist is difficult when applying the linear GARCH model because the usual norms measuring persistence often do not agree. Investors always want to know how long shocks to conditional variance persist. As suggested by Poterba and Summers (1986) if volatility shocks persist indefinitely, the term structure of the risk premium may change, and significantly impact investments in long-lived capital goods. Nelson (1991) argued the way to cope with the problem is to use an Exponential GARCH model. This new class of GARCH model addresses all the drawbacks of linear GARCH models as described above (see also Bhar, 2001).

The Quadratic ARCH model introduced by Engle and Ng (1993) and Sentana (1995) suggested that the analysis of economic and financial time-series data usually involves the study of the first, and possibly second, conditional moments of the series (given past behavior) in order to characterize the dependence of future observations on past values. In addition, Sentana (1995) points out that the first two conditional moments are often identified with important economic concepts. For example, considering the stochastic process for stock market excess return for a given information set, expected mean is usually associated with the risk premium for the stock market as a whole, and estimated volatility is the market risk.

Sentana (1995) combines many attractive features of several ARCH models while ensuring that estimated conditional variances are non-negative. She also combines the linear standard deviation model discussed by Robinson (1991). Sentana (1995) concludes that the combination has at least three non-trivial advantages over the linear GARCH models. First, many theoretical results derived for linear GARCH models still hold, with minor modifications for the Quadratic ARCH model. This includes model estimation and testing techniques, stationarity conditions and persistence properties, autocorrelation structure, temporal and contemporaneous aggregation, and forecasting. Second, Quadratic ARCH conditional variances can be easily integrated in economic models. Third, the Quadratic ARCH model is capable of improving the empirical success of the original ARCH models, since it avoids some of the criticisms without departing significantly from the standard specification. In particular, the Quadratic

ARCH model provides a very simple way of calibrating and testing for dynamic asymmetries in the conditional variance function of financial series (see also Black, 1975 and Nelson, 1991). The Quadratic ARCH model is also easy to incorporate in multivariate models to capture dynamic asymmetries that linear GARCH models rule out by assumption. Sentana (1995) applied a univariate model to daily US and monthly UK stock market returns and found that the Quadratic ARCH model adequately represents volatility and risk premiums.

The GJR model (sometimes called the Threshold ARCH model or TARCH) was introduced by Zakoian (1990), and Glosten, Jaganathan and Runkle (1993). This model is an implementation of the Quadratic ARCH model as described by Sentana (1995). Similar to the Exponential GARCH and Quadratic ARCH model, the Threshold ARCH model allows good news and bad news to have different impacts on conditional return volatility. Therefore, non-linear GARCH models allow good news and bad news to have differential effects on the conditional variance.

2.3 News Impacts on Volatility

In order to measure and test the impact of news on volatility, Engle and Ng (1993) defined the news impact curve which measures how new information is incorporated into volatility estimations. They contrasted the news impact curve with different GARCH models, and tried to determine whether the news impact curve of non-linear GARCH models differs from linear GARCH models. Non-linear (asymmetric) GARCH models allow good news and bad news to have differing impacts on volatility. Thus, comparing their implied news impact curves could illustrate the qualitative difference between competing GARCH models.

The differences between the news impact curves of the models have important implications for portfolio selection and asset pricing as suggested by Engle and Ng (1993). These authors found, after a major unexpected price drop like the 1987 security market crash, the predictable market volatilities given by the linear GARCH model and the EGARCH model differ as implied by relative news impact curves. As the market risk premium is related to market volatility, the two models imply different market risk premiums. This in turn indicates differing risk premiums for individual assets.

Differences in the news impact curves also have important implications for option pricing. A significant movement in predicted volatility after the arrival of major news leads to a significant difference in the current option price. As a consequence, dynamic hedging strategies will be affected by the differing volatility implied by the models.

2.4 Forecasting

Day and Lewis (1992) and Franses and Van Dijk (1996) examined the forecasting performance of the linear and non-linear GARCH models. They focused on out-of-sample forecasting for linear and non-linear GARCH models, and the performance of all of the GARCH models relative to simple random walk forecasting. Franses and Van Dijk (1996) reported that the Quadratic ARCH model was the best performing model. Gokcan (2000) forecasted the volatility of emerging stock markets for seven countries by using linear and non-linear GARCH models. Model estimation and out-of-sample forecasts indicate that the linear GARCH model performed better than the EGARCH model.

3. Data and Methodology

3.1 Data Sample

The security Industry Research Center of Asia-Pacific (SIRCA) and Reuters provided data for this research. The data was collected for 3-Year and 10-Year T-Bond futures from January 1996 to May 2002. The completed trade data contained the time of the trade, the trading price, and the trading volume. We are going to use the time-weighted average trade price for the first half of the night to obtain the daily trade price, as most of the quotes and trades occurred in the first half of the night as described in chapter 4. The return series will be obtained from the daily trade prices.

3.2 Methodology

First, we are going to describe the method suggested by McInish and Wood (1992) to generate the daily time-weighted average trading price. Then, the return series will be obtained from the daily price series. Linear and non-linear GARCH model estimations using the return series will be explained in detail. The similar methods suggested by Day and Lewis (1992), Pagan and Schwert(1990), and Franses and Van Dijk (1996) will be used to forecast out-of-sample volatility using linear and non-linear GARCH models. Finally, we are going to illustrate how to draw news impact curves following Engle and Ng (1993) for non-linear GARCH models, i.e. Exponential GARCH and Threshold ARCH models.

3.2.1 Time-Weighted Daily Price

Time-weighted average trading price will be calculated by using the method suggested by McInish and Wood (1992):

$$\text{Price}_t = \sum_{i=0}^{N} \frac{P_i(t_{i+1} - t_i)}{T - t_i} \tag{6.1}$$

where $(T - t_i)$ is the time interval for the next trade and P_i is the transaction price.

The return series will be obtained by taking the difference between t and t-1 of the natural log of prices:

$$r_t = \ln \text{Price}_t - \ln \text{Price}_{t-1} \tag{6.2}$$

where Price_t is the time-weighted average daily trading price from equation 6.1.

3.2.2 Linear GARCH Model

Engle (1982) designed the Autoregressive Conditional Heteroskedasticity (ARCH) model to measure and forecast conditional variance. The idea of the ARCH model was that the variance of the dependent variable (i.e. a time series) is modeled as a function of past values of the dependent variable and other independent variables. When developing an ARCH model it is necessary to consider two distinct specifications, one for the conditional mean, and one for the conditional variance.

Consider a particular time series. If the variance of the time series is not constant over time, we may write the basic linear ARCH(m) model as:

$$y_t = \phi x_t + \sigma_t \varepsilon_t \tag{6.3}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 y_{t-1}^2 + \alpha_2 y_{t-2}^2 + \ldots + \alpha_m y_{t-m}^2 \tag{6.4}$$

where y_t is the volatility of the time series which is changing over time (time varying) and σ_t^2 is the variance of the residual.

Bollerslev (1986, 1987) extended the basic ARCH model by placing a moving average term into the ARCH estimation. This is called the Generalized ARCH model (GARCH model). The following is a GARCH (1,1) model estimation for a time series:

$$y_t = \phi x_t + \varepsilon_t \sigma_t \qquad (6.5)$$

$$\sigma^2_t = \varpi + \alpha\varepsilon^2_{t-1} + \beta\sigma^2_{t-1} \qquad (6.6)$$

Equation 6.5 is the mean equation, and the x in equation 6.5 represents exogenous or predetermined variables. Equation 6.6 is the conditional variance equation. σ^2_t is the one-period ahead forecast variance based on past information. It is determined by the mean ϖ, the ε^2_{t-1}, and the σ^2_{t-1}.

We consider ε^2_{t-1} as the news about volatility from the previous period, measured as the lag of the squared residual from the mean equation 6.5. We consider σ^2_{t-1} as last period's forecast variance. In a financial sense an investor estimates the current period's variance by forming a weighted average of constant terms (the mean), the forecasted variance from last period (the GARCH term), and information about volatility observed in the previous period (the ARCH term). If the financial asset's return was unexpectedly large in either the upward or the downward direction, then the investor will increase the estimate of next period's variance.

The GARCH model suggests that the variance of a time series follows a heteroskedastic ARMA(1,1) process. More specifically the variance is a function of the autoregressive root which is the coefficient (α +β) in equation 6.6. The coefficient (α +β) measures the volatility shock. Much of the previous literature (see Engle and Bollerslev, 1986) indicated that the coefficient (α +β) is very close to unity, so that volatility shocks are persistent which means that the conditional variance converges to the steady state quite slowly. This indicates that it may take a relatively long time for volatility decreases to return to a steady state.

Equations 6.5 and 6.6 describe the situation where we are only concerned about one period before. If we wish to consider more periods, we could simply put higher orders into the GARCH model as the following GARCH(p, q) model illustrated:

$$y_t = \phi x_t + \varepsilon_t \qquad (6.5a)$$

$$\sigma_t^{\ 2} = \alpha_0 + \sum\alpha_i\, \varepsilon^2_{t-i} + \sum\beta_j\sigma^2_{t-j} \qquad (6.6a)$$

where i = 1, 2, ..., p and j = 1, 2, ..., q.

So if p=2, q=2, we may conclude that the conditional variance will be influenced by past information from the previous two periods.

3.2.3 The GARCH-M Model[45]

Engle and Bollerslev (1986) and Engle, Lilien and Robins (1987) introduced an alternative ARCH model which placed the conditional variance σ^2_t into the mean equation 6.5. The name of this model was the ARCH-in-Mean (ARCH–M) model, where the conditional variance is included in the conditional mean equation as:

$$y_t = \phi x_t + \delta\sigma^2_t + \varepsilon_t \qquad (6.7)$$

where x_t is a predetermined variable and σ^2_t is the conditional variance.

The ARCH–M model is often applied in financial time series when the expected return on an asset is related to the expected asset risk. The coefficient δ in equation 6.7 is the

[45] See Bollerslev, Chou and Kroner (1992) for a survey of GARCH and GARCH-M models.

estimated coefficient for the expected risk, and it is a measure of the risk return tradeoff of the financial asset.

3.2.4 Exponential GARCH Model

As suggested by Nelson (1991), the EGARCH (p, q) model can be written as:

$$\log\sigma^2_t = \alpha_0 + \sum_{i=1}^{p} \beta_i \log^2(\sigma_{t-i}) + \sum_{j=1}^{q} \alpha_j \left[\frac{|\varepsilon_{t-i}|}{\sqrt{\sigma_{t-1}}} - \sqrt{2/\pi} \right] + \gamma \frac{\varepsilon_{t-i}}{\sqrt{\sigma_{t-1}}} \quad (6.8)$$

In equation 6.8, α_0, α_i, γ, and β_j are constant parameters. With the linear GARCH model, there are no restrictions on the parameters to ensure non-negative variances, but the EGARCH model allows positive return shocks and negative return shocks to have differing impacts on volatility (Engle and Ng, 1993). The parameter γ measures the asymmetry. If $\gamma=0$, then goods news (positive return shocks) will have the same effect on volatility as bad news (negative return shocks) of the same amount (Gokcan, 2000). Any other value for γ allows the possibility of asymmetric news shocks.

According to equation 6.8, good news will have $(\alpha+\gamma)$ impacts on return volatility, while bad news will have $(\alpha-\gamma)$ impacts on volatility. So if $\alpha>0$ and $\gamma>0$, positive return shocks (good news) will have greater impacts on return volatility than negative return shocks (bad news). The presence of leverage effects can be tested by the hypothesis that $\gamma\neq0$. Many past studies found the γ parameter to be negative, which means negative return shocks cause greater volatility changes than positive return shocks.

3.2.5 The TARCH Model

The threshold ARCH or TARCH model was introduced by Zakoian (1990), and Glosten, Jaganathan and Runkle (1993). The conditional variance equation in this model is described as:

$$\sigma^2_t = \varpi + \alpha\varepsilon^2_{t-1} + \gamma\, \varepsilon^2_{t-1}\, d_{t-1} + \beta\sigma^2_{t-1} \qquad (6.9)$$

where d_t[46] equals one if ε_t is less than zero, and d_t equals zero if ε_t is greater than zero.

In equation 6.9, good news ($\varepsilon_t > 0$), and bad news ($\varepsilon_t < 0$) have different effects on the conditional variance. Good news has an α impact on volatility, while bad news has an $(\alpha+\gamma)$ impact on volatility. So if $\gamma \neq 0$ a leverage (asymmetric) effect might exist. If $\gamma=0$, the TARCH model becomes a linear GARCH model, and the news impact is symmetric.

3.2.6 The News Impact Curve

As described in Engle and Ng (1993), we can examine the implied relation between σ^2 and the unexpected return ε_t (good news and bad news) by introducing the idea of a news impact curve, which captures the impact of past return shocks on return volatility implicit in a volatility model (see also Braun, Nelson and Sunier, 1995). Engle and Ng (1993) explained that this curve, with all the lagged conditional variances evaluated at the level of the asset return unconditional variance, relates past return shocks to current volatility. Thus, the construction of a news impact curve for non-linear GARCH models will give us a qualitative measure to evaluate different non-linear GARCH models.

[46]When forecasting this model, we assume that the residual distribution is symmetric so that d = 1 half of the time. Thus d_t was set to 0.5 for all observations.

According to Engle and Ng (1993) the equation for the GARCH (1,1) news impact curve is

$$h_t = A + \alpha\, \varepsilon^2_{t-1} \qquad (6.10)$$

where h is the conditional variance at time t, ε_{t-1} is the unpredictable return at time t-1, $A = \varpi + \beta\, \sigma^2$, σ is the unconditional return standard deviation, ϖ is the constant term, and β is the parameter corresponding to h_{t-1} in the GARCH conditional variance equation. So the news impact curve for a GARCH(1,1) model will be symmetric with the curve centered at zero.

The EGARCH (1,1) news impact curves are represented by the following equations suggested by Engle and Ng (1993):

$$\sigma_t = A \cdot \exp\left[\frac{(\gamma+\alpha)}{\sigma'} \cdot \varepsilon_{t-1}\right], \text{ for } \varepsilon_{t-1} > 0 \qquad (6.11)$$

and,

$$\sigma_t = A \cdot \exp\left[\frac{(\gamma-\alpha)}{\sigma'} \cdot \varepsilon_{t-1}\right], \text{ for } \varepsilon_{t-1} < 0 \qquad (6.12)$$

where $A \equiv \sigma^{2\beta}\exp[\varpi - \alpha\sqrt{2/\pi}]$, σ' is the unconditional return standard deviation, ϖ is the constant term, and α, β, and γ are the parameters corresponding to the EGARCH variance equation. Thus, if there are any positive shocks (i.e. good news), the impact on volatility will be $\alpha + \gamma$. If there are any negative shocks (i.e. bad news), the impact on volatility will be $\alpha - \gamma$.

The TARCH model news impact curve is represented by the following equations suggest by Engle and Ng (1993):

$$\sigma_t = A + \alpha\, \varepsilon^2_{t-1} \qquad \text{for } \varepsilon_{t-1} > 0 \qquad (6.13)$$

$$\sigma_t = A + (\alpha + \gamma)\, \varepsilon^2_{t-1} \qquad \text{for } \varepsilon_{t-1} < 0 \qquad (6.14)$$

where $A \equiv \varpi + \beta\, \sigma'^2$, σ' is the unconditional return standard deviation, ϖ is the constant term, and α, β, and γ are the parameters corresponding to the TARCH conditional variance equation. Thus, if there are any positive shocks (i.e. good news), the impact on volatility will be α. If there are any negative shocks (i.e. bad news), the impact on volatility will be $\alpha + \gamma$.

3.2.7 Out-Of-Sample Forecasting

Linear and non-linear GARCH models will be compared by testing their forecasting powers. We will use the method suggested by Day and Lewis (1992), Pagan and Schwert (1990), Franses and Van Dijk (1996), and Gokcan (2000) to forecast volatility (see also Pindyck and Rubinfeld, 1991).

The following formula will be used to find the actual volatility:

$$\sigma^2_t = (r_t - r^{\wedge})^2 \qquad (6.15)$$

where r_t is the actual daily return for time t, and $r^{\wedge}$ is the expected return for time t. The expected return for a particular day is measured by calculating the arithmetic average of daily return, before that particular day. This is repeated for the last 100 observations considered as out-of-sample in our database.

We use the following equation to calculate the out-of-sample forecasting errors for different GARCH models:

$$v_{t+1} = \sigma^2_{t+1} - h^{\wedge}_{t+1} \qquad (6.16)$$

where ν_{t+1} is the forecasting error of the GARCH models, and $h^\wedge_{t+1}$ is the forecasted variance from the various types of GARCH models. We estimate the different GARCH models by using data from a predetermined period of time. These estimated parameters are entered into the conditional variance equation for the different GARCH models to obtain the forecasted variances. Then equation 6.16 is used to subtract the forecasted variance from the actual volatility we get from equation 6.15 to obtain the forecasting errors. Finally, the models are compared to identify the one which has the lowest forecasting error.

4. Analysis

Firstly, descriptive statistics are presented for our return series before we proceed to model estimations. Secondly, we are going to apply linear GARCH models (i.e. the GARCH(1,1) and GARCH (1,1)-M models) as well as non-linear GARCH models (i.e. the Exponential GARCH(1,1) and the Threshold ARCH(1,1) models) to measure futures market volatility patterns. Once the parameters and goodness-of-fit statistics are generated we will identify the most accurate model for each of the return volatility series. Thirdly, out-of-sample forecasting will be conducted to evaluate model performance. Finally, Engle and Ng's (1993) news impact curves will be constructed to measure return volatilities responses to good and bad news. More specifically, we plot news impact curves for the underlying 3-Year and 10-Year T-Bond future return volatilities from non-linear GARCH models (the EGARCH(1,1) and Threshold ARCH (1,1) models). The news impact curve illustrates how T-Bond futures return volatility responds to information shocks. The news impact curve gives an in-depth illustration whether or not it is necessary to use a non-linear model to estimate return volatility.

4.1 Descriptive Statistics

First, we present the 3-Year and 10-Year T-Bond futures return volatility patterns for the period from January 1996 to May 2002. Then, descriptive statistics including the sample size, the mean of the sample, the standard deviation, the normality test, the skewness, the kurtosis, and the ARCH test will be reported.

4.1.1 Return Volatility Patterns for Australian T-Bond Futures

Figure 6.1 displays the return volatility patterns for 3-Year T-Bond futures from January 1996 to May 2002. The return series shows volatility clustering as we observe variance changes over time. The conclusion whether this clustering is statistically significant must wait until the ARCH tests are presented in the next section. However, the observed pattern may indicate that GARCH-type models would be necessary to model return volatility patterns for 3-Year T-Bond futures.

Figure 6.2 displays the return index patterns for 10-Year T-Bond futures from January 1996 to May 2002. Similar to the 3-Year T-Bond futures, the return volatility for 10-Year T-Bond futures also display volatility clustering as we observe variance changes over time. This indicates that GARCH types of models may be necessary to model the return index for the 10-Year T-Bond futures. The conclusion whether this clustering is statistically significant must wait until the ARCH tests are presented in the next section.

Figure 6.1 Patterns of Return Index for the Underlying 3-Year T-Bond Futures
The return series for the 3-Year T-Bond futures are obtained by taking the first difference of the natural log of the time-weighted daily average trading price. The time-weighted daily average trading price is calculated using a similar method to the one suggested by McInish and Wood (1992) for trades occurring during the night. X-axis stands for the time period (daily), y-axis stands for the return.

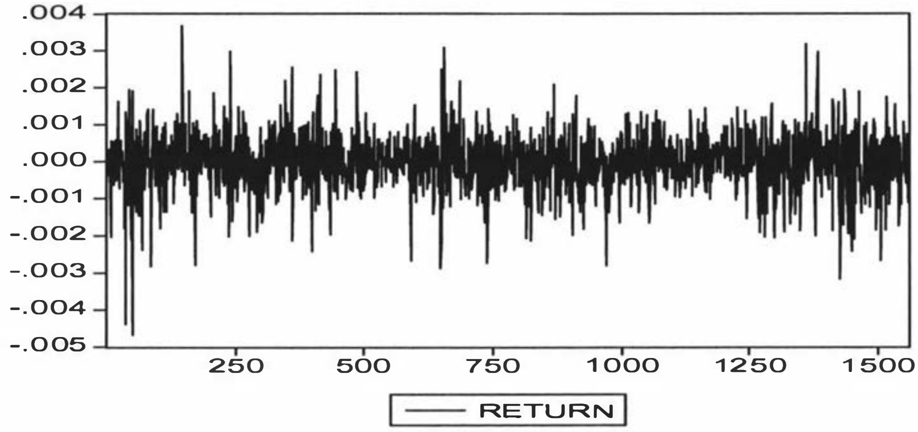
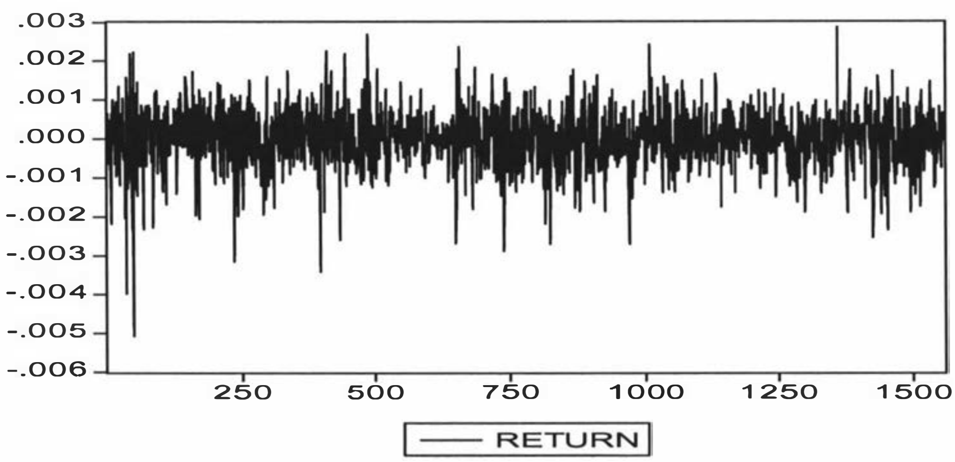


Figure 6.2 Patterns of Return Index for the Underlying 10-Year T-Bond Futures
The return series for the 10-Year T-Bond futures are obtained by taking the first difference of the natural log of the time-weighted daily average trading price. The time-weighted daily average trading price is calculated using a similar method to the one suggested by McInish and Wood (1992) for trades occurring during the night. X-axis stands for the time period (daily), y-axis stands for the return.



