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Three Essays on: Hedging in China's Oil futures market; Gold, Oil and Stock Market Price Volatility links in the USA; and, Currency Fluctuations in S.E. and Pacific Asia

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Abstract

This thesis empirically evaluates three key financial and macroeconomic issues:

Essay 1 examines the effectiveness of China fuel oil futures in hedging a domestic spot fuel oil position as well as hedging a spot position in the Singapore fuel oil market. To the best of our knowledge, this is the first study of this kind. Dynamic Bi-variate GARCH and constant volatility models are estimated to derive the optimal hedging ratios and hedging effectiveness of China fuel oil futures. That effectiveness is assessed by several criteria, for both in- and out-of-sample periods.

Essay 2 aims to investigate the relationship between the oil, gold and US stock markets. By employing a Tri-variate GARCH(1,1) model, this is the first study to explore how volatility is transmitted among those three markets. Additionally, this is the first study to compare Tri-variate GARCH and Bi-variate GARCH modelling strategies as vehicles for determining the volatility interrelations between these markets.

Essay 3 explores the power of conventional macroeconomic factors to explain the currency fluctuations over recent years, including the 1997 crises, in six Asian countries. Two regimes Markov Switching TGARCH and constant volatility models are used to determine the causes of market pressures on exchange rates, and the probability of the timing of a currency attack. The Markov Switching models do not require an ex-ante definition of a threshold value to distinguish stable and volatile state like Logit models do, and they can capture the appreciating currency attacks as well as the depreciating ones. The Markov Switching models are also compared with Multinomial Logit models in their ability to detect crises.

Dedication

To my dearest parents and the soul of Wei

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ESSAY 2 VOLATILITY SPILLOVERS AMONG OIL, GOLD AND US STOCK MARKET

ABBREVIATIONS

ADF	Augmented Dickey-Fuller Unite Root Test
ARCH	Autoregressive Conditional heteroskedasticity
BHHH	Berndt, Hall, Hall, and Hausman Estimation Method
BFGS	Broyden, Fletcher, Goldfarb and Shanno Estimation Method
DRM2	First Difference of RM2
DRER	First Difference of RER
DGDC	First Difference of GDC
ERM	European Exchange Rate Mechanism
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
GDC	Growth of Real Domestic Credit
GSB	Global Squared Bias
GSV	Generalized Semivariance
IFS	International Financial Statistics.
JB	Jaque-Bera test
KPSS	The Kwiatkowski, Phillips, Schmidt and Shin Unit Root test
LF	Price of China Fuel Oil Futures in Logarithm
LG	The Price of Gold Futures in Logarithm
LO	The Price of Oil Futures in Logarithm
LPM	Lower Partial Moment
LPS	Log Probability Score
LR	Log Likelihood Ratio
LS	The Price of China Fuel Oil Spot in Logarithm
LSP	The Price of S&P500 Index in Logarithm
LSX	The Price of Singapore Platt's Fuel Oil Spot in Logarithm
MEG	Mean Extended-Gini coefficient
M-GSV	Optimal Generalized Semivariance
MLogit	Multinomial Logit

M-MEG	Optimal Mean Extended-Gini Coefficient
MP	Market Pressure
MV	Minimum Variance
OHRs	Optimal Hedge Ratios
OLS	Ordinary Least Squares
PPP	Purchasing power parity
QLR	Quasi-likelihood Ratio
QPS	Quadratic Probability Score
RER	Real Exchange Rate
RF	The Return of China Fuel Oil Futures
RG	The Return of Gold Futures
RM2	Ratio of international reserves to broad money M2
RO	The Return of Oil Futures
RS	The Return of China Fuel Oil Spot
RSP	The Return of S&P500 Index
RSX	The Return of Singapore Platt’s Fuel Oil Spot
SHFE	The Shanghai Futures Exchanges
TGARCH	Threshold GARCH
VaR	Value at Risk
VAR	Vector Autoregressive Model

Introduction

With the development of complex financial markets, inter-related futures markets, massive cross border capital flows, globalisation and international integration, it is now widely agreed that financial and real assets' return volatilities and correlations are time-varying, interrelated with each other and with persistent dynamics. This is true across assets, asset classes, time periods, and countries. Variation in market returns and other economy-wide risk factors is a main feature of asset and portfolio management and play a key role in asset evaluation, especially in derivatives and pricing models. Volatility becomes central to finance, whether in asset pricing, portfolio allocation, or market risk measurement. Considerable evidence indicates that financial market volatility is related to news (arrival of information). Hence econometricians have devoted considerable attention to analyse behaviour under uncertainty, based on an analytical framework with a central feature of modelling the second moments. One of the most prominent tools used to model the second moments is due to Engle (1982). Engle (1982) suggested that these unobservable second moments could be modelled by specifying functional form for the conditional variance and modelling the first and second moments jointly, giving what is called in the literature the Autoregressive Conditional Heteroskedasticicity (ARCH) model. This linear ARCH model was generalized by Bollerslev (1986) and extended in many other ways, thus called the GARCH type of models. These models have been applied extensively in the literature. However, given the growing complexity of asset markets, and the changing structure of the transmission mechanism for shocks to the system, more research needs to be done in particular to test for market efficiency and mean reversion.

This thesis consists of three different topics, discussing several major issues in the analyses of financial and commodity markets. Although the topics are different and disparate, they are united in the common methodological, institutional and globalised structure discussed above. All of these three studies endogenise market risk and set up model based on the GARCH framework to take the second moments (volatility) into consideration, so as to investigate the optimal hedging strategies of futures contract, to explore the volatility transmission between markets and to detect the timing of financial crises.

1) The first study

The prices of fuel and its derivatives have risen considerably in recent years, as has their trend. China is the largest consumer of fuel oil in Asia. Its fuel oil demand has increased dramatically concomitant with its rapid economic growth. On 25 August 2004, China launched the fuel oil futures at the Shanghai Futures Exchanges (SHFE). Because hedging has widely been viewed as a major market activity and also the reason for the existence of futures markets, examining the effectiveness of China fuel oil futures as a vehicle for hedging is of paramount importance.

In Essay 1, in order to derive optimum hedge ratios and hedging strategies in the futures market, we estimate models that assume dynamic relationships in and between the volatilities of the returns in the two markets, as well as constancy in those volatilities. Considering the important role that Singapore fuel oil market plays in the pricing of China fuel oil futures, cross hedging of China fuel oil futures in the Singapore market is also examined for comparison. To the best of our knowledge, this is the first study to investigate the hedging strategies and hedge effectiveness of China's fuel oil futures market.

One critical thing in hedging is to derive the optimal hedge ratios. Three approaches are employed to derive the hedge ratios in our study, which are the minimum variance hedge ratio, the maximum expected utility hedge ratio and the minimum semivariance hedge ratio. Accordingly, the hedging effectiveness is evaluated, respectively, by the variance reduction criterion, expected utility maximisation criterion and the risk reduction criterion based on the semivariance.

Empirical findings confirm the theoretical advantage of dynamic models over the constant models in the in-sample period, under all three criteria, for both domestic and cross hedging. However, in the out-of-sample period, the dynamic models lose their superiority, especially under the variance reduction criterion. One distinctive finding of this study is the outstanding hedging performance of China fuel oil futures when using the semivariance risk reduction criterion, in both in- and out-of-sample periods. Although the China fuel oil futures generates somewhat disappointing hedging outcome when designed to reduce the total risk, it is an effective tool in reducing the downside risk, which would be more useful in practice, therefore, should investors only want to avoid the downside risk whilst maintaining the upside profit potential.

2) The second study

The increasing integration of major financial markets throughout the world has generated great interest in examining the transmission of financial market shocks across markets. A particular focus has been the conditional (or predictable) volatility spills over from one market to another. Essay 2 contributes to the existing literature by investigating the volatility spillovers between oil, gold and stock markets. Our research is the first of this kind to investigate the relations between these three markets. This research, for example, can provide information for risk assessment and forming optimal hedging strategies across markets and the volatilities derived in the study can be used as important inputs into macro-econometric models.

Tri-variate GARCH models are employed to capture the interrelationships (which are shown to exist) between the second moments across the oil, gold and stock markets.

Such models allow the conditional variance of one market potentially to be dependent upon the past information from its own market, as well as from the other two markets. The conditional variance also depends upon the conditional covariance of each pair of the three markets. The Tri-variate GARCH estimates for the three markets are compared with the estimates from Bi-variate GARCH models for each pair of the markets to discover the “true” relationships across those markets. The data that we use in this study are for the world oil and gold markets and the US stock market, ranging from April 1999 to November 2007. Data are split into three sub-sample periods according to their relative volatility. Such division is warranted by the fact that the variance-covariance structure of the return series is dynamic, conditional on the past information in the markets.

We find volatilities spill over from the oil market to the stock market, from the gold market to the stock market. The gold market is exogenous in terms of its second moment: its volatility affects both oil market and stock market, but is not affected by these two markets, confirming that gold is the “safe” investment when market is very volatile. The volatility spillovers between oil and stock market are bi-directional.

We also discover that, by adding an additional market to the existing Bi-variate GARCH framework, the Tri-variate GARCH can reveal some otherwise unobserved breaks in, or break, some existing relationships between the markets. In forecasting the variance of a market or the covariance between any two markets, taking into consideration of the third market can provide useful information.

3) The third study

The outbreak of the Asian financial crises in 1997-98 triggered a surge in both theoretical and empirical studies on the factors that contribute to the occurrence of a currency crisis. The first generation currency crisis models (e.g. Krugman 1979, Agenor et al., 1992 Flood and Garber, 1984) showed that fiscal and monetary policies inconsistent with the fixed exchange rate regime lead to a gradual loss in reserves and ultimately to a speculative attack against the currency. The second generation models (see, e.g. Obstfeld, 1996) emphasized the importance of market expectation. The economy can jump from a good, “no attack”, equilibrium to an “attack equilibrium” triggered by an unexpected shift in market expectation. Thus a crisis can arise mainly because the macroeconomic fundamentals are in the zone of vulnerability. Economies with strong fundamentals are impervious to changing market sentiments. Essay 3 evaluates empirically the first and second generation models in explaining 1997-98 Asia crises by exploring the effect of macroeconomic variables on exchange market.

Exchange market pressure, MP, is measured as a weighted average of the change in the exchange rate, the loss in reserves and the change in domestic interest rate, with the weights being the inverse of their respective variance. Markov Regime-Switching approaches are adopted to account for the presence of two potential regimes: stable and volatile. The attractiveness of the Markov Regime-Switching approach is that there is no need to distinguish ex-ante between stable and volatile states. Such information will be supplied in the estimation results. By allowing regression parameters to switch between different regimes, Markov Regime-switching mimics the existence of multiple equilibria in the exchange market.

Markov models with a TGARCH specification and with constant variance are examined. Those models are also compared with the Multinomial Logit models in terms of their ability to detect appreciating and depreciation currency crises. The empirical findings give credence to the view that fundamental variables can still explain the market pressure on the exchange rate and the Asian currency crises. However, we did not find that the Markov Regime-Switching models with dynamic variance (i.e., with TGARCH specification) completely dominated the Markov Switching constant models, although in general they were superior.

Our study differs in several ways from previous published studies on currency crises. For example, we determine the number of potential regimes though Neyman's $C(\alpha)$ test, in addition to the conventional (and somewhat inexact) log likelihood ratio test. More substantially, we test for the presence of more than one regime by determining whether the residuals from the estimation from the assumption of only one regime are or are not normally distributed. Any deviation from normality points to distortion arising from the presence of other regimes being embodied in the set of observations. Bootstrapping methods are used for that purpose. Additionally, having established that more than one regime exists, using the estimates of the conditional probabilities that the currency market is in a given regime, we test which regime relates to which state in the market (for example, volatile or stable) using score based tests, including the quadratic probability score (QPS) test, the log probability score (LPS) test and the Global squared bias (GSB) test.

Essay 1 Hedging effectiveness of China fuel oil futures

1.1 Introduction: China fuel oil market

Fuel oil is a very important energy source, especially for the fast growing emerging market. It is mainly used in power generation, transportation and petrochemical industries. China is the largest consumer of fuel oil in Asia. Its fuel oil demand has increased dramatically with China's rapid economic growth. In 2004, China imported 30 million tones of fuel oil, while in 1995 the number was just 6 million tones. Since 2004, the demand for fuel oil in China keeps decreasing, but the amount is still large. The domestic supply, however, is limited. The increasingly larger demand in domestic fuel oil market has to be fulfilled by importing. China is the biggest importer of fuel oil in Asia, whose imports take up to 50% of China's fuel oil consumption in recent years.

Fuel oil is regarded as the most liberalised oil product in China, being the least controlled by the government. On 25 August 2004, the fuel oil futures was launched at the Shanghai Futures Exchanges (SHFE). For about five years, it has successfully attracted many domestic investors, and the trading of the fuel oil futures continuously increasing (see Figures 1.B.1 and 1.B.2). According to the SHFE's position-hold list, the majority of fuel oil importers and some end-user have participated in trading. Among them, speculators hold the majority of long positions, while the bulk of short positions are held by physical players in oil market who trade in futures market with the main aim to hedge the risks of trading in physical market.

Singapore is one of the main refined product markets and distribution center. It provides about 30% of fuel oil imports to China. The Mean of Platts Singapore (MOPS) is the benchmark for Singapore fuel oil price, as well as the benchmark for China's fuel oil import price. According to a survey by the National Statistics Bureau, 70% of the China fuel oil prices are determined by the prices in the Singapore fuel oil market. The Platts 180CST fuel oil has the quality mostly close to China's fuel oil futures's underlying fuel oil commodity. It's the main constitute in MOPS thus the base of pricing fuel oil in Singapore, and its price is also an important factor that is used in pricing of fuel oil futures in China.

Since its launch, the China fuel oil futures were highly correlated with WTI crude oil futures. However, such correlation was gradually decreasing. According to a report from SHFE, from 1 Dec 2004 to 15 April 2009, the correlation of Shanghai fuel oil futures and WTI crude oil futures is 0.93, where the correlation reduced to 0.62 in the first four months of 2009. The correlation between China fuel oil futures prices and Singapore 180CST fuel oil spot prices decreases as well, reducing from 0.94 between Jan 2005 and Dec 2008 to 0.5 in the first four month of 2009. There is a trend that the China fuel oil futures market is decreasingly impacted by Singapore and the international oil market passively, but increasingly reflects the supply and demand in domestic market.

In recent years, the fluctuation of fuel oil prices poses a large risk to those companies that trade or consume large volumes of fuel oil. Volatile fuel prices make budgeting difficult. The potential increase in fuel costs may exceed the profit margin of the business. For example, Figure 1.B.3 portrays the influence of the fuel oil price on the domestic small oil refineries. There are times that the sales price may fall short of the import prices and therefore generate losses in those oil refinery firms. As risk management has become one of the most important objectives for enterprises, hedging of the extensive oil price risk is of paramount importance for those firms. Futures no doubt is the most wildly used and effective tool for hedging. Using futures market to hedge is to take opposite positions in these two markets, in order to offset the price movements and reduce the volatility. Figure 1.B.4 portrays the fuel oil spot and futures prices[1]. We can observe that that both spot and futures prices are trending upward. As the China fuel oil futures is the only oil futures product in the Chinese market, it is not surprising that trading in that market are increasing, especially with the big turmoil in the oil market in recent years.

There are other reasons for why the fuel oil futures has become a popular tool for hedging: first, not like in the spot market with strict short selling restriction, investors can short sell the futures contracts as well as long in them. Second, same as other commodity futures, fuel oil futures provide low transaction cost comparing to trading in physical products. Third, the higher leverage that can be used in futures trading can

[1] In the Figure, the Huangpu physical price is used as the representative of fuel oil spot price in China. Such is explained in the Data section.

create possible speculative gains (losses) with relative small amount of investment required.

Because hedging has widely been viewed as a major function and also the reason for the existence of futures markets, examining the effectiveness of China fuel oil futures as a tool of hedging is of paramount importance. Hence, in this study, we examine the effectiveness of China fuel oil futures in hedging a domestic spot position. In addition to the domestic hedging, this study also investigate the cross hedging of China fuel oil futures in hedging a corresponding spot position in the Singapore market. As discussed earlier, Singapore and China's fuel oil market are closely related, and the fuel oil spot price in Singapore is an important indicator for the pricing of China fuel oil futures. Moreover, Singapore, as Asia's main bunkering port, has decades of trading experiences together with integrated and expanding network of refineries and storage facilities. Its fuel oil market is more liberalised, involving less restrictions and barriers than the China fuel oil market. Though China is ambitious to shrug off Singapore's dominance and establish its own pricing system for fuel oil product, that will take time. Investigating the cross hedging of China fuel oil futures in the Singapore market can give a hint on the usefulness of China fuel oil futures in the international market.

Academic studies of China's fuel oil futures market are limited. To the best of our knowledge, this is the first study to explore the hedging strategies and hedging effectiveness of the China fuel oil futures, in both domestic hedging as well as cross hedging in the Singapore market. Moreover, most applications of time-varying models of hedging have imposed constant variance or dynamic conditional variance with GARCH process, where positive or negative shocks have the same impact on the conditional volatility[2]. So far, only Switzer and El-Khoury (2006) incorporate asymmetries in volatility in the oil market to derive optimal hedge ratios. In this study, we also incorporate asymmetric information in volatility to generate hedging ratio and investigate whether incorporating such asymmetric effects can improve the hedging performance. Differ from most of the studies of hedging effectiveness, we have specifically included the test of equality for means and variances of the hedged portfolios, to see if any significant changes exist in the mean and variance of the hedged portfolio (measured according to Ederington, 1979) when it is constructed under different hedging models.

The remainder of this study is organized as follows. Section 2 provides a brief review of the literature. Section 3 lists theoretical framework for deriving optimal hedging ratios and various criteria for evaluating hedging performances. In Section 4, we describe our data and methodology. Empirical results for dynamic and constant variance models are provided in Section 5. In Sections 6 and 7, we present efficiency tests and hedging analysis for in-sample and out-of-sample period. Summaries and conclusions are provided in section 8.

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[2] See the methodology section for more information on the symmetric and asymmetric effects of positive/negative shocks.

1.2 Literature review

Among various techniques available for reducing and managing risk, the simplest and perhaps the most widely used is hedging by means of futures contracts. Traditionally, investors simply measure the position in the underlying asset and take an equal but opposite position in the futures contract to hedge risk. This method is nowadays referred to as a naïve approach. Studies suggest that for hedging effectively, investors need to determine the proportions of spot to futures positions for an asset, which are commonly referred to as Optimal Hedge Ratios (OHRs). The optimal hedge ratios depend on the particular objective function to be optimised. One of the most widely-used hedging strategies is to employ a minimum-variance (MV) framework, which is based on minimisation of the variance of the hedged portfolio (e.g., see Ederington, 1979; Johnson, 1960; Myers & Thompson, 1989).

For several reasons the minimum-variance framework has become the benchmark in the hedging literature. First, MV hedge ratio is optimal for exceptionally risk averse traders (Ederington, 1979; Kahl, 1983). Second, as has been verified in several empirical studies (for example, Baillie and Myers, 1991; Martin and Garcia, 1981) the MV hedge ratio is still optimal when futures markets are unbiased. However, one drawback is that the MV hedge ratio completely ignores the expected return of the hedged portfolio. Therefore, this strategy generally is not consistent with the mean variance framework unless the individuals are infinitely risk averse or futures prices follow a pure martingale process (i.e., expected futures price change is zero) (Chen et al., 2003). Moreover, the minimum variance hedge ratio has been criticized because negative and positive returns are given equal weight, whereas investors may concern more about the variability in losses rather than in gains. A survey by Adams and Montesi (1995) points out that corporate managers care about the “downside risk” much more than the “upside potential”. Investors adopting a hedging strategy may wish to keep the upside potential whilst eliminating the downside risks. In such case, the conventional minimum variance hedge strategy is inappropriate.

As a result, strategies that incorporate both the expected return and risk (variance) of the hedged portfolio and the strategies considering the asymmetry in upside and downside risk were developed. For the former, these strategies can be consistent with a mean-variance expected utility framework (e.g., see Cecchetti, Cumby, & Figlewski, 1988; Howard & D’Antonio, 1984; Hsin, Kuo, & Lee, 1994). The maximisation of expected utility approach (e.g., Cecchetti et al., 1988; Lence, 1995, 1996) requires the use of a specific utility function and specific return distribution. It can be shown that if the futures price follows a pure martingale process, then the optimal mean-variance hedge ratio will be the same as the MV hedge ratio. The latter strategies consist of minimisation of the mean extended-Gini (MEG) coefficient hedge ratio (e.g., see Cheung, Kwan, & Yip, 1990; Kolb & Okunev, 1992, 1993; Lien & Luo, 1993a; Lien & Shaffer, 1999; Shalit, 1995), and the generalized semivariance (GSV) or lower partial moments (e.g., see Chen, Lee, & Shrestha, 2001; De Jong, De Roon, & Veld, 1997; Lien & Tse, 1998, 2000). Most recent development is to derive the OHR based on the VaR (Value at Risk), which is proposed by Hung, Chin and Lee (2006) and Cotter and Hanly (2006). Details of these methods are given in Section 1.3.1.

However, in part because of the theoretical justification of finding unbiased markets and in part because components of the MV hedge ratio may be retrieved from variance and covariance estimates of underlying spot and futures prices (see, e.g., Baillie and Myers, 1991; Kroner and Sultan, 1993), MV has continued to be the most widely applied methodology.

Early studies in the estimation of OHR provide empirical support for MV using traditional OLS technique, where OHR is simply derived from the slope coefficient when the spot price series is regressed against the futures price series. Because the hedge ratio derived from this method is constant, this is the so called constant model. Despite its robustness during the early stages, the OLS approach has been subject to many challenges. Many studies criticized the inefficiency of the residuals in the OLS method used to estimate the OHRs. For example, Herbst, Kare and Marshall (1989) argue that the OLS residuals suffer from the problem of serial correlation and are thus inappropriate to be used in the estimation of OHR. Park and Bera (1987) point out the simple regression model ignores the heteroskedasticity often encountered in cash and futures price series. Another obvious shortcoming of the conventional methodology is that it assumes the covariance matrix of cash and futures prices—and hence the hedge ratio—is constant throughout time. Many studies (for example, Bell and Krasker, 1986; Mers and Thompson, 1989) argue that the covariance between dependent and explanatory variable and the variance of the explanatory variable under the optimal hedging rule should be conditional moments which depend on the information set available at the time the hedging decision is made. Therefore the hedge ratio should be adjusted continuously based on conditional information and thus on the conditional variance and covariance which are changing over time.

Introduced by Engle (1982) and generalized by Bollerslev (1986), the Autoregressive Conditional Heteroskedasticity (ARCH) framework, with various extensions, has proved to be an effective method to solve the above mentioned problems. The ARCH and GARCH (Generalised ARCH) specifications take the heteroskedasicity of the spot and futures prices series into consideration. Instead of searching for possible information variables, they call upon their own history of spot and futures prices to explain the variations in variances and covariances in estimating the optimum hedge ratios. In the early stage of incorporating the GARCH model in OHR estimation, most studies assume time-varying conditional variances but constant correlation between the spot returns and futures returns (Cecchetti et al, 1988; Baillie and Myer, 1991; Kroner and Sultan, 1993; etc.). However, Haigh and Holt (2000) argue that this, while parsimonious, does not allow the spot-futures covariance (and, therefore, OHRs) to switch signs in the short run as spot and futures prices move in opposite directions, implying that such a specification may be overly restrictive.

Research has now been extended to finding a dynamic sequence of optimal hedge ratios while making allowances for time varying conditional variances and also the covariance of spot and futures returns, using multivariate GARCH models. Given the apparent theoretical advantages of its dynamic feature over the static ones and over the dynamic ones with constant correlations, a number of studies have employed the Bi-variate GARCH framework to examine the hedging performance of various assets. For example, Gagnon, Lypny and McCurdy (1998) model the time variation in the variances and covariances between components of a hedge with a Bi-variate GARCH process. Park and Switzer (1995), using three types of stock index futures, find that the Bi-variate GARCH-based dynamic hedging strategy provides improvements in forecasting accuracy over the static hedge. Most of these studies have shown that, by accounting for the time-variation in the joint distribution of the changes in spot and futures prices, the dynamic hedging models perform better than the constant or traditional OLS models. They offer greater risk-reduction and utility maximisation than the constant hedge models do.

Asymmetry is another feature that typically found in equities, of which negative price shocks associate with greater volatility than positive price shocks do; resulting in the so-called leverage effects. Such effects can be modelled by the Threshold GARCH model (TGARCH model, also called GJR model, after its originators Glosten, Jagannathan, and Runkle, 1993). Some hedging studies take such asymmetric effects into consideration. Brooks, Henry, and Persand (2002) demonstrate that there are benefits in allowing for asymmetry effects in volatility when deriving optimal hedge ratios for commodity futures. Switzer and El-Khoury (2006), for the first time, incorporate asymmetries in volatility in the oil market to derive optimal hedge ratios for oil and conclude that hedging performance is improved when such asymmetries are incorporated into the hedging procedures, based on out-of-sample estimates.

More recently, econometric methods have allowed regime switches to affect the spot and futures dynamics. They argue that GARCH model tend to impute a high degree of persistence to the conditional volatility. It is argued that if regime switches occur, the optimal hedge ratio is also likely to be state dependent, so that by allowing the volatility to switch stochastically between different processes under different market conditions, one may obtain more robust estimates of the conditional second moments and, as a result, more efficient hedge ratios compared to other methods such as GARCH models or OLS (Alizadeh, Nomikos and Pouliasis, 2007). Despite the conceptual superiority of utilizing a model that allows for regime switches, there is mixed support for the use of regime switching models in estimating OHR. For example, Alizadeth and Nomikos (2004) find that constant volatility Markov Switching models outperform conventional measures in the in sample period, for the S&P500 and FTSE100. However, in the out of sample, a multivariate GARCH model provided the greatest variance reduction for the S&P500. Lee and Yoder (2007) used a Bivariate Markov Switching GARCH process to estimate dynamic OHRs for corn and nickel contracts. They find that although by allowing the covariance matrix to be state dependent improves out of sample hedging effectiveness, the improvements are statistically insignificant. Given the mixed performance of Markov Switching models and the fact that the oil market is relatively stable in our sample period, we only experiment with GARCH and constant models in this study.

The performances of these models are assessed by their hedging effectiveness. Ederington (1979) defines hedging effectiveness as the reduction in variance and states that the objective of a hedge is to minimise the risk. Howard and D'Antonio (1984) define hedging effectiveness as the ratio of the excess return per unit of risk of the optimal portfolio consisting of the spot and the futures instrument, to the excess return per unit of risk of the portfolio containing the spot position alone. However, it is argued that the second order conditions derived by Howard and D'Antonio are incorrect (see, Chang and Shanker, 1987; Satyanarayan, 1998 and Section 1.3.1). Hsin et al (1994) derive the OHR by considering both risk and returns in the hedging, thus utility maximisation can be used to gauge the hedging effectiveness. Cotter and Hanly (2006) illustrate some new developments in evaluating hedging performances, which include the risk reduction based on semivariance criterion, the Lower Partial Moment (LPM) criterion and VaR criterion. More detailed theoretical discussion about hedging performance evaluation methods are given in Section 1.3.2.

Thus far, the dynamic models seem to outperform the conventional models at least in markets “where trading restrictions are minimal, trading information is more readily available, and timeliness of trading information is high and market liquidity is higher” (e.g. see, Park and Switzer, 1995; Gagnon and Lypny, 1997; Lypny and Powalla,1998; and Yang, 2001, Ford, Pok and Poshakwale, 2005). However, despite statistical soundness of dynamic models and greater risk-reduction they can provide than the constant hedging models according to the in-sample period comparisons, their advantage are not as significant in some other cases, especially, in the out-of-sample period comparisons. A number of explanations have been offered for the inability of the GARCH models to achieve ex ante superior hedging performance. First, Ghose and Kroner (1994) suggest common persistence in the conditional variances of spot and futures prices as a possible explanation for the similar performance between conventional and GARCH hedge strategies. Second, the long-term forecast performance of the GARCH model is very poor. Unless the GARCH estimators are updated frequently, the forecasts of variances and covariances will be unreliable; as, therefore, will the GARCH hedge ratios. Third, given the persistence in the conditional covariance matrix and poor long-term forecasting ability, the presence of an outlier can erroneously affect the investor’s hedging position enormously and for a number of subsequent time periods. This could very well destabilize the investor’s portfolio variance. Fourth, the estimated GARCH parameters could be time-varying leading to possible biases in the assumed hedging position. Also, there is the problem that the hedging instrument (i.e. the nearby futures contract in most cases) continually expires. Hence, the futures price series does not describe the behaviour of a single asset.

1.3 Theoretical framework on optimal hedge ratios and hedging performance evaluation

1.3.1. Alternative theories for deriving the optimal hedge ratios and criteria for measuring hedging effectiveness

One of the main theoretical issues in hedging involves the determination of the optimal hedge ratio, which is defined by Hull (2003) as “the ratio of the size of the portfolio taken in futures contracts to the size of the exposure”. Only with correct hedge ratios, effective hedging can be achieved. The optimal hedge ratio depends on the particular objective function to be optimized. Based on the objective functions, optimal hedge ratios are derived and hedging effectiveness are evaluated. Many different objective functions are currently being used. Here we illustrate several alternative approaches with the corresponding criteria to assess hedging effectiveness

1.3.1 a) Minimum variance hedge ratio and risk reduction based on variance

The Minimum variance hedging is the most widely-used hedging strategy. It is based on minimisation of the variance of the hedged portfolio (Johnson, 1960; Ederington, 1979). This is the well-known MV hedge ratio.

Assuming that the only hedging instrument available to the investor is the futures contract, a hedge portfolio consisting of spot and futures is constructed. Let us consider the following model, which allows for time-varying variances of the spot and futures prices. Assume an investor purchases one unit of the spot and shorts (short sell) in β_t units of the futures at time t, the payoff (return) of the hedged portfolio, X_{t+1}, at time *t+1* is X_{t+1}:

$$X_{t+1} = s_{t+1} - \beta_t f_{t+1} \tag{1.1}$$

Where f_{t+1} is the changes in the prices of the futures between time *t* and *t+1*, and s_{t+1} is the changes in the prices of the spot between time *t* and *t+1*.

The variance of the hedged portfolio is

$$\begin{aligned} Var(X_{t+1}) &= Var(s_{t+1} - \beta_t f_{t+1}) \\ &= Var(s_{t+1}) + \beta_t^2 Var(f_{t+1}) - 2\beta_t Cov(s_{t+1,} f_{t+1}) \end{aligned} \tag{1.2}$$

To minimise $Var(X_{t+1})$, according to the first order condition,

$$\frac{\partial(\mathrm{var}(X_{t+1}))}{\partial(\beta_{t+1})} = 2\beta_t Var(f_{t+1}) - 2Cov(s_{t+1,} f_{t+1}) = 0 \tag{1.3}$$

Thus we get the optimal hedge ratio:

$$\beta_t^* = \frac{\sigma_{sf,t+1}}{\sigma_{f,t+1}^2} \tag{1.4}$$

For the conventional time-varying MV hedge ratio strategy, the hedging effectiveness of the different portfolios is measured as the percentage reduction in the variance of the hedged portfolio in comparison to the unhedged portfolio (Ederington1 (1979), following the work of Working (1953, 1962), Johnson (1960) and Stein (1961)).

Hence, the measure of hedging effectiveness (κ) is herein defined as the ratio of the variance of the unhedged portfolio minus the variance of the hedged position, over the variance of the unhedged position:

$$\kappa = \frac{Var(U) - Var(H)}{Var(U)} \tag{1.5}$$

Here, $Var(U)$ denotes the variance of unhedged portfolio (spot position) and $Var(H)$ represents the variance of the hedged portfolio.

1.3.1 b) Expected Utility maximisation hedge ratio and utility maximisation criterion

Several models to determine the OHRs are based on the corresponding utility maximisation of the investors (e.g. Hsin et al., 1994; Lence, 1995). One distinct advantage of these models is that they have incorporated both risk and return in the derivation of hedge ratios.

With the payoff of the hedged portfolio is given in Equation (1.1), the investor with a mean-variance expected utility function will maximize the following function (see, e.g., Hsin et al, 1994):

$$E_t U(x_{t+1}) = E_t(x_{t+1}) - \gamma \sigma_t^2 (x_{t+1}) \tag{1.6}$$

Where the constant term, γ, denotes the level of risk aversion. The expectation and variance operators are subscripted with *t* to denote that they are calculated conditional on all information available at time *t*. By definition, the predictable component of volatility in the return is the conditional variance, and thus, risk is measured by conditional variance. The utility maximizing hedge ratio at time *t* is

$$\beta_t^* = \frac{-E_t(f_{t+1}) + 2\gamma\sigma_t(s_{t+1}, f_{t+1})}{2\gamma\sigma_t^2(f_{t+1})} \tag{1.7}$$

Assuming that the investment in futures contracts is a zero sum game, or futures prices are martingale (i.e. $E_t(F_{t+1}) = F_t$, then $E_t(f_{t+1}) = 0$), Equation (1.6) simplifies to

$$\beta_t^* = \frac{\sigma_t(s_{t+1}, f_{t+1})}{\sigma_t^2(f_{t+1})} \tag{1.8}$$

Which is the conventional MV hedge ratio.

Thus the corresponding criterion used to evaluate the hedging performance is based on the utility comparison. Utility of different modelling specifications can be calculated using the following equation(1.6):

$$E_t U(x_{t+1}) = E_t(x_{t+1}) - \gamma\sigma_t^2(x_{t+1})$$

Different value of γ may give different rankings of a same set of models. Hence, the utility maximization criterion also reflects the role an investor's risk preference plays in his choices of hedging strategies

1.3.1 c) Sharpe hedge ratio and Sharpe ratio criterion

Another way of incorporating the portfolio return in the hedging strategy is to use Sharpe ratio based criterion, which considers the risk-return tradeoff as well. Howard and D'Antonio (1984) consider the optimal amount of futures contracts by maximizing the ratio of the portfolio's excess return to its volatility:

$$\max_{\beta} \theta = \frac{E(X) - R_f}{\sigma_X} \tag{1.9}$$

Where $\sigma_X^2 = Var(X)$ and R_f represents the risk-free interest rate. In this case the optimal hedge ratio is:

$$\beta^* = -\frac{(\sigma_s / \sigma_f)\left[(\sigma_s / \sigma_f)(E(f)/(E(s) - R_f)) - \rho\right]}{\left[1 - (\sigma_s / \sigma_f)(E(f)\rho/(E(s) - R_f))\right]} \tag{1.10}$$

Where $\sigma_s^2 = Var(s)$ and $\sigma_f^2 = Var(f)$, ρ is the correlation coefficient between s and f (see Howard and D'Antonio, 1984 for detailed derivations).

Again, if $E(f) = 0$, then β reduces to:

$$\beta = \frac{\sigma_s}{\sigma_f} \rho \tag{1.11}$$

which is same as the MV hedge ratio.

One drawback of this approach, as pointed out by Chen et al. (2001), is that the Sharpe ratio is a highly non-linear function of the hedge ratio. This lead to the possibility that the hedge ratio derived from first order condition (i.e. the first derivative with respect to the hedge ratio equal to zero) would minimize the Sharpe ratio, instead of maximizing it, when the second derivative is positive.

The hedging performance of this approach can be evaluated in two ways. First, the hedging effectiveness can be defined as the ratio of the Sharpe Ratio of the hedged portfolio over the Sharpe Ratio of the unhedged portfolio.

$$\kappa = \frac{(E(H) - R_f)/\sigma_H}{(E(U) - R_f)/\sigma_U} \tag{1.12}$$

The higher the ratio, the better the hedging performance.

Another way is to define the hedge effectiveness as the different between the Sharpe ratios of the hedged and unhedged portfolio, which is shown as follows:

$$\kappa = \frac{E(H) - R_f}{\sigma_H} - \frac{E(U) - R_f}{\sigma_U} \tag{1.13}$$

1.3.1 d) Minimum Mean extended-Gini coefficient hedge ratio and risk reduction based on MEG coefficient

Another type of hedge ratio is the Mean extended Gini (MEG) coefficient hedge ratio (Cheung et al., 1990; Kolb and Okunev, 1992; Lien and Luo, 1993; Shalit, 1995; and Lien and Shaffer, 1999). This approach of deriving the OHRs is consistent with the concept of stochastic dominance and involves the use of the MEG coefficient. The

OHRs can be derived by minimizing the MEG coefficient $\Gamma_v(X)$, which is defined as follow:

$$\Gamma_v(X) = -vCov(X,(1-G(X))^{v-1}) \tag{1.14}$$

Here, *G* is the cumulative probability distribution and *v* is the risk aversion parameter. Note that $0 \leq v < 1$ implies risk seekers, $v = 1$ implies risk-neutral investors, and $v > 1$ implies risk-averse investors. Shalit (1995) shows that the minimum-MEG hedge ratio will reduce to the MV hedge ratio if the futures and spot returns are jointly normally distributed.

There are different ways to estimate the MEG hedge ratio. Kolb and Okunev (1992) proposed the empirical distribution method to estimate the MEG hedge ratio where the cumulative probability density function is estimated by ranking the observed return on the portfolio. Alternatively, Shalit (1995) use the instrumental variable (IV) method to find the MEG hedge ratio, which is an analytical solution. Lien and Luo (1993) derived the MEG hedge ratio by estimating the cumulative distribution function using a non-parametric kernel function instead of using a rank function as in Kolb and Okunev (1992).

The corresponding hedge effectiveness measurement criterion has not been address in literature. But base on the objective function, hedging effectiveness κ can be defined as the risk reduction based on MEG coefficient:

$$\kappa = 1 - \frac{\Gamma_v(H)}{\Gamma_v(U)} \tag{1.15}$$

1.3.1 e) Optimal Mean extended-Gini coefficient hedge ratio and utility maximisation based on MEG coefficient

The minimum MEG hedge ratio does not consider the risk return trade-off. To address this issue, Kolb and Okunev (1993) consider maximizing the utility function based on GEM coefficient. The objective function is defined as follows:

$$U(X) = E(X) - \Gamma_v(X) \tag{1.16}$$

The hedge ratio derived from the above objective function is denoted as M-MEG hedge ratio, which considers the expected return on the hedged portfolio. It manifests under the condition of joint normal distribution of futures and spot returns or if the futures returns follow a pure martingale.

Hedging performance is measured by the magnitude of the utility derive based on the above function (Eq. 1.16). The higher the utility, the better the hedging strategy.

1.3.1 f). Minimum Generalized semivariance hedge ratio and risk reduction based on the Generalised semivariance

An alternative approach for determining the hedge ratio has been suggested by Chen et al., 2001; De Jong et al., 1997; Lien & Tse, 1998, 2000, which focus on the downside risk. A survey by Adams and Montesi (1995) also points out that the managers care about the variability of losses (e.g. the return below a target value) much more than variability of gains. The variability of losses is normally denominated as the “downside risk” and the variability of gains as “upside potential” (Lee and Rao, 1988). The investors using hedging instrument with the purpose of minimizing the downside risk whilst preserving the upside potential will find the conventional minimum variance hedge strategy inappropriate (lien and Tse, 2000). When an investors try only to avoid the downside risk, Bawa (1975)’s general definition of downside risk—the generalized semivariance (GSV) or Lower Partial Moments (LPM), and Fishburn (1977)’s (α, δ) model are more appropriate. The development of GSV is a milestone in measuring the downside risk. In this case, the optimal hedge ratio is obtained by minimising the GSV the objective function as follows:

$$V_{\delta,\alpha}(X) = \int_{-\infty}^{\delta} (\delta - X)^{\alpha} \, dG(X), \qquad a > 0 \tag{1.17}$$

where $G(X)$ is the probability distribution function of the return on the hedged portfolio. The parameters δ and α are both real numbers, they are used to represent the target return and risk aversion, respectively. The function assumes that investors consider the investment as risky only when return is below the target return. It can be shown (see Fishburn, 1977) that $\alpha < 1$ represents a risk-seeking investor and $\alpha > 1$ represents a risk-averse investor. Again, the Minimum GSV hedge ratio would be the same as the MV hedge ratio if the futures and spot returns are jointly normally distributed and if the futures price follows a pure martingale process, as shown by Lien and Tse (1998).

Correspondingly, the hedge performance is evaluated by calculation the risk reduction of the downside risk, GSV of the hedged portfolio comparing to the unhedge underlying[3].

$$\kappa = 1 - \frac{V_{\delta,\alpha}(H)}{V_{\delta,\alpha}(U)} \tag{1.18}$$

The GSV approach has several advantages as an examination of hedging performances. First, it has been shown by Bawa (1975) that GVS is robust to non-normalitiy. Thus it does not require the assumption of normality in the return distribution. Second, analyzing the hedging performance under GSV criterion may reveal information with respect of the asymmetry of the joint distribution between spot and futures returns for a given asset. Therefore, it overcomes the primary shortcoming of conventional variance based on risk reduction measure of hedging performance which assumes symmetric information. Eftekhari (1998) provides evidence that the lower partial moment (GSV) hedge ratios are effective in reducing downside risk and increasing returns.

1.3.1 g). Minimum Semivariance hedge ratio and risk reduction based on the semivariance

[3] This is the LMP hedging effectiveness criterion in Cotter and Hanly (2006).

Semivariance is defined as the variability of returns below the mean. The minimum semivariance approach[4] is a special case of the minimum GSV hedge ratio, where risk aversion parameter is assumed to be equal to 2, and the target return is set to be the expected return. Thus the objective function to be optimised is:

$$SemiVar = \int_{-\infty}^{\delta} (\delta - X)^2 dG(X), \qquad a > 0 \tag{1.19}$$

Where δ, the target return, is set to be the expected return. As before, the hedge ratio would be same as the MV hedge ratio if the futures and spot returns are jointly normally distributed and the futures price follows a pure martingale process.

The hedging performance is then measured by the reduction in the semivariance of the hedged portfolio to the unhedged position. It is shown as

$$\kappa = 1 - \frac{SemiVar(H)}{SemiVar(U)} \tag{1.20}$$

From the Equation (1.19), we can see that the deviations from the target return $(\delta - X)$ are squared. As a result, if the distribution is symmetric and the target return is set to mean, then the semivariance is just half of the variance. Then the hedging performance evaluated by risk reduction in semivariance will be the same as that evaluated by the risk reduction in variance. However, for a non-symmetric distribution, the results from the two methods are different. The semivariance can address the primary shortcoming of the variance measure when hedging downside risk is more of the concern.

[4] Following the work by Roy (1952), which proposes the safety-first criterion.

1.3.1 h). Optimal generalized semivariance hedge ratio and utility maximisation based on the generalised semivariance

Chen et al. (2001) extend the GSV hedge ratio to a mean-GSV (M-GSV) hedge ratio by considering the mean return in the optimal hedge ratio, which enables incorporating the risk and return trade-off into the GSV strategy. The M-GSV hedge ratio is obtained by maximising the following utility function:

$$U(X) = E(X) - V_{\delta,\alpha}(X) \tag{1.21}$$

Again, the M-GSV hedge ratio would be the same as the MV hedge ratio if the futures prices follow a pure martingale process and returns are jointly normal.

The hedging effectiveness is measured by the magnitude of expected utility based on GSV of the hedged and unhedged positions, using Equation (1.21)

1.3.1 i) VaR hedge ratio and risk reduction based on VaR

In recent years a new approach for determine the hedge ratio has been developed. This approach uses VaR (Value at Risk) as a measure of downside risk. Due to the simplicity of quantitative measurement, VaR emerges as the essential and standard risk management tools of many financial institutions and is widely used for investment decisions, supervisory decisions and capital allocations decisions. Using Jorion (2000)'s definition of VaR as an absolute size of losses associated with the hedging strategy, the downside risk of the hedged portfolio over a period τ and confidence level α as the object function (see, Hung, Chiu and Lee, 2006):

$$\min_{\beta} VaR(X) = Z_a \sigma_X \sqrt{\tau} - E(X)\tau \tag{1.22}$$

Where $VaR(X)$ represent the absolute VaR of the hedged portfolio and Z_α is the left percentile at α for the standard normal distribution. Generally, VaR is the $(100-\alpha)th$ percentile of return distribution of the change in the asset/portfolio over the period τ. Therefore, VaR gives the return that is exceeded with $(100-\alpha)\%$ probability. It is possible, however, that two portfolios with the same VaR will have different potential losses. This is because VaR does not account for the magnitude of losses beyond the $(100-\alpha)th$ percentile. Conditional VaR developed by Tasche (2002) addresses such shortcomings.

The hedge ratio for this kind of VaR approach is (see Chun et al., 2006 for detailed derivation of the hedge ratio):

$$\beta = \rho \frac{\sigma_s}{\sigma_f} - E(f) \frac{\sigma_s}{\sigma_f} \sqrt{\frac{1-\rho^2}{Z_\alpha^2 \sigma_f^2 - E(f)^2}} \tag{1.23}$$

Similarly, the VaR hedge ratio converges to MV hedge ratio if the martingale property of futures holds.

Cotter and Hanly (2006) give the performance measuring criterion as the percentage reduction in VaR, using 1% significant level (or 99% confidence level).

$$\kappa = 1 - \frac{VaR_{1\%}(H)}{VaR_{1\%}(U)} \tag{1.24}$$

1.3.2 Approaches to determine the optimal hedge ratio and hedging evaluation criteria in this study

This study derives the optimal hedge ratios based on three objective functions: the traditional risk minimizing, “expected utility” maximisation and semivariance minimisation[5]. Accordingly, we access the hedging effectiveness of different models used to derive the optimal hedge ratio based on three criteria, namely, risk reduction base on variance (variance reduction), expected utility maximization and risk reduction based on semivariance. The three methods are chosen for the following reasons.

First, the variance reduction criterion is the most widely used in the literature. However, as we discussed before, it has several shortcomings, including that it doesn’t take the expected mean values into consideration and give positive and negative returns equal weight, etc. The other two criteria are employed to address these issues. The expected utility maximization criterion is used to account for the risk and return trade-offs of the hedged portfolio. Meanwhile, because there is a risk aversion

[5] More detailed technical introduction of these is given in next section.

parameter in the expected utility function, this criterion also takes into account investor's risk preference. The minimum semivariance hedge ratio and the risk reduction based on semivariance hedging performance evaluation criterion is employed to address the downside risk for the investor, which is believe to be more crucial. Such approach seems more practical as most investors tend to avoid the downside risk but desire to maintain the upside potential.

Second, as shown in the later sections, our empirical estimates show that the futures prices follow a martingale process. If the futures prices follow a martingale process, that is, the expected futures return is zero, we know that the Sharpe hedge ratio and VaR hedge ratio will be the same as the MV hedge ratio. Therefore, the hedged returns will be the same that derived using Minimum Variance criterion, so will the rankings of different models.

Third, in theory, the Maximum Utility hedge ratio also reduces to MV hedge ratio when the expected value of futures return is zero. However, in this study, we still derive and examine the hedging effectiveness of different hedging strategies using the utility maximisation criterion by incorporating the actual (expected) mean futures returns of the sample being examined. We do so because, although those values are statistically not different from zero, excluding the constant term in the mean equation of the models[6] will make the estimations unable to achieve convergence. Thus we

[6] Different models are described in the next section.

retain the actual intercept value in deriving the hedge ratios under the Utility Maximisation criterion. Because the intercept value is very close to zero, the hedge ratios derived under Utility Maximisation criteria will be only slightly different from those derived under Variance Minimisation criteria, so should be the rankings. Moreover, this approach enables us to examine the effect of the investors' risk aversion on deriving the hedge ratios and choosing hedging strategies.

Forth, although the futures prices follow a martingale process, the spot and futures price series are not jointly normally distributed. MEG and M-MEG hedge ratio, GSV and M-GSV hedge ratio should be different from the MV hedge ratio. However, the hedge ratios under those objective functions cannot be found mathematically, or could be very difficult to calculate because the complexity of the mathematical methods. Most studies on those use approximations. Because of these, we only examine one special case, that is, the semivariance hedge ratio, where MV hedge ratio is used as the proxy. We access the ability of those models in reducing downside risk given the circumstance that hedge ratios are derived with the objective function of minimising variance of the hedged portfolio.

1.4 Data and Methodology

1.4.1 Data

Data for the China fuel oil futures are from Shanghai Futures Exchanges (SFHE). As any futures contract is associated with expiration, it is necessary to construct a continuous series of futures prices. The conventional approach relies upon the prices of the "most nearest to maturity" contracts, because these tend to be the most liquid and therefore the best delegates for the futures market information, except perhaps during the maturity month. However, an examination of the Shanghai futures markets reveals a different story. Peck (2004) finds that the most nearest to maturity futures contract is hardly the most liquid contract in China. It was reported that the most liquid contracts are 4 or 5 months to maturity for copper and 3 or 4 months to maturity for aluminum. For the oil futures, we can determine from the data that the most liquid contracts are 2 to 3 months to maturity. Thus the futures data we used in this study corresponds to daily closing prices of the most active nearby contracts. For the spot prices, we follow the commonly adopted practice in the literature by using the daily closing prices of the corresponding commodity.

We note that there is no standard fuel oil price series in the Chinese market. Guangdong province in Huanan area takes 80% of the fuel oil imports and accounts for 35% of the total oil demand in China, and the Huanan fuel oil market is the most active and closest to a perfectly competitive market in China. Hence we choose Huanan 180CST fuel oil prices (also called Huagpu 180CST) as the underlining spot prices for the Chinese market.

The Platts 180CST industry fuel oil has quality mostly similar to the contracted fuel oil in SHFE. Moreover, it is used as the benchmark of pricing fuel oil prices in Singapore. Thus we use the Platts 180CST fuel oil as the underlying spot in the cross hedging, which is compared with the domestic hedging in assessing the China fuel oil futures. The data for the Huanan (Huangpu) 180CST and Platts 180 CST fuel oil prices series are taken from Heilongjiang Tianqi Futures Exchange [7] (http://www.tqfutures.com). The data begin on August 25, 2004 (the day when the futures started to trade) and end on September 29, 2006[8]. Returns of the futures and spot prices are calculated by computing the first differences in the natural logarithm of price series multiplied by 100. In total, we have 548 observations of which the first 500 (from August 25 2004 to July 25, 2006) observations are used for estimation purposes and the remaining 48 observations (from July 26 to September 06) are used for out-of-sample forecasting.

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[7] An Exchange for commodity futures in China.

[8] Data end on September 2006 because it was the most up-to-date data at the time the research was conducted. In the final revision of the thesis, I attempted to update the data to April 2009, reexamining the hedging effectiveness of China fuel oil futures and comparing the first two years performance with the most recent two years performance. However, data on spot fuel oil prices are no longer available from the source.

1.4.2 Methodology

1.4.2 (A) Estimation of Optimal Hedge Ratios

To derive the time-varying OHRs for China fuel oil futures, we estimate Bi-variate GARCH(1,1) and TGARCH(1,1) models to capture time-varying second moment effects in the joint distribution of spot and futures returns. TGARCH models were used because of the possibility of capturing the measure of any asymmetric information effect. Thus we compare five models, Bi-variate GARCH(1,1) general and diagonal, Bi-variate TGARCH(1,1) general and diagonal and traditional constant models.

The most general representation of the joint distribution of spot and futures returns used can be expressed as (Ford, et al, 2005):

$$y_t = \mu_t + \kappa EC_t + G_t\omega + V_t\zeta + \varepsilon_t; \qquad \varepsilon_t \mid \Omega_{t-1} \sim N(0, H_t) \tag{1.25}$$

Where $y_t = (f_t, s_t)'$ is a vector of observations of the spot and futures returns (log-differenced price series), $\mu_t = (\mu_{st}, \mu_{ft})'$ is a vector of conditional means to be estimated and $\varepsilon_t = (\varepsilon_{ft}, \varepsilon_{st})'$ is a vector of residuals. ω and ζ are column vectors of parameters,; EC is the error correction term from any cointegrating relationship between the two prices; G is a (2×2) diagonal matrix with conditional variance terms from GARCH(1,1) estimation on the diagonal. The term $V\zeta$ represents the possible variables that can determine the returns of spot and futures, multiplied by their parameters. The inclusion of the error correction term is due to the important role that any cointegration between spot and futures prices can play in determining optimal hedge ratios. Ghosh (1993) and Lien (1996) argued that if spot and futures are cointegrated and the resultant error-correction term is not included in the regression, minimum variance hedge ratio estimates are biased downwards due to mis-specification.

We assume that the residuals are normally distributed and are conditional on past information, Ω_{t-1}, with zero mean vector and with conditional variance-covariance matrix:

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon_{t-1}{}'A + B'H_{t-1}B \tag{1.26}$$

Where C, A and B are (2×2) parameter matrices. This is the Bi-variate GARCH(1,1) setting. The conditional variance and covariance matrix H_t is estimated recursively and must be a positive definite matrix for all possible evaluations of $\varepsilon_{i,t-1}$. In addition, the GARCH process must be stationary. Various parameterizations of the multivariate GARCH process have been proposed (see Engle and Bollerslev, 1986). In this study, we adopt the parameterization introduced by Engle and Kroner (1995), henceforce the BEKK representation, which (whereas in H_t in Eq.(1.27)) defines the C matrix to be lower triangular to ensure that the conditional covariance matrix is positive definite. In explicit format, the conditional-variance and covariance matrix H is:

$$H_t = \begin{bmatrix} h_{ff,t} & h_{sf,t} \\ h_{sf,t} & h_{ss,t} \end{bmatrix} = \begin{bmatrix} c_{11} & 0 \\ c_{12} & c_{22} \end{bmatrix} \begin{bmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{bmatrix}$$
$$+ \begin{bmatrix} \alpha_{11} & \alpha_{21} \\ \alpha_{12} & \alpha_{22} \end{bmatrix} \begin{bmatrix} \varepsilon^2_{f,t-1} & \varepsilon_{s,t-1}\varepsilon_{f,t-1} \\ \varepsilon_{f,t-1}\varepsilon_{s,t-1} & \varepsilon^2_{s,t-1} \end{bmatrix} \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix} \tag{1.27}$$
$$+ \begin{bmatrix} \beta_{11} & \beta_{21} \\ \beta_{12} & \beta_{22} \end{bmatrix} \begin{bmatrix} h_{ff,t-1} & h_{sf,t-1} \\ h_{sf,t-1} & h_{ss,t-1} \end{bmatrix} \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix}$$

This system can be estimated with no restrictions on H and is thus referred to here as the general model. The diagonal model proposed by Bollerslev, Engle and Wooldridge (1988) restricts the off-diagonal elements of A and B to be zero, i.e., $H_0 : \alpha_{12} = \alpha_{21} = \beta_{12} = \beta_{21} = 0$. Covariance Stationary of the GARCH(1,1) process requires the eigenvalues of $(A \otimes A + B \otimes B)$ be less than one in modulus[9] (See Engle and Kroner, 1995).

The static or constant model arises when all elements of A and B are set to zero, i.e. $H_0 : \alpha_{11} = \alpha_{22} = \alpha_{12} = \alpha_{21} = \beta_{11} = \beta_{22} = \beta_{12} = \beta_{21} = 0$. The hedge ratio that the static model produces is constant and equivalent to that obtained by using traditional OLS estimations. Diagonal and constant models can be seen as nested models: the constant model is nested in the diagonal model and diagonal in the general. So the competing structures can be evaluated by likelihood ratio test.

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[9] For the Bi-variate GARCH(1,1) model, $H_t = C'C + A'\varepsilon_{t-1}\varepsilon_{t-1}{}' A + B'H_{t-1}B$, hence we have $h_t = vec(H_t) = vec(C'C) + (A \otimes A)vec(\varepsilon_{t-1}\varepsilon_{t-1}^{'}) + (B \otimes B)vec(H_{t-1})$. It follows that the unconditional covariance matrix is $[I - (A \otimes A) - (B \otimes B)]^{-1} vec(C'C)$. For the diagonal model, the stationary condition can be reduced to $a_{ii}^2 + b_{ii}^2 < 1, i = 1, 2$, because the eigenvalues of a diagonal matrix are simply the elements along the diagonal and the conditions detailed imply that all other diagonal elements are also less than 1 in absolute value.

The general and diagonal models of hedging impose symmetry on the responses of volatility to positive or negative shocks. This study also examines the asymmetric effect of oil futures by employing an asymmetric model, the TGARCH specification. El-Khoury (2006) suggests that incorporating the asymmetric effect could improve the hedge effectiveness for the NYMEX's Light Sweet Crude Oil contract. We examine if this is the case in the Chinese oil market. The asymmetric general model (TGARCH General) differs from the symmetric general Bi-variate GARCH approach in that the covariance matrix Eq. (1.26) is replaced by :

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon_{t-1}{}'A + B'H_{t-1}B + D'\eta_{t-1}\eta_{t-1}{}'D \tag{1.28}$$

Where D is a (2×2) matrix of coefficients, and η_t is the additional quadratic form of the vector of *negative return shocks*, defined as $\varepsilon_{t-1}I_{t-1}$, where $I_t = 1$ if $\varepsilon_t < 0$ and 0 otherwise. The inclusion of η_t in the conditional variance-covariance matrix not only accounts for any asymmetry effects in the conditional variances but also allows for possible asymmetric effects in the conditional covariance. The TGARCH Diagonal model restricts the off-diagonal elements of matrix A, B, D to be zero. The constant model restricts all elements in matrices A, B and D to be zero. The stationarity of the TGARCH(1,1) process requires that the eigenvalues of $(A\otimes A + B\otimes B + D\otimes D)$ be less than one in modulus.

All these models are estimated through maximum likelihood. Under conditional normality, the log likelihood function is as follow:

$$L(\Theta) = -T\log(2\pi) - \frac{1}{2}\sum_{t=1}^{T}(\log\left|H_t(\Theta)\right| - \varepsilon_t(\Theta)H_t^{-1}(\Theta)\varepsilon_t{}'(\Theta)) \tag{1.29}$$

Where T is the number of observations of the sample. Θ is the parameter vector to be estimated. $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t})$ is a 1x2 vector of residuals at time t. $H_t = \mathrm{cov}(\varepsilon_t | \Omega_{t-1})$, where the diagonal elements of H_t are the conditional variances, the cross diagonal elements are the conditional covariances of the spot and futures returns. The log-likelihood function is maximised subject to the constraint that the conditional variances be positive. Initial values are required for all the parameters and those found from the univariate GARCH regressions are used for this purpose. For those parameters for which the initial guesses cannot be obtained from the univariate GARCH estimations, we used a value 0.05 for all parameters in most of the cases.

1.4.2 (B) Accessing hedging effectiveness in- and out-of-sample

This study derives the optimal hedge ratios based on three objective functions: the traditional variance minimisation, the "expected utility" maximisation and the semivariance minimisation[10]. Accordingly, we access the hedging effectiveness of different models used to derive the optimal hedge ratio based on three criteria, namely, risk reduction base on variance (variance reduction), expected utility maximisation and risk reduction based on semivariance (semivariance reduction).

[10] More detailed technical introduction of these is given in the previous section.

For the variance minimisation criterion, the MV hedge ratio, β_{t-1}^{*} will be:

(1) for the constant model

$$\beta^{*} = \frac{Cov(s, f)}{Var(f)} \tag{1.30}$$

(2) for the dynamic model

$$\beta^{*} = \frac{Cov(s_t, f_t \mid \Omega_{t-1})}{Var(f_t \mid \Omega_{t-1})} = \frac{\hat{h}_{sf,t}}{\hat{h}_{f,t}} \tag{1.31}$$

where $\hat{h}_t$ is the conditional variance estimated at time *t-1*.

For the "expected utility" maximisation criterion, we use the mean-variance representation of expected utility following Kroner and Sultan (1993). As a result, the objective functions to be maximised to obtain the optimal hedge ratios are:

(1) for a constant model

$$E_t U(R_t) = E_t(R_t) - \gamma Var(R_t) \tag{1.32}$$

(2) for the dynamic models

$$E_t U(R_t \mid \Omega_{t-1}) = E_t(R_t \mid \Omega_{t-1}) - \gamma Var(R_t \mid \Omega_{t-1}) \tag{1.33}$$

Where $R_t = s_t - \beta_{t-1}^{*} f_t$, is the return of the hedged portfolio, and γ is the coefficient of risk aversion. Thus the utility maximisation distinguishes investors who may have different risk preferences.

The maximisation of expected utility gives the β_{t-1}^{*} as below:

(1)for the constant model

$$\beta^{*} = \frac{Cov(s, f)}{Var(f)} - \frac{1}{2\gamma}\frac{E(f)}{Var(f)} \tag{1.34}$$

(2) for the dynamic model:

$$\beta* = \frac{Cov(s_t, f_t \mid \Omega_{t-1})}{Var(f_t \mid \Omega_{t-1})} - \frac{1}{2\gamma}\frac{E(f_t \mid \Omega_{t-1})}{Var(f_t \mid \Omega_{t-1})} \tag{1.35}$$

There is an additional term in the β^*_{t-1} comparing to MV OHRs, which describes the speculative demand for futures which reflect the mean and variance trade-off in the unhedged futures positions as well as the investors' attitude toward risk.

To derive the optimal hedge ratio under semivariance minimisation objective, the optimisation of the econometric models should be based on semivariance instead of variance as we did for the MV hedge ratios. The semivariance assumes that the positive and negative returns distribute asymmetrically. If the returns are symmetric, there will be no difference between minimising semivariance and minimising variance because semivariance is just half of the variance. However, when the residuals are not normally distributed, the use of maximum likelihood to estimate the GARCH and constant models is not appropriate. Under such circumstance, derivation of the optimal hedge ratios under the semivariance minimisation criterion is impossible or can only be done by incorporating very complex methods[11]. As a result, most recent literatures use the MV hedge ratio to approximate the semivariance hedge ratio (e.g. Cotter and Hanly, 2005, 2006). Therefore, we also use MV hedge ratios as an approximation and based on these ratios, we examine the hedging performance of

[11] For example, kernel density estimation method was used by Lien and Tse (2000), conditional heteroscedastic model was employed by Lien and Tse (1998) to estimate the optimal hedge ratios.

those competing models in reducing the downside risk.

Hedging effectiveness of different models is examined in both in- and out-of-sample periods. The traditional approach measures the hedging as the percentage reduction in the variance of the hedged position in comparison to the unhedged position (Ederington, 1979), following the work of Working (1953, 1962), Johnson (1960) and Stein (1961). The hedge effectiveness (κ) is measured using the formula:

$$\kappa = \frac{Var(H) - Var(U)}{Var(U)} \tag{1.36}$$

Where $Var(U) = Var(s_t)$, and $Var(H) = Var(s_t - \beta^*_{t-1} f_t)$.

The variance reduction is on an average basis over the whole of the in-sample and out-of-sample period and at each day during that latter period. The model that records the highest percentage variance reduction would be the one considered to be the most effective. Unlike most of the existing literatures, we also include equality tests for the means and variances of the hedged portfolio to see if there is any significant change in means and variances of the hedged portfolio derived from different hedging models, following Ford et al. (2005).

The expected utility comparisons in assessing the model performance for both in- and out-of-sample hedging strategies are based on the values of obtained from using Eq. (1.32) and (1.33). In terms of expected utility the comparison is based on the average of expected utility values over of the forecast period and also on the time path of expected utility values over each day of the forecast period. The higher value of expected utility the model can generate the superior the model is relative to other models. Equality tests for the means and variances of the hedged portfolio under risk minimisation criterion are employed as well.

The risk reduction based on the semivariance is accessed using the following equation:

$$\kappa = \frac{SemiVar(H) - SemiVar(U)}{SemiVar(U)} \tag{1.37}$$

Where $SemiVar(U) = SemiVar(s_t)$, and $SemiVar(H) = SemiVar(s_t - \beta^*_{t-1} f_t)$.

Same to the variance reduction criterion, we access the semivariance risk reduction based on both average and time path of the forecast period, and the model that records the highest percentage semivariance reduction would be the one considered to be the most effective.

One important issue in accessing the hedging performance is the computation of hedging ratios in the out-of-sample period. Unlike the in-sample hedge ratios which are calculated from the conditional variance and covariance, the computation of the out-of-sample hedge ratios is more complicated. The latter are computed based on the parameters obtained from the in-sample estimation for the out-of-sample period to up-date H_t continuously. Therefore, the out-of-sample hedge ratios are based on all information that is available at the time each hedging decision is made. The information set Ω_{t-1} contains the history of spot and futures rates of returns to the given current time during the forecast period. The predicted hedged portfolio returns are then obtained based on the calculated hedge ratios to forecast the following day return of the hedged portfolio.

1.5 Estimation results

1.5.1 Descriptive Statistics

Table 1.1 reports some basic statistics for daily returns for the China fuel oil futures returns (denoted as RF), China Huanan fuel oil spot returns (denoted as RS) and Singapore Platt's fuel oil price returns (denoted as RSX). Returns are calculated as the difference of the nature logarithms of the closing prices multiplied by 100.

Table 1. 1Descriptive Statistics of return series of Futures and Spot returns

	RF	RS	RSX
Mean	0.054093	0.068074	0.065437
Median	0.091827	0.000000	0.000000
Maximum	4.222263	7.020426	8.318446
Minimum	-5.016596	-5.706072	-11.21173
Std. Dev.	1.422809	1.194955	1.931239
Skewness	-0.207686	0.255625	-0.637181
Kurtosis	4.149266	8.654918	8.361978
Jarque-Bera	34.03585	734.7913	692.2925
Probability	0.000000	0.000000	0.000000
$Q(5)$	11.741**	6.169	6.7104
$Q^2(5)$	22.774***	16.819***	16.923***
ARCH-LM	13.3119**	15.0571**	15.98175***

Note: $Q(5)$ and $Q^2(5)$ denote the Ljung-Box Q statistics for the test of significance of autocorrelations up to 5th order in return and squared returns series respectively. *, **, *** denote statistical significance at the 10%,5% and 1% level.

From Table 1.1, we can observe that the mean returns of the futures are lower than that of the spot returns in both of the Chinese and Singapore markets. However, the standard deviation for the futures returns is larger than the standard deviation of spot returns in the Chinese market, which is smaller than that in the Singapore market. This may due to the fact that trading in The Singapore market is more active. Skewness[12], kurtosis[13] and thus Jacque Bera (JB) statistics[14] for all three series are significant, so rejecting the null hypothesis of normal distributions. Kurtosis for the spot returns is much higher than for the futures return, so that the spot returns have more peakedness. The Ljung-Box (1987) Q(5) statistics for the futures return series is significant but not for the two spot return series; while Q(5) statistics for the squared return series are mostly significant, which indicate that although autocorrelation in returns series is not strong, it is strong for the squared returns. Thus, the second moments of returns are time varying and changing in a predictable fashion. This kind of volatility clustering —large changes tend to be followed by large changes, of either sign, and small changes tend to be followed by small changes, of either sign—can be observed in Figure 1.1. In sum, the return series in this study exhibit all the typical characteristics of high frequency financial return series: skewness, leptokurtosis, and highly significant linear and nonlinear serial correlations. Moreover, the significance of the ARCH-LM test (Engle, 1982) statistics also suggests that an ARCH/GARCH type model is an appropriate specification.

[12] Skewness is a measure of asymmetry of the distribution of the series around its mean; the skewness of a symmetric distribution, such as the normal distribution, is zero.
[13] Kurtosis measures the peakedness or flatness of the distribution of the series, in other words, how fat the tails of the distribution are. The kurtosis of the normal distribution is 3.
[14] A JB statistic for a normal distribution is 0, which indicates that the distribution has a skewness of 0 and a kurtosis of 3. Skewness values other than 0 and a kurtosis values farther away from 3 lead to increasingly large JB values. And the Critical value for normal distribution at 5%level is 5.99.

The correlations of the three returns are reported in Table 1.2. We can observe that those of China's fuel oil futures are more related to the spot prices changes in the Singapore market. The price in the Chinese market is largely influenced by the price changes in the Singapore market.

Table 1. 2 Correlations between RF, RS and RSX

	RF	RS	RSX
RF	1.000000	0.355813	0.467944
RS	0.355813	1.000000	0.324992
RSX	0.467944	0.324992	1.000000

1.5.2 Diagnostic checks on the distributional properties

As discussed in the previous section that the presence of a cointegrating relationship between spot and futures prices will produce downwardly biased hedge ratios unless an error correction term is incorporated into the mean equation. Also for an adequate estimation with Bi-variate GARCH we need to ensure that the components variables (the mean returns) are stationary. Thus unit root tests are necessary. In this study, we conduct both the Augmented Dickey-Fuller (ADF) and Kwiatkowski, Phillips, Schmidt and Shin (KPSS) tests to test for stationary in the natural logarithm of prices series and also in the return series. The null hypothesis for the ADF test is that the series has a unit root; while the null hypothesis for KPSS is that the series is stationary. The test results are reported in Table 1.3.

Table 1. 3 Unit root test

(1) Unit Root test for the level series (log of the prices series)						
	LF		LS		LSX	
	ADF	KPSS	ADF	KPSS	ADF	KPSS
intercept						
Lag 1	-1.31614	24.69540*	-1.57216	23.88512*	-1.67102	22.84567*
Lag 2	-1.34791	16.48799*	-1.60328	15.95067*	-1.65577	15.2699*
Lag 3	-1.37309	12.38246*	-1.60734	11.98272*	-1.65825	11.48018*
Lag 4	-1.42362	9.918913*	-1.60901	9.601885*	-1.71471	9.205771*
Lag 5	-1.39602	8.276574*	-1.61353	8.01461*	-1.65381	7.689283*
Trend and intercept						
Lag 1	-0.28649	2.934404*	-0.51119	3.505677*	-1.48543	3.543713*
Lag 2	-0.02025	1.975631*	-0.68915	2.354065*	-1.44472	2.386529*
Lag 3	-0.32942	1.495056*	-0.7394	1.777943*	-1.43759	1.80712*
Lag 4	-0.29891	1.206754*	-0.54393	1.432338*	-1.35666	1.459327*
Lag 5	-0.15025	1.014756*	-0.50723	1.201965*	-1.02593	1.227515*

(2) Unit Root test for the Return series (log differences of the prices series)						
	RF		RS		RSX	
	ADF	KPSS	ADF	KPSS	ADF	KPSS
None						
Lag 1	-18.21708*	-	-14.98325*	-	-16.44549*	-
Lag 2	-13.10897*	-	-12.32162*	-	-13.44293*	-
Lag 3	-11.34618*	-	-11.51614*	-	-11.91796*	-
Lag 4	-10.5497*	-	-10.36032*	-	-11.69414*	-
Lag 5	-10.0398*	-	-9.341099*	-	-11.32247*	-
intercept						
Lag 1	-18.25134*	0.28769	-15.03655*	0.340917	-16.45982*	0.170777
Lag 2	-13.14702*	0.30941	-12.3811*	0.322044	-13.46278*	0.170692
Lag 3	-11.39320*	0.30395	-11.58804*	0.309994	-11.94648*	0.171005
Lag 4	-10.60281*	0.30204	-10.44012*	0.308774	-11.73007*	0.172901
Lag 5	-10.09977*	0.30635	-9.42671*	0.309055	-11.36721*	0.180307

Note: Critical value (for 5% significance) for ADF test: with intercept, - 2.865; with trend and intercept, -3.417.

Critical value (for 5% significance) for KPSS test : with intercept, 0.463, with intercept and trend, 0.146.

Here * indicate rejection of null hypothesis at 5% significance level.

Figure 1.2 portrays the three log price series (LF, LS and LSX represent the log of China fuel oil futures, China fuel oil and Singapore fuel oil spot price series). We can observe that all the series are upward slopping. Thus the units root tests with intercept and trend for the log price series. Results from both the ADF test and the KPSS test reveal that all of the three price series are non-stationary at 5% significant level. For the return series, we can observe from the figure there is no intercept or trend in the series. Hence we only perform unit roots test with "none" as well as "with intercept". ADF test results for all three series reject the null hypothesis of non-stationarity, and the KPSS test results show the null hypothesis of stationary should not be rejected at 5% significant level. As the return series is the first difference of log prices series, the above results indicate that the log futures and spot price series are all following an I(1) process. We then adopt Johanson's cointegration test (1991, 1995) to test whether the cointegration relationships between futures and spot prices exists. The results are reported in Table 1.4.

As shown in Table 1.4, both the Trace and Max-eigenvalue tests indicate that there is no cointegrating relationship between the fuel oil futures and China fuel oil spot prices. While for China fuel oil futures and spot prices in the Singapore market, both the Trace and Max-eigenvalue tests indicate there exists one cointegrating relationship. However, we have to cast doubt on such. Cointegration states the long run co-movements of two series, but we have only two years data available. The time span is too short for us to draw any meaningful conclusions from the tests. Moreover, we cannot find consistent cointegration vectors because the residuals are not normally distributed, although in most cases we find that the coefficient on the futures return in the first cointegration vector was 1 or nearly 1, which is approximately the value in theory. When we assumed that such a cointegration relation exists and used an error correction term composed as the difference between the one period lag of the two prices in the regression for the hedging in the Singapore market, we found that it did not have a statistically significant impact on the returns. Additionally, the inclusion of the error correction term made it impossible to obtain estimates of the parameters of H_t sometimes; or making the system singular or non-convergent. Consequently, no results from using an error correction term are reported here.

Table 1. 4 Johanson's cointegration test

(1) Cointegration test for China fuel oil futures prices and China Huanan fuel oil spot prices

Hypothesized	Trace Test		Max-Eigen	
No. of CE(s)	Statistic	Prob.	Statistic	Prob.
None	14.79088	0.0636	12.40089	0.0965
At most 1	2.389989	0.1221	2.389989	0.1221

(2) Cointegration test for China fuel oil futures prices and Singapore fuel oil spot prices

Hypothesized	Trace Test		Max-Eigen	
No. of CE(s)	Statistic	Prob.	Statistic	Prob.
None	26.94548*	0.0006	24.46388*	0.0009
At most 1	2.481599	0.1152	2.481599	0.1152

Note: * denotes rejection of the hypothesis at the 0.05 level

1.5.3 Models Estimation Results

We investigate the hedging ability of China fuel oil futures when it is used to hedge spot positions in the domestic and Singapore markets. We employ different models with different variance specifications (TGARCH-General, TGARCH-Diagonal, GARCH-General, GARCH-Diagonal and constant model) in order to unveil the most appropriate one for deriving the optimum hedging ratios.

Numerous variations of the models were experimented with, for a given structure of H_t, in respect of the specification of each of the mean equations. We found that, for both the Bi-variate GARCH(1,1) and TGARCH(1,1) models, the most minimal specifications with random means were generally the most acceptable, statistically speaking. Such is consistent with Ford et al. (2005). Thus the estimation results we report here are for GARCH and TGARCH models with the mean structure containing only intercepts. A further point that might need highlighting is the estimation of GARCH and TGARCH structure. Engle and Kroner (1995) suggest that the BHHH (Berndt, Hall, Hall and Hausman, 1974) optimization algorithm[15] might be the most appropriate for estimation of multivariate GARCH models. However, Ford et al (2005)

[15] The BHHH algorithm follows Newton-Raphson, but replaces the negative of the Hessian by an approximation formed from the sum of the outer product of the gradient vectors for each observation's contribution to the objective function. The advantages of approximating the negative Hessian by the outer product of the gradient are that (1) we need to evaluate only the first derivatives, and (2) the outer product is necessarily positive semi-definite. The disadvantage is that, away from the maximum, this approximation may provide a poor guide to the overall shape of the function, so that more iterations may be needed for convergence.

point out that the Marquardt algorithm[16] provided estimates that were identical to or better than those obtained from the use of BHHH. Our experiments confirm those findings.

The maximum likelihood estimation results for the hedging-ability of the China fuel oil futures in hedging a domestic spot position are reported in Table 1.5 and the estimation results for hedging a spot position in the Singapore market are reported in Table 1.6.

First, consider the mean structure for futures and spot returns. From Tables 1.5 and 1.6, we observe that the estimated mean of futures returns μ_f are not significantly different from zero at 5% significant level for all the models. The expected means for Chinese fuel oil spot returns and Singapore fuel oil commodity returns are insignificantly different from zero as well. Comparing the two tables, we find that the estimated mean spot returns in the Chinese market are smaller than those in the Singapore market. Although the estimation results suggest that the futures returns are not significantly different from zero at a 5% significance level and therefore the futures prices follows a martingale process, we cannot estimate the dynamic GARCH models with the mean equations being just dependent upon white noise, because convergence were not able to be achieve; or even when convergence was ensured, the

[16] The Marquart algorithm modifies the Gauss-Newton algorithm in exactly the same manner as quadratic hill climbing modifies the Newton-Raphson method by adding a correction matrix (or ridge factor) to the Hessian approximation. The ridge correction handles numerical problems when the outer product is near singular and may improve the convergence rate. The algorithm pushes the updated parameter values in the direction of the gradient.

covariance stationary of the GARCH structures were violated. However, including those intercept variables will make the coefficients in A, B, and C matrix changed slightly[17]. Thus in calculating the utility maximisation hedge ratios, the actual expected value is used instead of zero, which make the hedge ratios slightly differ from the MV hedge ratios, so as the ranking of different models.

Now we turn to the covariance structure for the domestic and cross border hedging. From Table 1.5 (a) we can observe that for the TGARCH(1,1) general and diagonal models, all the estimated coefficients d_{ij}, which capture the asymmetric effects (positive and negative shocks increase the variances by different magnitudes) are insignificant at 95% significant level. We further perform the Wald exclusion tests for the asymmetric coefficients. The test result (5.0008 with p-value equal 0.2872) cannot reject the null hypothesis that these coefficients are jointly zero, implying that markets react to positive and negative shocks in a similar manner. Such results diverge from those in the existing literature on the asymmetric effects in equity returns, most of which indicate the negative shocks have greater and longer effects than positive shocks. For the general models and diagonal models reported in Table 1.5(b), we observe most parameters are significant, implying that the distribution of spot and futures variances and covariances are time-varying. For the constant model, all the coefficients are significant at a 5% significance level. The Ljung-Box Q-statistics for residuals and squared residuals in their normalised form are calculated to test the

[17] Not their significance, but values.

Table 1. 5 Maximum Likelihood Estimation for the China fuel oil futures when used for hedging the spot position in the domestic market.

(A) TGARCH(1,1) and constant model

	TGARCH-General			TGARCH-Diagonal			Constant		
	Coeff.	Std. Err	T-stat	Coeff.	Std. Err	T-stat	Coeff.	Std.Err	T-stat
Mean Structure									
μ_f	0.0797	0.0577	1.3815	0.1001	0.0585	1.7122	0.1056	0.0618	1.7093
μ_s	0.0835	0.0555	1.5064	0.0920	0.0515	1.7869	0.1024	0.0542	1.8882
Covariance Structure									
c_{11}	0.4254**	0.1228	3.4648	0.3631**	0.0623	5.8329	1.3758**	0.0347	39.6115
c_{21}	0.8486**	0.2030	4.1803	0.1351**	0.0254	5.3200	0.4266**	0.0446	9.5681
c_{22}	0.3794	0.3834	0.9897	0.1016	0.0647	1.5697	1.1177**	0.0202	55.2120
a_{11}	0.2709**	0.0932	2.9067	0.4229**	0.0473	8.9330	-	-	-
a_{12}	-0.4993**	0.0452	-11.0503	-	-	-	-	-	-
a_{21}	0.0191	0.0600	0.3177	-	-	-	-	-	-
a_{22}	0.2261**	0.0681	3.3226	0.1190**	0.0160	7.4365	-	-	-
b_{11}	0.9530**	0.0312	30.5633	0.8795**	0.0216	40.7860	-	-	-
b_{12}	0.2070**	0.0603	3.4351	-	-	-	-	-	-
b_{21}	-0.1704	0.1739	-0.9803	-	-	-	-	-	-
b_{22}	0.1652	0.1317	1.2546	0.9815**	0.0068	144.74	-	-	-
d_{11}	0.0340	0.4621	0.0737	0.0018	14.6257	0.0001	-	-	-
d_{12}	0.0394	0.3619	0.1088	-	-	-	-	-	-
d_{21}	0.0385	0.2688	0.1431	-	-	-	-	-	-
d_{22}	0.1671	0.2000	0.8355	0.0016	3.6078	0.0004	-	-	-
Ljung-Box Statistics									
Futures	Q-statistic	P-value		Q-statistic	P-value		Q-statistic	P-value	
$Q_S(15)$	13.8620	0.5360		14.1960	0.5110		20.7910	0.1440	
$Q_s^2(15)$	11.4540	0.7200		7.7706	0.9330		42.5820	0.0000	
Spot	Q-statistic	P-value		Q-statistic	P-value		Q-statistic	P-value	
$Q_S(15)$	18.8230	0.2220		15.4540	0.4190		19.0200	0.2130	
$Q_s^2(15)$	12.0410	0.6760		13.0010	0.6020		28.6650	0.0180	
LF	-1567.73			-1581.36			-1627.58		
LR				27.2520			92.4460		

Covariance Stationary tests

TGARCH-General Model: Eigenvalues: 0.9701; 0.0890; 0.2111 and 0.2677

TGARCH-Diagonal Model: Eigenvalues: 0.9136; 0.9136; 0.9524 and 0.9775

Note: ** represents significant at 5% significant level. The critical values for T-test is 1.96.

Log-likelihood and likelihood ratio test statistics of the restrictions denoted as LF and LR respectively. LR statistics reported here test the general against diagonal and diagonal against constant. LR is distributed as Chi-square (χ^2) with degrees of freedom equal to the number of restrictions. The critical value for $\chi^2(6)$ at 5% significant level is 12.59.

(B) GARCH(1,1) and constant model

	GARCH-General			GARCH-Diagonal			Constant		
	Coeff.	Std.Err	T-stat	Coeff.	Std. Err	T-stat	Coeff.	Std.Err	T-stat
Mean Structure									
μ_f	0.0797	0.0567	1.4045	0.0908	0.0576	1.5780	0.1056	0.0618	1.7093
μ_s	0.0770	0.0530	1.4541	0.0840	0.0518	1.6220	0.1024	0.0542	1.8882
Covariance Structure									
c_{11}	0.4106**	0.1347	3.0484	0.3542**	0.0576	6.1447	1.3758**	0.0347	39.6115
c_{21}	0.9185**	0.2587	3.5507	0.1608**	0.0233	6.8960	0.4266**	0.0446	9.5681
c_{22}	-0.2521	0.8338	-0.3024	0.0004	13.2148	0.0000	1.1177**	0.0202	55.2120
a_{11}	-0.2834**	0.0811	-3.4947	0.4331**	0.0394	10.9838	-	-	-
a_{12}	0.4899**	0.0400	12.2316	-	-	-	-	-	-
a_{21}	-0.0059	0.0532	-0.1111	-	-	-	-	-	-
a_{22}	-0.2037**	0.0553	-3.6845	0.1455**	0.0140	10.4178	-	-	-
b_{11}	0.9485**	0.0299	31.7405	0.8810**	0.0189	46.5407	-	-	-
b_{12}	0.1993**	0.0601	3.3144	-	-	-	-	-	-
b_{21}	-0.1368	0.1635	-0.8368	-	-	-	-	-	-
b_{22}	0.1676	0.1388	1.2076	0.9802**	0.0049	200.6259	-	-	-
Ljung-Box Statistics									
Futures	Q-statistic	P-value		Q-statistic	P-value		Q-statistic	P-value	
$Q_S(15)$	13.7620	0.5440		14.0740	0.5200		20.7910	0.1440	
$Q_s^2(15)$	11.6220	0.7070		7.6953	0.9350		42.5820	0.0000	
Spot	Q-statistic	P-value		Q-statistic	P-value		Q-statistic	P-value	
$Q_S(15)$	18.8660	0.2200		14.8890	0.4590		19.0200	0.2130	
$Q_s^2(15)$	13.2140	0.5860		10.4490	0.7910		28.6650	0.0180	
LF	-1570.98			-1583.80			-1627.58		
LR				25.65			87.5560		

Covariance Stationary tests

TGARCH-General Model: Eigenvalues: 0.9714; 0.2095; 0.0553 and 0.2469

TGARCH-Diagonal Model: Eigenvalues: 0.9265; 0.9334; 0.9637 and 0.9896

Note: ** represents significant at 5% significant level. The critical values for T-test is 1.96 at 5% significant level.

Log-likelihood and likelihood ratio test statistics of the restrictions denoted as LF and LR respectively. LR statistics reported here test the general against diagonal and diagonal against constant. LR is distributed as Chi-square (χ^2) with degrees of freedom equal to the number of restrictions. The critical value for $\chi^2(6)$ at 5% significant level is 12.59.

Table 1. 6 Maximum Likelihood Estimation for the China fuel oil futures when used for hedging the spot position in the Singapore market.

(A) TGARCH(1,1) and constant models

	TGARCH-General			TGARCH-Diagonal			Constant		
	Coeff.	Std. Err	T-stat	Coeff.	Std. Err	T-stat	Coeff.	Std. Err	T-stat
Mean Structure									
μ_f	0.0948	0.0621	1.5273	0.1047	0.0603	1.7351	0.1056	0.0620	1.7031
μ_s	0.0957	0.0902	1.0620	0.0991	0.0823	1.2039	0.1131	0.0885	1.2780
covariance Structure									
c_{11}	0.3443**	0.0543	6.3439	0.4903**	0.0643	7.6225	1.3758**	0.0353	39.0293
c_{21}	-0.0215	0.0898	-0.2390	0.2363**	0.0424	5.5768	0.8873**	0.0777	11.4133
c_{22}	-0.0004	74.510	0.0000	0.2206**	0.0684	3.2250	1.6986**	0.0306	55.5574
a_{11}	0.3217**	0.0492	6.5373	0.3788**	0.0492	7.7016	-	-	-
a_{12}	-0.1367**	0.0442	-3.0924	-	-	-	-	-	-
a_{21}	-0.0164	0.0334	-0.4927	-	-	-	-	-	-
a_{22}	0.2738**	0.0396	6.9223	0.2716**	0.0270	10.0455	-	-	-
b_{11}	0.9211**	0.0229	40.1847	0.8571**	0.0302	28.3655	-	-	-
b_{12}	0.1061**	0.0247	4.2935	-	-	-	-	-	-
b_{21}	-0.0059	0.0132	-0.4481	-	-	-	-	-	-
b_{22}	0.9336**	0.0155	60.4149	0.9499**	0.0094	101.2110	-	-	-
d_{11}	-0.0722	0.2988	-0.2418	-0.0951	0.1884	-0.5049	-	-	-
d_{12}	0.0001	0.2672	0.0004	-	-	-	-	-	-
d_{21}	0.0174	0.1445	0.1202	-	-	-	-	-	-
d_{22}	0.0678	0.1897	0.3575	0.0438	0.1320	0.3313	-	-	-
Ljung-Box Statistics									
Futures	Q-statistic	P-value		Q-statistic	P-value		Q-statistic	P-value	
$Q_S(15)$	14.5010	0.4880		15.1510	0.4410		20.7910	0.1440	
$Q^2_s(15)$	9.2718	0.8630		9.2723	0.8630		42.5820	0.0000	
Spot	Q-statistic	P-value		Q-statistic	P-value		Q-statistic	P-value	
$Q_S(15)$	23.6210	0.0720		15.3200	0.1210		28.5480	0.0180	
$Q^2_s(15)$	5.0264	0.9920		4.7467	0.9940		38.2260	0.0010	
LF	-1776.00			-1779.36			-1836.00		
LR				6.7100			113.2760		

Covariance Stationary tests

TGARCH-General Model: Eigenvalues: 0.9468±0.0685i; 0.9593 and 0.9419

TGARCH-Diagonal Model: Eigenvalues: 0.8871; 0.9128; 0.9593 and 0.9780

Note: ** represents significant at 5% significant level. The critical values for T-test is 1.96 at 5% significant level..

Log-likelihood and likelihood ratio test statistics of the restrictions denoted as LF and LR respectively. LR statistics reported here test the general against diagonal and diagonal against constant. LR is distributed as Chi-square (χ^2) with degrees of freedom equal to the number of restrictions. The critical value for $\chi^2(6)$ at 5% significant level is 12.59.

(B) GARCH(1,1) and constant models.

	GARCH-General			GARCH-Diagonal			Constant		
	Coeff.	Std. Err	T-stat	Coeff.	Std. Err	T-stat	Coeff.	Std. Err	T-stat
Mean Structure									
μ_f	0.0963	0.0611	1.5775	0.1044	0.0594	1.7584	0.1056	0.0620	1.7031
μ_s	0.0926	0.0831	1.1141	0.0990	0.0802	1.2346	0.1131	0.0885	1.2780
Covariance Structure									
c_{11}	0.4172**	0.0619	6.7410	0.4882**	0.0632	7.7221	1.3758**	0.0353	39.0293
c_{21}	0.0273	0.0941	0.2906	0.2256**	0.0401	5.6272	0.8873**	0.0777	11.4133
c_{22}	0.0006	53.6582	0.0000	0.2317**	0.0602	3.8488	1.6986**	0.0306	55.5574
a_{11}	0.3584**	0.0496	7.2192	0.3820**	0.0401	9.5229	–	–	–
a_{12}	-0.1396**	0.0444	-3.1419	–	–	–	–	–	–
a_{21}	-0.0241	0.0359	-0.6710	–	–	–	–	–	–
a_{22}	0.2917**	0.0406	7.1913	0.2756**	0.0251	10.9872	–	–	–
b_{11}	0.8910**	0.0289	30.7886	0.8589**	0.0292	29.4055	–	–	–
b_{12}	0.1039**	0.0282	3.6771	–	–	–	–	–	–
b_{21}	-0.0001	0.0146	-0.0044	–	–	–	–	–	–
b_{22}	0.9327**	0.0154	60.6049	0.9496**	0.0088	108.5054	–	–	–
Ljung-Box Statistics									
Futures	Q-statistic	P-value		Q-statistic	P-value		Q-statistic	P-value	
$Q_S(15)$	14.7880	0.4670		15.1150	0.4430		20.7910	0.1440	
$Q_s^2(15)$	8.4913	0.9030		9.0493	0.8750		42.5820	0.0000	
Spot	Q-statistic	P-value		Q-statistic	P-value		Q-statistic	P-value	
$Q_S(15)$	23.5990	0.0720		23.2980	0.0780		28.5480	0.0180	
$Q_s^2(15)$	4.8186	0.9940		4.7225	0.9940		38.2260	0.0010	
LF	-1776.12			-1779.55			-1836.00		
LR				6.8520			112.8980		

Covariance Stationary tests

General Model: Eigenvalues: 0.9366±0.0356i; 0.9429 and 0.9321

Diagonal Model: Eigenvalues: 0.8837; 0.9209; 0.9209 and 0.9777

Note: ** represents significant at 5% significant level. The critical values for T-test is 1.96 at 5% significant level.

Log-likelihood and likelihood ratio test statistics of the restrictions denoted as LF and LR respectively. LR statistics reported here test the general against diagonal and diagonal against constant. LR is distributed as Chi-square (χ^2) with degrees of freedom equal to the number of restrictions. The critical value for $\chi^2(6)$ at 5% significant level is 12.59.

robustness of these models. We can observe that for the all dynamic models, Q-statistics for up to 15 lags are insignificant, for both level and squared normalised residuals, which suggest that the dynamic models can effectively remove the serial correlations both in levels and in their second movements. However, the Q-statistics for the constant models are significant, which implies that constant specification cannot remove the serial correlation in these series; heteroscedasticity still remains in the residuals. Consequently, we can conclude the dynamic models are more robust than the constant models and the optimal hedge ratios are indeed time-varying. The likelihood ratio (LR) tests are employed to test the general specifications against the diagonal and the diagonal against the constant. LR statistics are given at the bottom of Table 1.5 and also summarized in Table 1.7. The statistics suggest that the general models dominate diagonal models and the diagonal models dominate the constant model. The GARCH General model seems to be the most appropriate and should be accepted. Covariance stationary tests of these dynamic GARCH models are also provided. We can observe that for each modelling specifications all the eigenvalues have modulus less than 1, which indicate stationary in covariance.