4.1.2 Descriptive Statistics

Return volatility descriptive statistics are presented in Table 6.1 for the 3-Year and 10-Year T-Bond futures. It displays the sample size, the mean, standard deviation, skewness, kurtosis, Ljung-Box Q-Statistics, Jarque-Berra normality test, and the ARCH test. From these tables, we are able to determine if the return volatilities for the underlying 3-Year and 10-Year T-Bond futures are normally distributed. We will also test if the return volatility distributions are independent, and if the variances are constant over time.

Table 6.1 presents the selected descriptive statistics for the 3-Year and 10-Year T-Bond futures. Volatility, as measured by the standard deviation is, 0.08% for both the 3-Year and 10-Year T-Bond futures. Kurtosis is 5.8155 for the 3-Year T-Bond futures, and is 5.6239 for the 10-Year T-Bond futures. Since the Kurtosis statistic is greater than three, the returns for both the 3-Year and 10-Year T-Bond futures are leptokurtic[47]. Skewness is -0.3671 for the 3-Year T-Bond futures, and is -0.5582 for the 10-Year T-Bond futures. This indicates that return volatilities are negatively skewed for both the 3-Year and 10-Year T-Bond futures (left skewness)[48]. Negative skewness indicates that the lower tail of the distribution is thicker than the upper tail. This suggests that in Australian T-Bond futures market, prices fell more often than prices rose. So we may conclude that it may be necessary to use a non-linear GARCH model to describe the return volatility patterns for the underlying 3-Year and 10-Year T-Bond futures, and we will verify these results in the following sections.

The Ljung-Box Q-Statistic at lag 5[49] suggests that the 3-Year T-Bond futures return volatility displays no serial autocorrelation. But the ARCH test is statistically significant

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[47] The kurtosis for a normal distribution is three.
[48] The skewness for a normal distribution is zero as the mean is centered on zero.
[49] The ACF and PACF never die out for the return series, thus we simply choose lag of 5 to indicate that there is persistent autocorrelation in the return series.

at the 5% level, which indicated that the return volatility contains non-constant variance, and in turn suggests the return volatility series contains heteroskedasticity. So GARCH types of models should be used to measure return volatility for the 3-Year T-Bond futures return volatility.

The Ljung-Box Q-Statistic at lag 5[50] is not statistically significant for the 10-Year T-Bond futures, but the ARCH test shows a statistically significant result at the 5% level. This indicates that return volatility contains non-constant variance, but is free from autocorrelation. However, GARCH types of models may still be used to measure return volatility for the 10-Year T-Bond futures.

Table 6.1 Descriptive Statistics for 3-Year and 10-Year T-Bond Futures

Descriptive statistics for the 3-Year and 10-Year T-Bond futures return series in Figures 6.1 and 6.2 are shown below. These include sample size, mean, standard deviation, skewness, kurtosis, Ljung-Box Q-Statistics at lag 5, Jarque-Berra normality test, and the ARCH test. The return series is the time-weighted average transaction price using the trades that occur during the trading night.

Index	Sample Size	Mean (10^{-5})	Standard deviation (%)	Skewness	Kurtosis	Q(5)[a]	Normality test[b]	ARCH test
3-Year	1558	1.05	0.0790	-0.3671	5.8155	3.8886	549.2541**	4.8059*
10-Year	1558	1.34	0.0763	-0.5582	5.6239	1.7477	527.5255**	4.0252*

[a] Ljung-Box Q-Statistics at lag 5.
[b] Jarque-Berra normality test.
* Significant at the 5% level.
** Significant at the 1% level.

4.2 Model Estimation

Given the above descriptive statistics, we estimate return volatilities for the 3-Year and 10-Year T-Bond futures using linear GARCH and non-linear GARCH models. More specifically, the term linear GARCH model refers to the GARCH model suggested by Bollerslev (1986), the non-linear GARCH models refers to the Exponential GARCH

[50] The ACF and PACF never die out for the return series, thus we simply choose lag of 5 to indicate that there is persistent autocorrelation in the return series.

model described by Nelson (1991), and the Threshold ARCH model refers to the model described by Zakoian (1990) and Glosten, Jaganathan and Runkle (1993).

Also, we will apply the ARCH-In-Mean model, as suggested by Engle, Lilien and Robins (1987), to linear and non-linear GARCH models. Goodness-of-fit statistics are presented in order to determine the best model to use when estimating and measuring return volatilities. Goodness-of-Fit statistics include the R^2, the mean squared error, the sum squared residual, the Akaike Information Criterion (AIC), the Schwarz Criterion (SC), and the Durbin-Watson Statistic. The best model will have the lowest mean squared error, sum squared residual, AIC and SC. It will also have the highest R^2; and its Durbin-Watson statistic must be approximately two[51].

4.2.1 GARCH Model Estimations

Now that we have decided to use both linear and non-linear GARCH(1,1) models to estimate the return volatility for both the 3-Year and 10-Year T-Bond futures, we can proceed with the model estimations. But sometimes the residuals of the estimated GARCH (1,1) models (linear and non-linear) still exhibited autocorrelation and non-constant variance. To address these problems, AR(1) and/or MA(1) variables may be placed into the mean equation 6.5.

4.2.1.1 Parameter Estimations for the 3-Year and 10-Year T-Bond Futures

Panels A and B in Table 6.2 present parameter estimations for the underlying 3-Year and 10-Year T-Bond futures, the z-statistics are in parenthesis. All the β coefficients for

[51] For a normally distributed residual, the Durbin-Watson statistic is two.

conditional variance in the linear GARCH and non-linear GARCH models are positive and statistically significant at the 1% level for both the 3-Year and 10-Year T-Bond futures return series. This indicates that variance clusters for Australian 3-Year T-Bond futures return series exist. The α and β parameters are positive for all linear and non-linear models. Overall, volatility shocks appear persistent for both the 3-Year and 10-Year T-Bond futures return series.

In model estimations, we also placed conditional variances into the mean equations for linear and non-linear GARCH(1,1) models. The coefficients (δ) of the conditional variance in the mean equation for the ARCH-In-M models are statistically insignificant for all linear and non-linear GARCH models for both 3-Year and 10-Year T-Bond futures. This suggests it is unnecessary to put conditional variance into the mean equation for these models.

Next the results from the EGARCH(1,1) and EGARCH(1,1)–M models are considered. The left hand side of equation 6.8 has a factor which is the log of the conditional variance, which can be used to approximate a leverage effect. Nelson (1991) suggests that the asymmetric or leverage effect is exponential, and the forecasts of the conditional variance are guaranteed to be non-negative. The presence of leverage effects can be tested by the hypothesis that $\gamma \neq 0$.

Table 6.2 Parameter Estimations for 3-Year and 10-Year T-Bond Futures

Linear and non-linear GARCH(1,1) models are applied to measure the 3-Year T-Bond futures return volatilities. The ARCH-In-Mean is also applied to all linear and non-linear GARCH(1,1) models. The following linear and non-linear GARCH models are used.

The mean equation for the linear and non-linear GARCH(1,1) model is:

$$y_t = c + ma(1) + \sigma_t \varepsilon_t$$

The conditional variance equation for the linear GARCH(1,1) model is:

$$\sigma^2_t = \varpi + \alpha\varepsilon^2_{t-1} + \beta\sigma^2_{t-1}$$

The conditional variance equation for the EGARCH(1,1) model is:

$$\log\sigma^2_t = \alpha_0 + \sum_{i=1}^{p} \beta_i \log^2(\sigma_{t-i}) + \sum_{j=1}^{q} \alpha_j \left[\frac{|\varepsilon - i|}{\sqrt{\sigma t - 1}} - \sqrt{2/\pi} \right] + \gamma \frac{\varepsilon t - i}{\sqrt{\sigma t - 1}}$$

The conditional variance equation for the TARCH(1,1) model is:

$$\sigma^2_t = \varpi + \alpha\varepsilon^2_{t-1} + \gamma\, \varepsilon^2_{t-1} d_{t-1} + \beta\sigma^2_{t-1}$$

When the ARCH-In-Mean model is applied, the mean equation for the linear and non-linear GARCH(1,1) is:

$$y_t = \phi x_t + \delta\sigma^2_t + ma(1) + \varepsilon_t$$

An autoregressive and a moving average term with lag 1 are placed into the mean equations to make the residuals from the model estimations independent.

Panel A 3-Year T-Bond Futures

	Parameters				
Model	α_0	α	β	γ	δ
GARCH(1,1)	0.0000(0.81)	0.0539(2.73)***	0.8706(14.78)***	-	-
GARCH-M	0.0000(0.86)	0.0508(2.63)***	0.8870(17.99)***	-	-4.2234(0.97)
EGARCH(1,1)	-1.6584(-1.76)*	0.1345(2.83)***	0.8912(13.83)***	-0.0533(-1.48)	-
EGARCH-M	-1.4701(-1.77)*	0.1329(2.83)***	0.9043(16.00)***	-0.0493(-1.41)	-18.5262(-0.14)
TARCH(1,1)	0.0000(0.91)	0.0209(1.16)	0.8556(13.94)***	0.0600(1.77)*	-
TARCH-M	0.0000(0.93)	0.0200(1.23)	0.8679(15.00)***	0.0552(1.61)	-17.9353(-0.15)

Panel B 10-Year T-Bond Futures

	Parameters				
Model	α_0	α	β	γ	δ
GARCH(1,1)	0.0000(0.86)	0.0391(2.26)**	0.9165(17.70)***	-	-
GARCH-M	0.0000(3.07)***	0.0370(5.04)***	0.9243(50.61)***	-	-72.4057(-0.47)
EGARCH(1,1)	-1.2030(-1.15)	0.0195(0.53)	0.9176(12.74)***	-0.0488(-1.71)*	-
EGARCH-M	-0.8431(-1.88)*	0.0958(2.39)**	0.9465(31.43)***	-0.0395(-1.80)*	-115.7248(-0.86)
TARCH(1,1)	0.0000(1.00)	0.0058(0.36)	0.8922(20.93)***	0.0574(2.22)**	-
TARCH-M	0.0000(1.01)	0.0072(0.45)	0.8989(21.96)***	0.0536(2.07)**	-27.7831(-0.21)

Values in () are z-statistics.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

In Table 6.2 Panels A and B, the parameter of γ is -0.0533 and insignificant for the 3-Year T-Bond futures return volatility, and is -0.0488 and statistically significant at the 10% level for the 10-Year T-Bond futures return volatility. These indicate that leverage (asymmetric) effects in Australian 10-Year T-Bond futures returns series may exist during the sample period. As reported in Black (1976), Nelson (1991), and Schwert

(1990) this coefficient is typically negative, which means positive return shocks usually generate less volatility than negative return shocks, all else being equal. Consistent with previous findings, our γ coefficient for both the 3-Year and 10-Yera T-Bond futures is negative. According to the conditional variance equation for the EGARCH(1,1) model (equation 6.8), if there are positive return shocks (good news), the impact on return volatility will be $(\alpha + \gamma)$, and if there are negative return shocks (bad news), the impact on return volatility will be $(\alpha - \gamma)$.

Since γ is negative, the impact on return volatility for bad news will be greater than the impact for good news. This indicates that the negative return shocks (bad news) will generate more volatility than the positive return shocks (good news) for Australian 3-Year and 10-Year T-Bond futures. This is consistent with what we found in the descriptive statistics where the distribution of the return is left skewed. Thus, we may conclude an asymmetric effect exists for 10-Year T-Bond futures, and a non-linear GARCH model is necessary to measure its return volatility. We also found that the γ coefficient for the EGARCH-M model is negative and statistically significance. This is consistent with what we found for the EGARCH model. But for the 3-Year T-Bond futures, the γ coefficient is insignificant, we may conclude that it is unnecessary to use a nonlinear GARCH model to measure its return volatility.

Next we consider the TARCH model representation. In this model good news ($\varepsilon_t > 0$) has an impact of α on volatility, and bad news ($\varepsilon_t < 0$) has an impact of $(\alpha + \gamma)$ on volatility. If $\gamma \neq 0$ the news impact is asymmetric. From Table 6.2 Panels A and B, the parameter γ is statistically significant at the 10% level for the 3-Year T-Bond futures.

The parameter γ is statistically significant at the 5% level for the 10-Year T-Bond futures. As we also observed a significant γ coefficient when using the EGARCH (1,1) model for the 10-Year T-Bond futures, the results from TARCH (1,1) model may again verify that non-linear GARCH models is appropriate to model the return volatility for the underlying 10-Year T-Bond futures. Also we may conclude that a nonlinear model may be appropriate for the 3-Year T-Bond futures return volatility, as we found the parameter γ is statistically significant at the 10% level. Our results also suggest that by using a non-linear GARCH model, it may give additional insight concerning volatility reactions to good or bad news.

4.2.1.2 Goodness-Of-Fit Statistics for the 3-Year and 10-Year T-Bond Futures

Table 6.3 Panels A and B report the results of goodness-of-fit tests of linear and non-linear GARCH models for the 3-Year and 10-Year T-Bond futures return volatility. Values of R^2, mean square error, sum squared residual, log likelihood, Akaike Information Criterion (AIC), Schwarz Criterion (SC), and Durbin-Watson Statistics are presented.

In Panel A in Table 6.3, the Goodness-of-fit statistics indicate that the TARCH(1,1) model outperforms the other GARCH models considered, as its AIC and SC are relatively lower, its Log Likelihood is relatively larger, and its Durbin-Watson statistic is approximately 2. But among the differing models, the differences are marginal. We may conclude that an asymmetric model could be used to measure 3-Year T-Bond futures return volatility. This result is consistent with what we find from the parameter estimations. Whether we should choose the EGARCH or the TARCH model, will be verified by the news impact curve in a later section.

In Panel B in Table 6.3, the Goodness-of-fit statistics indicate that the non-linear TARCH(1,1) model outperforms the other GARCH models as its MSE, SSE, and AIC statistics are lower, its R^2 and Log Likelihood statistics are larger, and the Durbin-Watson statistic is better than the other models considered. But among competing models, the differences are marginal. We may conclude that an asymmetric model could be also used to measure 10-Year T-Bond futures return volatility. This result is consistent with what we find from the parameter estimations. Whether we should choose the EGARCH or the TARCH model, will be verified by the news impact curve in a later section.

It can be concluded that asymmetric information effects may exist for both 3-Year and 10-Year T-Bond futures return volatility. Thus, taking into consideration the goodness-of-fit statistics and parameter estimations, we may conclude that the non-linear EGARCH(1,1) or TARCH(1,1) models are appropriate to use when estimating the 3-Year and 10-Year T-Bond futures return volatility. However, it would be useful to verify our results by using out-of-sample return volatility forecasts and drawing the news impact curve. This will occur in the following sections.

Table 6.3 Goodness-Of-Fit Statistics for 3-Year and 10-Year T-Bond Futures
Goodness-of-Fit statistics include the R^2, the mean square error, the sum squared residuals, the Log Likelihood, the Akaikie Information Criterion (AIC), the Schwarz Criterion (SC), and the Durbin-Watson statistics. These are the statistics from our model estimations for linear and non-linear GARCH models. We use these statistics to contrast considered models.

Panel A 3-Year T-Bond Futures

			Goodness-Of-Fit Statistics				
Model	R^2(%)	MSE	SSR	Log L	AIC	SC	D-W Stat
GARCH(1,1)	0.1251	0.0008	0.0010	8939.6800	-11.4768	-11.4596	2.0081
GARCH-M	0.1209	0.0008	0.0010	8939.5950	-11.4754	-11.4548	2.0088
EGARCH(1,1)	0.1264	0.0008	0.0010	8939.8460	-11.4757	-11.4551	2.0082
EGARCH-M	0.1079	0.0008	0.0010	8939.6830	-11.4742	-11.4502	2.0091
TARCH(1,1)	0.1271	0.0008	0.0010	8942.9980	-11.4798	-11.4592	2.0070
TARCH-M	0.1050	0.0008	0.0010	8942.6700	-11.4781	-11.4540	2.0081

Panel B 10-Year T-Bond Futures

			Goodness-Of-Fit Statistics				
Model	R^2(%)	MSE	SSR	Log L	AIC	SC	D-W Stat
GARCH(1,1)	-0.0473	0.0008	0.0010	8990.9330	-11.5426	-11.5254	2.0407
GARCH-M	-0.0737	0.0008	0.0010	8991.6300	-11.5422	-11.5216	2.0406
EGARCH(1,1)	-0.0302	0.0008	0.0010	8982.5690	-11.5306	-11.5100	2.0284
EGARCH-M	-0.0884	0.0008	0.0010	8993.0600	-11.5428	-11.5187	2.0471
TARCH(1,1)	-0.0493	0.0008	0.0010	8994.4240	-11.5458	-11.5252	2.0440
TARCH-M	-0.0754	0.0008	0.0010	8994.7300	-11.5449	-11.5209	2.0446

4.3 Out-of-Sample Forecasting

The model estimations to date were in-sample estimations. To examine the robustness of the results, out-of-sample estimations will be used to confirm the forecasting powers of the different GARCH models. Equations 6.15 and 6.16 will be used to calculate out-of-sample forecasting errors for the different GARCH models.

The unconditional volatility in equation 6.15 will be calculated from the actual daily return (r_t) and the expected return for a particular date (r). We use a sample of 100 observations in our data set for out-of-sample forecasting. The expected return will be measured by calculating the arithmetic average of the daily returns, using all of the observations before each testing date. v_{t+1} is the forecasting error of the GARCH models and $\sigma\hat{}_{t+1}$ is the forecasted variance from the conditional variance equations for the different GARCH models. To evaluate the quality of forecasts from different GARCH models, the forecast errors will be presented and compared.

We use the mean squared error and the mean absolute error as measures of forecast accuracy. The smaller the error, the better the forecasting ability of the model. We also use the mean absolute percentage error and Theil Inequality Coefficient statistics[52] to measure the forecasting powers of the different models. The Theil Inequality Coefficient varies between zero and one.

The mean squared error can also be decomposed into three proportions. They are the bias proportion, the variance proportion, and the covariance (Pindyck and Rubinfeld, 1991). The bias proportion indicates how far the mean of the forecast is from the mean of the actual series. The variance proportion tells us how far the variation of the forecast is from the variation of the actual series. The covariance proportion measures the remaining unsystematic forecasting errors. Thus, if the forecast is accurate, the bias and variance proportions would be small, and the remaining bias would be attributable to the covariance proportion.

Table 6.4 Panels A and B present out-of-sample forecasting results of several different GARCH model specifications for the 3-Year and 10-Year T-Bond futures. We consider the relative performance among differing models.

[52] See Appendix 6 for the detailed forecast error statistics computation.

Table 6.4 Out-of-Sample Forecasting for 3-Year T-Bond Futures Overnight Options

The following will be used to find the actual volatility:

$$\sigma^2_t = (r_t - r^\wedge)^2$$

where r_t is the actual daily return for time t, and $r^\wedge$ is the expected return for time t.

The unconditional volatility in the above will be calculated from the actual daily return (r_t) and the expected return for that particularly date (r). We will use a forecast sample of 100 observations in our data set for out-of-sample forecasting. The expected return will be measured by calculating the arithmetic average of the daily return by using all of the observations before each testing date. v_{t+1} is the forecasting error of the GARCH models and $\sigma^\wedge_{t+1}$ is the forecasted variance from the conditional variance equations for the different GARCH models. We use the following equation to find the out-of-sample forecasting errors for different GARCH models:

$$v_{t+1} = \sigma^2_{t+1} - h^\wedge_{t+1}$$

where v_{t+1} is the forecasting error of the GARCH models, $h^\wedge_{t+1}$ is the forecasted variance from the different specifications of GARCH models.

Panel A 3-Year T-Bond Futures

Forecast Statistics

	MSE	MAE	MAPE	Theil Coefficient	Bias	Variance	Covariance
GARCH(1,1)	0.0008	0.0007	105.3217	0.9602	0.0079	0.9137	0.0784
GARCH-M	0.0008	0.0007	106.3815	0.9592	0.0085	0.9126	0.0789
EGARCH(1,1)	0.0008	0.0007	103.2700	0.9611	0.0069	0.9146	0.0785
EGARCH-M	0.0008	0.0007	107.5774	0.9586	0.0092	0.9134	0.0774
TARCH(1,1)	0.0008	0.0007	103.4122	0.9616	0.0070	0.9157	0.0774
TARCH-M	0.0008	0.0007	107.5522	0.9590	0.0092	0.9143	0.0765

Panel B 10-Year T-Bond Futures

Forecast Statistics

	MSE	MAE	MAPE	Theil Coefficient	Bias	Variance	Covariance
GARCH(1,1)	0.0007	0.0006	100.2138	0.9691	0.0021	0.9559	0.0420
GARCH-M	0.0007	0.0006	110.4952	0.9281	0.0100	0.9506	0.0394
EGARCH(1,1)	0.0007	0.0006	100.2766	0.9699	0.0023	0.9680	0.0297
EGARCH-M	0.0007	0.0006	117.2969	0.9074	0.0165	0.9459	0.0375
TARCH(1,1)	0.0007	0.0006	99.3890	0.9726	0.0015	0.9532	0.0453
TARCH-M	0.0007	0.0006	102.3160	0.9586	0.0035	0.9534	0.0431

From Panels A and B in Table 6.4, we observe that the non-linear TARCH(1,1) model has the best forecasting power among the models considered. The TARCH(1,1) model has the lowest mean squared error, mean absolute error, and the Theil inequality coefficient is small. The forecasted mean is accurate, as the mean bias is only 0.0070 for the 3-Year T-Bond futures, and 0.0015 for the 10-Year T-Bond futures. This indicates that the non-linear TARCH(1,1) model forecasts the volatility for the 3-Year and 10-Year T-Bond futures quite well in comparison to other models.

However, if the statistics from Panels A and B in Table 6.4 are reexamined, the differences among competing models are minor. So, taking the parameter estimations, the Goodness-of-Fit and forecast statistics into consideration, it could still be concluded that non linear models should be used to measure and forecast the 3-Year and 10-Year T-Bond futures return volatility. It is still not clear whether the EGARCH or the TARCH model should be chosen as the best model, thus, the news impact curve in the next section will give us further insight whether to choose the EGARCH or the TARCH model.

4.4 Plotting the Estimated News Impact Curve

Engle and Ng (1993) introduced News Impact Curves when measuring return volatilities response to good and bad news. It may be useful to plot the estimated news impact curves from the EGARCH (1,1) and the TARCH (1,1) models for the underlying 3-Year and 10-Year T-Bond futures to see which model would do a better job. Figures 6.3 and 6.4 present news impact curves from the EGARCH (1,1) and the TARCH (1,1) model estimations for the 3-Year and 10-Year T-Bond futures respectively.

Panels A and B in Figure 6.3 presents the news impact curve from the EGARCH(1,1) and the TARCH(1,1) model for the 3-Year T-Bond futures. Panel A indicates that the news impact curves from the EGARCH(1,1) is asymmetric for good news and bad news. It shows that negative return shocks (i.e. bad news) have greater effects on volatility than positive return shocks (i.e. good news) for the 3-Year T-Bond futures, as the slope of the impact curve is steeper when z is less than zero (bad news), than when z is greater than zero (good news). However, the news impact curve from the TARCH(1,1) model is almost symmetric for good news and bad news. Thus, we may tentatively conclude that the non-linear EGARCH(1,1) model should be used to estimate the underlying 3-Year T-Bond futures return volatility patterns.

Panel A in Figure 6.4 indicates that the news impact curves from the EGARCH(1,1) is asymmetric for good news and bad news for the 10-Year T-Bond futures. It shows that negative return shocks (i.e. bad news) have greater effects on volatility than positive return shocks (i.e. good news) for the 3-Year T-Bond futures, as the slope of the impact curve is steeper when z is less than zero (bad news), than when z is greater than zero (good news). However, the news impact curve from the TARCH(1,1) model is almost symmetric for good news and bad news. Thus, we may tentatively conclude that the non-linear EGARCH(1,1) model should be used to estimate the underlying 10-Year T-Bond futures return volatility patterns.

The differences between news impact curves generated by EGARCH and TARCH models have important implications for portfolio selection and asset pricing. Different models imply different market risk premiums, and the market risk premium is a critical component of the capital asset pricing model (CAPM). Also, as volatility has a large influence on option pricing (i.e. Black-Schole model), differing volatility estimates will result in different option prices. This may impact hedging strategies.

Figure 6.3 News Impact Curves for the 3-Year T-Bond Futures

The EGARCH (1,1) model news impact curves are represented by the following equations suggested by Engle and Ng (1993):

$$\sigma_t = A \cdot \exp\left[\frac{(\gamma + \alpha)}{\sigma'} \cdot \varepsilon_{t-1}\right], \text{ for } \varepsilon_{t-1} > 0$$

and,

$$\sigma_t = A \cdot \exp\left[\frac{(\gamma - \alpha)}{\sigma'} \cdot \varepsilon_{t-1}\right], \text{ for } \varepsilon_{t-1} < 0$$

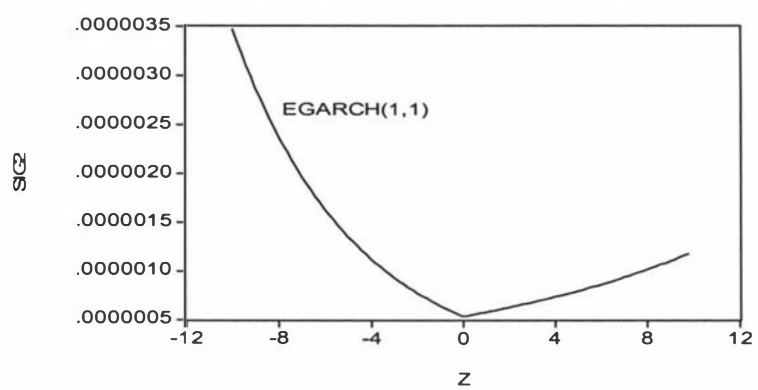
where $A \equiv \sigma'^{2\beta} \exp[\varpi - \alpha \sqrt{2/\pi}]$, σ' is the unconditional return standard deviation, ϖ is the constant term, and α, β, and γ are the parameters corresponding to the EGARCH variance equation. Thus, if there are any positive shocks (i.e. good news), the impact on volatility will be $\alpha + \gamma$. If there are any negative shocks (i.e. bad news), the impact on volatility will be $\alpha - \gamma$. The volatility (denoted as SIG2 in the figure) will be plotted against the impacts of news (denoted as z in the figure), which $z = \varepsilon / \sigma$, where $\log \sigma^2_t = \omega + \beta \log \sigma^2_{t-1} + \alpha| z_{t-1}| + \gamma z_{t-1}$

The TARCH (1,1) model news impact curves are represented by the following equations suggested by Engle and Ng (1993):

$$\sigma_t = A + \alpha \varepsilon^2_{t-1} \quad \text{for } \varepsilon_{t-1} > 0$$
$$\sigma_t = A + (\alpha + \gamma) \varepsilon^2_{t-1} \quad \text{for } \varepsilon_{t-1} < 0$$

where $A \equiv \varpi + \beta \sigma'^2$, σ' is the unconditional return standard deviation, ϖ is the constant term, and α, β, and γ are the parameters corresponding to the TARCH conditional variance equation. Thus, if there are any positive shocks (i.e. good news), the impact on volatility will be α. If there are any negative shocks (i.e. bad news), the impact on volatility will be $\alpha + \gamma$. The volatility (denoted as SIG2 in the figure) will be plotted against the impacts of news (denoted as z in the figure), which $z = \varepsilon / \sigma$, where $\log \sigma^2_t = \omega + \beta \log \sigma^2_{t-1} + \alpha| z_{t-1}| + \gamma z_{t-1}$

Panel A The EGARCH(1,1) Model



Panel B The TARCH(1,1) Model

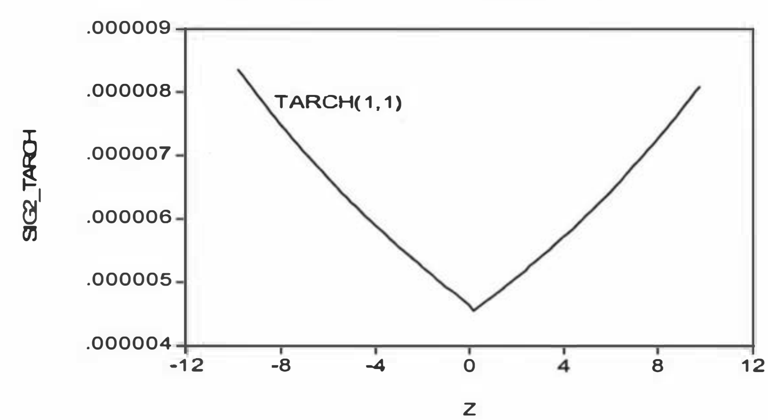


Figure 6.4 News Impact Curves for 10-Year T-Bond Futures

The EGARCH (1,1) model news impact curves are represented by the following equations suggested by Engle and Ng (1993):

$$\sigma_t = A \cdot \exp\left[\frac{(\gamma + \alpha)}{\sigma'} \cdot \varepsilon_{t-1}\right], \text{ for } \varepsilon_{t-1} > 0$$

and,

$$\sigma_t = A \cdot \exp\left[\frac{(\gamma - \alpha)}{\sigma'} \cdot \varepsilon_{t-1}\right], \text{ for } \varepsilon_{t-1} < 0$$

where $A \equiv \sigma'^{2\beta} \exp[\varpi - \alpha \sqrt{2/\pi}]$, σ' is the unconditional return standard deviation, ϖ is the constant term, and α, β, and γ are the parameters corresponding to the EGARCH variance equation. Thus, if there are any positive shocks (i.e. good news), the impact on volatility will be $\alpha + \gamma$. If there are any negative shocks (i.e. bad news), the impact on volatility will be $\alpha - \gamma$. The volatility (denoted as SIG2 in the figure) will be plotted against the impacts of news (denoted as z in the figure), which $z = \varepsilon / \sigma$, where $\log \sigma^2_t = \omega + \beta \log \sigma^2_{t-1} + \alpha | z_{t-1} | + \gamma z_{t-1}$

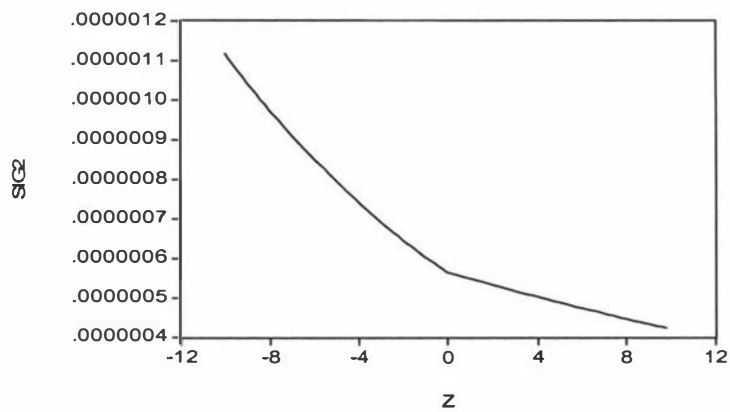
The TARCH (1,1) model news impact curves are represented by the following equations suggested by Engle and Ng (1993):

$$\sigma_t = A + \alpha \varepsilon^2_{t-1} \quad \text{for } \varepsilon_{t-1} > 0$$

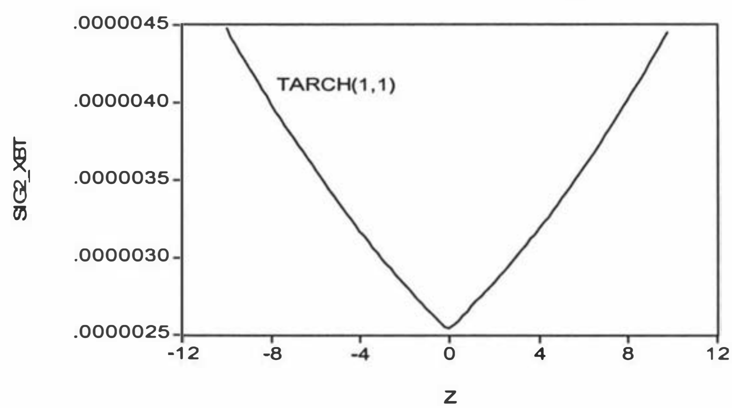
$$\sigma_t = A + (\alpha + \gamma) \varepsilon^2_{t-1} \quad \text{for } \varepsilon_{t-1} < 0$$

where $A \equiv \varpi + \beta \sigma'^2$, σ' is the unconditional return standard deviation, ϖ is the constant term, and α, β, and γ are the parameters corresponding to the TARCH conditional variance equation. Thus, if there are any positive shocks (i.e. good news), the impact on volatility will be α. If there are any negative shocks (i.e. bad news), the impact on volatility will be $\alpha + \gamma$. The volatility (denoted as SIG2 in the figure) will be plotted against the impacts of news (denoted as z in the figure), which $z = \varepsilon / \sigma$, where $\log \sigma^2_t = \omega + \beta \log \sigma^2_{t-1} + \alpha | z_{t-1} | + \gamma z_{t-1}$

Panel A The EGARCH(1,1) Model



Panel B The TARCH(1,1) Model



5. Conclusions

Previous studies have reported that information flows may influence the market place, particularly return volatilities. They have reported that negative information shocks (bad news) may have a greater impact on return volatility than positive information shocks (good news). How traders perceive these information effects on return volatility will change the way they execute trading strategies. Therefore, we have performed a comprehensive analysis on overnight options' underlying futures return volatility patterns to describe how the underlying markets return volatilities respond to information shocks. The objective was to identify the optimal model with which to measure and forecast the underlying markets return volatility.

There are many techniques to choose from when modeling return volatility of a financial security. In order to estimate the return volatility quantitatively, linear and non-linear GARCH models are applied to estimate and forecast the Australian T-Bond futures volatility patterns. Estimations from the models examined suggest that there is a significant asymmetric information effect impact in the return volatility of the 3-Year and 10-Year T-Bond futures, where bad news had a greater impact on volatility than good news. We conclude that a non-linear GARCH model should be used to measure and forecast the 3-Year and 10-Year T-Bond futures return volatility. After we perform out-of-sample forecasting, we find consistent results from previous estimations which indicate nonlinear GARCH models are appropriate to measure the 3-Year and 10-Year T-Bond futures return volatility. But we cannot determine whether the EGARCH model or the TARCH model is the better choice.

After plotting Engle and Ng's (1993) news impact curves from the EGARCH(1,1) and the TARCH(1,1) models, results show that the news impact curve is asymmetric for the 3-Year and 10-Year T-Bond future from the EGARCH(1,1) model and is symmetric from the TARCH(1,1) model. Since negative information shocks (bad news) have a greater impact on return volatility than positive information shocks (good news) for the 3-Year and 10-Year T-Bond futures return volatility, the nonlinear EGARCH(1,1) model should be used to describe volatility patterns for both the 3-Year and 10-Year T-Bond futures.

This study has several implications for investors who wish to effectively trade, hedge, or speculate with the overnight options markets, as underlying futures markets volatility is an important component when pricing overnight options. While this study was, in a sense, comprehensive, there are several outstanding issues that could be addressed. Quite often the underlying markets may have significant influences on their derivative markets. It may be useful to determine the relationship between the overnight options market and its underlying futures market by testing how information is transmitted between them. If there is a causal relationship between the overnight options market and its underlying futures market, it may be possible to use one market to predict the other. This may provide market participants with important information regarding when and how to execute trades in the overnight options market and the underlying futures market. However, these questions are left for future studies.

Chapter 7 Implied, Forecasted, and Realized Volatility of Overnight Options

1. Introduction

In Chapter 6, we found that the SFE T-Bond futures return volatility clustered and we reported that the nonlinear EGARCH model should be used to estimate and forecast the underlying future market's return volatility, as the volatility from the underlying futures market is an important component when pricing overnight options. Alternatively, it is believed that implied volatility is informationally superior to other volatility measures. The implied volatility is the market perception about future volatility. For longer-dated options, we may interpret implied volatility as an option's future return volatility over the remaining life of the option. As in Christensen and Prabhala (1998), if option markets are efficient, implied volatility should be an efficient forecast of future volatility, i.e. implied volatility should subsume the information contained in all other variables in the market information set when explaining future volatility. So this chapter consider the role that implied volatility may play in forecasting volatility.

For short-dated options, i.e. SFE overnight options, we may investigate their implied volatility to discover the market perception of information content in overnight options volatility for the next time period. Treasury-Bond futures overnight options last for one SYCOM [53]session and have advantages over long dated options when calculating implied volatility. Overnight put and call options are available on futures contracts for the nearest quarter month ahead. This avoids measurement errors of overlapping data

[53] See Chapter 2 for detailed information about SYCOM.

which occur for long-dated options when calculating implied volatility using the Black-Scholes formula. Thus, overnight options' implied volatility may give investors an accurate idea of how the market is going to act in the next period (i.e. next SYCOM night trading session).

In this chapter, we first investigate whether or not implied volatility is an unbiased and efficient forecast of underlying futures volatility. Second, we test whether or not implied volatility contains information about future volatility for underlying 3-Year and 10-Year Australian T-Bond futures. Finally, we use multiple regression models to determine an optimal model that describes the relationship between implied, forecasted, and realized volatility.

2. Literature Review

Black (1976) first illustrates how to value European futures options by extending what was developed in Black (1975), Black and Scholes (1973), and Merton (1973). The underlying assumption is that futures' prices have the same lognormal property that is assumed for stock prices. Almost all parameters in the Black-Scholes option pricing model are observable. However, there is one parameter in the Black-Scholes pricing formula that cannot be directly observed, which is the volatility of the underlying futures. We may estimate this parameter from actual (realized) historical data of the underlying futures, but price volatility of most derivative securities varies over time. This makes it hard to accurately identify. There are two additional approaches which may be used to estimate futures volatility. One may calculate implied volatility by solving the Black-Scholes formula or to use an appropriate model to estimate volatility.

As described in Christensen and Prabhala (1998), if option markets are efficient, implied volatility should be an efficient forecast of future volatility. Implied volatility is interpreted as an efficient volatility forecast in a wide range of settings (see also Day and Lewis, 1988, Harvey and Whaley, 1992, and Poterba and Summers, 1986). Thus, whether or not implied volatility can predict future volatility, and whether or not it does so efficiently, are both empirically testable questions. Latane and Rendleman (1976) document that stocks with higher implied volatility may also have higher *ex post* realized volatility. They focus on static cross-sectional tests. More recent studies focus on the information content of implied volatility in dynamic settings, i.e. Day and Lewis (1992), Jorion (1995), Lamoureus and Lastrapes (1993), Canina and Figlewski (1993), Fleming (1998), and Blair, Poon and Taylor (2001).

Christensen and Prabhala (1998) report that S&P 100 index option's implied volatility is an unbiased and efficient measure for future volatility, in contrast to most previous studies which report that implied volatility is a biased and inefficient forecast of future volatility. Christensen and Prabhala (1998) adjust the conventional regression analysis for information content of implied volatility. They do this by putting an instrumental variable into the regression for the implied volatility. Then, the fitted implied volatility replaces the implied volatility in the conventional model. This addresses the Error-In-Variable problem (EIV) which many authors consider present in empirical models.

Day and Lewis (1992) compare the information content of the implied volatility from call options on the S&P 100 index to GARCH (Generalized Autogressive Conditional Heteroskedasticity) and Exponential GARCH models of conditional volatility. They place the implied volatility into GARCH and EGARCH models as an exogenous variable. The within-sample result suggests that implied volatility may contain incremental information relative to the conditional volatility from GARCH and EGARCH models. They also find strong within-sample evidence that the conditional volatility estimates from GARCH and EGARCH models reflect incremental information relative to implied volatility. Thus, their results imply neither implied volatility, nor the conditional volatility from GARCH and EGARCH models completely characterizes within-sample conditional stock market volatility, when the excess market return is assumed to be a linear function of conditional volatility. Day and Lewis (1992) explore this issue by using out-of-sample data. Although the results are consistent with the hypothesis that implied volatility and the GARCH and the EGARCH forecasts are unbiased, there is not strong evidence that the information content of GARCH forecasted volatility and implied volatility is related.

Jorion (1995) reported that implied volatility for options on currency is an efficient predictor of future return volatility for foreign currency futures at Chicago Mercantile Exchange, although it is biased. He also applied simulations to investigate the robustness of his result and found that measurement errors and statistical problems can substantially distort inferences. Lamoureus and Lastrapes (1993) examined options on equity and found that implied volatility is biased and inefficient, and that past volatility contains predictive information about future volatility beyond that contained in implied volatility. As recognized by Christensen and Prabhala (1998), both Day and Lewis (1992) and Lamoureus and Lastrapes (1993) used overlapping samples. Their research is therefore characterized by a maturity mismatch problem. Thus, their results may be biased due to the error in variables problem.

Canina and Figlewski (1993) found implied volatility to be a poor forecast of subsequent realized volatility. They report that implied volatility has little correlation with future volatility, and that it does not incorporate the information contained in recent observed volatility (see also Areal and Taylor, 2002). One possible explanation as suggested by Christensen and Prabhala (1998) is that index option markets process volatility information inefficiently. However, this explanation is unlikely given the liquidity, market depth, and trading activity in the S&P index options. A second possible explanation is that the Black and Scholes (1973) options pricing model (which is commonly used to compute implied volatility) cannot be used to price index options due to the presence of transaction costs. These costs may make it prohibitive to hedge options in the spot market. However, this explanation is incomplete as the Black-Scholes formula does not necessarily require continuous trading in the cash market to be usefully applied.

The application of ARCH or GARCH type models to estimate and forecast volatility has been widely used, as we described in Chapter 6. The model (Bollerslev, 1986, 1987) relates tomorrow's conditional distribution to today's return and/or previous returns. The model can be expanded by using information like implied volatility calculated from the price of options that are near expiry to define the conditional distribution. For example, Fleming (1998) and Day and Lewis (1992) observe that the information provided by implied volatility improves the measurement of the conditional distribution.