For the covariance structure of the futures returns and spot returns in the Singapore market (shown in Table 1.6), we find similar results. For the asymmetric models, all the coefficients (d_{ij}) capturing asymmetric effects are insignificantly different from zero. For the coefficient matrix A (a_{ij}) and coefficient matrix B(b_{ij}), most of their components are significant under the dynamic modelling specifications, which provide strong support for the claim that the variances and covariances are time varying and conditional on past information. For the constant models, all the parameters are significant at the 5% level. However, the constant models are not robust because there are serial correlations in the residual series as well as in the second moment of the residuals, as shown by the Ljung-Box Q statistics. The Q statistics also show that the dynamic models remove all the serial correlations and heteroscedasticity in the return series and thus are robust. The Likelihood ratio test for model restrictions are provided at the bottom of the table and also summarized in Table 1.7. According to the LR values for joint restrictions between different models reported in Table 1.7, we see that the LR statistics is not significant for the TGARCH General model to be nested to TGARCH Diagonal, nor is for GARCH General to be nested to GARCH Diagonal. This implies that for the cross-hedging of the Singapore oil spot, the GARCH Diagonal model seems to be the most appropriate. Again, as suggested by the eigenvalues, all the dynamic modelling specifications are covariance stationary.

Table 1. 7 Summary of Log Likelihood Ratio (LR) Statistics between different models

	Domestic Hedging	Cross Hedging
TG-General to TG-Diagonal	27.252	6. 71
TG-General to Constant	119.698	119. 986
TG-Diagonal to Constant	92.446	113. 276
G-General to G-Diagonal	25.650	6. 852
G-General to Constant	113.206	119. 75
G-Diagonal to Constant	87.556	112. 898
TG-Genearl to G-General	6.492	0. 236
TG-Diagonal to G-Diagonal	4.89	0. 378

Note: At 5% significant level, The critical value for $\chi^2(6) = 12.59$, $\chi^2(4) = 9.49$, and $\chi^2(2) = 5.99$

1.6 Hedging performance in-sample

1.6.1 Hedging ratios under different criteria

1.6.1 (A) Descriptive statistics of the covariance matrices and hedge ratios under Risk Minimisation criterion

Figures 1.4(b) to 1.9(b) portray the estimated in-sample conditional variance and covariance of spot and futures returns from the five different models for both domestic hedging and cross hedging. At the same time, we also portray the unconditional variance and covariance of the spot and futures returns together with their conditional variables, in Figures 1.4(a) to 1.9(a). The descriptive statistics of the conditional covariance matrices from the five models and the unconditional variance and covariance of spot and futures returns for the in-sample period are given in Tables 1.8 and 1.9. Table 1.8 reports those statistics for domestic hedging and Table 1.9 for hedging in the Singapore market. From Figures 1.4 to 1.9, we can see that for almost all the dynamic models, the properties of the estimated conditional risks are generally "smoother" than their unconditional counterparts. This is also the case for the constant model. Relative statistics provided in Tables 1.8 and 1.9 further substantiate such a view. In addition, we notice there is bigger divergence between the estimated conditional variances and covariances under different modelling specifications for the domestic hedging than for hedging in the Singapore market. This implies that there is more unexpected turbulence in the domestic spot market.

Figure 1.10 portrays the estimated in-sample OHRs when China fuel oil futures is used for hedging the spot positions in the domestic market. Figure 1.11 portrays the estimated optimal hedge ratios for hedging the spot positions in the Singapore market. Throughout the period there is a wide divergence between hedge ratios estimated using dynamic models and constant models, in both markets. The hedge ratios clearly change as new information arrives and are time-varying. For hedging of domestic spot risks, we can observe from Figure 1.10 that the OHRs estimated under the GARCH General model diverge from the hedge ratios estimated under other three dynamic models throughout. However, for hedging of Singapore spot positions, the estimated hedge ratios under different dynamic modelling specifications move more or less in synergy. Comparing the two figures we can also observe that the hedge ratios for hedging the Singapore spot position are much higher than for the domestic hedging.

These figures only give a general picture of the features of the hedge ratios. We further examine the dynamics of these hedge ratios, using simple time-series analysis. Tables 1.10 and 1.11 report the summary statistics for the hedge ratios estimated in-sample under different model specifications for futures and spot series in both the domestic and the Singapore market.

For the domestic hedging, Table 1.10 shows that the mean hedge ratio of the diagonal

Table 1. 8 Conditional and unconditional variances and covariances for the domestic hedging: In-sample period

	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
TG-Gen h_{11}	2.0052	6.1595	0.6421	1.0525	1.1521	4.0519	133.1334
TG-Dia h_{11}	2.0725	7.4015	0.6603	1.2042	1.5380	5.6643	343.6287
G-Gen h_{11}	2.0034	6.0517	0.6503	1.0370	1.1190	3.9266	121.7522
G-Gen h_{11}	2.1406	7.7353	0.6468	1.2719	1.5203	5.5716	329.0538
Const h_{11}	1.8930	1.8930	1.8930	0.0000	NA	NA	NA
Var(f)	1.8955	25.7266	0.0000	3.3839	3.2900	15.8908	4346.4930
TG-Gen h_{22}	1.4662	5.9917	0.9563	0.7437	3.0061	13.6977	3124.6780
TG-Dia h_{22}	1.3391	2.3200	0.8744	0.3321	0.7392	2.9169	45.4921
G-Gen h_{22}	1.4619	5.8204	1.0006	0.6999	3.0609	14.1319	3348.9230
G-Gen h_{22}	1.4292	2.8937	0.7864	0.4739	0.8326	3.1153	57.8125
Const h_{2}	1.4313	1.4313	1.4313	0.0000	NA	NA	NA
Var(s)	1.4324	48.3335	0.0000	3.9413	7.1562	68.9965	94627.9400
TG-Gen h_{12}	0.5743	1.5603	-1.6551	0.3678	-2.1305	11.8602	2005.6770
TG-Dia h_{12}	0.5784	1.4969	-0.0339	0.2352	1.2061	4.6882	179.8645
G-Gen h_{12}	0.5685	1.4208	-1.7696	0.3766	-2.4350	13.0331	2580.8710
G-Gen h_{12}	0.6912	1.8456	-0.0706	0.2954	1.2121	4.6784	180.3886
Const h_{12}	0.5869	0.5869	0.5869	0.0000	NA	NA	NA
Cov(f,s)	0.5886	23.0249	-7.6132	2.2127	4.0361	32.7965	19774.5500

Table 1. 9 Conditional and unconditional variances and covariances for hedging in the Singapore market: In-sample period

	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
TG-Gen h_{11}	1.9303	5.3975	0.8402	0.8736	1.1948	4.1634	146.5620
TG-Dia h_{11}	1.9598	6.2304	0.9471	0.9086	1.7591	6.8189	559.4629
G-Gen h_{11}	1.9265	5.6482	0.9090	0.8725	1.4390	5.1900	271.3992
G-Gen h_{11}	1.9601	6.1293	0.9516	0.8988	1.7039	6.4834	492.7429
Const h_{11}	1.8930	1.8930	1.8930	0.0000	NA	NA	NA
Var(f)	1.8955	25.7266	0.0000	3.3839	3.2900	15.8908	4346.4930
TG-Gen h_{22}	3.8079	17.5175	1.4194	2.2729	2.3994	10.4220	1620.8730
TG-Dia h_{22}	3.9022	18.2302	1.5385	2.5331	2.2534	8.9969	1167.6730
G-Gen h_{22}	3.8551	18.3909	1.5365	2.3770	2.4481	10.6073	1698.2480
G-Gen h_{22}	3.9211	18.4469	1.5355	2.5560	2.2571	9.0385	1179.4520
Const h_{2}	3.6725	3.6725	3.6725	0.0000	NA	NA	NA
Var(s)	3.6745	127.2376	0.0000	10.3940	7.5601	74.9770	112243.1000
TG-Gen h_{12}	1.2022	3.8820	-0.7671	0.5918	0.9589	5.1021	168.0041
TG-Dia h_{12}	1.2825	4.4741	-0.2184	0.6142	1.7167	7.2773	624.2249
G-Gen h_{12}	1.1864	3.8703	-0.9222	0.5633	0.9652	5.7701	236.5462
G-Gen h_{12}	1.2947	4.6917	-0.2534	0.6464	1.7393	7.4071	654.0964
Const h_{12}	1.2208	1.2208	1.2208	0.0000	NA	NA	NA
Cov(f,s)	1.2231	28.7417	-10.0058	3.3600	3.7522	24.0325	10347.6500

Table 1. 10 Statistics for estimated hedge ratios for domestic hedging: In-sample period

	TG-Gen	TG-Dia	G-Gen	G-Dia	Constant
Mean	0.3652	0.3351	0.3603	0.3908	0.3101
Median	0.3567	0.3212	0.3697	0.3672	0.3101
Maximum	0.7577	0.8043	0.8427	0.9721	0.3101
Minimum	-0.0737	-0.0088	-0.4835	-0.0176	0.3101
Std. Dev.	0.1578	0.1482	0.2161	0.1789	0.0000
Skewness	-0.0764	0.4284	-0.7206	0.4898	NA
Kurtosis	2.5473	2.8385	4.2802	2.9429	NA
Jarque-Bera	4.7374	15.7742	77.1094	19.9782	NA
Probability	0.0936	0.0004	0.0000	0.0000	NA
ADF	-5.2518	-4.1124	-8.1993	-4.0987	
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	
PP	-5.4764	-4.2476	-13.2868	-4.2506	
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	

Table 1. 11 Statistics for estimated hedge ratios for cross hedging: In-sample period

	TG-Gen	TG-Dia	G-Gen	G-Dia	Constant
Mean	0.6750	0.7079	0.6784	0.7115	0.6449
Median	0.6669	0.6852	0.6699	0.6832	0.6449
Maximum	1.8257	1.8031	1.8611	1.8822	0.6449
Minimum	-0.1919	-0.1006	-0.2078	-0.1180	0.6449
Std. Dev.	0.2811	0.2913	0.2955	0.3039	0.0000
Skewness	0.5674	1.0613	0.6334	1.1951	NA
Kurtosis	4.8498	5.3203	4.8707	5.7263	NA
Jarque-Bera	97.7268	205.2026	105.9124	272.7746	NA
Probability	0.0000	0.0000	0.0000	0.0000	NA
ADF with	-5.0859	-4.7690	-5.5072	-4.7367	
Intercept	[0.0000]	[0.0000]	[0.0000]	[0.0000]	
PP with	-5.0859	-4.7540	-5.6603	-4.7367	
Intercept	[0.0000]	[0.0000]	[0.0000]	[0.0000]	

model (0.3908) exceeds that of the TGARCH general model (0.3652) and General model (0.3603), which exceeds that of the TGARCH Diagonal model (0.3351). The Constant model generates the lowest hedge ratio (0.3101). The hedge ratios estimated from the GARCH General model have the largest standard deviation; while hedge ratios estimated using TGARCH diagonal model have the lowest variation. The estimated hedging ratios for cross-hedging in the Singapore market which are reported in Table 1.11, exhibit similar characteristics. The dynamic models yield higher mean hedge ratio than the constant models; within the dynamic models, diagonal model yields the largest mean hedge ratio. However, in the Singapore market, hedge ratios estimated from the TGARH General model have the lowest standard deviation.

Comparing Tables 1.10 and 1.11, we find that the means of hedge ratios for hedging spot positions in the Singapore market are much higher than their counterparts in the domestic market, no matter which specification is employed. Meanwhile, the standard deviations for the hedge ratios in the Singapore market are also higher. Both ADF and PP unit root tests on the estimated hedge ratios from the dynamic models reject the null hypothesis of the existence of unit root for all models in both markets, implying that the hedge ratio are by and large I(0). This suggests that the oil futures hedge ratios are mean reverting and any impact of a shock to the hedge ratio eventually becomes negligible. Jarque-Bera statistics are all significant, implying that the hedge ratios calculated from the conditional information set exhibit a high degree of non-normality. This may be due to the fact that the returns tend to be clustered through time and thus so are the hedge ratios.

1.6.1 (B) Descriptive statistics of Hedge ratios derived from maximizing expected utility

Tables 1.12 and 1.13 report the descriptive statistic for the hedge ratios derived from utility maximisation for domestic and cross hedging, with different risk aversion assumptions. We can see from the tables that hedge ratios differ with when investors risk preferences differ. As discussed before that if the futures returns follow a Martingale process, i.e., if the conditional expected value of futures returns is zero, then the optimal hedge ratios under variance minimisation criterion are identical to from those under utility maximisation. However, the actual mean values instead of zero value for the futures returns are used, thus the hedge ratios estimated under variance minimisation may be different from those estimated under utility maximisation. For the same reason, the hedge ratios also change with the different assumptions of the value of the risk aversion parameter. Figures 1.12 to 1.15 portray the hedge ratios under different risk aversion assumption when using different models (we only report two models for domestic and cross-border hedging each; other models give similar results). We can observe there is divergence between hedge ratios estimated under different criterion and with different risk aversion assumptions.

Table 1. 12 Descriptive statistics of OHRs derived from maximizing expected utility under different risk aversion assumption for domestic hedging: In-sample period

(1) $\lambda = 0.25$

λ = 0.25	TG-Gen	TG-Dia	G-Gen	G-Dia	Constant
Mean	0.2504	0.2087	0.2594	0.2780	0.1984
Median	0.2566	0.1953	0.2867	0.2560	0.1984
Maximum	0.6066	0.5900	0.6034	0.7718	0.1984
Minimum	-0.1104	-0.0610	-0.5337	-0.0629	0.1984
Std. Dev.	0.1238	0.1110	0.1821	0.1431	0.0000
Skewness	-0.0022	0.7029	-1.2508	0.6762	NA
Kurtosis	3.0202	3.8804	5.4380	3.7189	NA
Jarque-Bera	0.0089	57.0853	253.1897	48.6718	NA
Probability	0.9956	0.0000	0.0000	0.0000	NA
ADF with	-5.3981	-4.0402	-9.8332	-4.0238	
Intercept	[0.0000]	[0.0013]	[0.0000]	[0.0014]	
PP with	-5.5804	-4.0463	-15.6522	-4.1255	
Intercept	[0.0000]	[0.0013]	[0.0000]	[0.0010]	

(2) λ = 0.5

λ = 0.5	TG-Gen	TG-Dia	G-Gen	G-Dia	Constant
Mean	0.3078	0.2719	0.3099	0.3344	0.2542
Median	0.3026	0.2586	0.3289	0.3162	0.2542
Maximum	0.6707	0.6937	0.7202	0.8707	0.2542
Minimum	-0.0921	-0.0349	-0.5086	-0.0403	0.2542
Std. Dev.	0.1393	0.1274	0.1984	0.1595	0.0000
Skewness	-0.0825	0.5255	-0.9681	0.5599	NA
Kurtosis	2.7311	3.2783	4.7876	3.2754	NA
Jarque-Bera	2.0653	24.5233	144.0993	27.5899	NA
Probability	0.3561	0.0000	0.0000	0.0000	NA
ADF with	-5.3533	-4.0354	-8.9393	-4.0421	
Intercept	[0.0000]	[0.0014[	[0.0000]	[0.0013]	
PP with	-5.5892	-4.1742	-14.4758	-4.2037	
Intercept	[0.0000]	[0.0008[	[0.0000]	[0.0007]	

(3) $\lambda = 1$

$\lambda = 1$	TG-Gen	TG-Dia	G-Gen	G-Dia	Constant
Mean	0.3365	0.3035	0.3351	0.3626	0.2822
Median	0.3291	0.2879	0.3488	0.3416	0.2822
Maximum	0.7137	0.7490	0.7814	0.9210	0.2822
Minimum	-0.0829	-0.0219	-0.4960	-0.0289	0.2822
Std. Dev.	0.1483	0.1374	0.2071	0.1689	0.0000
Skewness	-0.0872	0.4675	-0.8395	0.5195	NA
Kurtosis	2.6259	3.0317	4.5167	3.0935	NA
Jarque-Bera	3.5347	18.1576	106.2304	22.5836	NA
Probability	0.1708	0.0001	0.0000	0.0000	NA
ADF with	-5.3064	-4.0688	-8.5513	-4.0676	
Intercept	[0.0000]	[0.0012]	[0.0000]	[0.0012]	
PP with	-5.5370	-4.1986	-13.8767	-4.2417	
Intercept	[0.0000]	[0.0000]	[0.0000]	[0.0006]	

Table 1. 13 Descriptive statistics of OHRs derived from maximizing expected utility under different risk aversion assumption for cross hedging: In-sample period

(1) $\lambda = 0.25$

$\lambda = 0.25$	TG-Gen	TG-Dia	G-Gen	G-Dia	Constant
Mean	0.5562	0.5792	0.5601	0.5859	0.5333
Median	0.5460	0.5368	0.5409	0.5384	0.5333
Maximum	1.6980	1.7009	1.7354	1.7862	0.5333
Minimum	-0.2393	-0.1971	-0.2916	-0.2152	0.5333
Std. Dev.	0.2616	0.2686	0.2738	0.2822	0.0000
Skewness	0.7364	1.3482	0.8027	1.4447	-2.9106
Kurtosis	5.3794	6.4308	5.4638	6.7749	9.4714
Jarque-Bera	178.1456	433.1856	196.7251	514.1136	1723.6390
Probability	0.0000	0.0000	0.0000	0.0000	0.0000
ADF with	-5.4466	-5.2388	-5.9267	-5.1963	
Intercept	[0.0000]	[0.0000]	[0.0000]	[0.0000]	
PP with	-5.4466	-5.2388	-6.1206	-5.1963	
Intercept	[0.0000]	[0.0000]	[0.0000]	[0.0000]	

(2) $\lambda = 0.5$

λ = 0.5	TG-Gen	TG-Dia	G-Gen	G-Dia	Constant
Mean	0.6128	0.6390	0.6157	0.6446	0.5891
Median	0.5956	0.6085	0.6042	0.6050	0.5891
Maximum	1.7618	1.7520	1.7982	1.8311	0.5891
Minimum	-0.2156	-0.1488	-0.2497	-0.1666	0.5891
Std. Dev.	0.2677	0.2756	0.2814	0.2883	0.0000
Skewness	0.6581	1.2310	0.7207	1.3476	NA
Kurtosis	5.1653	5.9983	5.2056	6.4052	NA
Jarque-Bera	146.0732	342.4180	157.9293	429.0597	NA
Probability	0.0000	0.0000	0.0000	0.0000	NA
ADF with	-5.4453	-5.1468	-5.8978	-5.1104	
Intercept	[0.0000]	[0.0000]	[0.0000]	[0.0000]	
PP with	-5.4453	-5.1193	-6.1017	-5.1104	
Intercept	[0.0000]	[0.0000]	[0.0000]	[0.0000]	

(3) $\lambda = 1$

λ = 1	TG-Gen	TG-Dia	G-Gen	G-Dia	Constant
Mean	0.6411	0.6988	0.6434	0.6740	0.6170
Median	0.6281	0.6744	0.6391	0.6391	0.6170
Maximum	1.7938	1.8031	1.8296	1.8567	0.6170
Minimum	-0.2037	-0.1006	-0.2288	-0.1423	0.6170
Std. Dev.	0.2715	0.2844	0.2858	0.2920	0.0000
Skewness	0.6153	1.1032	0.6773	1.2923	-2.9106
Kurtosis	5.0358	5.5263	5.0590	6.1920	9.4714
Jarque-Bera	128.74	255.95	138.19	383.76	1723.64
Probability	0.0000	0.0000	0.0000	0.0000	0.0000
ADF with	-5.4369	-5.0637	-5.8764	-5.0685	
Intercept	[0.0000[	[0.0000]	[0.0000]	[0.0000]	
PP with	-5.4369	-5.0552	-6.0841	-5.0685	
Intercept	[0.0000]	[0.0000]	[0.0000[	[0.0000]	

1.6.2 Hedging performance Evaluation under different criteria

1.6.2 (A) Risk minimisation and variance reduction

Tables 1.14 and 1.15 report the variance reduction comparisons for the in-sample hedging of spot positions in the domestic and the Singapore markets. Tables 1.16 and 1.17 report the equality test results for means and variances of the hedged portfolios in both hedging. Such equality tests enable us to tell if there are any significant changes across different hedging models.

Table 1. 14 Variance reduction for hedging in the domestic market: In-sample period

	No hedge	TG-Gen	TG-Dia	G-Gen	G-Dia	Constant
Mean	0.10239	0.05641	0.06517	0.05300	0.05889	0.06963
Variance	1.43414	1.18037	1.19003	1.17257	1.18717	1.25179
Variance reduction		-0.17695	-0.17021	-0.18239	-0.17221	-0.12715
Ranking		(2)	(4)	(1)	(3)	(5)

Table 1. 15 Variance reduction for hedging in the Singapore market: In-sample period

	No hedge	TG-Gen	TG-Dia	G-Gen	G-Dia	Constant
Mean	0.11307	0.06276	0.06477	0.06342	0.06591	0.04493
Variance	3.67988	2.76403	2.77491	2.76885	2.77832	2.89097
Variance reduction		-0.24888	-0.24592	-0.24757	-0.24500	-0.21438
Ranking		(1)	(3)	(2)	(4)	(5)

We can observe from Table 1.14 and 1.15 that the hedging effectiveness of China fuel oil futures in terms of risk reduction is very low. Previous studies show that the risk reduction of commodity futures is normally around 70% to 90% in the developed markets with little market friction and around 50-70% in the emerging market with immature regulation and market frictions. However, the risk reduction for the China fuel oil futures in hedging domestic fuel oil commodity is below 20%, and is around 25% in hedging the Singapore fuel oil price fluctuations. For the hedging of a spot position in the Singapore market, because it is a cross-border hedging, considering the regulation restrictions and China's controlled exchange rate, etc, the 25% risk reduction is in line with expectation. These administrative obstacles and restrictions could prevent an efficient hedging across the border. However, the risk reduction of China's fuel oil futures in hedging of the domestic spot position was expected to be higher. There are some reasons for the limited realized gains in domestic hedging: First, China fuel oil futures prices are largely determined by the price changes of the fuel oil in the Singapore market. Second, the physical fuel oil price in China is still largely controlled and adjusted by the government. Thus the spot prices do not reflect the market demand and supply, nor do they adjust to the information shock effectively. The adjustments in prices tend to occur with a lag. On the other hand, fuel oil futures are much more volatile and fluctuated with the international oil prices. Fuel oil futures are much more volatile than the price of the underlying spot. If a spot position is over hedged, the hedging strategy may actually introduce additional volatility than desired.

Comparing the unhedged and the hedged positions in Tables 1.14 and 1.15, we find that the hedged portfolios have lower expected returns than the unhedged positions, but the risk associated is also lower. Ranking of different models are provided in the bottom of the two tables. We observe that the constant model provides the lowest degree of variance reduction, no matter domestic hedging or hedging of Singapore spot positions. The dynamic models are obviously superior to the constant model in terms of variance reduction.

For the hedge effectiveness within the dynamic modelling framework, we can observe from Tables 1.14 and 1.15 that the TGARCH General model is better than the TGARCH Diagonal model, and the GARCH General model is better than the GARCH Diagonal model, for both domestic and cross hedging. This implies that the general models, with or without taking the asymmetric information effect into consideration, provide better performance than when they are restricted to diagonal models, in terms of risk reduction. Comparing the TGARCH General to the GARCH General model, the ranking of their risk reduction ability for domestic hedging is opposite to their ranking for cross hedging. It seems that for cross hedging, taking asymmetric effects into consideration in calculating conditional variance and covariance (indicated by d_{ij} s) would help achieve better hedging results, but not for the domestic hedging. Given that all the asymmetric parameters (d_{ij}) are insignificant, any conclusion about the relative performance of these models would be dubious. This is also the case for TGARCH Diagonal versus GARCH Diagonal models.

Within the dynamic models, we can also observe from these two tables that the model which generates higher risk reduction (i.e. has smaller variance) has lower mean return as well. This implies that the dynamic models follow the risk and return trade-off rule, that the one which generates higher returns is associated with higher risk. However, when taking the constant model into consideration, the risk-return trade-off is sometimes violated. In the cross hedging, the mean return for the hedged portfolio constructed using the constant framework is the lowest but the variance is the highest. Thus the dynamic models outperform the constant models not only in terms of risk reduction, but sometimes even in terms of mean return.

Descriptive statistics of the returns of hedged portfolio are given in Tables 1.16 and 1.17, and the equality tests for the means and variances of the returns of the hedged portfolio are provided in Table 1.18 and 1.19. It is worth noting that no matter which method we use, the equality test results suggest that the means and variances of the hedged portfolio by different modeling specifications only marginally different from each other. Consequently, the disparities between them might not be statistically significant. Therefore the superiority of any modelling method is not obvious and may be subject to data and the time period under consideration. For our in-sample period, all the competing dynamic and constant models are in fact effectively identical.

Table 1. 16 Statistics summary of the actual spot returns, and returns of the hedged portfolio constructed using different models in the in-sample period for domestic hedging

	Actual	TG-Gen	TG-Dia	G-Gen	G-Dia	Constant
Mean	0.1024	0.0564	0.0652	0.0530	0.0589	0.0696
Median	0.0000	0.0455	0.0491	0.0451	0.0364	0.0500
Maximum	7.0204	6.5418	6.5870	6.6370	6.5171	6.3611
Minimum	-5.7061	-5.1537	-5.1601	-5.0614	-5.1722	-5.1703
Std. Dev.	1.1976	1.0865	1.0909	1.0829	1.0896	1.1188
Skewness	0.4014	0.3700	0.3833	0.3943	0.3600	0.3755
Kurtosis	8.5187	7.8622	8.1836	7.9716	7.9310	8.0790
Jarque-Bera	645.3322	501.9077	569.7408	525.7799	515.2967	546.9847
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
ADF with	-21.3502	-24.0044	-23.9834	-23.5330	-24.5584	-23.5119
Intercept	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
PP with	-21.3316	-24.1942	-24.1465	-23.6878	-24.7968	-23.6313
Intercept	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]

Note: Probability of ADF and PP Unite root tests are give in [ ].

Table 1. 17 Statistics summary of the actual spot returns, and returns of the hedged portfolio constructed using different models in the in-sample period for cross hedging

	Actual	TG-Gen	TG-Dia	G-Gen	G-Dia	Constant
Mean	0.1131	0.0628	0.0648	0.0634	0.0659	0.0449
Median	0.0000	0.0432	0.0278	0.0458	0.0281	0.0552
Maximum	8.3184	7.0724	7.0073	6.9905	6.9315	7.7681
Minimum	-11.2117	-9.1249	-9.2100	-9.2241	-9.2155	-9.6043
Std. Dev.	1.9183	1.6625	1.6658	1.6640	1.6668	1.7003
Skewness	-0.6683	-0.6422	-0.6576	-0.6532	-0.6553	-0.6401
Kurtosis	9.0544	8.4093	8.3840	8.4277	8.3343	9.0441
Jarque-Bera	797.6794	641.3797	637.3773	646.7023	626.0668	792.0320
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
ADF with	-21.2911	-22.6574	-22.7603	-22.6103	-22.7794	-22.9219
Intercept	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
PP with	-21.5401	-23.3067	-23.4500	-23.2075	-23.4533	-24.6449
Intercept	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]

Note: Probability of ADF and PP Unite root tests are give in [ ].

Table 1. 18 Equality Test of Means and Variances for the returns of the hedged portfolios for the domestic hedging: in-sample period

	Mean of return		*Variance of return*	
	F-statistic	*Probability*	*F-statistic*	*Probability*
TGGeneral-TGDiagonal	0.016139	0.8989	1.008182	0.9277
TGDiagonal-Constant	-0.063659	0.9493	1.051898	0.5730
TGGeneral-Constant	0.035798	0.8500	1.060505	0.5128
TGGeneral-GGeneral	0.008603	0.9261	1.014295	0.8744
TGDiagonal-GDiagonal	0.091036	0.9275	1.002411	0.9786
TGGeneral-GDiagonal	0.005217	0.9424	1.013626	0.8801
TGDiagonal-GGeneral	0.001289	0.9714	1.005756	0.9490
General-Diagonal	0.003203	0.9549	1.020133	0.8243
General-Constant	0.009699	0.9216	1.075664	0.4165
Diagonal-Constant	0.023584	0.878	1.054435	0.5549

Table 1. 19 Equality Test of Means and Variances for the returns of the hedged portfolios for the cross hedging in the Singapore market: in-sample period

	Mean of return		*Variance of return*	
	F-statistic	*Probability*	*F-statistic*	*Probability*
TGGeneral-TGDiagonal	0.000216	0.9883	1.003779	0.9664
TGDiagonal-Constant	0.033646	0.8545	1.041917	0.647
TGGeneral-Constant	0.169067	0.8658	1.045855	0.6171
TGGeneral-GGeneral	-0.004278	0.9966	1.001663	0.9852
TGDiagonal-GDiagonal	0.000128	0.9910	1.001244	0.9889
TGGeneral-GDiagonal	0.000677	0.9793	1.005027	0.9554
TGDiagonal-GGeneral	0.000108	0.9917	1.002113	0.9812
General-Diagonal	0.000472	0.9827	1.003359	0.9702
General-Constant	0.030008	0.8625	1.044118	0.6302
Diagonal-Constant	0.037861	0.8458	1.040623	0.6570

1.6.2 (B) Expected utility maximisation hedge ratios and comparison of the expected utilities of competing models.

Now we turn to comparing the competing models under utility maximisation criterion. Expected utility of the hedged portfolios generated by different modelling strategies are reported in Tables 1.20 and 1.21, for domestic and Singapore hedging respectively. As the expected utility also depends upon the assumption of the investors risk aversion parameter, we examine the results when the risk aversion is assumed to be 0.25, 0.5 and 1.

Table 1. 20 Expected Utility of domestic hedging: in-sample

	TG-Gen	TG-Dia	G-Gen	G-Dia	Constant
$\lambda = 0.25$	-0.22985	-0.22712	-0.23196	-0.22759	-0.23679
	(3)	(1)	(4)	(2)	(5)
$\lambda = 0.5$	-0.52939	-0.52936	-0.52909	-0.52888	-0.55206
	(4)	(3)	(2)	(1)	(5)
$\lambda = 1$	-1.12091	-1.12585	-1.11649	-1.12382	-1.17817
	(2)	(4)	(1)	(3)	(5)

Table 1. 21 Expected Utility of cross hedging in the Singapore market: in-sample

	TG-Gen	TG-Dia	G-Gen	G-Dia	Constant
$\lambda = 0.25$	-0.62459	-0.62336	-0.62514	-0.62299	-0.67046
	(3)	(2)	(4)	(1)	(5)
$\lambda = 0.5$	-1.31871	-1.32061	-1.32055	-1.32110	-1.39470
	(1)	(3)	(2)	(4)	(5)
$\lambda = 1$	-2.70020	-2.70773	-2.70449	-2.70994	-2.83876
	(1)	(3)	(2)	(4)	(5)

Note: Ranking of different models is given in ()

From Tables 1.20 and 1.21, we can see that the expected utility of the hedged portfolio under constant model is smaller than those from the dynamic estimation, in both the domestic and the Singapore market, regardless the assumption on the risk aversion parameter. Such a result indicates that the dynamic models are superior to the constant models in term of utility maximisation. This is same as our previous findings under the risk minimisation criterion. However, within the dynamic specifications, there is no certain pattern regarding the ranking of their performances. This is because the expected utility does not only depend on the estimated hedging ratios, which is influenced by the conditional variance, conditional expected return, but also on the assumption of the risk aversion factors. The lack of surety in ranking of the dynamic models further substantiates our findings in the risk minimisation that all the dynamic models are in fact effectively identical. We cannot conclude which one is superior to the other.

1.6.2 (C) Risk reduction based on semivariance

Most recent approaches to evaluate hedging performance emphasis investors react differently to downside risk and upside risk. Investors using futures to hedge their positions desire to eliminate the downside return but retain the upside potential. In such case, the MV is inappropriate. More intuitive measures of hedging performance focusing on downside risk have been developed, including the risk reduction based on the semivariance, the GSV and VaR. In this study, we examine the hedging performance under semivariance risk reduction criterion.

The semivariance criterion is based on the concept that an investor preferring to minimize the probability of falling below some predefined level of returns. This return is the target return or the minimum acceptable return for the investor. Choosing the target return is critical under the semivariance risk reduction criterion because when the target return differs, optimal hedging ratio and risk reduction ability of the model would differ as well. In this study, we set the target value to be zero. For one reason, investors try to avoid negative returns in practice; for another, the mean of hedged portfolio returns are quite close to zero.

The risk reduction under semivariance criterion is reported in Tables 3.22 and 3.23, respectively, for the domestic and cross hedging. We observe that all model perform quite well, comparing to the variance reductions we examined earlier. The semivariance reduction of the hedged portfolio in the Chinese market is about 40%, and for Singapore is about 30%. China fuel oil futures are more affective in hedging the downside risk than the total risk.

For both domestic and cross hedging, the constant model always ranks at the bottom. This is consistent with the conclusion drawn from the minimum variance risk reduction criterion; the dynamic models are superior to the constant model.

Within the dynamic model, the GARCH Diagonal model is the most superior and the GARCH General model is the most inferior one, for both domestic and cross hedging. Asymmetric models lie in between. Such is different from the minimum variance reduction. Another distinct feature under semivariance risk reduction criterion is that the domestic hedging can achieve higher risk reduction than the cross hedging.

Table 1. 22 In-sample variance reduction for domestic market spot returns based on semivariance minimisation criterion

	No hedge	TG-Gen	TG-Dia	G-Gen	G-Dia	Constant
Mean	0. 10239	0. 05641	0. 06517	0. 05300	0. 05889	0. 06963
Variance	1. 94657	1. 13075	1. 13509	1. 13880	1. 11428	1. 19276
Variance reduction		−0. 41911	−0. 41687	−0. 41497	−0. 42757	−0. 38725
		(2)	(3)	(4)	(1)	(5)

Table 1. 23 In-sample variance reduction for Singapore market spot returns based on semivariance minimisation criterion

	No hedge	TG-Gen	TG-Dia	G-Gen	G-Dia	Constant
Mean	0.11307	0. 06276	0. 06477	0. 06342	0. 06591	0. 04493
Variance	4.51620	3. 02324	2. 98139	3. 02766	2. 95527	3. 22324
Variance reduction		−0. 33058	−0. 33985	−0. 32960	−0. 34563	−0. 28629
		(3)	(2)	(4)	(1)	(5)

1.7 Out-of-sample predictions of volatility and variance reduction and expected utility comparisons over time

The parameter estimates of each model from the in-sample period were used to update H_t (except, of course for the constant model) continuously throughout the 48 out-of-sample observations. The subsequent time series of the variances of the two returns and their covariance for each model, along with the unconditional values of those variances and covariances, are depicted in Figures 1.16 to 1.21.

Those figures suggest that in general all models tend to underestimate the actual variances and covariances. Moreover, there are greater divergences between the estimated variances and covariances under different modelling specifications in the domestic hedging than they are in the cross hedging in the Singapore market: the results are more stable for Singapore. This may be due to the fact that the Chinese oil market is still in an early stage of its development and trading can be influenced by plenty of noise and speculation. Hence, returns are much harder to predict than that of the comparatively mature and well-regulated Singapore market. This also implies that in the out-of-sample periods, it is harder for the hedging models to perform well in the domestic market than it is in the Singapore market, as confirmed by the risk reduction results reported later. Detailed descriptive statistics for the estimated conditional and unconditional variance and covariance of the China fuel oil futures, fuel oil spots in the Chinese and the Singapore markets are given in Tables 1.24 and 1.25. The predictions do not track the unconditional values well for all the models in the out-of-sample period.

Table 1. 24 Statistics of conditional and unconditional variances and covariances for positions in the Chinese market in the out-of-sample period

	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
TG-Gen h_{11}	3.0108	5.7545	1.2907	1.3869	0.5276	1.7147	5.5309
TG-Dia h_{11}	3.1512	6.8160	1.0719	1.6579	0.7091	2.1864	5.3460
G-Gen h_{11}	2.7326	5.0731	1.4096	1.0924	0.6907	2.1112	5.3969
G-Gen h_{11}	3.2638	7.1010	1.0887	1.7412	0.7085	2.1770	5.3705
Const h_{11}	1.8930	1.8930	1.8930	0.0000	NA	NA	NA
Var(f)	3.3490	23.1250	0.0077	5.1574	2.3786	8.3805	103.1637
TG-Gen h_{22}	1.5018	2.0662	1.1773	0.2420	0.8328	2.6338	5.8168
TG-Dia h_{22}	1.2821	1.6453	1.1103	0.1478	1.0081	2.8653	8.1665
G-Gen h_{22}	1.1342	1.8007	0.8866	0.1853	1.9206	6.5019	54.0357
G-Gen h_{22}	1.3684	1.9150	1.1147	0.2187	1.0405	2.9689	8.6629
Const h_{22}	1.4313	1.4313	1.4313	0.0000	NA	NA	NA
Var(s)	1.3810	27.5037	0.0047	4.0835	5.6615	36.4446	2493.5040
TG-Gen h_{12}	0.5959	1.0507	0.1704	0.1864	0.3866	3.3121	1.3904
TG-Dia h_{12}	0.6091	1.3192	0.2479	0.3009	0.7131	2.3985	4.7918
G-Gen h_{12}	0.6330	1.2702	-0.2927	0.2979	-0.4469	4.4243	5.6547
G-Gen h_{12}	0.7294	1.6102	0.2816	0.3741	0.7078	2.3901	4.7523
Const h_{12}	0.5869	0.5869	0.5869	0.0000	NA	NA	NA
Cov(f,s)	0.7731	11.5772	-1.6585	2.2702	3.1868	13.8436	316.4131

Table 1. 25 Statistics of conditional and unconditional variances and covariances for positions in the Singapore market in the out-of-sample period

	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
TG-Gen h_{11}	2.7592	5.3057	1.3156	1.1729	0.6274	1.9699	5.2716
TG-Dia h_{11}	2.7719	5.5102	1.1942	1.2559	0.7286	2.2212	5.4593
G-Gen h_{11}	2.7011	5.2656	1.2568	1.1703	0.6423	2.0186	5.2272
G-Gen h_{11}	2.7266	5.4401	1.2011	1.2312	0.7634	2.3037	5.6324
Const h_{11}	1.8930	1.8930	1.8930	0.0000	0.0000	0.0000	0.0000
Var(f)	3.3490	23.1250	0.0077	5.1574	2.3786	8.3805	103.1637
TG-Gen h_{22}	4.0673	6.5453	2.7232	0.9573	0.9733	3.5173	8.1139
TG-Dia h_{22}	3.6483	6.1286	1.7464	1.1435	0.2042	2.3055	1.2981
G-Gen h_{22}	3.9416	6.5930	2.4559	1.0277	0.8456	3.2717	5.8679
G-Gen h_{22}	3.6402	6.1493	1.7436	1.1430	0.2377	2.3503	1.2962
Const h_{22}	3.6725	3.6725	3.6725	0.0000	0.0000	0.0000	0.0000
Var(s)	4.2535	30.6032	0.0002	6.7347	2.4745	8.9118	118.8834
TG-Gen h_{12}	1.5531	2.9150	0.4995	0.5698	0.7599	3.3587	4.8765
TG-Dia h_{12}	1.5815	3.6139	0.6709	0.6632	0.8855	3.3616	6.5338
G-Gen h_{12}	1.4772	2.9081	0.3357	0.5791	0.5385	3.2441	2.4389
G-Gen h_{12}	1.6077	3.6638	0.6352	0.6961	0.8382	3.1674	5.6772
Const h_{12}	1.2208	1.2208	1.2208	0.0000	0.0000	0.0000	0.0000
Cov(f,s)	1.9117	23.5243	-3.8065	4.5976	2.6738	12.0564	221.2305

1.7.1 Performance of hedging models out-of-sample: Risk minimisation and variance reduction

1.7.1(A) Estimated hedge ratios under the risk minimisation criterion

As there are obvious divergences in the variance and covariance predicted under different models, it can be reasonable to assume that the minimum variance hedge ratios estimated by different models will be different in the out-of-sample period. The forecasted hedge ratios are depicted in Figures 1.22 and 1.23 for domestic and cross hedging, respectively, and the descriptive statistics for the two predicted hedge ratio series are reported in Tables 1.26 and 1.27. From Figures 1.22 and 1.23 we observe that predicted hedge ratio is more different between one and the other for the domestic hedging. From the descriptive statistics, we observe that, different from the in-sample findings, constant models give the highest mean hedge ratios in the out-of-sample forecasting. TGARCH general models have a higher standard deviation than the TGARCH Diagonal models, and the GARCH general have a higher standard deviation than the Diagonal model. All the estimated hedge ratio series are not normally distributed; they are skewed and have large pickedness. For most dynamic models, the hedge ratio series follow an I(0) process and are thus mean reverting. However, for the hedge ratios estimated from the TGARCH general and the GARCH Diagonal models in the domestic market, they exhibit a unit root in the series. This suggests that the hedge ratios estimated in out-of-sample forecasting are more likely to veer away from its mean.

Table 1. 26 Descriptive statistics for estimated hedge ratios in the out-of-sample period when hedging the domestic spot positions

	TG-Gen	TG-Dia	G-Gen	G-Dia	Constant
Mean	0.2367	0.2078	0.2569	0.2397	0.3101
Median	0.2241	0.1988	0.2778	0.2317	0.3101
Maximum	0.5079	0.3612	0.4115	0.4257	0.3101
Minimum	0.0401	0.0977	-0.0624	0.1132	0.3101
Std. Dev.	0.1082	0.0703	0.1060	0.0843	0.0000
Skewness	0.3004	0.3659	-1.1107	0.3938	NA
Kurtosis	2.7130	2.1266	4.0527	2.1296	NA
ADF	-3.1260	-2.6288	-5.9984	-2.5679	
	[0.0312]	[0.0943]	[0.0000]	[0.1066]	
PP	-3.1279	-2.4061	-6.1292	-2.3393	
	[0.0311]	[0.1454]	[0.0000]	[0.1643]	

Table 1. 27 Descriptive statistics for estimated hedge ratios in the out-of-sample period when hedging the Singapore spot positions

	TG-Gen	TG-Dia	G-Gen	G-Dia	Constant
Mean	0.6108	0.6034	0.5969	0.6189	0.6449
Median	0.6043	0.5945	0.6003	0.6118	0.6449
Maximum	1.0315	1.0746	1.0833	1.0951	0.6449
Minimum	0.2173	0.2616	0.1355	0.2518	0.6449
Std. Dev.	0.2044	0.1749	0.2223	0.1799	0.0000
Skewness	-0.1258	0.3494	-0.0992	0.3212	NA
Kurtosis	1.9728	2.8858	2.2986	2.8977	NA
Jarque-Bera	2.2369	1.0025	1.0626	0.8464	NA
Probability	0.3268	0.6058	0.5878	0.6550	NA
ADF with	-2.1350	-2.1576	-2.1806	-2.0800	
Intercept	[0.2323]	[0.2240]	[0.2158]	[0.2534]	
PP with	-2.2857	-2.3317	-2.3292	-2.2816	
Intercept	[0.1806]	[0.1665]	[0.1673]	[0.1819]	

1.7.1(B) Out-of-sample variance Reduction

For the out-of-sample hedging performance of different models, the results are quite different from the in-sample findings. Table 1.28 illustrates the variance reduction comparison for the out-of-sample hedging of spot positions in the domestic market. All the models underperform in terms of variance reduction in the out-of-sample period, which reduce the variance by only around 3% to 9%. The mean return of China's fuel oil spot is lower than the mean return of any hedged portfolio, no matter which method is used. Meanwhile, the magnitude of mean returns of the hedged portfolios is not associated with their variances. For the dynamic models, we can observe that the two diagonal models, TGARCH diagonal and GARCH diagonal, outperform their general counterparts, TGARCH general and GARCH General, in terms of risk reduction based on variance, which is contrary to the in-sample findings. In general, the diagonal models surpass the constant model and the constant models surpass the general models in the out-of-sample period, although the reduction is really small.

Table 1.29 shows the variance reduction comparison for the out-of-sample hedging in the Singapore market under different model specifications. In general, the hedged portfolios have higher mean returns and lower variance than the unhedged positions. Compared with the in-sample variance reduction, all the models have poorer performance in the out-of-sample period. The constant model reduces the risk to the largest extent, thus outperforming all dynamic models. Among the dynamic models, two general models yield the higher variance reduction than their diagonal counterpart, same as the ranking in the in-sample period of the domestic hedging.

Table 1. 28 Out-of-sample variance reduction for the domestic hedging

	No hedge	TG-Gen	TG-Dia	G-Gen	G-Dia	Constant
Mean	-0.28652	-0.15007	-0.16463	-0.17814	-0.14545	-0.14256
Variance	1.28188	1.23665	1.17133	1.22593	1.18643	1.21134
Variance reduction		-0.03528	-0.08624	-0.04364	-0.07446	-0.05503
Ranking		(5)	(1)	(4)	(2)	(3)

Table 1. 29 Out-of-sample variance reduction for the cross hedging in The Singapore market

	No hedge	TG-Gen	TG-Dia	G-Gen	G-Dia	Constant
Mean	-0.39687	-0.09631	-0.09696	-0.10567	-0.09260	-0.09743
Variance	4.12307	3.28003	3.30362	3.27764	3.31314	3.23101
Variance reduction		-0.20447	-0.19875	-0.20505	-0.19644	-0.21636
Ranking		(3)	(4)	(2)	(5)	(1)

For both domestic and cross hedging, the dynamic models lose their superiority in the out-of-sample period. One reason is, as argued before, due to that the long-term forecast performance of the GARCH model is very poor. The presence of any outlier could erroneously affect the investors' hedged positions enormously and for a number of subsequent time periods.

In any case, the risk reduction based on variance for all the constant and dynamic models is very low. The most plausible reason is that although the fuel oil is the most liberalised oil product in China with the least control by the government, its prices are still largely influenced by the government, thus the existence of the lag in price adjustment compared to the futures. Under such a situation, the futures are far more volatile than the spot market. Any over-hedged positions might lead to additional risk. Another reason may be related to the fact that investors trading fuel oil futures are more likely to be driven by speculative motivations rather than the hedging of risk. Consequently, markets are influenced by a large stream of trading noise, which make the power of theoretical forecast very poor. The forecasting results imply that on average, the fuel oil futures is not a good tool in hedging risk for the investors, at least in short term. However, this aggregated results do not diminishing the potential usefulness of fuel oil futures in individual transactions, for either speculating or hedging.

Overall, the differences in risk reduction between each pair of models are very small. Any significant differences across different models need to be examined further. We employ equality tests in dealing with this issue.

Before performing the equality test, we depict the return of hedged portfolio under different hedging strategies in Figures 1.24 and 1.25. As we can observe, although the hedge ratios appear to be obviously different from each other, the returns of the hedged portfolio are not. They tend to move in a similar pattern. We give the descriptive statistics of the returns of different hedged portfolios in Tables 1.30 and 1.31 and also depict their histogram diagram in Figures 1.26 and 1.27, for hedging in the domestic and Singapore market respectively. From those tables and graphs, it is clear that the returns of hedged portfolios are moving together and following a similar pattern. We further perform mean and variance equality tests and the results are reported in Table 1.32 and 1.33 implying that all the models are actually giving similar results so we cannot simply conclude which one is outperforming the other.

Table 1. 30 Summary of statistics of the actual spot returns, and returns of hedged portfolios computed using different models in the out-of-sample period for the Chinese market.

	Actual	TG-Gen	TG-Dia	G-Gen	G-Dia	Constant
Mean	-0.2865	-0.1501	-0.1646	-0.1781	-0.1455	-0.1426
Median	0.0000	-0.1884	-0.1213	-0.1987	-0.1215	-0.2571
Maximum	2.2285	2.1198	2.1126	2.0980	2.0925	2.1112
Minimum	-5.1762	-5.0971	-4.9033	-4.8559	-4.8549	-4.7351
Std. Dev.	1.1322	1.1120	1.0823	1.1072	1.0892	1.1006
Skewness	-1.6524	-1.6309	-1.6021	-1.3327	-1.5403	-1.2919
Kurtosis	8.8702	9.7648	9.2225	8.2168	8.8631	7.8575
Jarque-Bera	90.7628	112.8028	97.9734	68.6383	87.7314	60.5423
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
ADF with	-5.7776	-6.0109	-6.2425	-6.1167	-6.3592	-6.5340
Intercept	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
PP with	-5.7913	-6.0143	-6.2433	-6.1200	-6.3592	-6.5331
Intercept	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]

Table 1. 31 Summary statistics of the actual spot returns and returns of hedged portfolios computed using different models in the out-of-sample period in the Singapore market.

	Actual	TG-Gen	TG-Dia	G-Gen	G-Dia	Constant
Mean	-0.3969	-0.0963	-0.0970	-0.1057	-0.0926	-0.0974
Median	-0.0373	0.0954	0.0784	0.0517	0.0470	0.1680
Maximum	4.3318	3.9968	3.9709	4.0046	3.9423	3.8685
Minimum	-5.4638	-5.4568	-5.4554	-5.4595	-5.4557	-5.4432
Std. Dev.	2.0305	1.8111	1.8176	1.8104	1.8202	1.7975
Skewness	-0.3738	-0.4000	-0.4053	-0.4047	-0.4081	-0.4064
Kurtosis	3.1644	3.5571	3.6146	3.5947	3.5992	3.6275
Jarque-Bera	1.1718	1.9008	2.0699	2.0175	2.0502	2.1091
Probability	0.5566	0.3866	0.3552	0.3647	0.3588	0.3484
ADF with	-8.1356	-6.7288	-6.5145	-6.6800	-6.4197	-6.1333
Intercept	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
PP with	-8.1333	-6.7269	-6.5199	-6.6778	-6.4267	-6.1238
Intercept	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]

Table 1. 32 Test of Equality for Means and Variances of the hedged portfolio returns in the Chinese market: Out-of-sample period

	Mean of return		*Variance of return*	
	F-statistic	*Probability*	*F-statistic*	*Probability*
TGGeneral-TGDiagonal	0.004225	0.9483	1.055771	0.8532
TGDiagonal-Constant	0.009819	0.9213	1.034163	0.9088
TGGeneral-Constant	0.001108	0.9735	1.020895	0.9438
TGGeneral-GGeneral	0.015355	0.9016	1.008745	0.9763
TGDiagonal-GDiagonal	0.007488	0.9312	1.012898	0.9651
TGGeneral-GDiagonal	0.000423	0.9836	1.042328	0.8876
TGDiagonal-GGeneral	3.65E-03	0.9519	1.046619	0.8765
General-Diagonal	0.021259	0.8844	1.033291	0.9111
General-Constant	0.02494	0.8749	1.012044	0.9674
Diagonal-Constant	0.000168	0.9897	1.020994	0.9435

Table 1. 33 Test of Equality for Means and Variances of the hedged portfolio returns in the Singapore market: Out-of-sample period

	Mean of return		*Variance of return*	
	F-statistic	*Probability*	*F-statistic*	*Probability*
TGGeneral-TGDiagonal	3.12E-06	0.9986	1.007191	0.9805
TGDiagonal-Constant	1.60E-06	0.999	1.022472	0.9396
TGGeneral-Constant	9.25E-06	0.9976	1.015172	0.9591
TGGeneral-GGeneral	0.000641	0.9799	1.00073	0.998
TGDiagonal-GDiagonal	0.000138	0.9906	1.002883	0.9922
TGGeneral-GDiagonal	0.0001	0.992	1.010095	0.9727
TGDiagonal-GGeneral	0.000553	0.9813	1.007926	0.9785
General-Diagonal	0.001244	0.9719	1.010832	0.9707
General-Constant	0.000501	0.9822	1.014431	0.961
Diagonal-Constant	0.000171	0.9896	1.02542	0.9318

1.7.2 Hedge performance under utility maximisation criterion out-of-sample

Table 1.34 and Table 1.35 report the expected utility in the out-of-sample period for the two hedges. For domestic hedging, we can observe that, by and large, the diagonal models give a higher expected utility than the general counterparts, and constant models perform in between. This is similar to our findings under risk minimisation criterion. For the Singapore hedging, we find the constant models yield higher expected utility than the dynamic models, except when the risk aversion equals 0.25.

Table 1. 34 Expected Utility of domestic hedging: out-of-sample

	TG-Gen	TG-Dia	G-Gen	G-Dia	Constant
λ = 0.25	-0.48521	-0.48313	-0.51303	-0.45501	-0.48008
	(4)	(3)	(5)	(1)	(2)
λ = 0.5	-0.76608	-0.75196	-0.82725	-0.73342	-0.74589
	(4)	(3)	(5)	(1)	(2)
λ = 1	-1.36295	-1.31648	-1.47508	-1.30826	-1.32359
	(4)	(2)	(5)	(1)	(3)

Table 1. 35 Expected Utility of cross hedging: out-of-sample

	TG-Gen	TG-Dia	G-Gen	G-Dia	Constant
λ = 0.25	-0.93796	-0.93901	-0.93006	-0.92579	-0.93216
	(4)	(5)	(2)	(1)	(3)
λ = 0.5	-1.71140	-1.72936	-1.71963	-1.72408	-1.62373
	(2)	(5)	(3)	(4)	(1)
λ = 1	-3.31150	-3.33757	-3.31792	-3.33978	-3.25887
	(2)	(4)	(3)	(5)	(1)

For the estimated covariance matrix, the hedge ratios and the hedged portfolio returns all follow the same pattern as those estimated under risk minimisation; we do not provide figures of the series and tables for the descriptive statistics. Also we do not provide the equality test results for the same reason. In fact all the strategies produce similar performances and the small changes in variance reduction do not significantly support the existence of a systematically superior optimal hedge ratio estimation technique.

1.7.3 Hedging performance under risk reduction based on semivariance risk reduction: out-of-sample

The out-of-sample risk reductions of China oil fuel futures in hedging domestic spot positions based on semivariance are reported in Table 1.36 and Table 1.37 report that for hedging of Singapore spot positions.

At a glance, the risk reductions based on semivariance are much higher than that based on the variance, for both domestic and cross hedging. Although it seems that the China fuel oil is not a good hedging instrument in reducing the overall risk, at lease during the first two years since its launches, it is an effective hedging tool in reducing the downside risk. In practice, avoiding downside risk and maintain upside potential is more important for investors. Thus we argue that the China fuel oil futures is very successful market wide in hedging downside risks. There is no doubt why the China fuel oil futures become increasingly popular in the market.

Different from the hedging performance based on variance reduction criterion, domestic hedging have higher risk reduction based on the semivariance than the cross hedging in Singapore market. But same as the hedging performance based on variance reduction criterion, there is no clear pattern which model is more superior to the other in the out-of-sample period. The dynamic models lose their superiority in the domestic hedging. Although for the cross hedging in the Singapore market the constant model still generates the smallest risk reduction, the divergence between constant and dynamic models is much smaller than in the in-sample period.

Comparing the in-sample and out-of-sample hedging based on semivariance reduction, we find that the models give even higher reduction in the out-of-sample period for the domestic hedging. In contrast, for the cross hedging, the models show less effective performance in the out-of-sample period. Comparing the in-sample and out-of-sample hedging for both hedging under the two risk reduction criteria, we find that the hedging in the Singapore market have more stable results, while the risk reduction is quite different for the fuel oil hedging in domestic market based on the two criteria. This may be caused by the fact that the returns of fuel oil in the Chinese market, which is less developed, have larger negative sknewess and asymmetric distribution.

On the other hand, the returns are more symmetrically distributed in the Singapore market.

Table 1. 36 Out of sample variance reduction for domestic market spot returns based on semivariance minimisation criterion

	No hedge	TG-Gen	TG-Dia	G-Gen	G-Dia	Constant
Mean	-0.28652	−0. 15007	−0. 16463	−0. 17814	−0. 14545	−0. 14256
Variance	2.50095	1. 36325	1. 42943	1. 26795	1. 40681	1. 32310
Variance reduction		−0. 45491	−0. 42845	−0. 49301	−0. 43749	−0. 47096
		(3)	(5)	(1)	(4)	(2)

Table 1. 37 Out of sample variance reduction for Singapore market spot returns based on semivariance criterion minimisation criterion

	No hedge	TG-Gen	TG-Dia	G-Gen	G-Dia	Constant
Mean	-0.39687	−0. 09631	−0. 09696	−0. 10567	−0. 09260	−0. 09743
Variance	5.45792	3. 80928	3. 84380	3. 84016	3. 84137	3. 90409
Variance reduction		−0. 30206	−0. 29574	−0. 29640	−0. 29618	−0. 28469
		(1)	(4)	(2)	(3)	(5)

1.7.4 Hedging performance: time path of risk reduction based on variance and semivariance and of expected utility maximisation

The above provides the performance comparison of average risk reduction and average expected utility over the out-of-sample period. However, more useful comparisons between the performances of the models are those between the time paths of the variance reductions under different modelling specifications and between the time paths of expected utility given a risk aversion parameter. We calculate these attributes of the models upon a day-by-day revision of the forecasts of variance reduction and of expected utilities. Thus better information can be provided about the models than do the average estimates of variance reduction or expected utility over a given period. Figures 1.28 to 1.29 graph, for domestic and cross hedging respectively, the time paths of the variance reductions based on variance of different hedging strategies when hedging decision are updated each day to incorporate all available information. Accordingly, Figures 1.30 and 1.31 portray the time paths of the expected utility, and Figure 1.32 and 1.33 depict the time paths of the risk reduction based on semivariance for the domestic and cross hedging.

On this basis, the dynamic models seem to be superior to the constant model, no matter under the two risk minimisation criteria or expected utility criterion, for hedging in both markets. For the domestic hedging, the general model seems to be superior in terms of variance reduction, and the diagonal model is superior in terms of utility maximization and semivariance reduction. On the other hand, for hedging in the Singapore market, the TGARCH General model seems to beat others in terms of variance reduction and expected utility maximisation, diagonal model is superior in terms of semivariance reduction.

The best models are seen to possess the GARCH(1,1) dynamic structures. The

Constant model is the inferior to them. It performance cannot match the dynamic models under all three criteria. The plausible reason is that the constant model ignoring some of the factors that affect the volatility of spot and futures returns. Investors relay on the dynamic models to formulating hedging strategies should update the forecast more frequently to generate outstanding performance.

1.8 Summary and conclusion

This study investigates the optimal futures hedging using both dynamic and constant models. As proved in the literature, the distribution of futures and spot returns both have the characteristics of non-normality. Thus a GARCH framework in the derivation of OHRs, which are dependent upon to their variance and covariance structure, has distinct theoretical advantage over the constant models and hence should provide a better hedging performance. Many previous studies provide evidences for such statistical and economic improvements of dynamic models, although most are based on data in the developed market where there are little market frictions.

In this study, we examined the effectiveness of dynamic hedging models for the fuel oil futures traded in SHFE, which has only two years history by the time we conduct the study. To provide the most useful information to market participants, we also take into consideration of the close relation between the fuel oil market in China and that in Singapore by comparing the fuel futures hedging for spot positions in both markets. Our findings provide to the hedgers, speculators and policy makers some insight information about the performance of the China fuel oil futures as a hedging tool.

The empirical findings for the in-sample period analysis are consistent with those of previous studies in that the dynamic models surpass the constant model. When investigating the asymmetric effect of positive and negative shocks in influencing the hedging ability of China fuel oil futures, we find the coefficients capturing the asymmetric effect for both domestic and cross border hedging are insignificant and the likelihood ratio test statistics suggest that these parameters should be omitted in the model specification. However, by including the asymmetric matrix in our modelling specification, we do get higher variance reductions for cross hedging in the Singapore market, although this is not the case for the domestic hedging. Results from likelihood tests suggest that the GARCH General model is the best accepted model for the domestic hedging and the GARCH Diagonal is superior to other modelling specifications for the cross hedging in the Singapore Market.

Three different criteria are employed to assess the hedging performance of different hedging strategies from different perspectives, including the hedging ability to minimise total risk, to minimise downside risk and to maximise the expected utility. In terms of variance reduction, we find that GARCH General is the best modelling strategy for domestic hedging followed by TGARCH General, GARCH Diagonal and TGARCH Diagonal. For hedging in the Singapore market, TGARCH general is more superior, followed by the GARCH general, TGARCH Diagonal and GARCH Diagonal. Under the utility maximisation criterion, we find the constant models are still always inferior to the dynamic models. However, within the dynamic specification, there is no certain pattern for the relative ranking of each model, since the expected value of futures returns are not effectively zero in our sampling period.

Moreover, we can conclude that individuals risk preferences also influence their choice of hedging strategies. Under the semivariance reduction criterion, the GARCH Diagonal model is the most superior and constant model is the most inferior. Further evidence is found on that the dynamic models perform better than the constant model.

In the in-sample period, there are some findings that are unique for the China fuel oil futures. First, the reductions in variance for hedging in both markets are very low, much lower that the hedging effectiveness of other oil futures in the international oil market that have been studied so far. Second, the domestic hedging have even lower variance reduction than the cross border hedging in the Singapore market. Third, China fuel oil futures are more effective in hedging downside risks based on the semivariance reduction than total risk reduction. And in terms of hedging downside risk, domestic hedging is more effective than the cross hedging in the Singapore market. Fourth, the models do not strictly follow the risk and return trade-off rule; the model that yields a higher reduction may also generate higher hedged portfolio returns.

Our empirical findings in the out-of-sample period are somewhat disappointing for hedging of the spot positions in the Chinese market under variance minimisation criterion, where all the dynamic and constant models perform extremely poorly. The risk reduction results based on variance imply the inability of China oil futures in hedging spot risks, on the market average. For hedging in the Singapore market, all models underperform the in-sample ones, especially the dynamic models. The Constant model gives a relatively stable variance reduction both in- and out-of-sample. Such results are consistent with some of the literature in that dynamic hedging modeling does not have obvious advantages over the constant modeling in terms of risk reduction in the out-of-sample period due to the limitations of GARCH models in forecasting. In contrast, the findings of the China fuel oil futures' ability in hedging market downside risk are promising, especially for the domestic hedging. The hedging effectiveness with all the models increases in terms of semivariance reduction in the out-of-sample period where there is more uncertainty in the market.

Empirically, hedging downside risk is more important to the market participates because returns below some target value could be disastrous for them; whereas returns above the target value could be beneficial. In this sense, we believe that the China fuel oil futures market is an effective hedging instrument, especially for the investors in domestic fuel oil market. For those who use the China fuel oil futures to hedge the downside risk, dynamic model is obviously a good choice than the constant model.

In evaluating the out-of-sample hedging performance, this study also provides the performance comparison of the time path of the risk reduction and of the time path of the expected utility of different hedging strategies. Different from the out-of-sample period performance evaluation based on the average risk reduction and average expected utility, the dynamic models constantly give superior result than the constant models, for both domestic and cross hedging.

Comparing to the existing literature, we take a further step to investigate our findings by conducting an equality test for means and variances of the hedged portfolios. According to the insignificance of most results in the equality test, we find that one hedging strategy is not significantly outperforming the other, for both domestic and cross hedging.

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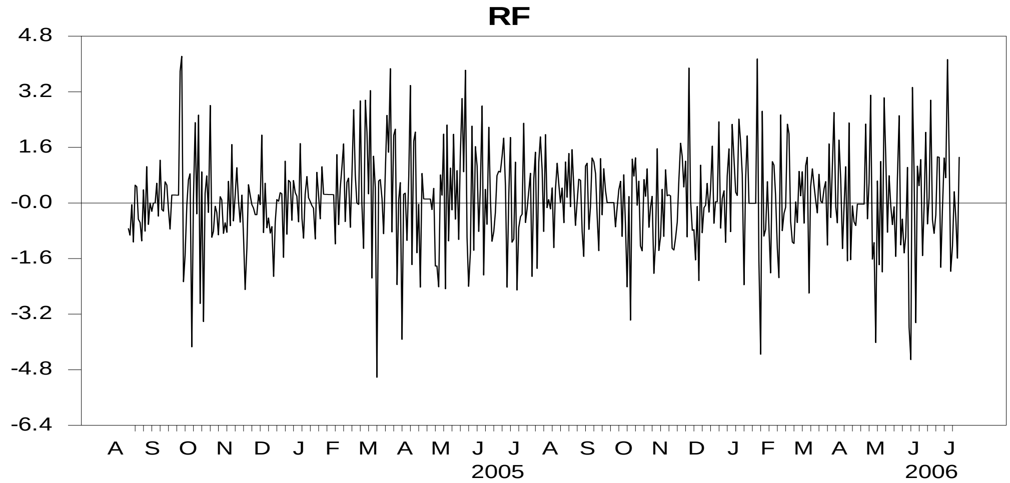
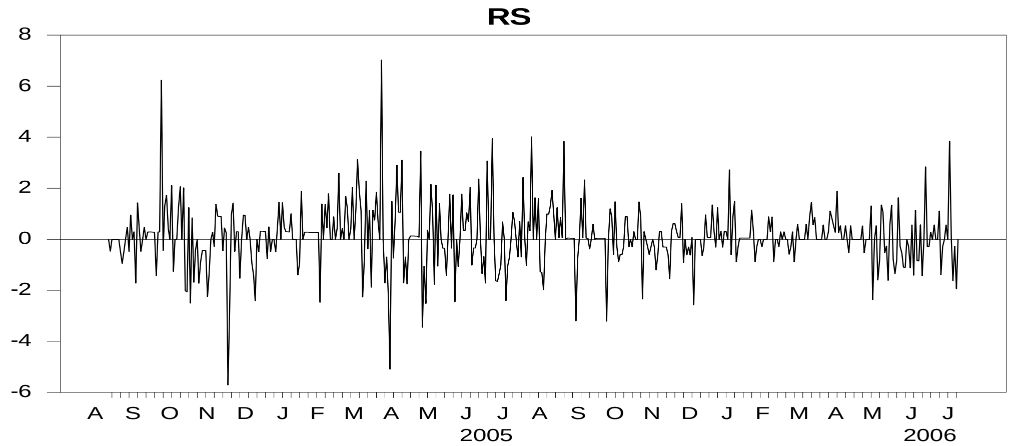
Appendix 1 A

Figure 1. 1 Daily return series





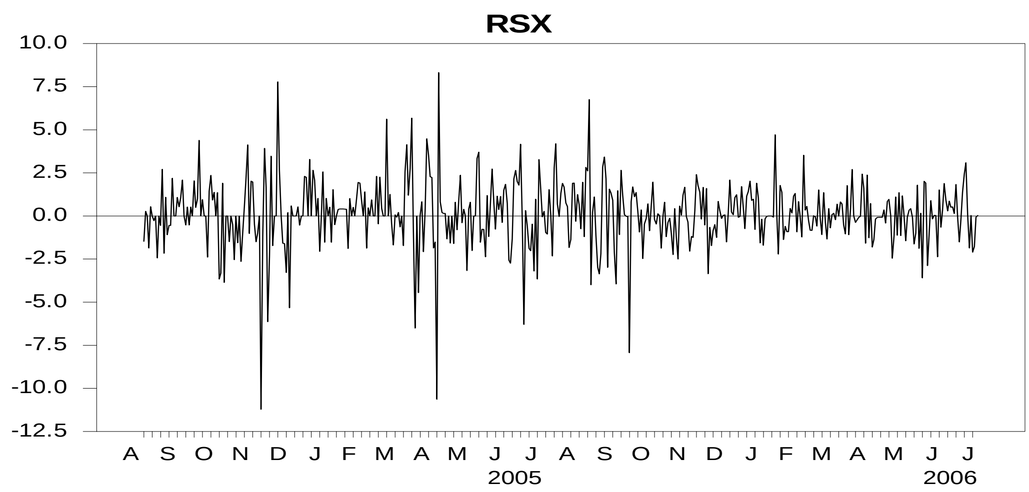
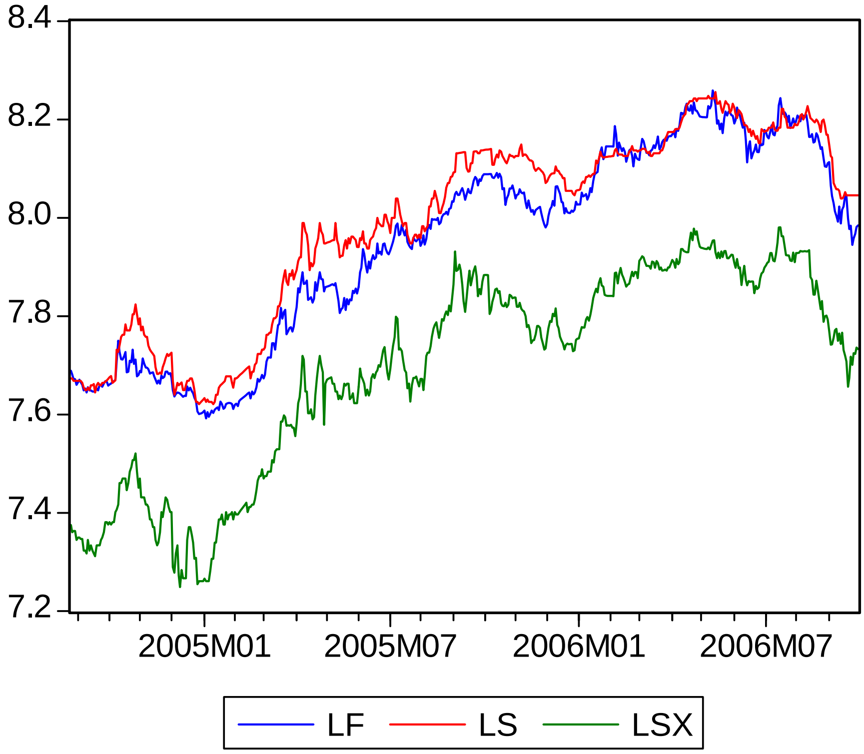


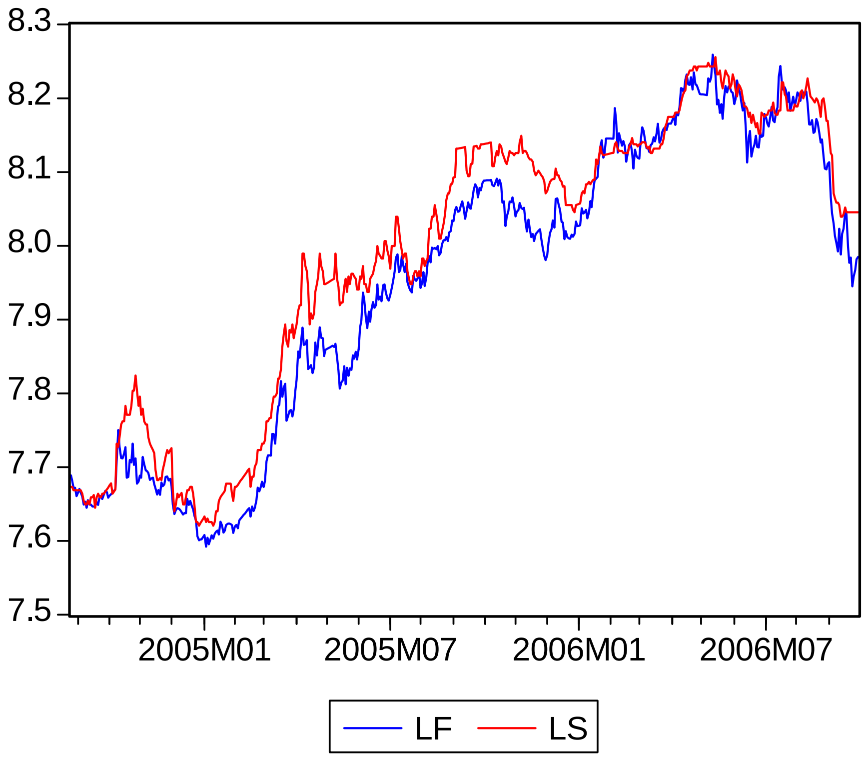
Figure 1. 2 Daily Log price series



Note: LF represents the log price of China fuel oil futures. LS represents the log price of China fuel oil spot and LSX represents the log price of Singapore fuel oil spot.

Figure 1. 3 Pairs of daily log price series

(1) LF and LS



(2) LF and LSX

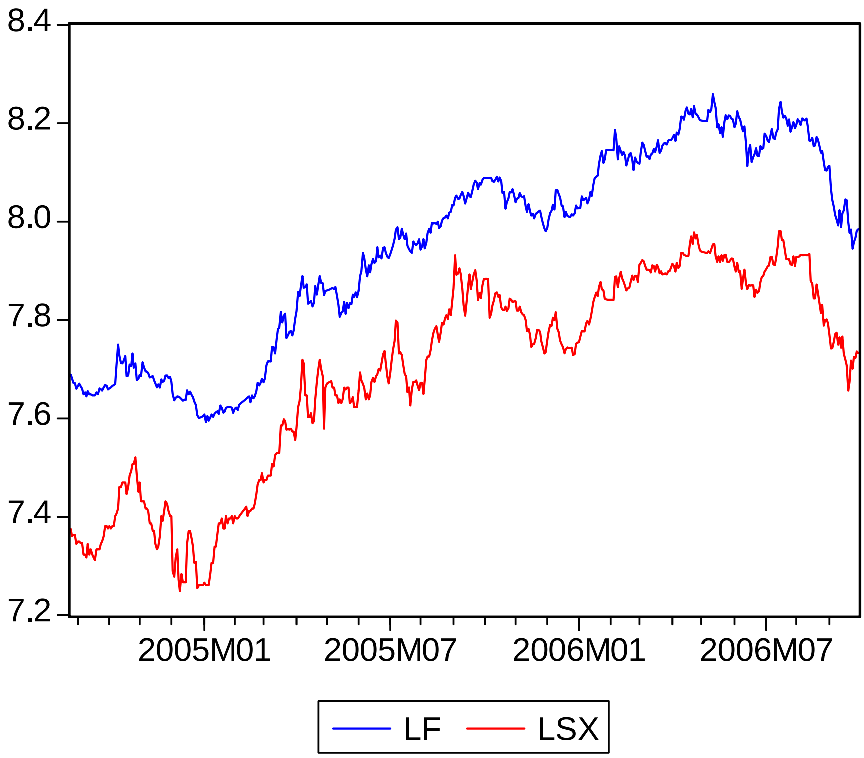
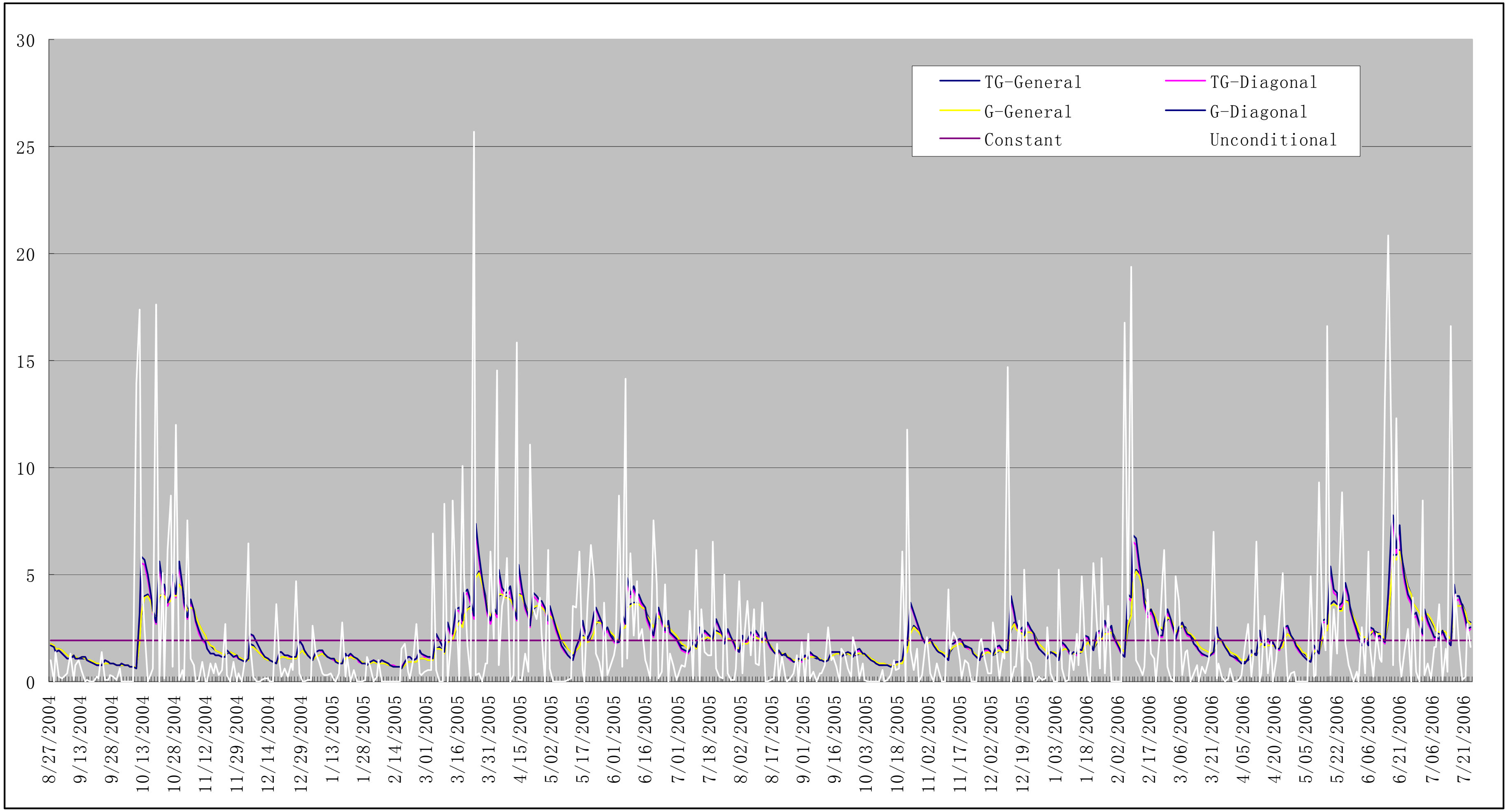
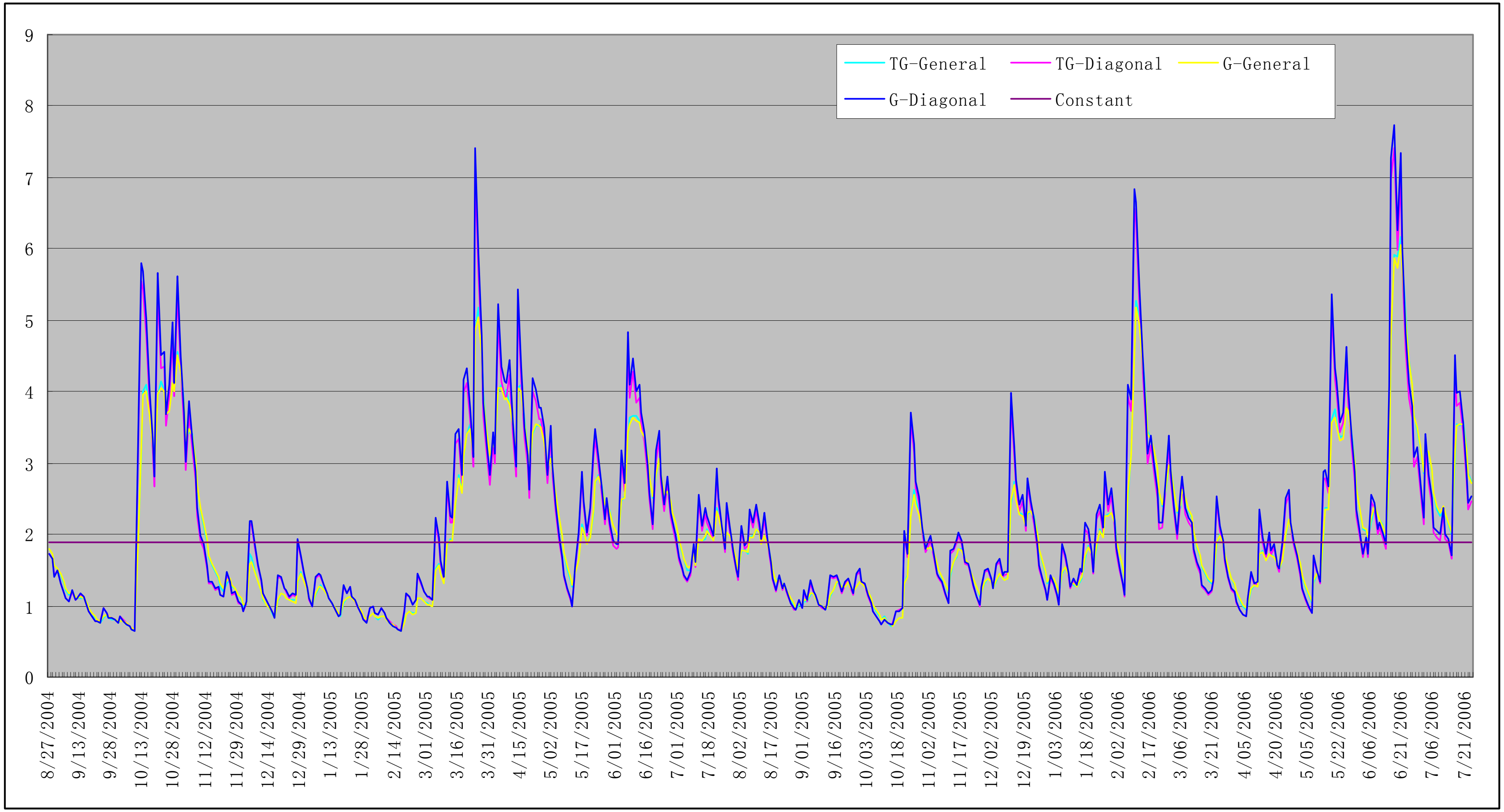


Figure 1. 4 Conditional Variances of Futures Returns for Domestic Hedging: In-sample period

(a)



(b)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TG-Diagonal
G-General
G-Diagonal
Constant
0
1
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8
9
8/27/2004
9/13/2004
9/28/2004
10/13/2004
10/28/2004
11/12/2004
11/29/2004
12/14/2004
12/29/2004
1/13/2005
1/28/2005
2/14/2005
3/01/2005
3/16/2005
3/31/2005
4/15/2005
5/02/2005
5/17/2005
6/01/2005
6/16/2005
7/01/2005
7/18/2005
8/02/2005
8/17/2005
9/01/2005
9/16/2005
10/03/2005
10/18/2005
11/02/2005
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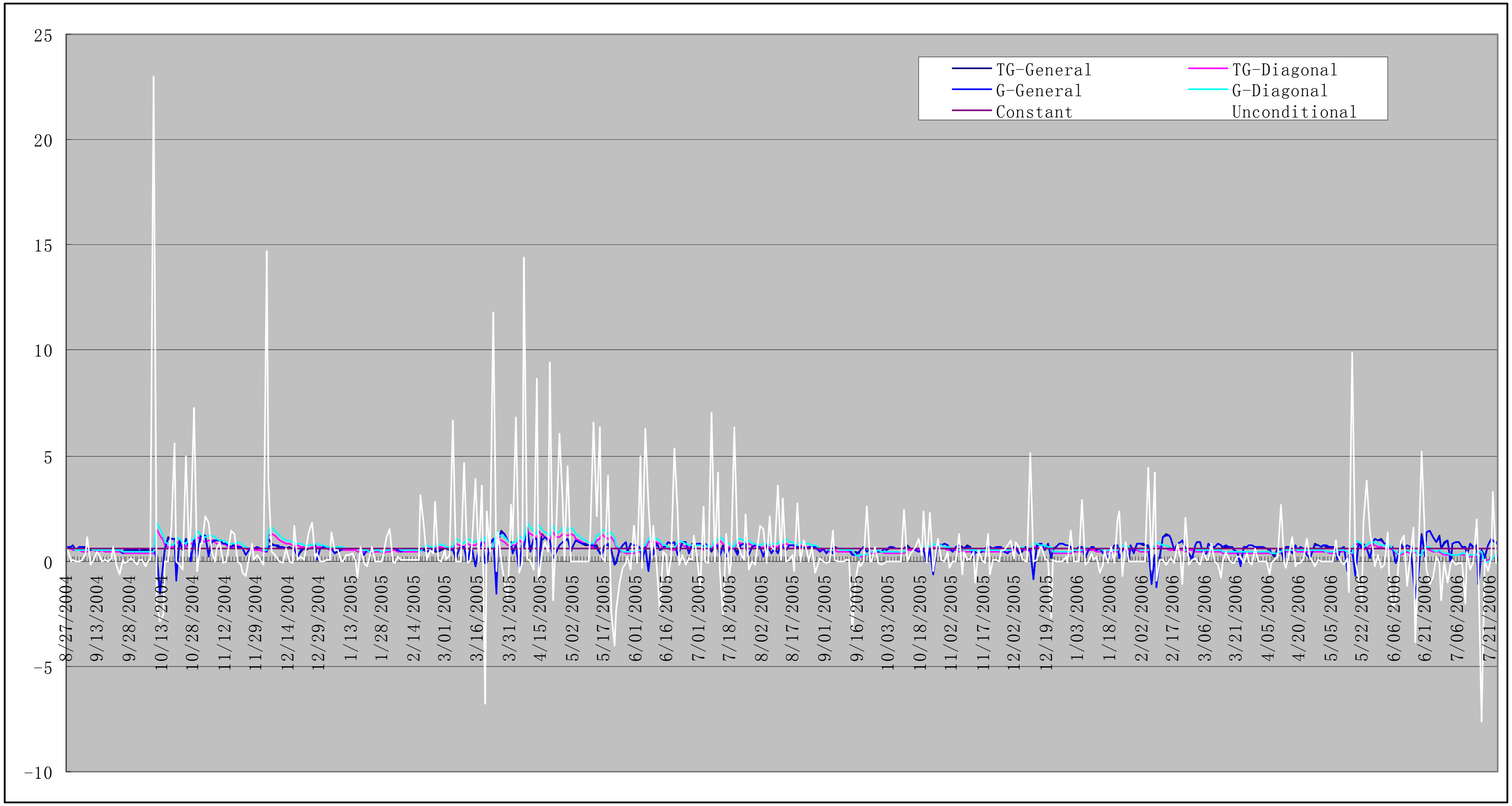
12/19/2005
1/03/2006
1/18/2006
2/02/2006
2/17/2006
3/06/2006
3/21/2006
4/05/2006
4/20/2006
5/05/2006
5/22/2006
6/06/2006
6/21/2006
7/06/2006
7/21/2006

Figure 1. 5 Conditional Covariance of Spot and Futures Returns for Domestic Hedging: In-sample period

(a)



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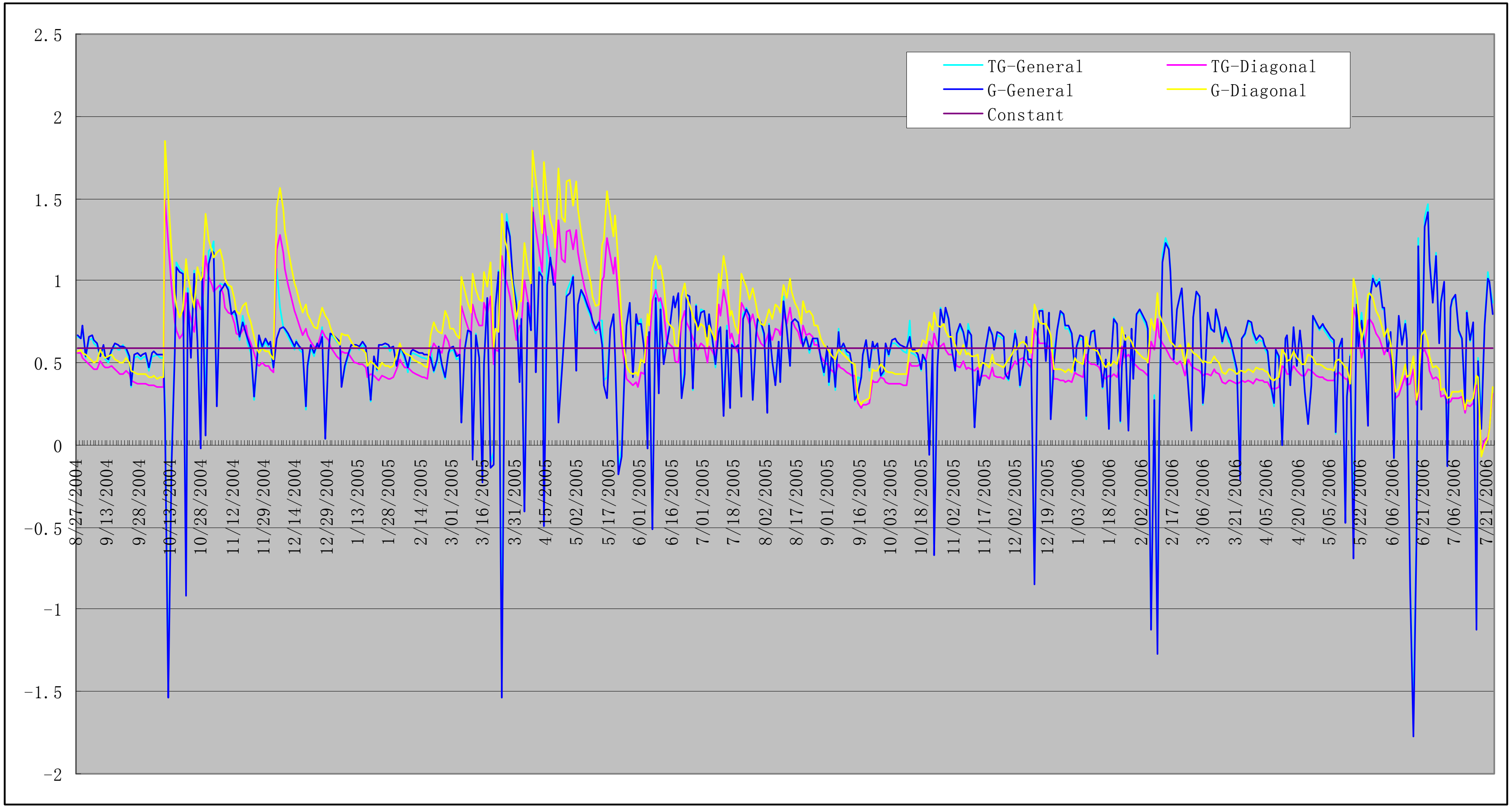
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G-General
G-Diagonal
Constant
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2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
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9/13/2004
9/28/2004
10/13/2004
10/28/2004
11/12/2004
11/29/2004
12/14/2004
12/29/2004
1/13/2005
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3/01/2005
3/16/2005
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7/01/2005
7/18/2005
8/02/2005
8/17/2005
9/01/2005
9/16/2005
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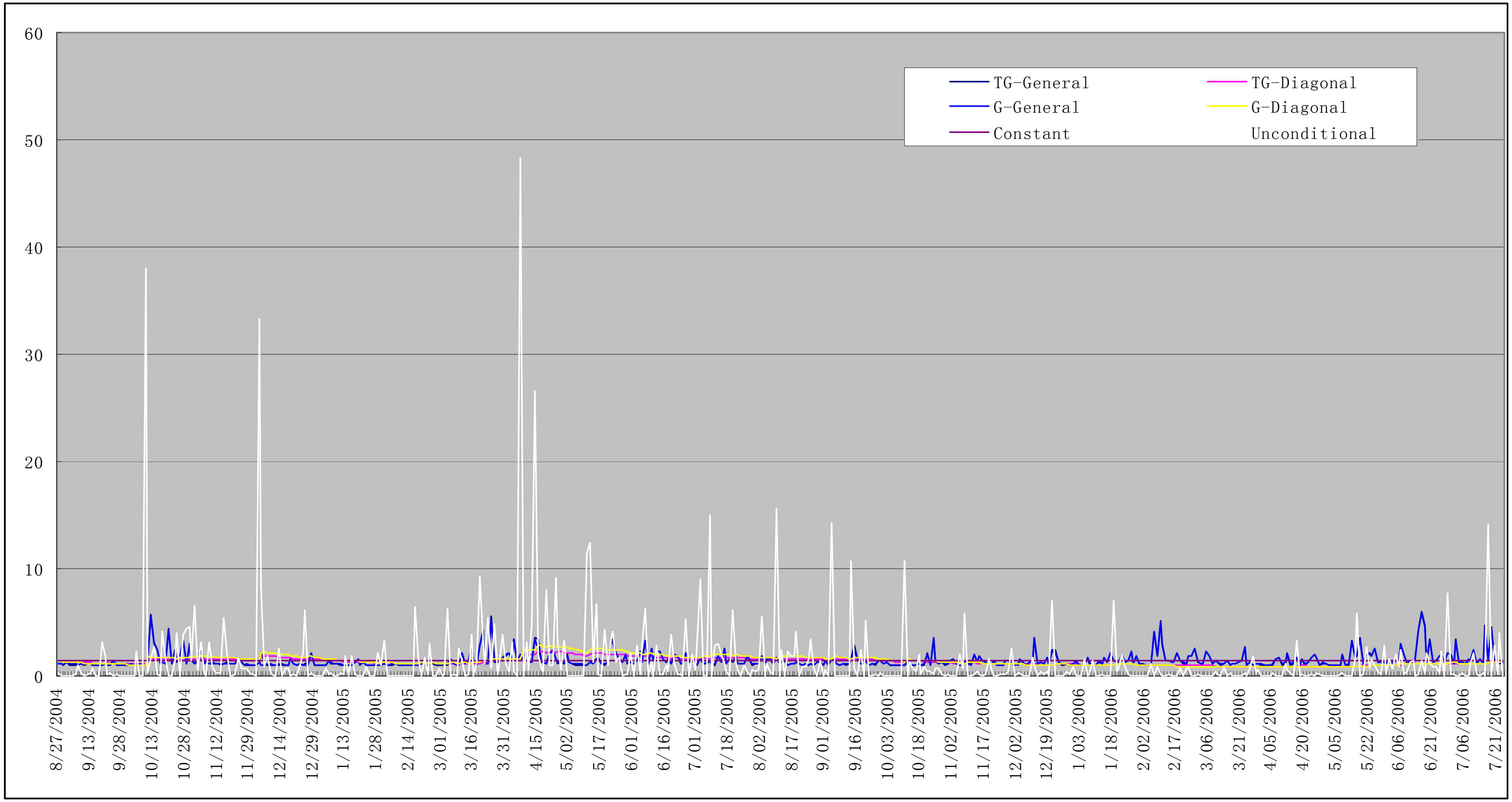
1/18/2006
2/02/2006
2/17/2006
3/06/2006
3/21/2006
4/05/2006
4/20/2006
5/05/2006
5/22/2006
6/06/2006
6/21/2006
7/06/2006
7/21/2006

Figure 1. 6 Conditional Variance of Spot Returns for Domestic Hedging: In-sample Period

(a)



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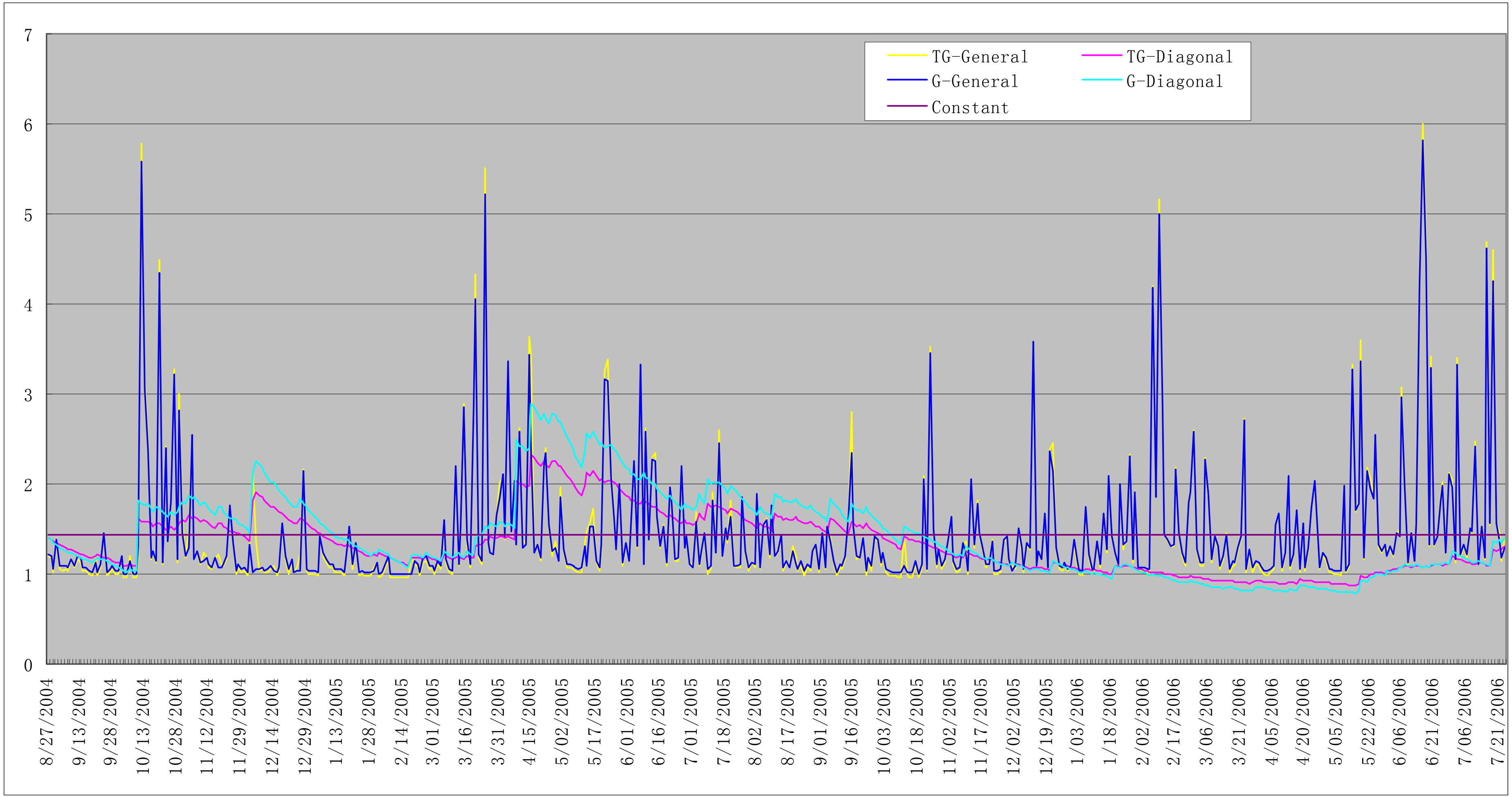
TG-General
TG-Diagonal
G-General
G-Diagonal
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8/27/2004
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10/13/2004
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2/14/2005
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3/06/2006
3/21/2006
4/05/2006
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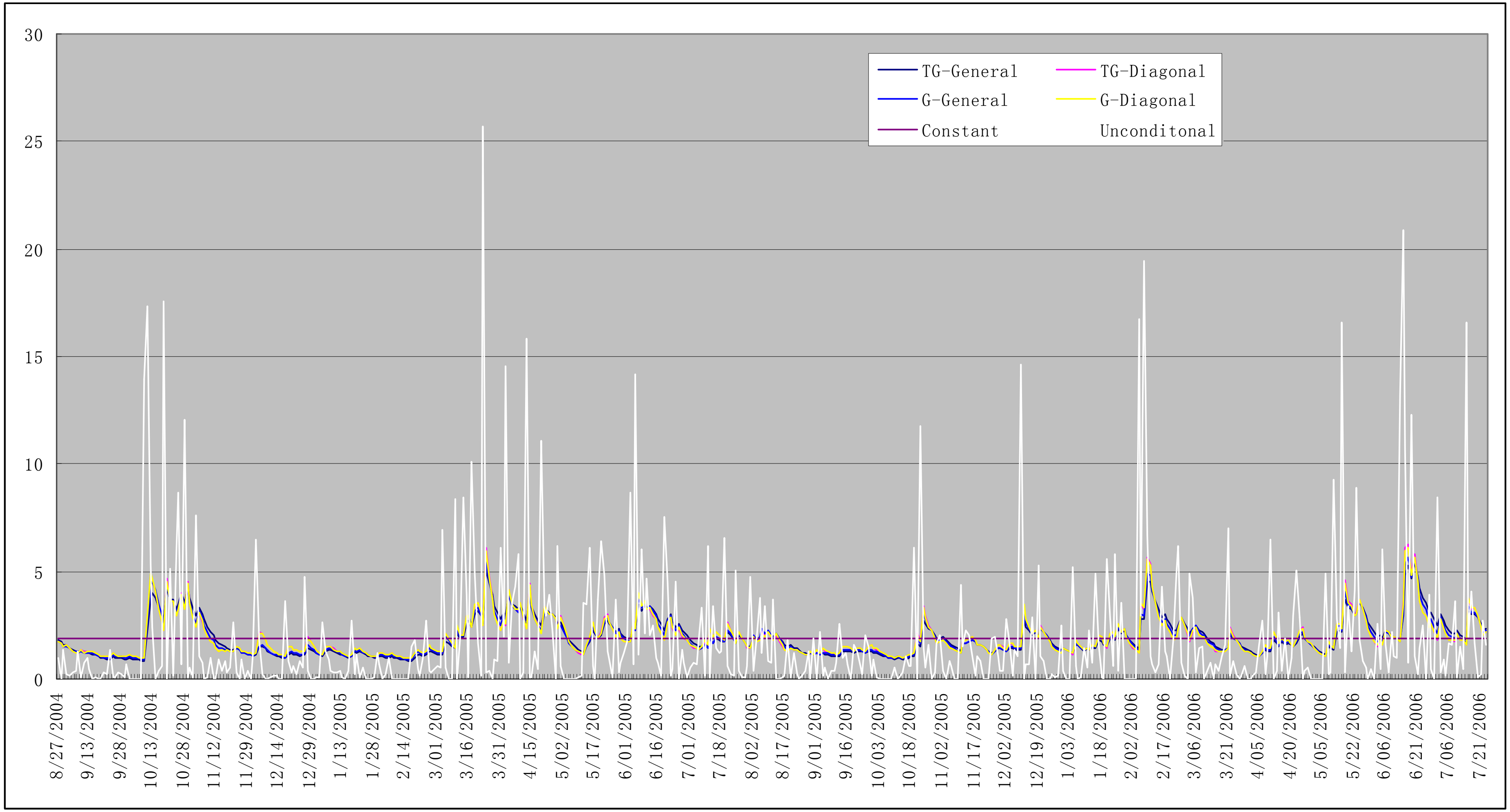
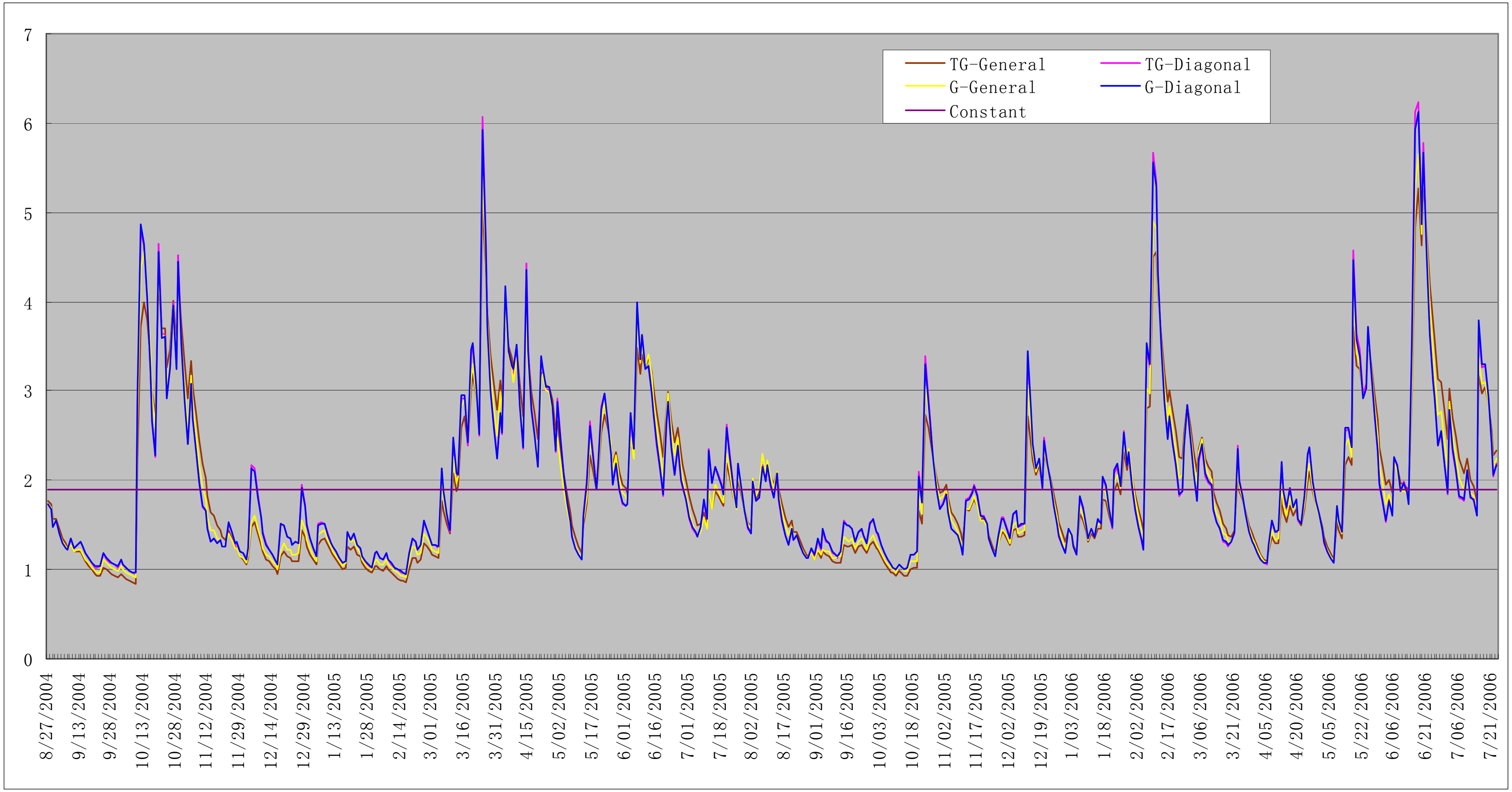
5/05/2006
5/22/2006
6/06/2006
6/21/2006
7/06/2006
7/21/2006

Figure 1. 7 Conditional Variance of Futures Returns for Cross Border Hedging: In-sample period

(a)



(b)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TG-General
TG-Diagonal
G-General
G-Diagonal
Constant
8/27/2004
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10/13/2004
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11/12/2004
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12/14/2004
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1/13/2005
1/28/2005
2/14/2005
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4/20/2006
5/05/2006
5/22/2006
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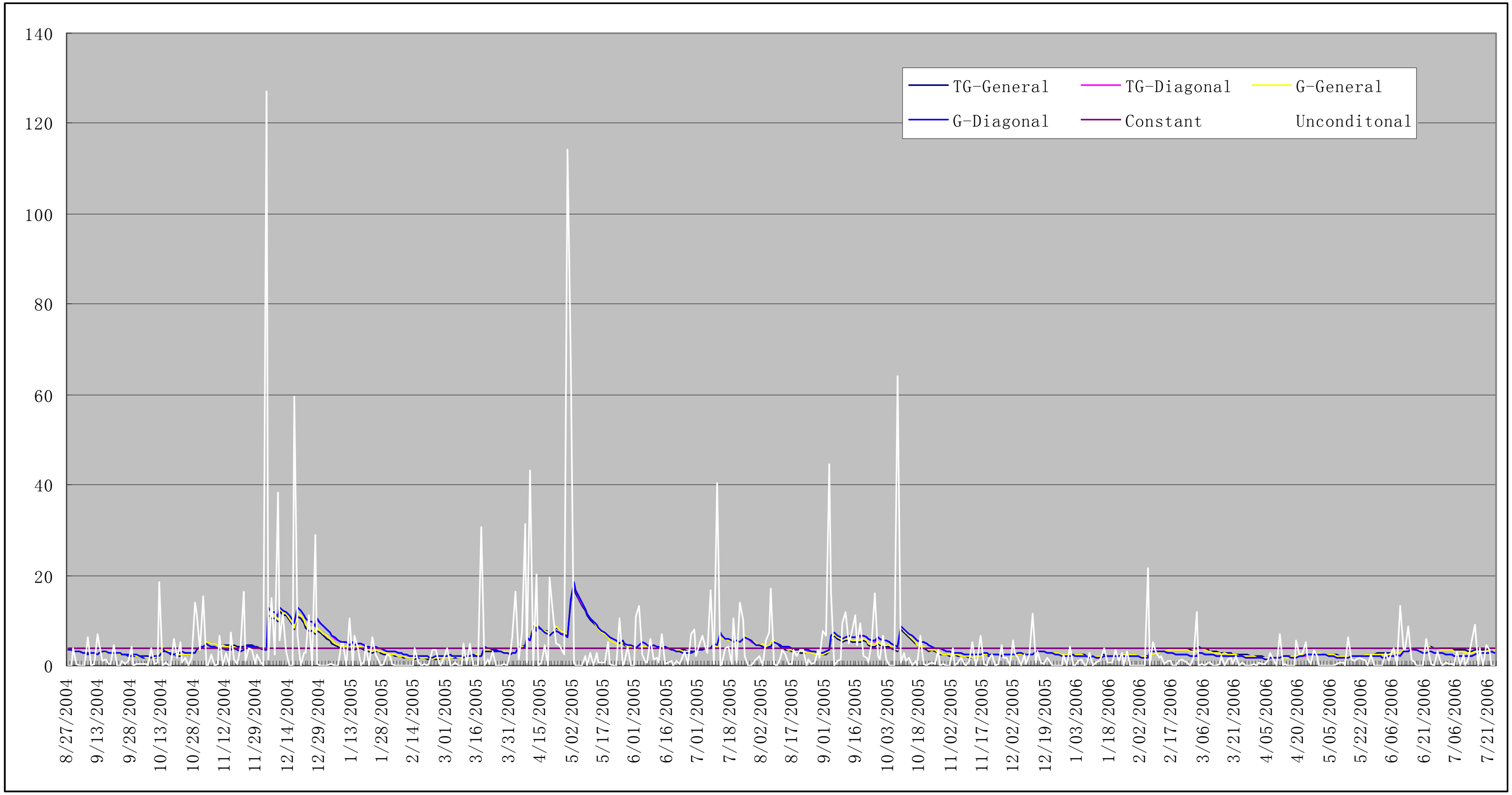
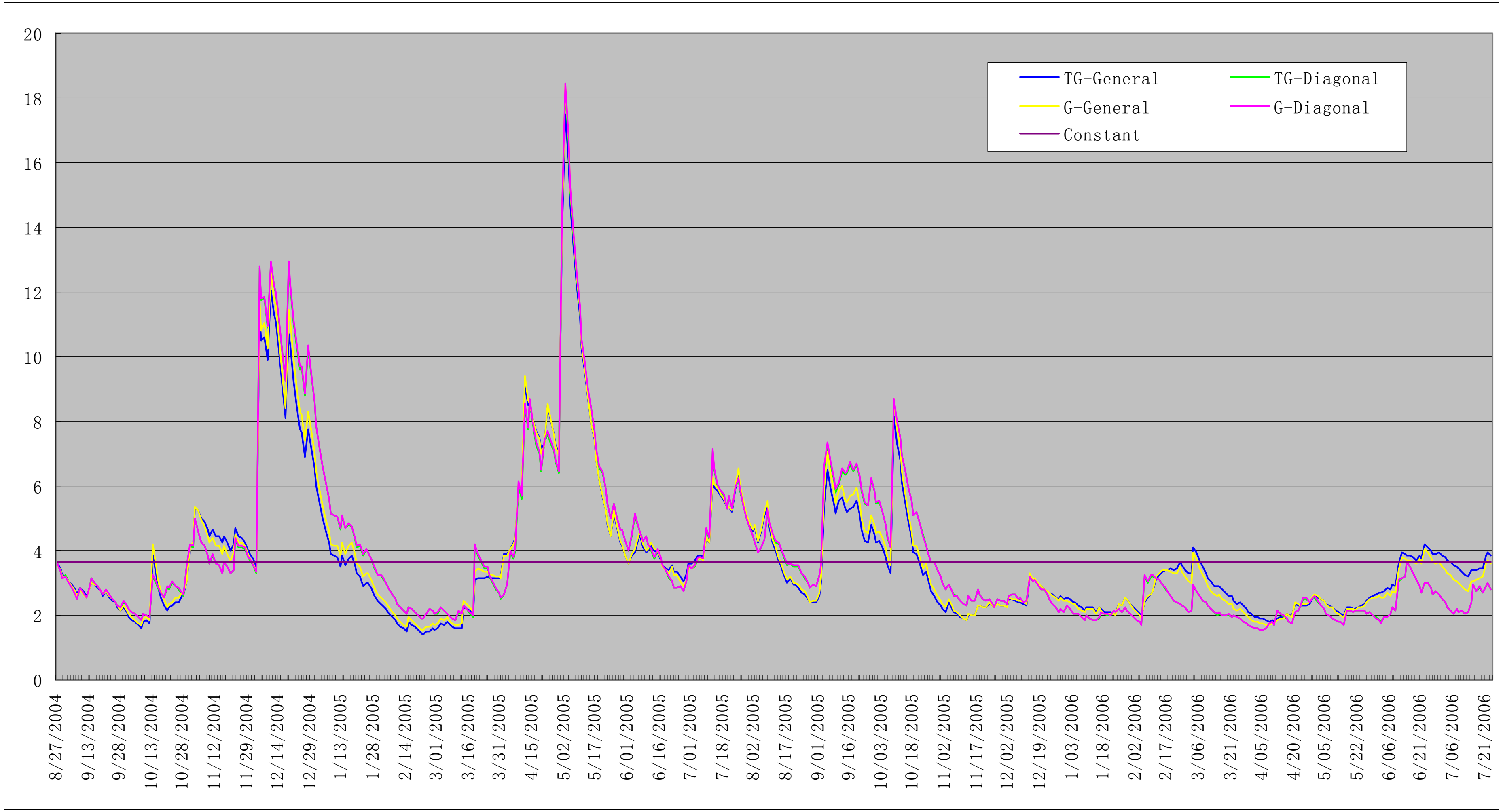
6/21/2006
7/06/2006
7/21/2006

Figure 1. 8 Conditional Variance of Spot Returns for Cross Hedging: In-sample period

(a)



(b)



20
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TG-General
TG-Diagonal
G-General
G-Diagonal
Constant
8/27/2004
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9/28/2004
10/13/2004
10/28/2004
11/12/2004
11/29/2004
12/14/2004
12/29/2004
1/13/2005
1/28/2005
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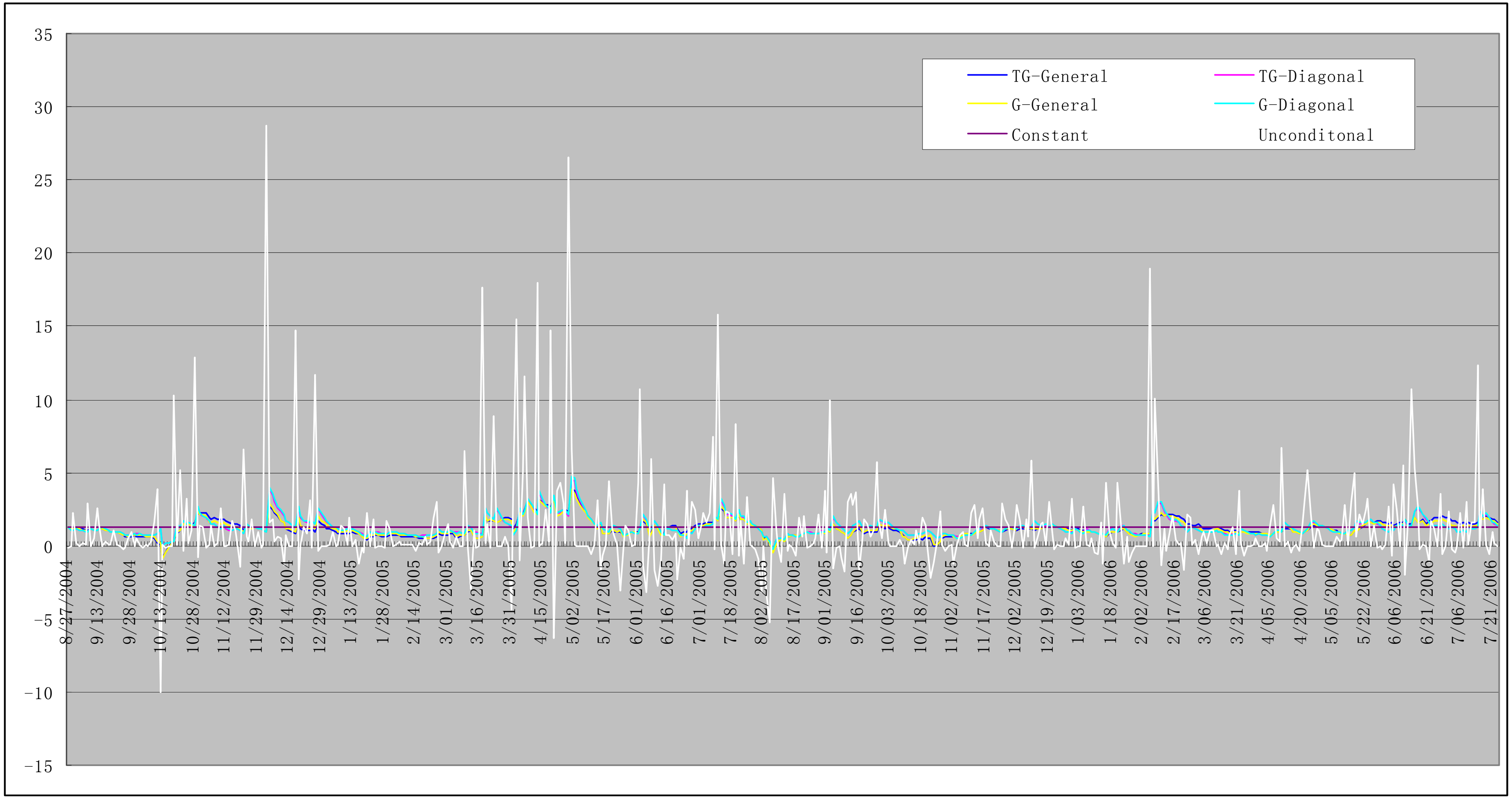
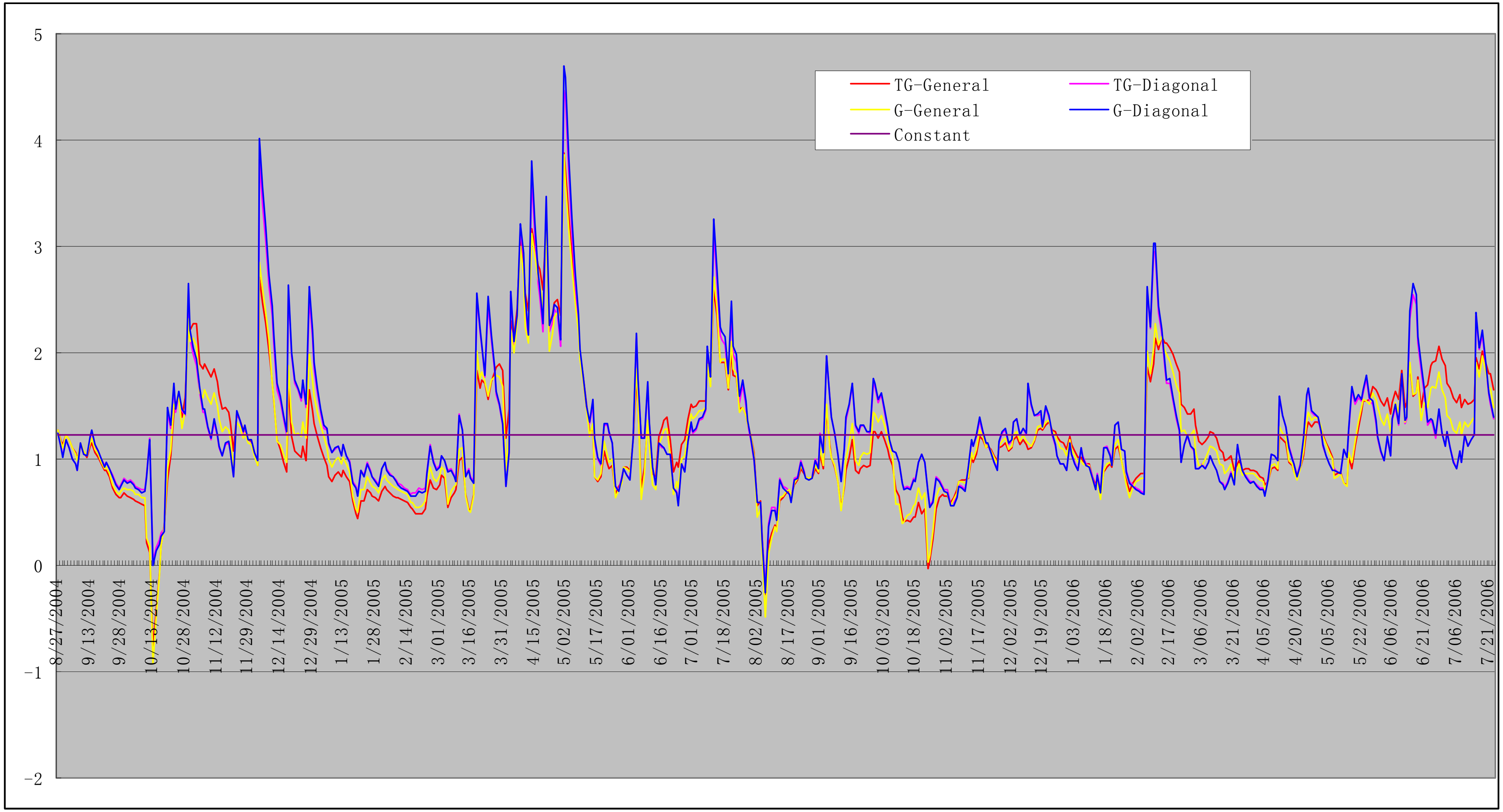
7/06/2006
7/21/2006

Figure 1. 9 Conditional Covariance of Spot and Futures Returns for Cross Hedging: In-sample period

(a)



(b)



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TG-Diagonal
G-General
G-Diagonal
Constant
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Figure 1. 10 Estimated hedge ratios of the domestic hedging: In-sample period

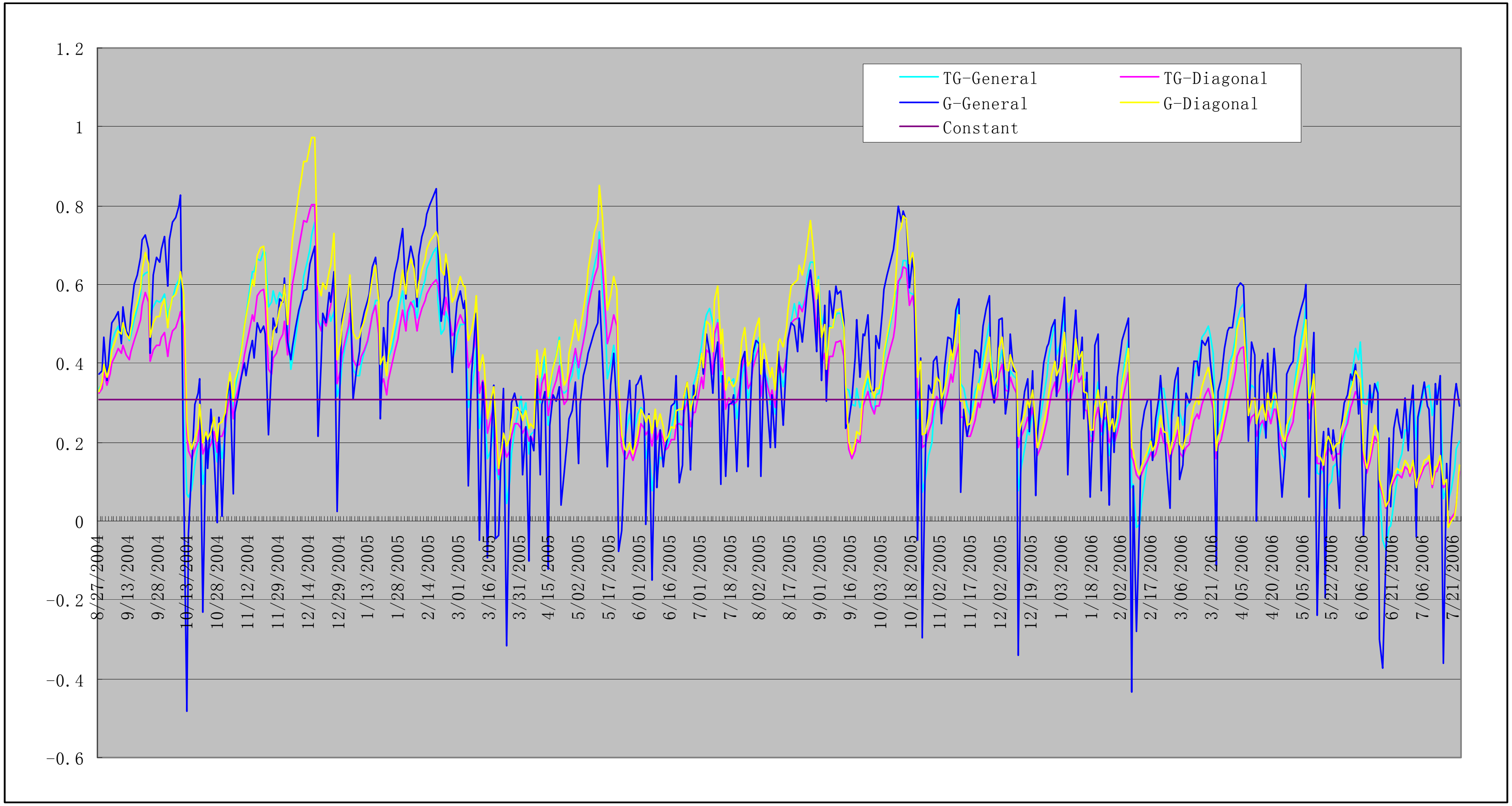


Figure 1. 11 Estimated hedge ratios for cross hedging in the Singapore market: In-sample period

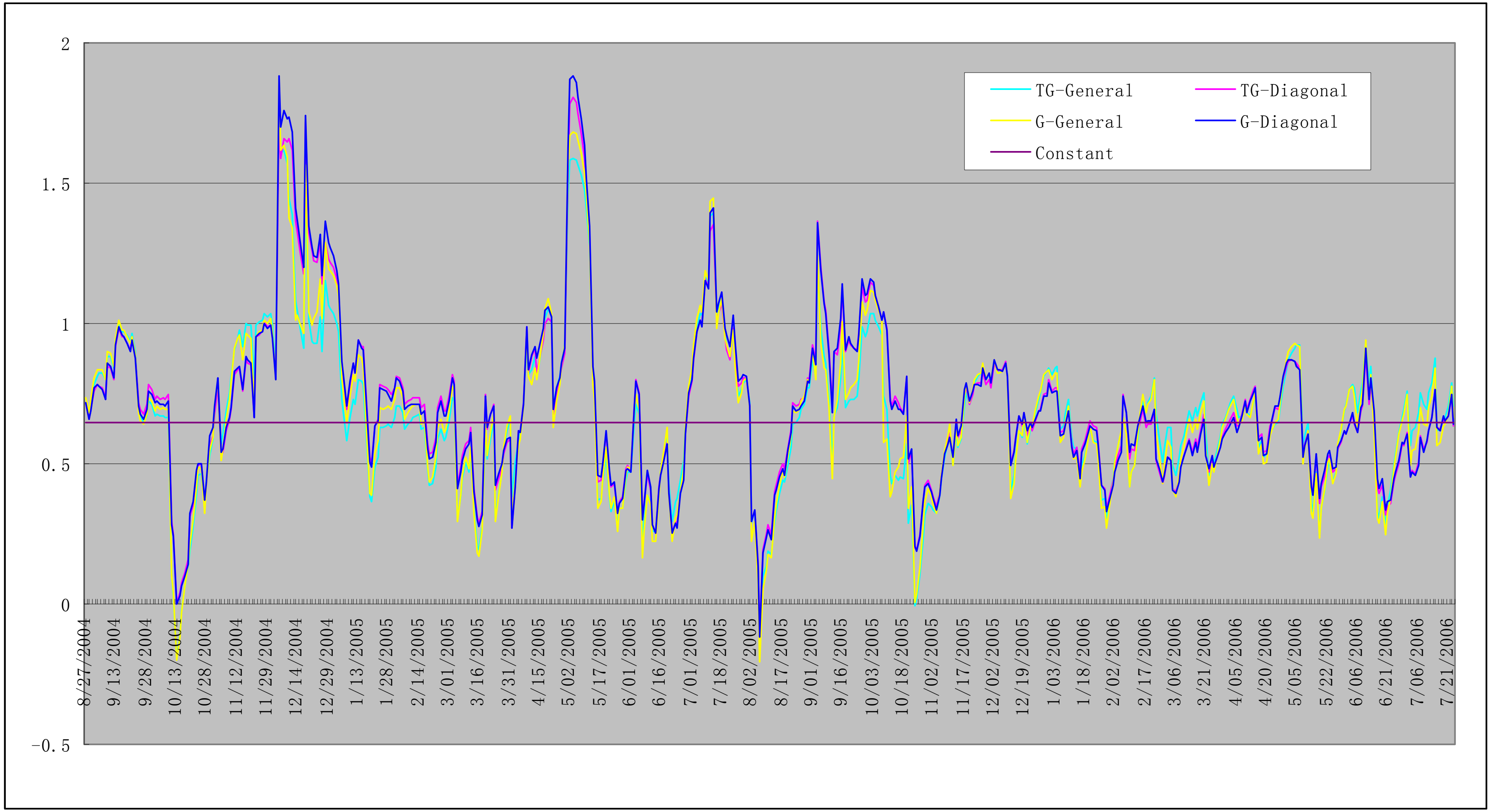


Figure 1. 12 Estimated hedge ratios with the TGARH General model for domestic hedging under Utility Maximisation criterion: In-sample period

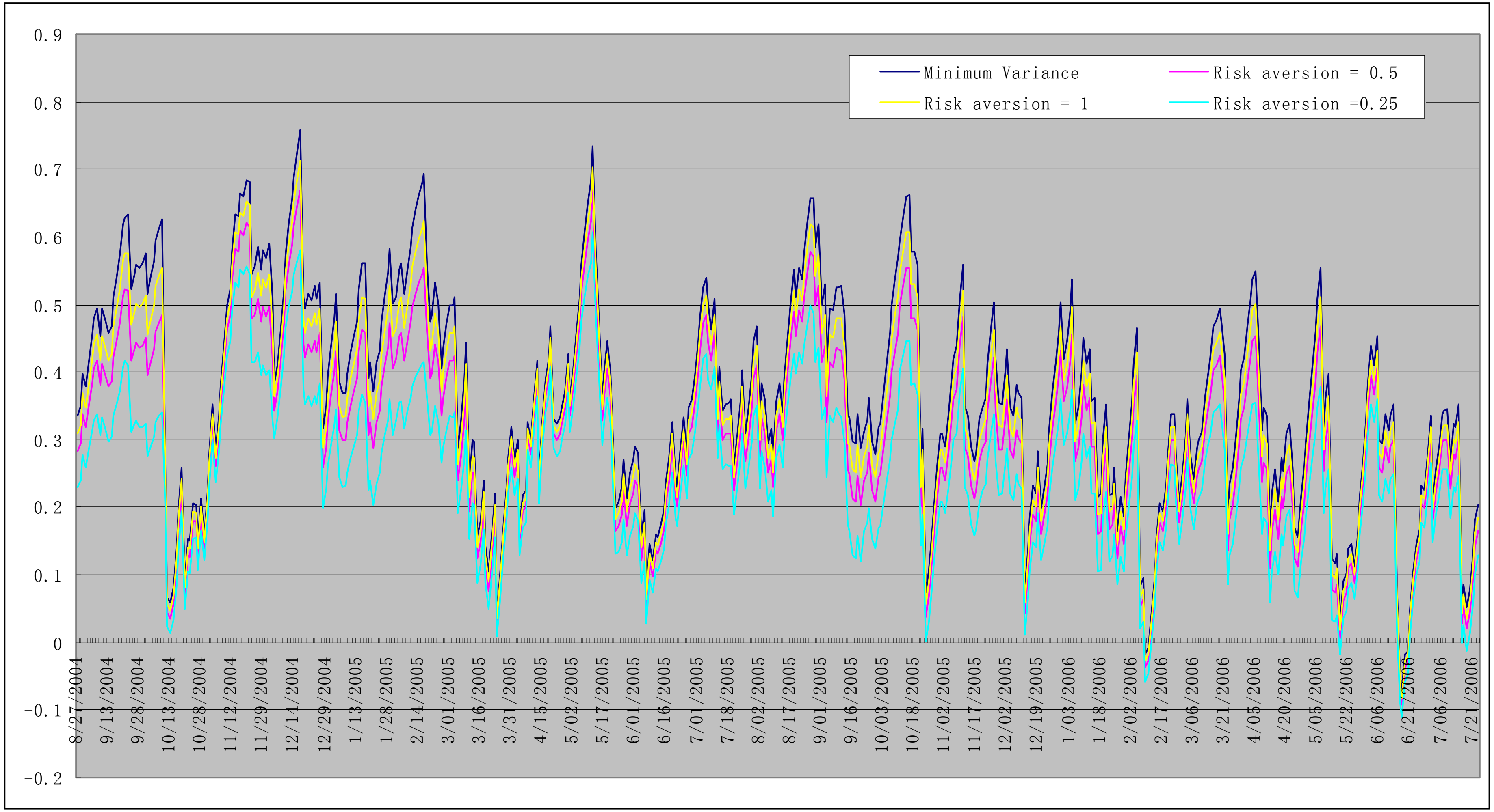


Figure 1. 13 Estimated hedge ratios under the TGARCH-Diagonal model for domestic hedging under Utility Maximisation criterion: In-sample period

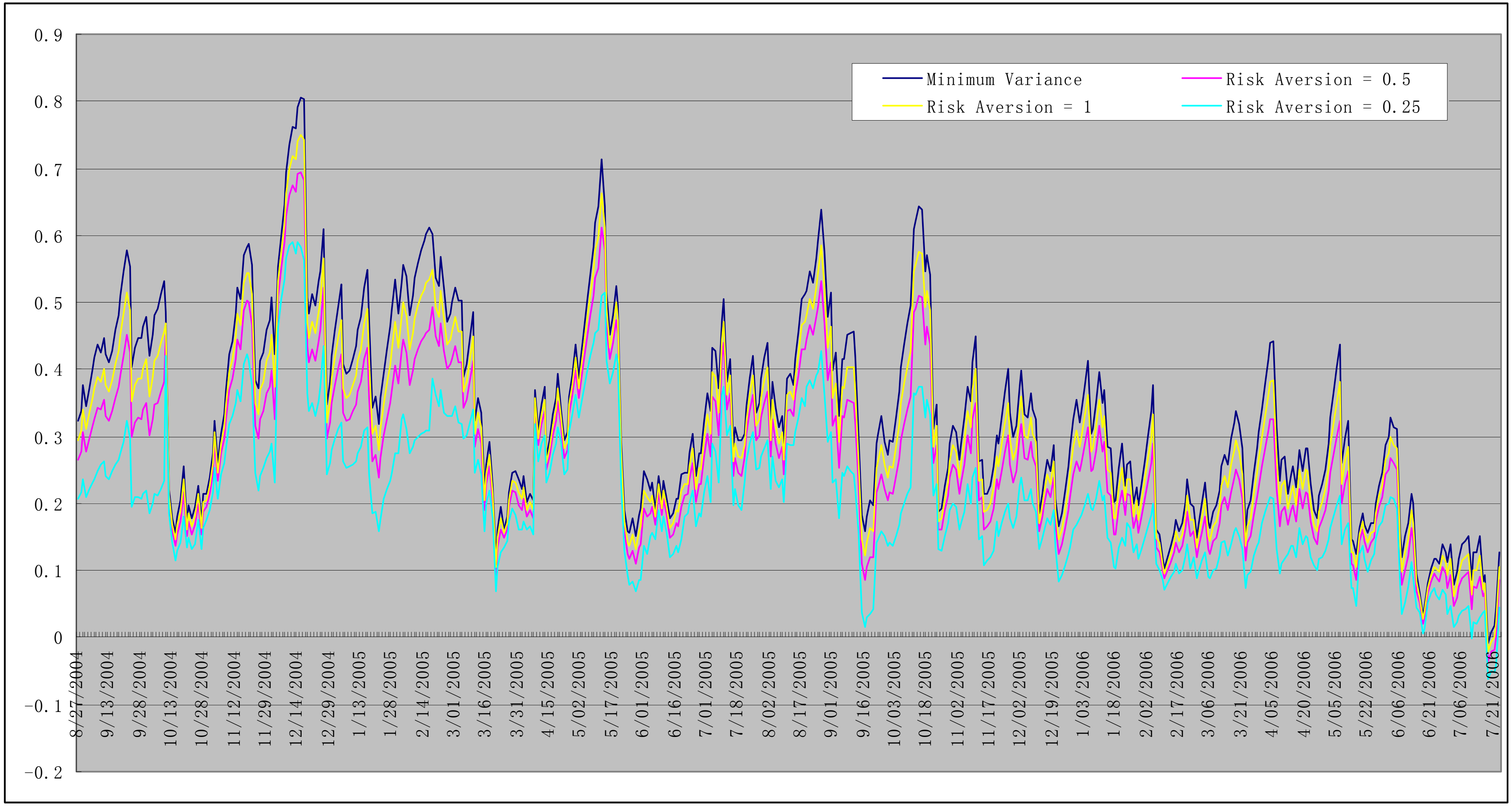


Figure 1. 14 Estimated hedge ratios using the TGARCH general for cross hedging under Utility Maximisation criterion: In-sample period

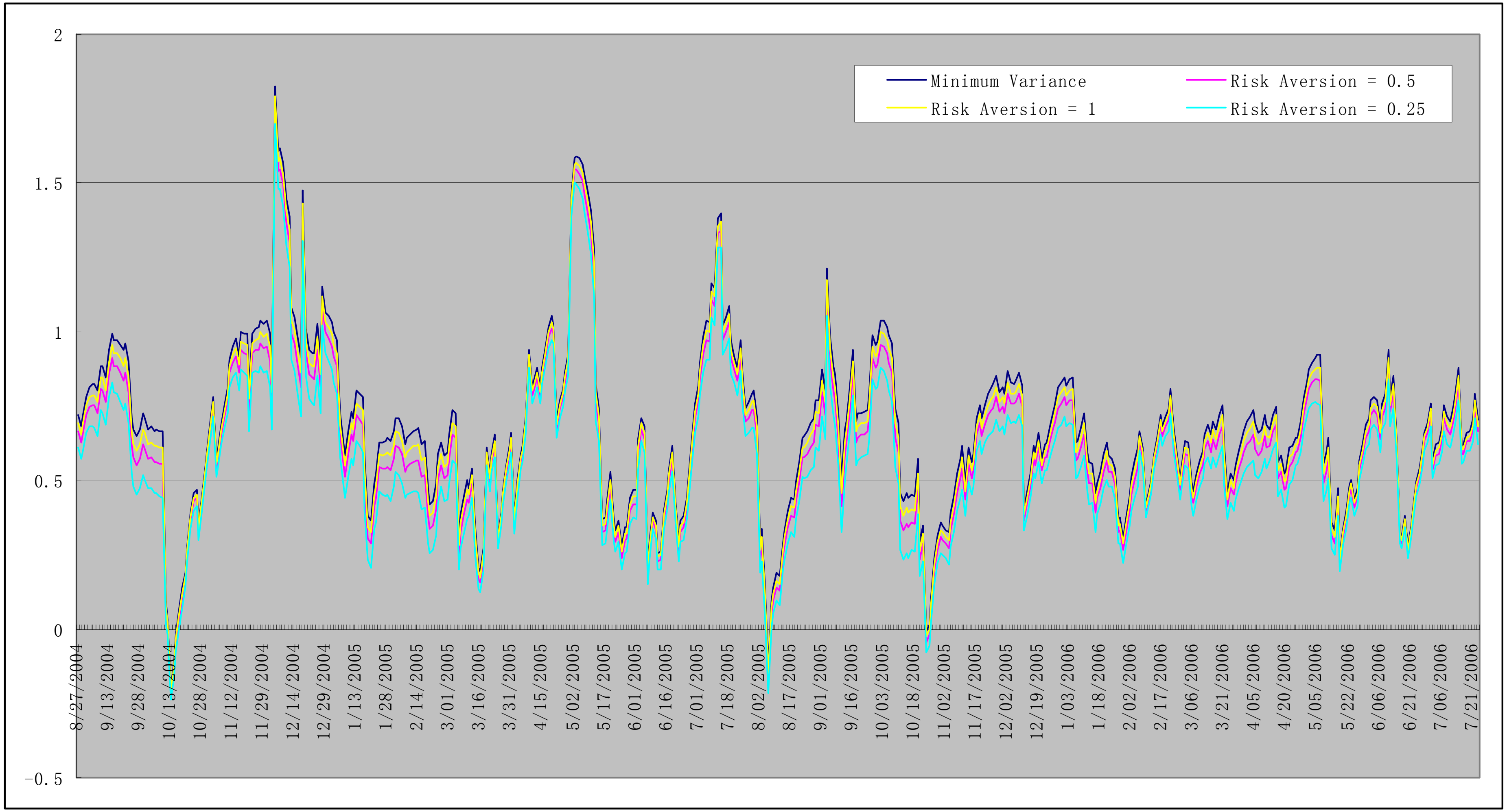


Figure 1. 15 Estimated hedge ratios using the GARCH General model for the cross hedging under Utility Maximisation criterion: In-sample period

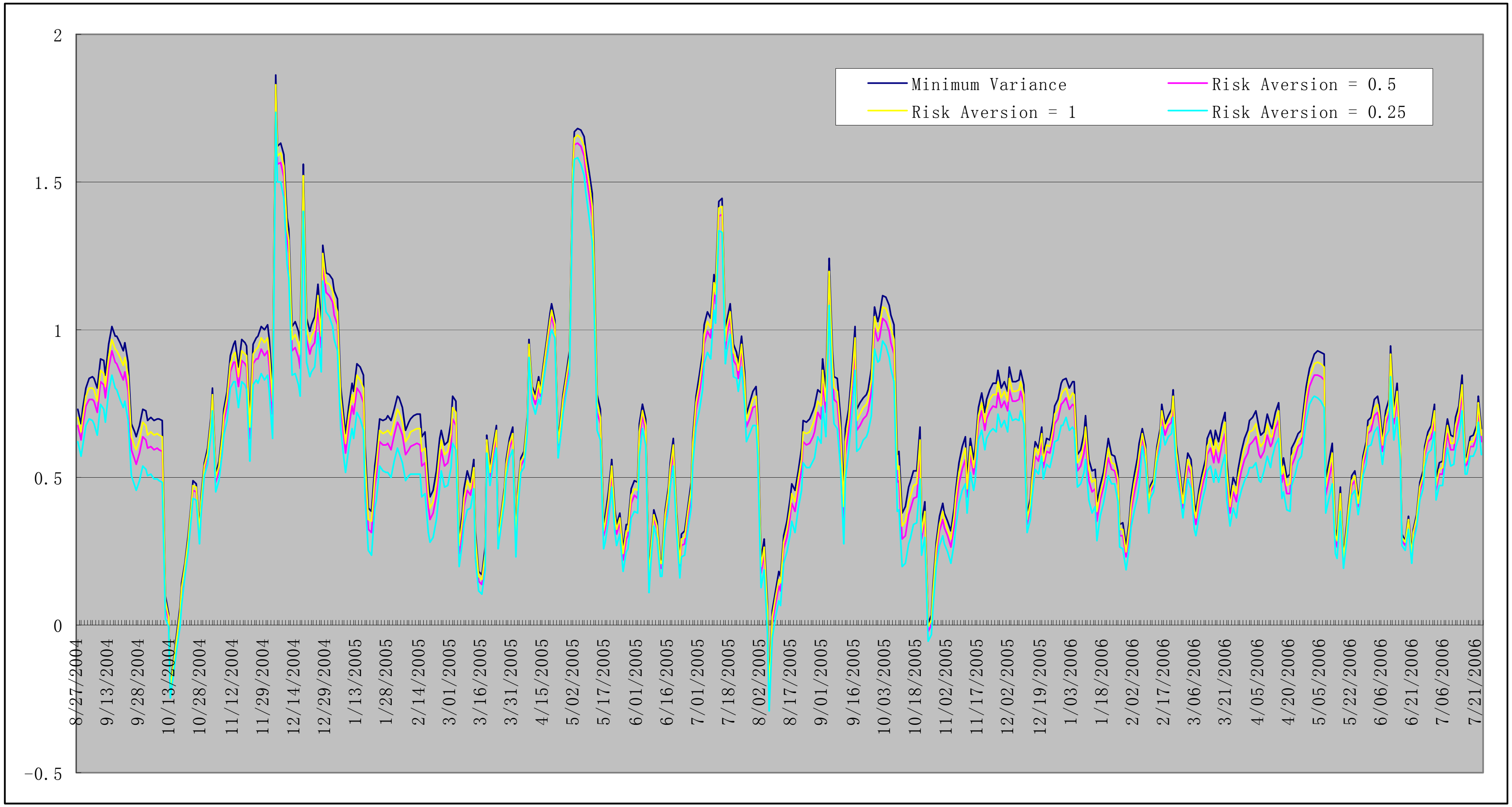
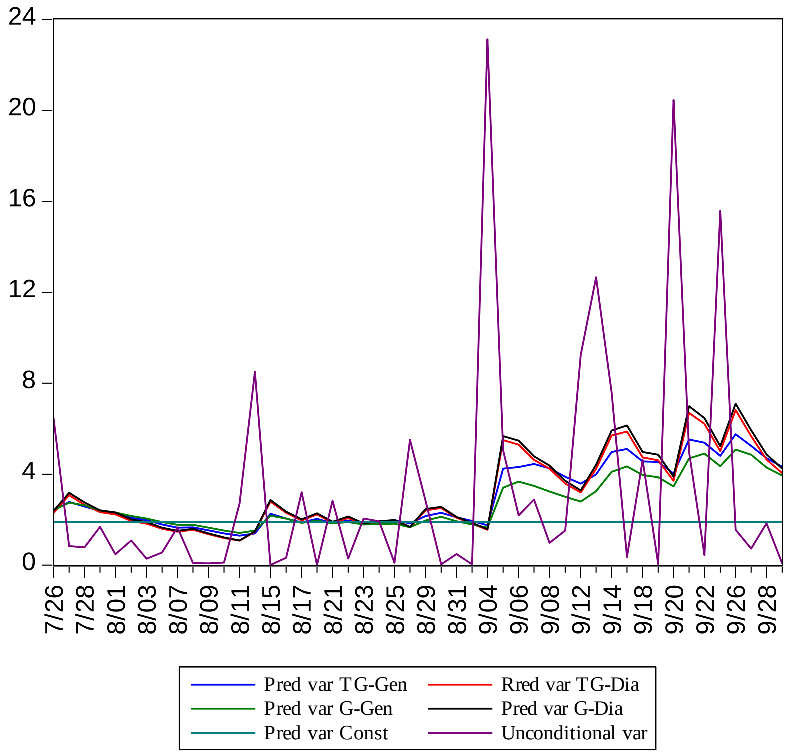


Figure 1. 16 Predicted variance (Pred var) and the unconditional variance (Unconditional var) of futures returns for the domestic hedging: out-of-sample



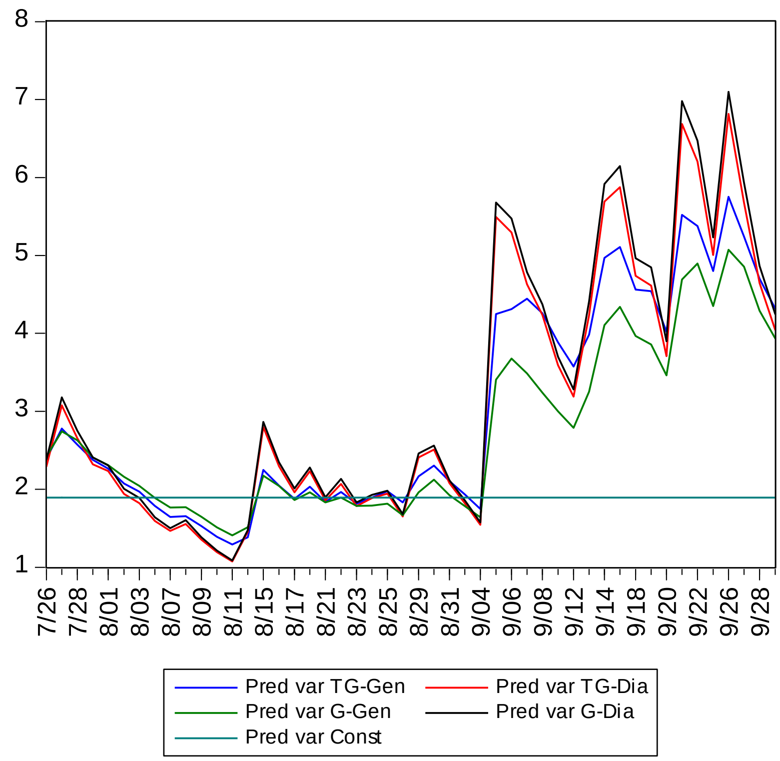
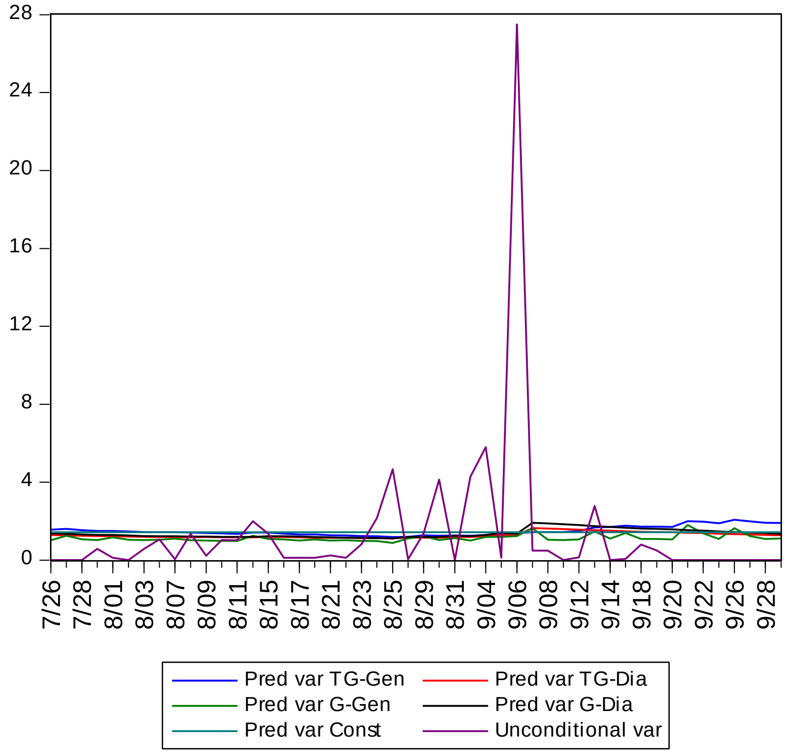


Figure 1. 17 Predicted variance (Pred var) and the unconditional variance (Unconditional var) of the spot returns for the domestic hedging: out-of-sample



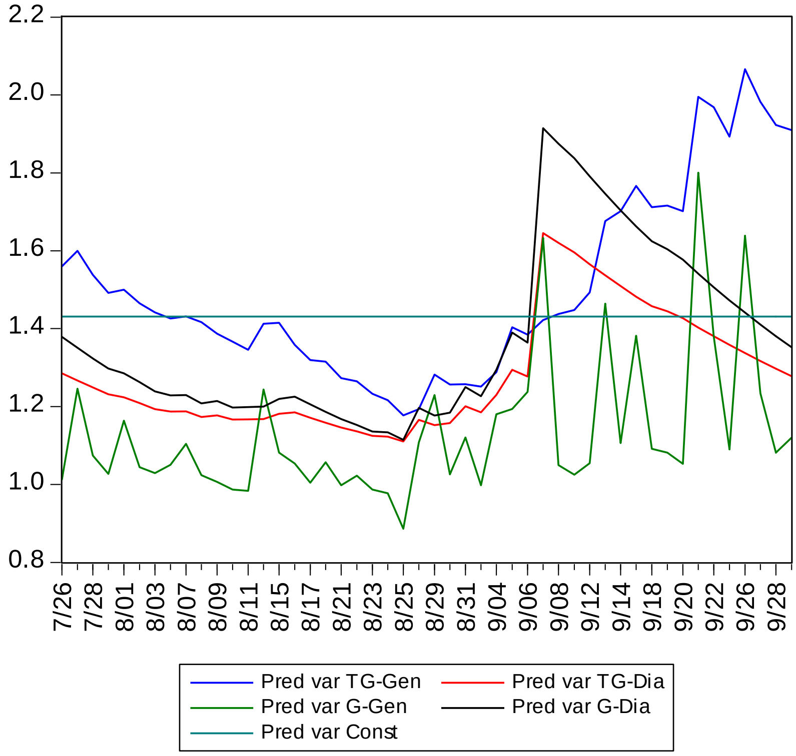
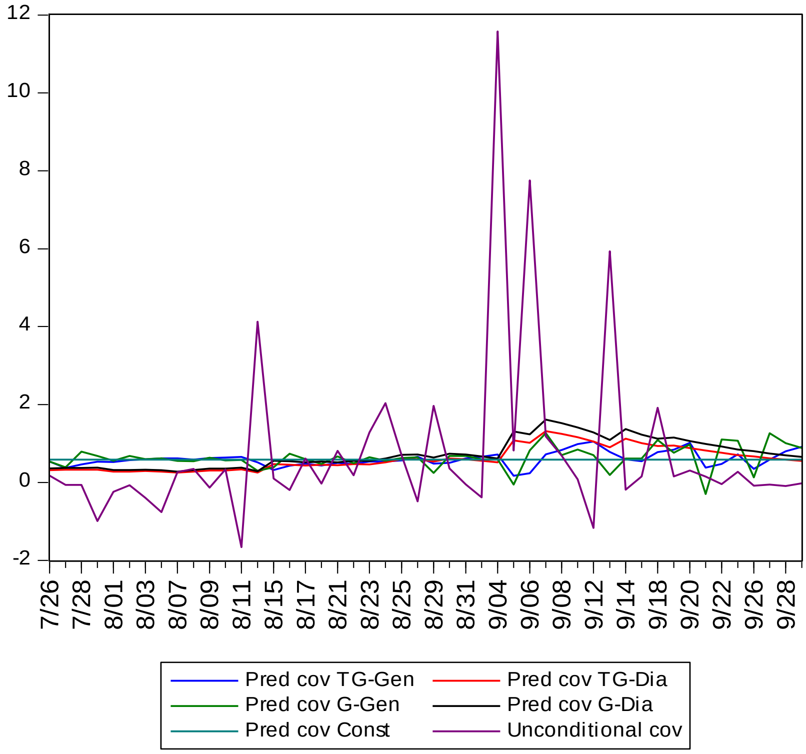


Figure 1. 18 Predicted covariance (Pred cov) and the unconditional covariance (Unconditional cov) of Spot and futures returns for the domestic hedging: out-of-sample



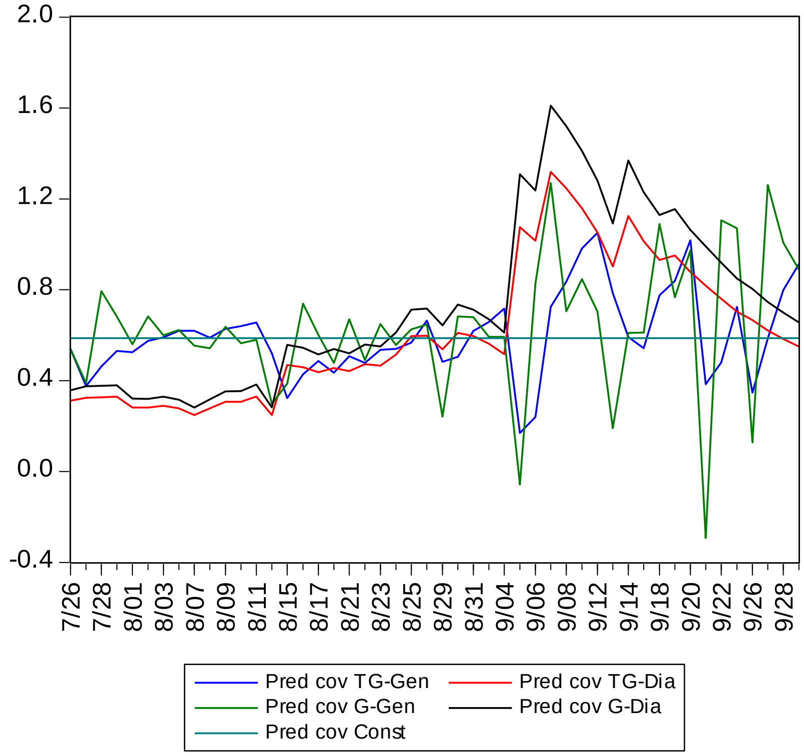
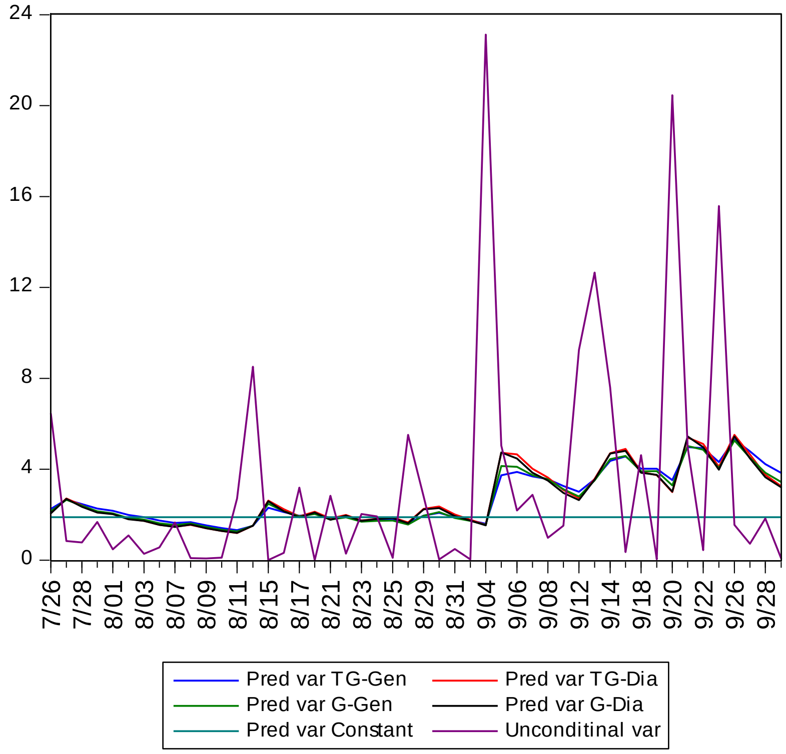


Figure 1. 19 Predicted variance (Pred var) and the unconditional variance (Unconditional var) of futures returns for the cross hedging: out-of-sample



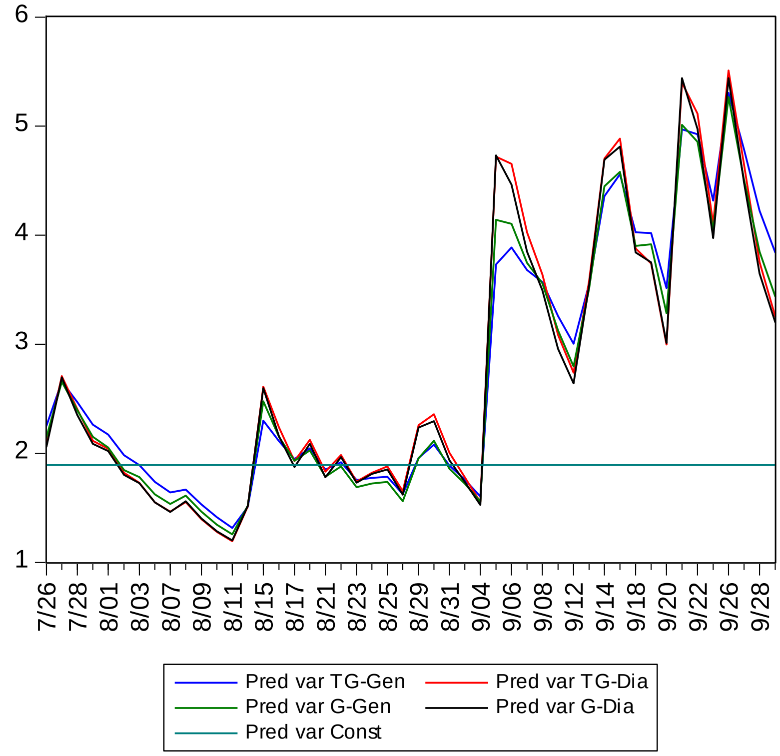
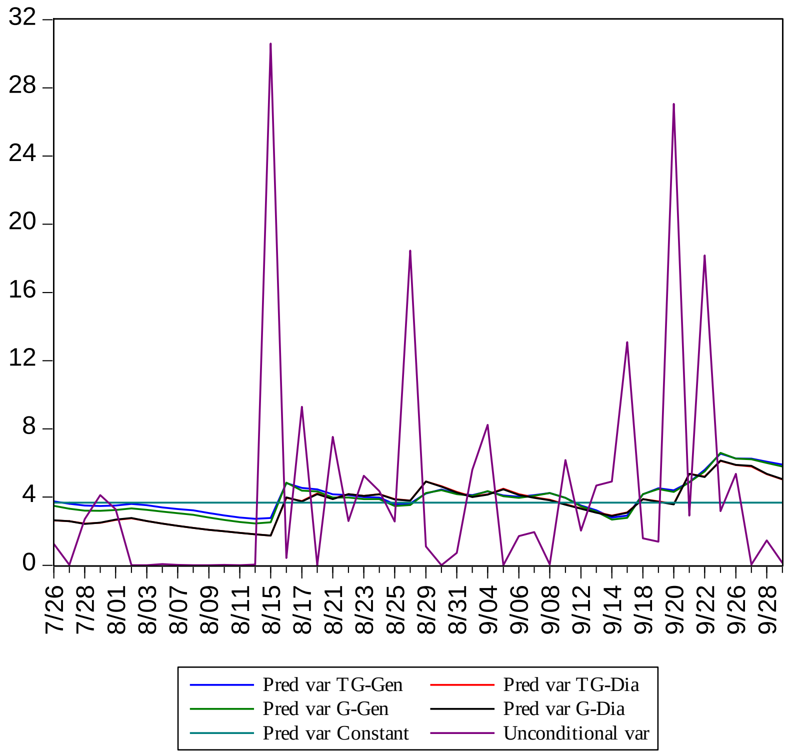


Figure 1. 20 Predicted variance (Pred var) and the unconditional variance (Unconditional var) of spot returns for the cross hedging: out-of-sample



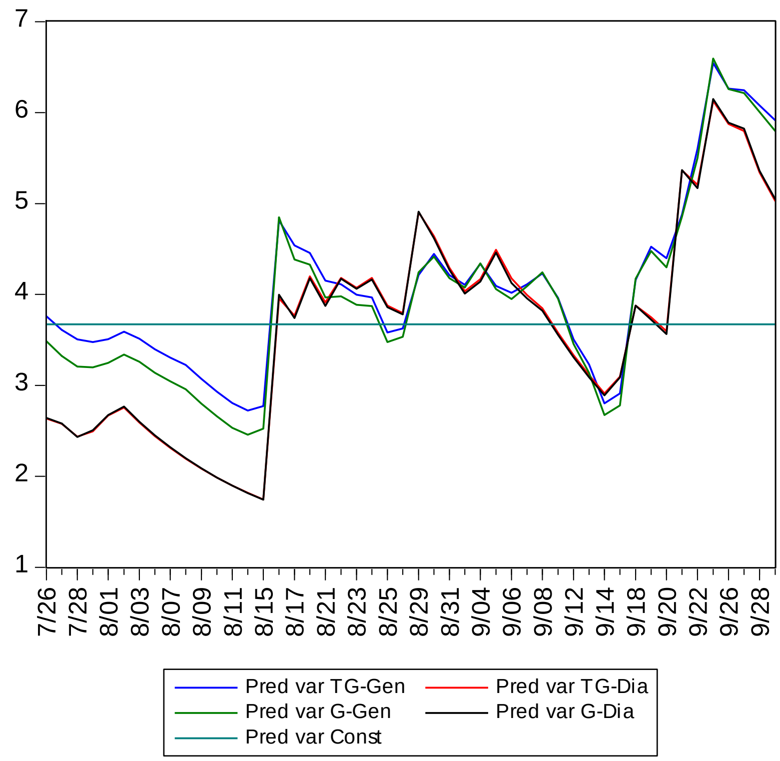
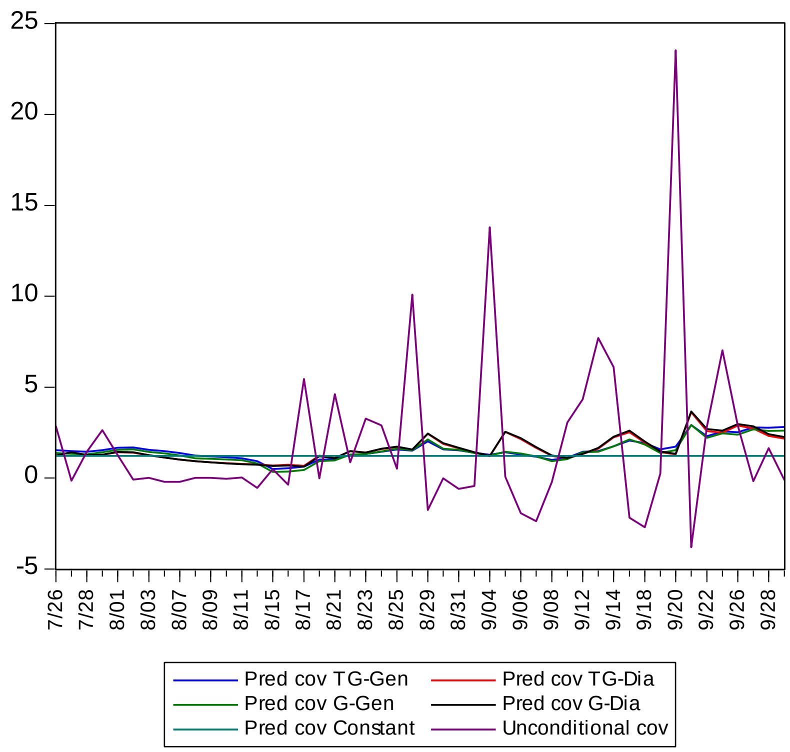


Figure 1. 21 Predicted covariance (Pred cov) and the unconditional covariance (Unconditional cov) of Spot and futures returns for the cross hedging: out-of-sample



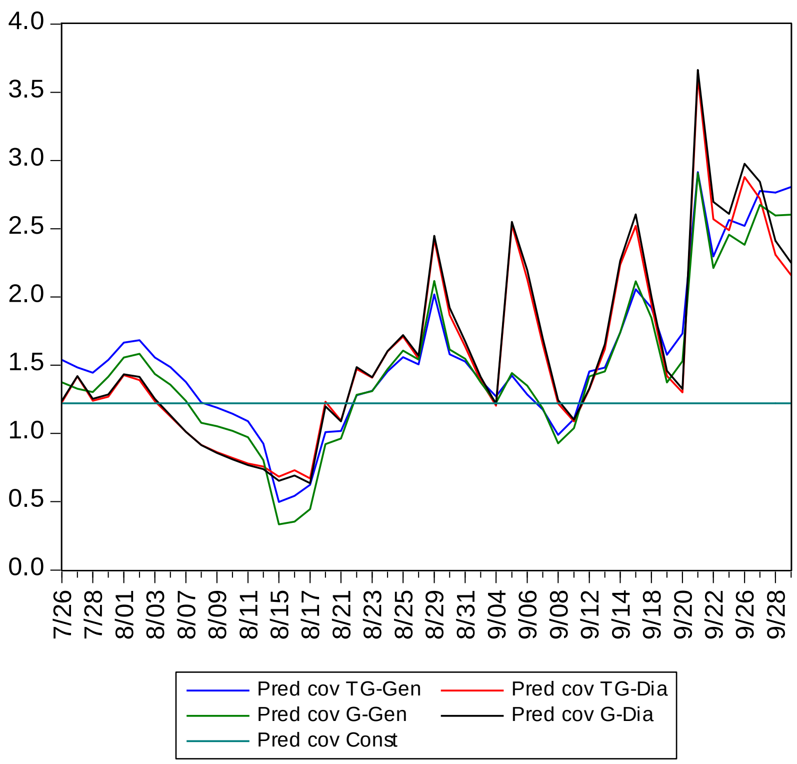


Figure 1. 22 Predicted hedge ratios of hedging domestic spot positions: out-of-sample period

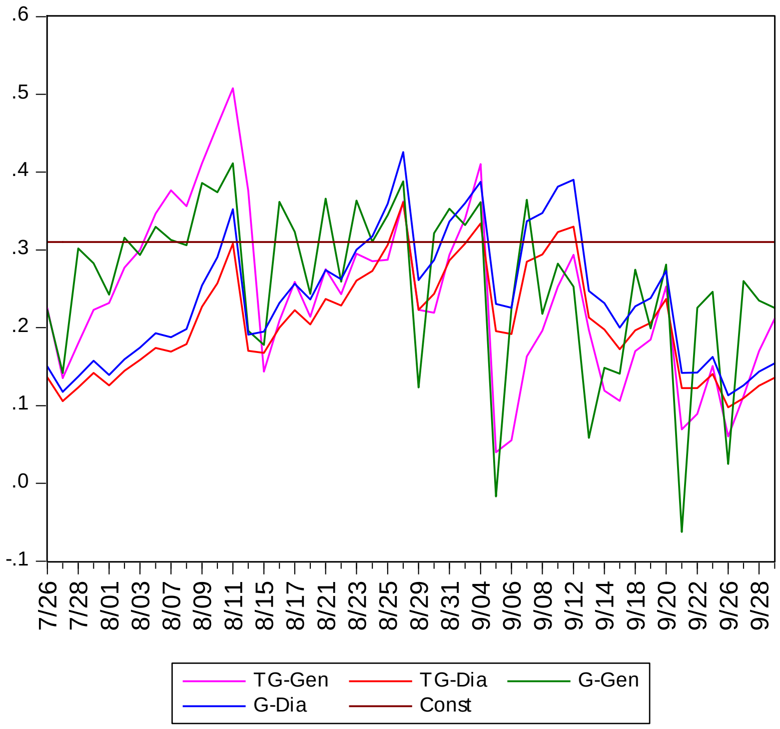


Figure 1. 23 Predicted hedge ratios of cross hedging in the Singapore market: out-of-sample period

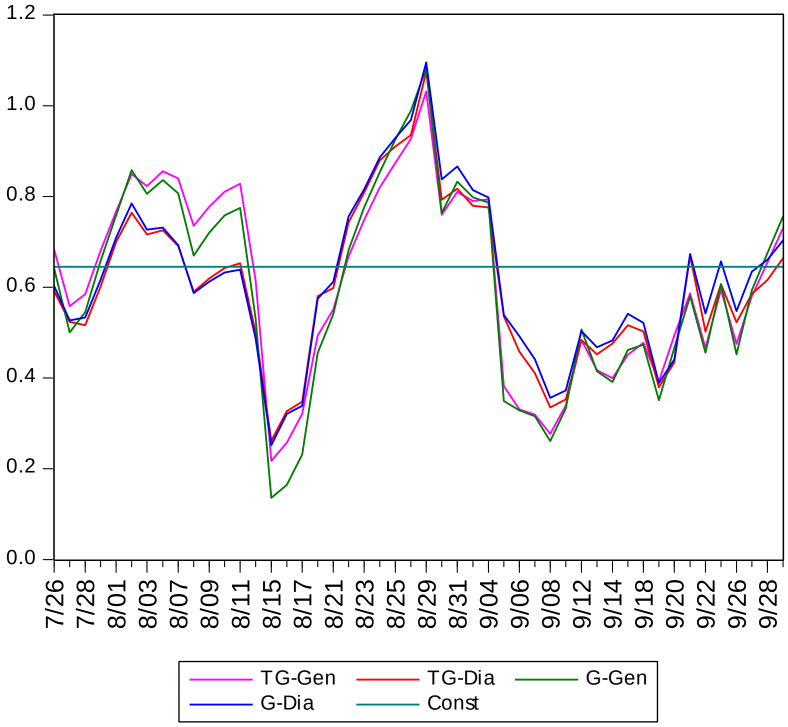


Figure 1. 24 Return of hedged portfolios of the domestic hedging under variance minimisation: out-of-sample

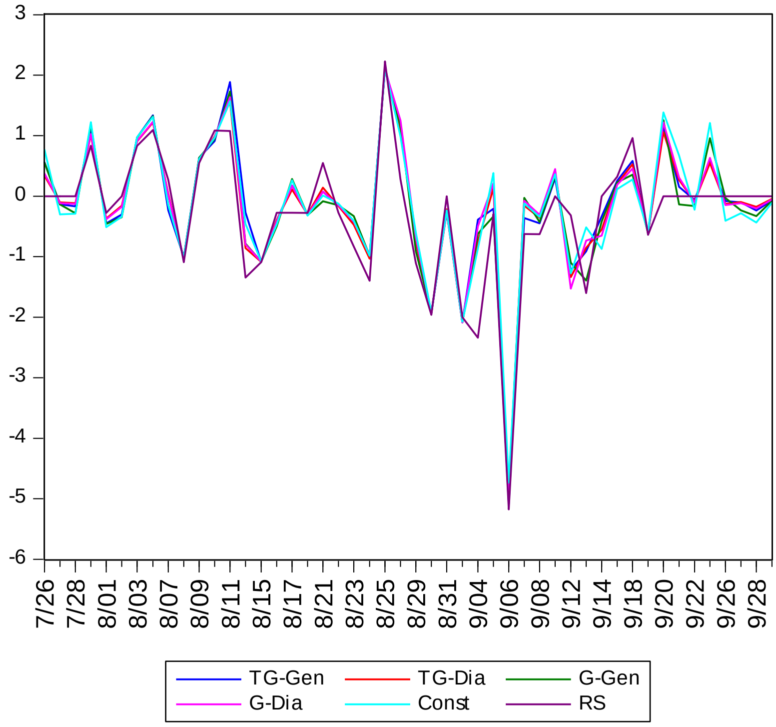


Figure 1. 25 Return of hedged portfolios of the cross hedging in the Singapore market under variance minimisation: out-of-sample

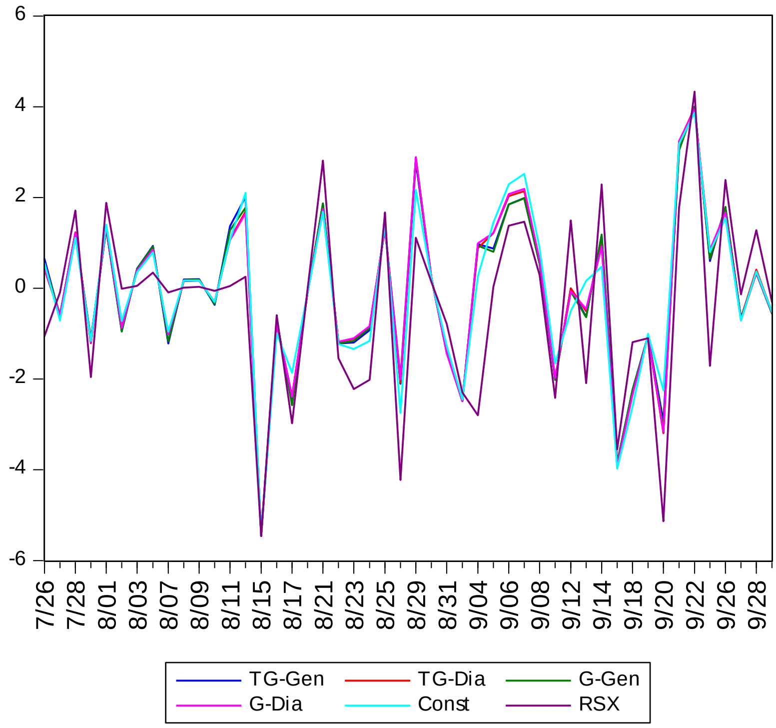


Figure 1. 26 Histogram of hedge ratios estimated using different models for the domestic hedging: out-of-sample period

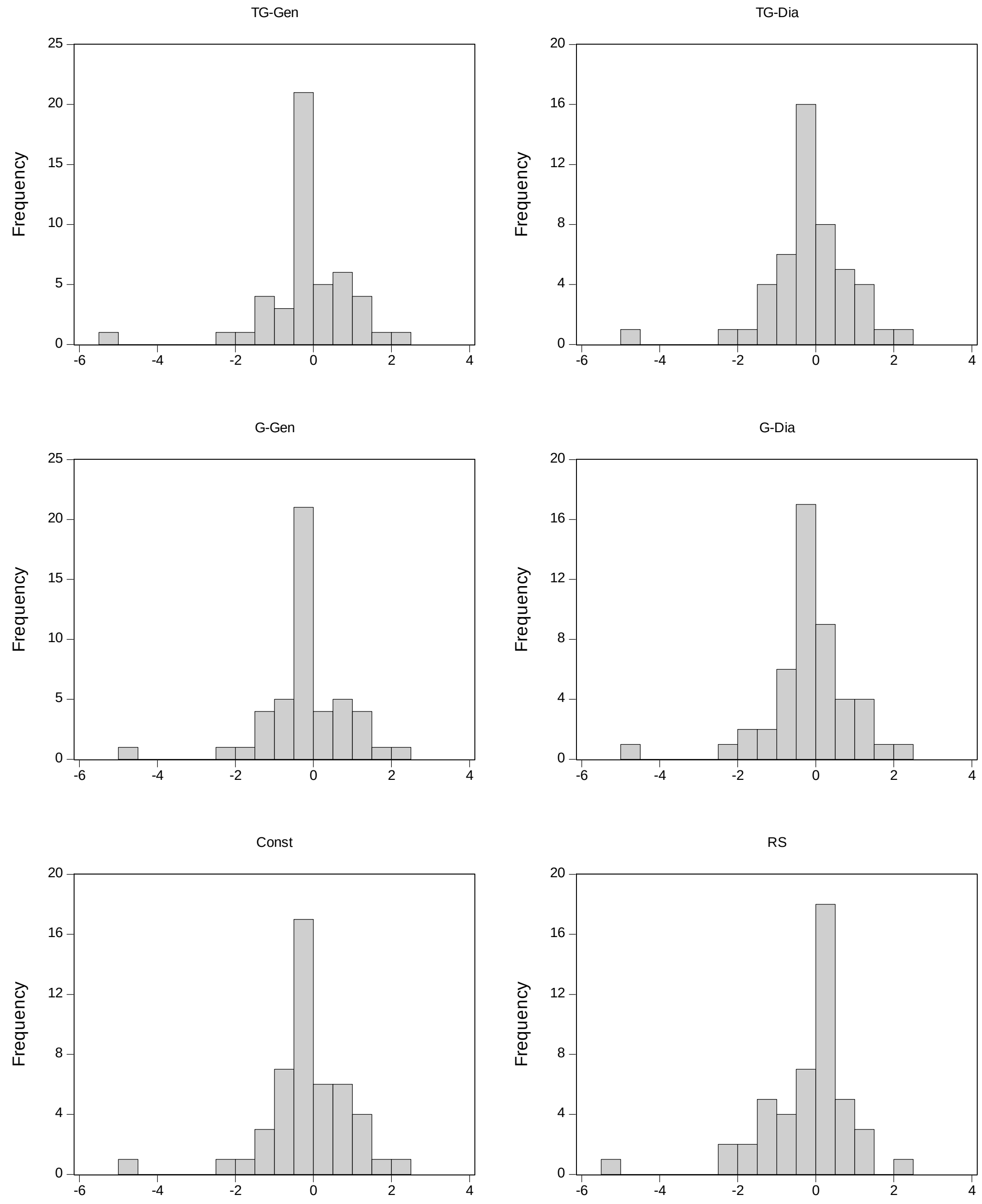


Figure 1. 27 Histogram of hedge ratios estimated using different models for the cross hedging in the Singapore market: out-of-sample period

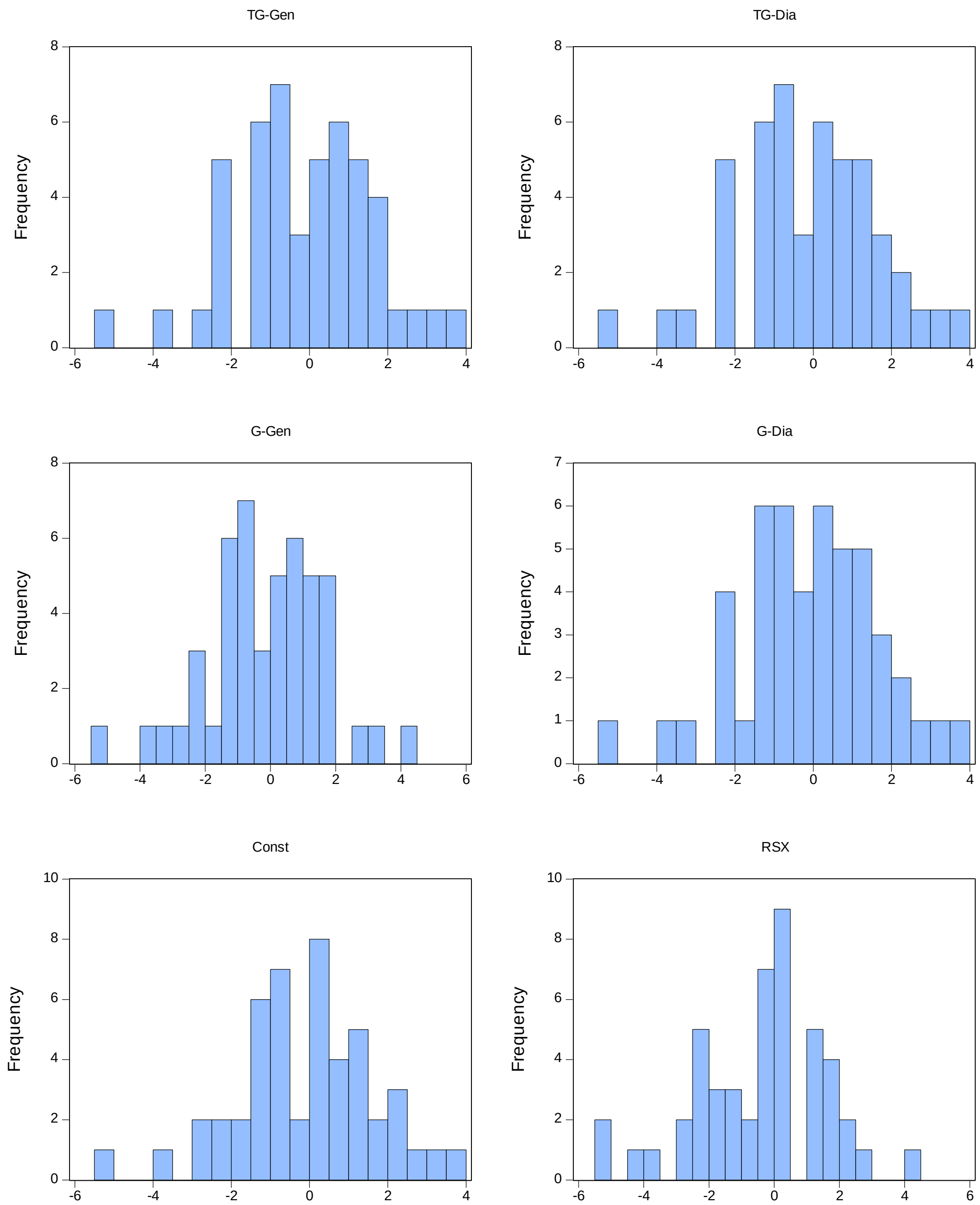


Figure 1. 28 Time path of risk reduction of the domestic hedging under risk minimisation criterion: out-of-sample period