Blair, Poon and Taylor (2001) deduced that stock returns may or may not have incremental information when modelling index volatility, depending on the sources of information that move stock prices. Blair, Poon and Taylor (2001) incorporate leverage effects and dummy variables for the 1987 crash, as well as aggregate measures of stock return volatility. The analysis of daily volatility of the S&P 100 index from 1984 to 1998 reports that there is some incremental volatility information in returns from the 100 shares that are included in the index.

In this chapter, we use the approaches adopted by Day and Lewis (1992) and Christensen and Prabhala (1998) to test whether or not overnight options' implied volatility is an unbiased and efficient forecast of future volatility. We also investigate the information content of implied volatility and the relationship between implied, forecasted, and realized volatility.

3. Data and Methodology

3.1 Data Sample

The Security Industry Research Centre of Asia-Pacific (SIRCA) and Reuters provided data for this research. The data was collected for 3-Year and 10-Year T-Bond futures and their overnight options from January 1996 to May 2002. Intra-night data included in the time-stamped trade data are: the time of the trade, the trading price and the trading volume. We report that most of the quotes and trades occurred in the first half of the night for 3-Year and 10-Year T-Bond futures overnight options (see chapter 4). Thus, we use the time-weighted average transaction price during the first half of the trading night for underlying 3-Year and 10-Year T-Bond futures. The intra-night trade data during the first half of the trading night for 3-Year and 10-Year T-Bond futures overnight call and put options are used to calculate the intra-night implied volatility for each transaction occurring in the single period. We will split the data set into overnight call options and overnight put options for both 3-Year and 10-Year T-Bond futures before proceeding with the analysis.

3.2 Methodology

3.2.1 Implied Volatility

As indicated in Chapter 2, Australian 3-Year and 10-Year T-Bond futures overnight options are European-type options. Thus, for each observed 3-Year and 10-Year T-Bond futures overnight call and put options price[54] (C_t and P_t), we calculate implied volatility σ_{it} by solving the following Black's models[55] for valuing futures options (Hull (2000)):

$$C_t = e^{-rT}(F_t N(d_1) - X_t N(d_2)) \quad (7.1)$$

$$P_t = e^{-rT}(X_t N(-d_2) - F_t N(d_1)) \quad (7.2)$$

where
$$d_1 = \frac{\ln(F_t / X_t) + \sigma_{it}^2 T / 2}{\sigma_{it}\sqrt{T}}$$

$$d_2 = \frac{\ln(F_t / X_t) - \sigma_{it}^2 T / 2}{\sigma_{it}\sqrt{T}} = d_1 - \sigma_{it}\sqrt{T}$$

and F_t is the price[56] at time t for the underlying 3-Year and 10-Year T-Bond futures, X_t is the exercise price at time t, r is the risk free rate (we use Australian 90-Day Treasury Notes as the risk free rate), T is the time-to-maturity, and $N(d_1)$ and $N(d_2)$ are the natural log normal distribution function. We take the mean implied volatility from the intra-night data.

[54] We only use in-the-money options.
[55] We need to adjust the Black's (1976) model when the options are subject to futures style margining. The model should not have the interest rate discount factor in it, because the holder of the overnight option does not pay the premium up-front, although its effect will be largely immaterial in the resulting options price (because the options has less than one day to maturity).
[56] We find the nearest futures price according to the overnight option's trading time.

3.2.2 Realized Volatility from Trade Prices

There are different approaches to estimate the volatility of underlying futures empirically which may be considered. A simple approach such as calculating the standard deviation of the return for different time intervals is widely used. Here, we will use a more sophisticated approach involving linear and non-linear GARCH models to estimate the return volatility for underlying 3-Year and 10-Year T-Bond futures. We adopt the results in Chapter 6 to obtain the realized volatility for underlying 3-Year T-Bond and 10-Year T-Bond futures. Thus, the EGARCH(1,1) model is used to measure the 3-Year and 10-Year T-Bond futures return volatility.

3.2.3 Forecasted Volatility from GARCH Models

As discussed earlier, the EGARCH(1,1) model is used to measure return volatility for the 3-Year and 10-Year T-Bond futures. Thus, forecasted volatility is generated from the EGARCH(1,1) model for the 3-Year and 10-Year T-Bond futures return series.

3.2.4 Estimation From ARIMA(p, d, q) Model

Autoregressive Moving Average (ARMA) models are used to describe the properties of the time series. In order to discover the back-shift operator from the autoregressive term, and the first difference operator from the moving average term, we fit Autoregressive(p), Moving Average(q), Autoregressive Moving Average (p,q), and Autoregressive Integrated Moving Average (p,d,q) models to implied, forecasted, and realized volatility, and their log forms.

3.2.4.1 Autoregressive Model

An autoregressive series of order p AR(p) has p lags for the y_t series is characterized by:

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \ldots + \phi_p y_{t-p} + e_t \quad (7.3)$$

We can rewrite equation 7.3 as:

$$\phi(B)y_t = e_t, \text{ where } \phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_p B^p$$

We can choose the value of p using the Akaike Information Criterion (AIC) or Schwarz Bayesian Criterion (SIC) with k=p+1. Thus, we may choose the value of k that minimises these criteria:

Akaike Information Criterion $AIC(k) = \log(\sigma^2) + 2k/n$

Schwarz Bayesian Criterion $SIC(k) = \log(\sigma^2) + k\log(n)/n$

where σ^2 is the estimated variance for error series e_t.

3.2.4.2 Moving Average Model

An moving average series of order q MA(q) has q lags for the error series e_t is characterized by:

$$y_t = e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \ldots + \theta_q e_{t-q} \quad (7.4)$$

We can rewrite equation 7.4 as:

$$y_t = \theta(B)e_t, \text{ where } \theta(B) = 1 + \theta_1 B + \theta_2 B^2 + \ldots + \theta_p B^p$$

We use the AIC and SIC described above to determine the value of q.

3.2.4.3 Autoregressive Moving Average Model

An autoregressive Moving Average series ARMA(p,q) with p lags for y_t and q lags for the error series e_t is characterized by:

$$y_t - \phi_1 y_{t-1} + \phi_2 y_{t-2} + \ldots + \phi_p y_{t-p} = e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \ldots + \theta_q e_{t-q} \quad (7.5)$$

We can rewrite equation 7.5 as:

$$\phi(B)y_t = \theta(B)e_t$$

where $$\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_p B^p$$

$$\theta(B) = 1 + \theta_1 B + \theta_2 B^2 + \ldots + \theta_p B^p$$

We use the AIC and SIC criteria to determine the value of p and q.

3.2.4.4 Autoregressive Integrated Moving Average Model

Autoregressive Integrated Moving Average models are non-stationary models with at least one unit root. If it is assumed that differencing of order d is required for stationarity, then we have the following ARIMA(p,d,q) model:

$$\phi(B)\Delta^d y_t = \theta(B)e_t \qquad (7.6)$$

where $\Delta^d y_t = (1-L)^d y_t$. Usually d is 0 or 1, p and q are 0, 1, or 2 and

$$\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_p B^p$$

$$\theta(B) = 1 + \theta_1 B + \theta_2 B^2 + \ldots + \theta_p B^p$$

As before, we use the AIC and SIC criteria to determine the value of d, p and q.

3.2.5 The Relation Between Implied, Forecasted, and Realized Volatility

We use regression analysis to test the relation between implied, forecasted, and realized volatility for 3-Year and 10-Year T-Bond futures overnight call and put options respectively. First, we use the ordinary least square approach to analyse the relationship between each pair of implied, forecasted, and realized volatility in their level series. Second, lag values will be added to determine if past values of a particular variable influence current values. Finally, we use multiple regressions to test the interrelationships between the implied, forecasted, and realized volatility for both 3-Year and 10-Year T-Bond futures overnight call and put options.

3.2.5.1 Regression Analysis

As suggested by Christensen and Prabhala (1998), the information content of implied volatility is assessed by the following regression:

$$r_t = \alpha_0 + \alpha_1 i_t + \varepsilon_t \quad (7.7)$$

$$f_t = \alpha'_0 + \alpha'_1 i_t + u_t \quad (7.8)$$

where r_t denotes the realized volatility for period t, i_t denotes the implied volatility at the beginning of period t, and f_t denotes the forecasted volatility.

We may test three hypotheses for both equations 7.7 and 7.8. First, for equation 7.7, if α_1 is non-zero and statistically significant, we may conclude that implied volatility contains information about future volatility. Second, if α_0=0, and α_1=1, we may conclude that implied volatility is an unbiased forecast of realized volatility. Third, if the residual from equation 7.7 is white noise and independent, we may conclude that implied volatility is an efficient means to explain futures volatility with any variable in the market information set. A similar argument can be made regarding equation 7.8 for forecasted volatility and implied volatility.

As is generally known, we can use historical data to predict future volatility. Thus, past-realized volatility may be helpful in explaining future volatility. Therefore, we insert the lagged value of realized volatility (i.e lag of 1[57]) into the right side of equations 7.7 and 7.8, and rewrite these equations as:

$$r_t = \alpha_0 + \alpha_1 i_t + \alpha_2 r_{t-1} + \varepsilon_t \tag{7.9}$$

$$f_t = \alpha'_0 + \alpha'_1 i_t + \alpha'_2 f_{t-1} + \varepsilon_t \tag{7.10}$$

We test the statistical significance and the magnitude of α coefficients in equations 7.9 and 7.10 to compare the information content of implied volatility to past-realized volatility.

3.2.5.2 Alternative Regression Analysis

Christensen and Prabhala (1998) point out that if α_1 in equation 7.7 is less than unity, this could be a consequence of an errors-in-variable (EIV) problem. According to their study, the error may be attributed to; (i) nonsynchronous measurement of option prices and index levels, (ii) early exercise and dividends (which are ignored in the Black-Scholes formula), (iii) bid-ask spreads, (iv) the *wild-card* option which allows option traders to deliver on a futures contract at the closing price for a period of time after the close of trading, and/or (v) misspecification of the stochastic process governing index returns. EIV may cause implied volatility to be biased and inefficient, although many of the errors mentioned here do not apply to overnight options due to the special nature of the product. If the errors are present, the ordinary least square regression estimates from equation 7.7 may be inconsistent and lead to inaccurate conclusions. Christensen and Prabhala (1998) use an instrumental variables (IV) procedure to solve this problem. Under the IV framework, implied volatility i_t is regressed on an instrument and/or any other exogenous variables as in the following equation.

[57] This value is determined by looking at the time series properties.

$$i_t = \beta_0 + \beta_1 i_{t-1} + \beta_2 r_{t-1} + \varepsilon_t \qquad (7.11)$$

Equation 7.11 uses past implied volatility as the instrumental variable. Equation 7.11 indicates that implied volatility may endogenously depend on its own past volatility if option prices reflect volatility information. Equation 7.11 is similar to a GARCH(1,1) model specification suggested by Bollerslev (1986). First, a fitted value from regression equation 7.11 is used to replace implied volatility in equation 7.9, and then the specifications are re-estimated by OLS.

3.2.6 Putting It All Together

We use three multiple regression models to determine the relationship between implied, forecasted, and realized volatility for 3-Year and 10-Year T-Bond futures overnight call and put options, which best describes the relationship between implied, forecasted, and realized volatility. The following three regression equations are used:

$$i_t = \alpha_0 + \alpha_1 i_{t-1} + \alpha_2 i_{t-2} + \alpha_3 f_t + \alpha_4 f_{t-1} + \alpha_5 f_{t-2} + \alpha_6 r_t + \alpha_7 r_{t-1} + \alpha_8 r_{t-2} + \varepsilon_t \qquad (7.12)$$

$$f_t = \alpha_0 + \alpha_1 i_t + \alpha_2 i_{t-1} + \alpha_3 i_{t-2} + \alpha_4 f_{t-1} + \alpha_5 f_{t-2} + \alpha_6 r_t + \alpha_7 r_{t-1} + \alpha_8 r_{t-2} + \varepsilon_t \qquad (7.13)$$

$$r_t = \alpha_0 + \alpha_1 i_t + \alpha_2 i_{t-1} + \alpha_3 i_{t-2} + \alpha_4 f_t + \alpha_5 f_{t-1} + \alpha_6 f_{t-2} + \alpha_7 r_{t-1} + \alpha_8 r_{t-2} + \varepsilon_t \qquad (7.14)$$

where i_t, f_t, and r_t are the implied, forecasted, and realized volatility for 3-Year and 10-Year T-Bond futures and their overnight call and put options.

4. Analysis

We test 3-Year and 10-Year T-Bond futures and their overnight call and put options separately. Firstly, descriptive statistics are presented for implied, forecasted, and realized volatility, and their respective log forms. Secondly, autoregressive, moving average, and autoregressive moving average processes are fitted to identify the time series properties. Finally, we use regression to test relationships between implied, forecasted and realized volatility for 3-Year and 10-Year T-Bond futures overnight call and put options.

4.1 Descriptive Statistics for Implied, Forecasted and Realized Volatility

Descriptive statistics for implied, forecasted, and realized volatility and their log forms are presented in Tables 7.1 and 7.2 for 3-Year and 10-Year T-Bond futures and their overnight options.

4.1.1 3-Year T-Bond Futures and its Overnight Options

Table 7.1 reports descriptive statistics for the underlying 3-Year T-Bond futures and its overnight call and put options. Both the mean implied and the mean forecasted volatility, and their log forms exceed the mean realized volatility, and its log form. This indicates that the actual volatility obtained from the EGARCH(1,1) model for the underlying 3-Year T-Bond futures is smaller than the volatility implied by the Black's option pricing model, and the volatility forecasted by the EGARCH(1,1) model. The mean differences between the log forms of implied and forecasted volatility with the log realized volatility is greater than the mean differences between the level series. Realized volatility yields the lowest standard deviation compared to the implied and the forecasted volatility. Overnight call options implied volatility is greater than overnight puts.

The skewness and kurtosis statistics indicate that the distributions of implied, forecasted and realized volatility are highly skewed and leptokurtic for the level series, but less so for the log forms. The positive skewness for implied, forecasted, and realized volatility in the level series indicates investors may be in favour of this, as investors may prefer positive skewness more than negative skewness. The ARCH test indicates that the variances for implied volatility are not constant for either the log form or the level series. The variances for forecasted volatility are non-constant for both the level and the log forms. For realized volatility the variances is constant for the log form, but is non-constant for the level series. The Jarque-Bera statistics indicate distributions of all the series are not normally distributed at the 1% significance level.

4.1.2 10-Year T-Bond Futures and its Overnight Options

Table 7.2 reports descriptive statistics for the underlying 10-Year T-Bond futures and its overnight call and put options. We found similar results in terms of the mean, the standard deviation, skewness, and kurtosis for 10-Year T-Bond futures overnight options as found for the 3-Year T-Bond futures overnight options, except for the implied volatility for put options in log form where we have larger kurtosis.

The variances of implied volatility are non-constant for the log form and the level series for overnight call and put options, whereas the variances of realized and forecasted volatility are constant for both the level series and the log form series. Jarque-Bera statistics indicate that distributions of all series are not normal for both the log form and the level series. The descriptive statistics in sections 4.1.1 and 4.1.2 indicate that it may be necessary to use the log form of the series to run the regression, and it may be also necessary to place the lagged value of the dependent variable into the regression equation.

Table 7.1 Descriptive Statistics for the 3-Year T-Bond Futures and Its Overnight Options Volatility

This table contains descriptive statistics for daily (first half of the trading night) implied, forecasted, and realized volatility of their level series and their natural logarithms. The implied volatility is calculated from solving the Black's future options valuation formula (Black (1976)) by using the intra-night trade prices of 3-Year T-Bond futures overnight call and put options. Then, mean implied volatility is used for the daily implied volatility. The realized and forecasted volatility is computed by fitting the EGARCH(1,1) model for the underlying 3-Year T-Bond futures. All series are from January 1996 to May 2002.

			Statistics			
Volatility	Mean	Standard Deviation	Skewness	Kurtosis	ARCH	Jarque-Bera Statistics
Implied - Calls	0.2990	0.1605	1.5098	4.7086	73.5904**	2884.2010**
Implied – Puts	0.2184	0.1055	2.1746	7.8831	89.4434**	1272.0960**
Realized	0.0119	0.0020	1.0858	4.8131	4.9158*	357.1399**
Forecasted	0.0931	0.0418	0.4838	3.1971	22.5880**	43.5057**
Log Implied - Calls	-1.4811	0.3115	1.5880	5.1793	71.1845**	431.4955**
Log Implied - Puts	-1.6035	0.3740	1.3266	4.0036	48.9913**	239.3744**
Log Realized	-4.4450	0.1563	0.5763	3.2772	1.3854	62.7196**
Log Forecasted	-2.4958	0.5383	-1.1142	5.1271	123.9098**	423.5097**

*Significant at the 5% level.
**Significant at the 1% level.

Table 7.2 Descriptive Statistics for the 10-Year T-Bond Futures and Its Overnight Options Volatility

This table contains descriptive statistics for daily (first half of the trading night) implied, forecasted, and realized volatility of their level series and their natural logarithms. The implied volatility is calculated from solving the Black's future options valuation formula (Black (1976)) by using the intra-night trade prices of 3-Year T-Bond futures overnight call and put options. Then, mean implied volatility is used for the daily implied volatility. The realized and forecasted volatility is computed by fitting the EGARCH(1,1) model for the underlying 10-Year T-Bond futures. All series are from January 1996 to May 2002.

			Statistics			
Volatility	Mean	Standard Deviation	Skewness	Kurtosis	ARCH	Jarque-Bera Statistics
Implied - Calls	0.2408	0.0982	2.5999	11.4931	34.8333**	514.5791**
Implied – Puts	0.2421	0.1480	1.7399	5.7243	28.4133**	833.3366**
Realized	0.0118	0.0008	0.6694	3.9227	2.3492	113.0201**
Forecasted	0.0717	0.0189	-0.5857	3.6168	1.1757	74.9143**
Log Implied - Calls	-1.3216	0.4542	0.8066	2.5767	35.0217**	118.9010**
Log Implied - Puts	-1.5732	0.5923	-1.9243	21.3058	12.3722**	14929.6600**
Log Realized	-4.4443	0.0684	0.4412	3.2828	0.4155	36.7099**
Log Forecasted	-2.6837	0.3478	-2.3826	12.3945	0.7118	4743.6970**

*Significant at the 5% level.
**Significant at the 1% level.

4.2 Time Series Properties for T-Bond Futures and its Overnight Options

In this section, we assess time series properties for both the underlying 3-Year and 10-Year T-Bond futures and their overnight call and put options to determine which series to use and how many lags to use for each variable in the following regression models. We fit autoregressive, moving average, autoregressive moving average, and autoregressive integrated moving average models for log forms of implied, forecasted, and realized volatility.

4.2.1 3-Year T-Bond Futures and its Overnight Options

Table 7.3 below reports Autoregressive, Moving Average, Autoregressive Moving Average, and Autoregressive Integrated Moving Average models of implied volatility, forecasted, and realized volatility (all in logarithm forms) for the underlying 3-Year T-Bond futures and its overnight call and put options. Coefficients of the parameter for the different models, the R squared, the Akaike Information Criteria (AIC), the Schwarz Criteria (SIC), the Durbin –Watson statistic, and the Q-Statistic for the residual from the model estimation, are also presented to assess the time series properties.

Panel A in Table 7.3 presents AR(1), AR(2), MA(1), MA(2), ARMA(1,1), and ARIMA(1,1,1) model for the 3-Year T-Bond futures overnight call option's implied volatility (log form). The Q-Statistic for the residual from the ARMA(1,1) is 5.3702 and insignificant. This is the lowest of all the models, suggesting that the ARMA(1,1) process appears to best describe the implied volatility for the 3-Year T-Bond futures overnight call options. After we fit an integrated ARIMA(1,1,1) model to the implied volatility, we found that the Q-Statistic were larger than for the ARMA(1,1) model.

This verifies our conclusion that the ARMA(1,1) process best describes the time series property of implied volatility for the 3-Year T-Bond futures overnight call options.

Panel B presents the result for 3-Year T-Bond futures overnight put options implied volatility (log form). We conclude that ARIMA(1,1,1) model best describes the time series properties for 3-Year T-Bond futures overnight options implied volatility. An AR(1) model best describes the realized volatility for the underlying 3-Year T-Bond futures, and an ARIMA(1,1,1) model best describes the forecasted volatility for the underlying 3-Year T-Bond futures.

4.2.2 10-Year T-Bond Futures Overnight Options

Table 7.4 presents Autoregressive, Moving Average, Autoregressive Moving Average, and Autoregressive Integrated Moving Average models of implied volatility, forecasted, and realized volatility (all in logarithm forms) for 10-Year T-Bond futures overnight call and put options. We found similar results to those found for the 3-Year T-Bond futures overnight options. For 10-Year T-Bond futures overnight call options, the ARMA(1,1,1) model best describes implied volatility, the ARIMA(1,1) model best describes forecasted volatility, and the AR(1) model best describes realized volatility. For 10-Year T-Bond futures overnight put options, we found that the ARIMA(1,1) model best describes implied volatility, the ARIMA(1,1,1) model best describes forecasted volatility, and the AR(2) model best describes realized volatility.