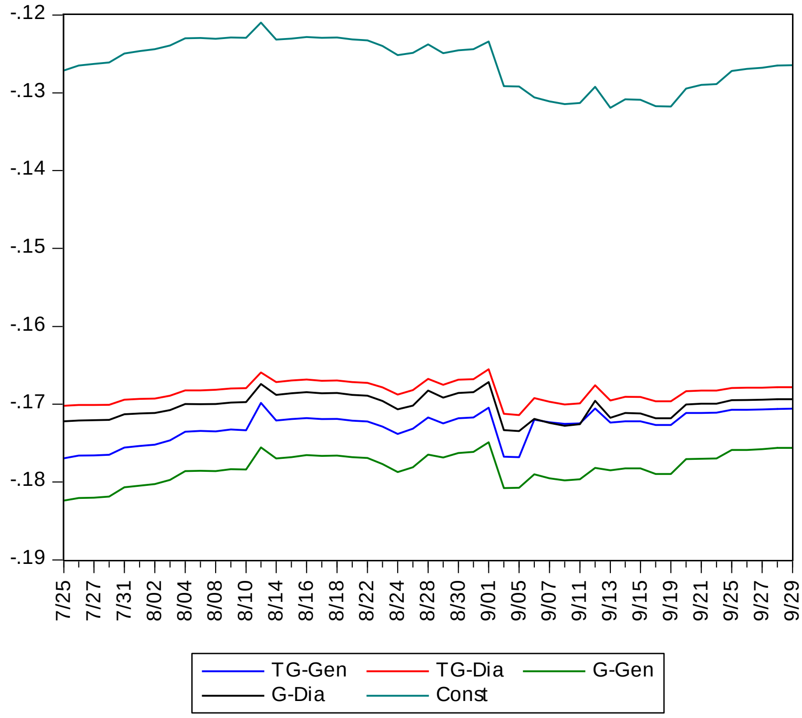


Figure 1. 29 Time path of risk reduction of the cross hedging over time under risk minimisation criterion: out-of-sample period

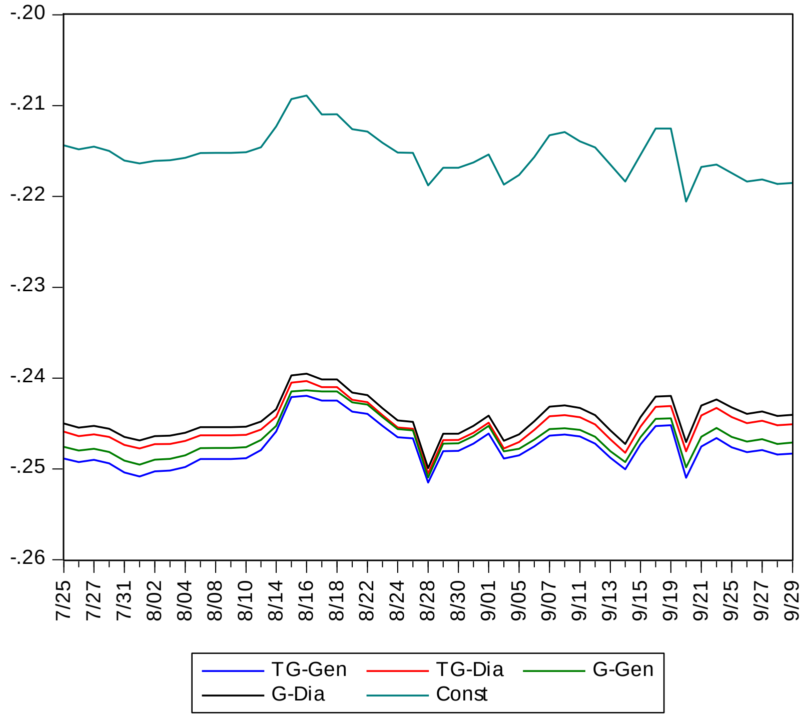
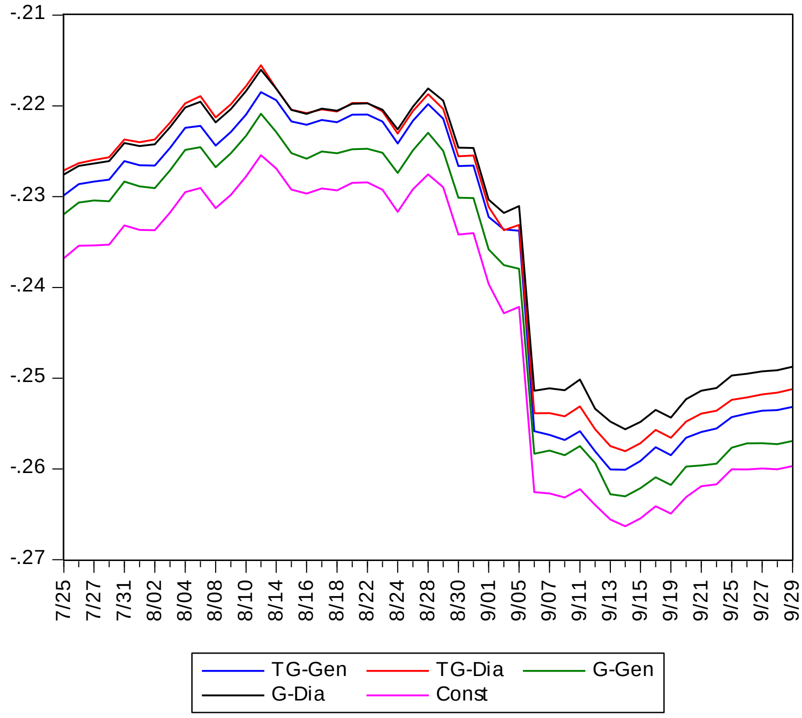


Figure 1. 30 Expected utility of the domestic hedging over time under utility maximisation criterion: out-of-sample period

(1) $\gamma = 0.25$



(2) $\gamma = 0.5$

(3) $\gamma = 1$

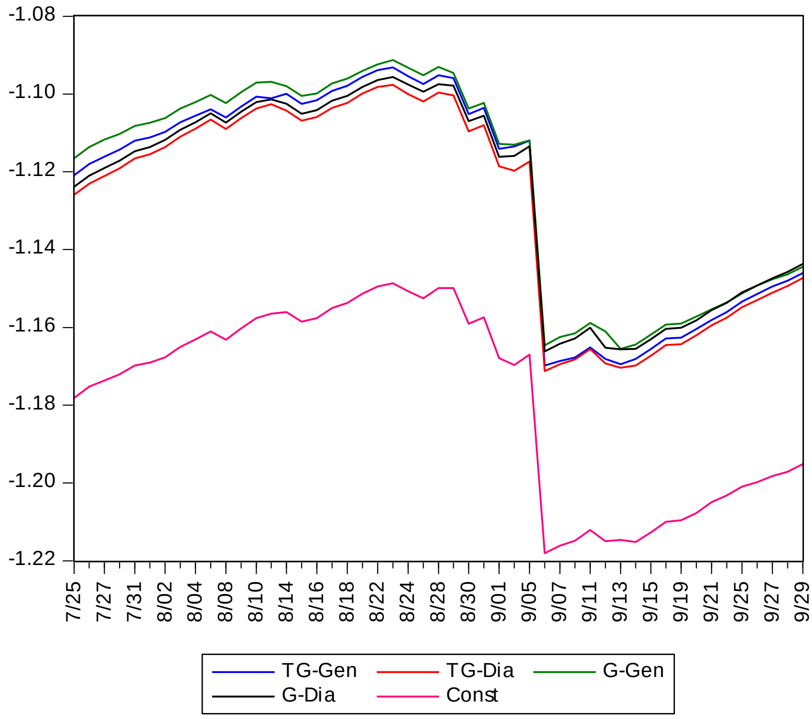
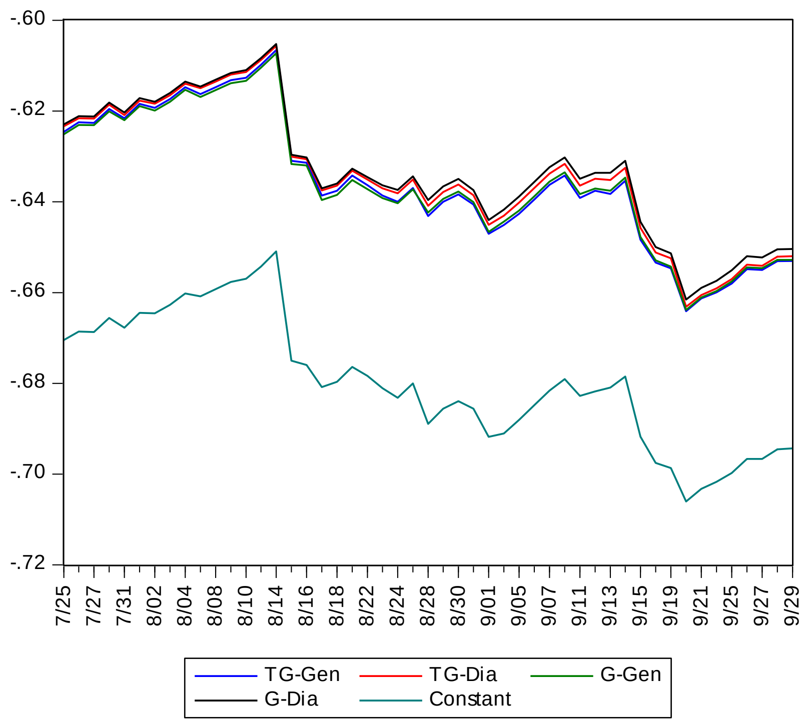
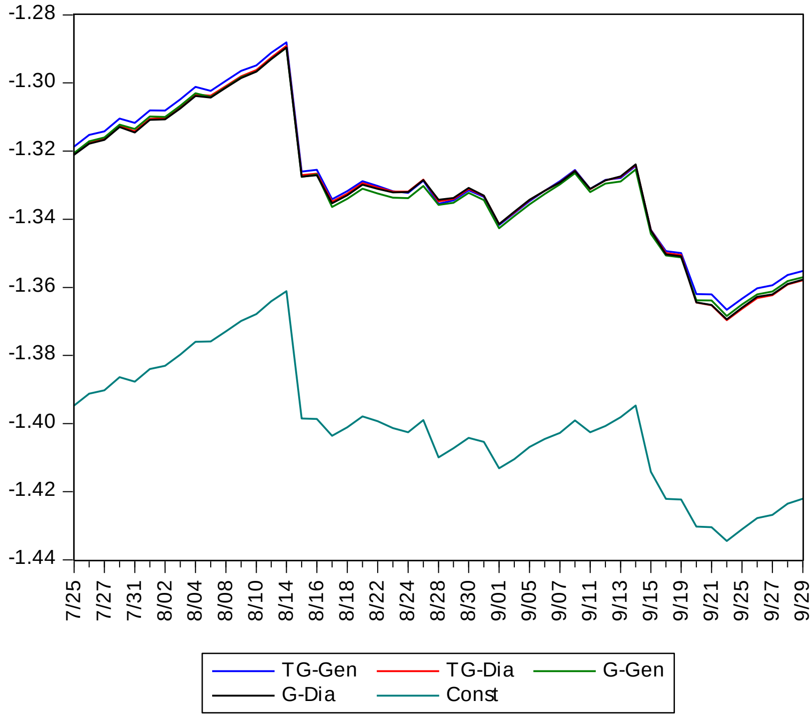


Figure 1. 31 Expected utility of the cross hedging in The Singapore market over time under utility maximisation criterion: out-of-sample period

(1) $\gamma = 0.25$



(2) $\gamma = 0.5$



(3) $\gamma = 0.1$

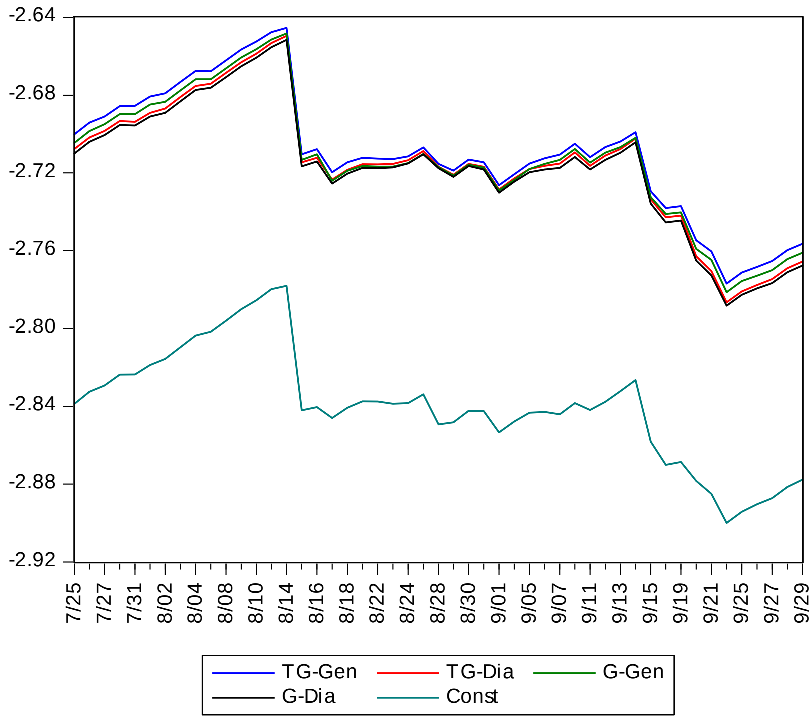


Figure 1. 32 Time path of risk reduction of the domestic hedging based on semivariance: out-of-sample period

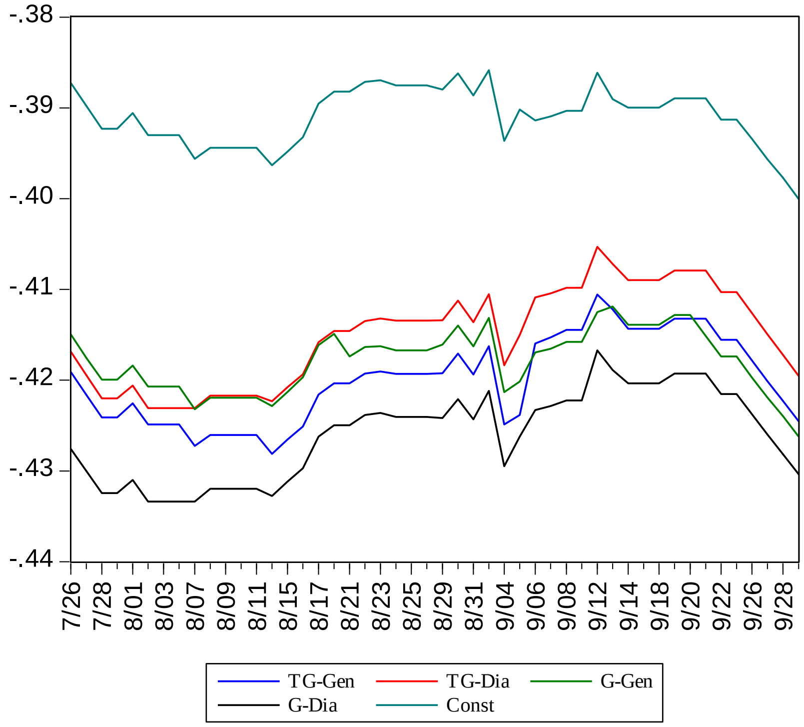
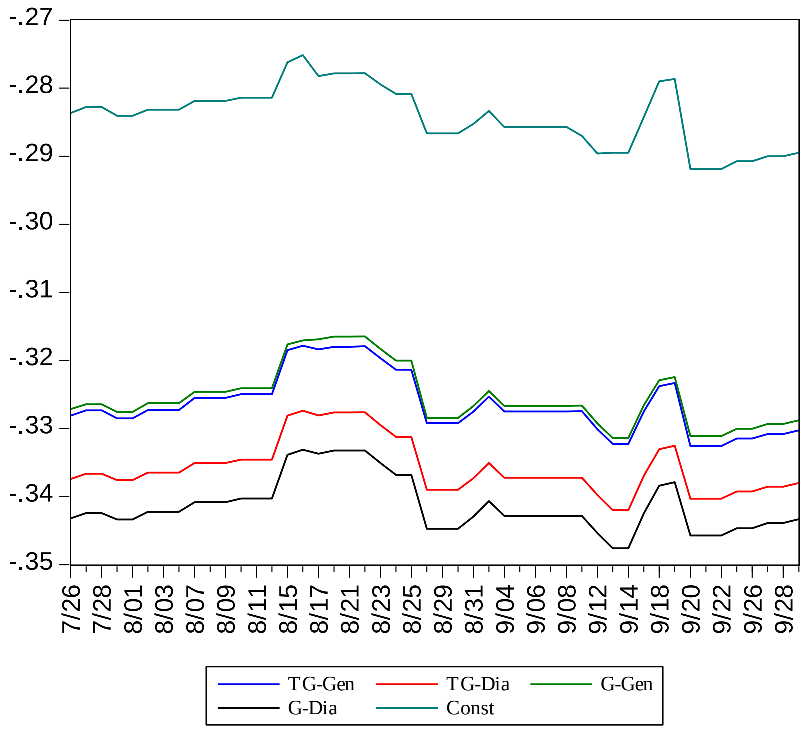


Figure 1. 33 Time path of risk reduction of the cross hedging based on semivariance: out-of-sample period



Appendix 1 B

Figure 1.B 1 Monthly position of China fuel oil futures (lot).

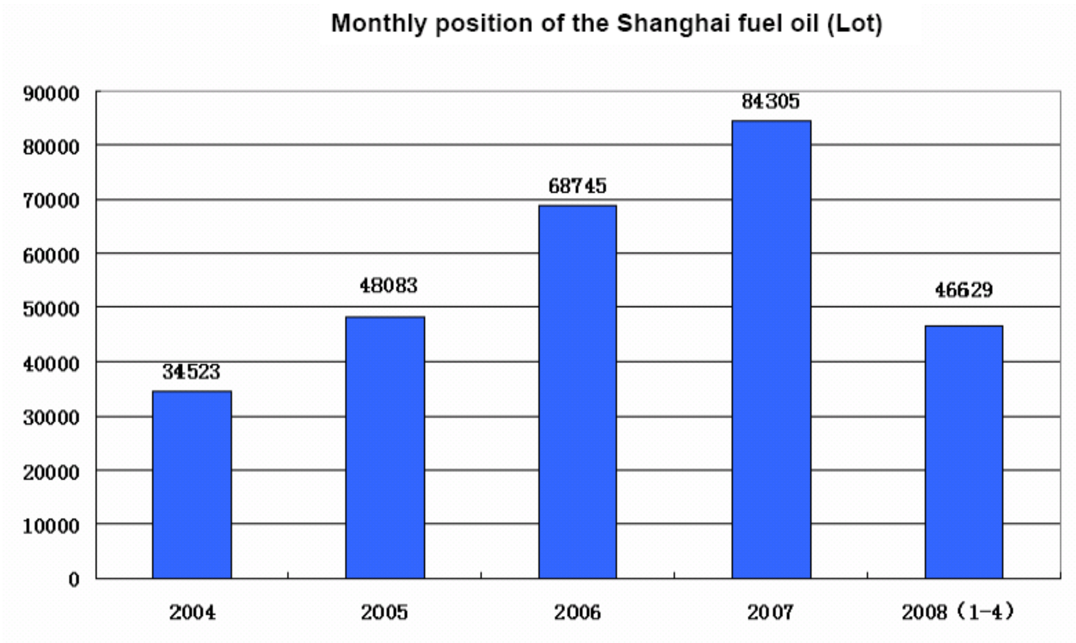


Figure 1.B 2 Average monthly turn of China fuel oil futures.

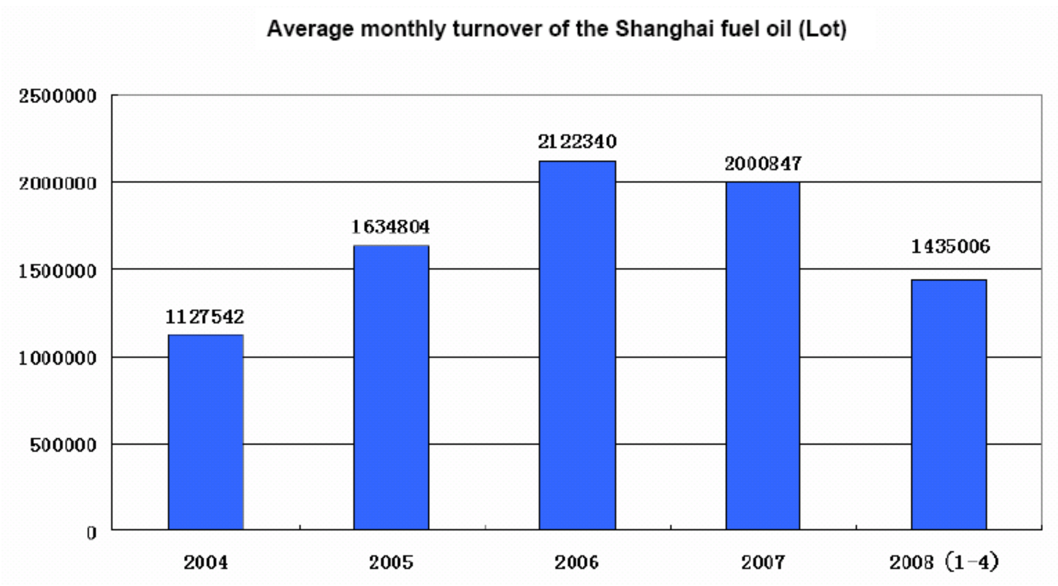
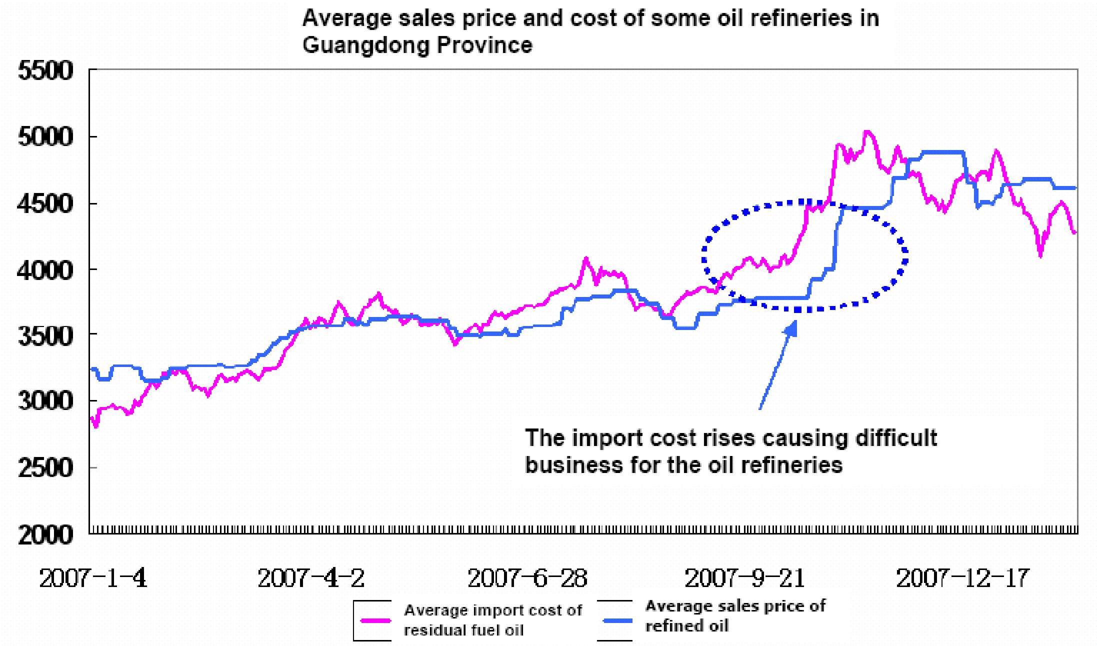
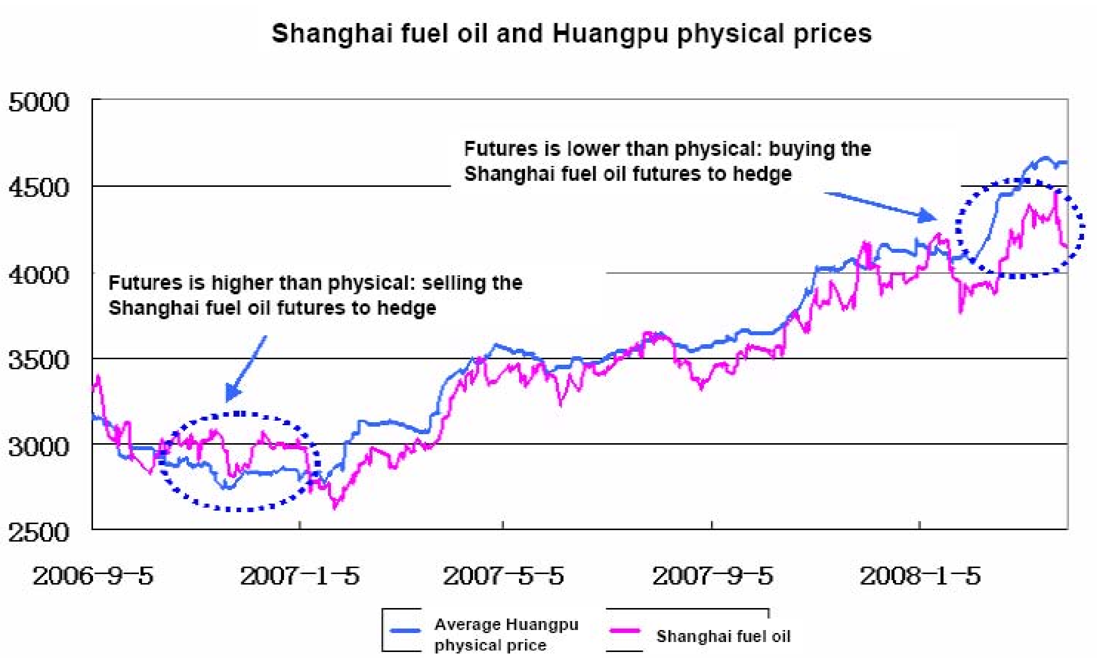


Figure 1.B 3 Sales price and cost of some oil refineries



Note: Guangdong province in China takes 80% of fuel oil imports.

Figure 1.B 4 China fuel oil futures and spot price series



Source of above figures: Guangzhou Twinace Petroleum and Chemicals Co., Ltd.

Essay 2 Volatility spillovers among oil, gold and US stock market

2.1 Background and Literature

Oil and gold are two very important commodities in the financial market. Oil, as one of goods with substantial volume of trades in world markets, is very essential in every economy. Its importance as a source of energy and economic growth can hardly be exaggerated. This is especially true for the world's leading economy, the U.S., where oil makes possible the functioning of nearly every component of the economy, directly or indirectly. It provides 40% of the nation's power supply—far more than any other source. Figure 2.B1 in Appendix 2.B shows the percentage of US to the world oil production, imports and demand. The US oil demand takes up to a quarter of the world total oil demand, much more than the percentage it can produce. Oil price have behaved with wide swings in history. Figure 2.B2 depicts the crude oil price for the past 50 years based on yearly average data. We have witnessed the general upward trend of the price of oil. The inflation adjusted oil price series portrayed in Figure 2.B3 show that the oil price has picked in 1980 and 2008[18], following 1997 currency crisis and 2007 financial crisis, both of which lead to severe economic recession.

The linkage between economic growth (hence, the stock price) and oil markets appears to be quite natural. Huang et al. (1996) opine that if oil plays an important role in an economy, it would be expected that changes in the oil price to be correlated with changes in stock prices. Mussa (2000) argues that by affecting economic activity,

[18] Oil price has started to drop from its peak in July 2008 (as shown in Figure 3.B4) and is averaged about 52 dollars a barrel in the first seven month in 2009.

corporate earnings, inflation and monetary policy, an increase in the oil price has implications for asset prices and financial markets. While summing up contemporary research relating to oil prices and capital markets, Jones et al. (2004) comment that: “Ideally stock values reflect the market’s best estimate of the future profitability of firms, so the effect of oil price shocks on the stock market is a meaningful and useful measure of their likely economic impact. Since asset prices are the present discounted value of the future net earning of firms, both the current and expected futures impacts of an oil price shock should be absorbed fairly quickly into stock prices and returns without having to wait for those impacts to actually occur.”

On the other hand, with the geopolitical uncertainties and some of the turmoil afflicting the financial markets, the price of gold has been sent soaring as well, as shown in Figure 2.B5. Gold is a precious metal which is also classed as a commodity and monetary asset. It has acted as a multi-faceted metal down through the centuries. It possesses similar characteristics to money in that it acts as a store of wealth, medium of exchange and a unit of value (Goodman 1956; Solt and Swanson, 1981). It has also played an important role as a precious metal with significant portfolio diversification properties (see, e.g., Ciner, 2001). It is used in industrial components, jewellery, as an investment asset as well as reserve asset. Gold is often used as a hedge against inflation, political risk, and currency exchange risk. According to Smith (2002), “when the economic environment becomes more uncertain attention turns to investing in gold as a safe haven.” The gold holding in the United States is on average up to one quarter of the world total holdings, as shown in Figure 2.B6.

As can be observed in the financial market for the past few decades, it is a general rule that when the price of crude oil rallies, the price of gold tends to follow suit. Higher oil prices act like an inflation tax on consumer and producers, whereas investing in the gold market turns out to be the best hedging strategy. Over the last 50 years or so, gold and oil have generally moved together in terms of price, with a positive price correlation of over 80 percent (Nick Barisheff, 2005). We depict the last 50 years oil and gold price series in Figure 2.B7 and their monthly price series since 1990s in Figure 2.B8.

From the Figures, we observe strong correlations between the oil and gold markets. Each of these two markets has significant effects on the economy, which is reflected in some way by the movement of the stock market in that economy. Despite the apparent links between the oil and gold markets, there are few studies on their relationship. For the literature on oil and stock market, while many studies have examined how changes in oil prices can affect the macroeconomy, especially its growth, the literature exploring the impact of oil on the stock markets still remains sparse, with only a few studies. Generally an adverse linkage between the higher oil prices and economic growth is well documented in the literature (e.g. Hamilton, 1983; Gisser and Goodwine, 1986; Mussa, 2000; IEA, 2004; Jones et al., 2004). For the relation between the oil and stock markets, Jones and Kaul (1996) provide evidence that aggregate stock market returns in the USA, Canada, Japan and the UK responsed negatively to oil price shocks on the economies of these countries. Using a standard cash-flow dividend valuation model, they found, however, that only in the US and Canada can this reaction be accounted for completely by the impact of the oil shocks on real cash flows. Huang, Masulis, and Stoll (1996) examined the relationship between daily oil futures returns and daily U.S. stock returns. Using a VAR model, they found that oil futures returns lead some individual oil company stock returns but they do not have much impact on the broad-based market indices such as the S&P 500. Sadorsky (1999), utilizing an unrestricted VAR and using US monthly data, examined the links among fuel oil prices, stock prices, short-term interest rate and industrial production of the economy. He found, in contrast to Huang et al.'s finding, that oil price movements are important in explaining movements in broad-based stock returns. Hammoudeh and Aleisa (2002), using monthly data from 1991 to 2000 and employing the two-step univariate GARCH models, found mean spillovers from oil markets to stock markets in the case of Bahrain, Indonesia, Mexico, and Venezuela. Hammoudeh, Dibooglu and Aleisa (2004) investigate the relationship among U.S. oil prices and oil industry equity indices based on daily data. They found that the oil futures market has a matching or echoing volatility effect on the stocks of some oil sectors and a volatility-dampening effect on the stocks of others. El-Sharif, Brown, Burton, Nixon and Russell (2005) study the relationship between the price of crude oil and equity values in the oil and gas sector using data relating to the United Kingdom and find the volatility in the price of crude oil has a positive and significant impact on share values within the sector.

The existing literature on the relationship between the gold market and stock market is even sparser. Chan and Faff (1998) investigate the extra-market sensitivity of the Australian industry equity returns to a gold price factor over the period 1975 to 1994. They find that there has been a widespread sensitivity of Australian industry returns to gold price returns, over and above market returns. The sensitivity is found to be positive for resource and mining sector industries, whereas it is negative for the industrial sector. They also find that the gold price sensitivities are changing over time. Blose and Shieh (1995) studied the elasticity of gold mining stocks to the changes in gold price. Using monthly data over a ten year period from 1981 through 1990, they found 23 out of 24 publicly traded gold mining companies in their sample have a gold price elasticity greater than one.

With the ever-increasing integration of financial markets, it is well accepted that the economic growth benefit from risk sharing, improvements in allocation efficiency and reductions in macroeconomic volatility and transaction costs (see Prasad et al., 2003; Baele at al., 2004). Whilst financial market integration encompasses many different aspects of the complex inter-relationships across various financial markets, we focus on the interrelation between oil, gold and US stock markets. As far as we know, there is not a single literature which has studied the linkage between these three markets. Understanding the links between financial markets is of great importance for a financial hedger, portfolio manager, asset allocator, or other financial analysts. The study of volatility spillover from one market to another is a crucial part of the issue. (Martin Agren, 2006). Thus, instead of studying the price and return movements, our study focuses on the volatilities spillover between these markets, that is, the linkage in their second moments. Although there is no existing literature exploring such second moment linkages between these three markets, there are many studies on the volatility spillover in financial markets, especially among different stock markets and currency markets. Most of these studies employ the GARCH framework, univariate or multivariate, as the GARCH model is generally believed to be the best to describe financial return data. For example, Kearney and Patton (2000) employed a multivariate GARCH model to study the volatility transmission mechanism among different exchange rates in the European Monetary System. Ewing, Malik, and Ozfidan (2002) used a similar model to study the linkage between the oil and natural gas markets. They find that there exists significant volatility spillover between the two markets. Malik and Hammoudeh (2005) used a Multivariate GARCH model to study the volatility and shock transmission mechanism among US equity, global crude oil market, and equity markets of Saudi Arabia, Kuwait, and Bahrain. They find significant transmission among second moments. In our study, we investigate the volatility linkage by employing both Tri-variate GARCH specification for the oil, gold and stock market returns and Bi-variate GARCH for each of the two markets. This enables us to examine how the variances of one markets is affected by the shocks from the another market. Meanwhile, by comparing the variances and covariances estimated from Tri-variate and Bi-variate GARCH models, we can investigate how, by including a third market to the existing two markets framework, the changes in the third market can affect the linkage between the two markets being investigated.

Daily data beginning April 1991 to November 2007[19] are used for the purpose of this study. Moreover, three sub-samples are examined (reasons of which are given in later section). We find that, in terms of volatility, the gold market is “exogenous”, despite the close price or return links between gold and the oil market. The gold market volatility spills over to the oil and stock markets. The spillovers between the oil and stock markets are generally bi-directional. This provides evidence of the existence of the strong linkage between the oil and the stock market, and with the US economy. Gold, being regarded as a “safe haven” asset and being largely held by individuals and institutional investors to hedge risk, had a low volatility itself and had not been affected by oil and stock market shocks. The existence of volatility spillovers between the oil and gold markets, indicated by the Bi-variate GARCH modelling, actually emanate from their relations with the third market, the stock market. Similarly, the volatility spillovers between the gold and stock markets are due to their links with the oil market.

The remainder of the chapter is organized as follows. Section 2 describes the data and methodology. Empirical findings are presented in Section 3. A summary and

[19] This period is chosen because of the financial integration growing rapidly since the early 1990s.

conclusion are provided in Section 4.

2.2. Data and Methodology

2.2.1 Data

The data used in this study, namely world oil, gold and US stock prices, are sourced from DataStream. World oil price is represented by the nearby futures price series of the world's most liquid and most actively traded oil futures contract, the NYMEX's Light Sweet Crude Oil contract. The futures prices are chosen instead of spot prices because the futures are far more heavily traded than the commodity itself and also are far more sensitive to the arrival of new information. The NYMEX's Light Sweet Crude oil futures is chosen over other oil futures because this contract is traded in the US market and is the world's largest futures contract in terms of trading volume on a physical commodity. It is widely used as the benchmark for determining crude oil and refined product prices in the United States and abroad. For similar reasons, we use the continuous gold futures price series from Chicago Mercantile Exchange as the indicator of world gold prices. For the stock index, S&P500 is generally used as the representative of the US stock market and the economy. The data begin on 1 April 1991 and end on 5 November 2007.

We also split our data set into three sub-sample periods for investigative purposes, which are detailed in Section 2.3. All returns are calculated by computing the differences in the natural logarithm of the price multiplied by 100.

2.2.2 Methodology

To explore the dynamics of the price volatility process, autoregressive conditional heteroskedasticity (ARCH) and generalised ARCH (GARCH) models that take into account the time-varying variances of time series data are employed (suitable surveys of ARCH modelling may be found in Bollerslev, et al. 1992; Bera and Higgins, 1993 and Pagan, 1996). The GARCH type models are more parsimonious than the ARCH type models and are commonly used to capture the features of financial data and to explore the volatility and volatility transmission of financial markets. In our study, we first employ the Tri-variate GARCH (1, 1)[20] model to examine the relations between oil, gold and US stock market. Then we employ a Bi-variate GARCH (1, 1)[21] model to examine the relation between each pair of the three markets. The results obtained from Tri-variate GARCH model are compared with those obtained from the Bi-variate GARCH model.

The most general Tri-variate GARCH(1,1) model we postulated to represent the joint distribution of the oil, gold and stock returns is:

$$Y_t = \mu_t + \sum_{i=1}^{n} \kappa_i Y_{t-i} + \varepsilon_t \; ; \qquad \varepsilon_t \mid \Omega_{t-1} \sim N(0, H) \tag{2.1}$$

[20] Tri-variate GARCH (*m,n*) (*m*>=1, *n*>=1) models are also experimented for this study. However, we found that when we include higher orders in the GARCH specification, all the parameters for conditional and unconditional variance, except for the first order, are mostly statistically insignificant from zero.
[21] Same as Tri-variate GARCH models, higher orders in Bi-variate GARCH specification were also experimented with in the study. The results also suggest that the Bi-variate GARCH (1,1) is the most appropriate.

Where $Y_t = (ro_{t,} rg_t, rsp)'$ is a vector of observations of the log-differenced prices of oil futures, gold futures and S&P 500 stock index, multiplied by 100, $\mu_t = (\mu_{ot}, \mu_{gt}, \mu_{st})'$ is a vector of conditional means to be estimated and $\varepsilon_t = (\varepsilon_{ot}, \varepsilon_{gt}, \varepsilon_{st})'$ is a vector of residuals. This is a general VAR for the mean equation where one variable is a function of its own lagged values, and lagged values of all the other variables, from time t-1, to time $t-n$. Starting from experiment with the most general model, we then reduce the mean structure to more parsimonious specifications. The residuals are assumed to be normally distributed and are conditional on past information, Ω_{t-1}, with zero mean vector and with conditional variance-covariance matrix:

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon_{t-1}{}'A + B'H_{t-1}B \tag{2.2}$$

Where C is (3×3) symmetric parameter matrix, and A and B are (3×3) parameter matrices. In our estimation, we use the most general form, all full rank A, B and C matrix for our maximum likelihood estimation. In the cases that estimation is not possible to obtain because the positive feature of H_t is violated, we adopt a positive definite parameterization following Engle and Kroner (1995), henceforce the BEKK representation, where $c_{21} = c_{31} = c_{32} = 0$. Such specification guarantees that the conditional covariance matrix is positive definite so that conditional variances are always nonnegative. In explicit format, we can express the conditional variance-covariance matrix H in the following form:

$$H_t = \begin{bmatrix} h_{oo,t} & h_{og,t} & h_{os,t} \\ h_{og,t} & h_{gg,t} & h_{gs,t} \\ h_{os,t} & h_{gs,t} & h_{ss,t} \end{bmatrix} = \begin{bmatrix} c_{11} & c_{21} & c_{31} \\ c_{12} & c_{22} & c_{32} \\ c_{13} & c_{23} & c_{33} \end{bmatrix} \begin{bmatrix} c_{11} & c_{12} & c_{13} \\ c_{21} & c_{22} & c_{23} \\ c_{31} & c_{32} & c_{33} \end{bmatrix}$$

$$+ \begin{bmatrix} a_{11} & a_{21} & a_{31} \\ a_{12} & a_{22} & a_{32} \\ a_{13} & a_{23} & a_{33} \end{bmatrix} \begin{bmatrix} \varepsilon_{o,t-1}^2 & \varepsilon_{o,t-1}\varepsilon_{g,t-1} & \varepsilon_{o,t-1}\varepsilon_{s,t-1} \\ \varepsilon_{o,t-1}\varepsilon_{g,t-1} & \varepsilon_{g,t-1}^2 & \varepsilon_{g,t-1}\varepsilon_{s,t-1} \\ \varepsilon_{o,t-1}\varepsilon_{s,t-1} & \varepsilon_{g,t-1}\varepsilon_{s,t-1} & \varepsilon_{s,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \quad (2.3)$$

$$+ \begin{bmatrix} b_{11} & b_{21} & b_{31} \\ b_{12} & b_{22} & b_{32} \\ b_{13} & b_{23} & b_{33} \end{bmatrix} \begin{bmatrix} h_{oo,t-1} & h_{og,t-1} & h_{os,t-1} \\ h_{og,t-1} & h_{gg,t-1} & h_{gs,t-1} \\ h_{os,t-1} & h_{gs,t-1} & h_{ss,t-1} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix}$$

The Tri-variate GARCH model is estimated using maximum likelihood method. Under conditional normality, the log likelihood function is as follow:

$$L(\Theta) = -T\log(2\pi) - \frac{1}{2}\sum_{t=1}^{T}(\log\left|H_t(\Theta)\right| - \varepsilon_t(\Theta)H_t^{-1}(\Theta)\varepsilon_t'(\Theta)) \quad (2.4)$$

Where T is the number of observations of the sample. Θ is the parameter vector to be estimated. $\varepsilon_t = (\varepsilon_{1,t}, \varepsilon_{2,t}, \varepsilon_{3,t})$ is a (1×3) vector of residuals at time t. $H_t = \mathrm{cov}(\varepsilon_t \left|\Omega_{t-1}\right.)$, with the diagonal elements of H_t are the conditional variances, the cross diagonal elements are the conditional covariances of spot and futures returns. The log-likelihood function is maximized subject to the constraint that the conditional variances be positive. The Tri-variate GARCH model is first estimated using the SIMPLEX[22] algorithm. Such preliminary estimation is used to refine the initial parameter values before switching to our final estimation method. With the values obtained from Simplex estimation are then used as initial values, the final parameters

[22] The Simplex Method is a search procedure which requires only function evaluations, not derivatives. It starts by selecting K+1 points in K-space, where K is the number of parameter. It is normally used as a preliminary estimation method to refine the initial parameter values before switching to one of the other estimation methods.

are estimated by the BFGS[23] method. The initial values for the Simplex estimation are found from the univariate GARCH estimation. For those parameters for which the initial guesses cannot be obtained from the linear estimations, we used a value 0.05.

The specification of the Bi-variate GARCH (1,1) model is as follows:

$$Y_t = \mu_t + \sum_{i=1}^{n} \kappa_i Y_{t-i} + \varepsilon_t \ , \quad \varepsilon_t \mid \Omega_{t-1} \sim N(0, H) \tag{2.5}$$

Where $Y_t = (y_{1t,} y_{2t})'$ is a vector of observations of the log-differenced prices of oil and gold, gold and S&P500 or oil and S&P500. $\mu_t = (\mu_{1t}, \mu_{2t})'$ is a vector of conditional means to be estimated and $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t})'$ is a vector of residuals. We assume that the residuals are normally distributed and are conditional on past information, Ω_{t-1}, with zero mean vector and with conditional variance-covariance matrix

$$\begin{aligned} H_t = \begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{12,t} & h_{22,t} \end{bmatrix} &= \begin{bmatrix} c_{11} & c_{21} \\ c_{12} & c_{22} \end{bmatrix} \begin{bmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{bmatrix} \\ &+ \begin{bmatrix} \alpha_{11} & \alpha_{21} \\ \alpha_{12} & \alpha_{22} \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} & \varepsilon_{1,t-1}^2 \end{bmatrix} \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix} \\ &+ \begin{bmatrix} \beta_{11} & \beta_{21} \\ \beta_{12} & \beta_{22} \end{bmatrix} \begin{bmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{12,t-1} & h_{22,t-1} \end{bmatrix} \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix} \end{aligned} \tag{2.6}$$

Similarly, the Bi-variate models are estimated by maximum likelihood, with the log

[23] The BFGS (Broyden, Fletcher, Goldfarb, Shanno) method uses the matrix of analytic derivatives of the log likelihood in forming iteration updates and in computing the estimated covariance matrix of the coefficients. At each iteration, it is updated based upon the changes in parameters and in the gradient in an attempt to match the curvature of the function.

likelihood function is as follow:

$$L(\Theta) = -T\log(2\pi) - \frac{1}{2}\sum_{t=1}^{T}(\log\left|H_t(\Theta)\right| - \varepsilon_t(\Theta)H_t^{-1}(\Theta)\varepsilon_t'(\Theta)) \tag{2.7}$$

This time, $\varepsilon_t = (\varepsilon_{1t} \quad \varepsilon_{2t})$ is a 1x2 vector of residuals at time t. The choice of initial values and estimation method follow those used for the Tri-variate GARCH.

Stationarity of the Multivariate GARCH(1,1) process, Bi-variate and Tri-variate GARCH in our case, requires that the eigenvalues of $(A \otimes A + B \otimes B)$ be less than one in modulus[24](See Engle and Kroner, 1995).

To give a more clear illustration of the volatility spillover, we expand the matrix form of the variance and covariance. For the Tri-variate GARCH models, the expanded matrix can be written as a set of equations, as show on next page (Eq 2.8). The error terms represent the previous day's shocks realized in that market. Whether such shocks, or information realized in one market can affect the conditional volatility of the other market can be examined by the significance of the parameters on the shocks.

---

[24] For the Multivariate GARCH(1,1) model, $H_t = C'C + A'\varepsilon_{t-1}\varepsilon_{t-1}'A + B'H_{t-1}B$, hence we have $h_t = vec(H_t) = vec(C'C) + (A \otimes A)vec(\varepsilon_{t-1}\varepsilon_{t-1}') + (B \otimes B)vec(H_{t-1})$. It follows that the unconditional covariance matrix is $[I - (A \otimes A) - (B \otimes B)]^{-1} vec(C'C)$. For the diagonal Bi-variate GARCH model, the stationary condition can be reduced to $a_{ii}^2 + b_{ii}^2 < 1, i = 1, 2$, because the eigenvalues of a diagonal matrix are simply the elements along the diagonal and the conditions detailed imply that all other diagonal elements are also less than 1 in absolute value. Similarly, the stationary condition for the diagonal Tri-variate GARCH model can be reduced to $a_{ii}^2 + b_{ii}^2 + c_{ii}^2 < 1, i = 1, 2, 3$.

For example, to investigate whether the oil shocks can affect the volatility of gold, we need to determine whether the coefficient a_{12}^2 is significantly different from zero. Similarly, the significance of coefficients a_{21}^2, a_{31}^2 can give indications of how the past shocks in the gold and stock markets, respectively, affect the conditional volatility in the oil market. Following the same algorithm, the significance of coefficients b_{ij}^2 represent the conditional variance of market i has significant impact on the conditional variance of market j. The coefficients a_{ii}^2 and b_{ii}^2 represent how the conditional variance of one market is affect by its own past shocks and past conditional variance. Thus there exists spillover from market i to market j when $a_{ij}^2 \neq 0$ and/or $b_{ij}^2 \neq 0$. If $a_{ij}^2 = 0$ and $b_{ij}^2 = 0$, volatilities do not spill over from market i to market j. The volatility spillovers for the Bi-variate models can be identified by the same mechanism. The expanded form of conditional variance and covariance for the Bi-variate GARCH model is as follows (Eq.2.9).

Eq.2.8. The conditional variance-covariance for oil, gold and stock index in an expanded form.

$$
\begin{cases}
h_{oo,t} = c_{11}^2 + b_{11}^2 h_{oo,t-1} + b_{21}^2 h_{gg,t-1} + b_{31}^2 h_{ss,t-1} + 2b_{11}b_{21}h_{og,t-1} + 2b_{11}b_{31}h_{os,t-1} + 2b_{21}b_{31}h_{gs,t-1} + \\
\qquad + a_{11}^2\varepsilon_{o,t-1}^2 + a_{21}^2\varepsilon_{g,t-1}^2 + a_{31}^2\varepsilon_{s,t-1}^2 + 2a_{11}a_{21}\varepsilon_{o,t-1}\varepsilon_{g,t-1} + 2a_{11}a_{31}\varepsilon_{o,t-1}\varepsilon_{s,t-1} + 2a_{21}a_{31}\varepsilon_{g,t-1}\varepsilon_{s,t-1} \\
h_{gg,t} = c_{11}^2 + c_{22}^2 + b_{12}^2 h_{oo,t-1} + b_{22}^2 h_{gg,t-1} + b_{32}^2 h_{ss,t-1} + 2b_{12}b_{22}h_{og,t-1} + 2b_{12}b_{32}h_{os,t-1} + 2b_{22}b_{32}h_{gs,t-1} + \\
\qquad + a_{12}^2\varepsilon_{o,t-1}^2 + a_{22}^2\varepsilon_{g,t-1}^2 + a_{32}^2\varepsilon_{s,t-1}^2 + 2a_{12}a_{22}\varepsilon_{o,t-1}\varepsilon_{g,t-1} + 2a_{12}a_{32}\varepsilon_{o,t-1}\varepsilon_{s,t-1} + 2a_{22}a_{32}\varepsilon_{g,t-1}\varepsilon_{s,t-1} \\
h_{ss,t} = c_{11}^2 + c_{22}^2 + c_{33}^2 + b_{13}^2 h_{oo,t-1} + b_{23}^2 h_{gg,t-1} + b_{33}^2 h_{ss,t-1} + 2b_{13}b_{23}h_{og,t-1} + 2b_{13}b_{33}h_{os,t-1} + 2b_{23}b_{33}h_{gs,t-1} + \\
\qquad + a_{13}^2\varepsilon_{o,t-1}^2 + a_{23}^2\varepsilon_{g,t-1}^2 + a_{33}^2\varepsilon_{s,t-1}^2 + 2a_{13}a_{23}\varepsilon_{o,t-1}\varepsilon_{g,t-1} + 2a_{13}a_{33}\varepsilon_{o,t-1}\varepsilon_{s,t-1} + 2a_{23}a_{33}\varepsilon_{o,t-1}\varepsilon_{g,t-1} \\
h_{og,t} = c_{11}c_{12} + b_{11}b_{12}h_{oo,t-1} + b_{21}b_{22}h_{gg,t-1} + b_{21}b_{32}h_{ss,t-1} + (b_{12}b_{21} + b_{11}b_{22})h_{og,t-1} + (b_{12}b_{31} + b_{11}b_{32})h_{os,t-1} + (b_{31}b_{22} + b_{21}b_{32})h_{gs,t-1} \\
\qquad + a_{11}a_{12}\varepsilon_o^2 + a_{21}a_{22}\varepsilon_g^2 + a_{21}a_{32}\varepsilon_s^2 + (a_{12}a_{21} + a_{11}a_{22})\varepsilon_o\varepsilon_g + (a_{12}a_{31} + a_{11}a_{32})\varepsilon_o\varepsilon_s + (a_{31}a_{22} + a_{21}a_{32})\varepsilon_g\varepsilon_s \\
h_{gs,t} = c_{12}c_{13} + c_{22}c_{23} + b_{12}b_{13}h_{oo,t-1} + b_{22}b_{23}h_{gg,t-1} + b_{32}b_{32}h_{ss,t-1} + (b_{12}b_{23} + b_{22}b_{13})h_{og,t-1} + (b_{32}b_{13} + b_{12}b_{33})h_{os,t-1} + (b_{32}b_{23} + b_{22}b_{33})h_{gs,t-1} \\
\qquad + a_{12}a_{13}\varepsilon_o^2 + a_{22}a_{23}\varepsilon_g^2 + a_{32}a_{33}\varepsilon_s^2 + (a_{12}a_{23} + a_{22}a_{13})\varepsilon_o\varepsilon_g + (a_{32}a_{13} + a_{12}a_{33})\varepsilon_o\varepsilon_s + (a_{32}a_{23} + a_{22}a_{33})\varepsilon_g\varepsilon_s \\
h_{os,t} = c_{11}c_{13} + b_{11}b_{13}h_{oo,t-1} + b_{21}b_{23}h_{gg,t-1} + b_{31}b_{33}h_{ss,t-1} + (b_{11}b_{23} + b_{21}b_{13})h_{og,t-1} + (b_{31}b_{13} + b_{11}b_{33})h_{os,t-1} + (b_{31}b_{23} + b_{22}b_{33})h_{gs,t-1} \\
\qquad + a_{11}a_{13}\varepsilon_o^2 + a_{21}a_{23}\varepsilon_g^2 + a_{31}a_{33}\varepsilon_s^2 + (a_{11}a_{23} + a_{21}a_{13})\varepsilon_o\varepsilon_g + (a_{31}a_{13} + a_{11}a_{32})\varepsilon_o\varepsilon_s + (a_{31}a_{23} + a_{22}a_{33})\varepsilon_{g,t-1}\varepsilon_{s,t-1}
\end{cases}
\tag{2.38}
$$

Eq.2.9. The conditional variance-covariance of a Bi-variate GARCH in an expanded form

$$
\begin{cases}
h_{11,t} = c_{11}^2 + b_{11}^2 h_{11,t-1} + b_{21}^2 h_{22,t-1} + 2b_{11}b_{21}h_{12,t-1} + a_{11}^2\varepsilon_{1,t-1}^2 + a_{21}^2\varepsilon_{2,t-1}^2 + 2a_{11}a_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} \\
h_{22,t} = c_{12}^2 + c_{22}^2 + b_{12}^2 h_{11,t-1} + b_{22}^2 h_{22,t-1} + 2b_{12}b_{22}h_{12,t-1} + a_{12}^2\varepsilon_{1,t-1}^2 + a_{22}^2\varepsilon_{2,t-1}^2 + 2a_{12}a_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} \\
h_{12,t} = c_{11}c_{12} + b_{11}b_{12}h_{11,t-1} + b_{21}b_{22}h_{22,t-1} + (a_{11}a_{22} + a_{12}a_{21})h_{12,t-1}
\end{cases}
\tag{2.39}
$$

2.3. Estimation results

2.3.1 Descriptive Statistics for the whole sample

Figure 2.1 and 2.2 in Appendix 2.A portray the *price* in logarithms for oil and gold futures and the S&P500 stock index. Table 2.1 reports the basic statistics for daily returns for the world oil futures returns (denoted as ro), gold futures *returns* (denoted as rg) and US stock market index S&P500 returns (denoted as rsp), including normality tests of the returns series and unit root tests, all of which are to ensure the modelling specifications we proposed are appropriate.

Table 2. 1 Descriptive statistics for return series

	RO	RG	RSP
Mean	0.0366	0.0187	0.0323
Median	0.0000	0.0000	0.0166
Maximum	14.2309	8.8872	5.5732
Minimum	-16.5445	-7.5740	-7.1127
Std. Dev.	2.0859	0.8704	0.9732
Skewness	-0.2517	0.0839	-0.1353
Kurtosis	7.0390	12.2394	7.3567
Jarque-Bera	2988.96	15406.51	3437.64
Probability	0.0000	0.0000	0.0000
Q(10)	15.06	21.26**	23.12**
$Q^2(10)$	207.30**	270.14**	1175.20**
ARCH_LM	26.91**	28.84**	85.45**
ADF	-65.49**	-66.95**	-67.15**
KPSS	0.2000	0.6805	0.2290

Note: Critical value (for 5% significance) for ADF test: with intercept, - 2.865; with trend and intercept, -3.417.

Critical value (for 5% significance) for KPSS test: with intercept, 0.463, with intercept and trend, 0.146.

Here ** indicate rejection of null hypothesis at 5% significance level.

From Table 2.1, we observe that the returns for oil gold and stock market are slightly positive. The oil market has the biggest deviation between maximum and minimum values. Standard deviations also suggest that the oil returns are more volatile than the gold futures returns and stock returns. Although we cannot observe noticeable significance in the skewness[25], a considerable significant kurtosis[26] is found in each of the three series, which suggests higher frequencies of extreme peakedness in these series. The significance of Jarque-Bera[27] (JB) statistics suggest that the series are not normally distributed, thus linear regressions cannot be used. Ljung-Box(1987) Q(10) statistics are significant for gold and S&P500 return series, which suggest the existence of serial correlations. Ljung-Box Q-statistics for all squared return series ($Q^2(10)$) are significant, indicating strong autocorrelation in the squared return series; thus, the second moments of returns are time varying and changing in a predictable fashion. This kind of volatility clustering —large changes tend to be followed by large changes, of either sign, and small changes tend to be followed by small changes, of either sign— can also be observed in Figure 2.3. In sum, the return series in this study exhibit all the typical characteristics of high frequency financial return series: skewness, leptokurtosis, and highly significant linear and nonlinear serial correlations. Empirical modelling shows that the GARCH type models are adequate for modeling

[25] Skewness is a measure of asymmetry of the distribution of the series around its mean; the skewness of a symmetric distribution, such as the normal distribution, is zero.
[26] Kurtosis measures the peakedness or flatness of the distribution of the series, in other words, how fat the tails of distribution are. The kurtosis of the normal distribution is 3.
[27] A JB statistic for normal distribution is 0, which indicates that the distribution has a skewness of 0 and a kurtosis of 3. Skewness values other than 0 and kurtosis values farther away from 3 lead to increasingly large JB values. And the Critical value for normal distribution at 5%level is 5.99.

daily price movements in financial market. The significance of the ARCH-LM test (Engle, 1982) statistics also suggests that ARCH/GARCH type model is an appropriate specification. For an adequate estimation with Bi-variate GARCH we need to ensure that the components variables (the mean returns) are stationary. Thus unit root tests become necessary. In this study, we conduct the Augmented Dickey-Fuller (ADF) and the Kwiatkowski, Phillips, Schmidt and Shin (KPSS) test to examine the existence of stationary in the return series. The null hypothesis for ADF test is that the series has a unit root; while the null hypothesis for KPSS is that the series is stationary. The test results are shown at the bottom of Table 2.1. ADF test for the return series are all significant at 95% significant level, and KPSS are all insignificant at 95% significant level. Both test results confirm that the three return series are covariance stationary.

ADF and KPSS tests are also performed on the natural logarithm of the three price series, with the results indicating that the price series are following an I(1) process. To ensure the adequacy of our estimation model, we need to test the possible existence of cointegration between variables. The cointegration relationships are normally regarded as the long run or stationary relationships between the endogenous variables. If cointegration relationships exist between variables, the model specifications need to be adjusted by inclusion of the lagged cointegration vectors (EC_{t-1}). If the log price series are cointegrated and the resultant error correction terms are not included in the regression, the estimation results will be biased. Johanson's cointegration test (1991,

1995) were adopted and the results are reported in Table 2.2. Based on the Figure 2.2 of the price series in logarithm, the Johanson's cointegration test specification we used assumes intercept but no trend in the cointegration vector.

Table 2. 2 Cointegration test for the price series

Unrestricted Cointegration Rank Test (Trace)				
Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None	0.003875	23.12317	29.79707	0.2401
At most 1	0.000955	6.320129	15.49471	0.6577
At most 2	0.000505	2.185199	3.841466	0.1393
Trace test indicates no cointegration at the 0.05 level				
* denotes rejection of the hypothesis at the 0.05 level				
**MacKinnon-Haug-Michelis (1999) p-values				

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)				
Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None	0.003875	16.80304	21.13162	0.1815
At most 1	0.000955	4.134930	14.26460	0.8448
At most 2	0.000505	2.185199	3.841466	0.1393
Max-eigenvalue test indicates no cointegration at the 0.05 level				
* denotes rejection of the hypothesis at the 0.05 level				
**MacKinnon-Haug-Michelis (1999) p-values				

As shown in Table 2.2, both the Trace and Max-eigenvalue[28] tests indicate that there is no cointegration relations between the three price series.

[28] The Max-eigenvalue test is not regarded as reliable as the Trace test.

2.3.2 Estimation results for the whole sample period[29]

In our estimation, we experimented with numerous specification of the mean equation, for the given structure of conditional variance and covariance (*H*). For the structure of the latter, we use full rank in the C matrix. However, when it is impossible to obtain estimates of the parameters of H, because of singularity or lack of convergence, we follow the BEKK strategy to set the upper off-diagonal elements equal zero, which ensures the positive definition of conditional variance and covariance matrix.

From all the permutations of the specification within and across the three returns of oil, gold futures and stock index for both Tri-variate the Bi-variate GARCH models, the most minimal specification, of random means, was generally the most acceptable statistically speaking[30]. Where this was not the case, the best mean equations contained only an intercept or an intercept and one period lagged variables.

The Tri-variate GARCH estimation results are reported in Appendix 2.A. Table 2.A1. As we can observe, most elements in A and B matrix are significantly different from zero, indicating that the variance and covariance of each returns series are time-varying and are impacted by the shocks from its own past and shocks from other

[29] Sample period will be divided into three sub-sample periods. Thus we use the whole sample period here. More explanations about the sample splitting are provided later.
[30] The appropriate mean settings are chosen by comparing the parameter significance statistics, LR test results for omitting one or more variables and also the log likelihood values for the estimation

market, hence the appropriateness of a GARCH framework. The parameters in matrix A capture the effects from unexpected shocks and the parameters in matrix B capture the effects from the past conditional volatilities. The diagnostic tests for the maximum likelihood estimations are provided at the bottom of Table 2.A1. The Ljung-Box Q(10) Statistics for error terms suggest the autocorrelations in the oil and gold futures returns have been removed, however, this is not the case for the stock index returns. Ljung-Box Q statistics for the squared error terms ($Q^2(10)$) are all significantly different from zero at 5% significance level, which indicate that the serial correlations still exist in the second moments of all series. Moreover, we can observe from the eigenvalues given in the bottom of Table 2.A1 that one of the eigenvalues exceeds 1. Therefore, the Tri-variate GARCH model for the whole sample period is not covariance stationary.

To investigate spillovers from Tri-variate GARCH estimation, we also compare these with the results from Bi-variate GARCH estimation of each pair of variables. The Bi-variate estimates are reported in Table 2.A2. Again we observe that most elements in the A and B matrices are significantly different from zero at the 5% significance level, pointing to the existence of GARCH relations among the error terms. However, the diagnostic tests suggest that the Bi-variate estimates for the whole sample period are not covariance stationary for the oil-gold and gold-stock market models (As reported in at the bottom of the Table 2.A.2, eigenvalues for the two models are not always smaller than one). The Q(10) statistics for the oil returns series are significant, suggesting the existence of serial correlations. Q(10) statistics for the squared return series in all of the three markets are strongly significant, so the autocorrelations in the second moments are not fully removed. Eigenvalues given in Table 2.2 also indicate the covariance stationary are not satisfied for the Bi-variate estimation of the relations between oil and gold market, or for the estimation between gold and stock market.

As discussed earlier, the transmission of volatility can be examined by the parameters in conditional covariance matrix. We summarize the volatility transmission patterns for Tri- and Bi-variate GARCH estimation of the oil, gold and stock market in Table 2.4. We can conclude from the three Bi-variate estimations that volatilities transmitted uni-directionally from the gold market to the oil market, from the stock market to the gold market, and bi-directionally from the oil to the stock market. Except for the transmission between the oil and stock markets, the relationships are not in line with a priori expectations. It is normally believed that during the past decade, when the oil price rallied, the gold price would follow suit. This is because an oil price increase will raise expected inflation. Investors will buy more gold as it is a reserve asset, which will raise its price. However, from the volatility point of view, oil market shocks do not affect gold market volatility directly, at least over a short period. This indicates that gold is a good hedging asset. On the other hand, the oil market is quite sensitive to gold market shocks. Gold market volatility is affected by the shocks emanating from the stock market, but not vice versa.

In contrast, the Tri-variate GARCH estimates show that the volatility spillovers are bi-directional between all three markets, which suggests that oil, gold and stock markets are intertwined through second moments. The difference between Bi-variate and Tri-variate GARCH estimation may come from the fact that the Bi-variate results are obtained when we do not control for any effects from the third market. It seems that we cannot omit the effect of the third market when we consider the relations between any pair of markets, at least when describing their second moment inter-dependence.

The conditional variance and covariance series estimated under different modelling specification for the three markets are portrayed in Figures 2.4 to 2.9. We can observe from the Figures 2.4 to 2.6 that the conditional volatility of oil, gold and stock market estimated by using Tri-variate and two Bi-variate GARCH models follow a similar pattern. In contrast, the conditional covariances estimated between different methods obviously diverge from each other, for each of the three markets. This is a confirmation that the correlations between the two specific markets are largely affected by the third market.

Descriptive statistics for the conditional variance and covariance series estimated using different modelling specification are reported in Tables 2.5 and 2.6. In general, the divergences are very small between different models, especially for the conditional variance. All the variance and covariance series exhibit non-normality.

We can also conclude from Table 2.5 and 2.6 that the variance and covariance estimated under Bi-variate GARCH models exhibit more peakedness in the estimated series and consequently larger Jarque-Bera statistics; and the standard deviation for the covariances estimated using Bi-variate models are higher than those estimated using the Tri-variate model. All those alternatives bear out the importance of a third, inter-correlating market.

To investigate whether the variance and covariance series estimated under different models are statistically similar or not, we perform Equality test for means and variances for all these series. The results are reported in Table 2.7.

Table 2. 3 Volatility spillovers for the whole sample period

	h_{ij}			ε_{ij}^2		
	oil	gold	stock	oil	gold	stock
oil	√	√	√	√	√	√
gold	√	√	√	x	√	x
stock	√	√	√	√	x	√
	oil	gold		oil	gold	
oil	√	√		√	√	
gold	x	√		x	√	
	oil	stock		oil	stock	
oil	√	√		√	√	
stock	√	√		√	√	
	gold	stock		gold	stock	
gold	√	√		√	x	
stock	x	√		x	√	

Note: √ indicate significant volatility spillover at 5% level

X indicate no significant volatility spillover at 5% level

Table 2. 4 Conditional variances estimated using different models for the whole sample period

	Var(oil)			Var(gold)			Var(S&P500)		
	Tri-GARCH	Bi-GARCH (RO&RG)	Bi-GARCH (RO&RSP)	Tri-GARCH	Bi-GARCH (RO & RG)	Bi-GARCH (RG &RSP)	Tri-GARCH	Bi-GARCH (RO & RSP)	Bi-GARCH (RG & RSP)
Mean	4.4547	4.4296	4.4568	0.8137	0.8099	0.8100	0.9544	0.9538	0.9535
Median	4.0836	4.0270	4.0424	0.6446	0.6322	0.6405	0.6454	0.6380	0.6461
Maximum	14.2323	17.9486	15.6205	4.5736	4.8943	4.6511	4.9246	5.2415	5.6397
Minimum	1.1525	1.2879	1.0727	0.0986	0.0964	0.0928	0.1830	0.1707	0.2242
Std. Dev.	2.1904	2.1467	2.3606	0.6549	0.6659	0.6587	0.7807	0.8082	0.8252
Skewness	1.3260	1.3885	1.5499	2.2077	2.3195	2.2327	2.0454	2.1742	2.3649
Kurtosis	5.2664	5.9702	6.1515	9.4735	10.1805	9.6362	7.8883	8.6279	9.7546
Jarque-Bera	2194.13	2980.79	3523.00	11070.29	13175.65	11534.79	7325.30	9119.35	12259.12
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 2. 5 Statistics for conditional covariances estimated using different models for the whole sample period

	Cov(oil,gold)		Cov(oil, sp)		Cov(gold, sp)	
	Tri-GARCH	Bi-GARCH (RO & RG)	Tri-GARCH	Bi-GARCH (RO & RSP)	Tri-GARCH	Bi-GARCH (RG & RSP)
Mean	0.2827	0.2883	-0.0524	-0.0456	-0.0667	-0.0608
Median	0.2126	0.1879	-0.0552	-0.0486	-0.0457	-0.0410
Maximum	1.7707	3.5514	1.4450	1.6626	0.4260	0.4835
Minimum	-1.5554	-0.9063	-1.5844	-1.7198	-0.7467	-0.9399
Std. Dev.	0.3571	0.4073	0.2777	0.3061	0.1298	0.1425
Skewness	0.9719	2.3527	0.2985	0.2574	-0.9522	-1.1643
Kurtosis	5.9036	13.3936	8.5007	8.5139	6.1712	8.0714
Jarque-Bera	2201.14	23468.35	5519.54	5529.23	2466.97	5614.42
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 2. 6 Equality test for the whole sample period

		Mean		Variance	
		Value	Probability	Value	Probability
Var(oil)	Tri-(oil,gole, s&p) & Bi-(oil,gold)	0.2895	0.5906	1.0411	0.1853
	Tri-(oil,gole, s&p) & Bi-(oil, s&p)	0.0019	0.9652	1.1615	0.0000
	Bi-(oil,gold)& Bi-(oil, s&p)	0.3149	0.5747	1.2092	0.0000
Var(gold)	Tri-(oil,gole, s&p) & Bi-(oil,gold)	0.0741	0.7854	1.0339	0.2723
	Tri-(oil,gole, s&p) & Bi-(gold, s&p)	0.0680	0.7943	1.0118	0.6999
	Bi-(oil,gold)& Bi-(gold, s&p)	0.0002	0.9897	1.0219	0.4762
Var(sp)	Tri-(oil,gole, s&p) & Bi-(oil,s&p)	0.0012	0.9720	1.0717	0.0228
	Tri-(oil,gole, s&p) & Bi-(gold, s&p)	0.0027	0.9589	1.1172	0.0003
	Bi-(oil,s&p)& Bi-(gold, s&p)	0.0003	0.9868	1.0425	0.1712
Cov(oil,gold)	Tri-(oil,gole, s&p) & Bi-(oil,gold)	0.4541	0.5004	1.3008	0.0000
Cov(oil,sp)	Tri-(oil,gole, s&p) & Bi-(oil, s&p)	1.1736	0.2787	1.2146	0.0000
Cov(gold,sp)	Tri-(oil,gole, s&p) & Bi-(gold, s&p)	4.0415	0.0444	1.2056	0.0000

From Table 2.7, we can observe that in most cases, the means of the conditional variance and covariance series estimated using different models are not significantly different from each other. However, their variances are different. For the conditional variance of oil, there is no big divergence between Tri-variate GARCH model and Bi-variate GARCH model for oil and gold. This suggests that including or not the stock index return into the endogenous variables group do not affect the estimation results of the oil variance. On the other hand, the gold shocks cannot be omitted for the estimation of conditional variance for oil. The variance of gold returns is somewhat independent from the oil and stock markets. The conditional variance of S&P returns are both related to oil and gold shocks, as shown by the significance of the equality test for variance estimated using Tri-variate and Bi-variate GARCH models. For the conditional covariance of each pair of variables, we can observe that they largely different between the Tri-variate and Bi-variate specifications. Link back to the statistic significance of the coefficients on variances and covariances, the equality tests provide confirmation that the Tri-variate specification is needed for analyzing the variance and covariance structure of the oil, gold and stock market.

The diagnostic tests for both Tri-variate and Bi-variate GARCH models show that the serial correlations in squared residuals have not been completely eliminated and models are not stationary. Thus the models we employed are not appropriate for describing the whole sample period data. However, we did find the existence of GARCH effects in the conditional volatility of these three return series. There is a need to redefine the sample period for the models to work. Given the data of conditional variance and covariance portrayed in Figure 2.4 to Figure 2.9 in Appendix 2.B, the non-stationary estimation results for Tri-variate and Bi-variate GARCH model are not of surprise. It further suggests that the variance and covariance structure is affected by the conditions surrounding the markets, which the compartmentalizing of the data via our three sub-periods aims to capture.

2.3.3 Results for the sub-periods analysis

2.3.3(A) Descriptive statistics for the three sub-samples

From Figure 2.4 and Figure 2.6, we observe that during Oct 1997 to July 2003, the conditional volatility of oil market and conditional volatility of stock market are much higher than during the rest of the sample period. Recall that in the late half 1997, there was huge turmoil in financial markets—the Asia financial crisis. The latter began to emerge on 2 July 1997 when Thailand abandoned its currency (Baht) peg to the US dollars. When the financial market opened that day, Baht plunged 15% against the US dollar and created a currency devaluation panic that spread over the rest of Southeast Asia. Contagion effects were felt in the whole of the world's financial markets. Thereafter, the US financial market experienced a relatively high volatility period, and the financial market experienced a record expansion after the Asia crisis until 2000.

During that period, many stocks had been overvalued, especially those of the internet companies. In August of 2000, the US stock market experienced a crash, as the dot-com bubble burst. Then after a short recovery, US stock market slid into a big Crash from September 11 2001, subsequent to the terrorist attacks on the United States. Oil prices also declined sharply, largely on increased fear of a sharper worldwide economic downturn (and therefore sharply lower oil demand). Until the end of 2001, the stock market began to rally as investors' confidence came back. However, staring from March 2002 stock indices started to slid, with dramatic decline in July and September leading to lows last reaches in 1997 and 1998. At the same time, oil prices began to increase due to oil production cuts by OPEC and non-OPEC at the beginning of 2002, plus unrest in the Middle East. At the end of 2003, the US economy started to resuscitate and the financial markets enter into a relatively low volatility period.

Thus, we split our whole sample into three sup-samples: pre-crisis period, from 1 April 1991 to 31 March 1997, with relatively low turmoil in the financial market; crisis period, from 1 April 1997 to 31 July 2003, with relatively high turmoil and thus high volatility in the financial market; and post-crisis period, 1 August 2003 to 5 November 2007, when volatility in financial market were relatively low.

The descriptive statistics for the three sub-sample periods are reported in Table 2.A3 to 2.A5 in Appendix 2.A, with unit root test results shown at the bottom of each table.

The cointegration tests have been performed on the price series to ensure an adequate modelling specification for our Tri- and Bi-variate GARCH specification. The Johanson's cointegration tests results are shown in Table 2.A6 to 2.A8.

Comparing Table 2.A3, 2.A4 and 2.A5, we can conclude that the mean returns for oil and gold market are increasing during time; the stock market, has its the largest mean return during the pre-crisis period and the smallest mean in the crisis period. The standard deviations for oil and stock returns increase in the crisis period, and then decrease in the post crisis period. For the gold market, the standard deviation is increasing throughout the three periods, with the post-crisis period exhibiting the highest volatility. All of the three return series have negative skewness in each period, expect for the gold return series which has a positive skewness in the crisis period. The kurtosis statistics are all much higher than the critical value at 5% significance level, so are the Jarque-Bera statistics. These suggest that the three return series in all periods have significant peakedness and are not normally distributed. The ADF test for unit root rejects the null hypothesis that a unit root exist in the series and the KPSS test result cannot reject the null hypothesis that a unit root does not exist in the return series. Hence all three series follow an I(0) process in all three sub-periods.

Both Trace and Maximum Eigenvalue test statistics for the Johanson's cointegration test shown in Tables 2.A6 to 2.A8 support that there is no cointegrating relationship between the three price series. These findings together with the fact that return series are all I(0) provide the preconditions for our modelling specification.

2.3.3(B) Estimation results for the three sub-sample periods.

Results for the Tri-variate and Bi-variate GARCH estimates of the conditional variance and covariance structures are reported in Table 2.A9 to Table 2.A14 in Appendix 2.A. We observe that the majority of the element in the A and B matrices are significantly different from zero. The diagnostic checks for both Tri-variate and Bi-variate GARCH specifications in all the three sub-periods are reported at the bottom of each table. The Ljung-Box Q(10) statistics show that, for both Bi-variate and Tri-variate estimation, serial correlations were successfully removed for all residuals and squared residuals, eliminating potential biases in the estimates. The eigenvalues for each modelling estimation all have modulus smaller than 1, so that both types of model are covariance stationary in the three sub-sample periods. Recall that covariance stationary was not satisfied for the whole sample period; variance and covariance do change with time and with changes in market conditions.

We summarise the volatility transmission between different markets for the three sub-sample periods in Table 2.8 to 2.10. In the pre-crisis period, from the Bi-variate GARCH estimation for oil and gold returns, we can observe that the previous days

Table 2. 7 Volatility spillovers for the pre-crisis period (1/04/91—31/03/97).

	h_{ij}			ε_{ij}^2		
	oil	gold	sp	oil	gold	sp
oil	√	x	√	√	x	√
gold	x	√	x	x	√	x
sp	x	√	√	√	√	√
	oil	gold		oil	gold	
oil	√	√		√	x	
gold	√	√		√	√	
	oil	sp		oil	sp	
oil	√	x		√	x	
sp	x	√		x	√	
	gold	sp		gold	sp	
gold	√	√		√	√	
sp	√	√		√	√	

Note: √ indicate significant volatility spillover at 5% level. X indicate no significant volatility spillover at 5% level

Table 2. 8 Volatility spillovers for the crisis period (1/04/97—31/07/03)

	h_{ij}			ε_{ij}^2		
	oil	gold	sp	oil	gold	sp
oil	√	x	x	√	√	x
gold	x	√	x	x	√	x
sp	√	√	√	√	x	√
	oil	gold		oil	gold	
oil	√	x		√	√	
gold	√	√		x	√	
	oil	sp		oil	sp	
oil	√	√		√	x	
sp	√	√		√	√	
	gold	sp		gold	sp	
gold	√	x		√	x	
sp	x	√		x	√	

Note: √ indicate significant volatility spillover at 5% level. X indicate no significant volatility spillover at 5% level

Table 2. 9 Volatility spillovers for the post-crisis period (1/08/03—5/11/07).

	h_{ij}			ε_{ij}^2		
	oil	gold	sp	oil	gold	sp
oil	√	x	√	√	√	x
gold	x	√	x	x	√	x
sp	√	x	√	x	x	√
	oil	gold		oil	gold	
oil	√	√		√	√	
gold	√	√		x	√	
	oil	sp		oil	sp	
oil	x	√		√	√	
sp	√	√		x	√	
	gold	sp		gold	sp	
gold	√	√		√	x	
sp	x	√		x	√	

Note: √ indicate significant volatility spillover at 5% level. X indicate no significant volatility spillover at 5% level

shocks in the oil market will spill over to the gold market directly, indicated by the significance of coefficient a_{12}^2. The insignificance of coefficient a_{21}^2 implies that shocks from the gold market in the previous day do not spill over to the oil market directly. However, the conditional volatility in the oil market is impacted by the conditional volatility of the gold market, represented by the coefficient b_{21}^2. Because the coefficient a_{22}^2 is significant, the conditional variance of the gold market is significantly affected by its own past shocks. Following a similar mechanism, we can conclude from the Bi-variate GARCH estimates for the oil and gold markets, that the volatility transmission is bi-directional. Bi-variate estimates for the oil and stock markets suggest that there is no volatility transmission between them. Bi-variate estimates for gold and S&P returns indicate that the transmission between them is bi-directional.

Tri-variate GARCH estimates indicate that volatility in the oil market is influenced by the shocks from its own market as well as by shocks from the stock market. The lagged gold market shocks have no direct impact on the oil volatility. Gold market volatility is not affected by shocks from the oil or the stock markets, while the stock market volatility is affected by the shocks from both gold and stock markets. Thus the volatility transmission between oil and stock markets is bi-directional. Gold market volatility looks exogenous. Instead of affect the oil market directly, gold market volatility transmits to stock market first and then exert impact on the oil market through its influence on the volatility of the stock market.

Comparing the conclusions we draw from Bi-variate and Tri-variate estimation, we find that Tri-variate GARCH estimation, which takes into consideration the effect of conditional and unconditional volatilities of each of the three markets and also the time varying covariance between each two markets, break the “connections” that seem to exist between oil and gold, gold and stock market under Bi-variate estimation. For example, the direct linkage in their second moment between the oil and gold markets disappear when taking the stock market impact on these two markets into consideration. In the other way round, we may explain the second moment linkage between the oil and gold markets as a result of their relations with the stock market. In contrast, the volatility transmission between the oil and stock markets, which is not obvious when estimated by the Bi-variate GARCH framework, is actually significant if a Tri-variate GARCH model is used to control the potential gold market impact on these two markets.

For the crisis period，when the prices for the oil and stock markets are quite volatile, we can observe from Table 2.9 that, under Bi-variate estimation, volatility between oil and gold markets is bi-directional. The oil and stock markets also have Bi-variate volatility transmission. The Bi-variate GRACH estimation results also suggest that there is no volatility transmission between the gold and stock markets.

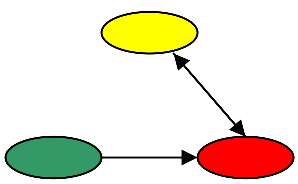
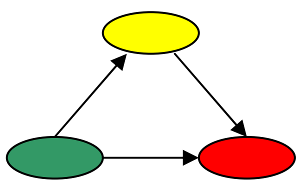
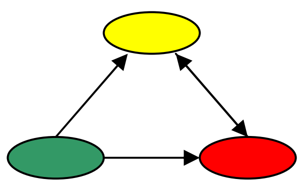
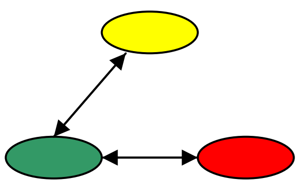
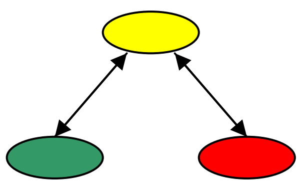
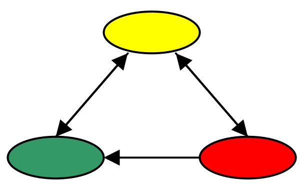
The Tri-variate GARCH estimation results reported in Table 2.9 show that volatility in gold market is exogenous, rather than being affected by the past shocks in oil market and/or the stock market. Volatility of the oil market is caused by its past shocks as well as the conditional variance of gold market. Stock market volatility is determined by its own past shocks, as well as by shocks from the oil and gold markets. Volatility transmission is uni-directional from the gold market to the oil market, from the oil market and gold markets to the stock market.

So, Tri-variate estimation gives different structures for the volatility transmission from the Bi-variate estimation. This again demonstrates that considering the third market impact can break certain relations that seemed to exist when the third market was excluded. Meanwhile, the Tri-variate estimation may also unveil some of the relations that seemed not to exist under the Bi-variate framework, for example, the volatility spillover from the gold market to the stock market.

For the post-crisis period, the volatility of the oil and stock markets become much smaller than in the crisis period. The volatility transmission relations are shown in Table 2.10. From the Bi-variate estimation between each pair of markets, we observe that the volatility transmission between the oil and gold markets are bi-directional, so is that between the oil and stock markets. Volatility is transmitted from the stock market to the gold market, but not vice versa. The Tri-variate estimates for the after crisis period show that the conditional variance, or the volatility of the oil market is affected by its own past shocks, shocks from stock market as well as shocks from gold market. The gold market volatility is still exogenous, independent of shocks realized in either the oil or stock markets. Stock market volatility is affected by its past shocks as well as shocks from the oil market. So, volatility transmission between the oil and stock markets is bi-directional. However, volatility spillover is unidirectional from the gold market to the oil market.

We sum up the volatility transmission mechanism between the three markets using different modelling specifications in Diagram 2.1. From the three-way volatility transmission modelled by a Tri-variate GARCH specification, we can observe that, although generally, in the financial market, when the price of oil goes up the gold price will follow; when it comes to volatility, the gold market takes the lead. There was insignificant volatility spillover between the oil and gold markets in the pre-crisis period. With the increasing importance of oil as a resource as well as a financial asset, we find there are significant volatility spillovers from the gold market to the oil market in the crisis and post-crisis periods. This suggests that gold is a financial asset with very low volatility and is not sensitive to the shocks in oil or stock markets. This explains why gold is one of the most favourable hedging instruments and is normally regarded as a "safe haven" asset.

Diagram 2.1

	Pre Crisis	Crisis	Post Crisis
Three-way Volatility Spillover (From Tri-variate GARCH)			
Two-way Volatility Spillover (From Bi-variate GARCH)			

Represent oil market, represent gold market and represent the US stock market.

Represent the direction of volatility spillover.

In contrast to the three-way estimation, the results from Bi-variate GARCH estimations for the oil and gold markets in the three sub-sample periods all indicate strong bi-directional linkage in their second moments. Compared with the Tri-variate estimation, we find that such links between the oil and gold markets is actually generated from their relations with the stock market. The oil market is very sensitive to shocks in the gold and stock markets, which accords with expectation. For example, Gold is a hedging asset largely used by oil companies and international financial institutions that hold large positions in the oil market. The linkage between the oil and stock markets is straightforward. Oil, as an extremely important industrial input, is largely used in every aspect of an economy nowadays. The changes in the economy, reflected in stock market indices can influence the demand and consumption of oil substantially.

From Diagram 2.1, we can also observe from the three-way volatility transmission that stock market volatilities are largely affected by the shocks from the oil and gold markets. We know that futures markets can normally absorb information quickly. Thus the spillover from the oil and gold futures markets to the stock market matches the economic theory. There is substantial hedging in oil and gold markets, altering the volatility transmission mechanisms across market, thus our results.

The descriptive statistics for the conditional variance and covariance for Tri-variate and Bi-variate GARCH estimation in the three sub-sample periods are reported in

Table 2.11 to Table 2.16, and corresponding data series are portrayed in Figures 2.10 to 2.27.

Comparing the data in Tables 2.11, 2.13 and 2.15, we observe that in the pre-crisis period, the means of conditional variance for all three series are the lowest. In both the oil and stock markets, the mean of volatility increased substantially (from around 2.7 to 6.2 for the oil market and from 0.4 to 1.7 for the stock market respectively) during the crisis period when there were large upheavals in financial markets, then falls after the crisis, but to a level higher than before the crisis period. Meanwhile, the standard deviation of the volatility series increases during the crisis period and falls after the financial market turmoil as well. However, the standard deviation for the oil market in the post-crisis period is smaller than the pre-crisis period, whereas that for gold market is higher in the post-crisis than in the pre-crisis period. In the gold market, mean and standard deviation for the conditional variance of gold returns increase over time.

The patterns of covariances between each pair of markets also change over time. The correlation is positive between the oil and gold markets, and negative between the oil and stock markets. Such findings are consistent with the literature. For example, Nick Barisheff (2005) state that gold and oil prices moved together with a positive price correlation. Hammoudeh, Dibooglu and Aleisa (2004) find positive correlation between the oil market and oil industry equity indices.

Table 2. 10 Statistics for the Conditional variances estimated using different models in the pre-crisis period (1/04/91—31/03/97).

	Var (oil)			Var (gold)			Var (S&P500)		
	Tri-GARCH	Bi-GARCH (RO & RG)	Bi-GARCH (RO & RSP)	Tri-GARCH	Bi-GARCH (RO & RG)	Bi-GARCH (RG & RSP)	Tri-GARCH	Bi-GARCH (RO & RSP)	Bi-GARCH (RG & RSP)
Mean	2.7667	2.7724	2.7823	0.3642	0.3622	0.3617	0.4173	0.4156	0.4086
Median	2.4612	2.4345	2.3989	0.2774	0.2736	0.2734	0.3922	0.3932	0.3953
Maximum	8.8675	8.4179	10.3275	2.0522	2.1906	2.2826	0.8607	0.8943	0.6714
Minimum	0.9856	1.0017	0.8767	0.0861	0.0808	0.0771	0.2418	0.2302	0.2490
Std. Dev.	1.3204	1.3183	1.4650	0.3038	0.3071	0.3146	0.1092	0.1180	0.0956
Skewness	1.4904	1.4679	1.7156	2.9771	3.0665	3.2002	0.7736	0.6707	0.4220
Kurtosis	5.8638	5.4946	6.8847	13.6892	14.6251	15.5957	3.1122	2.9404	2.2218
Jarque-Bera	1112.03	965.98	1748.42	9743.67	11243.54	12991.66	156.60	117.35	85.78
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 2. 11 Statistics for the conditional covariances estimated using different models in the pre-crisis sample period (1/04/91—31/03/97).

	Cov (oil,gold)		Cov (oil, sp)		Cov (gold, sp)	
	Tri-GARCH	Bi-GARCH (RO & RG)	Tri-GARCH	Bi-GARCH (RO & RSP)	Tri-GARCH	Bi-GARCH (RG & RSP)
Mean	0.0574	0.0613	-0.0661	-0.0621	-0.0548	-0.0530
Median	0.0384	0.0404	-0.0586	-0.0536	-0.0472	-0.0469
Maximum	0.8014	1.1334	0.3526	0.3923	0.1620	0.0952
Minimum	-0.6662	-0.3571	-0.6266	-0.6655	-0.2171	-0.3224
Std. Dev.	0.1766	0.1559	0.1390	0.1397	0.0500	0.0435
Skewness	0.4678	1.6914	-0.2987	-0.4021	-0.3712	-1.7003
Kurtosis	6.0373	9.9716	3.6645	4.0314	4.3080	9.2552
Jarque-Bera	657.38	3908.11	51.97	111.31	147.22	3299.22
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 2. 12 Statistics for the Conditional variances estimated using different models in the crisis period (1/04/97—31/07/03).

	Var(oil)			Var(gold)			Var(S&P500)		
	Tri-GARCH	Bi-GARCH (RO & RG)	Bi-GARCH (RO & RSP)	Tri-GARCH	Bi-GARCH (RO & RG)	Bi-GARCH (RG & RSP)	Tri-GARCH	Bi-GARCH (RO & RSP)	Bi-GARCH (RG & RSP)
Mean	6.2251	6.2437	6.2771	0.8524	0.8557	0.8509	1.7390	1.7340	1.7439
Median	5.5118	5.5294	5.5319	0.7630	0.7538	0.7602	1.5115	1.5159	1.4934
Maximum	31.6854	26.6439	27.8946	9.8043	8.4215	7.1668	5.1424	5.8889	6.0640
Minimum	3.5848	3.5016	3.5427	0.6596	0.6011	0.6038	0.8595	0.9423	0.8296
Std. Dev.	2.6672	2.6174	2.7695	0.4137	0.4491	0.4043	0.7203	0.7252	0.8079
Skewness	3.8549	3.3899	3.6462	11.2546	8.4411	7.5376	1.8754	2.3246	2.1460
Kurtosis	24.2076	18.9647	21.1056	186.4524	103.0052	82.6316	6.8371	9.3647	8.4661
Jarque-Bera	34986.62	20670.15	26177.51	2347177	706737.4	451307.7	1978.27	4268.53	3318.53
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 2. 13 Statistics for the conditional covariances estimated using different models in the crisis period (1/04/97—31/07/03).

	Cov(oil,gold)		Cov(oil, sp)		Cov(gold, sp)	
	Tri-GARCH	Bi-GARCH (RO & RG)	Tri-GARCH	Bi-GARCH (RO & RSP)	Tri-GARCH	Bi-GARCH (RG & RSP)
Mean	0.2987	0.3042	-0.0370	0.0040	-0.1339	-0.1346
Median	0.2714	0.2793	0.0375	0.0258	-0.1199	-0.1114
Maximum	3.2961	3.6978	1.7732	3.1121	2.6496	1.0645
Minimum	-6.0751	-4.4946	-5.5407	-6.9189	-0.9091	-0.9553
Std. Dev.	0.3939	0.4019	0.6214	0.6028	0.1917	0.1952
Skewness	-1.9191	-0.3970	-1.9071	-1.5084	2.6506	-0.2336
Kurtosis	51.1727	27.2533	12.5742	19.6102	38.8921	6.9996
Jarque-Bera	160457.7	40458.93	7297.76	19581.78	90443.69	1114.09
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 2. 14 Statistics for Conditional variances estimated using different models in the post crisis period (1/08/03—5/11/07).

	Var(oil)			Var(gold)			Var(S&P500)		
	Tri-GARCH	Bi-GARCH (RO & RG)	Bi-GARCH (RO & RSP)	Tri-GARCH	Bi-GARCH (RO & RG)	Bi-GARCH (RG & RSP)	Tri-GARCH	Bi-GARCH (RO & RSP)	Bi-GARCH (RG & RSP)
Mean	3.8826	3.9171	3.9021	1.1520	1.1681	1.1581	0.5087	0.5012	0.5023
Median	3.8404	3.7786	3.7957	1.0113	1.0121	1.0101	0.4651	0.4459	0.4580
Maximum	6.7500	7.2884	5.9833	3.7502	4.0884	3.7735	1.4965	1.4829	1.3618
Minimum	2.6896	2.5447	3.7011	0.5143	0.5063	0.5144	0.3050	0.2869	0.2986
Std. Dev.	0.7062	0.7213	0.2839	0.5775	0.6139	0.5830	0.1675	0.1799	0.1604
Skewness	1.1127	1.3158	2.9306	2.0464	2.1409	2.0579	2.4735	2.4578	2.3596
Kurtosis	4.9227	5.4315	14.1976	7.3992	7.9630	7.5289	11.2710	10.8358	10.3571
Jarque-Bera	400.04	593.73	7387.93	1669.79	1987.13	1732.10	4295.81	3957.33	3533.40
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 2. 15 Statistics for the conditional covariances estimated using different models in the after crisis sample period (1/08/03—5/11/07).

	Cov(oil,gold)		Cov(oil, sp)		Cov(gold, sp)	
	Tri-GARCH	Bi-GARCH (RO & RG)	Tri-GARCH	Bi-GARCH (RO & RSP)	Tri-GARCH	Bi-GARCH (RG & RSP)
Mean	0.5678	0.5544	-0.0349	-0.0367	0.0477	0.0461
Median	0.5206	0.4970	-0.0493	-0.0239	0.0423	0.0449
Maximum	1.8397	2.2956	0.4026	0.2223	0.3563	0.4294
Minimum	0.0756	-0.1313	-0.3474	-0.9950	-0.1932	-0.2841
Std. Dev.	0.3280	0.3884	0.1311	0.0885	0.0920	0.0832
Skewness	1.5030	1.4631	0.6222	-3.1798	0.2393	0.4502
Kurtosis	5.8548	5.9604	3.5305	24.6693	3.1491	6.3442
Jarque-Bera	794.83	801.36	84.64	23587.62	11.62	554.73
Probability	0.0000	0.0000	0.0000	0.0000	0.0030	0.0000

The correlation between gold and stock market is negative in the pre-crisis and crisis period, but positive after the crisis period. Chan and Faff (1988) found that gold has a positive sensitivity to the resource and mining sector industries, but negative sensitivity in industrial sectors. Thus it is not surprising to find that the correlation between the gold and stock markets is not constant during time, depending upon the effects across different sectors. Moreover, the intensive use of gold as a hedging method in the post-crisis period may also make the correlations between the gold and stock markets hard to capture. The correlation relationship may change with the change of time-span in consideration.

The comparison of variances and covariance between different models are portrayed in Figures 2.10 to 2.27, for pre-crisis, crisis, and post-crisis periods. The divergences between the conditional variances of oil, gold and stock returns estimated with different models are not obvious from the figures, except for the conditional variance of oil in the after crisis period. The conditional variance estimated from Bi-variate GARCH model for oil and S&P returns largely diverge from that estimated from the Tri-variate GARCH specification as well as from the Bi-variate GARCH specification between oil and gold. The divergence between covariance estimated using the Bi-variate and Tri-variate models is apparent. The graphs give a general idea of the estimated conditional variance and covariance comparisons. To examine these in a much clearer manner, we perform the equality test for the means and variances of those conditional series.

The Equality test results are reported in Tables 2.17-2.19 for each of the three sub-sample periods. The means of the conditional variance and covariance series are almost equal under different modelling strategies. However, most variances estimated using different modelling specifications are not equal. For the pre-crisis period, the conditional variance of oil is not significantly affected by its correlation with the stock market or by the correlation between the gold and stock markets. The conditional variance of gold is relatively exogenous. As shown in Table 2.17, the conditional variance for gold estimated using different models give similar answers. The conditional variance of oil is affected by shocks from both the oil and gold markets. The conditional covariance between the oil and gold, the gold and stock markets are different when estimated by Tri-variate or Bi-variate models. However, the conditional covariance of the oil and stock markets estimated using different models are more or less the same. For the crisis period, although the conditional variances estimated under different modelling strategies are different from each other, the conditional covariance between each two markets is more or less the same under Tri-variate and Bi-variate modelling strategy. For the after crisis period, the conditional covariances show large divergences between the Tri-variate or Bi-variate models, as they do in the pre-crisis period. Conditional variances generated using these two modelling strategies are also different in terms of variance equality.

Table 2. 16 Equality test for the pre-crisis period (1/04/91—31/03/97).

		Mean	Probability	Variance	Probability
Var(oil)	Tri-(oil,gole, s&p) & Bi-(oil,gold)	0.0144	0.9046	1.0032	0.9495
	Tri-(oil,gole, s&p) & Bi-(oil, s&p)	0.0974	0.7550	1.2309	0.0000
	Bi-(oil,gold)& Bi-(oil, s&p)	0.0395	0.8424	1.2349	0.0000
Var(gold)	Tri-(oil,gole, s&p) & Bi-(oil,gold)	0.0340	0.8537	1.0219	0.6688
	Tri-(oil,gole, s&p) & Bi-(gold, s&p)	0.0494	0.8242	1.0726	0.1661
	Bi-(oil,gold)& Bi-(gold, s&p)	0.0016	0.9682	1.0497	0.3385
Var(sp)	Tri-(oil,gole, s&p) & Bi-(oil, s&p)	0.1916	0.6616	1.1680	0.0022
	Tri-(oil,gole, s&p) & Bi-(gold, s&p)	5.6430	0.0176	1.3036	0.0000
	Bi-(oil, s&p) & Bi-(gold, s&p)	3.2642	0.0709	1.5225	0.0000
Cov(oil,gold)	Tri-(oil,gole, s&p) & Bi-(oil,gold)	0.4264	0.5138	1.2835	0.0000
Cov(oil,sp)	Tri-(oil,gole, s&p) & Bi-(gold, s&p)	0.6426	0.4228	1.0100	0.8439
Cov(gold,sp)	Tri-(oil,gole, s&p) & Bi-(gold, s&p)	1.2502	0.2636	1.3174	0.0000

Table 2. 17 Equality test for the crisis period (1/04/97—31/07/03)

		Mean	Probability	Variance	Probability
Var(oil)	Tri-(oil,gole, s&p) & Bi-(oil,gold)	0.0412	0.8391	1.0385	0.4437
	Tri-(oil,gole, s&p) & Bi-(oil, s&p)	0.3017	0.5829	1.0781	0.1269
	Bi-(oil,gold)& Bi-(oil, s&p)	0.1261	0.7226	1.1196	0.0219
Var(gold)	Tri-(oil,gole, s&p) & Bi-(oil,gold)	0.0483	0.8261	1.1783	0.0009
	Tri-(oil,gole, s&p) & Bi-(gold, s&p)	0.0113	0.9154	1.0473	0.3484
	Bi-(oil,gold)& Bi-(gold, s&p)	0.1049	0.7461	18.1759	0.0000
Var(sp)	Tri-(oil,gole, s&p) & Bi-(oil, s&p)	0.0396	0.8423	1.0135	0.7857
	Tri-(oil,gole, s&p) & Bi-(gold, s&p)	0.0326	0.8568	1.2581	0.0000
	Bi-(oil, s&p) & Bi-(oil,gold)	0.1349	0.7134	1.2413	0.0000
Cov(oil,gold)	Tri-(oil,gole, s&p) & Bi-(oil,gold)	0.1583	0.6908	1.0411	0.4141
Cov(oil,sp)	Tri-(oil,gole, s&p) & Bi-(oil, s&p)	3.6988	0.0545	1.0629	0.2159
Cov(gold,sp)	Tri-(oil,gole, s&p) & Bi-(gold, s&p)	0.0123	0.9116	1.0367	0.4640

Table 2. 18 Equality test for the post-crisis period (1/08/03—5/11/07).

		Mean	Probability	Variance	Probability
Var(oil)	Tri-(oil,gole, s&p) & Bi-(oil,gold)	1.2934	0.2556	1.0435	0.4784
	Tri-(oil,gole, s&p) & Bi-(oil, s&p)	0.7239	0.3949	6.1870	0.0000
	Bi-(oil,gold)& Bi-(oil, s&p)	0.4167	0.5186	6.4559	0.0000
Var(gold)	Tri-(oil,gole, s&p) & Bi-(oil,gold)	0.4009	0.5267	1.1300	0.0417
	Tri-(oil,gole, s&p) & Bi-(gold, s&p)	0.0610	0.8050	1.0192	0.7512
	Bi-(oil,gold)& Bi-(gold, s&p)	0.1528	0.6959	1.1087	0.0856
Var(sp)	Tri-(oil,gole, s&p) & Bi-(oil, s&p)	1.0240	0.3117	1.1536	0.0173
	Tri-(oil,gole, s&p) & Bi-(gold, s&p)	0.8490	0.3569	1.0898	0.1518
	Bi-(oil, s&p) & Bi-(oil,gold)	0.0211	0.8845	1.2572	0.0001
Cov(oil,gold)	Tri-(oil,gole, s&p) & Bi-(oil,gold)	0.7600	0.3834	1.4019	0.0000
Cov(oil,sp)	Tri-(oil,gole, s&p) & Bi-(oil, s&p)	0.1511	0.6975	2.1941	0.0000
Cov(gold,sp)	Tri-(oil,gole, s&p) & Bi-(gold, s&p)	0.1837	0.6682	1.2240	0.0008

2.4 Conclusion and further research

2.4.1 Conclusion

This research aims to examine the relationships between the oil, gold and stock markets. With the integration of financial markets and the increasing importance of oil and gold as commodities as well as financial instruments, an investigation of the relations between the three markets is very important. Instead of focusing on the price and returns relations, we focus on the second moments relationships. Our research is the first (to the best of our knowledge) of this kind and can be very useful in many aspects. For example, it can provide information for investors to speculate in financial markets, for investors or companies to hedge risk, or for decision markers to understand the market.

Tri-variate GARCH (1,1) models are adopted to examine volatility spillovers between oil, gold and stock markets. To investigate fully such volatility transmission relations, we compare the results from Tri-variate GARCH estimation to those from Bi-variate estimation for each pair of markets. US data are examined because it is the leading economy in the world and plays an important role in both the oil and gold markets. We also split the whole sample into three sub-sample periods for investigative purposes.

Our findings are consistent with the past literature in that we find volatility spills over from the oil market to the stock market, from the gold market to the stock market. Despite the obvious price and return links between oil and gold markets, the volatility inter-relations are not so obvious between them. The gold market is kind of exogenous in terms of volatility. The bi-directional volatility transmission between the oil and gold markets, which is suggested by the Bi-variate GARCH estimates, actually results from their linkage with the stock market. The oil market is quite sensitive to the shocks from both the gold and stock markets, and the stock market is strongly impacted by the volatility in the oil and gold markets.

Comparing the estimation results from Bi-variate and Tri-variate GARCH models, our research finds that the Tri-variate GARCH model, by adding an additional variable to the existing Bi-variate GARCH framework, can break some of the existing relationships between the variables and can also reveal some of the linkages we cannot observe in the Bi-variate estimation.

Equality tests are performed on the conditional variance and covariance series estimated using Tri-variate and Bi-variate modelling strategies to examine whether these estimated values are statistically different. Over all, the mean equality tests statistics for the variance are generally not significant at the 5% level. However, most variance equality tests statistics for the covariance are significantly different from zero. The mean and variance equality test statistics for the covariances are mostly significance at the 5% level. These indicate that the conditional variances and covariances estimated using the Tri-variate model and Bi-variate models are effectively different. The covariance between two markets is significantly affected by the third market. Tri-variate GARCH models can capture these effects and offer potentially more information concerning the inter-relationship between the three markets.

2.4.2 Further research

One possible use of this research is to provide useful information for market hedgers to hedge risk. For example, assume an investor hold a position in stock market. When stock market is not performing well, investors tend to buy gold as a means to reserve value (which may lead to higher gold value when the stock price falls). However, holding physical gold is costly. For one thing, holding gold in the beginning of the investment period instead of holding futures would tie up capital that could be invested in a market with potential higher return, e.g. stock market. This is the opportunity cost of holding physical gold commodity. For another, holding physical gold can lead to storage cost. An alternative choice for the investor is to use futures, which is more flexible and less costly. The investor can go long gold in the futures market if they expect a slump in the stock market in future. If the stock return does fall as expected or fall more than expected, the investor can buy gold with the price which has been locked up in the futures contract, which tend to be lower than the market gold price at that time. If the stock returns do not fall as expected, investors can just taking an offsetting position in the futures market. This could possibly lead to some losses in the futures trading, but the loss will be fully or partially offset by the gain in the stock market. One important issue for the hedging is deciding the number of gold futures contract to buy. In such case, the investor needs to calculate the optimal hedge ratios[31], which is a function of the variance and covariance of the stock and gold markets. Traditionally, only these two markets (products) will be considered to derive the optimal hedging ratio. However, these two markets are both linked to a third market, the oil market. Our study find that when taking the oil market into consideration, the conditional variance and covariance between the stock and gold market will change, and therefore the derived optimal hedge ratios. Such is also true for hedging strategies in other markets. One further study that may be very interesting is to investigate whether the hedging effectiveness can be improved when taking a third market impact into consideration.

This study can also be extended in other ways. For example, with the rapid growth of developing countries like China and India, their market-shares in the oil consumption and gold trading are increasing. Our research can be extended to examine how volatilities are transmitted across the world oil, gold markets and the stock market in developing countries. Moreover, different sectors have different oil and gold

[31] Optimal hedging ratio derivation and hedging effectiveness evaluation are discussed in the Essay 1 of this thesis.

sensitivity. To explore how different sectors in an economy are linked to the oil and gold markets is also a very interesting research topic to work on.

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Figure 2. 1 Oil and gold price in logarithm

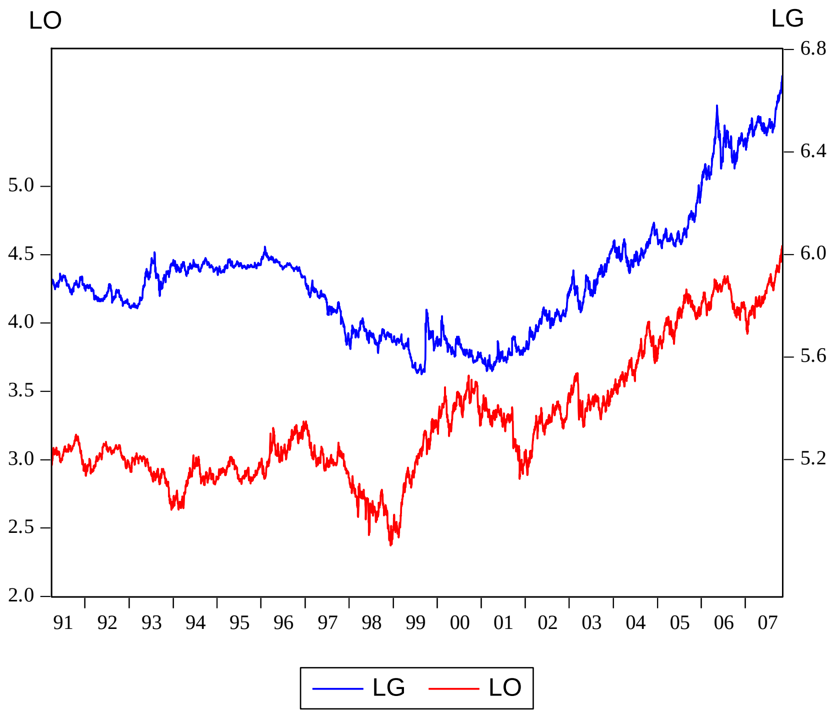


Figure 2. 2 Price series in logarithm

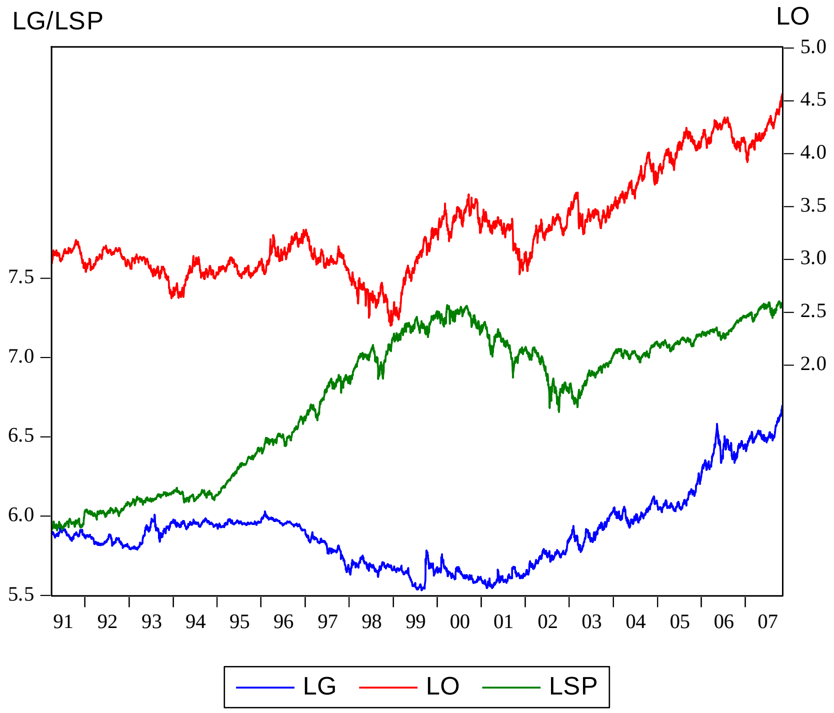


Figure 2. 3 Returns series for oil gold and stock index

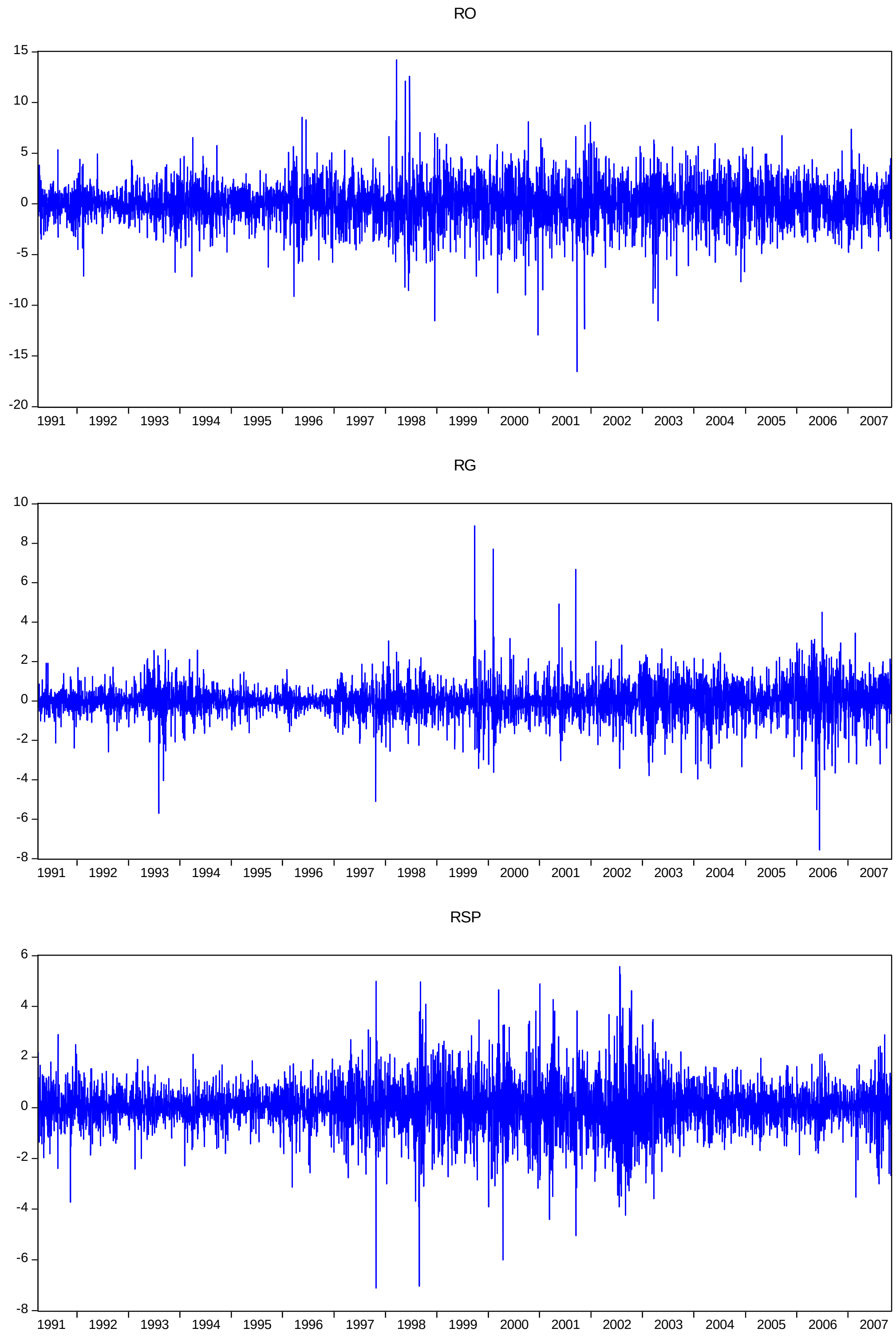


Figure 2. 4 Conditional variance of the oil returns for the whole sample period

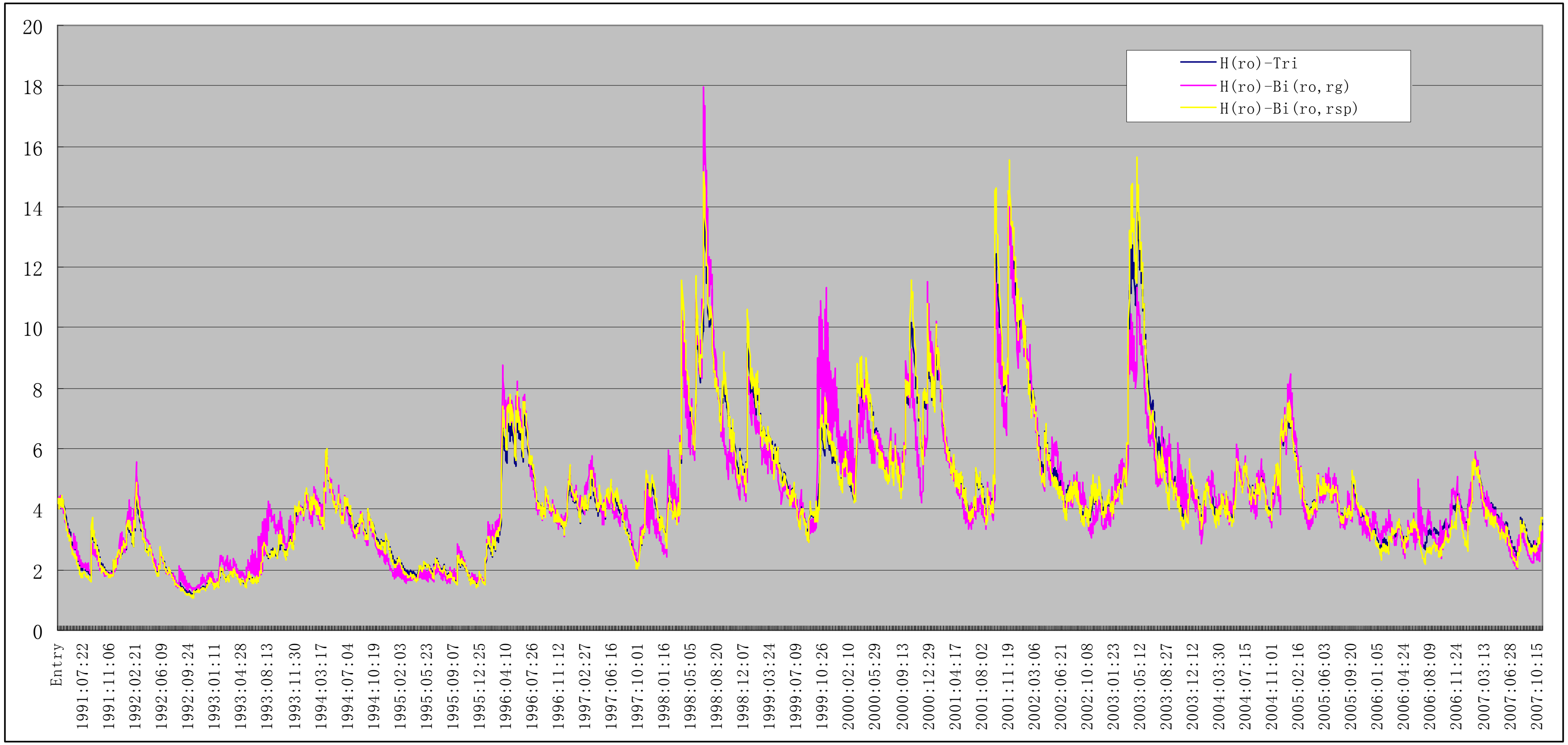


Figure 2. 5 Conditional variance of the gold returns for the whole sample period

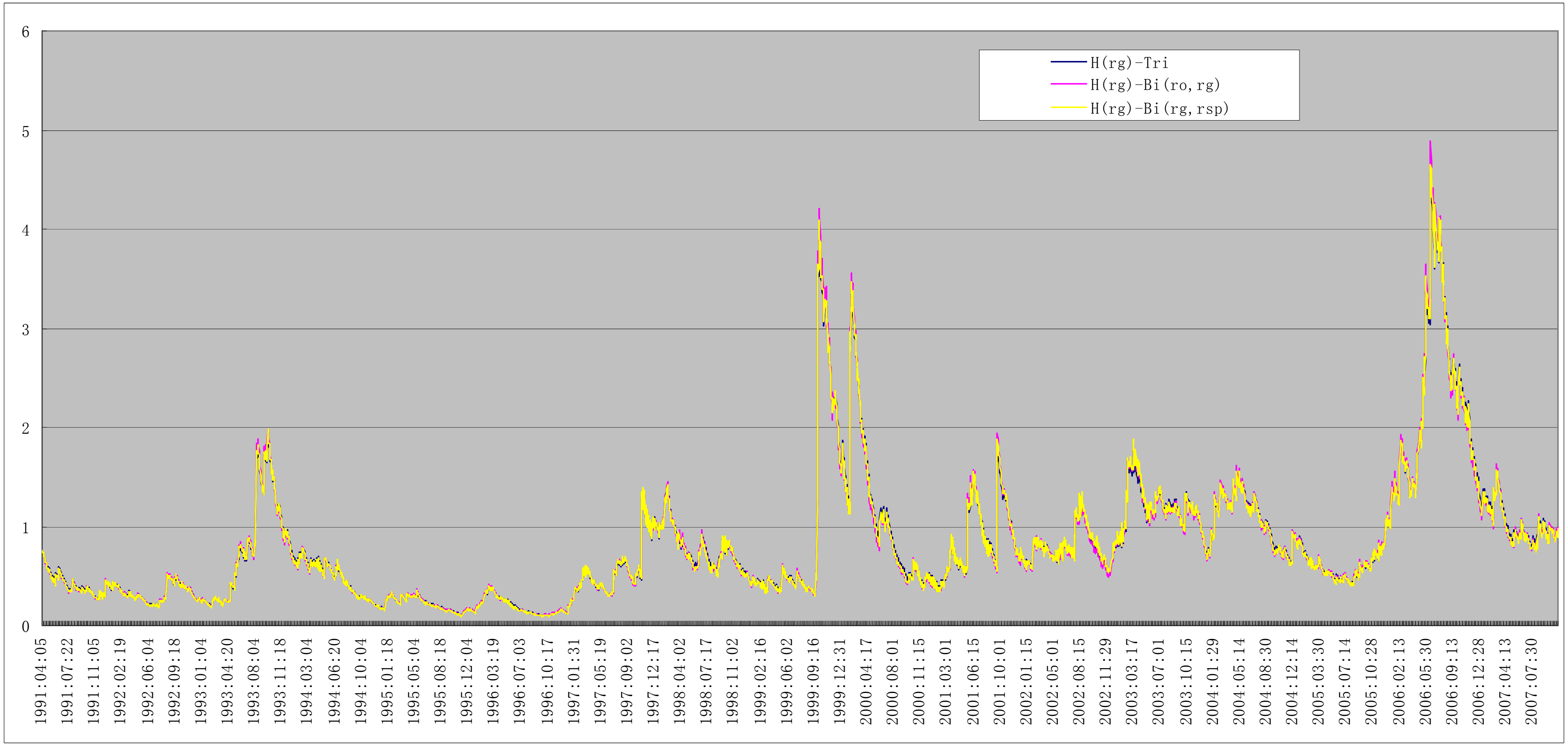


Figure 2. 6 Conditional variance of the stock index (S&P 500) returns for the whole sample period

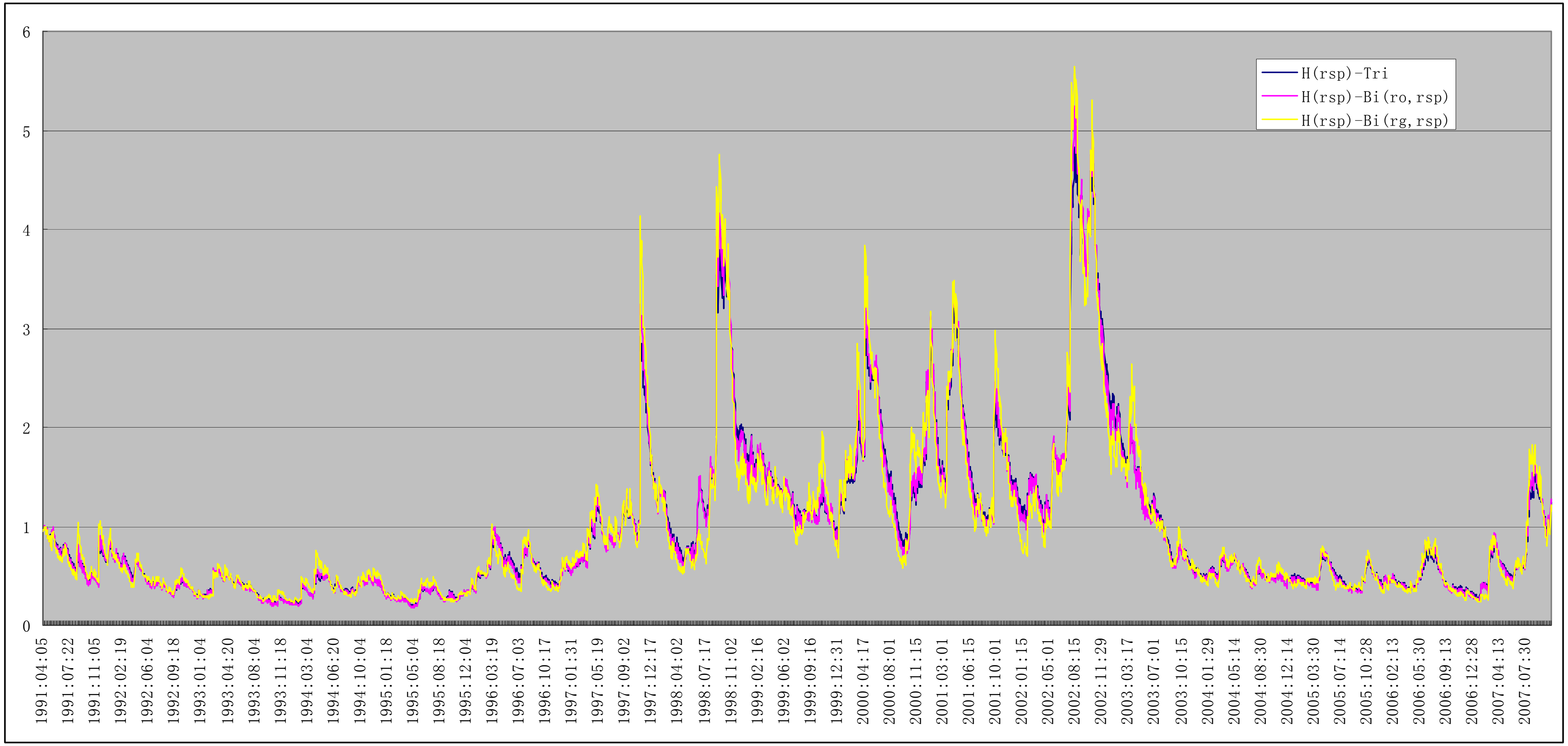


Figure 2. 7 Conditional Covariance between the oil and gold markets for the whole sample period

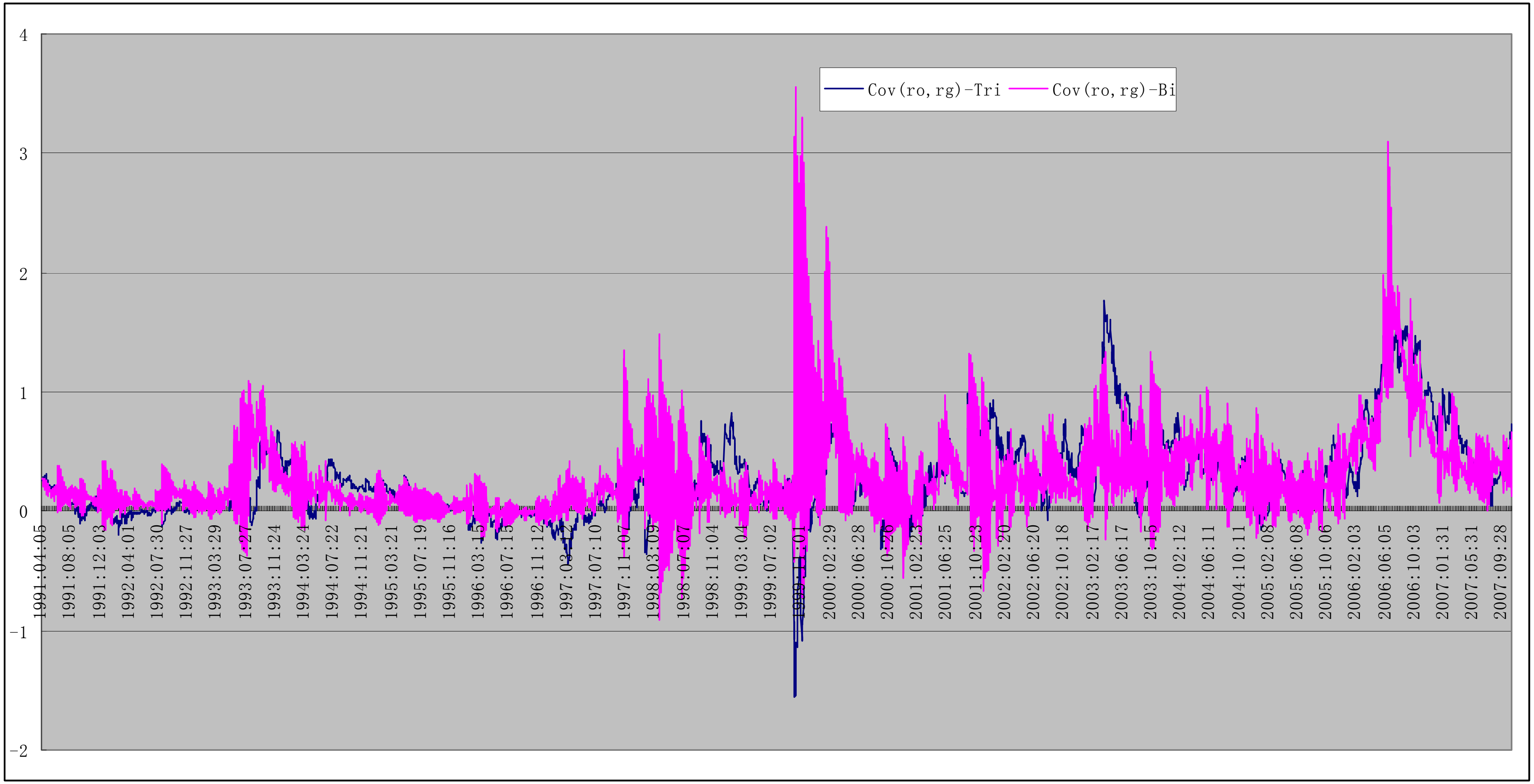


Figure 2. 8 Conditional Covariance between the oil and stock markets for the whole sample period

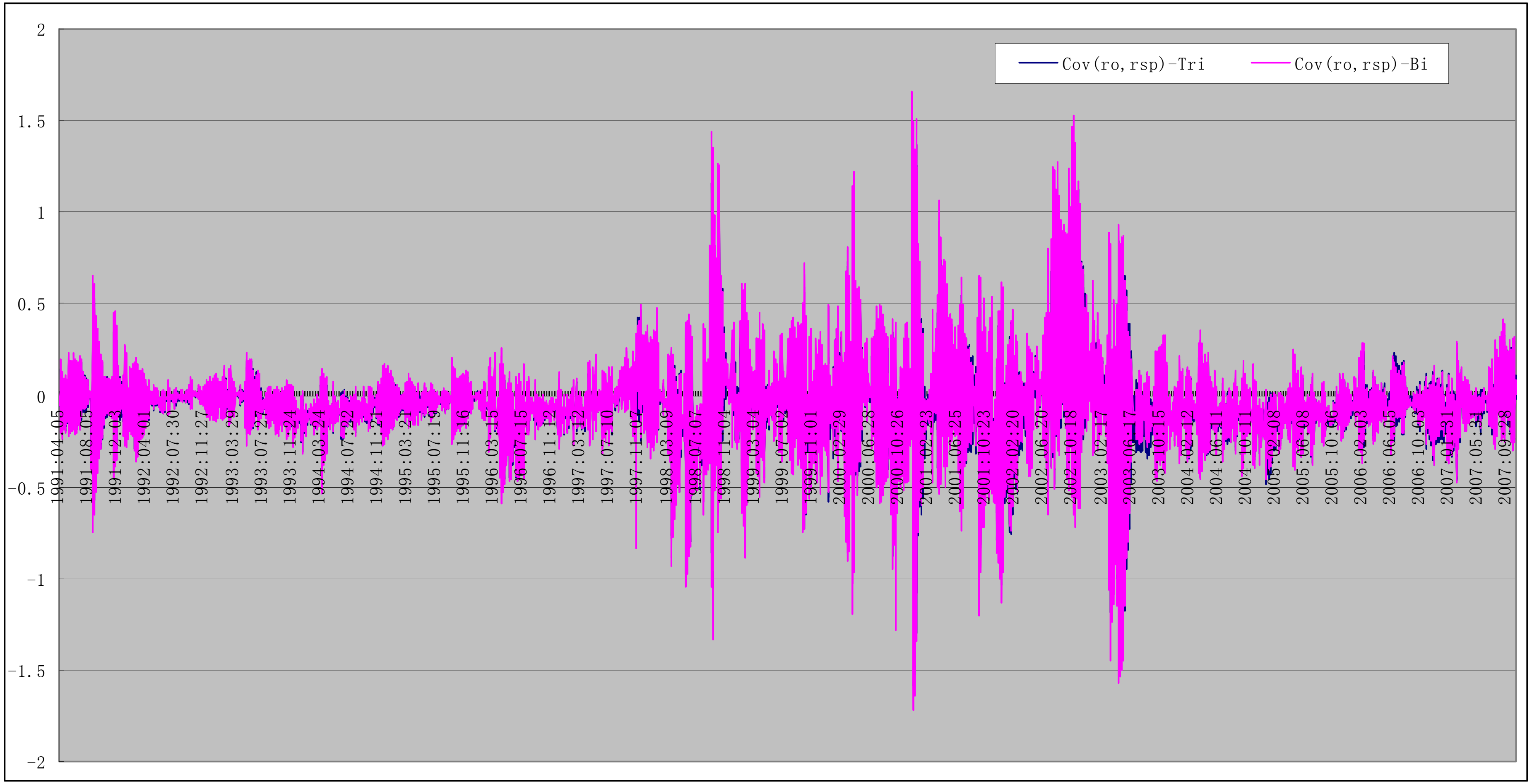


Figure 2. 9 Conditional Covariance between the gold and stock markets for the whole sample period

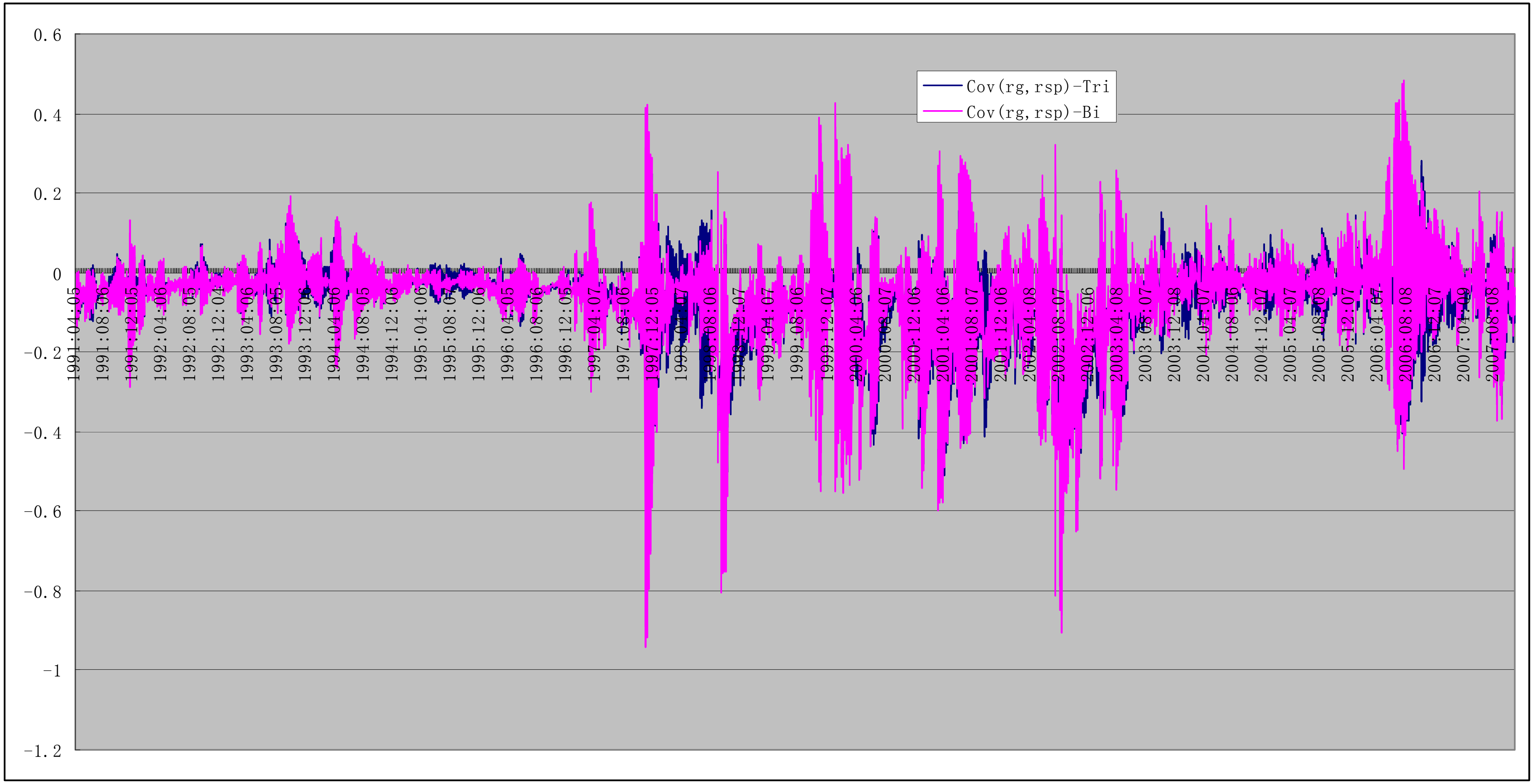


Figure 2. 10 Conditional variance of the oil returns in the pre-crisis period (1/04/91—31/03/97).

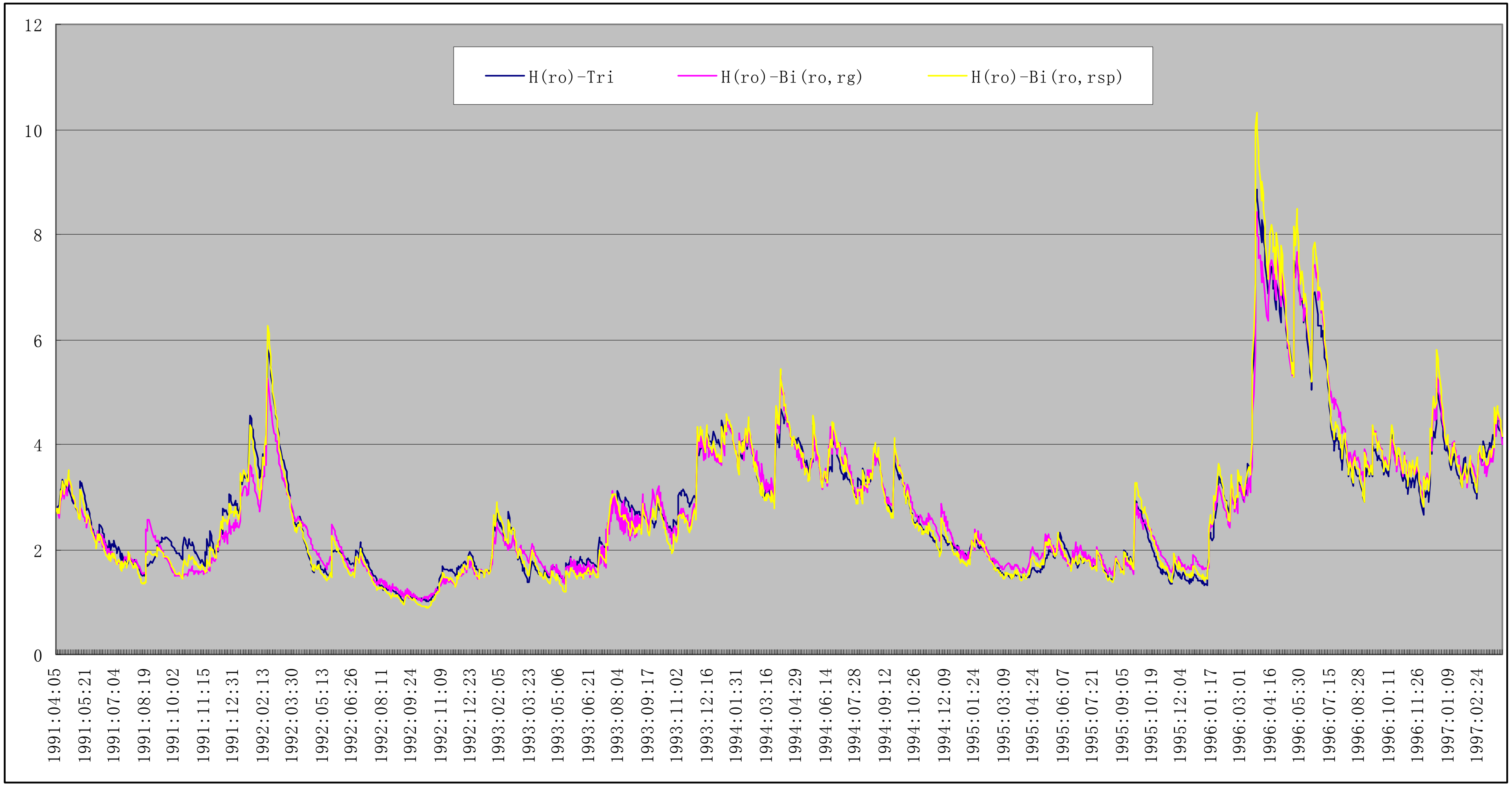


Figure 2. 11 Conditional variance of the gold returns in the pre-crisis period(1/04/91—31/03/97).

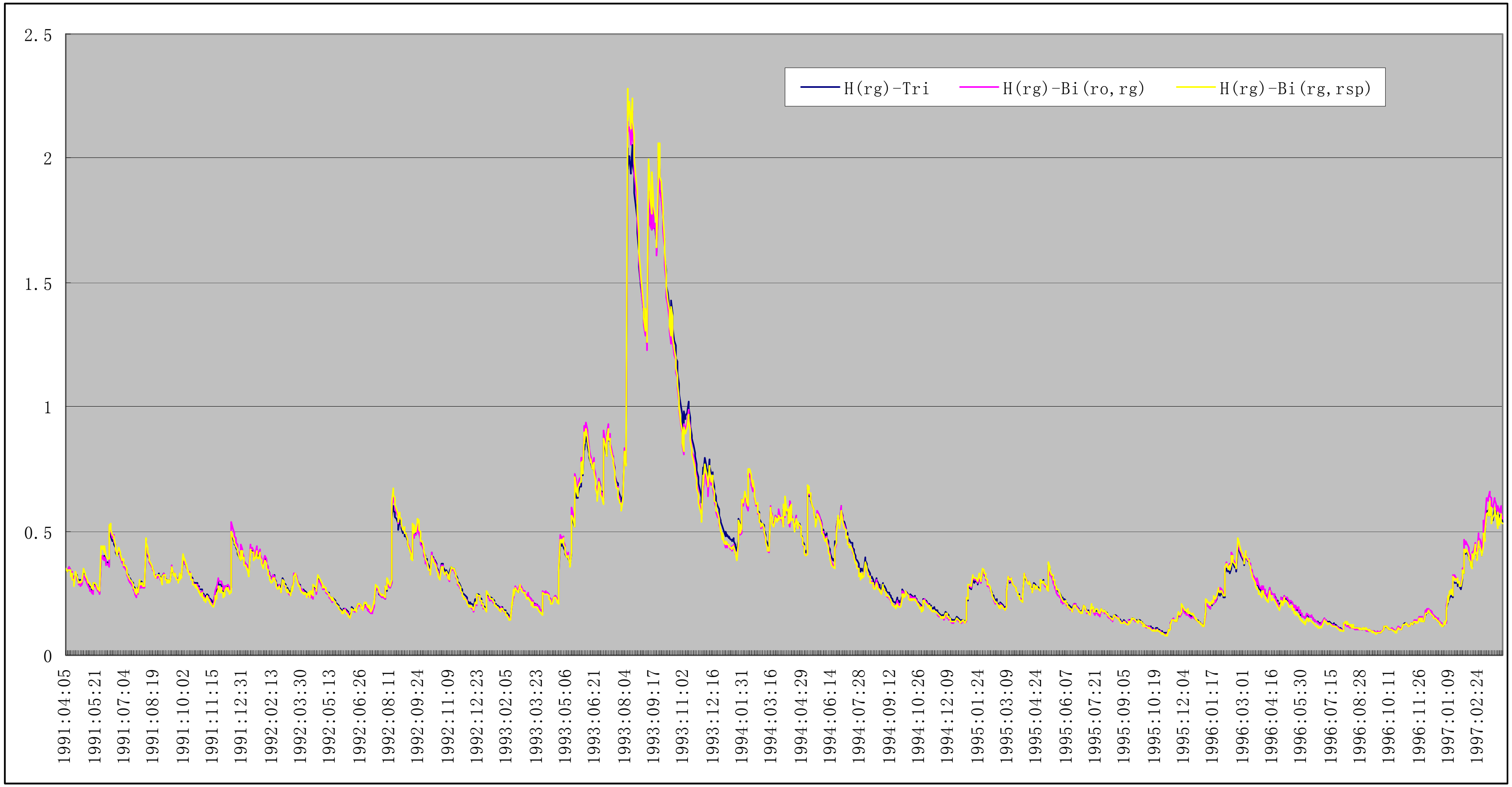


Figure 2. 12 Conditional variance of the stock returns in the pre-crisis period (1/04/91—31/03/97).

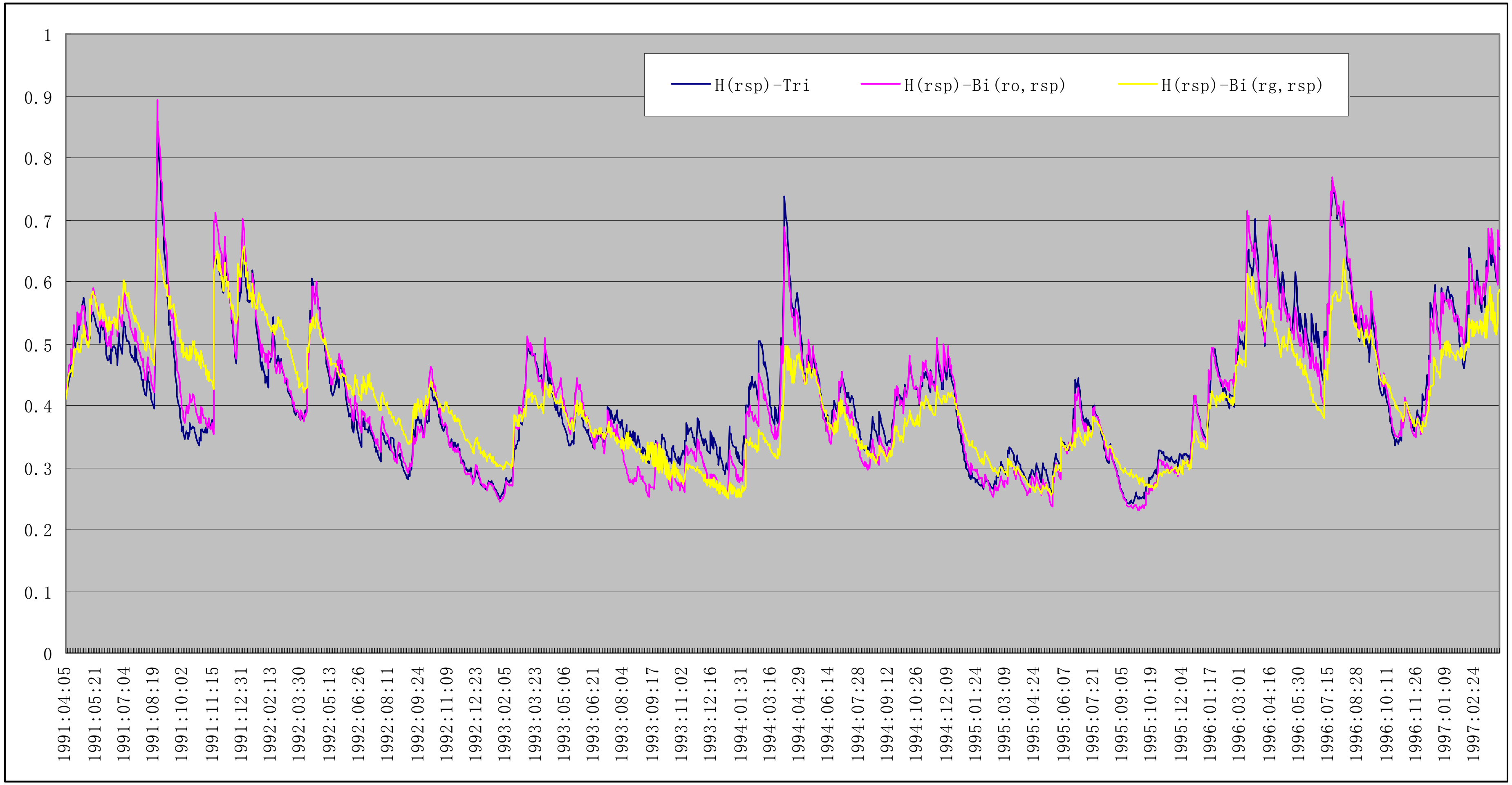


Figure 2. 13 Conditional Covariance between the oil and gold market in the pre-crisis period (1/04/91—31/03/97).

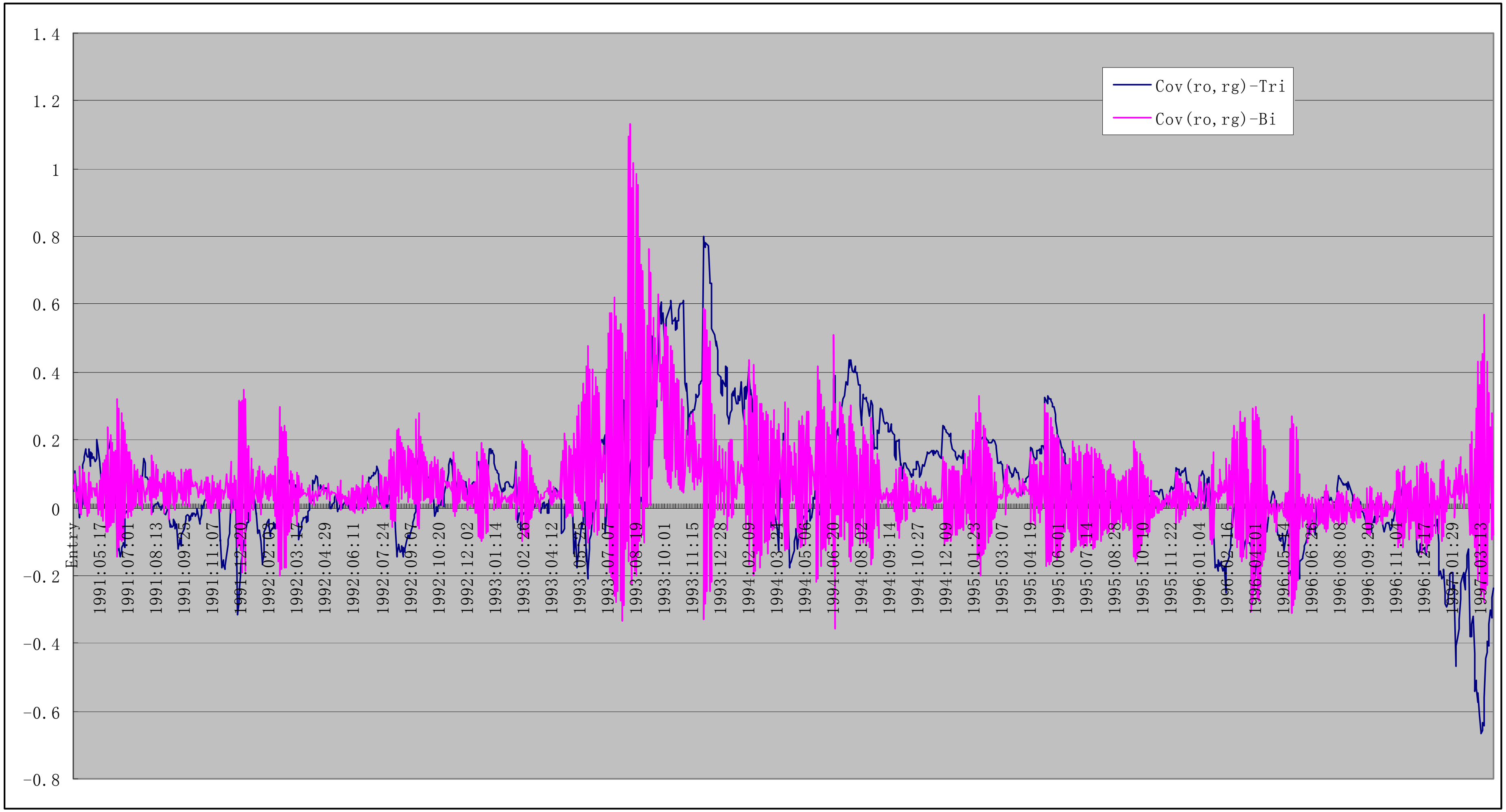


Figure 2. 14 Conditional Covariance between the oil and stock markets in the pre-crisis period (1/04/91—31/03/97).

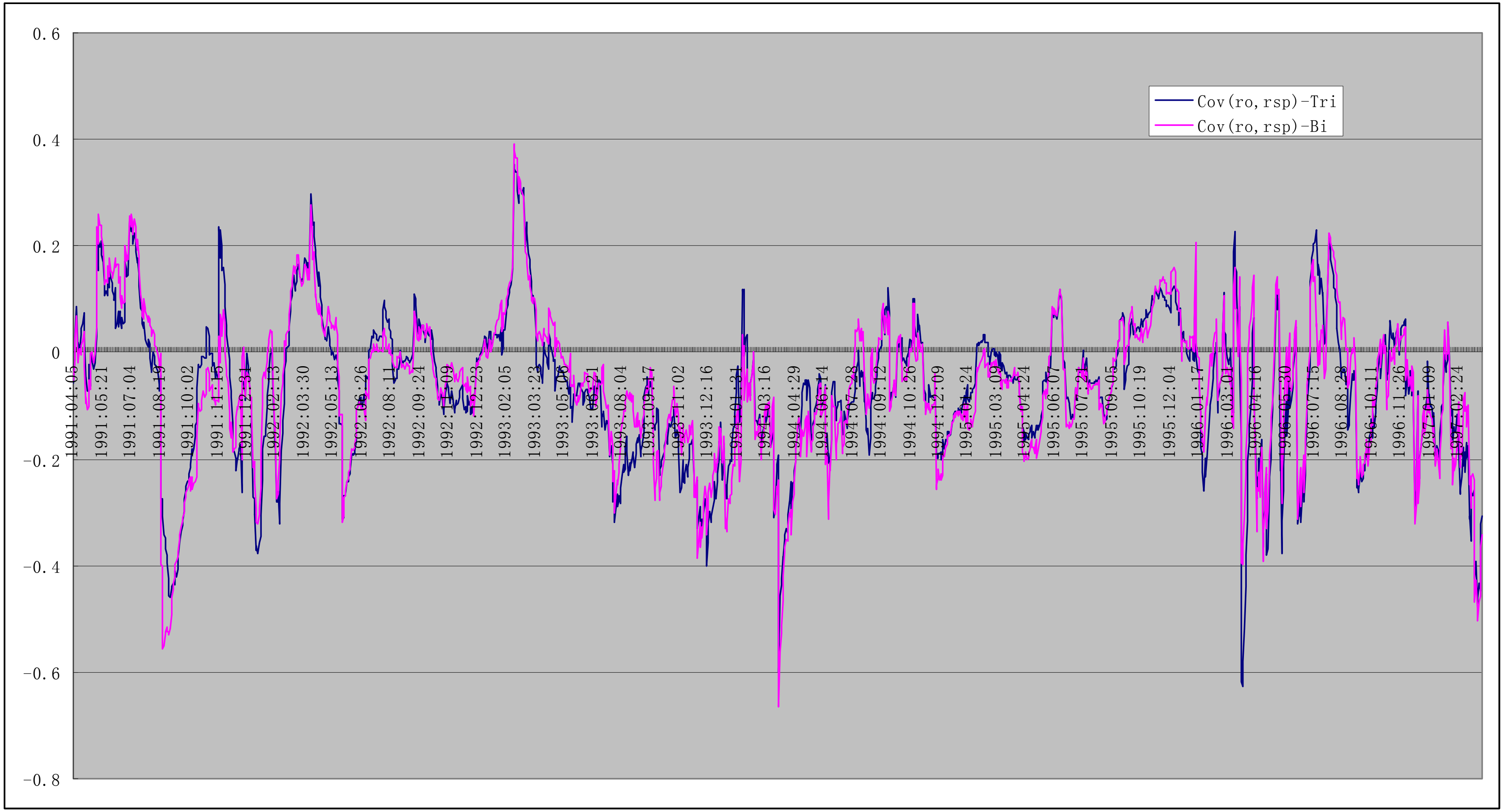


Figure 2. 15 Conditional Covariance between the gold and stock markets in the pre-crisis period (1/04/91—31/03/97).

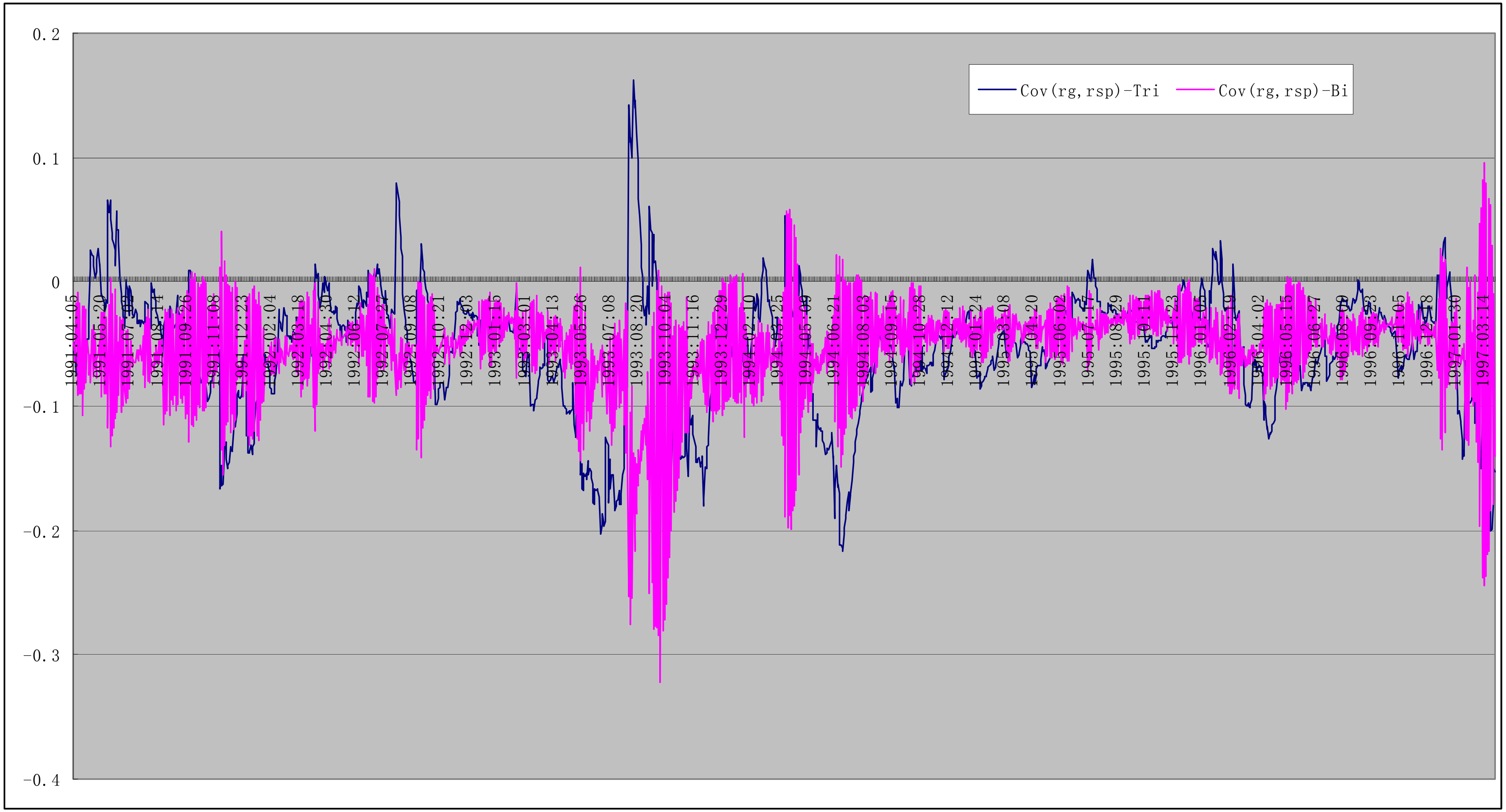


Figure 2. 16 Conditional variance of the oil returns in the crisis period (1/04/97—31/07/03).

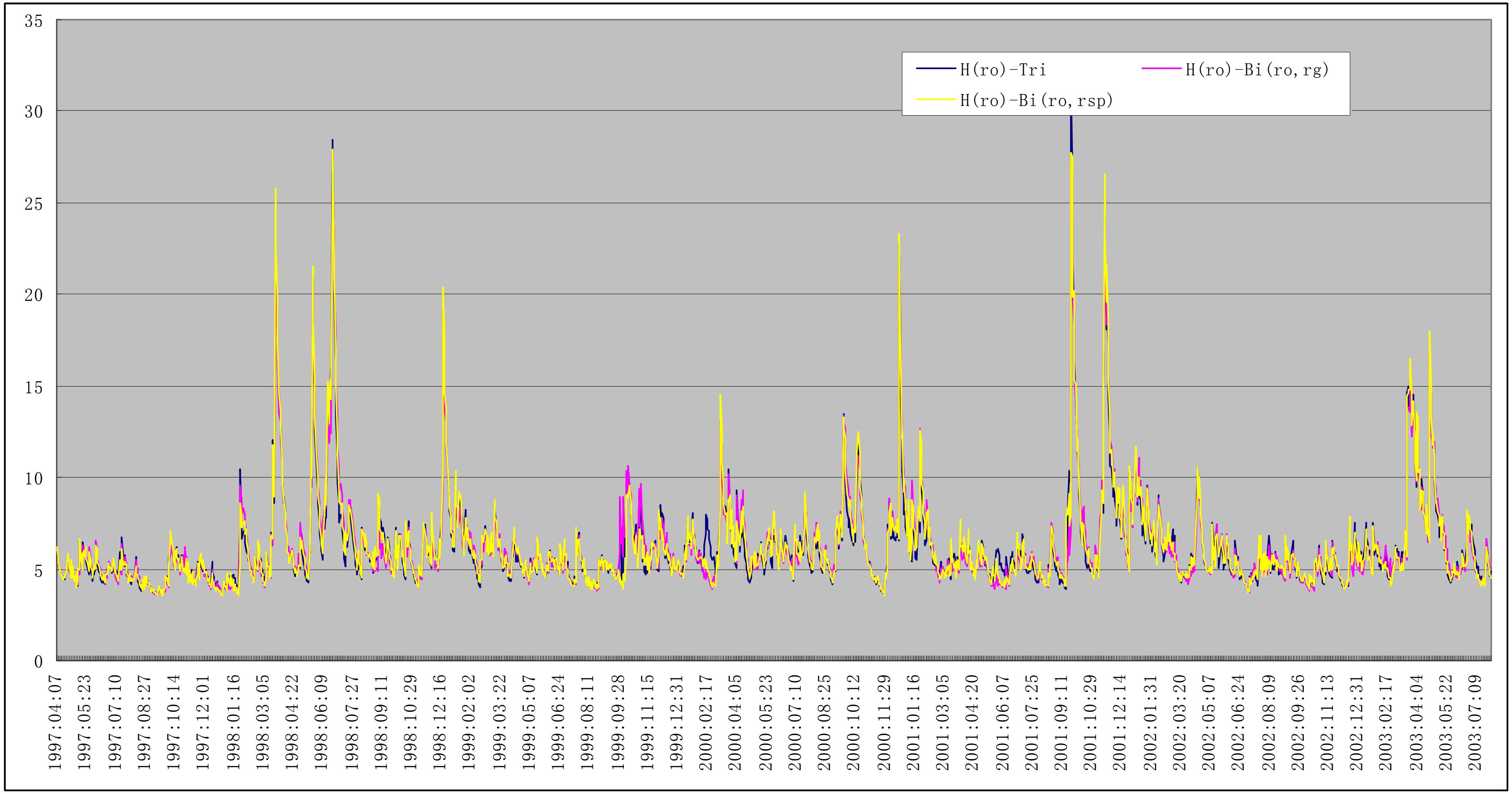


Figure 2. 17 Conditional variance of the gold returns in the crisis period (1/04/97—31/07/03).

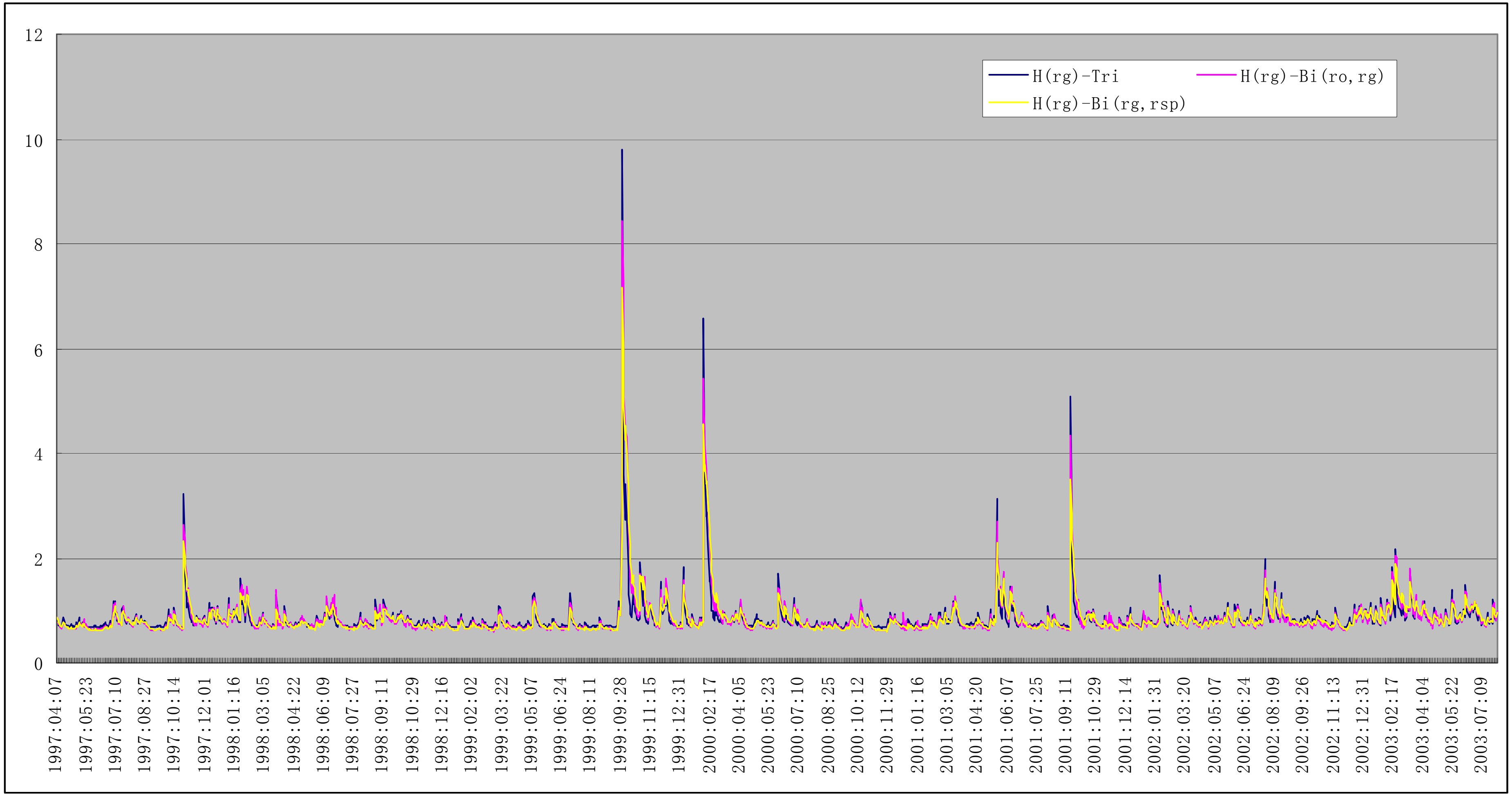


Figure 2. 18 Conditional variance of the S&P 500 returns in the crisis period (1/04/97—31/07/03).

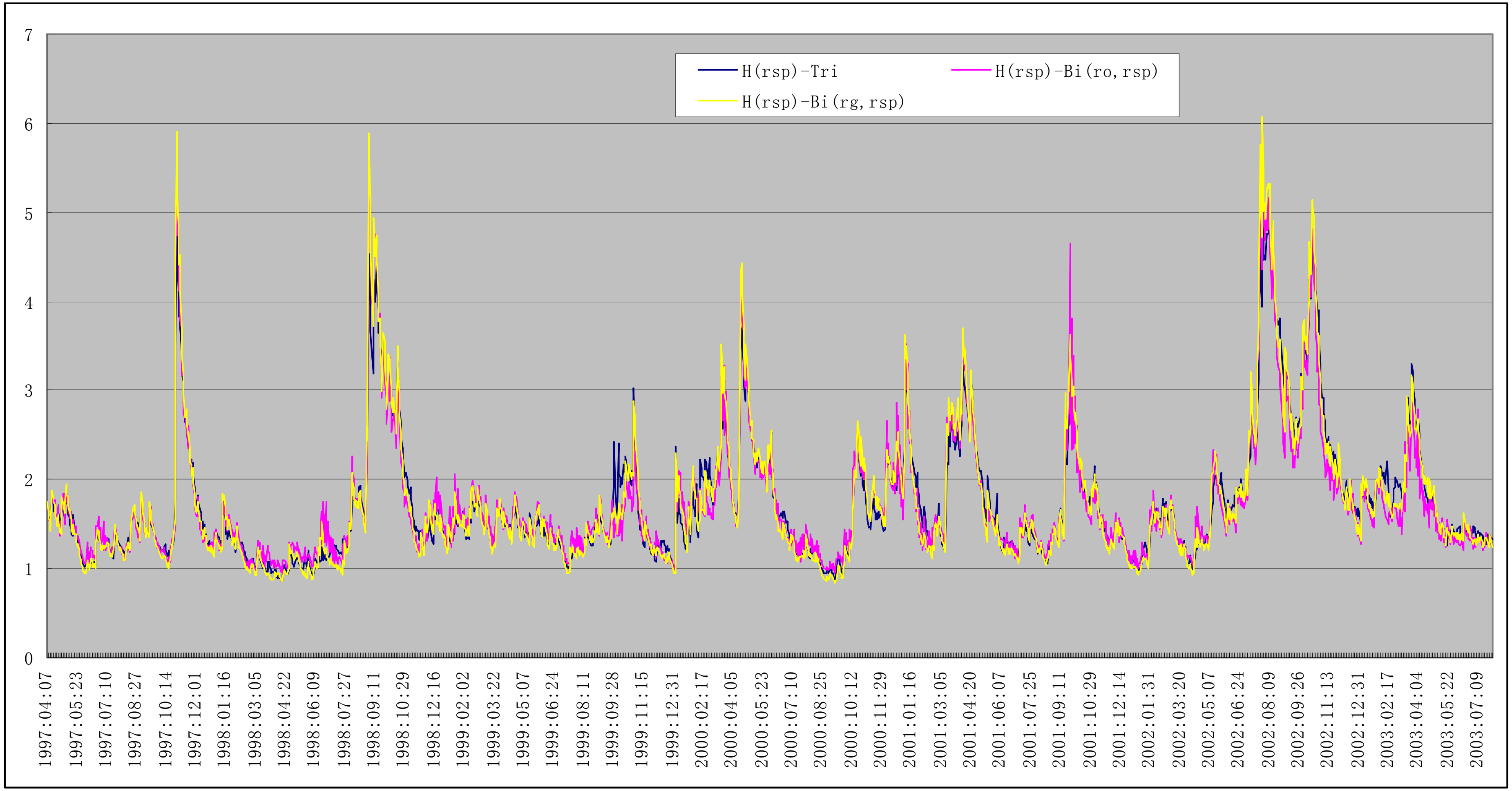


Figure 2. 19 Conditional Covariance between the oil and gold returns in the crisis period (1/04/97—31/07/03).

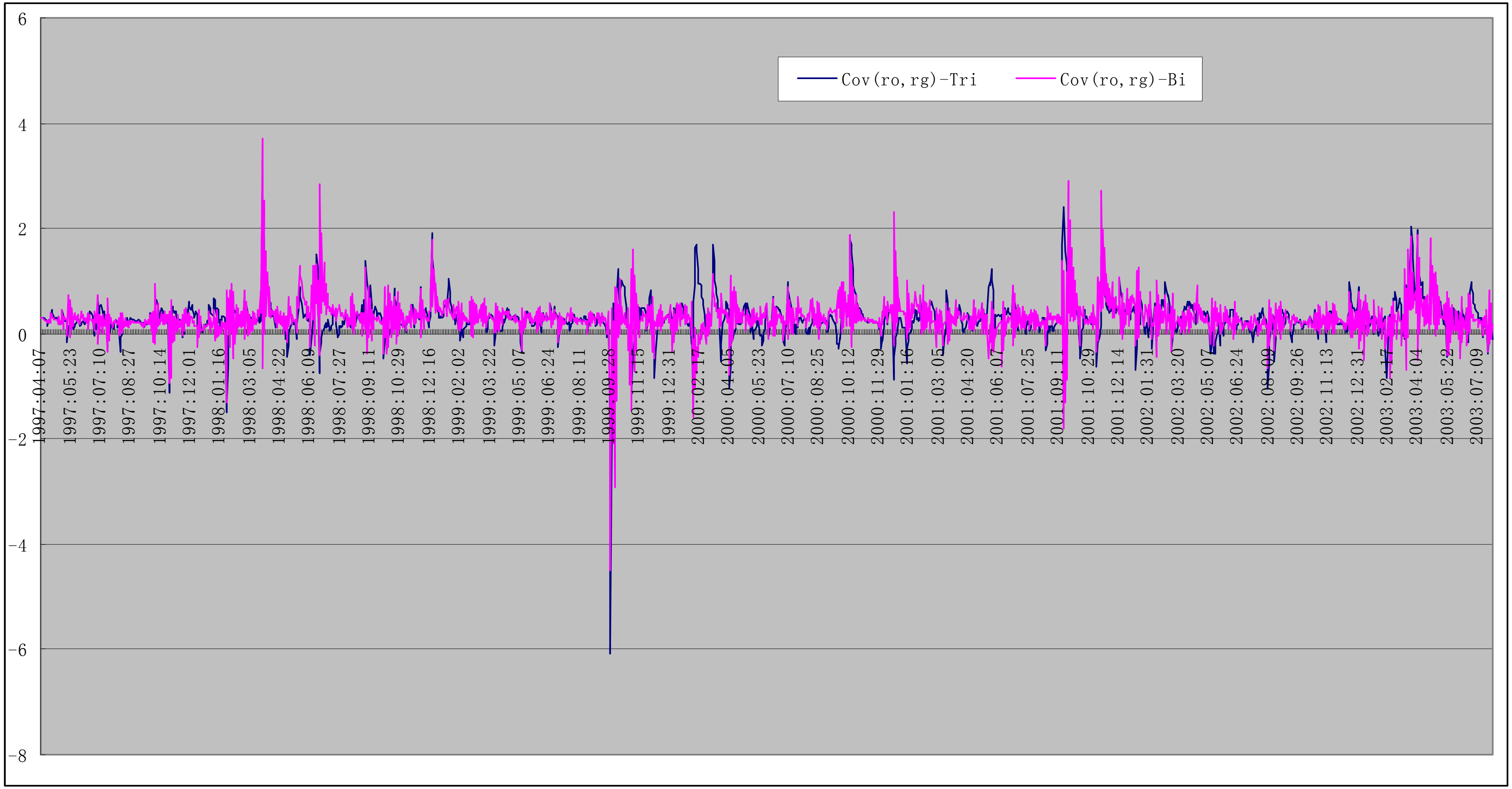


Figure 2. 20 Conditional Covariance between the oil and stock returns in the crisis period(1/04/97—31/07/03).

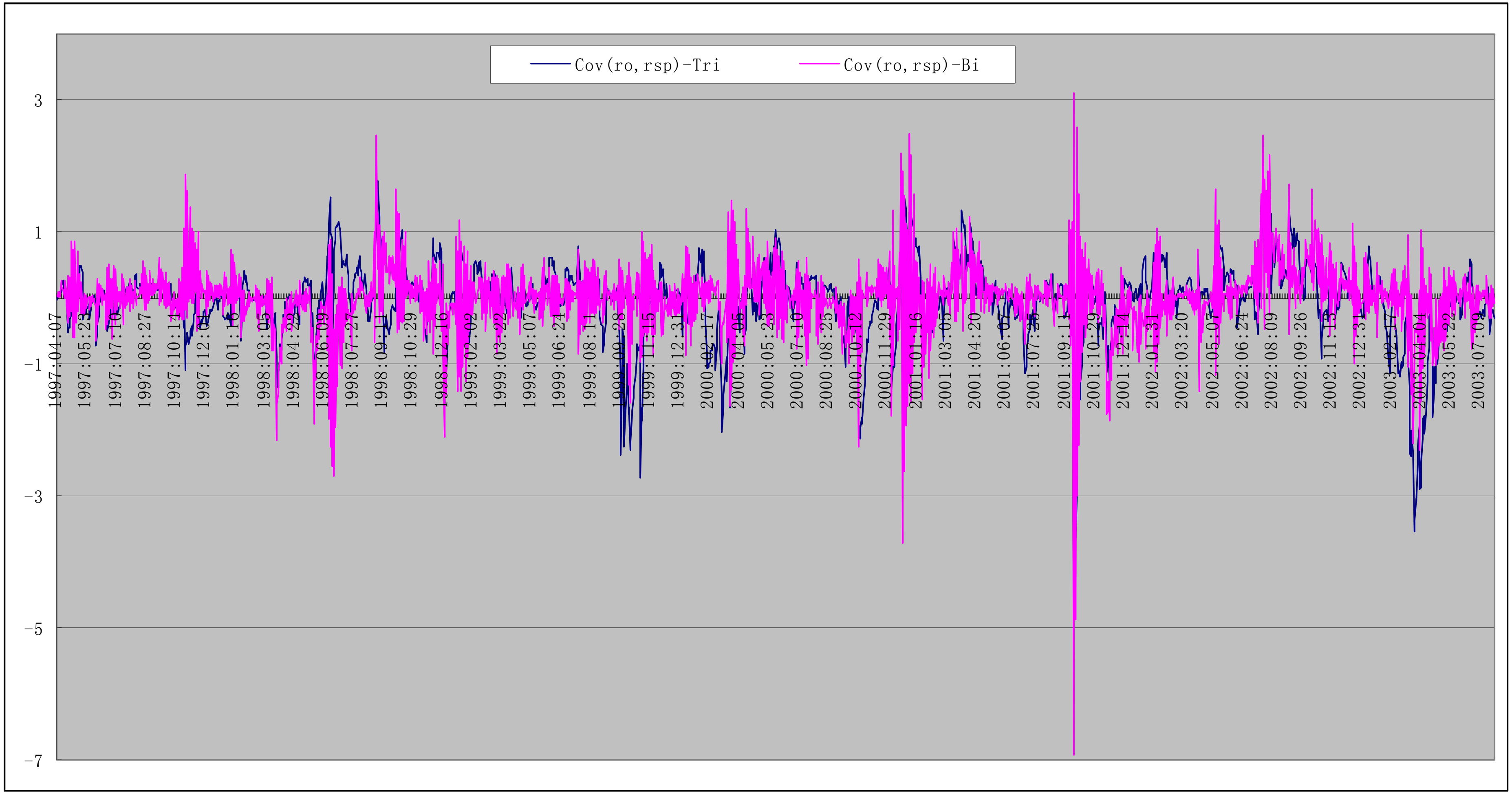


Figure 2. 21 Conditional Covariance between the gold and stock returns in the crisis period (1/04/97—31/07/03).

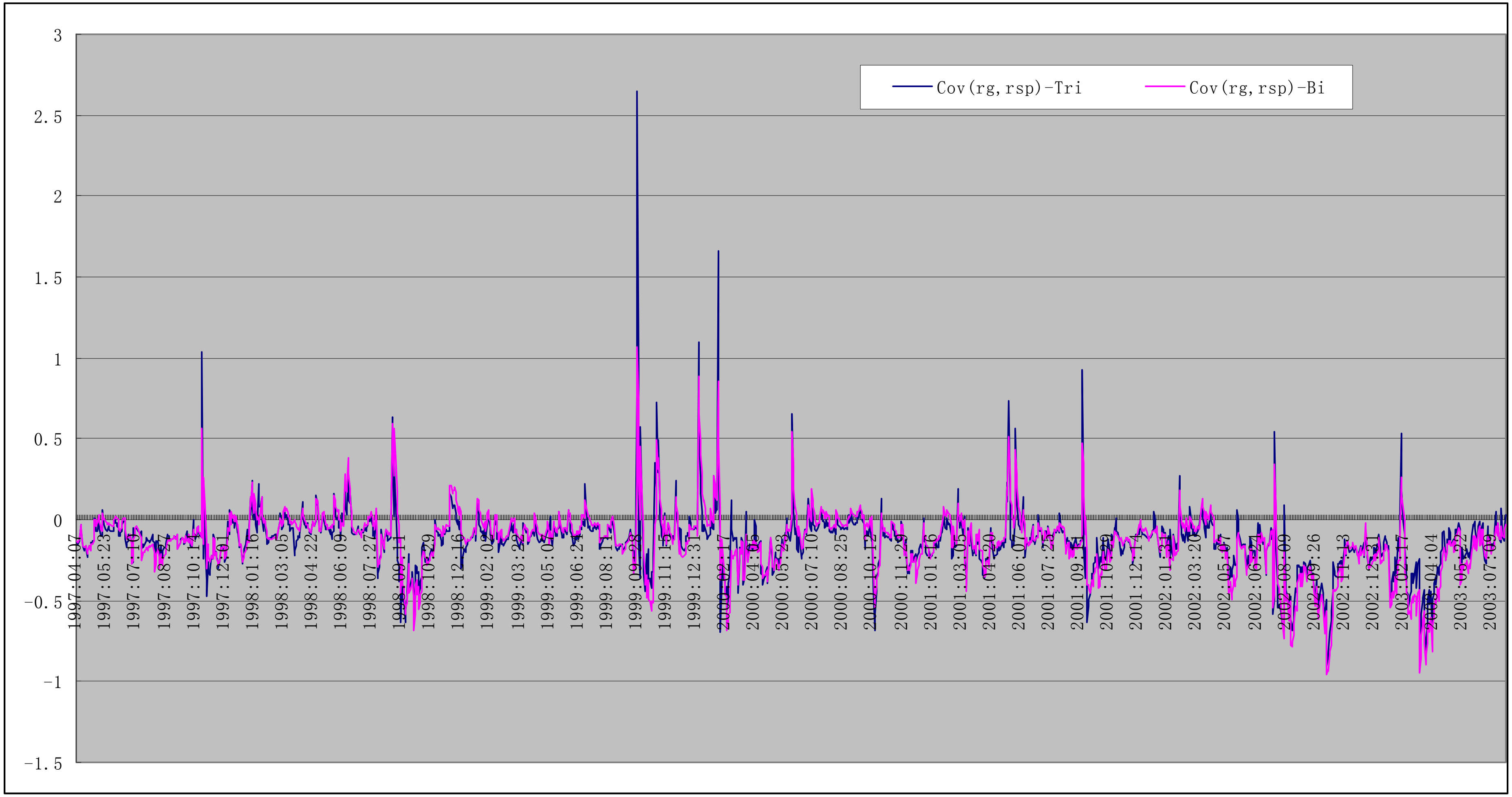


Figure 2. 22 Conditional variance of the oil returns in the post-crisis period (1/08/03—5/11/07).