Table 7.3 ARIMA(p,d,q) Models for 3-Year T-Bond Futures and Its Overnight Options' Implied, Forecasted, and Realized Volatility

AR(1), AR(2), MA(1), MA(2), ARMA(1,1), and ARIMA(1,1,1) models are fitted to the logarithm of implied, forecasted, and realized volatility for the underlying 3-Year T-Bond futures and its overnight call and put options. The following equations are used:

For autoregressive models: $y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \ldots + \phi_p y_{t-p} + e_t$

For moving average models: $y_t = e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \ldots + \theta_q e_{t-q}$

For autoregressive moving average models: $y_t - \phi_1 y_{t-1} + \phi_2 y_{t-2} + \ldots + \phi_p y_{t-p} = e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \ldots + \theta_q e_{t-q}$

For autoregressive integrated moving average models: $\phi(B)\Delta^d y_t = \theta(B)e_t$

where $\Delta^d y_t = (1-L)^d y_t$. Usually d is 1, p and q are 0, 1, or 2 and

$\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_p B^p$

$\theta(B) = 1 + \theta_1 B + \theta_2 B^2 + \ldots + \theta_p B^p$

Panel A Implied Volatility – Overnight Call Options (log)

Model	Intercept	ϕ_1	ϕ_2	θ_1	θ_2	Q-Statistics[a]	R^2	AIC	SIC	DW
AR(1)	-1.4806**	0.2720**				31.9950**	0.0740	0.4332	0.4463	2.0861
	(-94.8470)	(7.4525)								
AR(2)	-1.4802**	0.2286**	0.1574**			11.7690**	0.0967	0.4119	0.4315	2.0180
	(-80.8174)	(6.0946)	(4.1982)							
MA(1)	-1.4811**			0.2054**		56.2300**	0.0552	0.4524	0.4655	1.9203
	(-107.1729)			(5.5363)						
MA(2)	-1.4811**			0.2273**	0.1528**	23.8560**	0.0828	0.4257	0.4452	1.9814
	(-94.9598)			(6.0637)	(4.0751)					
ARMA(1,1)	-1.4796**	0.8500**		-0.6643**		5.3702	0.1117	0.3945	0.4141	1.9661
	(-59.1648)	(18.2301)		(-10.0314)						
ARIMA(1,1,1)	-0.0001	0.1716*		-0.9361**		12.0480**	0.3760	0.4188	0.4384	2.0305
	(0.1353)	(4.1733)		(-63.6072)						

Table 7.3 Continued

Panel B Implied Volatility – Overnight Put Options (log)

Model	Intercept	ϕ_1	ϕ_2	θ_1	θ_2	Q-Statistics[a]	R^2	AIC	SIC	DW
AR(1)	-1.6064**	0.2409**				10.0740*	0.0581	0.7851	0.7980	2.0383
	(-90.8752)	(6.6123)								
AR(2)	-1.6059**	0.2213**	0.0783*			4.3234	0.0635	0.7828	0.8021	2.0084
	(-83.9203)	(5.9030)	(2.0888)							
MA(1)	-1.6071**			0.2088**		19.4720**	0.0495	0.7939	0.8067	1.9582
	(-98.7318)			(5.6884)						
MA(2)	-1.6071**			0.2147**	0.0919*	10.2270*	0.0581	0.7877	0.8069	1.9844
	(-91.7057)			(5.7410)	(2.4574)					
ARMA(1,1)	-1.6063**	0.9626**		-0.8815**		12.4170**	0.0822	0.7620	0.7813	1.7926
	(-37.8407)	(50.8983)		(-26.7836)						
ARIMA(1,1,1)	-0.0000	0.1392**		-0.9442**		0.8950	0.3979	0.7597	0.7790	1.9971
	(0.0308)	(3.4624)		(-70.7478)						

Panel C Realized Volatility (log)

Model	Intercept	ϕ_1	ϕ_2	θ_1	θ_2	Q-Statistics[a]	R^2	AIC	SIC	DW
AR(1)	-4.4523**	0.9063**				0.8418	0.8339	-2.6812	-2.6719	1.9933
	(-215.3504)	(73.2203)								
AR(2)	-4.4524**	0.9094**	-0.0037			0.9018	0.8316	-2.6784	-2.6645	1.9990
	(-216.5202)	(29.6830)	(-0.1204)							
MA(1)	-4.4451**			0.7652**		1652.8000**	0.5789	-1.7364	-1.7271	0.9760
	(-812.2715)			(39.0348)						
MA(2)	-4.4458**			0.9632**	0.5488**	833.8500**	0.7189	-2.1388	-2.1248	1.4815
	(-698.3170)			(38.5765)	(22.0873)					
ARMA(1,1)	-4.4522**	0.9058**		0.0036		0.8666	0.8339	-2.6793	-2.6654	1.9994
	(-215.7845)	(66.6819)		(0.1081)						
ARIMA(1,1,1)	0.0002	0.8931		-0.9919		1.0285	0.0510	-2.6789	-2.6650	1.9838
	(0.9217)	(59.2273)		(-226.0277)						

Table 7.3 Continued

Panel D Forecasted Volatility (log)

Model	Intercept	ϕ_1	ϕ_2	θ_1	θ_2	Q-Statistics[a]	R^2	AIC	SIC	DW
AR(1)	-2.4954**	0.0435				6.0370	0.0019	1.6005	1.6098	1.9966
	(-145.0927)	(1.4219)								
AR(2)	-2.4964**	0.0434	0.0299			4.6310	0.0029	1.5994	1.6134	2.0034
	(-140.7045)	(1.4181)	(0.9765)							
MA(1)	-2.4958**			0.0412		6.1254	0.0018	1.6001	1.6094	1.9966
	(-145.8094)			(1.3466)						
MA(2)	-2.4958**			0.0406	0.0260	5.1132	0.0025	1.6012	1.6152	1.9971
	(-142.3248)			(1.3259)	(0.8511)					
ARMA(1,1)	-2.4955**	-0.3378		0.3688		7.3124	0.0021	1.6021	1.6161	1.9718
	(-148.2073)	(0.7596)		(0.7596)						
ARIMA(1,1,1)	-0.0000	0.0221		-0.9800**		1.8303	0.4793	1.5983	1.6123	2.0018
	(0.1769)	(0.7067)		(-155.0096)						

a This is the Q-Statistics at lag 5 of the model residual.
Values in brackets are t-statistics.
*Significant at the 5% level.
**Significant at the 1% level.

Table 7.4 ARIMA(p,d,q) Models for 10-Year Overnight Options' Implied, Forecasted, and Realized Volatility

AR(1), AR(2), MA(1), MA(2), ARMA(1,1), and ARIMA(1,1,1) models are fitted to the logarithm of implied, forecasted, and realized volatility for the 10-Year T-Bond futures overnight options. The following equations are used:

For autoregressive models: $y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \ldots + \phi_p y_{t-p} + e_t$

For moving average models: $y_t = e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \ldots + \theta_q e_{t-q}$

For autoregressive moving average models: $y_t - \phi_1 y_{t-1} + \phi_2 y_{t-2} + \ldots + \phi_p y_{t-p} = e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \ldots + \theta_q e_{t-q}$

For autoregressive integrated moving average models: $\phi(B)\Delta^d y_t = \theta(B)e_t$

where $\Delta^d y_t = (1-L)^d y_t$. Usually d is 1, p and q are 0, 1, or 2 and

$\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_p B^p$

$\theta(B) = 1 + \theta_1 B + \theta_2 B^2 + \ldots + \theta_p B^p$

Panel A Implied Volatility – Overnight Call Options (log)

Model	Intercept	ϕ_1	ϕ_2	θ_1	θ_2	Q-Statistics[a]	R^2	AIC	SIC	DW
AR(1)	-1.3230**	0.5695**				111.3100**	0.3243	0.8710	0.8806	2.3517
	(-48.8037)	(22.1560)								
AR(2)	-1.3225**	0.3925**	0.3126**			37.0970**	0.3914	0.7687	0.7832	2.1290
	(-35.1688)	(13.2177)	(10.5264)							
MA(1)	-1.3217**			0.3885**		545.7700**	0.2047	1.0335	1.0432	1.7252
	(-75.2472)			(13.4893)						
MA(2)	-1.3217**			0.3974**	0.2890**	265.2200**	0.2844	0.9299	0.9443	1.8559
	(-65.2901)			(13.2994)	(9.6616)					
ARMA(1,1)	-1.3446**	0.9816**		-0.8038**		5.8711	0.4639	0.6415	0.6559	1.9095
	(-12.0112)	(138.5988)		(-36.5933)						
ARIMA(1,1,1)	-0.0006	0.0823*		-0.8533**		1.6803	0.3749	0.6437	0.6581	2.0052
	(-0.3354)	(2.1993)		(-44.2918)						

Table 7.4 Continued

Panel B Implied Volatility – Overnight Put Options (log)

Model	Intercept	ϕ_1	ϕ_2	θ_1	θ_2	Q-Statistics[a]	R^2	AIC	SIC	DW
AR(1)	-1.5726**	0.4192**				105.3200**	0.1758	1.6003	1.6100	2.2009
	(-54.2934)	(14.7569)								
AR(2)	-1.5757**	0.3158**	0.2507**			36.6510**	0.2297	1.5320	1.5465	2.1088
	(-42.0165)	(10.4458)	(8.2920)							
MA(1)	-1.5734**			0.3055**		277.1500**	0.1206	1.6647	1.6744	1.8567
	(-69.4155)			(10.2617)						
MA(2)	-1.5734**			0.2864**	0.2047**	155.7800**	0.1630	1.6173	1.6317	1.9021
	(-62.2797)			(9.3593)	(6.6815)					
ARMA(1,1)	-1.6054**	0.9657**		-0.8032**		4.9732	0.3001	1.4388	1.4533	1.9377
	(-17.8409)	(89.3747)		(-32.0827)						
ARIMA(1,1,1)	-0.0011	0.0578		-0.8516**		4.2841	0.3870	1.4510	1.4655	1.9997
	(-0.4457)	(1.5442)		(-43.3307)						

Panel C Realized Volatility (log)

Model	Intercept	ϕ_1	ϕ_2	θ_1	θ_2	Q-Statistics[a]	R^2	AIC	SIC	DW
AR(1)	-4.4435**	0.8878**				1.9468	0.7903	- 4.0888	- 4.0792	2.0071
	(-509.8024)	(62.1004)								
AR(2)	-4.4433**	0.8834**	0.0043			1.9992	0.7898	- 4.0865	- 4.0721	1.9988
	(- 509.8225)	(28.2225)	(0.1368)							
MA(1)	-4.4443**			0.7168**		1366.7000**	0.5408	- 3.3029	- 3.2933	1.0746
	(-1788.9080)			(32.8822)						
MA(2)	-4.4442**			0.9283**	0.5209**	620.6900**	0.6838	- 3.6743	- 3.6599	1.5715
	(-1510.1980)			(34.7787)	(19.4937)					
ARMA(1,1)	-4.4435**	0.8890**		-0.0056		2.0333	0.7904	- 4.0869	- 4.0724	1.9983
	(-507.0876)	(55.5324)		(-0.1587)						
ARIMA(1,1,1)	0.0000	0.8854**		-0.9968**		1.8640	0.0550	- 4.0841	- 4.0697	2.0043
	(0.1041)	(60.6402)		(-586.3728)						

a This is the Q-Statistics at lag 5 of the residual.
Values in brackets are t-statistics.
*Significant at the 5% level.
**Significant at the 1% level.

Table 7.4Continued

Panel D Forecasted Volatility (log)										
Model	Intercept	ϕ_1	ϕ_2	θ_1	θ_2	Q-Statistics[a]	R^2	AIC	SIC	DW
AR(1)	-2.6838**	-0.0277				3.4947	0.0008	0.7290	0.7386	2.0021
	(-253.7028)	(-0.8846)								
AR(2)	-2.6840**	-0.0292	-0.0508			0.8823	0.0034	0.7288	0.7433	1.9978
	(-266.6651)	(-0.9332)	(-1.6261)							
MA(1)	-2.6838**			-0.0307		3.3974	0.0008	0.7279	0.7376	1.9965
	(-254.9374)			(-0.9827)						
MA(2)	-2.6838**			-0.0274	-0.0516	0.8748	0.0034	0.7274	0.7418	2.0012
	(-268.4636)			(-0.8761)	(-1.6506)					
ARMA(1,1)	-2.6841**	0.4967		-0.5348		2.1171	0.0022	0.7295	0.7439	1.9821
	(-266.8257)	(1.0563)		(-1.1683)						
ARIMA(1,1,1)	-0.0000	-0.0336		-0.9969**		4.3731	0.5151	0.7289	0.7434	2.0023
	(-1.4404)	(-1.0734)		(-560.2839)						

a This is the Q-Statistics at lag 5 of the model residual.
Values in brackets are t-statistics.
*Significant at the 5% level.
**Significant at the 1% level.

4.3 The Relation between Implied, Forecasted and Realized Volatility

In this section, we apply regression equations 7.7 to 7.10 and their modified formats to analyse the information content of implied volatility and the relationship between implied, forecasted and realized volatility for 3-Year and 10-Year T-Bond futures overnight options.

4.3.1 Implied and Realized Volatility for 3-Year T-Bond Futures Overnight Options

First we apply regression equations 7.7 and 7.9, to describe the relationship between the implied and the realized volatility for 3-Year T-Bond futures overnight call and put options. We also apply two modified equations from equations 7.7 and 7.9 in addition to equations 7.7 and 7.9. In Table 7.5 below, the relevant four regressions are presented.

For equation 1 in Table 7.5, we test three hypotheses using α_1. First, α_1 should be nonzero if implied volatility contains information about future volatility. Second, α_1 should equal 1 and α_0 should equal 0 if implied volatility is an unbiased forecast of future volatility. Third, the residual from the regression of equation 1 should be independent if implied volatility is efficient. Our results indicate that we cannot reject the first hypothesis for overnight call options, which indicates that 3-Year T-Bond futures overnight call options implied volatility contains information about future volatility as α_1 equals 0.0789 and is statistically significant at the 1% level. But the magnitude of the information content is low. It also appears that implied volatility is a biased forecast of futures volatility, as α_1 is not equal to one and α_0 is non-zero. The negative coefficients of the constant terms are due to the use natural logarithm values for implied volatility rather than the level series. For 3-Year T-Bond futures overnight put options, the coefficient is not statistically significant. This indicates that implied volatility does not contain information about future volatility for the overnight put option.

Durbin-Watson statistics are 0.2921 for overnight call options and 0.2582 for overnight put options. Both statistics are significantly different from 2. This indicates that the residual from equation 1 is auto-correlated. This again was verified by the Q-Statistic at lag 1 for the model residuals, which is significant at the 1% level. From this analysis, we may conclude that implied volatility is a biased and inefficient forecast of volatility for 3-Year T-Bond futures overnight call options, and it has information content. But this is not the case for 3-Year T-Bond futures overnight put options.

We use equations 2 and 3 in Table 7.5 to explain the information content of implied volatility, relative to past realized volatility. In equation 2, we use implied volatility as an explanatory variable along with past realized volatility. The regression coefficient for past volatility drops from 0.8770 in equation 3 to 0.8700 in equation 2 for overnight calls, and from 0.8751 to 0.8745 for overnight puts. Both statistics retain their significance. The coefficient for the implied volatility in equation 2 is small in magnitude (0.0245 for overnight calls and 0.0043 for overnight puts). It is significant at the 1% level for overnight calls, but it is not significant for overnight put options. This indicates implied volatility has less explanatory power than past realized volatility for both 3-Year T-Bond futures overnight call and put options.

Next we place implied volatility, its past value, and past realized volatility into regression equation 4. Results indicate past implied volatility has more explanatory power than current implied volatility for overnight put options, but not for overnight call options. However, past implied volatility still has less explanatory power than past realized volatility. Of the four models, equation 2 best describes the relationship between the implied and the realized volatility for 3-Year T-Bond futures overnight call options, and equation 4 best describes the relationship between the implied and the realized volatility for 3-Year T-Bond futures overnight put options.

Table 7.5 The Relation between Implied and Realized Volatility for 3-Year T-Bond Futures Overnight Options

Ordinary Least Square estimates of equations 7.7 and 7.9 are used to determine the relationship between implied and realized volatility for both 3-Year T-Bond futures overnight call and put options. The equations are:

$$r_t = \alpha_0 + \alpha_1 i_t + \varepsilon_t \qquad (1)$$

$$r_t = \alpha_0 + \alpha_1 i_t + \alpha_2 r_{t-1} + \varepsilon_t \qquad (2)$$

We also apply two extra equations in addition to equations 7.7 and 7.9:

$$r_t = \alpha_0 + \alpha_1 r_{t-1} + \varepsilon_t \qquad (3)$$

$$r_t = \alpha_0 + \alpha_1 i_t + \alpha_2 i_{t-1} + \alpha_2 r_{t-1} + \varepsilon_t \qquad (4)$$

Here, i_t denotes the natural logarithm of the Black's implied volatility for overnight call and put options. r_t denotes the actual volatility we estimated from the EGARCH(1,1) model for the underlying 3-Year T-Bond futures (the natural logarithm).

Panel A 3-Year T-Bond Futures Overnight Call Options

Dependent Variable: Log Realized Volatility (r_t)	Constant	i_t	i_{t-1}	r_{t-1}	Q-Statistics[58]	R^2	DW
Eq1	-4.3272**	0.0789**			510.5800**	0.0282	0.2921
	(-162.8500)	(4.4949)					
Eq2	-0.5416**	0.0245**		0.8700**	0.0300	0.7711	1.9818
	(-6.7025)	(2.8470)		(47.4576)			
Eq3	-0.5470**			0.8770**	0.1382	0.7684	1.9665
	(-6.7366)			(48.0237)			
Eq4	-0.5442**	0.0205*	0.0159	0.8654**	0.0855	0.7722	1.9730
	(-6.7448)	(2.3002)	(1.7872)	(46.8287)			

[58] This is the Q-Statistic at lag 1 for the residual from the regression.

Panel B 3-Year T-Bond Futures Overnight Put Options

Dependent Variable: Log Realized Volatility (r_t)							
	Constant	i_t	i_{t-1}	r_{t-1}	Q-Statistics[59]	R^2	DW
Eq1	-4.4137**	0.0240			539.5400**	0.0036	0.2582
	(-178.7052)	(1.6005)					
Eq2	-0.5525**	0.0043		0.8745**	0.5077	0.7680	2.0524
	(-6.8361)	(0.5925)		(48.2921)			
Eq3	-0.5566**			0.8751**	0.4362	0.7679	2.0485
	(-6.9152)			(48.4323)			
Eq4	-0.5377**	-0.0007	0.0209**	0.8720**	0.4825	0.7706	2.0513
	(-6.6711)	(-0.0946)	(2.8235)	(48.3395)			

*Significant at the 5% level. **Significant at the 1% level.

4.3.2 Implied and Realized Volatility for 10-Year T-Bond Futures Overnight Options

Table 7.6 below presents the four regression models for the 10-Year T-Bond futures overnight call and put options. As we found in the previous section, equation 1 in Table 7.6 results indicate that we cannot reject the first hypothesis for overnight call options, which indicates that 3-Year T-Bond futures overnight call options implied volatility contains information about future volatility as α_1 equals 0.0078 which is statistically significant at the 10% level. But the magnitude of the information content is low. It also appears that implied volatility is a biased forecast of futures volatility, as α_1 is not equal to one and α_0 is non-zero and significant at the 1% level. The negative coefficient of the constant terms is due to the use the natural logarithm values for implied volatility rather than the level series. For 10-Year T-Bond futures overnight put options, the coefficient of the implied volatility is not statistically significant. This indicates that implied volatility does not contain information about future volatility for the 10-Year T-Bond futures overnight put option.

[59] This is the Q-Statistic at lag 1 for the residual from the regression.

Durbin-Watson statistics are 0.2235 for overnight call options and 0.2298 for overnight put options. Both statistics are significantly different from 2. This indicates that the residual from equation 1 is auto-correlated. This again was verified by the Q-Statistic at lag1 for the model residuals, which is significant at the 1% level. From this analysis, we may conclude that implied volatility is a biased and inefficient forecast of volatility for 10-Year T-Bond futures overnight call options, and it has some information content. But this is not the case for 10-Year T-Bond futures overnight put options.

We use equations 2 and 3 in Table 7.6 to explain the information content of implied volatility, relative to past realized volatility. In equation 2, we use implied volatility as an explanatory variable along with past realized volatility. The regression coefficient for past volatility drops from 0.8878 in equation 3 to 0.8873 in equation 2 for overnight calls, and increase from 0.8842 to 0.8847 for overnight puts. Both statistics retain their significance. The coefficient for the implied volatility in equation 2 is small in magnitude (0.0016 for overnight calls and 0.0042 for overnight puts). It is significant at the 1% level for overnight puts, but it is insignificant for overnight call options. This indicates implied volatility has less explanatory power than past realized volatility for 10-Year T-Bond futures overnight call options. But for 10-Year T-Bond futures overnight put options, when we put the past realized volatility into the regression equation, the coefficient of the implied volatility becomes significant.

Next we place implied volatility, its past value, and past realized volatility into regression equation 4. In contrast to what we found for the 3-Year T-Bond futures overnight options, results for 10-Year T-Bond futures overnight options indicate past implied volatility and current implied volatility have no explanatory power for overnight call options. Implied volatility has less explanatory power than past realized volatility for overnight put options. Of the four models, equation 2 best describes the relationship between the implied and the realized volatility for 10-Year T-Bond futures overnight call and put options.