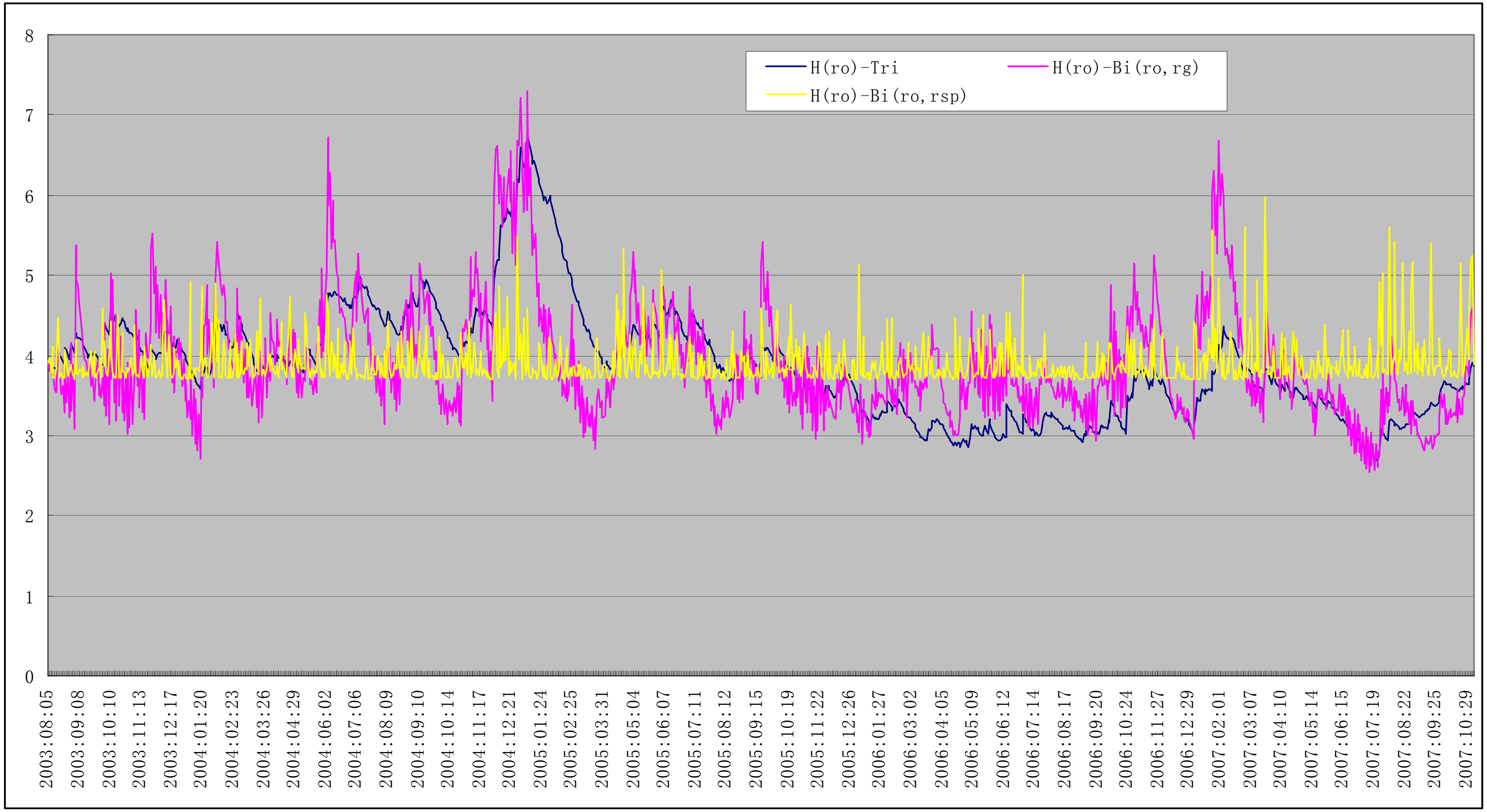


Figure 2. 23 Conditional variance of the gold returns in the post-crisis period (1/08/03—5/11/07).

Figure 2. 24 Conditional variance of the stock returns in the post-crisis period (1/08/03—5/11/07).

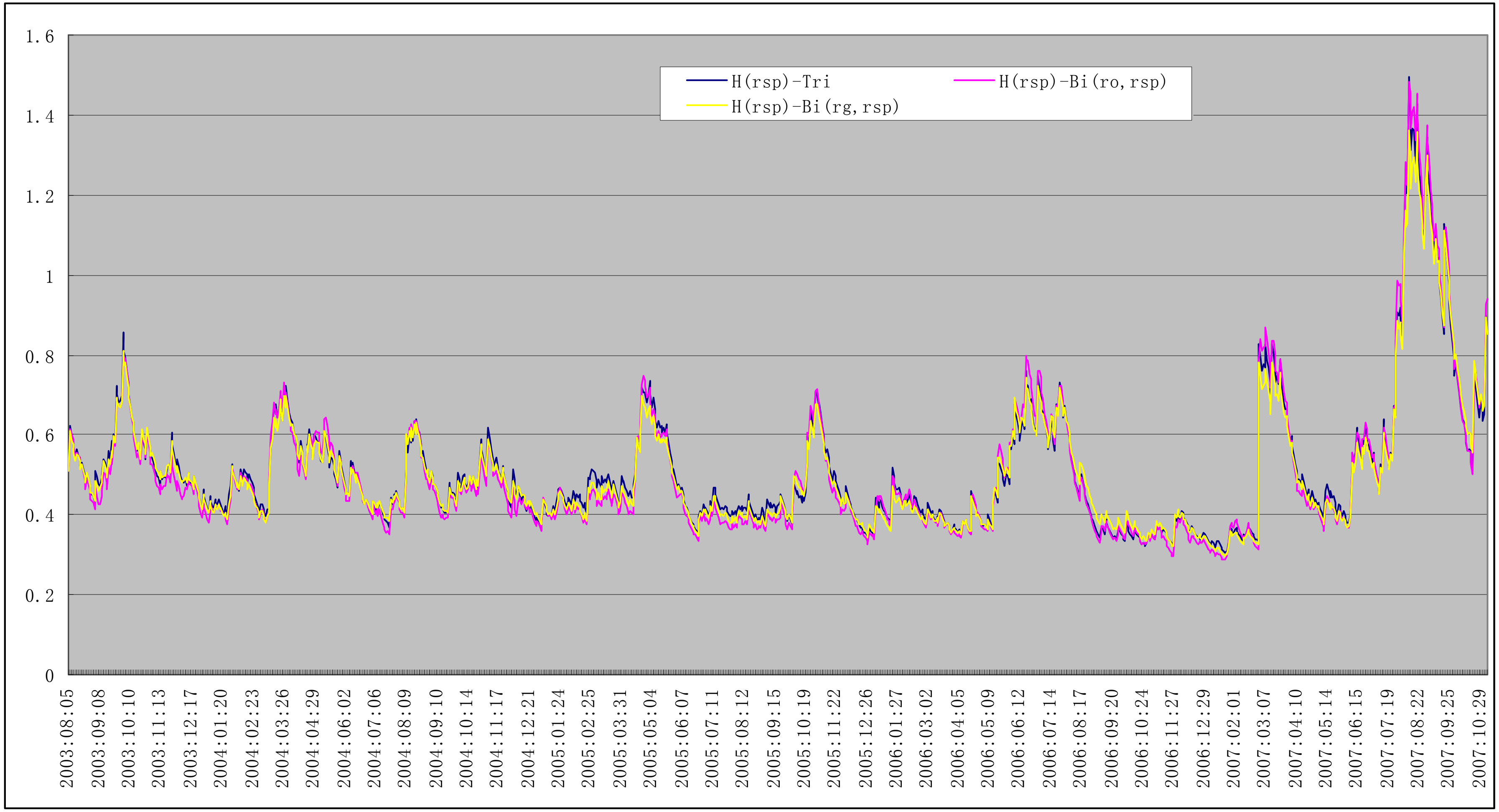


Figure 2. 25 Conditional Covariance between the oil and gold returns in the post-crisis period (1/08/03—5/11/07).

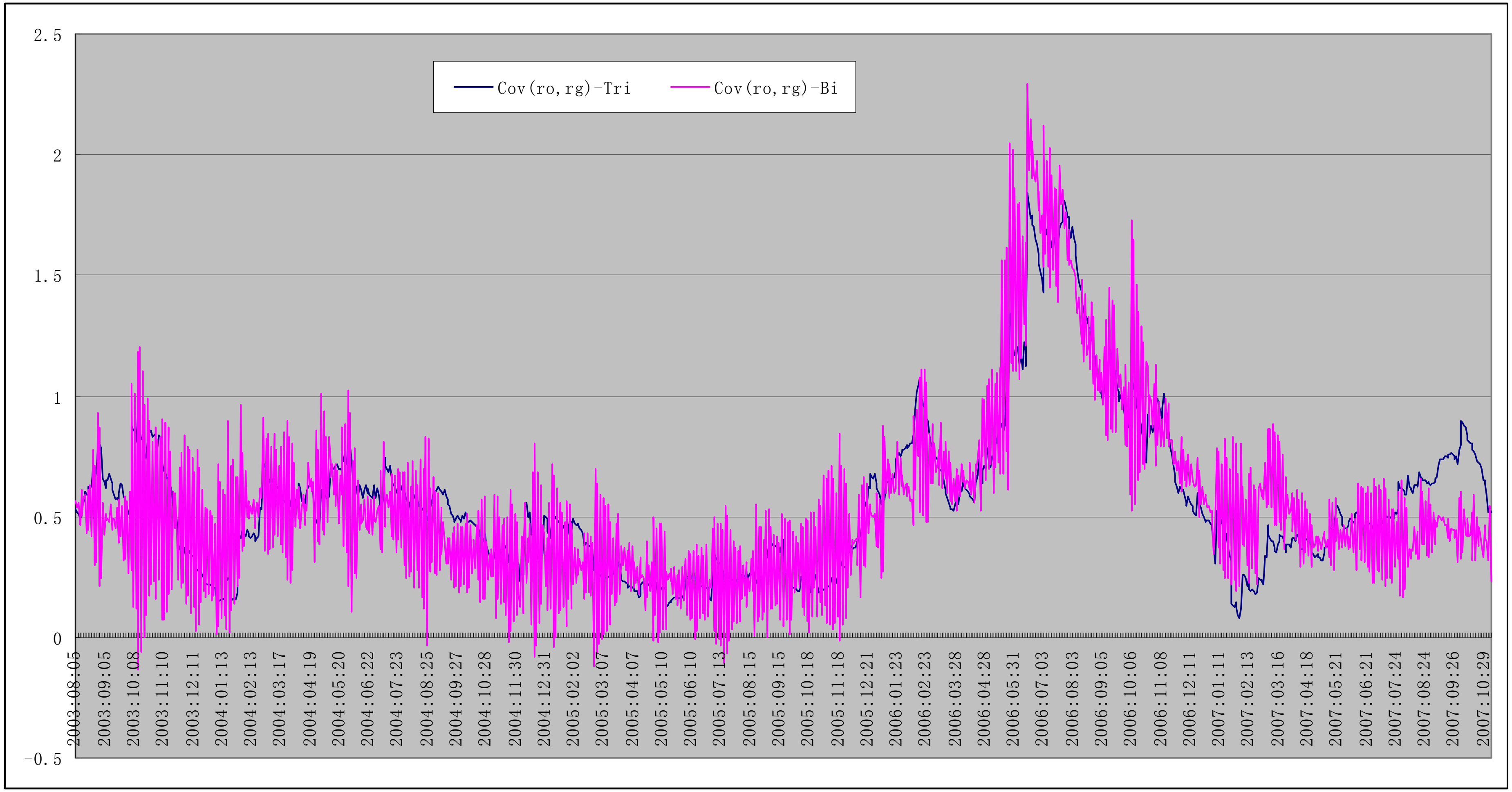


Figure 2. 26 Conditional Covariance between the oil and stock returns in the post-crisis period (1/08/03—5/11/07).

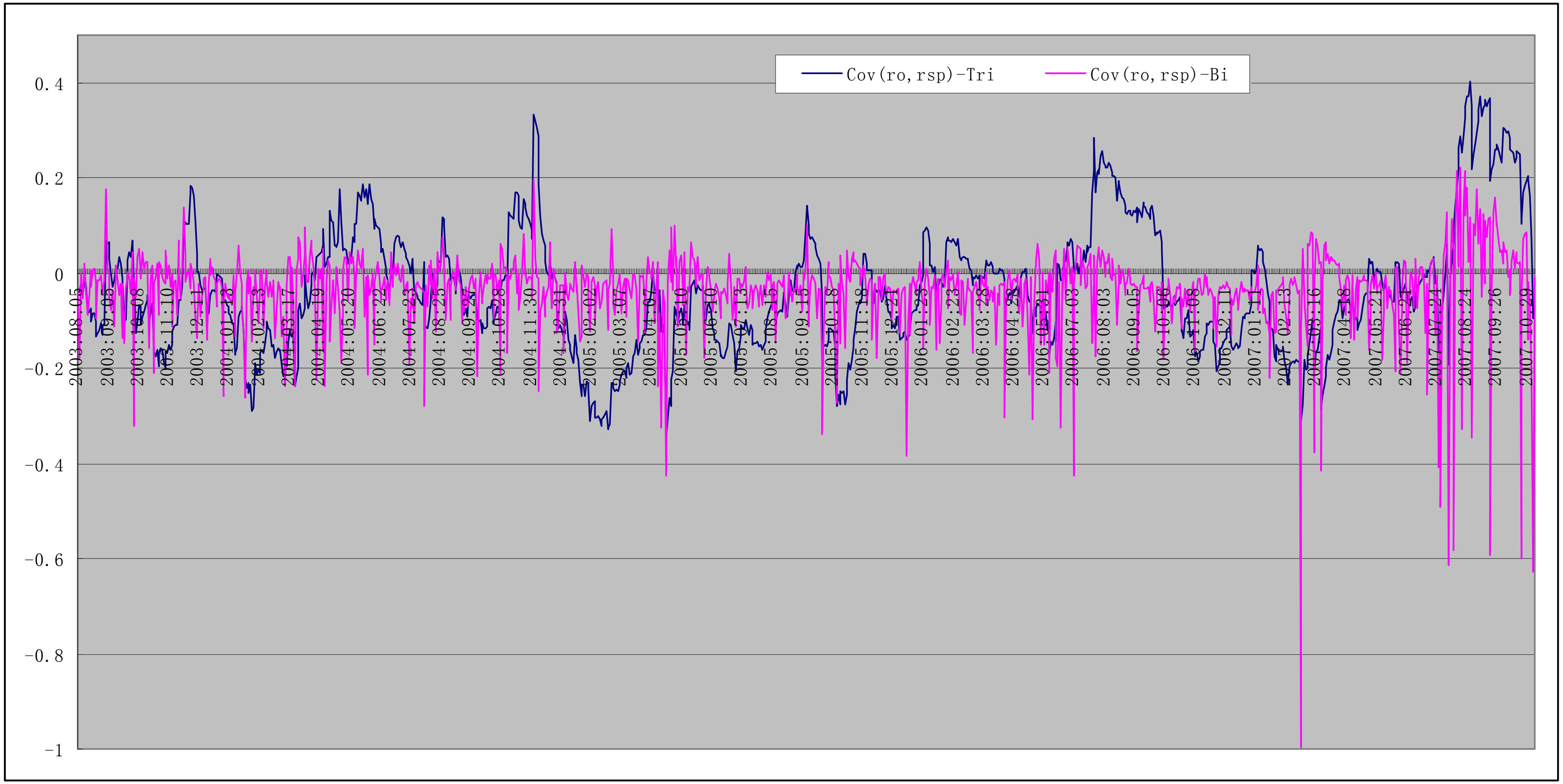
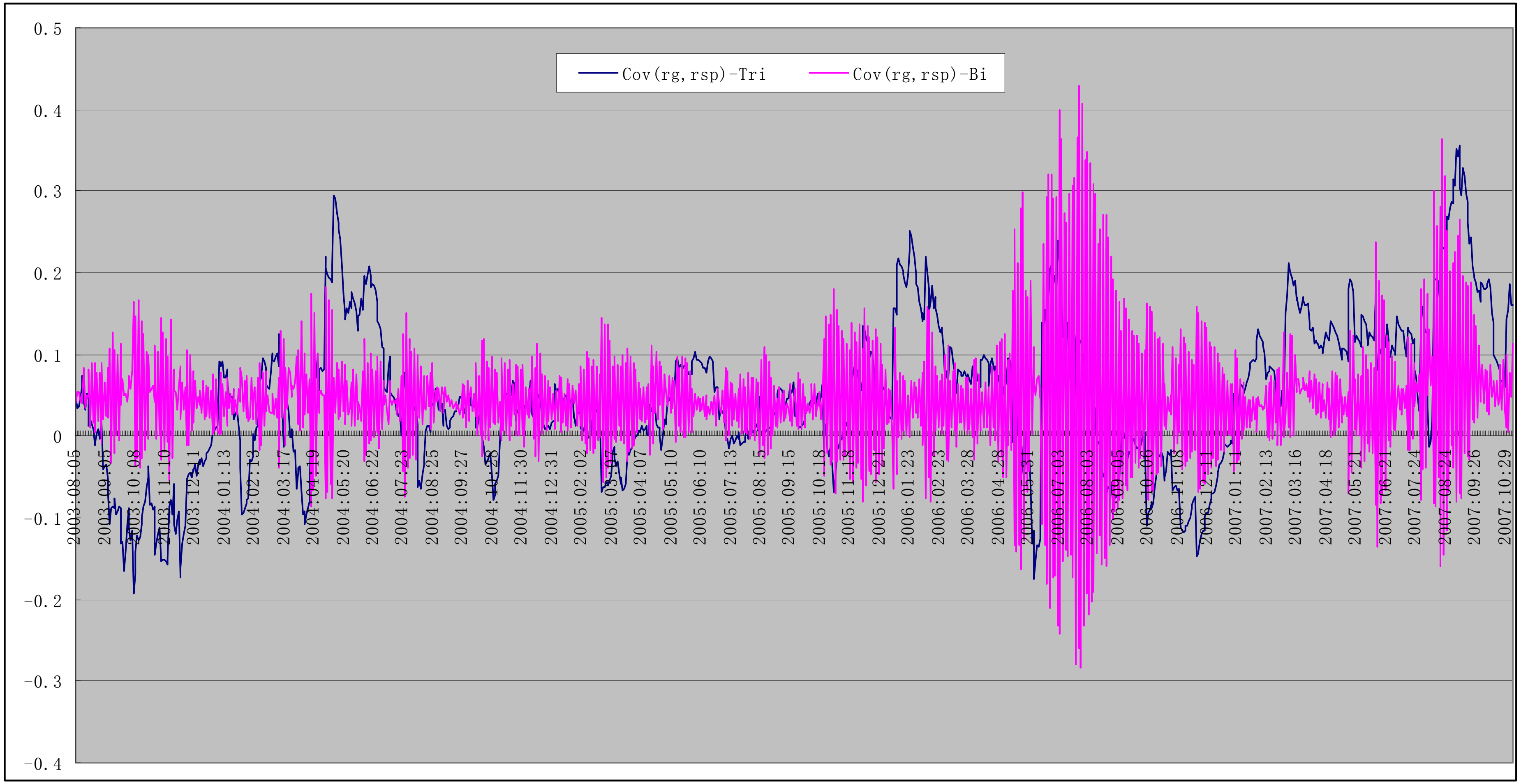


Figure 2. 27 Conditional Covariance between the gold and stock returns in the post-crisis period (1/08/03—5/11/07).



Appendix 2 A

Table 2.A 1 Estimation results from the Tri-variate GARCH model in the whole sample period

$$H_t = \begin{bmatrix} h_{oo,t} & h_{og,t} & h_{os,t} \\ h_{og,t} & h_{gg,t} & h_{gs,t} \\ h_{os,t} & h_{gs,t} & h_{ss,t} \end{bmatrix} = \begin{bmatrix} c_{11} & c_{21} & c_{31} \\ c_{12} & c_{22} & c_{32} \\ c_{13} & c_{23} & c_{33} \end{bmatrix} \begin{bmatrix} c_{11} & c_{12} & c_{13} \\ c_{21} & c_{22} & c_{23} \\ c_{31} & c_{32} & c_{33} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{21} & a_{31} \\ a_{12} & a_{22} & a_{32} \\ a_{13} & a_{23} & a_{33} \end{bmatrix} \begin{bmatrix} \varepsilon^2_{o,t-1} & \varepsilon_{o,t-1}\varepsilon_{g,t-1} & \varepsilon_{o,t-1}\varepsilon_{s,t-1} \\ \varepsilon_{o,t-1}\varepsilon_{g,t-1} & \varepsilon^2_{g,t-1} & \varepsilon_{g,t-1}\varepsilon_{s,t-1} \\ \varepsilon_{o,t-1}\varepsilon_{s,t-1} & \varepsilon_{g,t-1}\varepsilon_{s,t-1} & \varepsilon^2_{s,t-1} \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix}$$

$$+ \begin{bmatrix} b_{11} & b_{21} & b_{31} \\ b_{12} & b_{22} & b_{32} \\ b_{13} & b_{23} & b_{33} \end{bmatrix} \begin{bmatrix} h_{oo,t-1} & h_{og,t-1} & h_{os,t-1} \\ h_{og,t-1} & h_{gg,t-1} & h_{gs,t-1} \\ h_{os,t-1} & h_{gs,t-1} & h_{ss,t-1} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix}$$

Variable	Coeff	Std Error	T-Stat	Signif
c_{11}	0.1325***	0.0255	5.1866	0.0000
c_{21}	----	----	----	----
c_{31}	----	----	----	----
c_{12}	-0.0153	0.0105	-1.4569	0.1451
c_{22}	0.0308***	0.0119	2.5829	0.0098
c_{32}	----	----	----	----
c_{13}	0.0160	0.0174	0.9173	0.3590
c_{23}	-0.0375***	0.0121	-3.0977	0.0020
c_{33}	0.0001	0.0311	0.0047	0.9962
b_{11}	0.9747***	0.0077	126.81	0.0000
b_{21}	0.0171***	0.0052	3.2791	0.0010
b_{31}	-0.2533**	0.1101	-2.3011	0.0214
b_{12}	0.0068***	0.0020	3.4802	0.0005
b_{22}	0.9820***	0.0030	322.27	0.0000
b_{32}	0.1517***	0.0231	6.5527	0.0000
b_{13}	-0.0807***	0.0198	-4.0667	0.0000
b_{23}	0.0479***	0.0111	4.3073	0.0000
b_{33}	-0.9698***	0.0076	-128.45	0.0000
a_{11}	0.1530***	0.0178	8.6101	0.0000
a_{21}	-0.0488*	0.0265	-1.8416	0.0655
a_{31}	-0.0858***	0.0294	-2.9137	0.0036
a_{12}	-0.0051	0.0046	-1.0928	0.2745
a_{22}	0.1704***	0.0188	9.0624	0.0000
a_{32}	-0.0106	0.0145	-0.7323	0.4640
a_{13}	0.0180***	0.0045	3.9861	0.0001
a_{23}	0.0036	0.0066	0.5520	0.5810
a_{33}	0.1702***	0.0227	7.4807	0.0000
Ljung-Box Statistics				

$Q(10)$	Q-Stat	P-Value
Oil	22.4036	0.4565
Gold	13.6303	0.1905
S&P	28.6129	0.0014
$Q^2(10)$		
Oil	71.8881	0.0000
Gold	164.42	0.0000
S&P	72.6336	0.0000
LL Value	-19542.46	
Covariance stationary test		
Eigenvalues:	0.09937, 1.0007, 0.9982, 0.9968, -0.9482, -0.9377, -0.9457, -0.9374 0.9972	

Note: ***, ** and * represents significant at 1%, 5% and 10% significant level.
Log-likelihood test results is denoted as LL Value

Table 2.A 2 Estimation results of the Bi-variate GARCH models for the whole sample period

$$H_t = \begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{12,t} & h_{22,t} \end{bmatrix} = \begin{bmatrix} c_{11} & c_{21} \\ c_{12} & c_{22} \end{bmatrix} \begin{bmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{bmatrix} + \begin{bmatrix} \alpha_{11} & \alpha_{21} \\ \alpha_{12} & \alpha_{22} \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} & \varepsilon_{1,t-1}^2 \end{bmatrix} \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix} + \begin{bmatrix} \beta_{11} & \beta_{21} \\ \beta_{12} & \beta_{22} \end{bmatrix} \begin{bmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{12,t-1} & h_{22,t-1} \end{bmatrix} \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix}$$

	oil and gold			oil and S&P			Gold and S&P		
Variable	Coeff	Std Error	T-Stat	Coeff	Std Error	T-Stat	Coeff	Std Error	T-Stat
c_{11}	-0.0941***	0.0228	-4.1184	0.1355***	0.0267	5.0688	0.0345***	0.0102	3.3939
c_{21}	0.0884***	0.0231	3.8306	----	----	----	----	----	----
c_{12}	0.0254***	0.0070	3.6443	0.0167	0.0394	0.4229	-0.0712***	0.0148	-4.8067
c_{22}	-0.0270***	0.0069	-3.8957	-0.0414	0.0297	-1.3932	-0.0064	0.0254	-0.2503
b_{11}	-0.9706***	0.0105	-92.0648	-0.9732***	0.0084	-115.77	0.9831***	0.0054	181.4681
b_{21}	0.8619***	0.1261	6.8347	0.2555**	0.1258	2.0307	0.1455***	0.0458	3.1746
b_{12}	0.0270	0.0185	1.4619	0.0741***	0.0230	3.2171	0.0305	0.0554	0.5503
b_{22}	0.9724***	0.0092	105.44	0.9716***	0.0079	123.2103	-0.9732***	0.0074	-131.17
a_{11}	0.1678***	0.0207	8.0908	0.1673***	0.0197	8.5075	0.1722***	0.0165	10.4366
a_{21}	-0.0830***	0.0244	-3.4049	-0.0970***	0.0239	-4.0573	-0.0202	0.0166	-1.2181
a_{12}	-0.0011	0.0035	-0.3236	0.0177***	0.0054	3.2652	0.0042	0.0130	0.3203
a_{22}	0.1794***	0.0201	8.9080	0.1853***	0.0227	8.1585	0.2082***	0.0205	10.1429
Ljung-Box Statistics									
$Q(10)$		Q-Stat	P-Value		Q-Stat	P-Value		Q-Stat	P-Value
	Oil	10.3549	0.4099	Oil	8.9532	0.5366	Gold	14.1439	0.1665
	Gold	12.6294	0.2451	S&P	29.4811	0.0010	S&P	24.3089	0.0068
$Q^2(10)$									
	Oil	51.0827	0.0000	Oil	59.6375	0.0000	Gold	170.4528	0.0000
	Gold	133.96	0.0000	S&P	61.9162	0.0000	S&P	24.5504	0.0063
LL	-14108			LL	-14520		LL	-10496	

Covariance stationary test

Eigenvalue of Bi-GARCH for oil and gold market : 0.9940, 1.004, -0.9369; -0.9371

For oil and S&P : 0.9253, 0.9971, -0.9001, -0.8968

For gold and S&P : 1.0007, 0.9260, -0.8900, -0.8899

Note: ***, ** and * represents significant at 1%, 5% and 10% significant level.

Table 2.A 3 Descriptive statistics of return series in pre-crisis period (1/04/91—31/03/97).

	RO	RG	RSP
Mean	0.0036	-0.0018	0.0455
Median	0.0000	0.0000	0.0155
Maximum	8.5395	2.6222	2.8962
Minimum	-9.1199	-5.7085	-3.7271
Std. Dev.	1.6629	0.5923	0.6452
Skewness	-0.1214	-0.6658	-0.2937
Kurtosis	5.6985	11.9599	5.2945
Jarque-Bera	478.68	5350.50	365.80
Probability	0.0000	0.0000	0.0000
$Q(10)$	20.05**	8.73	16.47
$Q^2(10)$	102.85**	119.43**	29.38**
ARCH_LM	11.74**	13.22**	4.39**
ADF	-38.81**	-40.30**	-37.86**
KPSS	0.0476	0.0995	0.2014

Note: ** represents significant at 1% significance level.

Table 2.A 4 Descriptive statistics of return series in crisis period (1/04/97—31/07/03).

	RO	RG	RSP
Mean	0.0244	0.0005	0.0162
Median	0.0000	0.0000	0.0000
Maximum	14.2309	8.8872	5.5732
Minimum	-16.5445	-5.1049	-7.1127
Std. Dev.	2.4792	0.9299	1.3201
Skewness	-0.3464	1.0892	-0.0490
Kurtosis	7.1659	14.5912	5.1359
Jarque-Bera	1228.37	9580.65	314.88
Probability	0.0000	0.0000	0.0000
$Q(10)$	15.3600	11.1900	10.2700
$Q^2(10)$	48.97**	97.94**	193.52**
ARCH_LM	7.78**	12.40**	17.25**
ADF	-30.40**	-40.59**	-41.57**
KPSS	0.0796	0.2715	0.4805

Note: ** represents significant at 1% significance level.

Table 2.A 5 Descriptive statistics of return series in post crisis period (1/08/03—5/11/07).

	RO	RG	RSP
Mean	0.1011	0.0745	0.0375
Median	0.0735	0.0460	0.0624
Maximum	7.3689	4.5008	2.8790
Minimum	-7.6977	-7.5740	-3.5343
Std. Dev.	1.9790	1.0808	0.7160
Skewness	-0.0398	-0.7822	-0.3101
Kurtosis	3.5915	6.8626	4.6991
Jarque-Bera	16.50	804.68	151.59
Probability	0.0003	0.0000	0.0000
$Q(10)$	10.71	13.49	17.30
$Q^2(10)$	33.10**	47.51**	142.14**
ARCH_LM	3.58**	5.28**	7.42**
ADF	-35.33**	-34.70**	0.04**
KPSS	0.0505	0.0801	-36.2180

Note: ** represents significant at 1% significance level.

Table 2.A 6 Cointegration test for logarithm price series in pre-crisis period (1/04/91—31/03/97).

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None	0.008597	17.79686	29.79707	0.5811
At most 1	0.002741	4.292770	15.49471	0.8785
At most 2	4.21E-07	0.000658	3.841466	0.9809

Trace test indicates no cointegration at the 0.05 level

* denotes rejection of the hypothesis at the 0.05 level

**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None	0.008597	13.50409	21.13162	0.4070
At most 1	0.002741	4.292112	14.26460	0.8273
At most 2	4.21E-07	0.000658	3.841466	0.9809

Max-eigenvalue test indicates no cointegration at the 0.05 level

* denotes rejection of the hypothesis at the 0.05 level

**MacKinnon-Haug-Michelis (1999) p-values

Table 2.A 7 Cointegration test for logarithm price series in crisis period (1/04/97—31/07/03).

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None	0.011026	29.08214	29.79707	0.0603
At most 1	0.004911	10.75451	15.49471	0.2270
At most 2	0.001582	2.617177	3.841466	0.1057

Trace test indicates no cointegration at the 0.05 level

* denotes rejection of the hypothesis at the 0.05 level

**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None	0.011026	18.32763	21.13162	0.1181
At most 1	0.004911	8.137328	14.26460	0.3649
At most 2	0.001582	2.617177	3.841466	0.1057

Max-eigenvalue test indicates no cointegration at the 0.05 level

* denotes rejection of the hypothesis at the 0.05 level

**MacKinnon-Haug-Michelis (1999) p-values

Table 2.A 8 Cointegration test for logarithm price series in post-crisis period (1/08/03—5/11/07).

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None	0.010491	18.49654	29.79707	0.5296
At most 1	0.005910	6.768937	15.49471	0.6047
At most 2	0.000159	0.177183	3.841466	0.6738

Trace test indicates no cointegration at the 0.05 level

* denotes rejection of the hypothesis at the 0.05 level

**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None	0.010491	11.72760	21.13162	0.5747
At most 1	0.005910	6.591755	14.26460	0.5385
At most 2	0.000159	0.177183	3.841466	0.6738

Max-eigenvalue test indicates no cointegration at the 0.05 level

* denotes rejection of the hypothesis at the 0.05 level

**MacKinnon-Haug-Michelis (1999) p-values

Table 2.A 9 Estimation results from the Tri-variate GARCH model in the pre-crisis period (1/04/91—31/03/97).

$$H_t = \begin{bmatrix} h_{oo,t} & h_{og,t} & h_{os,t} \\ h_{og,t} & h_{gg,t} & h_{gs,t} \\ h_{os,t} & h_{gs,t} & h_{ss,t} \end{bmatrix} = \begin{bmatrix} c_{11} & c_{21} & c_{31} \\ c_{12} & c_{22} & c_{32} \\ c_{13} & c_{23} & c_{33} \end{bmatrix} \begin{bmatrix} c_{11} & c_{12} & c_{13} \\ c_{21} & c_{22} & c_{23} \\ c_{31} & c_{32} & c_{33} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{21} & a_{31} \\ a_{12} & a_{22} & a_{32} \\ a_{13} & a_{23} & a_{33} \end{bmatrix} \begin{bmatrix} \varepsilon_{o,t-1}^2 & \varepsilon_{o,t-1}\varepsilon_{g,t-1} & \varepsilon_{o,t-1}\varepsilon_{s,t-1} \\ \varepsilon_{o,t-1}\varepsilon_{g,t-1} & \varepsilon_{g,t-1}^2 & \varepsilon_{g,t-1}\varepsilon_{s,t-1} \\ \varepsilon_{o,t-1}\varepsilon_{s,t-1} & \varepsilon_{g,t-1}\varepsilon_{s,t-1} & \varepsilon_{s,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix}$$
$$+ \begin{bmatrix} b_{11} & b_{21} & b_{31} \\ b_{12} & b_{22} & b_{32} \\ b_{13} & b_{23} & b_{33} \end{bmatrix} \begin{bmatrix} h_{oo,t-1} & h_{og,t-1} & h_{os,t-1} \\ h_{og,t-1} & h_{gg,t-1} & h_{gs,t-1} \\ h_{os,t-1} & h_{gs,t-1} & h_{ss,t-1} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix}$$

Variable	Coeff	Std Error	T-Stat	Signif
c_{11}	0.1126***	0.0390	2.8867	0.0039
c_{21}	----	----	----	----
c_{31}	----	----	----	----
c_{12}	-0.0215	0.0217	-0.9901	0.3221
c_{22}	0.0377*	0.0202	1.8682	0.0617
c_{32}	----	----	----	----
c_{13}	0.0767***	0.0201	3.8178	0.0001
c_{23}	0.0344	0.0754	0.4554	0.6488
c_{33}	0.0001	0.0737	0.0008	0.9994
b_{11}	0.9790***	0.0039	253.9343	0.0000
b_{21}	0.0185	0.0113	1.6421	0.1006
b_{31}	-0.0746**	0.0352	-2.1162	0.0343
b_{12}	-0.0003	0.0014	-0.2508	0.8020
b_{22}	0.9784***	0.0035	281.2925	0.0000
b_{32}	-0.0008	0.0055	-0.1506	0.8803
b_{13}	0.0098	0.0061	1.6101	0.1074
b_{23}	-0.0102**	0.0048	-2.1250	0.0336
b_{33}	0.9778***	0.0096	101.8052	0.0000
a_{11}	0.1672***	0.0244	6.8401	0.0000
a_{21}	-0.0686	0.0426	-1.6120	0.1070
a_{31}	0.1818**	0.0836	2.1750	0.0296
a_{12}	-0.0009	0.0049	-0.1751	0.8610
a_{22}	0.1989***	0.0207	9.5870	0.0000
a_{32}	0.0063	0.0132	0.4752	0.6347
a_{13}	-0.0330***	0.0103	-3.2007	0.0014
a_{23}	0.0398*	0.0208	1.9124	0.0558
a_{33}	0.1390***	0.0470	2.9574	0.0031
Ljung-Box Statistics				
Q(10)	Q-Stat			P-Value

Oil	10.2245	0.4210
Gold	11.6752	0.3074
S&P	12.9007	0.2293
$Q^2(10)$		
Oil	10.8304	0.3709
Gold	16.5473	0.0850
S&P	7.1713	0.7092
LL	-5638.65	
Covariance stationary test		
Eigenvalues: 0.9735±0.0289i, 0.9874±0.0099i, 0.9903, 0.9962, 0.9874±0.0101i 0.9876		

Table 2.A 10 Estimation results of the Bi-variate GARCH models in the pre-crisis period (1/04/91—31/03/97).

$$H_t = \begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{12,t} & h_{22,t} \end{bmatrix} = \begin{bmatrix} c_{11} & c_{21} \\ c_{12} & c_{22} \end{bmatrix} \begin{bmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{bmatrix} + \begin{bmatrix} \alpha_{11} & \alpha_{21} \\ \alpha_{12} & \alpha_{22} \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} & \varepsilon_{1,t-1}^2 \end{bmatrix} \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix} + \begin{bmatrix} \beta_{11} & \beta_{21} \\ \beta_{12} & \beta_{22} \end{bmatrix} \begin{bmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{12,t-1} & h_{22,t-1} \end{bmatrix} \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix}$$

	oil and gold			oil and S&P			Gold and S&P		
Variable	Coeff	Std Error	T-Stat	Coeff	Std Error	T-Stat	Coeff	Std Error	T-Stat
c_{11}	0.1656***	0.0354	4.674	0.1451***	0.0475	3.0563	0.0452***	0.0111	4.0619
c_{21}	----	----	----	----	----	----	----	----	----
c_{12}	0.0452***	0.0107	4.2456	0.0101	0.0654	0.1552	-0.001	0.0225	-0.0423
c_{22}	-0.00003	0.0053	-0.0056	0.0759***	0.0307	2.4698	0.058	0.047	1.2335
b_{11}	-0.9768***	0.0053	-184.09	-0.9752***	0.0078	-125.44	0.9840***	0.0056	176.13
b_{21}	0.4210***	0.1274	3.3057	0.0378	0.0843	0.4485	0.1340***	0.0315	4.2543
b_{12}	0.0147***	0.0023	6.3481	-0.0071	0.0112	-0.6324	-0.1379**	0.0565	-2.4394
b_{22}	0.9720***	0.0036	271.31	-0.9800***	0.0119	-82.13	-0.9977***	0.0143	-69.78
a_{11}	0.1745***	0.0224	7.7817	0.1980***	0.027	7.3428	0.2168***	0.0224	9.698
a_{21}	0.0627	0.0448	1.3993	0.1146	0.1881	0.6092	0.0272*	0.0157	1.734
a_{12}	-0.0069**	0.0032	-2.1995	-0.0252	0.0272	-0.9237	-0.0306**	0.0137	-2.2442
a_{22}	0.2117***	0.0195	10.83	0.1501***	0.0480	3.123	-0.1251**	0.0599	-2.0895
Ljung-Box Statistics									
$Q(10)$		Q-Stat	P-Value		Q-Stat	P-Value		Q-Stat	P-Value
	Oil	9.1896	0.5142	Oil	7.8938	0.6392	Gold	11.1324	0.3473
	Gold	11.7266	0.3038	sp	21.2177	0.0196	sp	13.7804	0.1832
$Q^2(10)$									
	Oil	8.1094	0.6182	Oil	8.5675	0.5736	Gold	11.4232	0.3255
	Gold	12.0096	0.2844	SP	7.5956	0.6683	SP	8.6022	0.5702
LL		-4167.71			-4416.22			-2725.55	

Covariance Stationary Test

Eigenvalue of Bi-GARCH for oil and gold market : 0.9911, 0.9953, -0.9190 and -0.9183

For oil and S&P : 0.9912, 0.9821±0.0134i, 0.9886

For gold and S&P : 0.9959, 0.9919, -0.9896, -0.9895

Table 2.A 11 Estimation results from the Tri-variate GARCH model in the crisis period (1/04/97—31/07/03).

$$H_t = \begin{bmatrix} h_{oo,t} & h_{og,t} & h_{os,t} \\ h_{og,t} & h_{gg,t} & h_{gs,t} \\ h_{os,t} & h_{gs,t} & h_{ss,t} \end{bmatrix} = \begin{bmatrix} c_{11} & c_{21} & c_{31} \\ c_{12} & c_{22} & c_{32} \\ c_{13} & c_{23} & c_{33} \end{bmatrix} \begin{bmatrix} c_{11} & c_{12} & c_{13} \\ c_{21} & c_{22} & c_{23} \\ c_{31} & c_{32} & c_{33} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{21} & a_{31} \\ a_{12} & a_{22} & a_{32} \\ a_{13} & a_{23} & a_{33} \end{bmatrix} \begin{bmatrix} \varepsilon_{o,t-1}^2 & \varepsilon_{o,t-1}\varepsilon_{g,t-1} & \varepsilon_{o,t-1}\varepsilon_{s,t-1} \\ \varepsilon_{o,t-1}\varepsilon_{g,t-1} & \varepsilon_{g,t-1}^2 & \varepsilon_{g,t-1}\varepsilon_{s,t-1} \\ \varepsilon_{o,t-1}\varepsilon_{s,t-1} & \varepsilon_{g,t-1}\varepsilon_{s,t-1} & \varepsilon_{s,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix}$$

$$+ \begin{bmatrix} b_{11} & b_{21} & b_{31} \\ b_{12} & b_{22} & b_{32} \\ b_{13} & b_{23} & b_{33} \end{bmatrix} \begin{bmatrix} h_{oo,t-1} & h_{og,t-1} & h_{os,t-1} \\ h_{og,t-1} & h_{gg,t-1} & h_{gs,t-1} \\ h_{os,t-1} & h_{gs,t-1} & h_{ss,t-1} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix}$$

Variable	Coeff	Std Error	T-Stat	Signif
c_{11}	0.5327	0.3562	1.4954	0.1348
c_{21}	-0.4604**	0.2088	-2.2052	0.0274
c_{31}	0.1774*	0.1029	1.7235	0.0848
c_{12}	0.2570**	0.1305	1.9686	0.0490
c_{22}	0.4805***	0.1446	3.3241	0.0009
c_{32}	-0.0344	0.0655	-0.5243	0.6001
c_{13}	0.0927	0.0823	1.1265	0.2600
c_{23}	0.1584**	0.0626	2.5316	0.0114
c_{33}	0.1488*	0.0817	1.8222	0.0684
b_{11}	0.8844***	0.0607	14.5802	0.0000
b_{21}	0.3378	0.2805	1.2045	0.2284
b_{31}	0.0444	0.0581	0.7650	0.4443
b_{12}	0.0021	0.0082	0.2496	0.8029
b_{22}	0.7353***	0.2015	3.6486	0.0003
b_{32}	-0.0293	0.0433	-0.6755	0.4993
b_{13}	0.0186**	0.0089	2.0958	0.0361
b_{23}	-0.1729***	0.0242	-7.1570	0.0000
b_{33}	0.9359***	0.0160	58.4032	0.0000
a_{11}	0.3004***	0.0550	5.4571	0.0000
a_{21}	-0.1973**	0.0923	-2.1369	0.0326
a_{31}	0.0129	0.0583	0.2204	0.8255
a_{12}	0.0019	0.0140	0.1338	0.8935
a_{22}	0.3132***	0.1164	2.6910	0.0071
a_{32}	0.0010	0.0635	0.0157	0.9874
a_{13}	-0.0271**	0.0129	-2.1011	0.0356
a_{23}	0.1007	0.0655	1.5385	0.1239
a_{33}	0.2214***	0.0342	6.4733	0.0000

Ljung-Box Statistics

Q(10)	Q-Stat	P-Value
Oil	13.2249	0.2114
Gold	4.7409	0.9078

S&P	8.4579	0.5842
$Q^2(10)$		
Oil	19.3644	0.0359
Gold	3.3327	0.9725
S&P	5.5936	0.8482
LL	-8648.67	
Covariance stationary test		
Eigenvalues: 0.6006, 0.9678, 0.8822, 0.9197, 0.7231, 0.7448, 0.9204, 0.7232, 0.7465		

Table 2.A 12 Estimation results of the Bi-variate GARCH models in the crisis period (1/04/97—31/07/03)

$$H_t = \begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{12,t} & h_{22,t} \end{bmatrix} = \begin{bmatrix} c_{11} & c_{21} \\ c_{12} & c_{22} \end{bmatrix} \begin{bmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{bmatrix} + \begin{bmatrix} \alpha_{11} & \alpha_{21} \\ \alpha_{12} & \alpha_{22} \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} & \varepsilon_{1,t-1}^2 \end{bmatrix} \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix} + \begin{bmatrix} \beta_{11} & \beta_{21} \\ \beta_{12} & \beta_{22} \end{bmatrix} \begin{bmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{12,t-1} & h_{22,t-1} \end{bmatrix} \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix}$$

	oil and gold			oil and S&P			Gold and S&P		
Variable	Coeff	Std Error	T-Stat	Coeff	Std Error	T-Stat	Coeff	Std Error	T-Stat
c_{11}	0.6815***	0.1752	3.8905	0.8539***	0.2152	3.9682	0.3079***	0.0962	3.2025
c_{21}	0.0839	1.0802	0.0777	-0.0367	0.2849	-0.1287	-0.1851*	0.0982	-1.8844
c_{12}	0.2231	0.4276	0.5217	0.2252***	0.0695	3.2395	0.2332***	0.0567	4.1131
c_{22}	0.3670***	0.0860	4.2676	-0.0097	0.1013	-0.0955	0.1463**	0.0674	2.1719
b_{11}	-0.8824***	0.0912	-9.6748	-0.8615***	0.0523	-16.4789	0.8824***	0.0793	11.1281
b_{21}	-0.4393	0.5254	-0.8361	0.4382*	0.2473	1.7718	-0.0148	0.0207	-0.7127
b_{12}	-0.1160*	0.0597	-1.9438	0.1582**	0.0670	2.3614	-0.0658	0.0581	-1.1316
b_{22}	0.8203***	0.1997	4.1066	0.9043***	0.0434	20.8571	0.9376***	0.0153	61.0846
a_{11}	0.2871***	0.0755	3.8009	0.2985***	0.0518	5.7639	0.2538***	0.0765	3.3188
a_{21}	-0.1980***	0.0645	-3.0674	0.0787	0.0744	1.0581	0.0061	0.0462	0.1332
a_{12}	0.0121	0.0136	0.8903	-0.0262**	0.0129	-2.0293	0.0522	0.0643	0.8117
a_{22}	0.2774**	0.1156	2.3992	0.2417***	0.0351	6.8789	0.2574***	0.0296	8.7087
Ljung-Box Statistics									
$Q(10)$		Q-Stat	P-Value		Q-Stat	P-Value		Q-Stat	P-Value
	Oil	12.6739	0.2425	Oil	12.7543	0.2377	Gold	3.0667	0.9798
	Gold	3.2703	0.9743	SP	8.0699	0.6220	SP	7.6371	0.6642
$Q^2(10)$									
	Oil	19.4061	0.0354	Oil	19.0893	0.0391	Gold	2.8843	0.9840
	Gold	3.3998	0.9704	SP	5.9706	0.8177	SP	5.6659	0.8425
LL		-5937.97			-6527.24			-4874.27	

Covariance stationary test

Eigenvalue of Bi-GARCH for oil and gold market : 0.9079, 0.8044, -0.6971, -0.6928

For oil and S&P : -0.7754, 0.8955, 0.9454, -0.7718

For gold and S&P : 0.8258, 0.8918, 0.9648, 0.8914

Table 2.A 13 Estimation results from the Tri-variate GARCH model in the post-crisis period (1/08/03—5/11/07).

$$H_t = \begin{bmatrix} h_{oo,t} & h_{og,t} & h_{os,t} \\ h_{og,t} & h_{gg,t} & h_{gs,t} \\ h_{os,t} & h_{gs,t} & h_{ss,t} \end{bmatrix} = \begin{bmatrix} c_{11} & c_{21} & c_{31} \\ c_{12} & c_{22} & c_{32} \\ c_{13} & c_{23} & c_{33} \end{bmatrix} \begin{bmatrix} c_{11} & c_{12} & c_{13} \\ c_{21} & c_{22} & c_{23} \\ c_{31} & c_{32} & c_{33} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{21} & a_{31} \\ a_{12} & a_{22} & a_{32} \\ a_{13} & a_{23} & a_{33} \end{bmatrix} \begin{bmatrix} \varepsilon_{o,t-1}^2 & \varepsilon_{o,t-1}\varepsilon_{g,t-1} & \varepsilon_{o,t-1}\varepsilon_{s,t-1} \\ \varepsilon_{o,t-1}\varepsilon_{g,t-1} & \varepsilon_{g,t-1}^2 & \varepsilon_{g,t-1}\varepsilon_{s,t-1} \\ \varepsilon_{o,t-1}\varepsilon_{s,t-1} & \varepsilon_{g,t-1}\varepsilon_{s,t-1} & \varepsilon_{s,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix}$$

$$+ \begin{bmatrix} b_{11} & b_{21} & b_{31} \\ b_{12} & b_{22} & b_{32} \\ b_{13} & b_{23} & b_{33} \end{bmatrix} \begin{bmatrix} h_{oo,t-1} & h_{og,t-1} & h_{os,t-1} \\ h_{og,t-1} & h_{gg,t-1} & h_{gs,t-1} \\ h_{os,t-1} & h_{gs,t-1} & h_{ss,t-1} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix}$$

Variable	Coeff	Std Error	T-Stat	Signif
c_{11}	0.0928**	0.0383	2.4235	0.0154
c_{21}	0.0000	0.0000	0.0000	0.0000
c_{31}	0.0000	0.0000	0.0000	0.0000
c_{12}	0.0758***	0.0208	3.6408	0.0003
c_{22}	0.0090	0.0386	0.2319	0.8166
c_{32}	0.0000	0.0000	0.0000	0.0000
c_{13}	-0.0252	0.0837	-0.3015	0.7630
c_{23}	0.1230**	0.0374	3.2903	0.0010
c_{33}	-0.0418	0.0573	-0.7303	0.4652
b_{11}	0.9940***	0.0023	434.0444	0.0000
b_{21}	-0.0077	0.0089	-0.8665	0.3862
b_{31}	0.0470**	0.0211	2.2253	0.0261
b_{12}	0.0001	0.0018	0.0726	0.9421
b_{22}	0.9856***	0.0032	312.6862	0.0000
b_{32}	0.0100	0.0154	0.6509	0.5151
b_{13}	-0.0051***	0.0017	-2.9429	0.0033
b_{23}	0.0013	0.0066	0.1920	0.8478
b_{33}	0.9614***	0.0119	80.6452	0.0000
a_{11}	-0.1041***	0.0191	-5.4530	0.0000
a_{21}	0.1342***	0.0319	4.2070	0.0000
a_{31}	-0.0652	0.0483	-1.3502	0.1770
a_{12}	0.0105	0.0103	1.0244	0.3056
a_{22}	0.1432***	0.0207	6.9086	0.0000
a_{32}	-0.0114	0.0478	-0.2383	0.8117
a_{13}	-0.0046	0.0082	-0.5598	0.5756
a_{23}	0.0022	0.0289	0.0775	0.9382
a_{33}	0.2000***	0.0237	8.4407	0.0000

Ljung-Box Statistics

$Q(10)$	Q-Stat	P-Value
Oil	9.1779	0.5153
Gold	4.2583	0.9349
S&P	11.2955	0.3350

$Q^2(10)$		
Oil	26.7801	0.0028
Gold	11.5327	0.3175
S&P	11.0184	0.3561
LL	-5040.0583	

Covariance stationary test

Eigenvalues: $0.9530 \pm 0.0170i$, 0.9944, 0.9923, $0.9698 \pm 0.0108i$, 0.9341

$0.9701 \pm 0.0118i$

Table 2.A 14 Estimation results of the Bi-variate GARCH models in the post-crisis period (1/08/03—5/11/07).

$$H_t = \begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{12,t} & h_{22,t} \end{bmatrix} = \begin{bmatrix} c_{11} & c_{21} \\ c_{12} & c_{22} \end{bmatrix}\begin{bmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{bmatrix} + \begin{bmatrix} \alpha_{11} & \alpha_{21} \\ \alpha_{12} & \alpha_{22} \end{bmatrix}\begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} & \varepsilon_{1,t-1}^2 \end{bmatrix}\begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix} + \begin{bmatrix} \beta_{11} & \beta_{21} \\ \beta_{12} & \beta_{22} \end{bmatrix}\begin{bmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{12,t-1} & h_{22,t-1} \end{bmatrix}\begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix}$$

	oil and gold			oil and S&P			Gold and S&P		
Variable	Coeff	Std Error	T-Stat	Coeff	Std Error	T-Stat	Coeff	Std Error	T-Stat
c_{11}	0.3474**	0.1560	2.2265	1.8908***	0.1114	16.9767	-0.0885***	0.0202	-4.3723
c_{21}	-0.3640***	0.1234	-2.9497	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
c_{12}	0.0509	0.0913	0.5579	-0.0343	0.0214	-1.5990	-0.0909***	0.0063	-14.3551
c_{22}	-0.0527	0.0974	-0.5407	0.0000	0.0448	0.0003	-0.0898***	0.0056	-16.0573
b_{11}	-0.9237***	0.0265	-34.9179	-0.1764	0.2830	-0.6233	0.9864***	0.0028	356.48
b_{21}	1.0203***	0.0949	10.7524	-0.2081**	0.1010	-2.0605	-0.1486**	0.0642	-2.3139
b_{12}	0.0446**	0.0207	2.1519	0.0454***	0.0097	4.7036	0.0086	0.0060	1.4286
b_{22}	0.9599***	0.0136	70.5830	-0.9685***	0.0085	-114.30	-0.9659***	0.0061	-157.08
a_{11}	-0.2015***	0.0358	-5.6209	-0.1711***	0.0628	-2.7236	0.1487***	0.0199	7.4655
a_{21}	0.1509***	0.0268	5.6288	-0.3895***	0.1441	-2.7027	0.0015	0.0310	0.0485
a_{12}	0.0123	0.0081	1.5153	-0.0023	0.0130	-0.1747	0.0094	0.0279	0.3369
a_{22}	0.1554***	0.0180	8.6404	0.1930***	0.0234	8.2641	-0.1901***	0.0310	-6.1287
Ljung-Box Statistics									
$Q(10)$		Q-Stat	P-Value		Q-Stat	P-Value		Q-Stat	P-Value
	Oil	8.4347	0.5865	Oil	10.7940	0.3738	Gold	4.3601	0.9296
	Gold	4.1254	0.9415	SP	10.0421	0.4368	SP	10.6339	0.3867
$Q^2(10)$									
	Oil	17.3645	0.0667	Oil	37.4626	0.0000	Gold	11.5329	0.3175
	Gold	12.2035	0.2717	SP	8.1964	0.6097	SP	9.6729	0.4696
LL		-3882.29			-3494.08			-2770.65	

Covariance stationary test

Eigenvalue of Bi-GARCH for oil and gold market : 0.9407, 0.9937, -0.9657, -0.9653

For oil and S&P : 0.1012±0.0103i, 0.9625, 0.1464

For gold and S&P :0.9936, 0.9676, -0.9793, 0.9798

Appendix 2 B

Figure 2.B 1 Percentage of oil production, imports and demand in US to the World

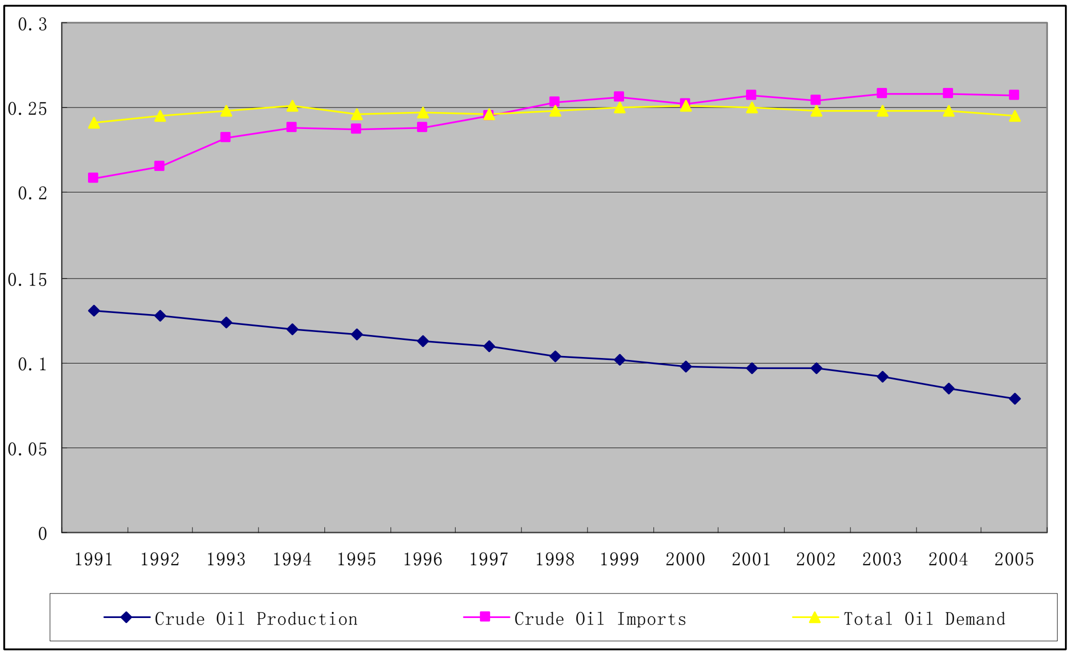


Figure 2.B 2 World crude oil price ($/bbl) for past 50 years (yearly average)

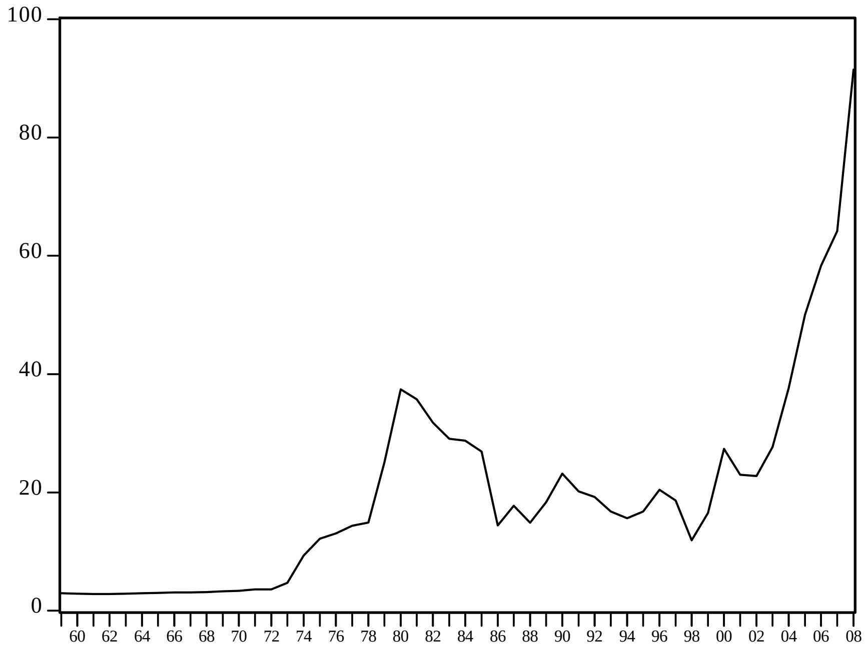


Figure 2.B 3 Inflation adjusted world oil prices over past 50 years (yearly average, $/bbl)

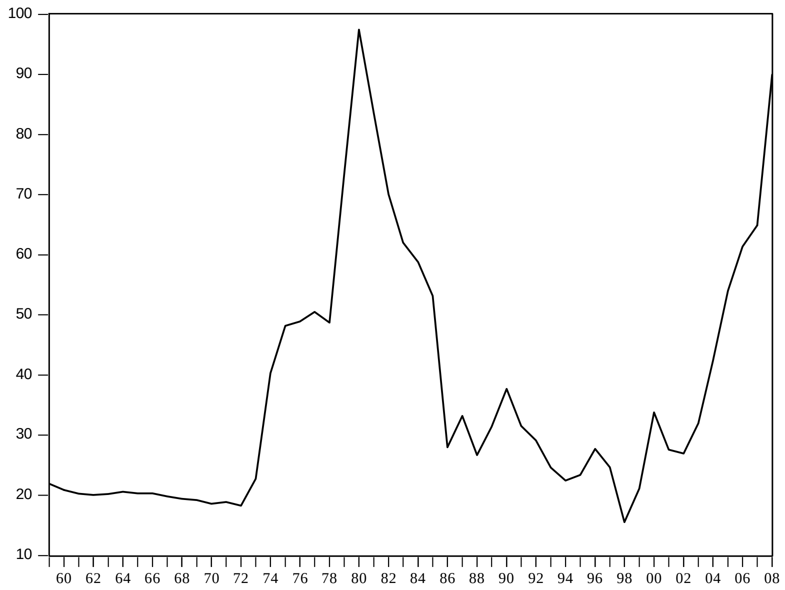


Figure 2.B 4 Monthly oil price series from 1990s

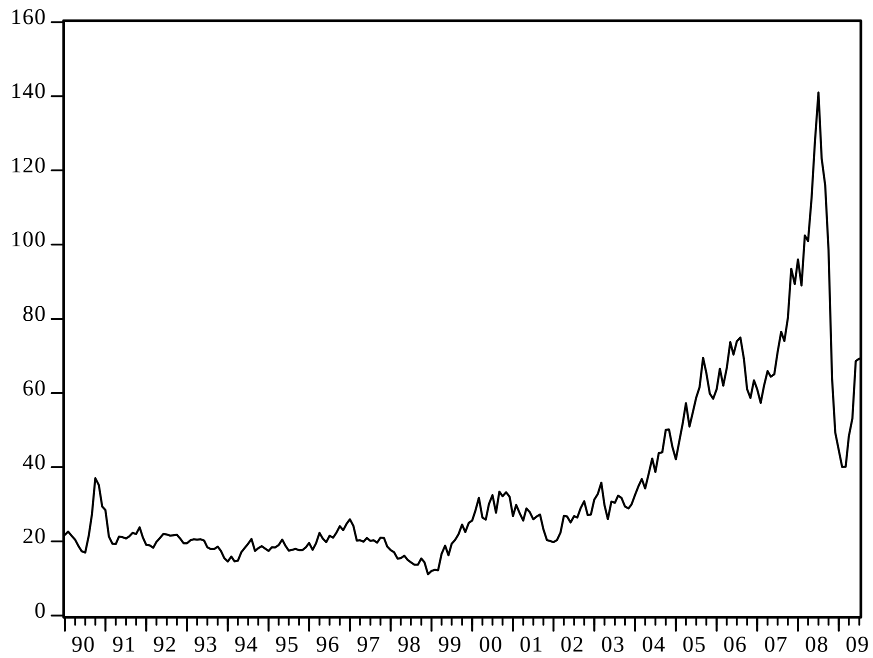


Figure 2.B 5 World gold price for past 50 years (yearly average, $/ounce)

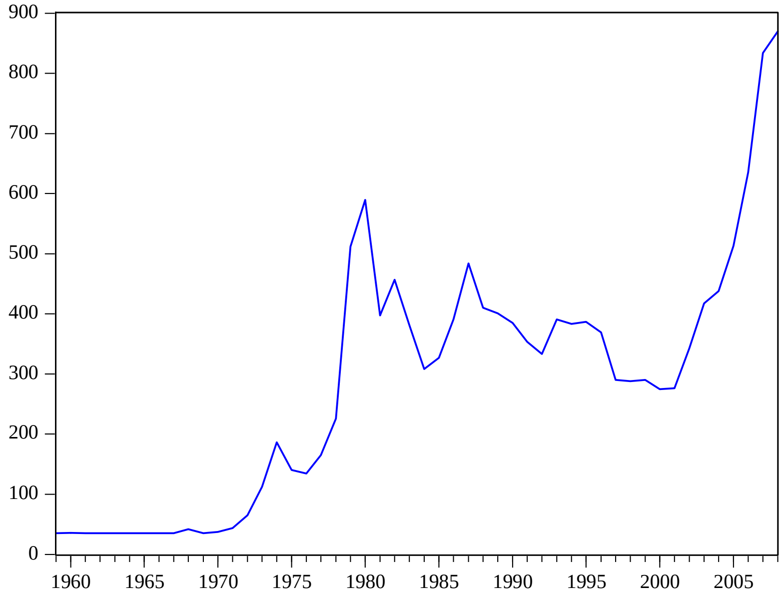


Figure 2.B 6 Percentage gold holding of US to the world

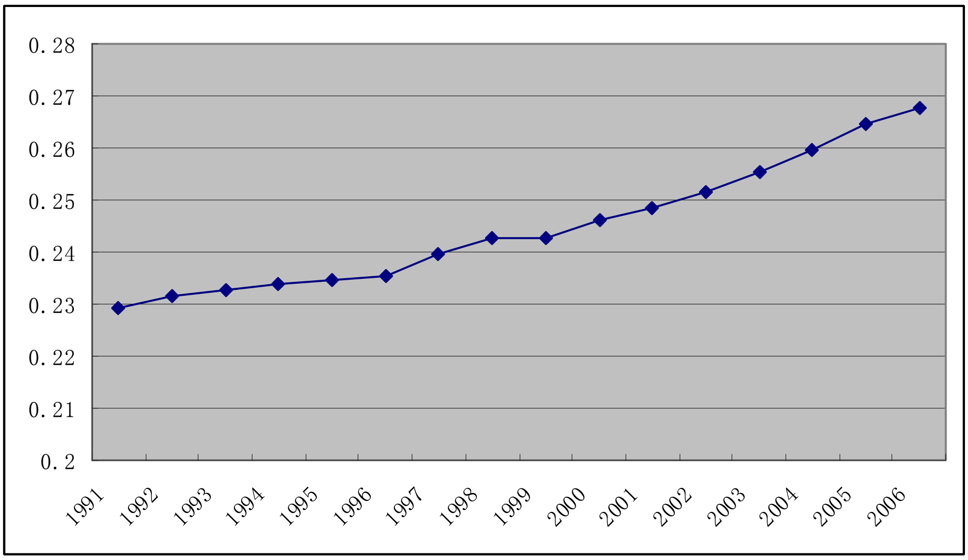


Figure 2.B 7 Oil and oil price over the past 50 years (Based on yearly data)

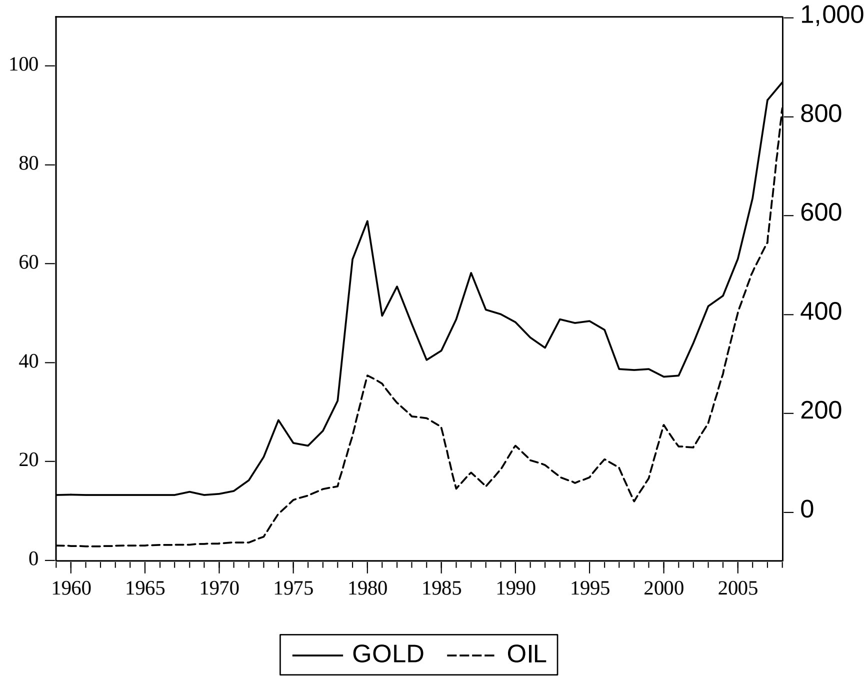
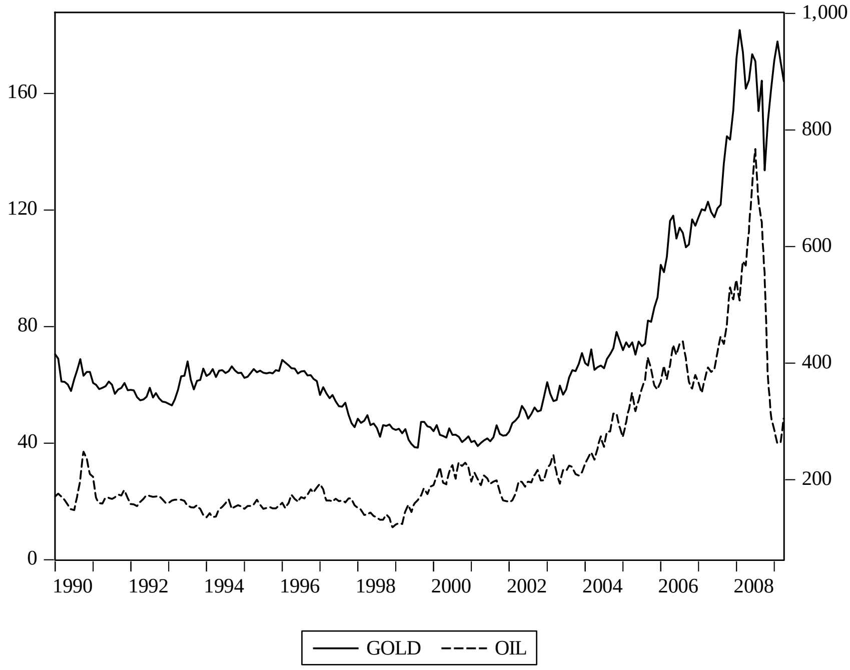


Figure 2.B 8 Oil and gold monthly price series since 1990s



Essay 3 Re-examining the Asian Currency Crises: A Markov Switching TGARCH approach

3.1. Introduction

The outbreak of the Asia financial crisis in 1997-1998 triggered a surge in both theoretical and empirical studies on the factors that contribute to the occurrence of a currency crisis. Some authors claim that the Asia currency crises were predictable and can be explained by economic fundamentals, whereas others contend that the crises are self-fulfilling, where speculative attacks on a country are based on the probability that the attacks will be successful and hence profitable, regardless of the macroeconomic fundamentals of a country.

Currency crises have been traditionally viewed as retribution for governments that have mismanaged the economy and/or lack credibility. The basic 'first generation' model (see e.g., Krugman, 1979) accentuates domestic fiscal and monetary policies inconsistent with the fixed exchange rate policy leading to currency overvaluation and reserve depletion. In these models the presence of inconsistent policies generates a speculative attack against the local currency, and pushes the economy into a crisis. The degree of severity of these inconsistencies will determine the timing of the crisis. The 'second generation' model (see e.g., Obstfeld, 1996) emphasizes the importance of market expectations which can trigger a crisis by shifting the macroeconomy from a "good" no-crisis equilibrium to a crisis equilibrium, even when macroeconomic policies are consistent with the exchange rate policy. These models emphasize the role of policymaker's preferences, and suggest that the option of abandoning a fixed exchange rate regime may be an ex-ante optimal decision for the policymakers, considering that economic authorities face tradeoffs. The ‘third generation’ model (see e.g., Corsetti et al., 1999) focuses on deficiencies in domestic and foreign financial sectors that result in a ‘feast and famine’ pattern of capital flows. Those models tend to focus on the financial liberalization in Asia capital markets, accompanied by a combination of asymmetric information and moral hazard problems and by the inadequate market regulation, supervision and management in this region, which led to excessive borrowing (e.g., Mishkin, 1999; Corsetti, Pesenti, & Roubini, 1999). Rather than following the path of the third generation models we confine ourselves to the potential of the first and second generation currency crisis models for explaining (or accounting for) the Asian currency crisis in this study.

A currency crisis is usually identified as an episode in which there is a sharp depreciation of the currency, a large decline in foreign reserves, a dramatic increase in domestic interest rate or a combination of these elements. The empirical literature on currency crisis are vast, and mainly focus on trying to explain and predict crises in the developing countries.

In this study, we use a Markov Switching approach to account for the presence of two potential regimes: stable and volatile. We also include an Asymmetric Generalised Autoregressive Conditional Heteroscedasticity (GARCH) specification to capture the fact that within each regime, the volatility of market pressure is not constant. The attractiveness of the Markov Switching approach is that we do not need to distinguish ex-ante between stable and volatile states. Instead, the estimation results will supply us with such information. By allowing regression parameters to switch between different regimes, Markov-switching mimics the existence of multiple equilibriums.

Moreover, the mainstream analyses and empirical studies concentrate on depreciating currency attacks. In reality, however, speculative attacks also take place when currency appreciates. The Markov Switching models we employed are also able to capture appreciating currency attacks. In stead of converting the measure of market pressure on the exchange rate into a binary variable (Eichengreen, Rose and Wyplosz, 1996, Frankel and Rose, 1996, and Kruger, Osakwe, and Page, 1998), we assume a currency will have higher probability to depreciate if it has high market pressure, and will appreciate when it has very low market pressure. When market pressure has very low or high values, it is considered to be potentially in a volatile state. When market pressure lies in the medium range, it is considered to be in a stable state.

Existing empirical studies have suggested that the deteriorating fundamentals do increase the probability of a crisis (see, e.g., Kaminsky, Lizondo and Reinhart, 1997; Berg and Patillo, 1998), but the timing of a crisis cannot be predicted with precision. In our approach, we examine the explanatory power of several fundamental variables, including the indicators for international reserves, the real exchange rate and domestic credit growth. The model can be used for out-of-sample forecasting. Unfortunately, due to the short data sample, we only limit our study to understanding the variables and modeling specifications.

The remainder of this paper is organized as follows. Section 3.2 and section 3.3 review the theoretical framework and empirical studies on currency crisis. Section 3.4 discusses the measure of market pressure on the exchange rate and the construction of macroeconomic fundamentals. Section 3.5 discusses the methodology: the Markov switching models with constant variances and with Asymmetric GARCH specification in variances. Empirical estimation results are presented in section 3.6. In section 3.7, we compare our findings from Markov switching model with the results from Multinomial Logit models. Section 3.8 concludes.

3.2 Theoretical Framework for currency crisis

This section provides a review of selected works on explanations for speculative attacks and currency crisis that have been presented in the theoretical literature. The aim is to provide some theoretical background and to provide an explanation why a variety of indicators have been used for currency crisis in our later empirical studies.

3.2.1 First Generation Crisis models: Fundamentals perspective

The first generation models explain currency crisis as a result of unsustainable development in fundamental macroeconomic variables, which widens the discrepancy between the promises and the proclaimed goal of the monetary authorities (e.g. Blejer, 1998). Krugman (1979) shows that, under a fixed exchange rate, domestic credit expansion in excess of money demand growth leads to a gradual but persistent loss of international reserves and ultimately to a speculative attack on the currency. This attack immediately depletes reserves and forces the authorities to abandon parity. The process ends with an attack because economic agents understand that a fixed exchange rate regime will ultimately collapse, and that in the absence of an attack the agents would suffer a capital loss on their holdings of domestic money. Krugman's analysis parallels obviously the analysis in the theory of exhaustible resources in that foreign reserves are used to peg an exchange rate. He illustrates a currency crisis from the viewpoint of monetary model. In this respect, his model predicts that exchange is dependent on the supply of domestic and foreign currency relative to demands. Due to non-linearities in his model, the Krugman (1979) model was not able to determine the timing of the collapse of the fixed exchange rate regime. Flood and Garber (1984) using a linear model provided a solution to the timing of the collapse.

Agenor, Bhandari and Flood (1992) present a framework to analyze the process leading to a balance of payments crisis, consisting of a simple continuous time and perfect foresight model. This model is a log linear formulation which can solve explicitly for the timing of a crisis by assuming that the exchange rate is allowed to float permanently in the post-crisis regime. We provide an examination of this model.

Consider a small open economy whose residents consume a single traded good whose domestic supply is exogenously fixed at $\bar{y}$. The central bank fixes the exchange rate of its currency relative to that of a large foreign country. Purchasing power parity (PPP) holds, so that $P = SP*$ (P is the domestic price level, S is the exchange rate the $P*$ is the foreign price level). In log notation with $P*$ normalized to 1, the PPP can be written as $p = s$. p and s are the domestic price level and exchange rate in logarithms. Assuming there are no private banks in the economy, the money supply equals the sum of domestic credit issued by the central bank and domestic currency value of foreign reserves held by the central bank. Domestic credit is assumed to grow at a constant rate μ. Finally, agents have perfect foresight. The model is defined as follow:

$$m_t - p_t = \phi \bar{y} - \alpha i_t \qquad \phi, a > 0 \tag{3.1}$$

$$m_t = \gamma d_t + (1-\gamma) r_t \qquad 0 < \gamma < 1 \tag{3.2}$$

$$\dot{d}_t = \mu \qquad \mu > 0 \tag{3.3}$$

$$p_t = s_t \tag{3.4}$$

$$i_t = i_t^* + E_t \dot{s}_{t+1} \tag{3.5}$$

All variables except interest are measured in logarithms. m_t denotes the nominal money stock, d_t is the domestic credit, r_t is the domestic currency value of the government's holding of foreign reserves, s_t is the spot exchange rate, p_t is the domestic price level, i_t is the domestic interest rate and i_t^* is the foreign interest rate. i_t^* is assumed to be constant. E_t denotes the expectation operator conditional on information available at time t. A dot over a variable denotes a time derivative.

Equation (3.1) defines real money demand as a positive function of income and a negative function of the domestic interest rate. Equation (3.2) is a log-linear approximation of the link between the money stock and reserves and domestic credit. γ denotes the share of domestic credit in the money stock[32]. Equation (3.3) gives that the domestic credit grows at a constant rate μ. Purchasing power parity and uncovered interest parity are assumed to be hold and are defined in Equation (3.4) and Equation (3.5), respectively. Under perfect foresight, $E_t \dot{s}_{t+1} = \dot{s}_{t+1}$.

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32 $\gamma = D_t / M_t$ at the point of linearisation, usually the sample mean. D_t denotes the domestic credit and M_t denotes the nominal money stock, in level.

From this model, the operating properties of a floating exchange rate and fixed exchange regime can be determined. For convenience, we set $\bar{y}=0$. Combining Equation (3.1), (3.4) and (3.5) yields,

$$s_t = \alpha i^* + m_t + aE_t\dot{s}_{t+1} \tag{3.6}$$

When the exchange rate is fixed at $\bar{s}$, the anticipated rate of change in exchange rate is zero, $E_t\dot{s}_{t+1}=0$. i^* is assumed to be constant and so the central bank must accommodate any change in money demand through the purchase from or sale to the public of foreign reserves. Using Equation (3.2) and (3.6) yields,

$$r_t = (s_t - \gamma d_t - \alpha i^*)/(1-\gamma) \tag{3.7}$$

And under these assumptions

$$\dot{r}_t = -\mu/\theta \qquad \text{where } \theta = (1-\gamma)/\gamma \tag{3.8}$$

When domestic credit is excessive (exceeding the demand for money), the continual growth in domestic credit will cause reserves to decline steadily as the central bank intervenes in foreign exchange markets to maintain the fixed exchange rate. If the central bank will not continue to defend the current exchange rate after the reserves reach a lower bound, $\bar{r}$, the exchange rate will be forced to float or will be devalued. The rational agents will anticipate that without speculation reserves will at some time fall to the lower bound and will anticipate the ultimate impending collapse of the fixed exchange rate. Hence, to avoid a loss of profit at the time of collapse rational agents will force a crisis before reserves reach $\bar{r}$.

In equilibrium under perfect foresight, agents will never expect a discrete jump in the level of exchange rate which will provide a profitable arbitrage opportunity. Arbitrage in the foreign exchange market fixes the exchange rate at the time of collapse equal to the fixed exchange rate prevailing at the time of attack. Thus the time of attack can be determined by two steps. First, from the law of motion of the exchange rate, we solve for the floating exchange rate given the current level of domestic credit and contingent on net reserves being at the minimum level of reverse. This contingent exchange rate is known as the shadow floating exchange rate, $\tilde{s}_t$. Second, we find the time T at which the shadow floating exchange rate $\tilde{s}_t$ equals the fixed exchange rate $\bar{s}$.

To find the shadow floating exchange rate, first assume that at the time of collapse, $r = 0$, so Equation (3.2) becomes

$$m_t = \gamma d_t \tag{3.9}$$

And so

$$\dot{m}_t = \gamma \dot{d} = \gamma\mu \tag{3.10}$$

Substitution in Equation (3.6), the solution for the floating exchange rate is

$$\bar{s}_t = \tilde{s}_t = \alpha i^* + \gamma d_t + \alpha\gamma\mu \tag{3.11}$$

In the post collapse regime, the exchange rate depreciates steadily and proportionally to the rate of domestic credit growth.

Assume that domestic credit grows with a deterministic trend: $d_t = d_0 + \mu \cdot t$ and at the time of collapse, $m_t = \gamma d_t$, then from Equation (3.11) we can determine the time of collapse

$$T_c = (\bar{s} - \alpha i^* - \gamma d_0 - \alpha\gamma\mu) / \gamma\mu \tag{3.12}$$

$$T_c = \frac{(\bar{s} - \alpha i^* - \gamma d_0)}{\gamma\mu} - \alpha \tag{3.13}$$

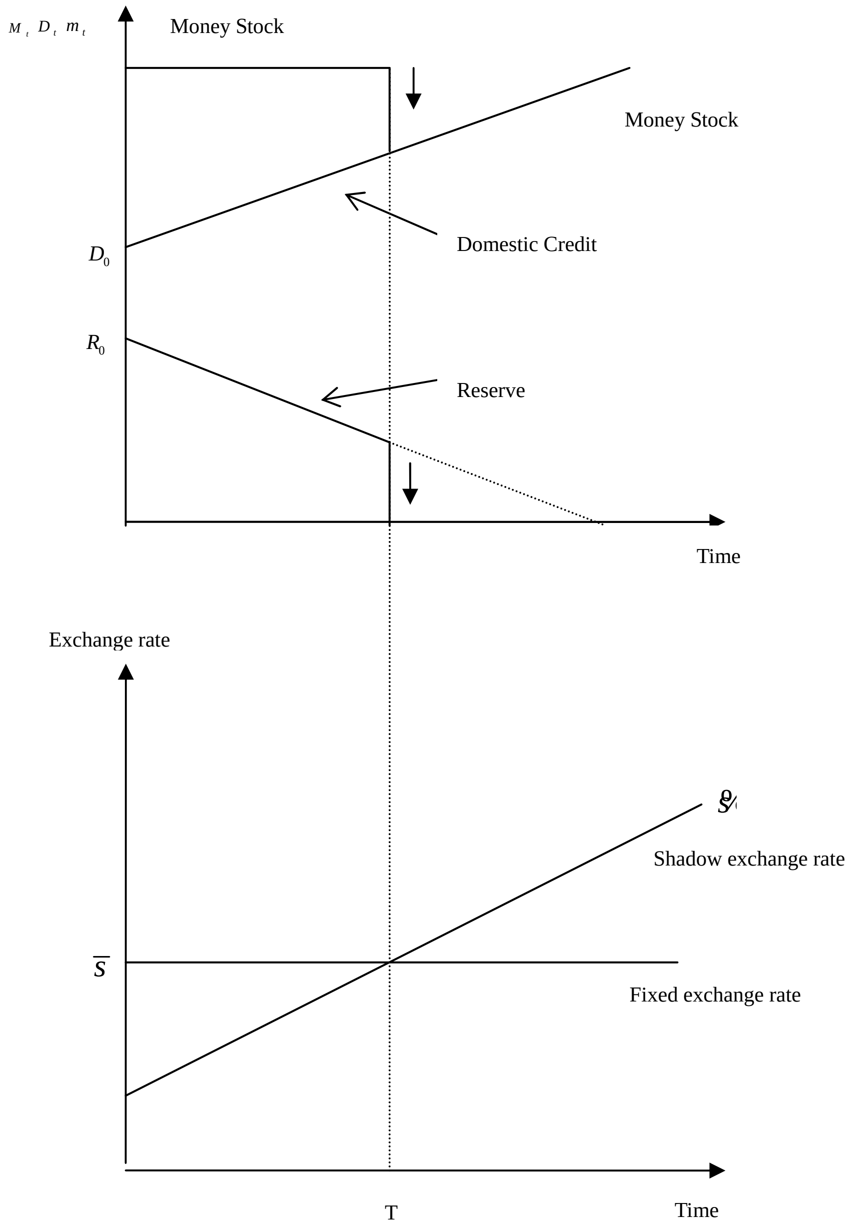
Given $\bar{s} = \alpha i^* + \gamma d_0 + (1-\gamma) r_0$

$$T_c = \frac{(1-\gamma) r_0}{\gamma\mu} - \alpha \tag{3.14}$$

Equation (3.13) shows that the higher initial stock of reserves or the lower the rate of domestic credit growth, the longer it will take before the collapse occurs in the absence of a speculative attack. The (semi) interest rate elasticity of money demand (α) determines the size of the downward shift in money demand and reserves when the fixed exchange rate collapses and the nominal interest rate rises to reflect the expected depreciation of the domestic currency. The larger the value of α, the sooner the collapse. Although it is assumed reserves are run down to zero to determine shadow floating rate, the model indicates that the attack always occurs before the central bank would have run out of reserves in the absence of speculation.

The model can be depicted in Figure 3.1. Prior to the attack, the exchange rate is fixed with no anticipated depreciation, so nominal money demand and supply are constant. Nevertheless, domestic credit is continuously rising, and this is matched by the fall in reserves. At the time of attack, nominal money demand falls discontinuously to D_{T_c}. The supply of money is reduced accordingly through an attack that drives reserves discontinuously to zero. From T_c onward, the money stock is identical to and grows

Figure 3. 1 Money, domestic credit and reserves in a speculative attack.



Source: Agenor, Bhandari and Flood (1992) with domestic credit. Note that if the right side of Equation (3.14) is negative, one should interpret the analysis as showing that a speculative attack must take place immediately on date 0 (Obstfeld and Rogoff, 1996).

3.2.2 The second generation models of currency crisis (Self-fulfilling speculative attacks)

The second generation models extend as well as modify the first generation models whereby dependence on market expectations for the occurrence of a crisis creates an element of uncertainty and multiple (non-unique) equilibria, rather than the fundamental macroeconomic variables and their developments cause a currency crisis. It focus on non-linearities in government behaviour, namely, what happens when government policy reacts to changes in private behaviour or when the government faces an explicit trade-off between the fixed exchange rate policy and other goals. Krugman (1996) point out that the policy dilemma facing by these countries have centered on such issues as real overvaluation, interest rates and unemployment, rather than facing a sharply defined foreign reserves constraint, to maintain a fixed exchange rate regime. Second generation models generally exhibit multiple equilibria so that speculative attacks can occur because of self-fulfilling expectations. “Then a fixed exchange rate that would have lasted indefinitely in the absence of a speculative attack may collapse because financial markets are persuaded, by otherwise irrelevant information, that the rate will not be sustained." (Krugman, 1996). For example, if private agents expect a high rate of devaluation, interest rate or wage demands can increase, worsening the prospects for lower debt service, a sounder banking system or reduced unemployment. The government will be more willing to actually allow for a high rate of devaluation because the situation implies a high "cost" to be paid by the government if the government does not actually change the exchange rate. The government's decision to devalue validates expectations, making expectations self-fulfilling (Marion, 1999).

The second generation models assume that the government in every single period of time evaluates the cost and the benefits from keeping the exchange rate fixed. Such is achieved by the government to optimise an explicit objective function (see, for example, Obstfeld, 1994). Consider the case of an agent, the government, which trying to minimise a loss function must decide whether or not to defend an exogenously determined exchange parity. We take directly from Krugman (1996) the reduced form representation, which derives the explicit loss function from a Mundell-Fleming type of open economy macro model with sticky prices. In such a model, output is a function of the real exchange rate and real interest rate.

$$y = \phi + \delta(s + p + p^*) - \lambda(i - \pi) \tag{3.15}$$

Where p^* and p are the foreign and domestic price levels in logarithm, and π is the expected rate of inflation. The money demand is a function of income and interest rate:

$$m - p = L(y, i) \tag{3.16}$$

Assuming perfect capital mobility with equalization of returns

$$i = i^{*} + \dot{s} \tag{3.17}$$

Where i^{*} is the foreign interest rate the $\dot{s}$ is the expected rate of depreciation. The government's loss function is stated in terms of deviation of output from a desired level:

$$H = (y - y^{d})^{2} \tag{3.18}$$

Now define the s^{d} as the log of the exchange rate that would leave the output equal to its target level in the absence of any expected depreciation. (i.e., s^{d} is the desired exchange rate). Hence:

$$y^{d} = \phi + \delta(s^{d} + p^{*} - p) - \lambda(i^{*} - \pi) \tag{3.19}$$

So that

$$s^{d} = 1/\delta\left[y^{d} - \phi + \delta(p - p^{*}) + \lambda(i^{*} - \pi)\right] \tag{3.20}$$

Therefore

$$H = \left[\delta(s^{d} - s) - \lambda(\dot{s})\right]^{2} \tag{3.21}$$

Let s^{d} be the exchange rate that government would choose if it faces no credibility concerns and $\bar{s}$ be the parity to which it has staked it reputation. $\dot{s}$ is the expected rate of depreciation: $s^{e} - s$, where s^{e} is the market expectation of the current exchange rate.

Assume that the government faces a fixed private cost if the government unexpectedly abandon the peg and let the currency devaluate, probability in the form of loss reputation. Sachs, et al (1996) show that such cost need not be proportional to the size of the devaluation or any other macroeconomic variable.

Assume the government's loss function is:

$$H = \left[\delta(s^d - s) - \lambda(s\&) \right]^2 + R(\cdot) \tag{3.22}$$

Where $R(\cdot)$ takes the value C when the government allows the exchange rate to change while $R(\cdot)$ equal 0 when the exchange rate does not change. Thus C is a fixed "reputation" cost that the government incurs when it abandons the peg.

Assume that the government is currently pegging its exchange rate. The market might expect that the government will continue to do so: $s^e = \overline{s}$, or that the government will abandon the peg in the next period, then $s^e = s^d$. Then the decision about whether to maintain the peg will depend on the comparison of the cost or loss from staying on the peg with the credibility cost of abandoning the peg, that is, whether

$$\min H = \left[\delta(s^d - \overline{s}) - \lambda(s^e - \overline{s}) \right]^2 > C \tag{3.23}$$

If the market does not expect a depreciation, then the second term in equation (3.23) will vanish and the government will want to maintain its peg, fulfilling the market expectations (i.e. $s^e = \overline{s}$) as long as

$$H = \left[\delta(s^d - \overline{s}) \right]^2 < C \tag{3.24}$$

On the other hand, if the market expects a depreciation (i.e., $s^e = s^d$), then the second term will become positive and the government will abandon the peg and fulfill market expectations as long as

$$H = \left[(\delta + \lambda)(s^d - \overline{s}) \right]^2 > C \tag{3.25}$$

Then we have multiple equilibria as long as

$$\left[\delta(s^d - \overline{s}) \right]^2 < C < \left[(\delta + \lambda)(s^d - \overline{s}) \right]^2 \tag{3.26}$$

Equation (3.26) shows that self-fulfilling crises are possible when the parameters of the economy are in a range. Whether the regime survives or collapses will depend on the government's reaction to market expectations. In loose terms, the above government objective function states that the conditions for a crisis-proof fixed exchange regime include a high cost to abandoning the peg and a peg that is very close to the desired or "right" level, s^d .

Some other versions of second generation models have also been developed (e.g. Obstfeld, 1996; Masson, 1999, etc). These models generally developed following the European Exchange Rate Mechanism (ERM) crisis in 1992/1993, when no critical developments in fundamental macroeconomic variables could be noticed. The second generation models stress the influence of self-fulfilling expectation and market panics on a currency, as well as the influence of "triggers" that initiate these panics and shift all the expectations in the market in the coherent or same direction.

According to second-generation models, a currency crisis occurs due to: 1) coherent self-fulfilling expectations, 2) rational heard behavior and 3) contagion (Blejer, 1998). Second generation models accurately describe developments immediately preceding a currency crisis. However, they overestimate the importance of expectation and triggers in setting off the wave of pessimism and coherent expectations in the market which results in currency devaluation (Babic and zigman, 2001). When the second-generation models are used as a complements to first-generation model, more sound theoretical results for currency crises can be achieved. The current economic policy of the government as well as its economic objectives and methods for achieving these objectives are reflected in the fundamental macroeconomic variables. The greater the deviation of the current economic policy from the optimum policy the government claimed to maintain the stability of the exchange rate regime (e.g. fixed exchange rate), the greater the probability of currency attack to take place and thus the occurrence of currency crisis. Due to various market fractions like transaction costs, difficulties in arranging credit lines for currency attack and the delay of revealing government policy indicators, currency crisis may not unfold as soon as the government policy begins to deviate from the proclaimed optimum policy. Accordingly, emphasis on the role of various events, especially various political events, that can trigger and turning point in market expectation has increased.

3.2.3 Summary of the models

First generation currency crisis models have focused on the primacy of deteriorating fundamentals in triggering a speculative attack. The deterioration of the fundamentals such as a growing budget deficit (perhaps financed by a growing domestic credit) or real exchange rate appreciation which implies a loss of competitiveness, leads invariably to a loss of reserves to the threshold level that triggers a speculative attack. The fixed exchange rate becomes increasingly incompatible with the state of fundamental, thereby raising the floating exchange rate above the peg. There are many extended version of first generation model (see, e.g. Floor and Garbet, 1984 and Santoso, 2001).

The second generation models endogenise government policy on the exchange rate. The peg is abandoned either as a result of deteriorating fundamental, or as a result of a speculative attack driven by self-fulfilling. The models focus on the market expectations which lead to currency crises, rather than the fundamental macroeconomic variables and their development. However, the fact that the attack is self-fulfilling does not mean that fundamental variables are no longer important, because these models require that the fundamentals in a vulnerable range for the attack to be successful.

Flood and Marion (1998) assert that the first- and second-generation model differ in a variety of ways, but most of the differences can be traced to one crucial assumption that first generation models assume the commitment to a fixed exchange rate is state invariant, whereas second generation models allow it to be state dependent. The assumption of a state-invariant commitment does not match well with common observation that monetary authority's commitment to the fixed exchange rate is often constrained by such factors as unemployment, the fragility of the banking system, the size of the public debt, or upcoming election. The state dependent behaviour inspires us to build an empirical model of the currency crisis that incorporates state/regime switching. The Markov Regime-Switching models are discussed in the section 3.4.

3.3 Previous empirical studies

The empirical literature on currency crisis is extensive, and mainly focuses on trying to explain and predict crises in the developing countries. There are three methods or approaches for predicting currency crises that have been developed in the literature.

One class of models is the probit/logit regression approach developed by Frankel and Rose (1996). They apply probit analysis on a panel of annual data for 105 developing countries for the period between 1971 and 1992 to investigate how international debt structure and external factors affect the probability of currency crises. Their model identifies the significant variables as output growth, foreign direct investment/total debt, reserves, domestic credit growth, external debt and foreign interest rates. Their findings also suggest that currency crises tend to occur when the growth of domestic credit and foreign interest rates are high, and foreign direct investment and output growth are low. Probit approach has also been used by Glick and Moreno (1999). Based on data from January 1972 to October 1997, they study the crises in Asia and Latin America. Results of their analysis suggest that reductions in real domestic credit and foreign reserves, as well as appreciation in the real exchange rate increase the probability of financial crises. Geochoco-Bautista (2000) uses a probit model based on data from the Philippines spanning the period between 1980 and 1997. Regression results indicate that the coefficient of short-term interest rate differential, change in international reserves, real exchange rate, and the growth of domestic credit to public sector are the significant variables in explaining the financial crisis in the Philippines. More recently, Bussiere and Fratzscher (2006) develop a new early warning system model based on a multinomial Logit with three outcomes (tranquil, pre-crisis and post-crisis) showing that such a specification leads to a better out-of-sample forecast and solves what they call the “post-crisis bias.”

A second class of models might be termed the “signal approach”, which attributed to Kaminsky et al. (1998). Macroeconomic series that behave abnormally during periods prior to a crisis are selected and a warning system based on signals issued by those variables is produced, normally with a threshold level beyond which a signal would be generated. Then they assess the individual and combined ability of those variables to predict crises. Kaminsky et al. (1998) find that the variables that have most explanatory power based on the noise-to-signal ratio are the deviation of real exchange rates from a deterministic trend, the occurrence of a banking crisis, the export growth rate, the stock price index growth rate, M2/reserves growth rate, output growth, excess M1 balances, growth of international reserves, M2 multiplier growth, and the growth rate of the domestic credit to GDP ratio. Berg and Pattillo (1999), by studying five European and eight emerging market economies from April 1970 to April 1995 under the signal approach, find that the crisis probabilities generated by this model for the period between May 1995 and December 1996 are statistically significant predictors of actual crisis occurrence over the following 24 months. They discover that the probability of a currency crisis increases when domestic credit growth is high, the real exchange rate is overvalued relative to trend, and the ratio of M2 to reserves is high. Using variants of the signals approach, Kaminsky (1998), Kaminsky and Reinhart (1999), and Goldstein et al. (2000) claim some success in predicting the Asian crisis.

A third class of models set up a crisis index and explain the currency crisis based on traditional linear or non-linear regression approach (for example, Tornell, 1999; IMF, World Economic Outlook, 1998; Radelet and Sachs, 1998; Corsetti, Pesenti and Roubini, 1999). Moreno (1995) builds a linear probability model for eight Asian countries based on monthly data from 1980 to 1994. He finds that depreciation is positively associated with larger budget deficits and higher growth in domestic credit. Sachs, Tornell and Velasco's (1996) use cross-country regressions to explain the Tequila (Mexican) crisis of 1995. Using a crisis index defined as the weighted sum of the percentage decrease in foreign reserves and the percentage depreciation of the peso, they conclude that countries have more severe attacks when they have low foreign reserves, their banking systems are weak and their currencies overvalued. Tornell’s (1999), using a linear model in studying the Tequila and Asian crises suggest that the crises did not spread in a purely random way. Rather, there was a set of fundamentals help to explain cross-country variation of severity of the crises, which includes the strength of the banking system, the real appreciation and the international liquidity of the country. He also finds that the same model that explains the spread of the crisis in Latin American in 1995 also explains the cross-country variation in the

1997 crisis. Krkoska (2000) estimates a restricted VAR on quarterly data from 1994 to 1999 to analyze the vulnerability in transition countries. Results of the VAR reveal that overvaluation, a slowdown in the EU, as well as the gap between the current account and FDI, are the significant predictors of vulnerability in transition countries. More recently, Markov Switching approach has been adopted to explain the currency crisis in different regimes. Abdul Abiad (2003) uses a time-varying transition probability Markov-switching model on monthly data for five Asian crisis economies from January 1972 to December 1999. He initially explores 22 indicators of macroeconomic imbalances, capital flow and financial fragility. The indicators that can explain the currency crisis for different countries are slightly different. Furthermore, he suggests that panel data regression models with parameter equality across countries may lead to incorrect estimates and poor predictive performance.

These approaches have limitations. For example, the signal approach requires the ex-ante definition of a threshold and the transformation of the variables into binary variables, with a significant loss of information; the Logit/Probit approach requires the definition of a crisis dummy, with potential misclassifications (Brunetti, Mariano, Scotti and Tan, 2007).

In summary, empirical studies suggest that deteriorating fundamentals increase the probability of a crisis. However, the exact timing of a crisis has not been predicted with high precision. Speculators will observe that weak fundamentals drive a currency to a vulnerable zone to be attacked. However, the decision to attack is determined by the probability that speculators will gain profit by attacking the currency.

3.4 Exchange Rate Market Pressure (MP) and explanatory variable

Exchange market pressure has been variously defined in the literature, but the most commonly used definition sees MP as an excess money phenomenon driven by abnormally large excess domestic currency demand or supply, which forces the monetary authorities to take measures to stem disruptive appreciation or depreciation of the currency. Defined in this way, MP reflects monetary disequilibrium that drives the demand for a safe-haven currency, and may be exacerbated by foreign exchange market intervention. Following the pioneering study of Girton and Ruper (1977), the measure of speculative market pressure on the exchange rate, MP, is measured as a weighted average of the percentage changes of exchange rate and the percentage change (loss) in international reserve, where the weights are equal to the inverse of the (sample period) standard deviation or variance[33]. Such design is used to capture the monetary authorities' interventions in attempting to stabilize the exchange rate. It is often argued that interest rate changes should be included in the weighted average (see, e.g., Eichengreen et al., 1996; Kaminsky & Reinhart, 2000), but these are frequently omitted since data on interest rates for developing economies are not complete[34]. Some other studies exclude interest rates as they argue that the increase in interest rates in the presence of speculative pressure is highly correlated with the

[33] In Girton and Ruper (1977) the weights were set at one, given the theoretical underpinnings of their work.
[34] In fact, these limitations on the measurement of MP have been faced by many researches (e.g. International Money Fund, 1998; Glick and Rose, 1998; and Tornell, 1999).

non-sterilized foreign exchange invention leading to a fall in the reserve. We include interest rate changes in the measure of MP.

MP is generally a good index of currency crisis as it reflects different manifestations of speculative attacks, be they successful or otherwise. The MP which consists of a weighted average of nominal exchange rate, reserves and interest rate changes usually implies a sample-dependent crisis threshold level which is set (arbitrarily), sometimes, to ensure a certain percentage of crisis in the sample (e.g., Caramazza et al, 2000). However, there are drawbacks in this method of identifying crisis: in large samples, a high volatility regime will tend to dominate the whole sample, and the fixed threshold will also fail to identify a crisis that happened in a low volatility regime. Therefore, a fixed threshold tends to ignore the shift in exchange rate regime. To avoid mistakenly identifying the effect of high inflation for speculative pressure, a separate definition of crisis is sometimes used for high inflation countries[35].

The (weighted average) exchange market pressure index may also be defined by removing the restriction of a fixed variance for the constituents of MP, thus the weights are the inverse of the conditional variances of the constituents. By allowing the conditional variance of the MP be time-varying, MP index will have higher volatility with this volatility being generated by market uncertainty or shocks[36]. The

[35] Kaminsky et al (1998) uses a different index for subsamples when inflation in the last 6 months exceeded 150%; Corsetti et al (1998) omits the changes in the depreciation component of the crisis index when the rate of depreciation is less than the previous three-year average.
[36] By using fixed weights (i.e., a fixed sample period specific variance) shocks and market uncertainty have the same influence.

weights (inverse of the conditional variance) may be set to be proportionate or specific to each constituent[37]. The one period ahead forecast variance (conditional variance) may be captured by the changes in nominal exchange rate conditioned on the macroeconomic variables that have the most impact on MP. Conditional variances are estimated using a GARCH (Generalized Autoregressive Conditional Heteroscedasticity) model. However, we find the use of GARCH structures makes it even harder to use any estimated Markov regime-switching model for "prediction" purposes. Thus in this study we use the constant weights based on the sample period data instead of using the time varying weights.

The macroeconomic variables we employed to explain the MP include (1) the ratio of international reserves to broad money, RM2; (2) the real exchange rate, RER; (3) the growth of real domestic credit, GDC; and (4) exchange risk premium, Risk. All these variables are familiar from the literature and will require no further analysis or rationalizations. Therefore, we provide just a brief description of these variables.

The ratio of international reserves to broad money, RM2, is calculated as foreign reserves (IFS[38] line 1l.d) converted into domestic currency using end of period exchange rate (IFS line AE) divided by broad money (IFS line 34 plus 35). RM2 serves as a proxy for the government's contingent liabilities (Sache et al., 1996).

[37] For example, Eichengreen et al (1995) use equal conditional variance weights and Lumdaine and Prasad (2003) use proportionate weights of the conditional variance of output growth fluctuations.
[38] IFS stands for International Money Fund's International Financial Statistics.

Tornell (1999) argues that if a government is not willing to let the exchange rate to depreciate, it must be prepared to cover all the liabilities of the banking system with reserves. During a crisis banks are likely to experience runs. If the central bank does not act as a lender of last resort, generalized bankruptcies are likely to follow. Since, in most circumstances, authorities will not find it optimal to allow the economy to experience generalized bankruptcies, the central bank will have to be prepared to exchange the amount withdrawn by depositors for foreign exchange. Thus, it is M2, and not simply the monetary base, that must be the relevant proxy of the central bank's contingent liabilities. Accordingly, the RM2 represents financial fragility due to reserves inadequacy. Esquivel and Iarrain (1998) argue that this measure of reserve availability reflects better the vulnerability of the central bank to possible runs against currency. An expected decline in RM2, i.e., rising reserves inadequacy tends to increase MP since the market foresees that the stock of reserves will be inadequate to defend the exchange rate in the event of a speculative attack. We expect to find a negative relation between RM2 and MP. However, it may also be possible that a rising RM2 could enhance the possibility of a crisis, since it may highlight the potential danger of reversal of capital inflows. The latter may have contributed to increasing M2 in the first instance.

The real exchange rate, RER, is measured in two steps (following Ford, et al, 2007). First, we take the natural logarithms of the average exchange rate of domestic currency against US dollars (IFS line RF) multiplied by US consumer price index

(IFS line 64) and divided by domestic consumer price index (IFS line 64). Second, we subtract the first figure from their past 36 months' average. This two-step procedure is a measure of the deviation of real exchange rate from its three years' previous average. One benefit of the two step procedure of measuring RER is that the resultant data will be more likely to be stationary than the unadjusted data. A positive (negative) real exchange rate indicates a real depreciation (appreciation) of domestic currency. The real exchange rate effect is ambiguous. An expected increase in the real exchange rate, i.e., a depreciating real exchange rate will tend to exert upward pressure on MP (e.g. see, Kaminsky and Reinhart, 1999; Corsetti et al, 1998; Sachs et al, 1996) if the increase is driven by rising pressure on the nominal exchange rate in a fixed or tightly managed exchange rate regime, by reducing the price competitiveness of exports, culminating in large current account deficits and eventually declining economic growth. This is highly probable if the market perceives rising macroeconomic imbalances such as credit growth and rising stock of non-performing loans, current account imbalances and declining reserves sustained over a period of time. Otherwise, a rising real exchange rate can be beneficial for an economy since it effectively improves the trade competitiveness of domestic exports. This can happen in normally high inflation economies where stabilization policies are effective. Another reasons for the exchange rate impact to be ambiguous is that the exchange rate have a tendency towards overshooting if the response of output to a currency depreciation is small following an increase in the money supply, under price rigidities (Obstfeld and Rogoff, 1995).

The growth of real domestic credit, GDC, is calculated as a first difference of the natural logarithm of total domestic credit (IFS line 32) adjusted for inflation using consumer price index (IFS line 64). It is widely accepted that linkage between domestic credit and speculative attacks on the currency exist. Excessive growth of domestic credit may serve as an indicator of the fragility of the banking system. Although it is not an ideal indicator for financial fragility, this variable is available on a timely basis and is comparable across countries[39]. Domestic Credit usually rises in the early phase of the banking crisis. It may be that as the crisis unfolds, the central bank may be injecting money to the banks to improve their financial situation. A larger amount of credit increases the chances of bad loans and bank failures (see, Mete Feridun, 2006). The growth of real domestic credit will reflect budgetary policy and the potential for inflation. Higher credit implies a larger amount of money supply. Currency crises have been linked to rapid growth in credit and the monetary aggregates. As the growth rate of domestic credit captures the effects of monetary policies, it is usually expected to have a positive effect on currency market pressure. A number of empirical studies in the literature have found that domestic credit is one of the significant indicators of currency crises (for example, Moreno, 1995; Frankel and Rose, 1996; Kaminsky et al., 1997; Berg and Patillo, 1999; Glick and Moreno, 1999; Geochoco-Bautista, 2000; Krkoska, 2000 and Krznar, 2004).

39 According to Aaron Tornell, 1999, ideally, one should measure the weakness of the banking system with the "true" share of bad loans. Unfortunately, this information is available neither on a timely basis nor in data sources that ensure cross-country comparability. First it may not comparable because the accounting rule they adopted, second is the problem arised from misreporting.

The risk premium, Risk, is calculated, following Frankel and MacArthur (1988), as the forward discount rate less the expected (proxied by the one period ahead; as per rational expectation) rate of depreciation of the domestic currency. The foreign exchange risk premium represents compensation required by risk-averse investors for holding an asset whose only risk depends on being issued in a particular currency. A decrease in the risk premium would produce an increase in the demand for home-currency denominated assets, thereby, easing or overturning the depreciating pressure on the domestic currency, therefore, lowering the exchange market pressure.

Data used in this study are monthly data over the period January 1980 to May 2008, and data source is the International Monetary Fund's *International Financial Statistics* (IFS). Using data from such source makes the data reliable and comparable across countries.

We plot the Market pressure and its components for the six countries in Figures 3.A.1 to 3.A.6, Appendix 3.A. Descriptive statistics and cross correlations between dependent and independent variables are reported in Tables 3.A.1 to 3.A.12. Augmented Dickey-Fuller(ADF) unit root test (1997) and Kwiatkowski Phillips Schmidt Shin test (KPSS) (1992) test[40] are employed to examine the rank of these variables, which confirms that all the variables are stationary, expect that the GDC

[40] The null hypothesis for ADF test is that the series has a unit root; while the null hypothesis for KPSS is that the series is stationary. Intercept but no trend was included in the test equations.

and RM2 for Thailand and Malaysia, RM2 for Korea and Philippines are I(1). ADF and KPSS unit root test statistics and critical values are given in the bottom of the tables. The equation has potential spurious relations since the dependent variable and the independent variables seem to contain similar information. However, the zero order correlation matrix as well as the cross correlation with 36 leads and lags[41] show small correlation coefficients between MP and each of the independent variables. Thus the concerns are not substantial and as a matter of fact, similar formulation has been used by International Monetary Fund (1998) and other literature (see for e.g. Tornell, 1999; Ford et al, 2007 and International Monetary Fund, 1998). Therefore, we can confirm that we can use the model for our analyses.

[41] The resultant extensive tables for the cross correlations are available upon request.

3.5 Methodology

Markov Switching models are chosen in this study to explain the exchange market pressure because it has several theoretical advantages. First, in contrast to OLS and Probit models, Markov switching allows for nonlinear behavior, that is, behaviour that varies depending on the state, thus do a better job in describing the speculative attack than the simple linear models (Jeanne and Masson, 2000; Piard, 1997 and Psaradakis et al. 1997). Second, Markov Switching can provide an explicit measure of the probability of a crisis as Probit/Logit models do. Meanwhile, it permits full use of the continuous dependent variable while endogenously determining the probability of a switching regime. This could overcome the problem of information loss and sample bias when using Probit/Logit modelling methods, which involves creation of the a discrete dependent variable and arbitrary cutoff in the underlying Market Pressure in defining a period of crisis according to an ex-ante threshold value[42].

Since the inception of the state-dependent Markov-switching model, which was developed by Hamilton (1989) to model time series with changes in regime, various extensions and empirical tests have been carried out. One development is to combine Markov-Switching with the ARCH (termed as SWARCH model) and GARCH

[42] Flood and Marion (1998) argue that many models of speculative attack indicate that unanticipated devaluations produce the largest jump in the MP. The size of jumps in the MP at the time of attack is reduced by the extent to which the attack is anticipated. Thus, selection of only extreme values of the MP (as inconstruction of the dependent variable for probit models) may reduce the share of predictable crises in the sample and reduce the number of crises that are likely to be correlated with fundamental economic determinant.

models, as introduced by Hamilton and Susmel (1994), Cai (1994) and Gray (1996). For all those models, the conditional volatility process is allowed to switch stochastically between a finite numbers of regimes. The timing of regime switching is usually assumed to follow a first-order Markov process. The transition probability of the Markov process determines the probability of switching to another regime, and thus the average length of time before a specific other regime is reached. Transition probabilities may be constant or a time-varying function of exogenous variables, depending on which is appropriate to describe the data. Hamilton and Susmel (1994) and Cai (1994) consider regime switching models with ARCH innovations. They argued that it cannot be extended into a switching GARCH model since the model is path-dependent and thus difficult to estimate. Gray (1996) introduced path-independent switching GARCH, which is more general regime switching model that allows for GARCH dynamics. In our study, we extend Gray's (1996) Markov Switching GARCH model by incorporating an asymmetric component in to the model. One argument about using GARCH type model is that such models can only have relevance, and indeed be found to be so, when weekly or daily data are being used. However, weekly and daily data are not available for most explanatory variables of the exchange market pressure. Although the argument in the literature seems to be valid, in the empirical work, better results were obtained by using GARCH, than assuming constant variances for market pressure across and within the two regimes (see, e.g., Ford, et al., 2007). Baillie and Bollerslev (1989) also shown that the GARCH type models is able to capture the volatility dynamics of exchange rates at monthly frequencies. Even if the GARCH effect dissipates as the length of the sampling interval increases, there is still heteroscedasticity and volatility clustering at monthly frequencies.

Recent studies provide strong evidence that real exchange rates are characterisd by mean reverting process (Taylor, 2000). It has been shown that adjustment to equilibrium value is related not only to the size but also to the sign of shocks (undervaluation and overvaluation, the so called asymmetric effect). Within the GARCH type models, Threshold GARCH (TGARCH) and Exponential GARCH (EGARCH) models are normally employed to incorporate the asymmetric effects. Although it is argued in some literature that EGARCH model is superior in modelling asymmetric effect by allowing the separation of good news effects from bad news effects, EGARCH model is too sophisticated that its performance is highly subject to data frequency. Given only monthly data are the availability for the fundamental variables to set up the model, the TGARCH model is chosen in this study rather than the EGARCH model.

Now we turn to the methodology we employed in this study. First, let's consider the regression model for currency crisis in a single economic regime. One observation that emerges from survey of the currency models is that MP rises to the crisis threshold level when macroeconomic fundamentals deteriorate. The market may perceive that the fundamentals are becoming increasingly inconsistent with the (implicit) peg, therefore, attack on the currency is launched, which induces reserves losses and consequently, a high MP. Because of market inefficiency, the market reacts to the changes in the state of the fundamentals with a lag. However, it is reasonable to expect that the current level of MP is determined by the "expected" values of the macroeconomic fundamentals held in the previous period, of the state of the fundamentals in the next period. The growing market integration makes this even more likely.

There are several ways to model the impact of *market expectations* of the fundamentals[43]. We adopt the specification of Duesenberry (1958)[44]. The mechanism of Duesenberry's specification is based on the premise that the market forms an expectation at time *t-1* of what the macroeconomic variables will be at time *t*, by reference to their experience of the past realized values of those variables and their recent change. In its simplest form, the expected value of x can be written as

$$E_{t-1}x_t = \alpha x_{t-1} + \phi(x_{t-1} - x_{t-2}) = \alpha x_{t-1} + \phi \Delta x_{t-1} \tag{3.27}$$

Alternatively, the expected value of x may be determined by its recent past value and its change at the end of the current period. Therefore, the expected value of x is as follows:

$$E_t x_t = \alpha x_{t-1} + \phi(x_t - x_{t-1}) = \alpha x_{t-1} + \phi \Delta x_t \tag{3.28}$$

43 For example, the adaptive expectations mechanism that was first popularized by Cagan (1956), the polynomial distributed lags (PDL) proposed by Almon (1965) and the specification proposed by Duesenberry (1958).

44 Duesenberry's formulation gives the best statistical results overall among the ones we experimented with.

Following the Duesenberry's type of adaptive expectations, the dynamic equation of MP can be written as

$$\begin{aligned} MP_t = \beta_0 &+ \underset{(+)or(-)}{\beta_1 RM2_{t-1}} + \underset{(+)or(-)}{\beta_2 RER_{t-1}} + \underset{(+)}{\beta_3 GDC_{t-1}} + \underset{(+)}{\beta_4 Risk_{t-1}} \\ &+ \underset{(+)or(-)}{\beta_5 DRM2_t} + \underset{(+)or(-)}{\beta_6 DRER_t} + \underset{(+)}{\beta_7 DGDC_t} + \underset{(+)}{\beta_8 DRisk_t} + \varepsilon_t \end{aligned} \tag{3.29}$$

where $DRM2_t = RM2_t - RM2_{t-1}$, $DRER_t = RER_t - RER_{t-1}$

$DGDC_t = GDC_t - GDC_{t-1}$, and $DRisk_t = Risk_t - Risk_{t-1}$

Equation (3.29) is the core/base equation for market pressure. We can write the equation using matrix

$$y_t = x_t\beta + \varepsilon_t \qquad \varepsilon_t \sim i.i.d.N(0,\sigma^2) \tag{3.30}$$

Where x_t is a $1\times k$ vector of exogenous variables (where $x_t = (RM2_{t-1}, RER_{t-1}, GDC_{t-1}, Risk_{t-1}, DRM2_t, DRER_t, DGDC_t, DRisk_t)'$ and $y_t = MP_t$.

To estimate the parameters of the model, the density and log likelihood functions are

$$f(y_t \mid x_t, \psi_{t-1};\theta) = \frac{1}{\sqrt{2\pi\sigma^2}}\exp\left(-\frac{(y_t - x_t\beta)^2}{2\sigma^2}\right) \tag{3.31}$$

$$\ln L(\theta) = \sum_{t=1}^{T} \ln\left[f(y_t \mid x_t, \psi_{t-1};\theta)\right] \tag{3.32}$$

The log likelihood function can be maximised with respect to β and σ^2. ψ_{t-1} denotes the vector of observations obtained through date *t-1* and θ is the vector of unknown parameter ($\theta \equiv (\beta', \sigma^2)'$).

Now we consider modelling the volatility. Following the standard assumption about the serial dependence of ε_t (Hamilton, 1994), the conditional variance can be modelled as

$$\varepsilon_t = \sqrt{h_t} \cdot \upsilon_t \tag{3.33}$$

Where υ_t is an i.i.d sequence with zero mean and unit variance. Hamilton (1994) maintains that 'even if those assumptions are invalid, the ARCH specification can still offer a reasonable result on which to base a linear forecast of the squared value of υ_t'.

The behaviour of h_t in equation (3.33) determines the presence and nature of any conditional heteroscedasticity. The specifications that we use in this study are:

1. No ARCH effects (constant volatility)

$$h_t = \sigma^2 = \text{constant} \tag{3.34}$$

2. TGARCH(1,1)[45] (Glosten, Jaganathan and Runkle, 1993)

$$h_t = V_0 + V_1\varepsilon_{t-1}^2 + V_2 h_{t-1} + V_3\varepsilon_{t-1}^2(\varepsilon_t < 0) \tag{3.35}$$

In this model, positive shock $(\varepsilon_t > 0)$ and negative shock $(\varepsilon_t < 0)$ have different impact on the conditional variance. Positive shock has an impact of V_1, and negative shock has an impact of $V_1 + V_3$. Should $V_3 \neq 0$, asymmetric information shock exists. The covariance stationary condition is satisfied when $V_1 + V_2 < 1$ or $V_1 + V_2 + V_3 < 1$.

Second, we relax the assumption of a single economic regime and let the regression coefficients differ in each regime to account for the possibility. Thus we have the

[45] Several GARCH-type specifications, including the general GARCH, TGARCH, and Diagonal GARCH, in both single regime models and 2 regimes Markov Switching models, were experimented with in this study. Among them, TGARCH models dominate the others, according to the LR test statistics and significance of the coefficients in the TGARCH specification.

regime switching model to account for the possibility that the economic mechanism that generates the dependent variables may undergo a finite number of changes over the sample period. In the Markov switching model, although the states are not observable, their probability of occurrence can be estimated, conditional on the given information set. In our study, we assume that the model has two states, S_t (in our study, the two states are a stable state and a volatile state). In regime 1, we have $S_t = 0$, and in regime 2, we have $S_t = 1$. Regime switching is assumed to be directed by a first-order Markov process with transition probabilities given by

$$\Pr = \begin{bmatrix} P_{11} & P_{21} \\ P_{12} & P_{22} \end{bmatrix} = \begin{bmatrix} P & 1-Q \\ 1-P & Q \end{bmatrix} \tag{3.36}$$

Where

$$\Pr\left[S_t = 0 \mid S_{t-1} = 0\right] = P$$

$$\Pr\left[S_t = 1 \mid S_{t-1} = 0\right] = 1-P$$

$$\Pr\left[S_t = 1 \mid S_{t-1} = 1\right] = Q$$

$$\Pr\left[S_t = 0 \mid S_{t-1} = 1\right] = 1-Q$$

S_t is the latent Markov chain of order one. P and Q are transitional probabilities, which determines the probability of the system remaining in the same state. We note the conditional probability that it is in state i at time *t*, given the latest observations on the variables in the system, as π_i, where $\pi_i = \Pr\{S_t = i \mid \psi_{t-1}\}$. ψ_{t-1} denotes the information on the system at the end of period *t-1*. The regime probability is thus the ex-ante probability of a particular state at time *t*, conditional on the information available at time *t-1* and is a key input for forecasting.

A model with a structural break in the parameter (Kim and Nelson, 1999) can be formulated as

$$y_t = x_t\beta + \varepsilon_t \qquad \varepsilon_t \sim i.i.d.N(0,\sigma^2) \tag{3.37}$$

$$\beta_{S_t} = \beta_{S_0}(1-S_t) + \beta_{S_1}(S_t) \tag{3.38}$$

$$h_{S_t} = h_{S_0}(1-S_t) + h_{S_1}(S_t) \tag{3.39}$$

$$S_t = 0 \quad \text{or} \quad S_t = 1 \tag{3.40}$$

β_{S_0} represent parameters in state $S_t = 0$, and β_{S_1} represent the parameters when $S_t = 1$, same for σ_{S_0} and σ_{S_1}.

If S_t is observable and known *a priori*, equation (3.37) can be estimated as a model with the dummy variable, S_t. However, if S_t is unobserved at time *t* and is not known *a priori*, Markov Switching model offers a way to estimate it (Kim and Nelson, 1999). First, the joint density of y_t and the unobserved S_t variable is a product of the conditional and marginal densities as follows:

$$f(y_t, S_t \mid \psi_{t-1}) = f(y_t \mid S_t, \psi_{t-1}) \cdot f(S_t \mid \psi_{t-1}) \tag{3.41}$$

Second, by summing over all possible values of S_t, the marginal density of y_t is:

$$\begin{aligned} f(y_t, \mid \psi_{t-1}) = {} & \frac{1}{\sqrt{2\pi\sigma_{S_0}^2}} \exp\left(-\frac{(y_t - x_t\beta_{S_0})^2}{2\sigma_{S_0}^2} \right) \cdot \Pr\left[S_t = 0 \mid \psi_{t-1}\right] \\ & + \frac{1}{\sqrt{2\pi\sigma_{S_1}^2}} \exp\left(-\frac{(y_t - x_t\beta_{S_1})^2}{2\sigma_{S_1}^2} \right) \cdot \Pr\left[S_t = 1 \mid \psi_{t-1}\right] \end{aligned} \tag{3.42}$$

Where

$$\begin{aligned} \Pr\left[S_t = 0 \mid \psi_{t-1}\right] = {} & \Pr\left[S_t = 0 \mid S_{t-1} = 0\right] \cdot \Pr\left[S_{t-1} = 0 \mid \psi_{t-1}\right] \\ & + \Pr\left[S_t = 0 \mid S_{t-1} = 1\right] \cdot \Pr\left[S_{t-1} = 1 \mid \psi_{t-1}\right] \\ & = P \cdot \Pr\left[S_{t-1} = 0 \mid \psi_{t-1}\right] + (1-Q) \cdot (1 - \Pr\left[S_{t-1} = 0 \mid \psi_{t-1}\right]) \end{aligned} \tag{3.43}$$

and

$$\begin{aligned}\Pr\left[S_t=1\,|\,\psi_{t-1}\right]&=\Pr\left[S_t=1\,|\,S_{t-1}=0\right]\cdot\Pr\left[S_{t-1}=0\,|\,\psi_{t-1}\right]\\&\quad+\Pr\left[S_t=1\,|\,S_{t-1}=1\right]\cdot\Pr\left[S_{t-1}=1\,|\,\psi_{t-1}\right]\\&=(1-P)\cdot\Pr\left[S_{t-1}=0\,|\,\psi_{t-1}\right]+Q\cdot(1-\Pr\left[S_{t-1}=0\,|\,\psi_{t-1}\right]\end{aligned}\tag{3.44}$$

The log likelihood function (L) is given by

$$\begin{aligned}\ln L&=\sum_{S_t=0}^{1}\ln\left[f(y_t\,|\,S_t,\psi_{t-1})\cdot\Pr\left[S_t\,|\,\psi_{t-1}\right]\right]\\&=\ln\left(f(y_t\,|\,S_0,\psi_{t-1})\cdot\Pr\left[S_0\,|\,\psi_{t-1}\right]+f(y_t\,|\,S_t,\psi_{t-1})\cdot\Pr\left[S_t\,|\,\psi_{t-1}\right]\right)\end{aligned}\tag{3.45}$$

At the end of time t, when y_t is observed, it is possible to make infer which regime was the more likely to have been responsible for producing the observation y_t (Hamlition, 1994). The filtered probability of regime $S_t=0$ is given by (Kim and Nelson, 1999; Hamilton, 1994)

$$\Pr\left[S_t=0\,|\,\psi_t\right]=\frac{f(y_t\,|\,S_t,\psi_t)\cdot\Pr\left[S_t=0\,|\,\psi_t\right]}{f(y_t\,|\,\psi_t)}\tag{3.46}$$

Whereas the filtered probability of the state $S_t=1$ is given by

$$\Pr\left[S_t=1\,|\,\psi_t\right]=1-\Pr\left[S_t=0\,|\,\psi_t\right]\tag{3.47}$$

The unconditional or steady state probability of S_t is given by

$$\kappa=\begin{bmatrix}\kappa_0\\\kappa_1\end{bmatrix}=\begin{bmatrix}\dfrac{1-Q}{2-P-Q}\\\dfrac{1-P}{2-P-Q}\end{bmatrix}\tag{3.48}$$

In this instance, we assume that the transitional probability is constant. The transitional probability can also be time varying, which was developed by Biebold et al. (1994). Actually, we estimated the models with time varying transitional probabilities for currency crisis following Peria (2002) and Brunetti et. al (2007)[46]. The time varying transitional probabilities were determined by the variables that are assumed to affect market pressure. However, the estimates produced were chaotic. There were no clear indications of different states. Moreover, models with constant transitional probability were preferred than the time varying counterparts as indicated by various tests. Therefore, this study abandoned the use of time varying transitional probability and focus on the models with constant transitional probability.

In practice, the log likelihood function is maximised by different non-linear algorithms[47]. Engle and Kroner (1995) suggest that BHHH is particularly advantageous for GARCH(1,1) models, by comparing the biasedness, the size and power of tests between the BHHH and BFGS. In this study, we estimated the models using both of the above two algorithms, we find that BHHH do not show more advantage than BFGS methods for the Markov Switching model with TGARCH(1,1) set up and BFGS methods helps to achieve convergence for the Markov Switching models.

---

[46] In Peria (2002), instead of modelling MP, the percentage change in the exchange rate itself were modeled by a 3-variable VAR regime switching model. The time varying transitional probabilities are estimated as logistic functions of a conditioning matrix x_{t-1}, as shown below

$$P = \frac{\exp(x'_{t-1}\beta_{S_0})}{1+\exp(x'_{t-1}\beta_{S_0})} \quad \text{and} \quad Q = \frac{\exp(x'_{t-1}\beta_{S_1})}{1+\exp(x'_{t-1}\beta_{S_1})}$$

[47] Hamilton (1994) shows that the mixture density in Equation (3.42) has the property that a global maximum of the log likelihood in Equation (3.45) does not exist. A singularity may arise, but normally it does not cause a serious problem, since numerical maximisation procedures typically converge to a reasonable local maximum rather than a singularity. If a numerical maximisation algorithm becomes stuck at a singular solution, we can simply ignore it and try again with different starting values.

Maximisation of the log likelihood Equation (3.45) provides a time-path of the conditional regime probability. By maximising the log likelihood equation, we estimate the parameters including the transitional probabilities of Markov Switching Model. Through the estimates of the transitional probabilities, we can estimate several important characteristics of each regime: (a) their unconditional probabilities, or "limit", which is given by κ ; (b) forecasts of the probability that a given regime will follow a currency regime in the next period, which is given by Equations (3.42) and (3.43); (c) when the system is in a given regime, the expected duration of each regime, which is given by $1/P_{12}$ and $1/P_{21}$.[48] In addition, which conditional probability relates to a given state of the economy at a particular period can be conjectured, by using indicators of when the market pressure is "high" or "low", as depictions of "volatile" regime/state, and when market pressure is in the middle range, as depiction of "stable" regime/state. Which unconditional probability applies to which type of regime can then be assessed by a probability forecasting statistics of those indicator, for example, quadratic probability score (QPS) used by Diebold and Rudebusch (1989). Additional statistics, such as the log probability score (LPS) test and the global squared bias (GSB) test are also employed in our study to access the forecast calibration of the probabilities[49], so to determine the state of the exchange market pressure at a given time.

[48] "Limit" is the description given in the mathematical literature on Markov chains (see, for example, Kemeny and Snell (1976)). Full detail on the derivations of (a), (c) can be found in that text: the relevant formulae are provided in Goldfeld and Quandt (1973). (b) is covered in Hamilton (1994), as is (a), amongst other sources.

[49] Such tests were also used in Ford, et al (2009) in a similar manner.

The determination of how many regimes (i.e. one regime versus two regimes) are there is also accessed in our study. This is not straightforward in these models. Applying the standard LR statistic to test one versus two regimes is problematic. As argued by Cho and White (2007), ‘this lead to the geometric growth of the population variance of the log-likelihood first derivative under the null, ruling out application of standard central limit results’. Moreover, the power of such a test turns out to be weaker than in the standard cases (e.g., Hansen, 1992, obtained a lower bound for the limiting distribution of a standardized LR statistic). Cho and White (2007) attempt to surmount these problems by formulating a Quasi-likelihood Ratio (QLR) test, which is sensitive to the mixture aspect of the regime–switching process and thus a test with appealing power, however, they can provide no general distributions by which we can evaluate QLR. As a result, most studies of regime-switching models rely upon the conventional LR test for determine the number of regimes (see, e.g. Peria, 2002). Lindsay (1995) gave an alternative test for whether more than one regime exists. He argued that such an assessment can be determined by an evaluation of the normality of residuals from one regime model. If the residuals from one regime model are not normally distributed, the assumption of only one regime is distorted by the existence of other regimes which those residuals cannot accommodate. Therefore, a Jaque-Bera test (JB) and Lindsay (1995) $C(\alpha)$ score distortion test can be used to test normality. Bootstrapping methods[50] were also employed as a supplement for such purpose. The

[50] Bootstrapping is the practice of estimating properties of an estimator (such as its variance) by measuring those properties when sampling from an approximating distribution. In the case where a set of observations can be assumed to be from an independent and identically distributed population, this can be implemented by constructing a number of resamples of the observed dataset (and of equal size to the observed dataset), each of which is obtained by random sampling

bootstrapping methods were used to establish that the residuals from the 1 Regime model estimates are random sample from a given population. Consequently, we assess the JB statistics for 500 replications of the distribution of the residuals. We do this to see if the JB statistic obtained can be acceptable at the 95% confidence level. Also, we use 100 replications to determine the number of modes in the distribution to see if the distribution to the residuals has more than 1 mode. If it should have more than 1 mode then the residuals cannot be normally distributed and there is an a priori presumption that more than 1 regime lies behind the data on the MP variable. Another alternative, which can be used to detect not only whether more than one regime exists, but also the number of regimes, is the Neyman's $C(\alpha)$ test. The test was designed to deal with hypothesis testing of a parameter of primary interest in the presence of nuisance parameters. Different from the version of Lindsay (1995) $C(\alpha)$ score distortion test, which is concerned with a measure of whether the residuals of the one regime model differ from normality thus we can use it to estimate only for the assumption that there is a single regime within the Markov switching model, this version of $C(\alpha)$ test is calculated by means of regressions to circumvent the fact that the second derivatives of the log likelihood with respect to the parameters will be zero, so making it impossible to use the Information Equality matrix to arrive at $C(\alpha)$. As this version is designed to deal with hypothesis testing of a parameter of primary interest in the presence of nuisance parameters, therefore can be used as a supplement to the problematic standard LR test to evaluate the number of regimes. There are two ways

with replacement from the original dataset.

of calculating Neyman's $C(\alpha)$ statistics, given by Davidson and Mackinnon (1993) and Breusch and Pagan (1980) respectively. We use the latter in this study. The matrix algebra (formula) and regression method of the $C(\alpha)$ test are given in Appendix 4.B. The critical values for the $C(\alpha)$ test can be obtained from a χ^2_γ distribution, with γ being the number of restrictions, when one regime is excluded[51].

To sum up, we have defined the conditional mean and the conditional variance for the single regime and Markov-switching models, for our estimation of exchange Market Pressure. The conditional mean for the single regime model is given by

$$\begin{aligned} MP_t &= \beta_0 + \beta_1 \underset{(+)or(-)}{RM2_{t-1}} + \beta_2 \underset{(+)or(-)}{RER_{t-1}} + \beta_3 \underset{(+)}{GDC_{t-1}} + \beta_4 \underset{(+)}{Risk_{t-1}} \\ &+ \beta_5 \underset{(+)or(-)}{DRM2_t} + \beta_6 \underset{(+)or(-)}{DRER_t} + \beta_7 \underset{(+)}{DGDC_t} + \beta_8 \underset{(+)}{DRisk_t} + \varepsilon_t \end{aligned} \tag{3.29}$$

The conditional variance is as formulated in Equations (3.34) and (3.35). The conditional mean for Markov-Switching two regime model is defined as

$$\begin{aligned} &MP_t = (\beta_{0S_0}(1-S_t) + \beta_{0S_1}S_t) + (\beta_{1S_0}(1-S_t) + \beta_{1S_1}S_t)RM2_t \\ &+(\beta_{2S_0}(1-S_t) + \beta_{2S_1}S_t)RER_t + (\beta_{3S_0}(1-S_t) + \beta_{3S_1}S_t)GDC_t + (\varepsilon_{S_0,t,}(1-S_t) + \varepsilon_{S_1,t}S_t) \end{aligned} \tag{3.49}$$

Where

$$(\varepsilon_{S_0,t}(1-S_t) + \varepsilon_{S_1,t}S_t) = (\sqrt{h_{S_0,t}}(1-S_t) + \sqrt{h_{S_1,t}}S_t) \tag{3.50}$$

The conditional variance for Markov-switching is given by:

(1) No ARCH effects (constant variance)

$$[h_{S_0t}(1-S_t) + h_{S_1t}S_t)] = \text{constant} \tag{3.51}$$

(2) Threshold or asymmetric GARCH(1,1) effects

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[51] An excellent exposition of the statistic and the related Rao score statistic (RS) can be found in Bera and Bilias (2001). They also provide an alternative regression method to that of Breusch and Pagan (2001). Also see Davidson and MacKinnon (1991) on the application of the regression method.

$$
\begin{aligned}
[h_{S_0,t}(1-S_t)+h_{S_1,t}S_t)] &= [V_{0S_0}(1-S_t)+V_{0S_1}S_t] \\
&+[V_{1S_0}(1-S_t)\varepsilon^2_{S_{0,t-1}}+V_{1S_1}S_t\varepsilon^2_{S_{1,t-1}}]+[V_{2S_0}(1-S_t)h_{S_{0,t-1}}+V_{2S_1}S_t h_{S_{1,t-1}}] \\
&+[V_{1S_0}(1-S_t)\varepsilon^2_{S_{0,t-1}}(\varepsilon_{S_{0,t-1}}<0)+V_{1S_1}S_t\varepsilon^2_{S_{1,t-1}}(\varepsilon_{S_{1,t-1}}<0)]
\end{aligned} \tag{3.52}
$$

One thing need to be mentioned is that the Markov Switching models we proposed above and Logit approaches (binary and multinomial Logit models) that we are going to discuss in section 3.7 which redefine MP in a “threshold” manner all use the market pressure as an indication of potential currency crisis. Apart from this, there are other ways to model currency crisis. One possible method is to model the percentage change in the exchange rate itself rather than MP, as in Peria (2002)’s study. Peria used a 3-variables VAR regime-switching model, which is based on a 3 equation VAR for the three constituents of MP (exchange rate change, change in reserves and interest rate change). It is also possible, of course, just to model the exchange rate depreciation/appreciation as function of the fundamental variables.

3.6 Empirical analysis

In this section, we present the results for the empirical estimations for six Asian countries, namely, Thailand, Malaysia, Korea, Indonesia, Singapore and Philippines, for the period from January 1980 to February 2008. For each country, the single regime constant (OLS) and TGARCH models were first estimated to evaluate the impact of the fundamental explanatory variables to the currency market pressure. Markov Switching models with constant variance and with TGARCH specification are then estimated. We find that when we model the exchange market pressure with two distinct regimes (stable and volatile), different behaviours for each regime emerge.

3.6.1 Empirical analysis for Korea

The constant (OLS) and TGARCH estimates for MP ignoring the possibility that alternative regimes exist, rather than the estimates from Markov-switching model under the assumption that there is one regime, is given in Table 3.1. For the constant model, the coefficients on RM2 and Risk are statistically not significantly different from zero at 5% significance level. For the TGARCH estimates, coefficients on RM2, GDC and DGDC are insignificant. All other fundamentals and risk variable have substantial impact on the exchange market pressure. However, the GDC, DGDC and

DRisk variables present incorrect expected sign. The Wald coefficient test is performed to test the joint restriction that the coefficients on the TGARCH conditional variances are jointly zero (i.e., $V_1 = V_2 = V_3 = 0$). The test statistics[52] reject the null hypothesis at 5% significance level. The significance of coefficients in the conditional variances imply that variance of market pressure is time dependent and conditional on past information. The significance of V_3 imply that asymmetric effect exist in the conditional variances, with positive shocks have larger effect on the volatility of market pressure. The conditional variance process is stationary, as $V_1 + V_2 + V_3 < 1$ in the conditional variance structure.

The graphs depicting the actual and fitted MP and the residuals from the fitted equations are portrayed on Figure 3.2, with constant model in Figure 3.2 (1) and TGARCH model in Figure 3.2(2). The estimated equation appears to track the movement market pressure well. This can also be proved by the estimation fitness, R^2 (reported at the bottom in Table 3.1), which indicate the around 80% of the market pressure can be explained by the fundamental variables in both of the single regime equation specifications. Jaque-Bera tests are larger than the critical value 5.99 at 5% significant level shows that the residuals from both estimations, which indicate the residuals are not normally distributed.

The empirical estimation results from the two regimes Markov Switching models for

[52] Wald test statistics (for all six countries in our study) are not reported in the table, but available upon request.

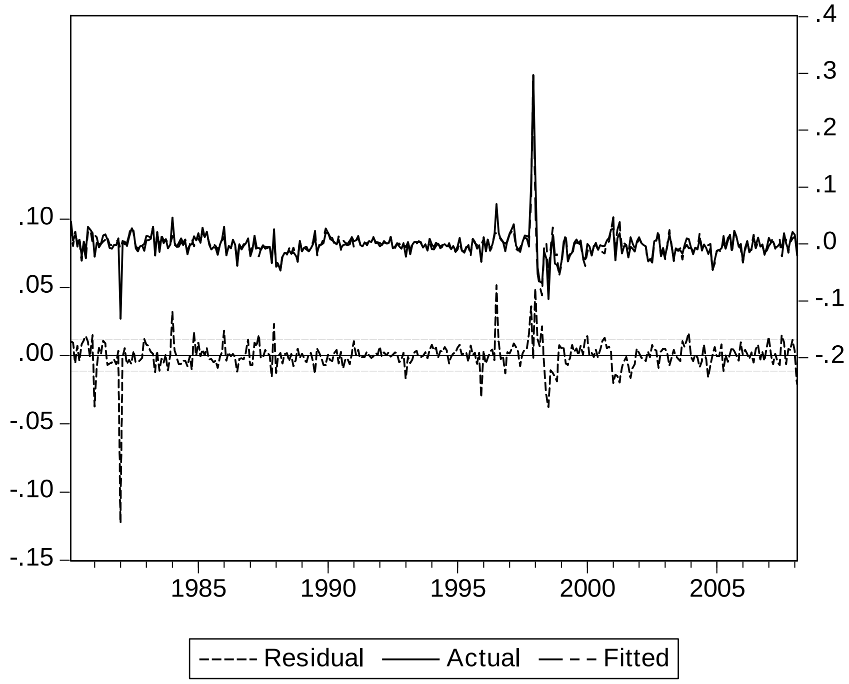
Table 3. 1 Estimation Results from Single Regime models for Korea

	Korea					
	Constant Variance			TGARCH		
	Coeff	Std Error	Signif	Coeff	Std Error	Signif
β_1	0.00237	0.00395	0.54970	0.00235	0.00238	0.32400
β_2	0.02989	0.00628	0.00000	0.03480	0.00743	0.00000
β_3	-0.20073	0.06182	0.00130	-0.00067	0.04832	0.98900
β_4	-0.00390	0.01361	0.77470	0.05123	0.00640	0.00000
β_5	-0.86115	0.07831	0.00000	-0.68450	0.06840	0.00000
β_6	0.83101	0.03100	0.00000	0.73579	0.04110	0.00000
β_7	-0.12518	0.04546	0.00620	-0.04542	0.03471	0.19070
β_8	-0.06934	0.01908	0.00030	-0.06190	0.02311	0.00740
v_0				0.00000	0.00000	0.90350
v_1				0.14072	0.03889	0.00030
v_3				-0.14703	0.03928	0.00020
v_2				0.94910	0.01198	0.00000
R^2	0.79772			0.77924		
$\bar{R}^2$	0.79342			0.77177		
JB	3516.18			1048.80		
Log(L)	1022.86			1047.66		
LR	49.60					

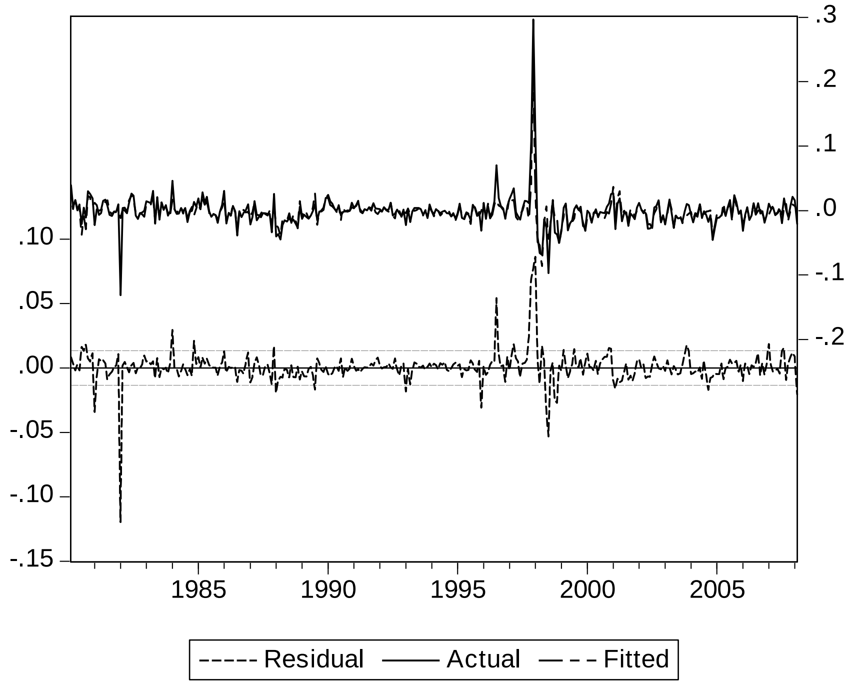
Note: The critical value for $\chi^2(3) = 7.81$, $\chi^2(2) = 5.99$

Figure 3. 2 Actual and fitted value of MP from single regime estimation: Korea

(1) Constant (OLS) model



(2) TGARCH(1,1) model



Korea are reported in Table 3.2. Those for 1 regime are not reported here but available upon request. Panel A is for the results from the Regime-Switching model with constant variances. Our finding confirms that the fundamental and risk variables play significant roles in triggering currency crisis. Coefficients on RER and Risk are not significant in the volatile state[53], but they are significant in the stable state. The coefficients on RM2 are not significant at 5% significance level in the stable state. All other variables have substantial on the market pressure in each state.

Now we turn to examine the Markov Switching TGARCH model for Korea reported in Table 3.2 Panel B. In the mean structure, majority of fundamental and risk variables are significant in the volatile state and all the explanatory variables are significant at 5% significant level in the stable state. Every variable has a statistically significant impact on market pressure in one regime or another.

In the conditional variance structure for the Markov-switching TGARCH model, coefficient V_1 measures the persistence of market pressure shocks and V_2 measures the persistence of shocks on conditional variance. The coefficient V_3 measures the asymmetric effect of positive and negative market pressure shocks. We can observe that the in the volatile state, all the three coefficients in the conditional variance are significant at 5% level. For the stable state, only the coefficient on the past squared

[53] The volatile and stable state can be readily identified in a 2 regime model, by drawing the probability of one regime against the MP series. However, statistical evidences for which regime represents which state (volatile or stable) is reported and discussed latter in this section. These methods to distinguish regimes of their states are particularly useful when there are more than two regimes, in which case the relationship between regimes and states are not that obvious.

residuals is significant. In both states, the V_3 coefficients are negative, which suggest that negative shocks have smaller effect. This means that the positive shocks, which increase currency market pressure, have larger impact on the market pressure volatility, though the impact is not significant in the stable state. In both state, we have $V_1 + V_2 + V_3 < 1$, and $V_1 + V_2 < 1$. Therefore, the TGARCH process is stationary[54].

As reported in Table 3.2, the transition probabilities of one regime switching to another, P_{12} and P_{21}, are significant at 95% confidence level. Since $2 - P_{12} - P_{21} > 1$, we can conclude that the process is likely to be persist in its current state rather than switching to the other. The average persistence of each state is reported in the bottom of the table. We can observe that the average persistence of volatile state is much lower than the persistence of the stable state. Another feature is the average persistence for the volatile states reduces in the TGARCH model comparing to in the constant model. In contrast, the average persistence for the stable state increases from 18.33 months under the constant model to 24.59 months under the TGARCH in the stable state. The unconditional probability of being in each regime (volatile or stable regime, represented by κ_{S_0} and κ_{S_1} respectively), is reported in the bottom of Table 3.2 as well. It is apparent that the unconditional probability of MP to be in the volatile state at a given time is much lower that the probability it is in the stable state.

We comment now to the comparison of the parameter significance across the constant

[54] It is also the case in the single-regime estimation.

variance (Panel A) and TGARCH Markov (Panel B) switching models. The likelihood ratio test is employed for this purpose. The likelihood ratio (LR) statistics are reported at the bottom of the table. The LR test follows a χ^2 distribution. Under the null hypothesis that the parameter for TGARCH (V_1, V_2 and V_3 are all zero in both state), we need to compare the LR Statistics to $\chi^2(6)$, with critical value of 12.59 at 5% significant level. Apparently, the LR statistics for Korea (39.75) is larger than the critical value, indicating the TGARCH effects are important in the Markov Switching model for Korea. Same conclusion can also be obtained from examining the significance of the TGARCH parameters in the variance, most of which are significant, especially in the volatile state.

Figure 3.3 (1) plots the actual and the fitted value of MP and residuals from the Markov Switching model with constant variance; and Figure 3.3 (2) for the Markov Switching TGARCH model. At a glance, we can see that the fitted values track the actual MP very well, for both constant and TGARCH models. Particularly they can track the increases in market pressure in Nov 1997 to Jan 1998. However, both models do not perform as well for the strong reduction in market pressure (possible appreciation currency crisis), for example, in the early period of 1982. In general, we can conclude the fundamental variables do have power in explaining the movement of MP.

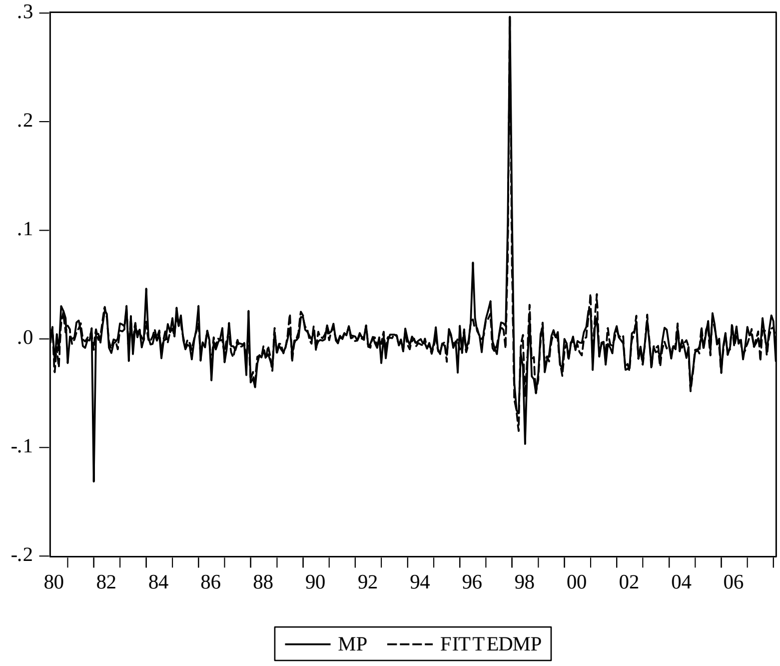
Table 3. 2 Parameter estimates and related statistics for Markov Regime Switching models: Korea

	Panel A						Panel B					
	Constant Variance: Korea						Threshold GARCH: korea					
	Regime 1 (Volatile State)			Regime 2 (Stable State)			Regime 1 (Volatile State)			Regime 2 (Stable State)		
Variable	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif
P_{12}/P_{21}	0.41683	0.10947	0.00014	0.05454	0.01624	0.00078	0.68902	0.16386	0.00003	0.04067	0.01459	0.00531
β_1	-0.08820	0.02648	0.00087	0.00028	0.00136	0.83869	-0.02380	0.02610	0.36179	-0.00363	0.00165	0.02753
β_2	0.03658	0.02534	0.14887	0.02569	0.00316	0.00000	0.13634	0.02195	0.00000	0.02824	0.00249	0.00000
β_3	-0.46334	0.12419	0.00019	-0.25477	0.02023	0.00000	-2.30885	0.14674	0.00000	-0.24412	0.01967	0.00000
β_4	0.01961	0.05026	0.69644	0.03313	0.00792	0.00003	0.24378	0.02579	0.00000	0.02081	0.00719	0.00377
β_5	-1.07692	0.35261	0.00226	-0.93009	0.02824	0.00000	-2.65854	0.34312	0.00000	-0.95275	0.03048	0.00000
β_6	0.87408	0.08103	0.00000	0.66611	0.01762	0.00000	0.73812	0.42277	0.08083	0.64105	0.02353	0.00000
β_7	0.29147	0.12656	0.02127	-0.21874	0.01582	0.00000	0.54503	0.06227	0.00000	-0.21735	0.01812	0.00000
β_8	-0.15391	0.03909	0.00008	-0.10588	0.01216	0.00000	-0.30196	0.10444	0.00384	-0.12942	0.01473	0.00000
v_0	0.00064	0.00009	0.00000	0.00003	0.00000	0.00000	0.00000	0.00002	0.85296	0.00002	0.00000	0.00000
v_1							0.19484	0.02465	0.00000	0.46666	0.14613	0.00141
v_2							0.75572	0.10924	0.00000	0.00004	0.10832	0.99969
v_3							-0.19109	0.02584	0.00000	-0.19053	0.18026	0.29051
κ	0.1157			0.8843			0.0557			0.9443		
Average Persistence	2.40			18.33			1.45			24.59		
Log(L)	1167.06						1186.94					
LR	39.75											

Note: The critical value for $\chi^2(6) = 12.59$

Figure 3. 3 Actual and fitted value of MP from Markov switching models: Korea

(1) Markov Switching constant variance model



(2) Markov Switching TGARCH model

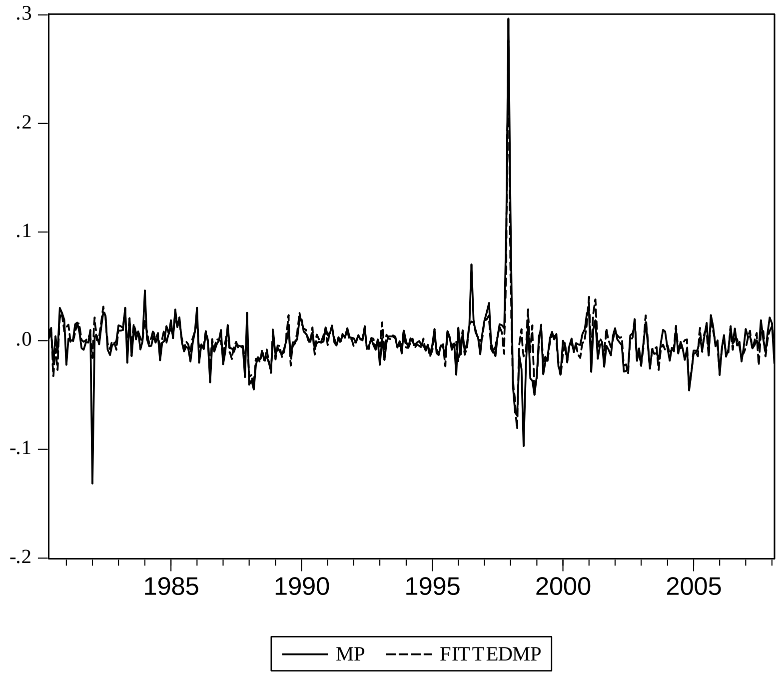
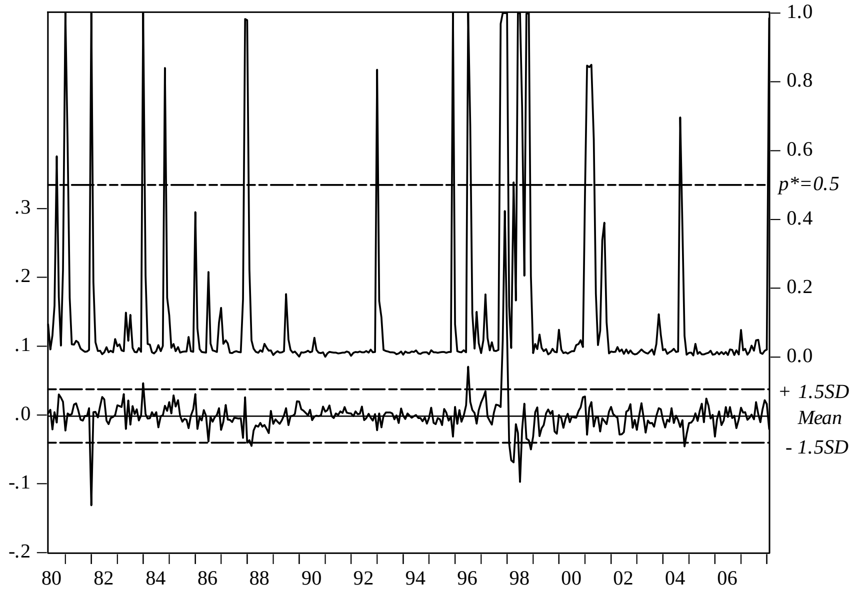
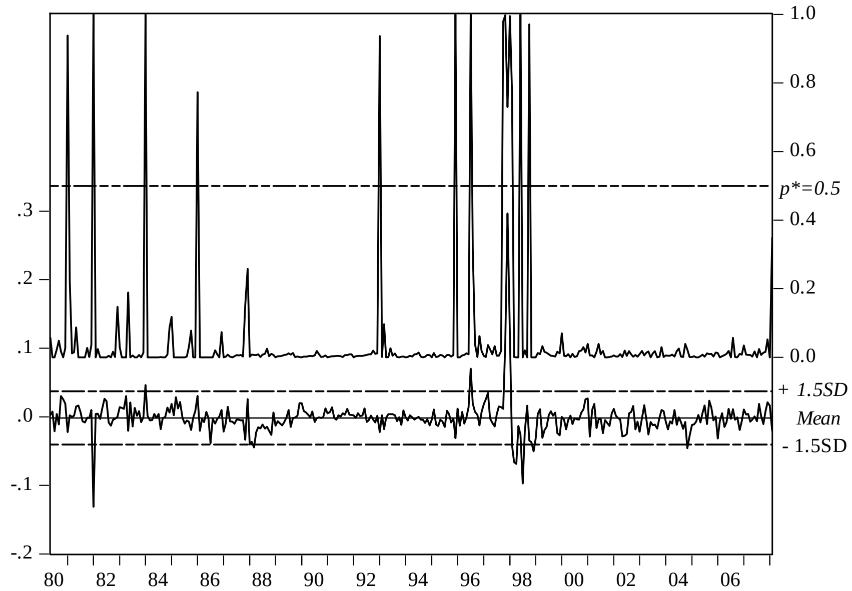


Figure 3. 4 Market Pressure and Probability of volatile state for Korea

(1) Markov Switching constant variance model



(2)Markov Switching TGARCH model



The Markov switching model can be used to predict for the 1997 crisis. We portray probability of potential crisis and MP with crisis band in Figure 3.4 (1) and (2), for constant and TGARCH estimates respectively. The upper halves of the figures give the inferred probabilities of being in the volatile state. This is the probability perceived by the agent in the currency market that the market is in the volatile state conditional on the past information about market pressure. Here, we assume that, when the inferred probabilities of being in regime one are higher than 0.5, which is $\Pr\left[S_t = 0 \mid \psi_{t-1}\right] > 0.5$ in our model set up (for simplicity, we use $p*$ to represent the inferred probability), we have a higher probability of being in the volatile state.

The lower parts of Figures 3.4 (1) and (2) portray the market pressure and the bands for considering currency market being in crisis or under a crisis attack. Previous studies using Logit models define a crisis occurring when $MP_t > mean(MP_t) + a * std(MP_t)$, where a is usually set at 1.5 or 2. We mentioned earlier that the Markov switching model can explain not only depreciating crisis attacks, but also appreciating currency attacks. Accordingly, we define the currency market is in the volatile state (with high potential of being attacked) when $MP_t > mean(MP_t) + a * std(MP_t)$ or when $MP_t < mean(MP_t) - a * std(MP_t)$ in our study. We assess the results when a is set equal to 1, 1.5 and 2, respectively. For reporting purposes, we only show the figures when a is equal to 1.5. Figures for other cases are available upon request. From Figure 3.4 (2), we can see that the inferred probabilities are very high when the currency crisis actually occurring. In

November 1997, when the crisis occurred in Korea, the inferred probability of crisis is 1 in the constant model and 0.98 in the TGARCH model. The Markov Switching constant and TGARH models can detect accurately the currency crises in 1997. As a matter of fact, both models have detected the crisis in October, one month earlier than the actual surge in the exchange market pressure. Comparing Figure 3.4 (1) and (2), it seems that the Markov switching TGARCH model can predict the currency crisis more precisely than the Markov switching constant variance model.

One important issue that we need to make comment on is the determination of number of regimes: whether two regimes is a better choice than a single regime for modelling the exchange market pressure. As we noted earlier on, we employ the standard LR test, normality tests for residuals from single regime estimation, and the Neyman's $C(\alpha)$ tests to address this issue.

Table 3. 3 Korea: Test for 2 regimes versus 1 regime.

TGARCH				
No. of Regimes	Log. Likelihood	*LR*	$C(\alpha)$	*JB*
2	1186.94			
1	1098.03	177.82	124.10	338.49

Constant Variance	Log. Likelihood	*LR*	$C(\alpha)$	*JB*
No. of Regimes				
2	1167.06			
1	1021.74	290.65	69.76	3619.93

Note: At 5% significant level, $\chi^2(14) = 21.06$ $\chi^2(11) = 19.68$, $\chi^2(2) = 5.99$

Table 3.3 summarises the tests statistics for the presence of one versus two regimes for Korea. First we perform the normality test on the residuals obtained from one regime estimation models. The JB statistics is much higher than the critical value $\chi^2(2)$=5.99. As stated previously, we also supplement the test using bootstrapping method to assessing the JB statistics for 500 resampled replications and assessing the number of modes using 100 replications. Both of these tests based on simulations indicate that the residuals from the constant single regime model are not normally distributed, nor did those from the TGARCH single regime model; and hence, possibly being distorted by the presence of at least another regime.

The log likelihood values for single and two regimes estimates are also quoted in Table 3.3. Accordingly we calculate the associated Likelihood Ratio (LR) statistics. LR is 177.82 for the TGARCH model, significantly larger than the critical value $\chi^2(14) = 21.06$ at 5% significant level. The significance of Neyman's $C(\alpha)$ test statistics confirms such results for the TGARCH models (with the critical value $\chi^2(14) = 21.06$). Similar results can be found for the Constant Variance models between single and two regimes, that LR and Neyman's $C(\alpha)$ test statistics both larger than the critical value $\chi^2(11) = 19.68$ at 5% significance level. All these tests give consistent implication that more than one regime should be examined. Thus two regimes Markov switching models should be more suitable than their one regime counterparts to explain the currency market pressure and the currency crisis.

Although by portraying the probability of a regime against MP, it is straightforward to distinguish which regime relate to which state in a 2 regimes Markov Switching model: high/low market pressure and thereby probably accompanying a volatile state; or a stable regime that market pressure fall in the medium range, we provide statistical evidence for the identification of the regimes in this study[55]. One method is to calculate Brier's (1950) quadratic probability score (QPS). QPS is often used to evaluate probability forecasts (see Diebold and Rudebush, 1989). The forecast accuracy, which refers to the closeness, on average, of predicted probabilities and observed realisations, is measured by a zero-one dummy variable. QPS is a function of the probability-forecast analog of mean squared error, which is formulated as

$$QPS = (1/T)\sum_{t=1}^{T} 2(Pr_t - R_t)^2 \qquad (3.53)$$

Here: Pr_t is the probability that the given regime will occur; and R_t is the realisation (1 or 0) that it has occurred. According to the formula, we need to specify two things to calculate the QPS: (i) the probability that one regime will occur, which can be by taking the estimate of the conditional probability for that regime, and (ii) the outcome, the realized state of a given MP. To capture the state of MP, we follow the Logit analysis literature, by comparing MP with some threshold values. Here we take various limiting values: the mean value of MP plus or minus 1 standard deviation, 1.5 standard deviations and 2 standard deviations. When MP exceeds the range of its mean value plus or minus 1/1.5/2 standard deviation, we refer the realized state as volatile state. When MP lies within the range, the state is referred to as the stable state.

[55] This can be particularly useful when there are more than two regimes.

Obviously, the QPS statistics ranges from 0 to 2, with a score of 0 corresponding to perfect accuracy. The QPS results for Korea are reported in Table 3.4(a). The statistics clearly indicate the regime 1 is the volatile state and regime 2 is the stable state for Korea, for both constant variance and TGARCH Markov switching models.

QPS achieves a strict minimum under truthful revelation of the probabilities by the forecaster. We also consider another strictly proper accuracy-scoring rule, the log probability score (LPS), given by:

$$LPS = -T^{-1}\sum_{t=1}^{T}[(1-R_t)\ln(1-Pr_t)+R_t\ln(Pr_t)] \tag{3.54}$$

Still, Pr_t is the forecasted probability that a given regime will occur; and R_t is the realisation (1 or 0) that it has occurred, defined in the same as in QPS. The LPS range from 0 to ∞, with a score of 0 corresponding to perfect accuracy. The LPS depends exclusively on the probability forecast of the event that actually occurred, assigning as a score of the log of the assessed probability (see Diebold and Rudebush, 1989).

An additional statistic, GSB, which can be appropriate for our purpose, is examined in our study. GSB is the global squared bias, which assesses the overall forecast calibration of the probabilities:

$$GSB = 2(\overline{Pr} - \overline{R})^2 \tag{3.55}$$

Here $\overline{Pr}$ is the average of the relevant probability values and $\overline{R}$ is the average of the realization of the outcome. LPS and GSB statistics are reported in Table 3.4 (b) and (c) for Korea, which confirm that regime one is the volatile state and regime two is the stable state.

Table 3. 4 Korea: QPS, LPS and GSB test statistics

(a)

QPS	Constant Variance		TGARCH	
	Regime 1	Regime2	Regime 1	Regime2
Volatile Zone				
MP Plus/minus 1 stdevs	0.17950	1.66463	0.18666	1.75612
MP Plus/minus 1.5 stdevs	0.12603	1.71810	0.07694	1.86584
MP Plus/minus 2 stdevs	0.11398	1.73015	0.06860	1.87419
Stable Zone				
MP Plus/minus 1 stdevs	1.66463	0.17950	1.75612	0.18666
MP Plus/minus 1.5 stdevs	1.71810	0.12603	1.86584	0.07694
MP Plus/minus 2 stdevs	1.73015	0.11398	1.87419	0.06860

(b)

LPS	Constant Variance		TGARCH	
	Regime 1	Regime2	Regime 1	Regime2
Volatile Zone				
MP Plus/minus 1 stdevs	0.32082	2.28501	0.35917	2.74582
MP Plus/minus 1.5 stdevs	0.17376	2.43207	0.13910	2.96589
MP Plus/minus 2 stdevs	0.16006	2.44577	0.09999	3.00500
Stable Zone				
MP Plus/minus 1 stdevs	2.28501	0.32082	2.74582	0.35917
MP Plus/minus 1.5 stdevs	2.43207	0.17376	2.96589	0.13910
MP Plus/minus 2 stdevs	2.44577	0.16006	3.00500	0.09999

(c)

GSB	Constant Variance		TGARCH	
	Regime 1	Regime2	Regime 1	Regime2
Volatile Zone				
MP Plus/minus 1 stdevs	0.00001	1.20155	0.00740	1.38877
MP Plus/minus 1.5 stdevs	0.01043	1.44482	0.00039	1.64947
MP Plus/minus 2 stdevs	0.01520	1.49616	0.00168	1.70430
Stable Zone				
MP Plus/minus 1 stdevs	1.20155	0.00001	1.38877	0.00740
MP Plus/minus 1.5 stdevs	1.44482	0.01043	1.64947	0.00039
MP Plus/minus 2 stdevs	1.49616	0.01520	1.70430	0.00168

3.6.2 Empirical analysis for Indonesia

Similarly, we perform single regime constant and TGARCH estimations first for the market pressure in Indonesia and the estimates are reported in Table 3.5. Most parameters in the two models are significant. For both models, the coefficients on GDC and DGDC do not differ from zero at 5% significant level. Thus the real domestic credit growth does not have significant impact on the exchange market pressure. Besides, it does not have the anticipated sign, in both of its level or first difference, so as the Risk variable in its first difference. Covariance stationary is achieved in the TGARCH model specification; however, in the case of Indonesia, the negative shocks of market pressure have larger impact on its volatility.

Actual and fitted MP and the residuals from the fitted equation are portrayed in Figure 3.5. The estimated equation appears to track the movement market pressure well. From Table 3.5, we can see that the fitness of estimation equation (R^2) is 67.86% for the constant and 65.05% for the TGARCH model.

The estimation results from 2 regimes Markov Switching Constant and TGARCH models for Indonesia are reported in Table 3.6 (1) and (2) respectively. For the constant model, we observe that in the stable state, all the variables are significant, with GDC, DGDC, and DRisk not having the expected signs; in the volatile state, GDC has insignificant impact on market pressure in both its level and first difference;

however, the signs are consistent with our expectation. Risk in its first difference does not have significant impact on the market pressure, nor is its sign following expectation. For the TGARCH model, we found that all the fundamental and risk variables have significant impact on the market pressure, although the signs for GDC, DGDC and Risk are not in line with anticipation. Most variables have larger impact in the volatile state than in the stable state, shows by the absolute value of their coefficients.

The covariance structure for the TGARCH model is stationary, as indicted by $V_1 + V_2 + V_3 < 1$ in both states. Same as in the single regime model, the coefficient V_3 is positive. This imply that asymmetric effects exist in Indonesia currency market, with negative shocks have larger impact on the market pressure. From the significance of LR test between the TGARCH and constant model, as well as the significance of most coefficients in the TGARCH variances specification, we can conclude that the variance is time varying and TGARCH specification for the conditionally variance is necessary in the Markov Switching model for Indonesia.

The transitional probability for each state is significantly different from zero at 95% confidence level for both constant and TGARCH Regime-Switching estimates. $2 - P_{12} - P_{21} > 1$ confirms the persistence of each state. Average persistence for the volatile state in Indonesia is under 4 months and under 26 months for the stable state.

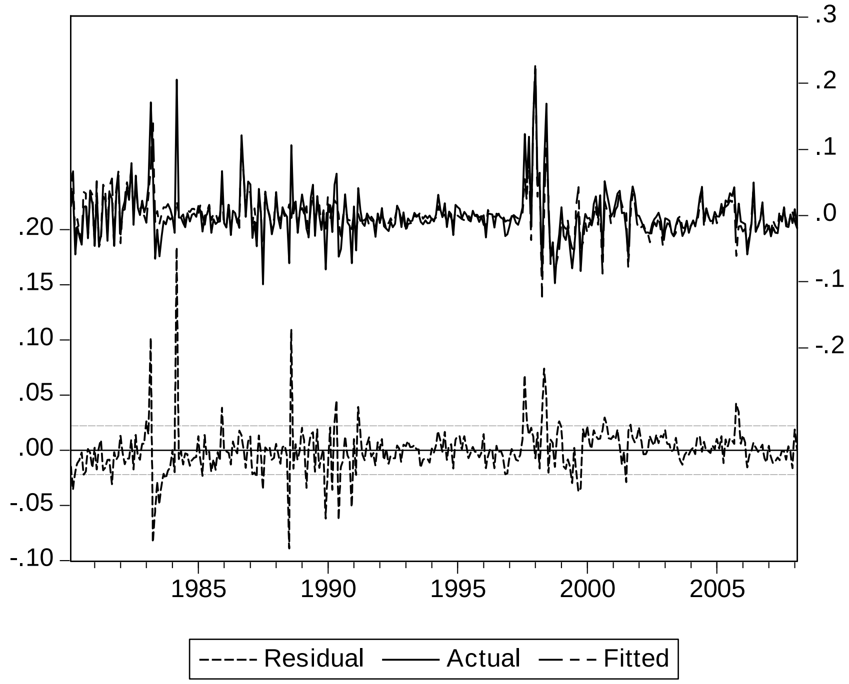
Table 3. 5 Estimation Results from Single Regime models for Indonesia

	Indonesia					
	Constant Variance			TGARCH		
	Coeff	Std Error	Signif	Coeff	Std Error	Signif
β_1	-0.02627	0.01451	0.07110	-0.02948	0.00994	0.00300
β_2	0.05322	0.00691	0.00000	0.07061	0.00504	0.00000
β_3	-0.00234	0.02695	0.93100	-0.02359	0.03359	0.48260
β_4	0.05735	0.01435	0.00010	0.11251	0.00821	0.00000
β_5	-1.08591	0.06903	0.00000	-1.03849	0.04520	0.00000
β_6	0.54389	0.03183	0.00000	0.49426	0.02258	0.00000
β_7	-0.01485	0.01982	0.45420	-0.02738	0.02597	0.29180
β_8	-0.05970	0.01622	0.00030	-0.04896	0.01493	0.00100
v_0				0.00001	0.00000	0.01380
v_1				0.04200	0.01516	0.00560
v_3				0.17587	0.06255	0.00490
v_2				0.86045	0.02241	0.00000
R^2	0.6786			0.6505		
$\bar{R}^2$	0.6708			0.6376		
JB	5085.74			499.00		
Log(L)	810.61			866.39		
LR	111.56					

Note: The critical value for $\chi^2(3) = 7.81$, $\chi^2(2) = 5.99$

Figure 3. 5 Actual and fitted value of MP from single regime estimation: Indonesia

(1) Constant (OLS) model



(2) TGARCH(1,1) model

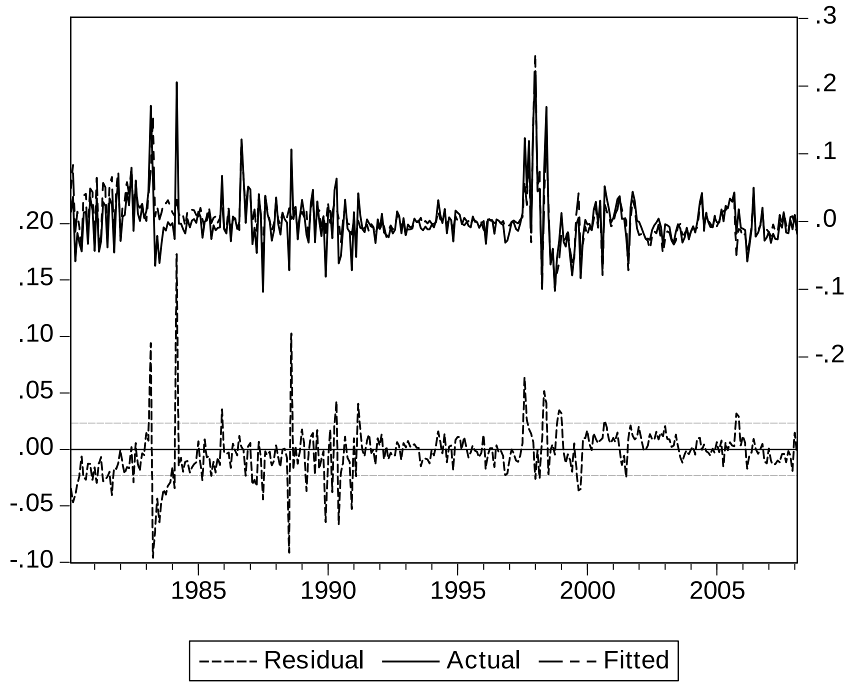


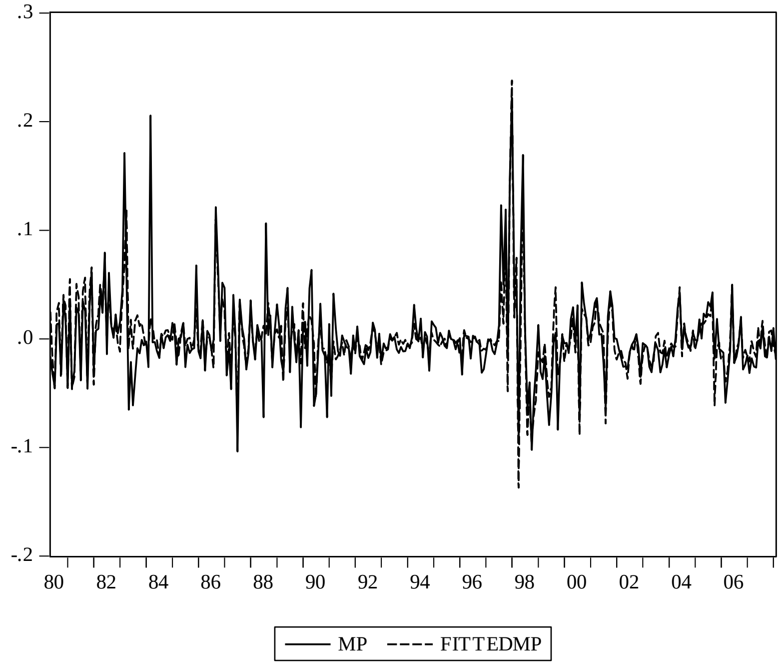
Table 3. 6 Parameter estimates and related statistics for Markov Regime Switching models: Indonesia

	Panel A Constant Variance:Indonesia						Panel B Threshold GARCH: Indonesia					
	Regime 1 (Volatile State)			Regime 2 (Stable State)			Regime 1 (Volatile State)			Regime 2 (Stable State)		
Variable	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif
P_{12}/P_{21}	0.25054	0.07957	0.00164	0.03946	0.01309	0.00257	0.37329	0.11278	0.00093	0.05055	0.01464	0.00055
β_1	0.18207	0.03160	0.00000	-0.01775	0.00237	0.00000	0.00400	0.00010	0.00000	-0.00376	0.00231	0.10402
β_2	0.05266	0.02874	0.06693	0.03077	0.00423	0.00000	0.12966	0.01282	0.00000	0.03692	0.00175	0.00000
β_3	0.23243	0.15249	0.12744	-0.03984	0.01049	0.00015	0.00735	0.00012	0.00000	-0.02785	0.00759	0.00024
β_4	0.20596	0.06290	0.00106	0.04230	0.00438	0.00000	0.23718	0.01873	0.00000	0.02897	0.00390	0.00000
β_5	-1.32433	0.20936	0.00000	-1.07729	0.03097	0.00000	-1.25319	0.09856	0.00000	-1.06797	0.02883	0.00000
β_6	0.45843	0.09117	0.00000	0.54445	0.01472	0.00000	0.48225	0.03231	0.00000	0.58705	0.01235	0.00000
β_7	0.17500	0.12382	0.15756	-0.03306	0.00694	0.00000	-0.00679	0.00012	0.00000	-0.03043	0.00537	0.00000
β_8	-0.01765	0.05087	0.72865	-0.08229	0.00936	0.00000	-0.02179	0.03000	0.00000	-0.05756	0.00739	0.00000
V_0	0.00222	0.00042	0.00000	0.00012	0.00001	0.00000	0.00238	0.00029	0.00000	0.00009	0.00000	0.00000
V_1							0.30825	0.07750	0.00000	0.20169	0.07962	0.01130
V_2							-0.23974	0.00952	0.00000	-0.00932	0.00373	0.01238
V_3							0.21871	0.00511	0.00000	0.11909	0.01905	0.00000
κ	0.1361			0.8639			0.1193			0.8807		
Average Persistence	3.99			25.34			2.68			19.78		
Log(L)	921.37						936.40					
LR	30.05											

Note: The critical value for $\chi^2(6) = 12.59$

Figure 3. 6 Actual and fitted value of MP from Markov switching models: Indonesia

(1) Markov Switching constant variance model



(2)Markov Switching TGARCH model

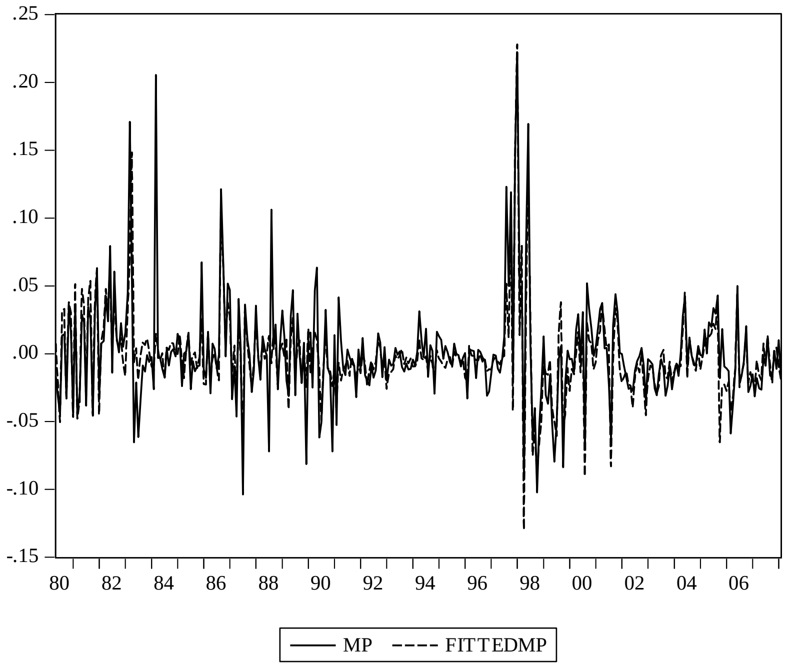
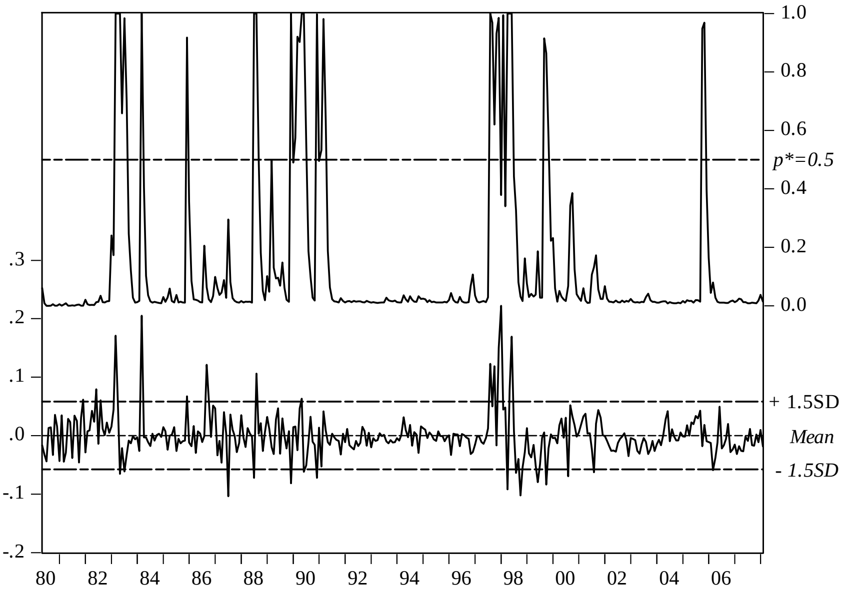
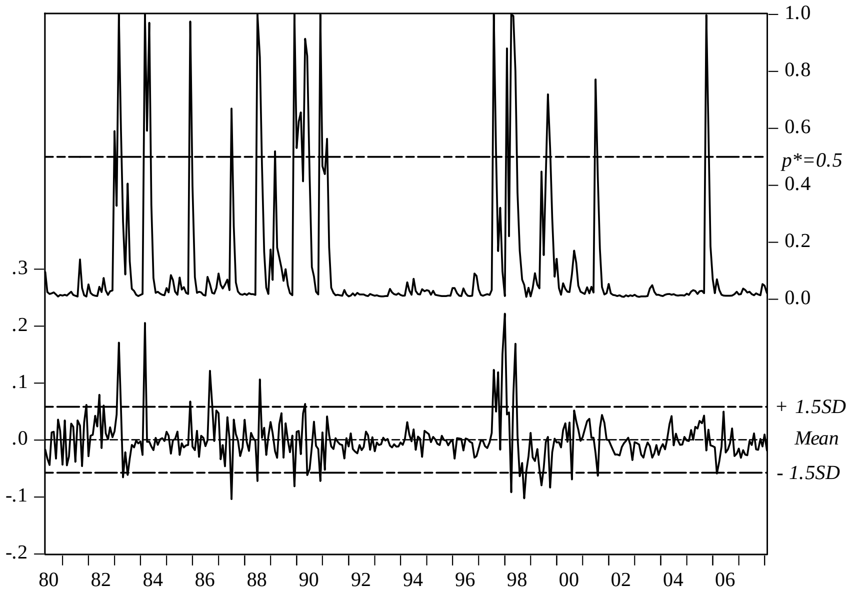


Figure 3. 7 Market Pressure and Probability of volatile state for Indonesia

(1) Markov Switching constant variance model



(2) Markov Switching TGARCH model



The actual and fitted MP are portrayed in Figure 3.6 (1) and (2), for the Markov Switching models with constant variance and with TGARCH conditional variance respectively. Still, the fitted MP tracks the actual MP well. We cannot tell from the figures whether TGARCH or constant models have better tracking ability than the other, nor can we tell, by comparing to Figure 3.5, whether the single regime or 2 regimes model is better in tracking the movement of MP. However, the ability of each model in correctly predicting the state of market pressure is provided and compared in the later section.