Table 7.6 The Relation between Implied and Realized Volatility for 10-Year T-Bond Futures Overnight Options

Ordinary Least Square estimates of equations 7.7 and 7.9 are used to determine the relationship between implied and realized volatility for both 10-Year T-Bond futures overnight call and put options. The initial equations are:

$$r_t = \alpha_0 + \alpha_1 i_t + \varepsilon_t \quad (1)$$

$$r_t = \alpha_0 + \alpha_1 i_t + \alpha_2 r_{t-1} + \varepsilon_t \quad (2)$$

We also apply two extra equations in addition to equations 7.7 and 7.9:

$$r_t = \alpha_0 + \alpha_1 r_{t-1} + \varepsilon_t \quad (3)$$

$$r_t = \alpha_0 + \alpha_1 i_t + \alpha_2 i_{t-1} + \alpha_2 r_{t-1} + \varepsilon_t \quad (4)$$

Here, i_t denotes the natural logarithm of the Black's implied volatility for overnight call and put options. r_t denotes the actual volatility we estimated from the EGARCH(1,1) for 10-Year T-Bond futures (the natural logarithm).

Panel A 10-Year T-Bond Futures Overnight Call Options

Dependent Variable: Log Realized Volatility (r_t)	Constant	i_t	i_{t-1}	r_{t-1}	Q-Statistics[60]	R^2	DW
Eq1	-4.4341***	0.0078*			809.2600***	0.0027	0.2235
	(-675.4681)	(1.6500)					
Eq2	-0.4985***	0.0016		0.8873***	0.0216	0.7905	2.0074
	(-7.8427)	(0.7392)		(61.9810)			
Eq3	-0.4983***			0.8878***	0.0200	0.7903	2.0271
	(-7.8424)			(62.1004)			
Eq4	-0.4983***	0.0023	-0.0012	0.8875***	0.0214	0.7905	2.0074
	(-7.8367)	(-0.8751)	(-0.4700)	(61.9444)			

Panel B 10-Year T-Bond Futures Overnight Put Options

Dependent Variable: Log Realized Volatility (r_t)	Constant	i_t	i_{t-1}	r_{t-1}	Q-Statistics[52]	R^2	DW
Eq1	-4.4397***	0.0028			801.1400***	0.0006	0.2298
	(-724.8977)	(0.7715)					
Eq2	-0.5058***	0.0042**		0.8847**	0.2102	0.7840	2.0272
	(-7.8124)	(2.4764)		(108.1668)			
Eq3	-0.5147***			0.8842***	0.2283	0.7827	2.0282
	(-7.9433)			(60.6423)			
Eq4	-0.5058***	0.0041**	0.0002	0.8846***	0.2150	0.7840	2.0276
	(-7.8093)	(2.1941)	(0.1250)	(60.7581)			

*Significant at the 10% level.
**Significant at the 5% level.
***Significant at the 1% level.

[60] This is the Q-Statistic at lag 1 for the residual from the regression.

4.3.3 Implied and Forecasted Volatility for 3-Year T-Bond Overnight Options

Now we use regression equations 7.8 and 7.10 to describe the relationship between the implied and the forecasted volatility for 3-Year T-Bond futures overnight call and put options respectively. Panels A and B in Table 7.7 report results from the four regression models.

For equation 1 in Table 7.7, results indicate that we cannot reject the first hypothesis for overnight put options. The results suggest that implied volatility contains information about future forecasted volatility as the coefficient for overnight put options is significant at the 1% level. This indicates that implied volatility contains information about forecasted volatility for 3-Year T-Bond futures overnight put options, but not for overnight call options. The magnitude (the regression coefficient) of the information content is greater for overnight call options than for put options. It also appears that implied volatility is a biased forecast of futures volatility as α_1 is not equal to one and α_0 is non-zero. The negative coefficient of the constant terms is due to the use of natural logarithm for implied volatility rather than the level series. Durbin-Watson statistics are 3.0040 for overnight call options and 3.0049 for overnight put options. Both statistics are significantly different from 2. This indicates that the residual from equation 1 is auto-correlated. Again this was verified by the significant Q-Statistic at lag 1 for the model residual. We may conclude that implied volatility is a biased and inefficient measure of forecasted volatility for 3-Year T-Bond futures overnight put options.

We use equations 2 and 3 in Table 7.9 to explore the information content of implied volatility relative to past forecasted volatility. In equation 2, we use implied volatility as an explanatory variable along with the past forecasted volatility. The regression coefficient for past forecasted volatility changes from -0.5049 in equation 3 to -0.5026 in equation 2 for overnight puts and from -0.5037 to -0.5040 for overnight call options. Both coefficients are significant for overnight put options, but not for overnight call options. The coefficient for the implied volatility in equation 2 is -0.1292, and significant at the 5% level for overnight puts, and -0.0807 and insignificant for overnight calls. These coefficients are smaller than the coefficients for past forecasted volatility. This indicates that implied volatility has relatively less explanatory power than the past forecasted volatility. But the overnight put options implied volatility has higher explanatory power than overnight call options.

Next we place implied volatility, its past value and past forecasted volatility into regression equation 4. We found the magnitude of the current implied volatility coefficient was greater for overnight put options, but the coefficient for implied volatility is insignificant for overnight call options. Thus, we may conclude that implied volatility may only contain information about forecasted volatility for overnight put options.

4.3.4 Implied and Forecasted Volatility for 10-Year T-Bond Overnight Options

We use regression equations 7.8 and 7.10 to describe the relationship between the implied and the forecasted volatility for 10-Year T-Bond futures overnight call and put options respectively. Panels A and B in Table 7.8 report results from four regression models. The results indicate that there is no explanatory power for forecasted volatility for both 10-Year T-Bond futures overnight call and put options, as almost all coefficients from the four regression models are insignificant (except equation 4 for past implied volatility of overnight call options).

Table 7.7 The Relation between Implied and Forecasted Volatility for 3-Year T-Bond Futures Overnight Options

Ordinary Least Square estimates of equations 7.8 and 7.10 are used to determine the relationship between implied and forecasted volatility for both 3-Year T-Bond futures overnight call and put options. The equations are:

$$f_t = \alpha_0 + \alpha_1 i_t + \varepsilon_t \quad (1)$$

$$f_t = \alpha_0 + \alpha_1 i_t + \alpha_2 ft_{-1} + \varepsilon_t \quad (2)$$

We also apply two extra equations in addition to equations 7.8 and 7.10:

$$f_t = \alpha_0 + \alpha_1 f_{t-1} + \varepsilon_t \quad (3)$$

$$f_t = \alpha_0 + \alpha_1 i_t + \alpha_2 i_{t-1} + \alpha_3 f_{t-1} + \varepsilon_t \quad (4)$$

Here, i_t denotes the natural logarithm of the Black's implied volatility for overnight call and put options. f_t denotes the forecasted volatility we forecasted from the EGARCH(1,1) model for the underlying 3-Year T-Bond futures (the natural logarithm).

Panel A 3-Year T-Bond Futures Overnight Call Options

Dependent Variable: Log Forecasted Volatility (r_t)

	Constant	i_t	i_{t-1}	f_{t-1}	Q-Statistics	R^2	DW
Eq1	0.0001	-0.0718			176.9100**	0.0012	3.0040
	(0.0043)	(-0.9195)					
Eq2	0.0007	-0.0807		-0.5040**	18.2130**	0.2549	2.3217
	(0.0284)	(-1.1954)		(-15.3595)			
Eq3	0.0007			-0.5037	18.3400**	0.2533	2.3228
	(0.0272)			(-15.3450)			
Eq4	0.0007	-0.0642	0.0356	-0.5034	18.5910**	0.2551	2.3250
	(0.0280)	(-0.8412)	(0.4659)	(-15.3165)			

Panel B 3-Year T-Bond Futures Overnight Put Options

Dependent Variable: Log Forecasted Volatility (r_t)

	Constant	i_t	i_{t-1}	f_{t-1}	Q-Statistics	R^2	DW
Eq1	-0.0001	-0.1554*			180.8400**	0.0082	3.0049
	(-0.0047)	(-2.4194)					
Eq2	-0.0003	-0.1292*		-0.5026**	24.0870**	0.2603	2.3669
	(-0.0101)	(-2.3244)		(-15.5225)			
Eq3	-0.0003			-0.5049**	24.0300**	0.2546	2.3663
	(-0.0129)			(-15.5527)			
Eq4	-0.0002	-0.1412*	-0.0282	-0.5039**	23.6070**	0.2605	2.3632
	(-0.0097)	(-2.2954)	(-0.4565)	(-15.4969)			

*Significant at the 5% level.
**Significant at the 1% level.

Table 7.8 The Relation Between Implied and Forecasted Volatility for 10-Year T-Bond Futures Overnight Options

Ordinary Least Square estimates of equations 7.8 and 7.10 are used to determine the relationship between implied and forecasted volatility for both 10-Year T-Bond futures overnight call and put options. The equations are:

$$f_t = \alpha_0 + \alpha_1 i_t + \varepsilon_t \quad (1)$$

$$f_t = \alpha_0 + \alpha_1 i_t + \alpha_2 f_{t-1} + \varepsilon_t \quad (2)$$

We also apply two extra equations in addition to equations 7.8 and 7.10:

$$f_t = \alpha_0 + \alpha_1 f_{t-1} + \varepsilon_t \quad (3)$$

$$f_t = \alpha_0 + \alpha_1 i_{t-1} + \alpha_2 f_{t-1} + \varepsilon_t \quad (4)$$

Here, i_t denotes the natural logarithm of the Black's implied volatility for overnight call and put options. f_t denotes the forecasted volatility we forecasted from the EGARCH(1,1) for the underlying 10-Year T-Bond futures (the natural logarithm).

Panel A 10-Year T-Bond Futures Overnight Call Options

Dependent Variable: Log Forecasted Volatility (r_t)

	Constant	i_t	i_{t-1}	f_{t-1}	Q-Statistics	R^2	DW
Eq1	-2.6649**	0.0143			0.8621	0.0003	2.0573
	(-79.7031)	(0.5973)					
Eq2	-2.7397**	0.0146		-0.0280	0.0064	0.0008	2.0021
	(-30.5158)	(0.6106)		(-0.8964)			
Eq3	-2.7580**			-0.0277	0.0024	0.0008	2.0021
	(-32.5990)			(-0.8846)			
Eq4	-2.7093**	-0.0174	0.0563*	-0.0286	0.0005	0.0048	2.0004
	(-29.7611)	(-0.5981)	(1.9337)	(-0.9159)			

Panel B 10-Year T-Bond Futures Overnight Put Options

Dependent Variable: Log Forecasted Volatility (r_t)

	Constant	i_t	i_{t-1}	f_{t-1}	Q-Statistics	R^2	DW
Eq1	-2.7421**	-0.0310			1.9074	0.0024	1.9137
	(-83.1857)	(-1.5800)					
Eq2	-2.6302**	-0.0326		0.0425	0.0107	0.0042	1.9932
	(-29.6009)	(1.6583)		(1.3569)			
Eq3	-2.5871**			0.0395	0.0050	0.0016	1.9951
	(-30.4243)			(1.2619)			
Eq4	-2.6145**	-0.0380	0.0129	0.0440	0.0096	0.0046	1.9935
	(-28.1860)	(-1.7535)	(0.5943)	(1.4002)			

*Significant at the 5% level.
**Significant at the 1% level.

4.4 An Alternative Specification of Implied and Realized Volatility

The previous sections suggest though implied volatility has some information content about futures volatility, it is a biased and inefficient variable. Christensen and Prabhala (1998) point out that if α_1 in equation 7.7 is less than unity, this could be a consequence of an errors-in-variable (EIV) problem. Christensen and Prabhala (1998) use an instrumental variable (IV) procedure to solve this problem. Under the IV framework, implied volatility i_t is regressed on an instrument and/or any other exogenous variables as in Equation 7.11 which uses past implied volatility as the instrumental variable. This indicates that implied volatility may endogenously depend on its own past volatility if option prices reflect volatility information. Equation 7.11 is similar to a GARCH(1,1) model specification suggested by Bollerslev (1986). Next, the fitted value from regression equation 7.11 is used to replace implied volatility in equation 7.9. Subsequently the specifications are re-estimated using the amended equation 7.9.

4.4.1 3-Year T-Bond Futures Overnight Options

Panels A and B in Table 7.9 present the alternative specification of implied and realized volatility for 3-Year T-Bond futures overnight call and put options respectively. The first part of Panels A and B reports results from the first step of the alternative specification. This involves regressing implied volatility with its past value and past realized volatility (Equation 7.11). The fitted value of implied volatility is used in the second part of Panels A and B. This step involves regressing realized volatility on the fitted implied volatility and its past value (Equation 7.9).

Results indicate that the model has improved relative to results in section 4.3.1 as the coefficients of implied volatility in the second part of Panels A and B are significant at the 1% level and greater in magnitude, and the R^2 improved. However, the coefficient is still far from unity. This indicates that implied volatility has some information content, but is biased and inefficient even after we adjust for an error-in-variable problem by using an instrumental variable in our regression equations.

Table 7.9Alternative Specification of Implied and Realized Volatility for 3-Year T-Bond Futures Overnight Options

Ordinary Least Square estimates of equation 7.11(part 1) is used as an alternative way to determine the relationship between implied and realized volatility for both 3-Year T-Bond futures overnight call and put options. The equation is:

$$i_t = \beta_0 + \beta_1 i_{t-1} + \beta_2 r_{t-1} + \varepsilon_t$$

Here, i_t denotes the natural logarithm of the Black's implied volatility for overnight call and put options. r_t denotes the actual volatility we estimated from the EGARCH(1,1) model for the underlying 3-Year T-Bond futures. The fitted value of the above regression equation replaces the i_t term in equation 7.9 (part 2) and the specifications are estimated again.

Panel A 3-Year T-Bond Futures Overnight Call Options

Part 1: IV Estimates (Equation 7.11)
Dependent Variable: Log Implied Volatility (i_t)
Independent Variables:

Constant	i_{t-1}	r_{t-1}	Q-Statistics	R^2	DW
-0.2475	0.2568**	0.1919*	0.9947	0.0819	2.0747
(-0.7188)	(6.9616)	(2.4440)			

Part 2: Specification Re-Estimation (Modified Equation 7.9)
Dependent Variable: log Realized Volatility (r_t)
Independent Variables:

Constant	i_t	r_{t-1}	Q-Statistics	R^2	DW
-0.5288**	0.0827**	0.8535**	0.0627	0.7704	1.9760
(-6.5096)	(2.4489)	(41.5008)			

Panel B 3-Year T-Bond Futures Overnight Put Options

Part 1: IV Estimates (Equation 7.11)
Dependent Variable: Log Implied Volatility (i_t)
Independent Variables:

Constant	i_{t-1}	r_{t-1}	Q-Statistics	R^2	DW
-0.7310	0.2382**	0.1107	0.2538	0.0600	2.0368
(-1.7950)	(8.1660)	(1.2127)			

Part 2: Specification Re-Estimation (Modified Equation 7.9)
Dependent Variable: log Realized Volatility (r_t)
Independent Variables:

Constant	i_t	i_{t-1}	r_{t-1}	Q-Statistics	R^2	DW
-0.4617**	0.0832**	0.0156	0.8607**	0.3610	0.7703	2.0441
(-5.2554)	(2.6681)	(0.4984)	(45.3509)			

*Significant at the 5% level.
**Significant at the 1% level.

4.4.2 10-Year T-Bond Futures Overnight Options

Panels A and B in Table 7.10 present the alternative specification of implied and realized volatility for 10-Year T-Bond futures overnight call and put options respectively. The first part of Panels A and B reports results from the first step of the alternative specification. This involves regressing implied volatility with its past value and past realized volatility (Equation 7.11). The fitted value of implied volatility is used in the second part of Panels A and B. This step involves regressing realized volatility on the fitted implied volatility and its past value (Equation 7.9).

Results indicate that the model has not improved relative to results in section 4.3.2 as the coefficients of implied volatility in the second part of Panels A and B are still insignificant and small in magnitude. This indicates that implied volatility has less information content and is biased and inefficient even after we adjust for an error-in-variable problem by using an instrumental variable in our regression equations for 10-Year T-Bond futures overnight call and put options.

4.5 Implied, Forecasted and Realized Volatility: Putting It Together

In this section, we use three multiple regression models (equations 7.12 to 7.14) to determine the relationship between implied, forecasted, and realized volatility for 3-Year and 10-Year T-Bond futures overnight call and put options, which best describes the relationship between implied, forecasted, and realized volatility.

Table 7.11 presents the results for the 3-Year T-Bond futures overnight options implied, realized and forecasted volatility. Equation 3 in Table 7.11 (the fourth column in Table 7.11) is the optimal model to use when describing the relationship between

Table 7.10 Alternative Specification of Implied and Realized Volatility for 10-Year T-Bond Futures Overnight Options

Ordinary Least Square estimates of equation 7.11(part 1) is used as an alternative way to determine the relationship between implied and realized volatility for both 10-Year T-Bond futures overnight call and put options. The equation is:

$$i_t = \beta_0 + \beta_1 i_{t-1} + \beta_2 r_{t-1} + \varepsilon_t$$

Here, i_t denotes the natural logarithm of the Black's implied volatility for overnight call and put options. r_t denotes the actual volatility we estimated from the nonlinear EGARCH(1,1) model for 10-Year T-Bond futures. The fitted value of the above regression equation replaces the i_t term in equation 7.9 (part 2) and the specifications are estimated again.

Panel A 10-Year T-Bond Futures Overnight Call Options

Part 1: IV Estimates (Equation 7.11)
Dependent Variable: Log Implied Volatility (i_t)
Independent Variables:

Constant	i_{t-1}	r_{t-1}	Q-Statistics	R^2	DW
-0.0261	0.5685**	0.1226	31.9370**	0.3246	2.3503
(-0.0345)	(22.0849)	(0.7169)			

Part 2: Specification Re-Estimation (Equation 7.9)
Dependent Variable: log Realized Volatility (r_t)
Independent Variables:

Constant	i_t	r_{t-1}	Q-Statistics	R^2	DW
-0.4984**	0.0001	0.8878**	0.0204	0.7903	2.0072
(-7.8386)	(0.0333)	(61.6542)			

Panel B 10-Year T-Bond Futures Overnight Put Options

Part 1: IV Estimates (Equation 7.11)
Dependent Variable: Log Implied Volatility (i_t)
Independent Variables:

Constant	i_{t-1}	r_{t-1}	Q-Statistics	R^2	DW
-1.8544	0.4198**	-0.2120	10.9429**	0.1764	2.2008
(-1.7099)	(14.7715)	(-0.8685)			

Part 2: Specification Re-Estimation (Equation 7.9)
Dependent Variable: log Realized Volatility (r_t)
Independent Variables:

Constant	i_t	r_{t-1}	Q-Statistics	R^2	DW
-0.5048**	0.0047	0.8848**	0.3684	0.7830	2.0363
(-7.7229)	(1.1504)	(60.6549)			

*Significant at the 5% level.
**Significant at the 1% level.

realized, forecasted, and implied volatility for the underlying 3-Year T-Bond futures and its overnight call and put options. For 3-Year T-Bond futures overnight call options, we found that the realized volatility is best explained by the current implied volatility, current forecasted volatility, and its own past value at lag 1. For 3-Year T-Bond futures overnight put options, we found that realized volatility is best explained by the past implied volatility at lag 1, current forecasted volatility, and its own past value at lag 1.

Table 7.12 presents the results for the 10-Year T-Bond futures overnight options implied, realized and forecasted volatility. Equation 3 in Table 7.11 (the fourth column in Table 7.11) is the optimal model to use when describing the relationship between realized, forecasted, and implied volatility for the underlying 10-Year T-Bond futures and its overnight call and put options. We found that the realized volatility is best explained by the current forecasted volatility and its own past value at lag 1 for both 10-Year T-Bond futures overnight call and put options.

The findings in this section provide investors an alternative way to measure the underlying futures volatility, and in turn improve accuracy when pricing overnight options. The results in this section verified what we found in the previous sections that overnight options implied volatility is biased and inefficient, and it has less explanatory power to explain realized volatility.

Table 7.11 Optimal Model for 3-Year T-Bond Futures Overnight Options Volatility

Three multiple regressions are used to determine an optimal model when describing the relation ship between implied, forecasted, and realized volatility. These are:

$$i_t = \alpha_0 + \alpha_1 i_{t-1} + \alpha_2 i_{t-2} + \alpha_3 f_{t-} + \alpha_4 f_{t--1} + \alpha_5 f_{t-2} + \alpha_6 r_{t-} + \alpha_7 r_{t-1} + \alpha_8 r_{t-2} + \varepsilon_t \quad (1)$$

$$f_t = \alpha_0 + \alpha_1 i_t + \alpha_2 i_{t-1} + \alpha_3 i_{t-2} + \alpha_4 f_{t--1} + \alpha_5 f_{t-2} + \alpha_6 r_{t-} + \alpha_7 r_{t-1} + \alpha_8 r_{t-2} + \varepsilon_t \quad (2)$$

$$r_t = \alpha_0 + + \alpha_1 i_t + \alpha_2 i_{t-1} + \alpha_3 i_{t-2} + \alpha_4 f_{t-} + \alpha_5 f_{t--1} + \alpha_6 f_{t-2} + \alpha_7 r_{t-1} + \alpha_8 r_{t-2} + \varepsilon_t \quad (3)$$

Where i_t denotes the implied volatility (log form) for 3-Year T-Bond futures overnight call and put options respectively, r_t and f_t denote the realized and forecasted volatility (log forms) for the underlying 3-Year T-Bond futures which generated from the non linear EGARCH(1,1) model.

Panel A Overnight Call Options

		Dependent Variables	
Independent Variables	Logimplied	Logforecasted	Logrealized
Constant	-	1.5615**	-0.4490**
		(3.0969)	(-7.1852)
Logimplied	-	-	0.0191**
			(2.8705)
Logimplied(-1)	0.2136**	-	-
	(5.6634)		
Logimplied(-2)	0.1426**	-	-
	(3.7836)		
Logforecasted	-	-	0.0813**
			(21.7452)
Logforecasted(-1)	-	-	-
Logforecasted(-2)	-	-	-
Logrealized	0.2145**	4.9650**	-
	(13.7138)	(21.7553)	
Logrealized(-1)	-	-4.0501**	0.8468**
		(17.7393)	(59.7039)
Logrealized(-2)	-	-	-
R-squared	0.1061	0.4093	0.8639
Durbin-Watson Statistic	2.0098	1.9568	1.9824
Q-Statistic	0.0182	0.3215	1.8907

Table 7.11 Continued

Panel B Overnight Put Options

Independent Variables	Logimplied	Logforecasted	Logrealized
		Dependent Variables	
Constant	-	1.4771**	-0.4505**
		(2.6719)	(-6.4790)
Logimplied	-	-	-
Logimplied(-1)	0.2209**	-	0.0122*
	(5.8452)		(1.9625)
Logimplied(-2)	0.0784*	-	-
	(2.0729)		
Logforecasted	-	-	0.0751**
			(18.9880)
Logforecasted(-1)	-	-	-
Logforecasted(-2)	-	-	-
Logrealized	-	4.5232**	-
		(18.9880)	
Logrealized(-1)	-	-3.8358**	0.8639**
		(-10.6770)	(22.8753)
Logrealized(-2)	-	-	-
R-squared	0.0713	0.3500	0.8486
Durbin-Watson Statistic	2.0085	2.0000	2.0008
Q-Statistic	0.0158	0.0000	0.0002

*Significant at the 5% level
**Significant at the 1% level.

Table 7.12 Optimal Model for 10-Year T-Bond Futures Overnight Options Volatility

Three multiple regressions are used to determine an optimal model when describing the relation ship between implied, forecasted, and realized volatility. These are:

$$i_t = \alpha_0 + \alpha_1 i_{t-1} + \alpha_2 i_{t-2} + \alpha_3 f_{t-} + \alpha_4 f_{t--1} + \alpha_5 f_{t-2} + \alpha_6 r_{t-} + \alpha_7 r_{t-1} + \alpha_8 r_{t-2} + \varepsilon_t \quad (1)$$

$$f_t = \alpha_0 + \alpha_1 i_t + \alpha_2 i_{t-1} + \alpha_3 i_{t-2} + \alpha_4 f_{t-1} + \alpha_5 f_{t-2} + \alpha_6 r_{t-} + \alpha_7 r_{t-1} + \alpha_8 r_{t-2} + \varepsilon_t \quad (2)$$

$$r_t = \alpha_0 + + \alpha_1 i_t + \alpha_2 i_{t-1} + \alpha_3 i_{t-2} + \alpha_4 f_{t-} + \alpha_5 f_{t--1} + \alpha_6 f_{t-2} + \alpha_7 r_{t-1} + \alpha_8 r_{t-2} + \varepsilon_t \quad (3)$$

Where i_t denotes the implied volatility (log form) for 3-Year T-Bond futures overnight call and put options respectively, r_t and f_t denote the realized and forecasted volatility (log forms) for the underlying 10-Year T-Bond futures which generated from the non linear EGARCH(1,1) model.

Panel A Overnight Call Options

	Dependent Variables		
Independent Variables	Logimplied	Logforecasted	Logrealized
Constant	-	-6.8579**	-0.6630**
		(-11.0819)	(-12.0091)
Logimplied	-	-	-
Logimplied(-1)	0.3918**	-	-
	(13.1298)		
Logimplied(-2)	0.3109**	-	-
	(10.4094)		
Logforecasted	-	-	-0.0620**
			(-30.2342)
Logforecasted(-1)	-	-	-
Logforecasted(-2)	-	-	-
Logrealized	-	-7.6449**	-
		(-30.2342)	
Logrealized(-1)	-	6.8593**	0.9143**
		(16.2930)	(29.0684)
Logrealized(-2)	-	-	-
R-squared	0.3929	0.4781	0.8899
Durbin-Watson Statistic	2.1341	1.9958	1.9980
Q-Statistic	4.7022*	0.0000	0.0020

Table 7.12 Continued

Panel B Overnight Put Options

Independent Variables	Dependent Variables Logimplied	Logforecasted	Logrealized
Constant	-	-6.3355**	-0.6270**
		(-9.2652)	-10.7455)
Logimplied	-	-	-
Logimplied(-1)	0.3204**	-	-
	(10.5537)		
Logimplied(-2)	0.2462**	-	-
	(8.1202)		
Logforecasted	-	-	-0.0551**
			(-26.3135)
Logforecasted(-1)	-	-	-
Logforecasted(-2)	-	-	-
Logrealized	-	-7.3679**	-
		(-26.3135)	
Logrealized(-1)	-	6.9844**	0.8897**
		(16.0777)	(28.2749)
Logrealized(-2)	-	-	-
R-squared	0.2380	0.4131	0.8722
Durbin-Watson Statistic	2.1098	2.0038	1.9966
Q-Statistic	3.1737	0.0042	0.0008

*Significant at the 5% level
**Significant at the 1% level.

5. Conclusions

In this chapter we addressed several questions in relation to implied volatility through the use of the Black's model, forecasted volatility and realized volatility. First, we explored whether or not implied volatility is an unbiased and efficient measure of future volatility. Second, we tested whether or not implied volatility contains information about future volatility. Third, we identified the relationship between the implied, the forecasted, and realized volatility. This relationship is important to investors who wish to use information about volatility to price overnight options, as volatility is the missing variable in the option pricing model.

We used intra-night time stamped trade data from January 1996 to May 2002 for both 3-Year and 10-Year T-Bond futures overnight options in this chapter. Many previous studies indicate that implied volatility is both biased and inefficient. Christensen and Prabhala (1998) in an effort to address EIV problem by placing an instrumental variable into a regression equation to examine the relationship between implied and realized volatility. They found that implied volatility is unbiased and efficient. Here we adopted a similar methodology to analyse 3-Year and 10-Year T-Bond futures overnight options. Our results suggest that implied volatility has some information content about future volatility for 3-Year T-Bond futures overnight options, but it is biased and inefficient. But for 10-Year T-Bond futures overnight options, we found implied volatility has almost no informational content. Thus, investors must use implied volatility with caution when predicting future volatility for use in pricing overnight options, as this can lead to inaccurate trading decisions.

Our regression analysis also indicates that a relationship exists between implied, forecasted and realized volatility. The realized volatility is best described by past implied volatility, the current forecasted volatility, and its own past values. This provides investors an alternative way to measure overnight options market's volatility, and in turn improves their accuracy when pricing overnight options.

Chapter 8 Conclusions

There have been many assets created in the derivative markets since the creation of the Black-Scholes-Merton options pricing model and its publication in 1973. In line with this, the introduction of Australian Treasury-Bond futures overnight options at the Sydney Futures Exchange (SFE) during 1993 offers a unique opportunity to examine trading behavior with a different market microstructure. This dissertation is the first study of its kind to investigate the market microstructure of the SFE overnight options market. It presents a comprehensive study on overnight options market, a relatively new product innovation. This work explores market microstructure aspects of Australian Treasury Bond futures overnight options regarding market liquidity, transaction costs, market order flows, information asymmetry, and market volatility. It provides important information about the market liquidity, transaction costs, trading volume, information asymmetry, and market volatility. It has also provided a study of overnight options introduction impacts on the underlying futures market.

As one of the four major trading products at the SFE, the interest rate products have been the most actively traded products in the SFE. There are three types of futures on interest rate products, namely 90-Day Bank Accepted Bill futures contracts, 3-Year Treasury-Bond (T-Bond) futures contracts and 10-Year Treasury-Bond (T-Bond) futures contracts. They provide investors with ways to trade futures with different maturity terms and also provide tools for risk management to hedge the underlying positions for short, medium, and long-term interest rate movements.

Overnight options were first introduced on 15^{th} November 1993; they are short dated European-Type of options based on the 3-Year and 10-Year T-Bond futures contracts. They last for one SYCOM (Sydney Computerized System) session and are expired after the SYCOM night session if the options are at-the-money or out-of-the-money. Those in-the-money options are exercised immediately after the SYCOM night session. Overnight options are important tools to hedge the overnight risk of their underlying futures position or the underlying Bank Bill / T-Bond positions. They also provide investors with a means to hedge event risk, e.g. a major economic information release from the US, as Australian night trading occurs while US markets are open.

Chapter 2 provides an introductory overview of the Sydney Futures Exchange with regard to its regulations, operations, participants, trading protocols, clearing and settlement procedures and the regulatory background. The elements described in this chapter have a large influence on market transparency, volatility, information transmission, the lead-leg relationship of different markets, as well as the liquidity of the market. Price formation, price discovery, market structure and design, information and disclosure are topics which described in market microstructure theory. These theories cover the determinants of trading costs, the relationship between price formation and trading protocols, and market transparency (the ability of market participants to observe information). All these necessary market elements will inevitably have an effect on trading. Market transparency, liquidity and volatility are influenced by these elements and the pricing of the securities is different under different market microstructures. Hence, the discussion of Chapter 2 has been designed to give reader a thorough understanding of the market structure of the SFE, the trading execution procedure, the price formation, the information transmission, and the market transparency. It provides useful information for investors and traders wishing to enter the futures and options trading market. It also sets the foundation for this work.

Chapter 3 details the interest rate products traded at the Sydney Futures Exchange in terms of past trading history, trading volume, contract specification, and valuation method. It gives us a good understanding about the product that we are going to discuss in details in the following chapters. The interest rate products traded at the SFE are the most active traded products. These include the interest rate futures contract, the interest rate futures options contract, the interest rate futures overnight options contract, and the interest rate futures intra-day options contract. All of these products provide us with a very rich database to undertake empirical analysis. This is particularly so for overnight options and intra-day options as they are relative new to investors and have different market microstructure and different risk-return characteristics. Thus, we expect to observe differing patterns of bid-ask spreads, trading volume and volatility.

Chapter 4 presents a descriptive analysis of intra-night trading behaviors of bid-ask spreads, trading volume and return volatility for 3-Year and 10-Year T-Bond futures overnight options. We found most quotes and trades occur in the first half of the trading night. The number of quotes and trades are thin during the second half of the night. One explanation may be related to the special nature of overnight options. As the overnight option only lasts for one night, it was designed to match the time zone for investors wishing to hedge US market risk. Anyone wishing to use the overnight option as a hedging tool will want to trade the overnight option at the beginning of the night.

Results indicated that over time the quoted bid-ask spread narrowed for both the 3-Year and 10-Year T-Bond futures overnight calls and puts, while trading volume and trading frequency increased for the 3-Year contracts. Trading volume and trading frequency fell for the 10-Year contracts. One reason for this result may be that the underlying 3-Year T-Bond futures market provides more liquidity than the 10-Year market, although in early years investors were using 10-Year contracts because of their larger tick size. This suggests that 3-Year T-Bond Futures overnight options are becoming more efficient as the underlying futures market provides more liquidity.

We observe there are no significant differences across different time intervals for intra-night bid-ask spreads for 3-Year T-Bond futures overnight call and put options. We also find there are significant differences between the first two time intervals and other intervals for 3-Year T-Bond futures overnight options. However, for 10-Year T-Bond futures overnight options, there are significant differences across all time interval during the first half night for 10-Year T-Bond futures overnight call and put options. We observe similar results for intra-night trading volume. It is found that there are significant differences across different time intervals, and for the first two intervals, from other intervals for 10-Year T-Bond futures overnight call and put options. However, for 3-Year T-Bond futures overnight options, there is no significant difference across different time intervals during the first half night. Results for intra-night volatility indicate that there are significant differences across different time intervals during the first half of the trading night for both 3-Year and 10-Year T-Bond futures overnight call and put options.

In order to access the impact of the US macroeconomic news releases, mean bid-ask spreads, trading volume, and volatility for the first two time intervals are examined using t-test. We report that volatility are significantly wider on days with US macroeconomic news releases for both 3-Year and 10-Year T-Bond futures overnight call and put options, whereas trading volume are significantly greater on days with US macroeconomic news releases only for 10-Year T-Bond futures overnight call and put options . There is no evidence there is any significant difference of the mean bid-ask spreads for both 3-Year and 10-Year T-Bond futures overnight options. Thus, this may imply that intra-night trading behaviour of Australian T-Bond futures overnight options market reflect US macroeconomic news releases with greater volatility and higher trading volume.

The impact of the introduction of overnight options on the underlying Australian T-Bond futures was tested in Chapter 5. Typically, new product introduction, particularly in derivative markets, will impact underlying markets. Changes in quoted bid-ask spread, trading volume, volatility and the pricing error variance before and after the introduction of the underlying 3-Year and 10-Year T-Bond Futures were tested to see if there any influence of the introduction.

It was found that the liquidity as measured by the quoted bid-ask spreads increased after the overnight options introduction for the 3-Year T-Bond futures, as the bid-ask spreads became smaller. But the liquidity for the 10-Year T-Bond futures decreased after the overnight options introduction, as the bid-ask spreads became larger. Order flows and return volatility fell after the overnight options introduction for both the 3-Year and 10-Year T-Bond futures. This indicated that the overnight options introduction may encourage greater speculative trading activities which may shift both informed and uninformed traders away from the underlying futures market. Lower speculative activities in the underlying market will result in a decrease in the volatility generated by speculators in the underlying market who create noisy trading. This in turn simultaneously decreases the trading volume (order flow) in the underlying market. Thus, results for order flows and return volatility are consistent with previous findings and market microstructure theory.

Previous studies have reported that information flows may influence the market place, particularly return volatilities. They have reported that negative information shocks (bad news) may have a greater impact on return volatility than positive information shocks (good news). How traders perceive these information effects on return volatility will change the way they execute trading strategies. Therefore, Chapter 6 tries to describe how underlying futures return volatilities respond to information shocks. The objective of Chapter 6 is to identify the optimal model with which to measure and forecast the underlying futures return volatilities.

In order to estimate the return volatility quantitatively, linear and non-linear GARCH models are applied to estimate and forecast the Australian T-Bond futures volatility patterns. Estimations from the models examined suggest that there is a significant asymmetric information effect impact in the return volatility of the 3-Year and 10-Year T-Bond futures, where bad news had a greater impact on volatility than good news. We conclude that a non-linear GARCH model should be used to measure and forecast the 3-Year and 10-Year T-Bond futures return volatility. After we perform out-of-sample forecasting, we find consistent results from previous estimations which indicate nonlinear GARCH models are appropriate to measure the 3-Year and 10-Year T-Bond futures return volatility. But we cannot determine whether the EGARCH model or the TARCH model is the better choice.

After plotting Engle and Ng's (1993) news impact curves from the EGARCH(1,1) and the TARCH(1,1) models, results show that the news impact curve is asymmetric for the 3-Year and 10-Year T-Bond future from the EGARCH(1,1) model and is symmetric from the TARCH(1,1) model. Since negative information shocks (bad news) have a greater impact on return volatility than positive information shocks (good news) for the 3-Year and 10-Year T-Bond futures return volatility, the nonlinear EGARCH(1,1) model should be used to describe volatility patterns for both the 3-Year and 10-Year T-Bond futures.

Chapter 6 has several implications for investors who wish to effectively trade, hedge, or speculate with the overnight options markets, as underlying futures markets volatility is an important component when pricing overnight options. While this study was, in a sense, comprehensive, there are several outstanding issues that could be addressed. Quite often the underlying markets may have significant influences on their derivative markets. It may be useful to determine the relationship between the overnight options market and its underlying futures market by testing how information is transmitted between them. If there is a causal relationship between the overnight options market and its underlying futures market, it may be possible to use one market to predict the other. This may provide market participants with important information regarding when and how to execute trades in the overnight options market and the underlying futures market. However, these questions are left for future studies.

Many previous studies indicate that implied volatility is both biased and inefficient. Christensen and Prabhala (1998) designed a research model by placing an instrumental variable into a regression equation to examine the relationship between implied and realized volatility. They found that implied volatility is unbiased and efficient. Here we adopted similar methodology to analyse 3-Year and 10-Year T-Bond futures overnight options. Our results suggest that implied volatility has information content about future volatility for 3-Year and 10-Year T-Bond futures overnight options, but it is biased and inefficient. Thus, investors must use implied volatility with caution when predicting future volatility for use in pricing overnight options, as this can lead to inaccurate trading decisions. But, interviewing overnight options traders in Australia, we found that they do use implied volatility as their primary decision rule when trading overnight options. Thus, traders should also re-evaluate the way they price overnight options.

Our regression analysis also indicates that a relationship exists between implied, forecasted and realized volatility. The realized volatility is best described by past implied volatility, the current and past forecasted volatility, and its own past values. This provides investors an alternative way to measure overnight options market's volatility, and in turn improves their accuracy when pricing overnight options.

In summary, we believe this dissertation have five contributions. The first contribution of this dissertation is a provision of an institutional overview of the Sydney Futures Exchange (SFE) and discussions about products traded at the SFE. This builds the foundation for the following empirical studies.

The second contribution of this dissertation is that it provides an examination of trading behaviors of 3-Year and 10-Year T-Bond futures overnight options by looking at intra-night bid-ask spreads, trading volume, and volatility patterns. It was observed that overnight options have different intra-night bid-ask spreads, trading volume, and volatility patterns compared to stocks and long dated options.

The third contribution of this dissertation is examination of the impact of overnight options introduction on the underlying 3-Year and 10-Year T-Bond futures market is examined. Results indicate that the introduction of overnight options has influences on the underlying 3-Year and 10-Year T-Bond futures.

The fourth contribution of this dissertation is the examination of information shocks on the underlying futures return volatility. We also present optimal time-varying models to estimate and forecast the underlying futures return volatility. The analysis undertaken allows us to recommend the most appropriate models for predicting return volatility for the underlying futures market, and hence presents a key element in the question of how best to price these innovative products.

The fifth contribution of this dissertation is that implied, forecasted, and realized volatility are examined to determine information content of implied volatility when predicting future volatility. This information may be useful to traders wishing to accurately price overnight options. The result also indicates that a relationship exists between implied, forecasted and realized volatility. Realized volatility is best described by past implied volatility, the current forecasted volatility, and its own past values. This provides investors with an alternative way to measure overnight options market's volatility, and in turn improve accuracy when pricing overnight options.

We may consider this dissertation as a foundation study of Australian T-Bond futures overnight options. It provides a market microstructure examination regrading market liquidity, order flows, and volatility. But, there are many aspects that may lead to further study. For example, it might be useful to perform a study concerning how information flows from one market to another, in terms of 3-Year and 10-Year T-Bond futures, their day options, their overnight options, and their intra-day options[61].

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[61] 3-Year and 10-Year T-Bond futures intra-day options are options last for one day-time SYCOM session, it was introduced by the SFE in April, 2002 with the success of overnight options' operation.

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Appendix 1 Chronological History of the SFE

1960	Trading n Greasy Wool (Deliverable) Futures began on 11 May
1964	Sydney Greasy Wool Futures Exchange became the world's leading wool Futures market
1972	Name changed to Sydney Futures Exchange Limited
1975	Trade Steers (deliverable) Futures listed on 16 July
1978	First gold Futures contract outside North America Launched on 19 April
1979	Frozen Boneless Beef Futures listed on 19th April 90 Day Bank Accepted Bill contract launched on 17 October – the first financial Futures contract outside the US
1980	Trading in US dollar Futures commenced on 19 March – the first Futures contract in the world to incorporate cash settlement Japanese Yen Futures listed on 19 March Pounds Sterling Futures listed on 25 November
1981	Fat Lamb Futures listed on 12 May Japanese Yen Futures suspended on 29 September Frozen Boneless Beef Futures suspended on 29 September Silver Futures listed on 15 October
1982	Pounds Sterling Futures Suspended on 31 March Export Bullocks Futures listed on 17 May
1983	All ordinaries Share Price Index contract listed on 16 February – the first stock index Futures product listed outside the US Export Bullocks Futures suspended on 19 September Revised Fat Lamb Futures listed on 31 October
1984	2-Year Treasury Bond Futures listed on 27 February – the first bond contract outside the US Fat Lamb Futures were launched on 29 February Fat Lamb Futures suspended on 7 March All Industrial Share Index Futures listed on 3 April Metals and Minerals Share Index Futures listed on 3 April Metals and Minerals Share Index Futures suspended on 27 September 10-Year Treasury Bond Futures listed on 5 December
1985	All Industrial Share Index Futures suspended on 28 March Revised Fat Lamb Futures suspended on 4 April US Dollar Options listed on 11 June All Ordinaries Share Price Index Options listed on 18 June 90 Day Bank Accepted Bill Options listed on 10 May 10-Year Treasury Bond Futures Options listed on 6 November Silver Futures suspended on 20 December
1986	2-Year Treasury Bond Futures suspended on 17 March Gold Futures suspended on 21 March Live Cattle (cash settled) Futures listed on 12 May Wool (cash settled) Futures listed on 22 July Trade Steers (deliverable) Futures suspended on 21 August Trading link with LIFFE established 23 October US Treasury Bond (LIFFE linked) Futures listed on 23 October 3 Month Eurodollar (LIFFE linked) Futures listed on 23 October Trading link with COMEX established 19 November

	Gold (COMEX linked) Futures listed on 19 November
1987	US Dollar Options suspended on 17 June Greasy Wool (deliverable) Futures suspended on 23 July US Dollar Futures suspended on 16 September
1988	First night trading session took place Australian Dollar Futures listed on 24 February Australian Dollar Options listed on 15 March 3-Year Treasury Bond Futures and Options introduced on 17 May and 16 June respectively SFE became first exchange in the world to gain a exemption from Part 30 of the Commodity Exchange Act, allowing its members to market in the US without a CFTC registration
1989	Moved to new trading floor in February which was acclaimed to be the most completely equipped and advanced in the world US Treasury Bond (LIFFE linked) Futures suspended on 28 April 3 Month Eurodollar (LIFFE linked) Futures suspended on 28 April Gold (COMEX linked) Futures suspended on 9 October 5-Year Semi-Government Bond (deliverable) Futures listed on 25 October World's first after hours trading system (SYCOM) introduced on 30 November with the listing of 10-Year Treasury Bond Futures, Live Cattle (cash settled) Futures and Wool (cash settled) Futures 5-Year Semi-Government Bond (deliverable) options listed on 12 December
1990	90-Day Bank Accepted Bill (deliverable) Futures listed on SYCOM on 11 January All Ordinaries Share Price Index Futures listed on SYCOM on 22 February 3-Year Treasury Bond Futures listed on SYCOM on 22 February 5-Year Semi-Government Bond (deliverable) Futures listed on SYCOM on 22 February 5-Year Semi-Government Bond (deliverable) Futures suspended on 15 June (also suspended on SYCOM) 5-Year Semi-Government Bond (deliverable) Options suspended on 15 June 10-Year Semi-Government Bond (cash settled) Futures listed on 3 October (also listed on SYCOM) 5-Year Semi-Government Bond (cash settled) Options listed on 31 October 10-Year Semi-Government Bond (cash settled) Options listed on 31 October
1991	5-Year Semi-Government Bond (cash settled) Futures and Options suspended on 21 February (also suspended on SYCOM) 10-Year Semi-Government Bond (cash settled) Futures and Options suspended on 21 February (also suspended on SYCOM) Australian Dollar Futures listed on SYCOM on 19 March Australian Dollar Futures and Options suspended on 23 September (also suspended on SYCOM) Sydney Futures Exchange Clearing House commenced operation on 1 December
1992	Fifty Leaders Share Price Index Futures and Options introduced on 29 January (also listed on SYCOM) One millionth contract traded on SYCOM in September Record 210,280 contracts exchanged in single trading session on 13 August Record year volume of 17.5 million contracts NZFOE officially became a subsidiary of SFE on 31 December

1993	The first Futures Exchange to launch Overnight Options on the 3-Year and 10-Year Treasury Bonds on 15 November SPI downsized from a value of $100 to $25 times the All Ordinaries Index on 11 October Overnight Options on 10-Year Bond Futures listed on SYCOM on 15 November Record annual volumes of 21.4 million contracts
1994	SYCOM trading extended by two hours to 6:00 am on 10 January and was further extended to 7:00 am close in November (during Australian summer time) Fifty Leaders Share Price Index Futures and Options suspended on SYCOM on 7 February SFECH commenced clearing NZFOE markets on 28 February SFE Floor Members gained access to NZFOE markets via the ATS dealing system on 1 March Live Cattle (cash settled) Futures suspended on SYCOM on 1 March Wool (cash settled) Futures suspended on SYCOM on 1 March SPI Overnight Options listed on 28 March Record monthly volume of 4,088,319 contracts and record daily volume of 278,529 contracts traded in March 90-Day Bank Accepted Bill (deliverable) Options listed on SYCOM on 26 April Share Futures launched on the individual shares of BHP, National Australian Bank and News Corporation on 16 May (also listed on SYCOM) Live Cattle (cash settled) Futures suspended on 25 May 3-Year Treasury Bond Options listed on SYCOM on 12 July 10-Year Treasury Bond Options listed on SYCOM on 12 July All Ordinaries Share Price Index Options listed on SYCOM on 19 July SFECH introduced SPAN margining on 22 August Four additional Share Futures listed on the individual shares of MIM, Western Mining Corporation, BYR Nylex, and Westpac Banking Corporation on 26 September SFE established trading links with New York Mercantile Exchange SFE Board approved the doubling of the size of the underlying value of the 90-Day Bank Bill contract from $500,000 to $1,000,000 Record annual volume of 31.6 million contracts – 46% higher than 1993 SFE awarded "International Derivatives Exchange of the Year" by industry publication, "International Financial Review" Fifty Leaders Share Price Index Futures and Options suspended 25 May
1995	MIM Holdings, Westpac Bank, BTR Nylex and Western Mining Sahre Futures listed on SYCOM on 27 February Greasy Wool (deliverable) Futures listed on 13 March (also listed on SYCOM) ANZ and Rio Tinto Share Futures listed on 13 March (also listed on SYCOM) Fosters Brewing Share Futures listed on 13 March Fosters Brewing Share Futures listed on SYCOM on 1 September Wool (cash settled) Futures suspended on 4 September BTR Nylex Share Futures suspended 29 September (also suspended on SYCOM) Pacific Dunlop Share Futures listed on 18 October (also listed on SYCOM) SFE voted "1995 Best Non-Banking Financial Institution" for the second consecutive year SFE/NYMEX trading link established World first Bond Overnight Options captured international attention as

	volumes surged SFE's premier contract, 90-Day Bank Accepted Bill Futures contract doubled in size Cross Border relation with New Zealand enhanced with the addition of New Zealand Futures and Options Exchange (NZFOE) Share Options to SFE Members' trading menu Second highest annual turnover with 25,751,354 futures and options contracts traded during the year, representing a daily average of 102,226 contracts
1996	SFE launched its World Wide Web site on 18 January Greasy Wool (deliverable) Options listed on 19 February (also listed on SYCOM) Wheat Futures and Options listed on 26 March (also listed on SYCOM) SFE listed deliverable share futures (converted from being cash settled) on 26 March SFE listed Serial Options on the 10-Year and 3-Year Treasury Bond Futures contracts and on the Share Price Index futures contract on 2 April SFE cemented its trading link with the New York Mercantile Exchange with the listing of COMEX Division gold, Silver and copper futures via electronic trading link on 10 April Overnight Options on All Ordinaries Share Price Index Futures suspended on SYCOM on 15 May New class of Associate Membership incorporating commodity trading Advisors (CTAs) introduced on 6 June Eight additional bank bill contract months listed on 29 July, effectively extending the bank bill yield from three years to five years SFE hosted Futures Week'96 in December SFE traded 25.5 million futures and options contracts during 1996
1997	February 17 – Re-listing of SPI Overnight Options March 17 – Introduction of Fast Market broadcast facility April 9 – SFECH is recognized for reducing counter-party risk weighting by SFA April 10 – Listing of an additional expiry month in the Wheat Option, taking the number of tradable expiries to five June 18 – Renaming of CRA Share Futures to Rio Tinto Limited Share Futures August 11 – Listing of an additional expiry month in the Wheat Options, ensuring a January options month is available at all times September 15 – Listing of two additional expiry months for all Share Futures contracts, taking the number of tradable expiries to four September 29 – SFE launched New South Wales and Victoria Electricity Futures on daytime SYCOM October 23 – SFE Board announces decision to move to electronic trading by the first quarter of 1999, subject to Member approval November 3 – Wheat and Greasy Wool Futures and Options moved from Floor trading to SYCOM November 17 – Launch of share futures contract on Telstra Installment Receipts November 28 – Launch of Telstra Share Futures December 1 – SFECH financial guarantee increased from A$100 million to A$150 million Total 1997 turnover is 28,409,539 contracts, which is the second highest on record. SFE becomes the largest financial futures and options exchange in the Asia-Pacific region

1998	January 19 – Broad (23 Micron) and Fine (19 micron) Wool Futures contracts launched June – Record monthly turnover at 4.4 million contracts. Gross open interest reached an unprecedented 2.4 million contracts. July – SFECH accepts USD as collateral for SFE and NZFOE initial margin obligations, the SFECH also accepts AUD to cover NZFOE initial margin obligations and NZD to cover SFE initial margin obligations. Any SFE House account excess currency can now be sued to cover initial margin obligations for NZFOE House and client positions and vice versa. Australian Commonwealth Government Securities will also be accepted as collateral for SFE initial margins August 24 – SFE and Austraclear sign Memorandum of Understanding to investigate joint clearing initiatives August 28 – Record volume during a single SYCOM session of 71,382 contracts September 1 – Australian Emissions Trading Forum (AETF) formally established
1999	March 15 – New South Wales and Victoria Peak Period Electricity contracts launched September 9 – Launch of futures and options contracts based on the 35 stock Dow Jones Asia Pacific Extra Liquid Series (AP/ELS) Australia index August 30 – SFE and New South Wales State Forests agree to develop the world's first carbon trading market September 30 – SPI transfers to screen-based trading November 12 – floor trading ceases for all remaining SFE products November 15 – SFE becomes a fully electronic exchange. All SFE trades are conducted exclusively via SYCOM December 13 – Expansion of communication hubs to Hong Kong, Tokyo and London allows global customers to connect directly to SFE's markets via SYCOM trading terminals
2000	May 2 – SPI 200 launched May 11 – SFE celebrates its 40 year anniversary June 20 – Barley, Canola, Sorghum grain contracts launched September 11 – SFE demutualises September 14 – SFE & Austraclear announce merger September 25 – AP/ELS contract delisted

Appendix 2 SYCOM Technical Specifications and Features

The latest trading platform is the SYCOM^R IV. It is a Windows NT upgrade of the UNIX based on SYCOM III. The SFE's market participants access the SYCOM via either a SFE Trader Workstation or a third party system. These systems connect to SYCOM^R via an open gateway computer called the SYCOM^R interface using an industry standard-based messaging protocol, FIX 4.0. SFE's Wide Area Network (WAN) enables the SYCOM^R trading system utilizes a high capacity, high availability, wide area IP network built with Cisco^R hardware. The network links market participant offices in Sydney, Melbourne, Auckland, Wellington, London, Tokyo and Hong Kong. Regulatory approval has also been given to locate SYCOM^R Trader Workstations in the United States. These hubs enable SFE to provide a global trading platform with access to SFE's markets around the clock.

Direct access to SYCOM^R is only available to the SFE full participants and can be obtained by two different methods, one is the SYCOM Trader Workstation and the other one is the SYCOM Trading Interface. The SYCOM Trader Workstation are computer terminals that run exclusively on the SYCOM system. It allows full participants to manually trade all SFE contracts directly from their own offices. The SYCOM Trading Interface would allow the full participant to directly connect their own propriety trading systems into SYCOM system. Orders are then routed electronically to SYCOM directly from the system in the full participant's office. The use of the trading interface is becoming increasingly popular amongst the SFE full participants, contributing approximately 20% of total contract turnover (www.sfe.com.au).

The SFE also provides SFE Internet trading platform that enables customers to trade via the Internet. The trading method (i.e. Internet or other electronic-based application) provided to the client by the participant, is at the discretion of the Participant. For those who are Non-Participants to trade SFE contracts, they use utilize an intermediary such as a registered futures broker – who is also an SFE Full Participant.

Appendix 3 Additional SYCOM Windows

- The Market Window

  "Traders may use the market window to quickly scan a stream of updated information on traditional market statistics including best buy and sell prices and the aggregate volumes available at those prices."

- The Intra-Spread Market Window

  "The intra-spread market window allows the trader to use calendar spread pricing between different futures contracts to enter the market."

- The Inter-Instrument Market Window

  "The inter-instrument window displays a set of exchange combined contracts and allows the trader to use spread pricing between different futures contracts to enter the market."

- The New Strategy Dialogue

  "The trader is able to either create and release an order directly to the market or create a strategy at a later time. Strategies remain in a pending state in the Trader Book to be released to the market at the trader's discretion."

- The Message Window

  "It holds system message, confirmed trades messages and other miscellaneous message. The Send Message dialogue allows the user to send a text message to the exchange or to another trader."

- The Custom Market Window

  "It allows traders to create user defined contract combinations for spread trades and other multi-legged strategies."

- Additional Features Window

  "SYCOM IV supports an Automated Order Entry Interface. The AOEI is an electronic interface between SYCOM and a member's order management, order routing or proprietary trading system. An AOEI workstation displays and operates in a similar manner to a standard SYCOM workstation.

Appendix 4 Contract Specifications

3-Year Treasury Bond Futures

Contract Unit:	Commonwealth Government Treasury Bonds with a face value of A$100,000, a coupon rate of 6% per annum and a term to maturity of three years, no tax rebate allowed
Contract Months:	March/June/September/December up to two quarter months ahead
Commodity Code:	YT
Listing Date:	17/05/1988
Minimum Price Movement:	Prices are quoted in yield per cent per annum in multiples of 0.01 per cent. For quotation purposes the yield is deducted from an index of 100. the minimum fluctuation of 0.01 per cent equals approximately $28 per contract, varying with the level of interest rates
Last Trading Day:	The fifteenth day of the contract month (or the next succeeding business day where the fifteenth day is not a business day). Trading ceases at 12:00 noon
Settlement Day:	The business day following the last permitted day of trading
Trading Hours:	5:10pm – 7:00am and 8:30am – 4:30pm (Australian winter time) 5:10pm – 7:30am and 8:30am – 4:30pm (Australian summer time)
Settlement Method:	The arithmetic mean, taken at 9:45 am, 10:30 am and 11:15 am on the last day of treading by 10 dealers, randomly selected for each time, at which they would buy and sell a series of bonds previously declared by the SFE for that contract month, excluding the two highest and two lowest buying quotations and the two highest and two lowest selling quotations for each bond. All bought and sold contracts in existence as at the close of trading in the contract month shall be settled by the Clearing House at the cash settlement price

Source: www.sfe.com.au

Options on 3-Year Treasury Bond Futures

Contract Unit:	One A$100,000 face value, 6% coupon, 3-Year Treasury Bond futures contract for a specified contract month on the Sydney Futures Exchange.
Contract Months:	Put and call options available on futures contracts for the nearest quarter month ahead.
Commodity Code:	YO
Listing Date:	15/11/1993
Minimum Price Movement:	Quoted in yield per cent per annum in multiple of 0.005 per cent.
Exercise Prices:	Set at intervals of 0.01 per cent per annum yield. Nine option exercise prices are available for trading with additional strike prices listed at the discretion of the Trading Manager or the Chief Executive of SFE.
Contract Expiry:	At the cessation of each SYCOM session.
Trading Hours:	5.10pm – 7.00am[62] (during US daylight saving time)[63] 5.10pm – 7.30am (during US non daylight saving time)
Settlement Method:	All options, which are in-the-money, are automatically exercised on the business day immediately following the SYCOM session. Exercise of an option results in the holder receiving a futures position at the options strike price. The settlement price is the weighted average of trade prices executed in the underlying contract between 8.30am and 8.40am on the business day immediately following the SYCOM session. Calculation of the settlement price is to 3 decimal places and rounded to 2 decimal places. When the third decimal place is five or above, the arithmetic mean is rounded up to the next highest decimal place.[8]

Source: www.sfe.com.au

[62] Unless otherwise indicated, all times are Sydney times.
[63] US daylight saving begins first Sunday in April and ends last Sunday in October.

Overnight Options on 3-Year Treasury Bond Futures

Contract Unit:	One A$100,000 face value, 6% coupon, 3-Year Treasury Bond futures contract for a specified contract month on the Sydney Futures Exchange.
Contract Months:	Put and call options available on futures contracts for the nearest quarter month ahead.
Commodity Code:	YO
Listing Date:	15/11/1993
Minimum Price Movement:	Quoted in yield per cent per annum in multiple of 0.005 per cent.
Exercise Prices:	Set at intervals of 0.01 per cent per annum yield. Nine option exercise prices are available for trading with additional strike prices listed at the discretion of the Trading Manager or the Chief Executive of SFE.
Contract Expiry:	At the cessation of each SYCOM session.
Trading Hours:	5.10pm – 7.00am[64] (during US daylight saving time)[65] 5.10pm – 7.30am (during US non daylight saving time)
Settlement Method:	All options, which are in-the-money, are automatically exercised on the business day immediately following the SYCOM session. Exercise of an option results in the holder receiving a futures position at the options strike price. The settlement price is the weighted average of trade prices executed in the underlying contract between 8.30am and 8.40am on the business day immediately following the SYCOM session. Calculation of the settlement price is to 3 decimal places and rounded to 2 decimal places. When the third decimal place is five or above, the arithmetic mean is rounded up to the next highest decimal place.[8]

Source: www.sfe.com.au

[64] Unless otherwise indicated, all times are Sydney times.
[65] US daylight saving begins first Sunday in April and ends last Sunday in October.

Overnight Options on 10-Year Treasury Bond Futures

Contract Unit:	One A$100,000 face value, 6% coupon, 3-Year Treasury Bond futures contract for a specified contract month on the Sydney Futures Exchange.
Contract Months:	Put and call options available on futures contracts for the nearest quarter month ahead.
Commodity Code:	XO
Listing Date:	15/11/1993
Minimum Price Movement:	Quoted in yield per cent per annum in multiple of 0.005 per cent.
Exercise Prices:	Set at intervals of 0.01 per cent per annum yield. Nine option exercise prices are available for trading with additional strike prices listed at the discretion of the Trading Manager or the Chief Executive of SFE.
Contract Expiry:	At the cessation of each SYCOM session.
Trading Hours:	5.10pm – 7.00am[66] (during US daylight saving time)[67] 5.10pm – 7.30am (during US non daylight saving time)
Settlement Method:	All options, which are in-the-money, are automatically exercised on the business day immediately following the SYCOM session. Exercise of an option results in the holder receiving a futures position at the options strike price. The settlement price is the weighted average of trade prices executed in the underlying contract between 8.30am and 8.40am on the business day immediately following the SYCOM session. Calculation of the settlement price is to 3 decimal places and rounded to 2 decimal places. When the third decimal place is five or above, the arithmetic mean is rounded up to the next highest decimal place.[8]

Source: www.sfe.com.au

[66] Unless otherwise indicated, all times are Sydney times.
[67] US daylight saving begins first Sunday in April and ends last Sunday in October.

Appendix 5[68] Tick Value Calculation

The dollar value of a 0.01% change in yield does not remain constant but rather varies in accordance with changes in the underlying interest rate. Accordingly, to establish what the dollar value of a futures tick will be at a given price, the following calculations are made:

1. Use the contract valuation formula to calculate the underlying value of the contract at the nominated futures price.
2. Apply the same formula to that same futures price minus 0.01(i.e. increase the yield by 0.01%).
3. The difference between the two contract values represents the dollar value of the tick at the nominated futures price.

For example, to determine the dollar value of a 0.01% change in yield on a 10-Year Bond contract trading at a price of 94.360 (i.e. A yield of 5.64%), the following calculations are performed.

1. Futures contract value at 94.360 (5.64%) = $102,723.06023
2. Futures contract value at 94.350 (5.65%) = $102,646.18658
3. Difference (Value of 0.01% of premium) = **$76.87365**

To determine the dollar value of a 0.01% change in yield on a 3-Year Bond contract trading at a price of 94.76 (i.e. a yield of 5.24%), the following calculations are performed.

1. Futures contract value at 94.76 (4.25%) = $102,084.713790
2. Futures contract value at 94.75 (5.25%) = $102,056.939570
3. Difference (Value 0.01% of premium) = **$27.77422**

[68] Source: www.sfe.com.au

Appendix 6 Forecasting Statistics

Suppose the forecast sample is j = T+1, T+2, ..., T+h, and denote the actual and forecasted value in period t as y_t and $\hat{y}_t$, respectively. The reported forecast error statistics are computed as follows:

Mean Square Error

$$\sqrt{\sum_{t=T+1}^{T+h} (\hat{y}_t - y_t)^2 / (h+1)}$$

Mean Absolute Error

$$\sum_{t=T+1}^{T+h} |\hat{y}_t - y_t| / (h+1)$$

Mean Absolute Percentage

$$\sum_{t=T+1}^{T+h} \left| \frac{\hat{y}_t - y_t}{y_t} \right| / (h+1)$$

Theil Inequality Coefficient

$$\frac{\sqrt{\sum_{t=T+1}^{T+h} (\hat{y}_t - y_t)^2 / (h+1)}}{\sqrt{\sum_{t=T+1}^{T+h} \hat{y}_t^2 / (h+1)} + \sqrt{\sum_{t=T+1}^{T+h} y_t^2 / (h+1)}}$$

The mean squared forecast error can be decomposed as:

$$\sum (\hat{y}_t - y_t)^2 / h = ((\sum \hat{y}_t / h) - \bar{y})^2 + (\hat{s}_y - s_y)^2 + 2(1-r)\hat{s}_y s_y$$

where $\Sigma \hat{y}_t$ /h, y, $s_{\hat{y}}$, s_y are the means and (biased)standard deviations of $\hat{y}_t$ and y_t and r is the correlation between $\hat{y}_t$ and y. The proportions are defined as:

Bias Proportion

$$\frac{((\sum \hat{y}_t / h) - \bar{y})^2}{\sum (\hat{y}_t - y_t)^2 / h}$$

Variance Proportion

$$\frac{(s_{\bar{y}} - s_y)^2}{\sum (\hat{y}_t - y_t)^2 / h}$$

Covariance Proportion $\frac{2(1-r)s_{\hat{y}}s_y}{\sum(\hat{y}_t - y_t)^2 / h}$

- The bias proportion tells us how far the mean of the forecast is from the mean of the actual series.
- The variance proportion tells us how far the variation of the forecast is from the variation of the actual series.
- The covariance proportion measures the remaining unsystematic forecasting errors.

Note that the bias, variance, and covariance proportions add up to one. If your forecast is "good", the bias and variance proportions should be small so that most of the bias should be concentrated on the covariance proportions (Pindyck and Rubinfeld (1991), Chapter12).