Table 3. 7 Indonesia: Test for 2 regimes versus 1 regime.

TGARCH				
No. of Regimes	Log. Likelihood	*LR*	$C(\alpha)$	*JB*
2	936.40			
1	818.99	234.81	27.40	704.46

Constant Variance				
No. of Regimes	Log. Likelihood	*LR*	$C(\alpha)$	*JB*
2	921.37			
1	802.53	237.69	22.87	5549.01

Note: At 5% significant level, $\chi^2(14) = 21.06$ $\chi^2(11) = 19.68$, $\chi^2(2) = 5.99$

Information on the criteria used to determine the number of regimes is provided in Table 3.7. Similarly, we assess JB statistics and using bootstrapping to establish resampled population of residuals from the single regime estimations to determine if the residuals are normally distributed. All these diagnostic tests suggest that the residuals are diverged from normal distribution, implying the existence of other regime/regimes. LR and Neyman's $C(\alpha)$ tests statistics also provide further evidence that 2 regimes rather than 1 regime should be used.

Figure 3.7 (1) and (2) depict the market pressure and the inferred probability of volatile state from the two Markov switching models. Again, both models detect the currency crisis in August 1997 in Indonesia.

Now we examine the identification of the 2 regimes. The QPS, GSB and LPS statistics are reported in Table 3.8. All these statistics indicate that regime 1 is the volatile state for Indonesia.

Table 3. 8 Indonesia: QPS, LPS and GSB test statistics

(a)

QPS	Constant Variance		TGARCH	
	Regime 1	Regime2	Regime 1	Regime2
Volatile Zone				
MP Plus/minus 1 stdevs	0.22717	1.60123	1.55654	0.23585
MP Plus/minus 1.5 stdevs	0.14848	1.67992	1.65982	0.13257
MP Plus/minus 2 stdevs	0.15524	1.67316	1.66839	0.12400
Stable Zone				
MP Plus/minus 1 stdevs	1.60123	0.22717	0.23585	1.55654
MP Plus/minus 1.5 stdevs	1.67992	0.14848	0.13257	1.65982
MP Plus/minus 2 stdevs	1.67316	0.15524	0.12400	1.66839

(b)

LPS	Constant Variance		TGARCH	
	Regime 1	Regime2	Regime 1	Regime2
Volatile Zone				
MP Plus/minus 1 stdevs	0.45369	2.25492	0.44472	2.12766
MP Plus/minus 1.5 stdevs	0.31247	2.39613	0.30075	2.27162
MP Plus/minus 2 stdevs	0.24490	2.46370	0.22373	2.34864
Stable Zone				
MP Plus/minus 1 stdevs	2.25492	0.45369	2.12766	0.44472
MP Plus/minus 1.5 stdevs	2.39613	0.31247	2.27162	0.30075
MP Plus/minus 2 stdevs	2.46370	0.24490	2.34864	0.22373

(c)

GSB	Constant Variance		TGARCH	
	Regime 1	Regime2	Regime 1	Regime2
Volatile Zone				
MP Plus/minus 1 stdevs	0.93911	0.00297	0.00615	0.98606
MP Plus/minus 1.5 stdevs	1.18295	0.00410	0.00161	1.23557
MP Plus/minus 2 stdevs	1.31541	0.01521	0.00988	1.37087
Stable Zone				
MP Plus/minus 1 stdevs	0.00297	0.93911	0.98606	0.00615
MP Plus/minus 1.5 stdevs	0.00410	1.18295	1.23557	0.00161
MP Plus/minus 2 stdevs	0.01521	1.31541	1.37087	0.00988

3.6.3 Empirical analysis for Thailand

Table 3.9 reports the constant and TGARCH estimates under the assumption that there is one regime. For the constant model, the RM2 and GDC are not statistically different from zero at 5% significance level. For the TGARCH model, RM2 and RER do not significantly different from zero. For both models, two out of four explain variables have significant impact on market pressure in their levels, with GDC has the wrong a priori sign. When turning to the changes (first difference) in the macro variables and risk, all have statistically significant impacts on exchange market pressure. However, the DGDC and DRisk variables present incorrect expected sign. The coefficients on the TGARCH conditional variances are all significant, indicating that variance of market pressure is time dependent and conditional on past information; and there is asymmetric effect in the conditional variances, with positive shocks have larger effects on the volatility of market pressure.

The graphs depicting the actual and fitted MP and the residuals from the fitted equations are portrayed in Figure 3.8. The estimated equation appears to track the movement of market pressure well. This can also be proved by the estimation fitness, R^2 (reported in the bottom of Table 3.1), which indicate that around 80% of the market pressure can be explained by the fundamental variables in the equations of single regime models. Jaque-Bera tests are larger than the critical value 5.99 at 5% significant level shows that the residuals from both estimations, which indicate the

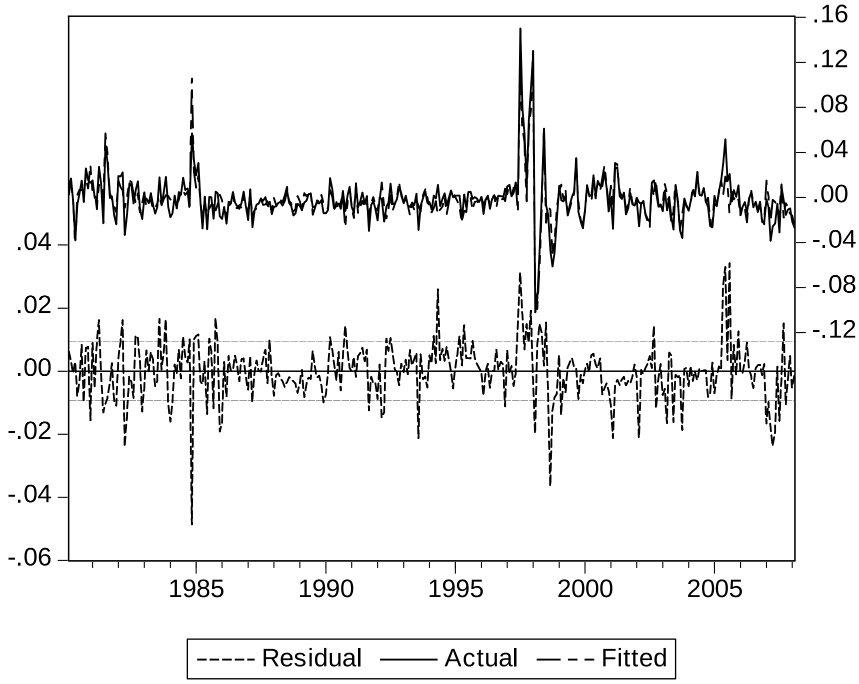
Table 3. 9 Estimation Results from Single Regime models for Thailand

	Thailand					
	Constant Variance			TGARCH		
	Coeff	Std Error	Signif	Coeff	Std Error	Signif
β_1	0.00080	0.00286	0.77910	-0.00269	0.00279	0.33520
β_2	0.02298	0.00569	0.00010	0.00667	0.00547	0.22220
β_3	-0.07836	0.05482	0.15380	-0.11082	0.04759	0.01990
β_4	0.04920	0.01675	0.00350	0.02993	0.01337	0.02510
β_5	-0.87408	0.06482	0.00000	-0.93860	0.06017	0.00000
β_6	0.79246	0.03219	0.00000	0.67889	0.02783	0.00000
β_7	-0.11341	0.04587	0.01390	-0.13755	0.03736	0.00020
β_8	-0.06641	0.01760	0.00020	-0.11566	0.00950	0.00000
v_0				0.00002	0.00001	0.00000
v_1				0.59028	0.17765	0.00090
v_3				-0.43661	0.16769	0.00920
v_2				0.37769	0.12335	0.00220
R^2	0.8175			0.7951		
$\bar{R}^2$	0.8136			0.7881		
JB	198.42			71.3318		
Log(L)	1101.90			1140.52		
LR	77.25					

Note: The critical value for $\chi^2(3) = 7.81$, $\chi^2(2) = 5.99$

Figure 3. 8 Actual and fitted value of MP from single regime estimation: Thailand

(1) Constant (OLS) model



(2) TGARCH(1,1) model

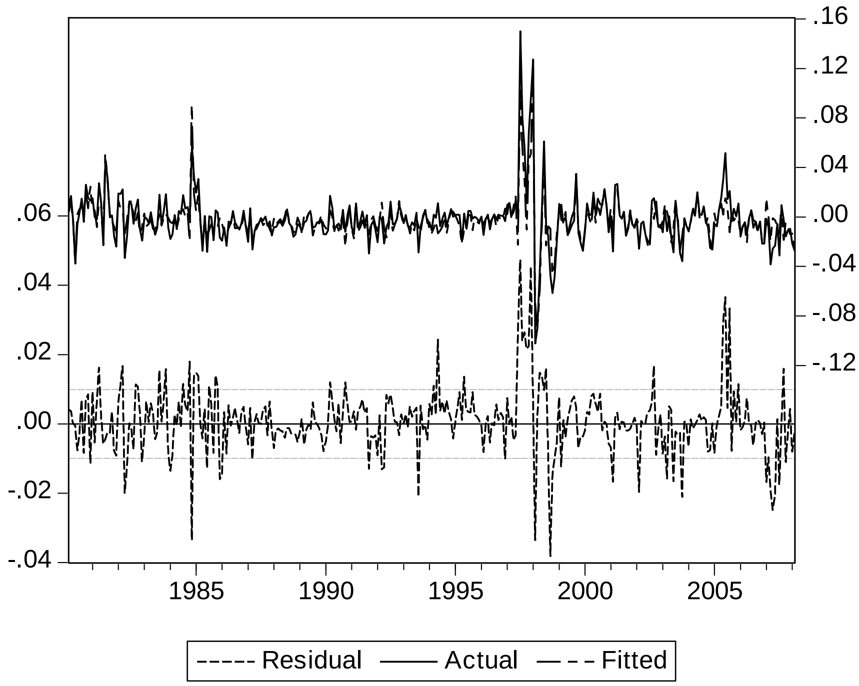


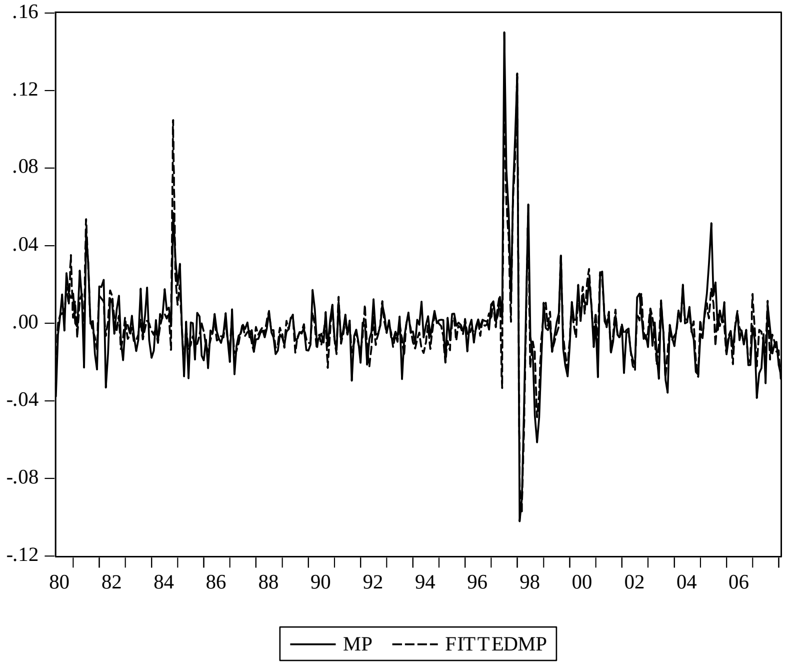
Table 3. 10 Parameter estimates and related statistics for Markov Regime Switching models: Thailand

	Panel A Constant Variance: Thailand						Panel B Threshold GARCH: Thailand					
	Regime 1 (Volatile State)			Regime 2 (Stable State)			Regime 1 (Volatile State)			Regime 2 (Stable State)		
Variable	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif
P_{12}/P_{21}	0.43510	0.14130	0.00207	0.06085	0.02574	0.01809	0.23665	0.08460	0.00515	0.12950	0.27743	0.00000
β_1	0.05747	0.02084	0.00583	-0.00461	0.00236	0.05033	0.02680	0.00060	0.00000	-0.00668	0.00274	0.01474
β_2	-0.08224	0.03473	0.01787	0.03642	0.00450	0.00000	0.04862	0.00392	0.00000	0.00673	0.00235	0.00423
β_3	0.17042	0.22678	0.45236	-0.08798	0.04946	0.07528	-0.41285	0.01783	0.00000	-0.06352	0.05100	0.21300
β_4	0.33240	0.10115	0.00102	0.01015	0.01377	0.46096	0.01937	0.00937	0.03860	0.02027	0.01472	0.16836
β_5	-1.77628	0.30334	0.00000	-0.83936	0.06308	0.00000	-1.77889	0.06476	0.00000	-0.76778	0.06780	0.00000
β_6	0.52296	0.12866	0.00005	0.78370	0.02765	0.00000	0.72797	0.02070	0.00000	0.67859	0.03343	0.00000
β_7	-0.05072	0.19148	0.79109	-0.13251	0.04063	0.00111	-0.36536	0.02217	0.00000	-0.11545	0.04536	0.01092
β_8	-0.07391	0.05317	0.16456	-0.07611	0.01613	0.00000	-0.04488	0.00830	0.00000	-0.16167	0.02154	0.00000
V_0	0.00013	0.00004	0.00257	0.00005	0.00001	0.00000	0.00000	0.00000	0.00037	0.00002	0.00000	0.00000
V_1							0.01299	0.00755	0.08512	0.57755	0.10951	0.00000
V_2							0.58324	0.05333	0.00000	0.32828	0.06403	0.00000
V_3							-0.01451	0.00809	0.07289	-0.41594	0.14252	0.00352
κ	0.1227			0.8773			0.3537			0.6463		
Average Persistence	2.30			16.43			4.23			7.72		
Log(L)	1128.92						1180.33					
LR	102.82											

Note: The critical value for $\chi^2(6) = 12.59$

Figure 3. 9 Actual and fitted value of MP from Markov switching models: Thailand

(1) Markov Switching constant variance model



(2)Markov Switching TGARCH model

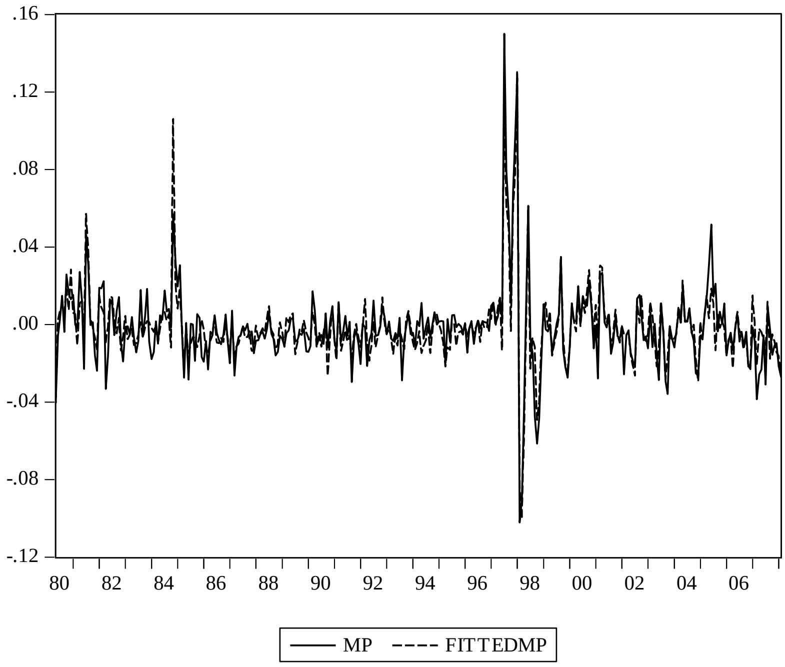
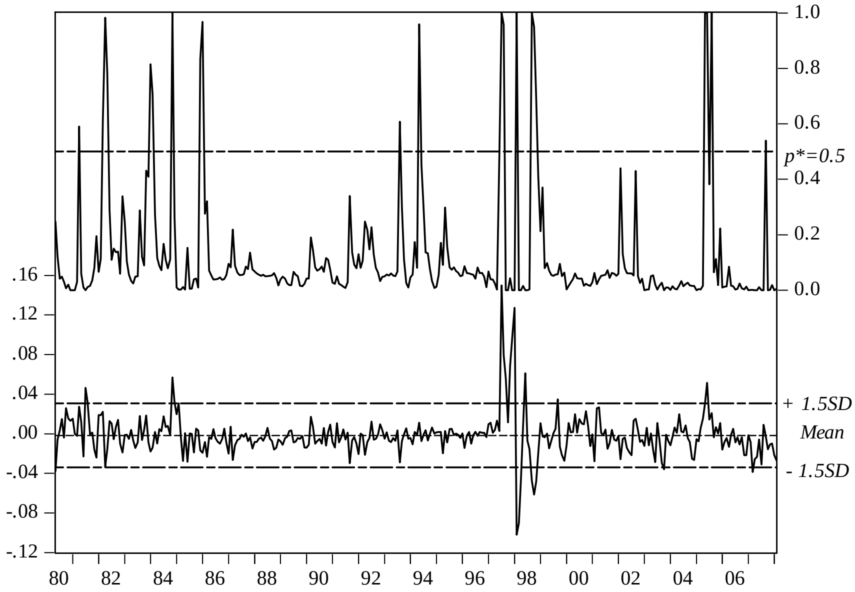
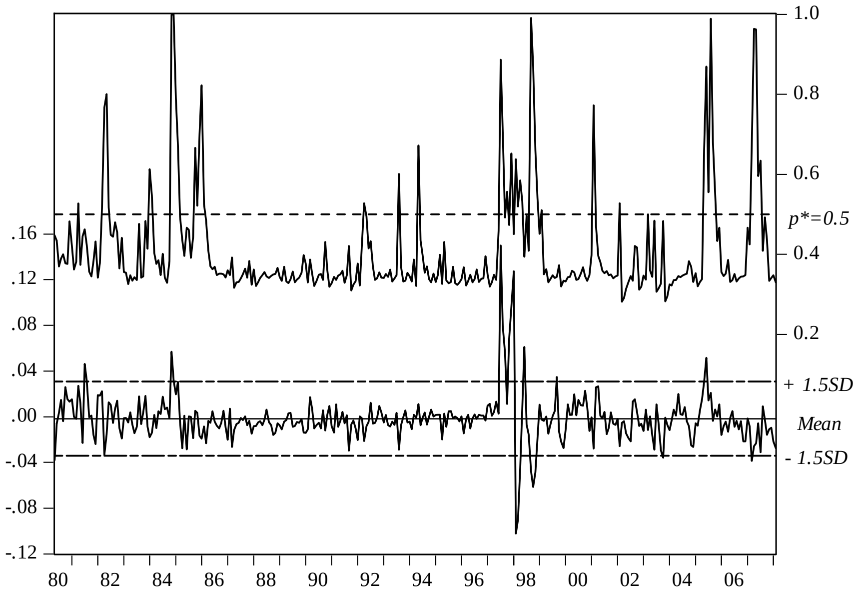


Figure 3. 10 Market Pressure and Probability of volatile state for Thailand

(1) Markov Switching constant variance model



(2) Markov Switching TGARCH model



residuals are not normally distributed.

The empirical estimates from the two regimes Markov switching models for Thailand are reported in Table 3.10. Panel A is for the results from the constant variances mode and Panel B is for that from the TGARCH model. In the mean structure, our findings confirm that the fundamental and risk variables play significant roles in triggering currency crisis, as all variables are significant in at least one regime or another, for both models. For the variance structure in the Markov switching TGARCH model, we can observe that asymmetric effects are significant with positive shocks have larger impact. Moreover, covariance stationary is guaranteed because $V_1 + V_2 + V_3 < 1$ and $V_1 + V_2 < 1$, in both volatile and stable states. Although V_1 and V_3 differ from zero at 10% instead of 5% significant level, the test for that the coefficients in the conditional variance structures are jointly zero has a LR statistics equal to 102.82, larger that than the critical value at the 5% level, implying imposing constraint on the TGARCH coefficients can be rejected. The TGACH model should not be nested to constant model.

The transitional probabilities P_{12} and P_{21} are significant at 90% confidence level. Since $2 - P_{12} - P_{21} > 1$, we conclude that the process is likely to persist in its current state rather than switching to the other. The average persistence of volatile state increase from 2.3 months with the constant model to 4.23 with the TGARCH model, however, the average persistence of stable states reduce from 16.43 to 7.72. The unconditional probabilities are given in the bottom of the table.

Figures 3.9 (1) and (2) depict the actual and fitted MP along with the residuals from the estimation models for Korea. And Figures 3.10 (1) and (2) present the inferred probability of volatile state and market pressure. It can be observed that the models track the MP well and can detect the currency crisis. Both constant and TGARCH Markov switching model can correctly predict the currency crisis in July 1997 for Thailand.

Table 3. 11 Thailand: Test for 2 regimes versus 1 regime.

TGARCH				
No. of Regimes	Log. Likelihood	*LR*	$C(\alpha)$	*JB*
2	1180.33			
1	1128.73	103.20	47.90	66.74

Constant Variance				
No. of Regimes	Log. Likelihood	*LR*	$C(\alpha)$	*JB*
2	1128.92			
1	1090.89	76.06	20.23	197.92

Note: At 5% significant level, $\chi^2(14) = 21.06$ $\chi^2(11) = 19.68$, $\chi^2(2) = 5.99$

Table 3.11 reports the tests for determining the number of regimes. The LR, JB Newman's $C(\alpha)$ test statistics, as well as bootstrapping tests all imply that there should be two regimes rather than one.

The QPS, GSB and LPS statistics are reported in Table 3.12 for identifying each regime. The statistics all corroborate our observation that regime 1 is the volatile state where currency crisis likely to happened and regime 2 is the stable state.

Table 3. 12 Thailand: QPS, LPS and GSB test statistics

(a)

QPS	Constant Variance		TGARCH	
	Regime 1	Regime2	Regime 1	Regime2
Volatile Zone				
MP Plus/minus 1 stdevs	0.23248	1.51926	0.32580	0.77564
MP Plus/minus 1.5 stdevs	0.15402	1.59773	0.33233	0.76910
MP Plus/minus 2 stdevs	0.12506	1.62669	0.33677	0.76466
Stable Zone				
MP Plus/minus 1 stdevs	1.51926	0.23248	0.77564	0.32580
MP Plus/minus 1.5 stdevs	1.59773	0.15402	0.76910	0.33233
MP Plus/minus 2 stdevs	1.62669	0.12506	0.76466	0.33677

(b)

LPS	Constant Variance		TGARCH	
	Regime 1	Regime2	Regime 1	Regime2
Volatile Zone				
MP Plus/minus 1 stdevs	0.81879	3.16228	0.57160	0.87123
MP Plus/minus 1.5 stdevs	0.63315	3.34792	0.55234	0.89049
MP Plus/minus 2 stdevs	0.55914	3.42193	0.55174	0.89109
Stable Zone				
MP Plus/minus 1 stdevs	3.16228	0.81879	0.87123	0.57160
MP Plus/minus 1.5 stdevs	3.34792	0.63315	0.89049	0.55234
MP Plus/minus 2 stdevs	3.42193	0.55914	0.89109	0.55174

(c)

GSB	Constant Variance		TGARCH	
	Regime 1	Regime2	Regime 1	Regime2
Volatile Zone				
MP Plus/minus 1 stdevs	0.00090	1.07698	0.14066	0.40028
MP Plus/minus 1.5 stdevs	0.00641	1.31760	0.23536	0.55171
MP Plus/minus 2 stdevs	0.01112	1.37656	0.26066	0.59009
Stable Zone				
MP Plus/minus 1 stdevs	1.07698	0.00090	0.40028	0.14066
MP Plus/minus 1.5 stdevs	1.31760	0.00641	0.55171	0.23536
MP Plus/minus 2 stdevs	1.37656	0.01112	0.59009	0.26066

3.6.4 Empirical analysis for Malaysia

Table 3.13 reports the estimation results for Malaysia from single regime constant and TGARCH models. Actual and fitted MP are portrayed in Figure 3.11. The macro and risk variables are all significant at 95% confidence level, expect the RM2, in both models. These variables can explain up to 85% of the MP in Malaysia. Asymmetric effect in the volatility is not significant for Malaysia in the TGARCH model, indicated by the insignificance of V_3.

The estimates from 2 regimes Markov Switching constant and TGARCH models are shown in Table 3.14. From the constant estimates, we found that, in the volatile state, DGC does not have substantial impact on MP, no matter in its level or first difference. RER is not significant in its level, but significant in the first difference. In the stable state, however, all variables expect RM2 are statistically significant. Signs on the coefficients are not always as anticipation, especially for the DGDC. For the TAGARCH Markov estimates, we find all variables are significant, expect the RM2 in the stable state. The model is covariance stationary in both volatile and stable state, as $V_1 + V_2 + V_3 < 1$. Coefficient V_3 is positive in the volatile state and negative in the stable state, however, both of which are not significantly different from zero. The LR test for the joint significance of the coefficients in the conditional variances (V_1, V_2 and V_3 are zero in both states) has a statistics of 1.01, smaller than the critical value $\chi^2(6) = 12.59$. Thus the null hypothesis that these coefficients are jointly zero cannot

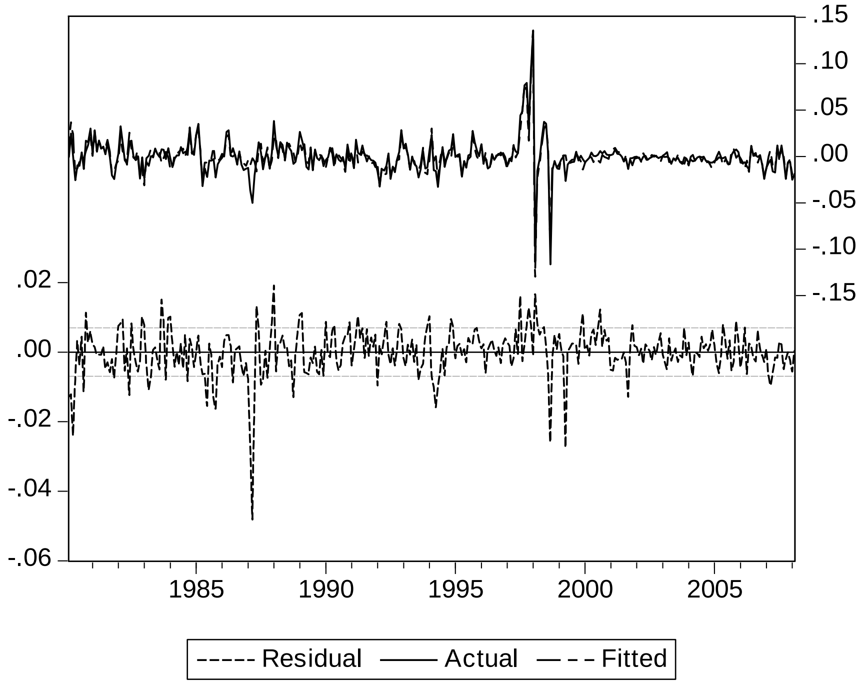
Table 3. 13 Estimation Results from Single Regime models for Malaysia

	Malaysia					
	Constant Variance			TGARCH		
	Coeff	Std Error	Signif	Coeff	Std Error	Signif
β_1	-0.00206	0.00149	0.16770	0.00022	0.00132	0.86690
β_2	0.02653	0.00459	0.00000	0.04066	0.00369	0.00000
β_3	-0.05032	0.01205	0.00000	-0.08628	0.01252	0.00000
β_4	0.04213	0.01174	0.00040	0.03062	0.01048	0.00350
β_5	-0.35652	0.02627	0.00000	-0.45686	0.02305	0.00000
β_6	0.83603	0.02576	0.00000	0.82125	0.01673	0.00000
β_7	-0.04749	0.00883	0.00000	-0.08333	0.00756	0.00000
β_8	-0.03664	0.01530	0.01720	-0.03985	0.00884	0.00000
v_0				0.00002	0.00000	0.00000
v_1				0.46559	0.15379	0.00250
v_3				0.54779	0.21747	0.01180
v_2				-0.02547	0.04155	0.53980
R^2	0.8659			0.84918		
$\bar{R}^2$	0.8630			0.84408		
JB	1074.02			23.8504		
$Log(L)$	1201.05			1253.81		
LR	108.13					

Note: The critical value for $\chi^2(3) = 7.81$, $\chi^2(2) = 5.99$

Figure 3. 11 Actual and fitted value of MP from single regime estimation: Malaysia

(1) Constant (OLS) model



(2) TGARCH(1,1) model

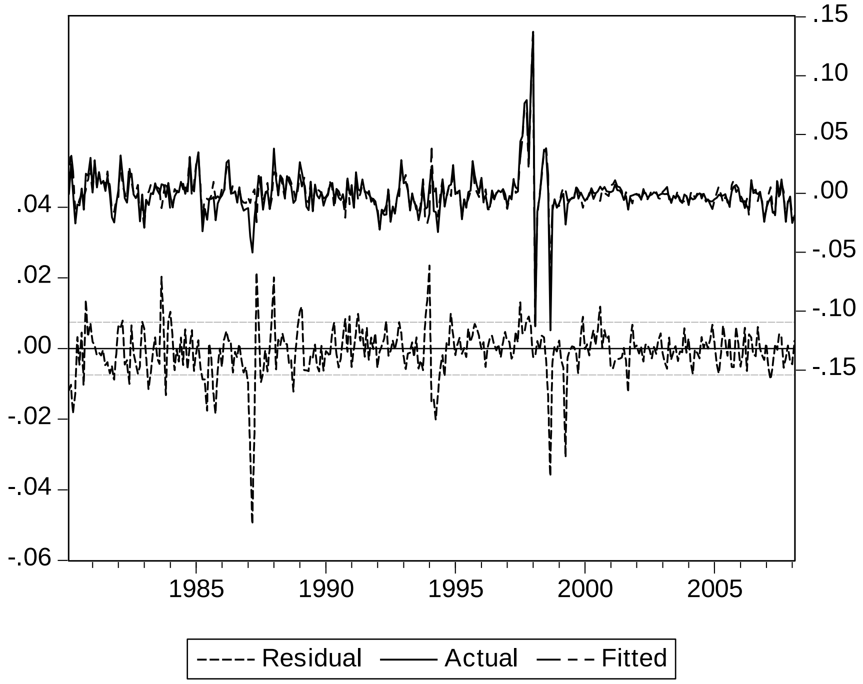


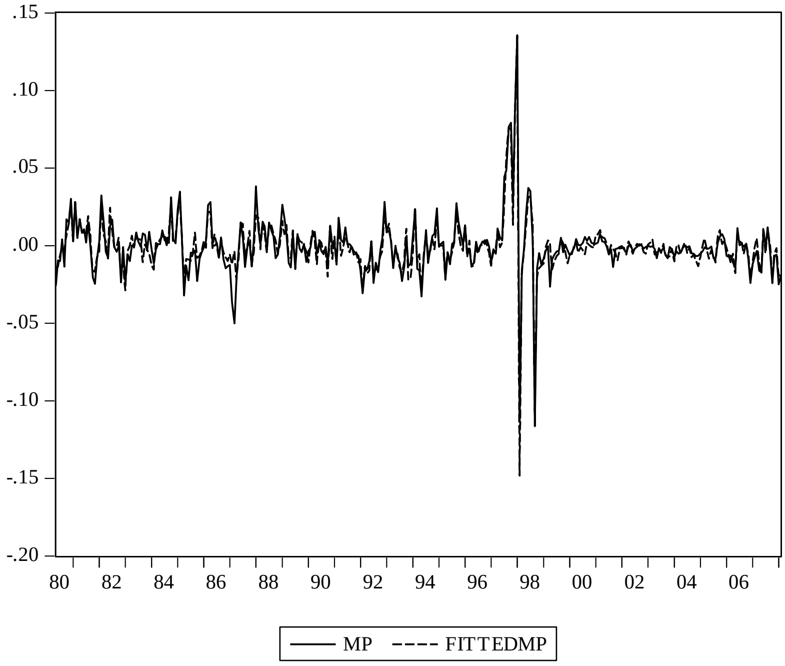
Table 3. 14 Parameter estimates and related statistics for Markov Regime Switching models: Malaysia

	Panel A Constant Variance: Malaysia						Panel B Threshold GARCH: Malaysia					
	Regime 1 (Volatile State)			Regime 2 (Stable State)			Regime 1 (Volatile State)			Regime 2 (Stable State)		
Variable	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif
p_{12}/p_{21}	0.15900	0.05860	0.00668	0.05310	0.01950	0.00655	0.27170	0.10530	0.00988	0.08420	0.03060	0.00595
β_1	-0.01190	0.00529	0.02411	-0.00014	0.00097	0.88164	-0.00168	0.00065	0.00000	-0.00095	0.00112	0.39469
β_2	0.00385	0.01010	0.70453	0.03400	0.00299	0.00000	0.02770	0.00131	0.00000	0.03420	0.00379	0.00000
β_3	0.04690	0.03610	0.19357	-0.08980	0.00840	0.00000	-0.02300	0.00115	0.00000	-0.07560	0.01140	0.00000
β_4	0.09140	0.03430	0.00775	0.03150	0.00800	0.00008	0.03630	0.00146	0.00000	0.04260	0.01010	0.00003
β_5	-0.35180	0.06250	0.00000	-0.43580	0.01420	0.00000	-0.38920	0.01120	0.00000	-0.39500	0.01970	0.00000
β_6	0.93170	0.05910	0.00000	0.72020	0.01750	0.00000	0.98650	0.23744	0.00000	0.73660	0.02060	0.00000
β_7	0.02450	0.02500	0.32810	-0.08520	0.00366	0.00000	-0.00558	0.00019	0.00000	-0.07280	0.00524	0.00000
β_8	-0.00888	0.03730	0.81199	-0.08750	0.01470	0.00000	-0.02710	0.00576	0.00000	-0.06060	0.01790	0.00071
v_0	0.00008	0.00001	0.00000	0.00002	0.00000	0.00000	0.00007	0.00005	0.00000	0.00001	0.00000	0.00000
v_1							0.36320	0.14320	0.01118	0.03250	0.04420	0.46196
v_2							-0.07540	0.01841	0.00000	0.26270	0.09210	0.00435
v_3							0.01800	0.14960	0.90447	-0.02890	0.05400	0.59200
κ	0.2504			0.7496			0.2366			0.7634		
Average Persistence	6.29			18.85			3.68			11.87		
Log(L)	1269.45						1269.96					
LR	1.01											

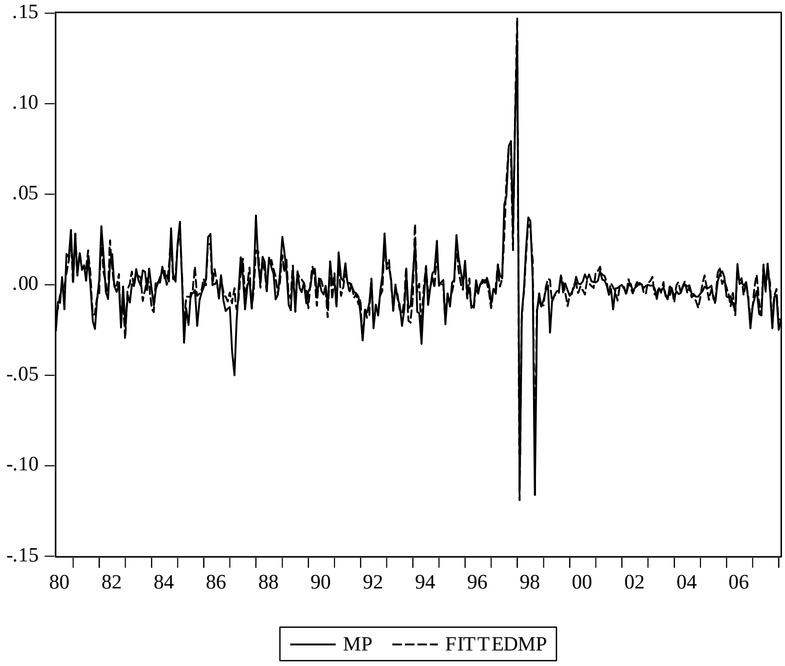
Note: The critical value for $\chi^2(6) = 12.59$

Figure 3. 12 Actual and fitted value of MP from Markov switching models: Malaysia

(1) Markov Switching constant variance model



(2)Markov Switching TGARCH model



be rejected. The LR test indicates the TGARCH structure in the Markov 2 regime switching model may be not necessary.

For the Markov switching models, we have the transitional probabilities for the volatile and stable state, P_{12} and P_{21}, are significantly differ from zero at 95% significance level. The average persistence of the volatile state reduces under the TGARCH modelling specification than under the constant modelling specification, so as that of the stable state. The unconditional probability of being in the stable state is more than 70%.

Figure 3.12 graphs the actual and fitted MP and model residuals for the Markov Switching models. Still, the fitted MP tracks the MP very well, indicating the explanatory power of the fundamental variables. Comparing Figure 3.12 with the results from single regime estimation, we cannot claim if the 2 regimes models are better than their one regime counterpart in terms of tracking MP. However, the LR and Newman's $C(\alpha)$ test statistics reported in Table 3.15 shows that the 2 regimes models rather than the 1 regime ones should be used. JB statistics and bootstrapping methods also support such conclusion.

Figure 3.13 present market pressure the inferred probability of volatile state and with presumed crisis band. In July 1997 when the market pressure is high, the inferred probability of volatile state is higher than 99%, for both constant and TGARCH model. The occurrence of crisis is correctly detected in Malaysia. The figure also shows that Markov switching TGARCH model can predict the currency crisis in a more precise manner than the constant variance model.

Finally we examine the identification of the 2 regimes. The QPS, GSB and LPS statistics are reported in Table 3.16. All these statistics clearly indicate that regime 1 is the volatile state for Malaysia.

Table 3. 15 Malaysia: Test for 2 regimes versus 1 regime.

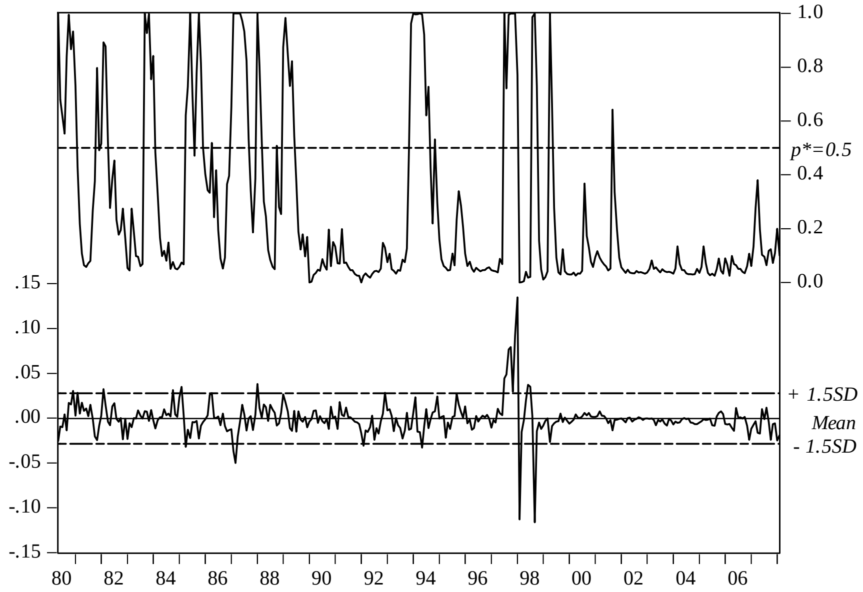
TGARCH				
No. of Regimes	Log. Likelihood	*LR*	$C(\alpha)$	*JB*
2	1269.96			
1	1246.48	46.95	25.23	22.45

Constant Variance				
No. of Regimes	Log. Likelihood	*LR*	$C(\alpha)$	*JB*
2	1269.45			
1	1199.54	139.83	21.14	1329.92

Note: At 5% significant level, $\chi^2(14) = 21.06$ $\chi^2(11) = 19.68$, $\chi^2(2) = 5.99$

Figure 3. 13 Market Pressure and Probability of volatile state for Malaysia

(1) Markov Switching constant variance model



(2)Markov Switching TGARCH model

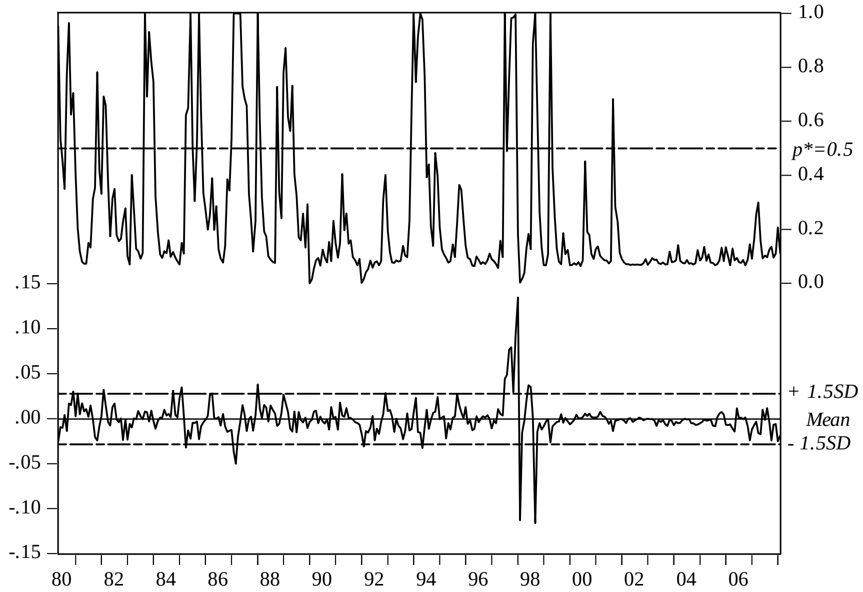


Table 3. 16 Malaysia: QPS, LPS and GSB test statistics

(a)

QPS	Constant Variance		TGARCH	
	Regime 1	Regime2	Regime 1	Regime2
Volatile Zone				
MP Plus/minus 1 stdevs	0.31091	1.32052	0.26053	1.27110
MP Plus/minus 1.5 stdevs	0.29828	1.33315	0.24627	1.28535
MP Plus/minus 2 stdevs	0.30088	1.33055	0.24489	1.28674
Stable Zone				
MP Plus/minus 1 stdevs	1.32052	0.31091	1.27110	0.26053
MP Plus/minus 1.5 stdevs	1.33315	0.29828	1.28535	0.24627
MP Plus/minus 2 stdevs	1.33055	0.30088	1.28674	0.24489

(b)

LPS	Constant Variance		TGARCH	
	Regime 1	Regime2	Regime 1	Regime2
Volatile Zone				
MP Plus/minus 1 stdevs	0.48649	1.65393	0.43236	1.46534
MP Plus/minus 1.5 stdevs	0.41315	1.72727	0.36082	1.53688
MP Plus/minus 2 stdevs	0.38461	1.75581	0.32755	1.57015
Stable Zone				
MP Plus/minus 1 stdevs	1.65393	0.48649	1.46534	0.43236
MP Plus/minus 1.5 stdevs	1.72727	0.41315	1.53688	0.36082
MP Plus/minus 2 stdevs	1.75581	0.38461	1.57015	0.32755

(c)

GSB	Constant Variance		TGARCH	
	Regime 1	Regime2	Regime 1	Regime2
Volatile Zone				
MP Plus/minus 1 stdevs	0.03019	0.72407	0.02618	0.74456
MP Plus/minus 1.5 stdevs	0.07123	0.89128	0.06499	0.91400
MP Plus/minus 2 stdevs	0.10365	0.99824	0.09609	1.02228
Stable Zone				
MP Plus/minus 1 stdevs	0.72407	0.03019	0.74456	0.02618
MP Plus/minus 1.5 stdevs	0.89128	0.07123	0.91400	0.06499
MP Plus/minus 2 stdevs	0.99824	0.10365	1.02228	0.09609

3.6.5 Empirical analysis for Singapore

Table 3.17 reports the estimation results for Singapore from single regime models. Actual and fitted MP are portrayed in Figure 3.14. We observe that all the macro and risk variables are significant at 95% confidence level. These variables can explain more than 80% of the MP. Asymmetric effect in the conditional volatility of market pressure is not significant in the TAGARCH single regime model.

The empirical estimates from the 2 regimes Markov switching models for Singapore are reported in Table 3.18. Panel A is for the results from the Markov switching model with constant variances. Our finding confirms that the fundamental and risk variables play significant roles in triggering currency crisis, as all the variables are significantly different from zero at 5% significance level for both states, expect for DGDC in the volatile state, which is significant at 10% significance level.

The TGARCH Markov Switching estimates are reported in Panel B. Similar to the constant model, all variables differ from zero at 95% confidence level expect for DGDC. Signs on the Risk and DGC variables, in their level or first difference, are still not always consistent with the theoretical expectation. The GARCH process is stationary in both volatile and stable state, as $V_1 + V_2 + V_3 < 1$. However, in the volatile state, $V_1 + V_2 > 1$. This indicate that when $\varepsilon_t > 0$, the volatility do not die away after periods but intent to expand instead. Coefficient V_3 is negative and significant in the volatile state, indicating that the asymmetric affect of positive shocks can increase the next period volatility of market pressure to a larger extent than the negative shocks. In the stable state, however, V_3 is positive, which means that the negative shocks have large impact on the conditional volatility in the next period. V_2 in both state are indifferent from zero at 5% significant level, implying that the volatility of market pressure do not depend on the past conditional volatility. However, past shocks has significant impact on the conditional volatility. The joint significance test for the TGARCH structure gives $LR = 48.34$, larger than the critical value, suggesting that the TGARCH structure should not be eliminated.

The transitional probability P_{12} and P_{21}, are significant at 95% confidence level in the constant model, However, for the TGARCH model, the transitional probability is not significant at 5% significance level for the stable state, but only significant at 10% level. Since $2 - P_{12} - P_{21} > 1$, we can conclude that the process is likely to persist in its current state rather than switching to the other. The average persistent is about 4 months for the volatile state and much larger for the stable state. The persistence of stable states in the constant model is higher than in the TGARCH model. On the other hand, the persistence of volatile state from the two modelling specification are more or less the same. The unconditional probabilities of the market pressure being in each state are given in the bottom of the table.

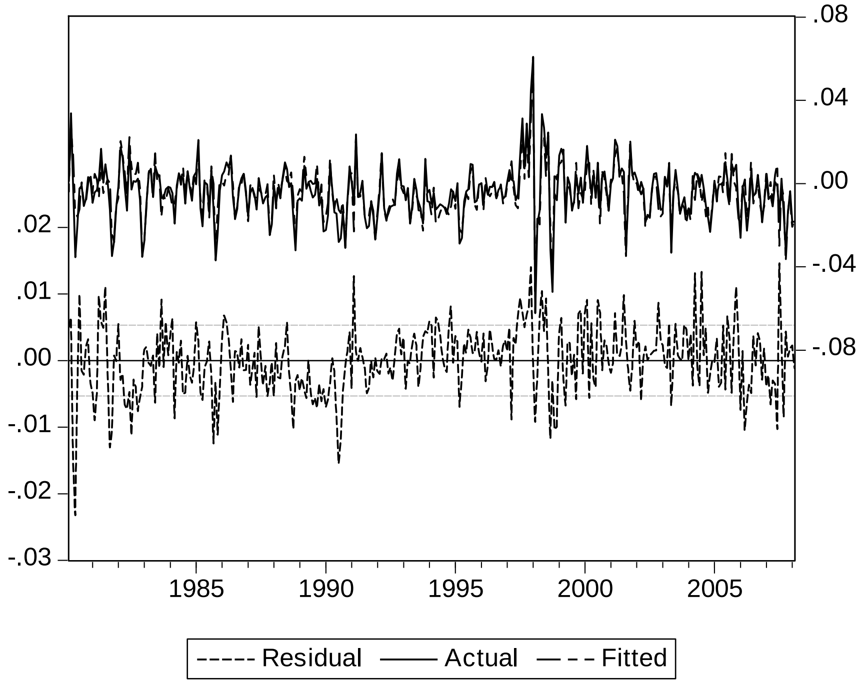
Table 3. 17 Estimation Results from Single Regime models for Singapore

	Singapore					
	Constant Variance			TGARCH		
	Coeff	Std Error	Signif	Coeff	Std Error	Signif
β_1	-0.00703	0.00055	0.00000	-0.00648	0.00048	0.00000
β_2	0.03479	0.00490	0.00000	0.03286	0.00460	0.00000
β_3	-0.04472	0.01172	0.00020	-0.04440	0.01170	0.00010
β_4	0.07905	0.01408	0.00000	0.06963	0.01284	0.00000
β_5	-0.12249	0.02053	0.00000	-0.12991	0.01433	0.00000
β_6	0.72834	0.02472	0.00000	0.68261	0.02278	0.00000
β_7	-0.03877	0.00768	0.00000	-0.04006	0.00474	0.00000
β_8	-0.08853	0.01622	0.00000	-0.11910	0.01313	0.00000
v_0				0.00000	0.00000	0.02740
v_1				0.24683	0.10406	0.01770
v_3				-0.00159	0.10229	0.98760
v_2				0.60859	0.11026	0.00000
R^2	0.8413			0.8380		
$\bar{R}^2$	0.8379			0.8325		
JB	19.2843			0.0490		
$Log(L)$	1290.81			1310.39		
LR	39.15					

Note: The critical value for $\chi^2(3) = 7.81$, $\chi^2(2) = 5.99$

Figure 3. 14 Actual and fitted value of MP from single regime estimation: Singapore

(1) Constant (OLS) model



(2) TGARCH(1,1) model

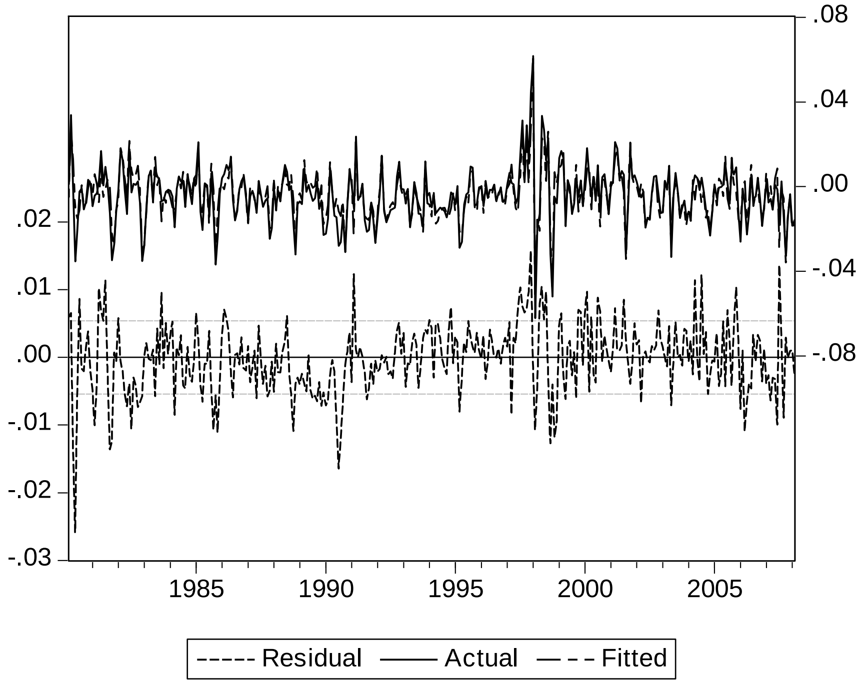


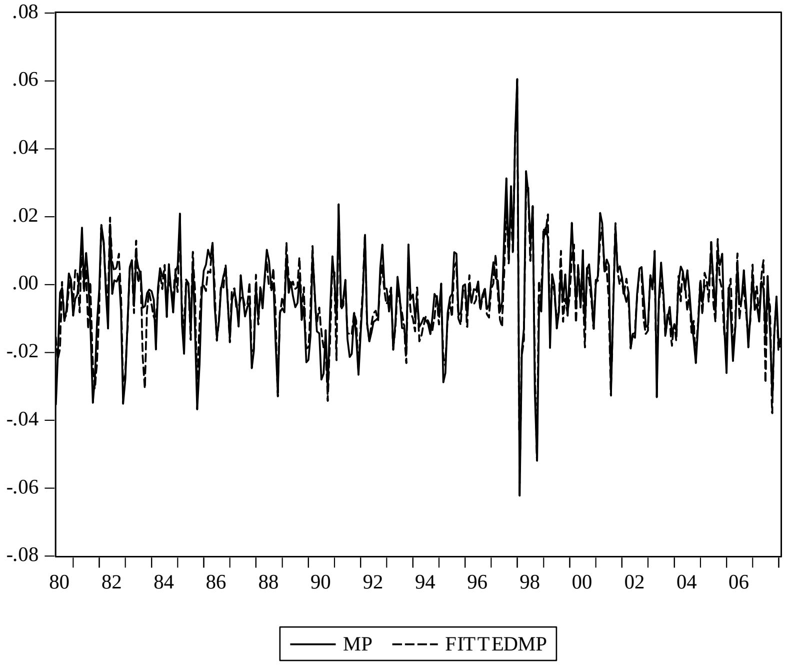
Table 3. 18 Parameter estimates and related statistics for Markov Regime Switching models: Singapore

	Panel A Constant Variance:Singapore						Panel B Threshold GARCH: Singapore					
	Regime 1 (Volatile State)			Regime 2 (Stable State)			Regime 1 (Volatile State)			Regime 2 (Stable State)		
Variable	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif
p_{12}/p_{21}	0.21000	0.06940	0.00247	0.03090	0.01450	0.03317	0.20568	0.07892	0.00916	0.05057	0.02942	0.08559
β_1	-0.01640	0.00217	0.00000	-0.00587	0.00050	0.00000	-0.00738	0.00043	0.00000	-0.00577	0.00049	0.00000
β_2	0.09470	0.01470	0.00000	0.03090	0.00504	0.00000	0.03713	0.00390	0.00000	0.03220	0.00440	0.00000
β_3	-0.12550	0.03240	0.00011	-0.06480	0.01300	0.00000	-0.03192	0.00948	0.00076	-0.06773	0.01137	0.00000
β_4	0.23910	0.03590	0.00000	0.04310	0.01330	0.00118	0.17105	0.01042	0.00000	0.03732	0.01337	0.00525
β_5	-0.06780	0.03000	0.02400	-0.16260	0.02200	0.00000	-0.16923	0.03442	0.00000	-0.14944	0.02254	0.00000
β_6	0.96390	0.04730	0.00000	0.64340	0.02480	0.00000	0.89744	0.02283	0.00000	0.63292	0.01285	0.00000
β_7	-0.02090	0.01220	0.08532	-0.05750	0.00963	0.00000	-0.01568	0.00516	0.00236	-0.05838	0.00727	0.00000
β_8	0.08180	0.02540	0.00131	-0.13150	0.01690	0.00000	0.02428	0.01701	0.15341	-0.14287	0.00477	0.00000
v_0	0.00002	0.00000	0.00030	0.00002	0.00000	0.00000	0.00000	0.00000	0.43604	0.00002	0.00000	0.00000
v_1							2.06228	0.45896	0.00001	-0.04248	0.00325	0.00000
v_2							0.15742	0.11690	0.17808	0.02181	0.06639	0.74258
v_3							-2.02622	0.46345	0.00001	0.61133	0.09889	0.00000
κ	0.1283			0.8717			0.1974			0.8026		
Average Persistence	4.76			32.41			4.86			19.77		
Log(L)	1315.34						1339.51					
LR	48.34											

Note: The critical value for $\chi^2(6) = 12.59$

Figure 3. 15 Actual and fitted value of MP from Markov switching models: Singapore

(1) Markov Switching constant variance model



(2)Markov Switching TGARCH model

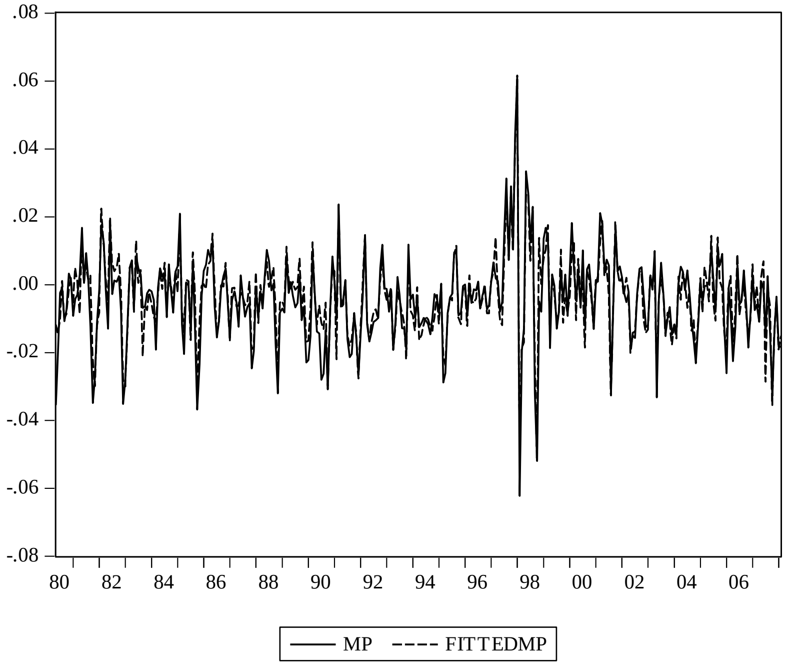
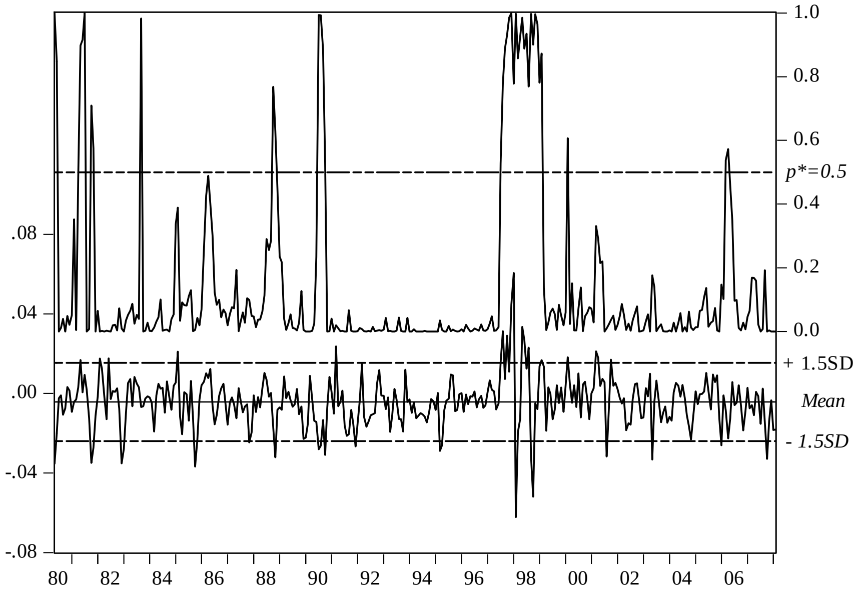
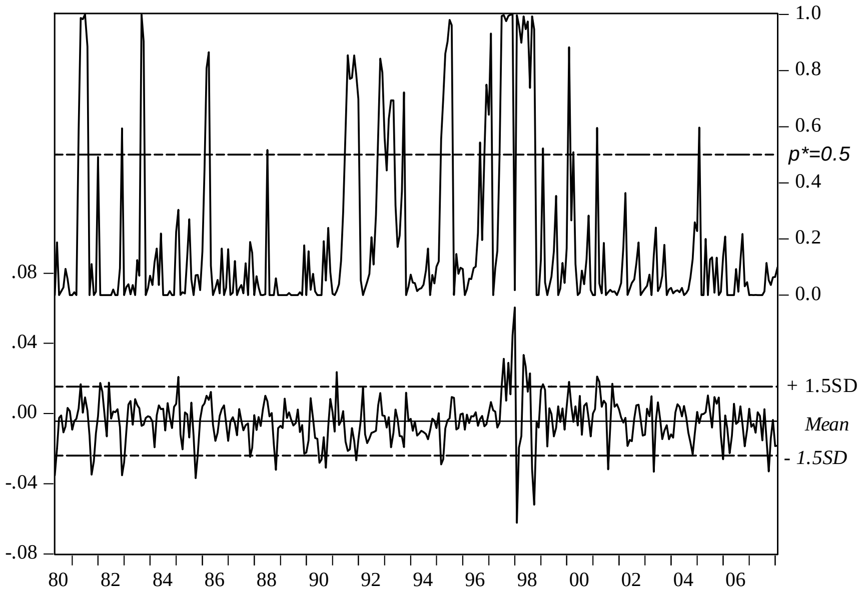


Figure 3. 16 Market Pressure and Probability of volatile state for Singapore

(1) Markov Switching constant variance model



(2)Markov Switching TGARCH model



Figures 3.15 (1) and (2) present the actual and fitted MP along with the residuals from the estimation models for Singapore; and Figure 3.16 (1) and (2) illustrate the inferred probability of volatile state and market pressure. From the figures we can see that the models have predictive power for the currency crisis. Both constant and TGARCH Markov switching model can correctly predict the 1997 currency crisis.

We turn now to Table 3.19 to comment on the determination of the number of regimes. The LR test statistics suggest that two regimes rather than one regime should be used. However, the Newman's $C(\alpha)$ test statistics is 4.81 for the TGARCH and 4.22 for the constant model respectively, both of which are less than their critical values. These results contradict with the LR test results and indicating that one regime may be proper. The JB statistics for the residuals from one regime model is larger than its critical value for the constant model, but smaller for the TGARCH model. However, when we use bootstrapping method to establish a population from the residuals and then use 500 replications for the JB and 100 replications to test for the number of modes in the residuals, these simulation test results give that the residuals are not normally distributed. The results from these tests do not agree with each other. Recall earlier we find that the transitionally probability in the stable state for the TGARCH estimation is not significant from zero at 5% significance level. The inconsistent test statistics together with the estimation results made us to be cautious in claiming the existence of a second regime in the Singapore exchange market. Further test may be needed before drawing any conclusion.

We turn now to the identification of the 2 regimes (if two 2 regimes are presented and Markov switching models are used). The QPS, GSB and LPS statistics are reported in Table 3.20, which all corroborate our observation that regime 1 is the volatile state where currency crisis likely to happened and regime 2 is the stable state.

Table 3. 19 Singapore: Test for 2 regimes versus 1 regime.

TGARCH				
No. of Regimes	Log. Likelihood	*LR*	$C(\alpha)$	*JB*
2	1339.51			
1	1301.29	76.44	4.81	0.26

Constant Variance				
No. of Regimes	Log. Likelihood	*LR*	$C(\alpha)$	*JB*
2	1315.34			
1	1283.02	64.64	4.22	18.68

Note: At 5% significant level, $\chi^2(14) = 21.06$ $\chi^2(11) = 19.68$, $\chi^2(2) = 5.99$

Table 3. 20 Singapore: QPS, LPS and GSB test statistics

(a)

QPS	Constant Variance		TGARCH	
	Regime 1	Regime2	Regime 1	Regime2
Volatile Zone				
MP Plus/minus 1 stdevs	0.29940	1.41944	0.39137	1.33942
MP Plus/minus 1.5 stdevs	0.28456	1.43428	0.28892	1.44187
MP Plus/minus 2 stdevs	0.28783	1.43101	0.25545	1.47534
Stable Zone				
MP Plus/minus 1 stdevs	1.41944	0.29940	1.33942	0.39137
MP Plus/minus 1.5 stdevs	1.43428	0.28456	1.44187	0.28892
MP Plus/minus 2 stdevs	1.43101	0.28783	1.47534	0.25545

(b)

LPS	Constant Variance		TGARCH	
	Regime 1	Regime2	Regime 1	Regime2
Volatile Zone				
MP Plus/minus 1 stdevs	0.43473	1.91435	0.54797	1.85123
MP Plus/minus 1.5 stdevs	0.38527	1.96382	0.41296	1.98624
MP Plus/minus 2 stdevs	0.37548	1.97361	0.32758	2.07162
Stable Zone				
MP Plus/minus 1 stdevs	1.91435	0.43473	1.85123	0.54797
MP Plus/minus 1.5 stdevs	1.96382	0.38527	1.98624	0.41296
MP Plus/minus 2 stdevs	1.97361	0.37548	2.07162	0.32758

(c)

GSB	Constant Variance		TGARCH	
	Regime 1	Regime2	Regime 1	Regime2
Volatile Zone				
MP Plus/minus 1 stdevs	0.03593	0.83052	0.00322	0.65675
MP Plus/minus 1.5 stdevs	0.07064	0.97524	0.01175	0.95166
MP Plus/minus 2 stdevs	0.08234	1.01750	0.03567	1.11509
Stable Zone				
MP Plus/minus 1 stdevs	0.83052	0.03593	0.65675	0.00322
MP Plus/minus 1.5 stdevs	0.97524	0.07064	0.95166	0.01175
MP Plus/minus 2 stdevs	1.01750	0.08234	1.11509	0.03567

3.6.6 Empirical analysis for Philippines

Single regime estimates from constant and TGARCH models are reported in Table 3.21. Actual and fitted MP are portrayed in Figure 3.17. We can observe that for both model, GDC and DGDC are not significant from zero, therefore do not have significant impact on the market pressure. All other fundamentals and risk variables are significant at 95% confidence level. These variables can explain more than 80% of the MP in Philippines. Covariance is stationary for TGARCH model, with significant asymmetric effect in the conditional volatility.

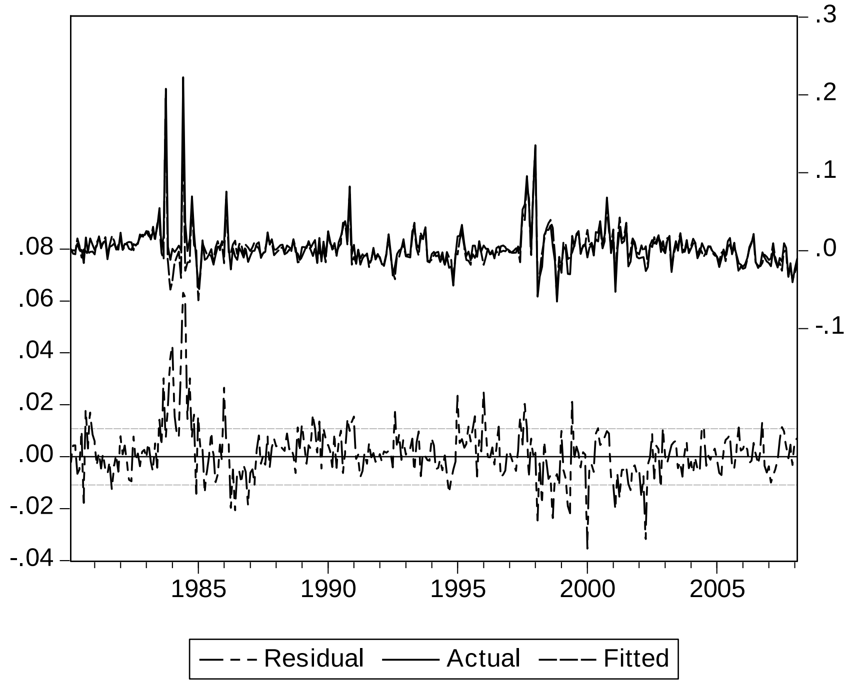
Table 3. 21 Estimation Results from Single Regime models for Philippines

	Philippine					
	Constant Variance			TGARCH		
	Coeff	Std Error	Signif	Coeff	Std Error	Signif
β_1	0.00616	0.00286	0.03200	0.00422	0.00227	0.06350
β_2	0.06858	0.00579	0.00000	0.04499	0.00487	0.00000
β_3	0.01301	0.01837	0.47930	0.01854	0.01782	0.29830
β_4	-0.01792	0.01129	0.11350	-0.02555	0.01068	0.01670
β_5	-0.18118	0.03486	0.00000	-0.19104	0.02824	0.00000
β_6	0.81748	0.02959	0.00000	0.79753	0.02131	0.00000
β_7	-0.01186	0.01422	0.40500	0.00060	0.01705	0.97220
β_8	-0.10443	0.01504	0.00000	-0.09378	0.00949	0.00000
v_0				0.00001	0.00000	0.00670
v_1				0.22764	0.04935	0.00000
v_3				0.00988	0.07084	0.88910
v_2				0.71260	0.03825	0.00000
R^2	0.8343			0.8232		
$\bar{R}^2$	0.8308			0.8172		
JB	825.82			33.6678		
Log(L)	1051.27			1117.48		
LR	132.41					

Note: The critical value for $\chi^2(3) = 7.81$, $\chi^2(2) = 5.99$

Figure 3. 17 Actual and fitted value of MP from single regime estimation: Philippines

(1) Constant (OLS) model



(2) TGARCH(1,1) model

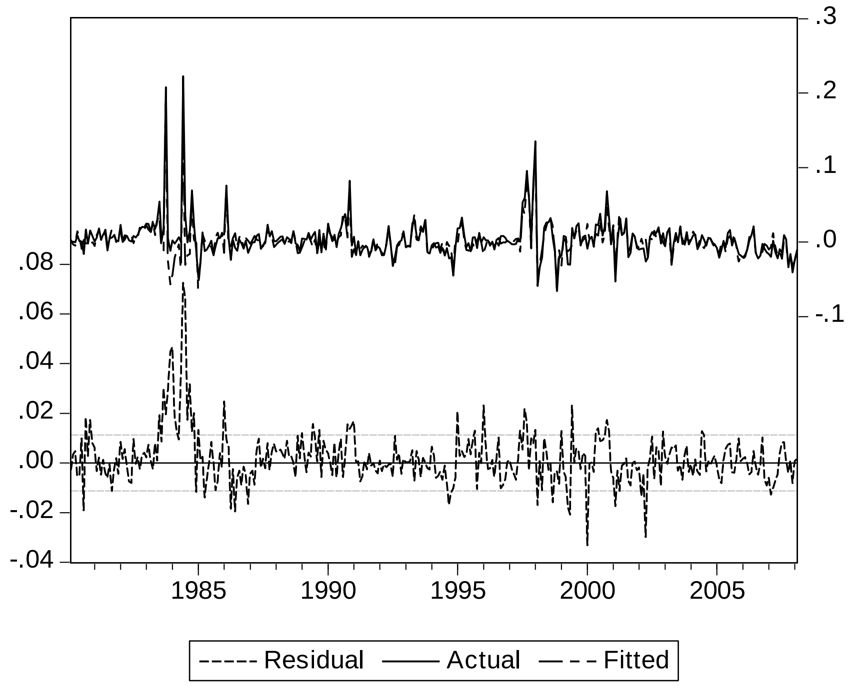


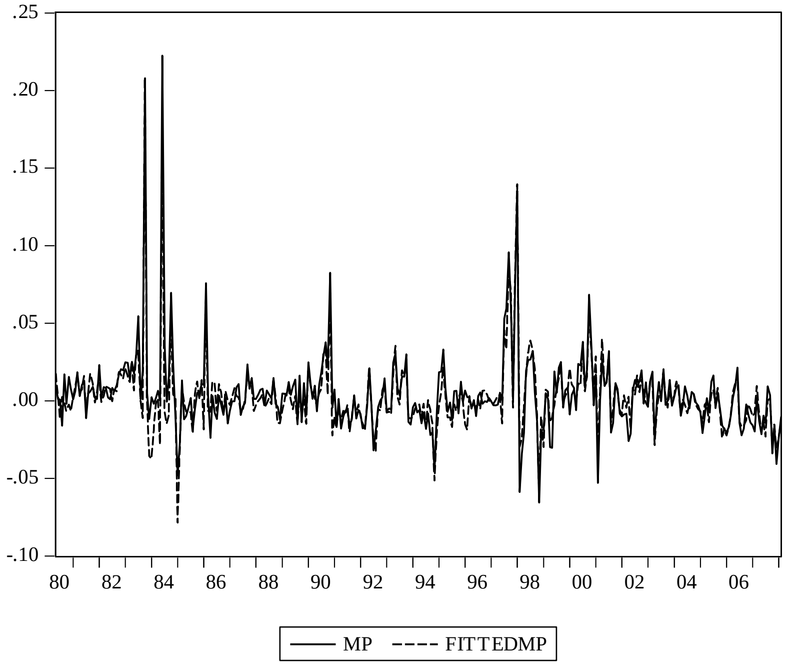
Table 3. 22 Parameter estimates and related statistics for Markov Regime Switching models: Philippines

	Panel A Constant Variance: Philippines						Panel B Threshold GARCH: Philippines					
	Regime 1 (Volatile State)			Regime 2 (Stable State)			Regime 1 (Volatile State)			Regime 2 (Stable State)		
Variable	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif
p_{12}/p_{21}	0.13980	0.05280	0.00807	0.04340	0.01580	0.00586	0.15200	0.01910	0.00000	0.04390	0.00916	0.00000
β_1	0.00427	0.00875	0.62517	0.00234	0.00169	0.16516	0.00690	0.00024	0.00000	0.00155	0.00162	0.33901
β_2	0.10950	0.01070	0.00000	0.03690	0.00402	0.00000	0.11750	0.02162	0.00000	0.03110	0.00284	0.00000
β_3	-0.12660	0.04430	0.00429	0.02460	0.01110	0.02736	0.03110	0.01117	0.00000	0.02070	0.00248	0.00000
β_4	0.04000	0.01680	0.01687	-0.02410	0.00655	0.00023	0.01410	0.00094	0.00000	-0.02500	0.00293	0.00000
β_5	-0.25480	0.10830	0.01857	-0.21450	0.02330	0.00000	-0.12910	0.00400	0.00000	-0.22890	0.00966	0.00000
β_6	0.89530	0.02760	0.00000	0.71610	0.02280	0.00000	0.80910	0.06026	0.00000	0.69810	0.03490	0.00000
β_7	-0.18800	0.03510	0.00000	0.00813	0.00978	0.40586	-0.06110	0.00205	0.00000	0.00531	0.00189	0.00497
β_8	-0.06600	0.01450	0.00001	-0.12040	0.01170	0.00000	-0.06870	0.00286	0.00000	-0.14050	0.01260	0.00000
v_0	0.00027	0.00004	0.00000	0.00004	0.00000	0.00000	0.00010	0.00001	0.00000	0.00001	0.00000	0.00000
v_1							0.86250	0.05085	0.00000	0.06930	0.01390	0.00000
v_2							-0.07950	0.00528	0.00000	0.69590	0.02300	0.00000
v_3							-0.01700	0.00049	0.00000	0.09470	0.04880	0.05230
κ	0.2369			0.7631			0.2241			0.7759		
Average Persistence	7.15			23.04			6.58			22.79		
Log(L)	1116.13						1128.47					
LR	24.68											

Note: The critical value for $\chi^2(6) = 12.59$

Figure 3. 18 Actual and fitted value of MP from Markov switching models: Philippines

(1) Markov Switching constant variance model



(2)Markov Switching TGARCH model

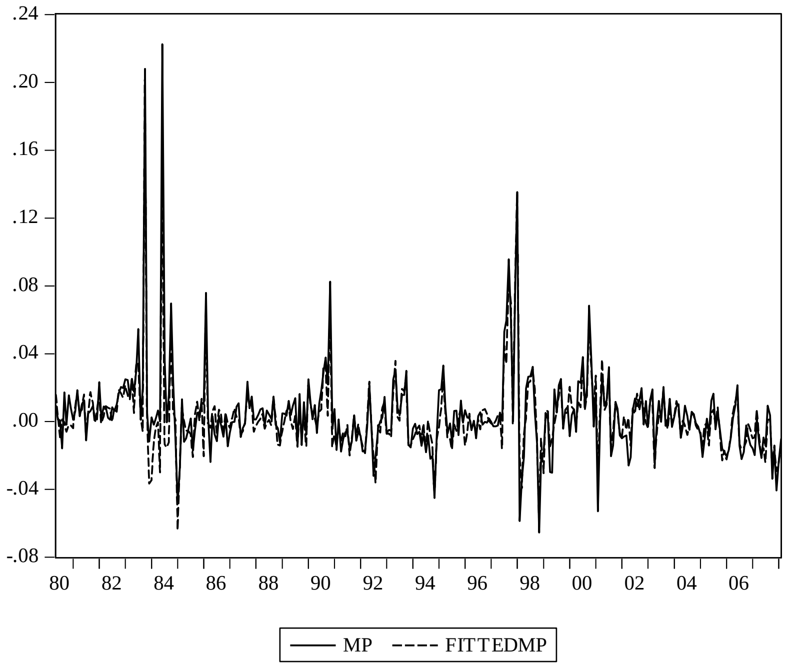
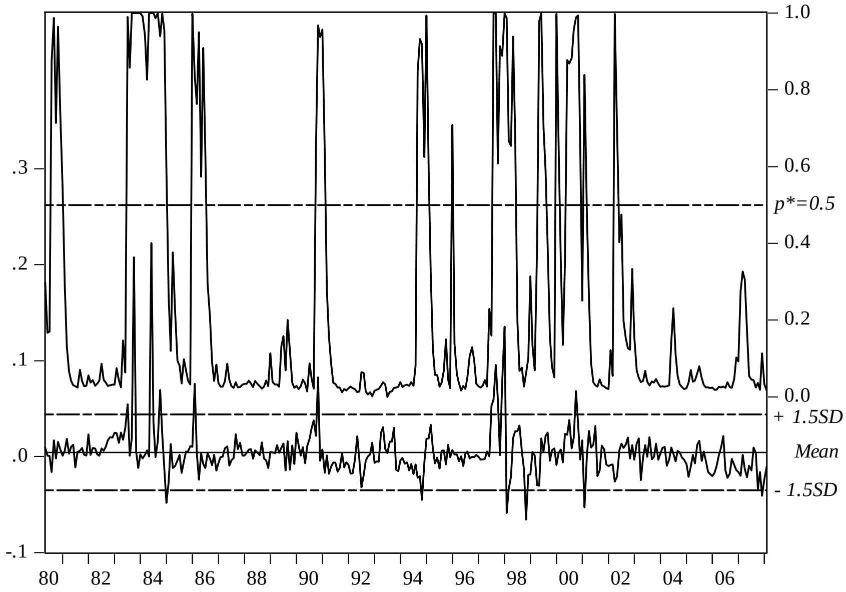


Figure 3. 19 Market Pressure and Probability of volatile state for Philippines

(1) Markov Switching constant variance model



(2)Markov Switching TGARCH model

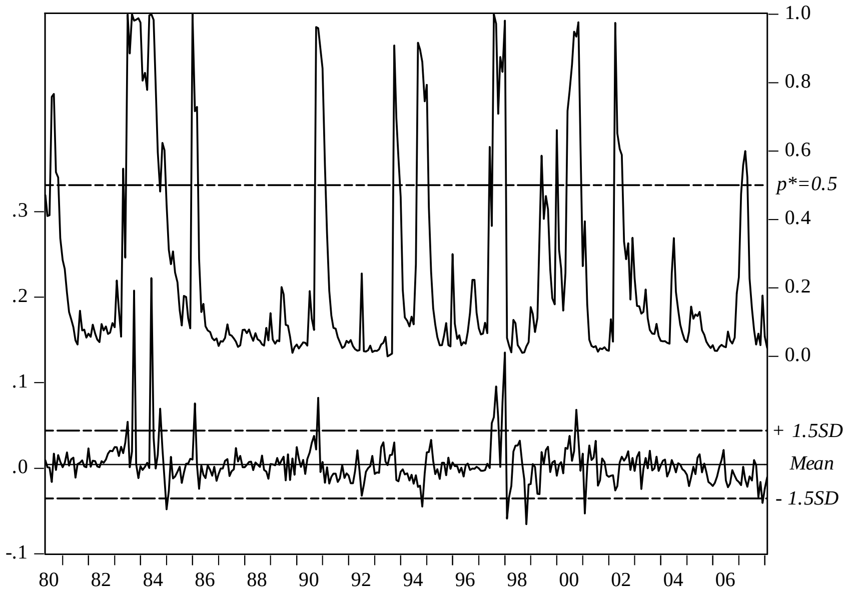


Table 3.22 reports the estimates from 2 regimes Markov Switching constant and TGARCH models for Philippines. In the constant model, we found that RM2 is not significant in both states, and DGDC is not significant in stable state. All variables are significant in the TGARCH switching model expect RM2 in the stable regime. Markov Switching TGARCH model is covariance stationary in every regime.

For the Markov switching models, the transitional probabilities are significantly different from zero at 95% significant level. The average persistence of volatile and stable state both reduces under the TGARCH modelling specification than under the constant modelling specification. The unconditional probability of being in the stable state is more than 75%.

Figure 3.18 graphs the actual and fitted MP and the residuals for the Markov Switching models with constant variance and with TGARCH conditional variance. Still, the fitted MP tracks the MP very well, indicating the explanatory power of the fundamental variables. But we can not tell which model perform better only through the graphs. For the information on 1 v.s. 2 regimes, the LR and Newman's $C(\alpha)$ test statistics reported in Table 3.23 give contradicting results. JB statistics and bootstrapping methods for the residuals from 1 regime estimates show that the residuals are not normally distributed, which support the 2 regimes rather than a single regime should be modelled.

Figure 3.19 presents market pressure the inferred probability of volatile state and with presumed crisis band. TGARCH model detects the currency crisis one month before the high market pressure took place in July 1997, however, the constant model only detect the currency crisis one month later after. For the identification of the 2 regimes, The QPS, GSB and LPS statistics are reported in Table 3.24. All these statistics clearly indicate that regime 1 is the volatile state for Philippines.

Table 3. 23 Philippines: Test for 2 regimes versus 1 regime.

TGARCH				
No. of Regimes	Log. Likelihood	LR	$C(\alpha)$	JB
2	1128.47			
1	1106.16	44.63	20.38	31.75

Constant Variance				
No. of Regimes	Log. Likelihood	LR	$C(\alpha)$	JB
2	1116.13			
1	1040.61	151.05	15.51	824.29

Note: At 5% significant level, $\chi^2(14) = 21.06$ $\chi^2(11) = 19.68$, $\chi^2(2) = 5.99$

Table 3. 24 Philippines: QPS, LPS and GSB test statistics

(a)

QPS	Constant Variance		TGARCH	
	Regime 1	Regime2	Regime 1	Regime2
Volatile Zone				
MP Plus/minus 1 stdevs	0.29940	1.41944	0.27935	1.33273
MP Plus/minus 1.5 stdevs	0.28456	1.43428	0.24034	1.37174
MP Plus/minus 2 stdevs	0.28783	1.43101	0.24467	1.36741
Stable Zone				
MP Plus/minus 1 stdevs	1.41944	0.29940	1.33273	0.27935
MP Plus/minus 1.5 stdevs	1.43428	0.28456	1.37174	0.24034
MP Plus/minus 2 stdevs	1.43101	0.28783	1.36741	0.24467

(b)

LPS	Constant Variance		TGARCH	
	Regime 1	Regime2	Regime 1	Regime2
Volatile Zone				
MP Plus/minus 1 stdevs	0.43473	1.91435	0.39784	1.79395
MP Plus/minus 1.5 stdevs	0.38527	1.96382	0.32635	1.86545
MP Plus/minus 2 stdevs	0.37548	1.97361	0.32003	1.87177
Stable Zone				
MP Plus/minus 1 stdevs	1.91435	0.43473	1.79395	0.39784
MP Plus/minus 1.5 stdevs	1.96382	0.38527	1.86545	0.32635
MP Plus/minus 2 stdevs	1.97361	0.37548	1.87177	0.32003

(c)

GSB	Constant Variance		TGARCH	
	Regime 1	Regime2	Regime 1	Regime2
Volatile Zone				
MP Plus/minus 1 stdevs	0.03593	0.83052	0.03214	0.84936
MP Plus/minus 1.5 stdevs	0.07064	0.97524	0.06528	0.99565
MP Plus/minus 2 stdevs	0.08234	1.01750	0.07654	1.03834
Stable Zone				
MP Plus/minus 1 stdevs	0.83052	0.03593	0.84936	0.03214
MP Plus/minus 1.5 stdevs	0.97524	0.07064	0.99565	0.06528
MP Plus/minus 2 stdevs	1.01750	0.08234	1.03834	0.07654

3.6.7 Comparison and summarisation of the empirical results of the six Asian countries

Now we turn to compare and summarise the empirical results of the six Asian countries. For all six countries, we find that most of the explanatory variables are significant in their levels and their first differences. The domestic credit growth, in its level and in its first difference, has the highest frequency of being insignificant. Moreover, the signs on the GDC variables violate the theoretical expectation quite often. Although domestic credit growth is a very important factor in the first and second generation models for currency crisis, the empirical results in these six Asian countries are not supportive. Another variable, Risk, in its level and in its first difference, also frequently have a sign do not match the theoretical anticipation. The RER variable is always significant in the stable state for all six countries, and mostly significant in the volatile state except that in the Markov switching constant model for Korea and Malaysia. RER always has a positive sign, and has larger impact in the volatile state than in the stable state, with the only exception in the volatile state of Thailand using constant model.

The covariance structure in the Markov Switching TGARCH model is always stationary for all six countries. In most cases, the asymmetric effect in the conditional volatility is significant. For all the countries except Malaysia, the LR test statistics reject the null hypothesis that parameters on the conditional variance are jointly zero.

The TGARCH specification for the conditional variance in the Markov Switching model should not be restricted to zero.

For Thailand, Indonesia, Malaysia and Philippines, the average persistence of volatile state is lower in the TGARCH model than in the constant model, so as that of the stable state. For Singapore, the TGARCH model reduces the average persistence of stable state but not that of the volatile state; and it is the opposite for Korea. In general, the TGARCH modelling specification tends to reduce the average persistence of either state.

All the Markov Switching models can correctly detect the currency crisis in 1997, as depicted in the market pressure and inferred probability of volatile state figures. However, it is hard to justify from the figures which model, TGARCH or Constant, is superior in tracking and detecting currency crisis. We provide further prediction evaluation for the Markov Switching TGARCH and Constant Variance models.

Assume that the trigger point for a currency attack is $mean(MP_t) \pm a * std(MP_t)$. When the inferred probability p* > 0.5 and at the same time

$$MP_t > mean(MP_t) + a * std(MP_t) \quad \text{or} \quad MP_t < mean(MP_t) - a * std(MP_t)$$

the observation is assigned a value one to indicate that the crisis is correctly predicted at the time. Similarly, when the inferred probability of stable state is bigger than 0.5, which is equivalent to that (1-p*)>0.5, and at the same time

$$mean(MP_t) - a * std(MP_t) \le MP_t \le mean(MP_t) + a * std(MP_t)$$

We assume a non-crisis state is correctly predicted at the time. Because as the value of *a* change, the predictive power of the model may change, we set *a* to equal to different values (1.5, 1 and 2) for evaluation purpose. The actual and correctly predicted total number of crisis and non-crisis state using Markov Switching TGARCH and Constant Variance models are listed in Table 3.25 (1) to (3), for $a = 1.5$, $a = 1$ and $a = 2$ respectively. Then the percentages of correct predictions are calculated.

From Table 3.25, we found that the "percentage correct" for non-crisis (stable) state is higher than for the crisis (or volatile) state, using both constant variance and TGARCH models, in all the six countries. When *a=1.5*, the correct percentage of the non-crisis state is higher than when *a=2* but lower than when *a=1*. In contrast, for the correct prediction of crisis state, it is highest when *a=2* and lowest when *a=1*, with when *a=1.5* lies in between. We also find that the TGARCH Markov switching models give better results in focusing non-crisis status and constant model is somewhat superior in focusing the crisis status. In any case, the correct percentage of prediction for the currency crisis is low. When *a=1.5* , the regime switching models for Philippines give the highest correct percentage in predicting crisis, with 63.16% under the TGARCH and 84.21% under the constant variance specifications; whilst the models give the lowest correct prediction percentage of crisis for Thailand, with only 29.17% under the constant model. The performance of TGARCH and constant models are mixed, we can not claim one is absolutely superior than the other in explaining and predicting exchange market pressure, albeit we claimed earlier, by considering the LR statistics, that the asymmetric GARCH specification in the conditional volatility of the Markov Switching models should not be restricted to constant.

Table 3. 25 Markov Switching Models Crisis Prediction Evaluation

(1) $a=1.5$

	Markov Switching Models					
	TGARCH			Constant Variance		
	Actual	Predicted	Percentage Correct	Actual	Predicted	Percentage Correct
Korea						
No Crisis	321	314	97.82	321	301	93.77
Crisis	13	7	53.85	13	8	61.54
Sum	334	321	96.11	334	309	92.51
Indonesia						
No Crisis	303	288	95.05	303	285	94.06
Crisis	31	15	48.39	31	18	58.06
Sum	334	303	90.72	334	303	90.72
Thailand						
No Crisis	312	280	89.74	312	299	95.83
Crisis	22	13	59.09	22	8	36.36
Sum	334	293	87.72	334	307	91.92
Malaysia						
No Crisis	310	269	86.77	310	256	82.58
Crisis	24	13	54.17	24	16	66.67
Sum	334	282	84.43	334	272	81.44
Singapore						
No Crisis	295	256	86.78	295	279	94.58
Crisis	39	18	46.15	39	21	53.85
Sum	334	274	82.04	334	300	89.82
Philippines						
No Crisis	315	266	84.44	315	260	82.54
Crisis	19	12	63.16	19	16	84.21
Sum	334	278	83.23	334	276	82.63

(2) *a=1*

	Markov Switching Models					
	TGARCH			Constant Variance		
	Actual	Predicted	Percentage Correct	Actual	Predicted	Percentage Correct
Korea						
No Crisis	296	292	98.65	296	282	95.27
Crisis	38	10	26.32	38	14	36.84
Sum	334	302	90.42	334	296	88.62
Indonesia						
No Crisis	275	264	96.00	275	264	96.00
Crisis	59	19	32.20	59	25	42.37
Sum	334	283	84.73	334	289	86.53
Thailand						
No Crisis	286	265	92.66	286	279	97.55
Crisis	48	24	50.00	48	14	29.17
Sum	334	289	86.53	334	293	87.72
Malaysia						
No Crisis	288	255	88.54	288	242	84.03
Crisis	46	21	45.65	46	24	52.17
Sum	334	276	82.63	334	266	79.64
Singapore						
No Crisis	256	228	89.06	256	247	96.48
Crisis	78	29	37.18	78	28	35.90
Sum	334	257	76.95	334	275	82.34
Philippines						
No Crisis	297	252	84.85	297	249	83.84
Crisis	37	16	43.24	37	23	62.16
Sum	334	268	80.24	334	272	81.44

(3) *a=2*

	Markov Switching Models					
	TGARCH			Constant Variance		
	Actual	Predicted	Percentage Correct	Actual	Predicted	Percentage Correct
Korea						
No Crisis	326	317	97.24	326	305	93.56
Crisis	8	5	62.50	8	7	87.50
Sum	334	322	96.41	334	312	93.41
Malaysia						
No Crisis	323	276	85.45	323	262	81.11
Crisis	11	7	81.82	11	9	81.82
Sum	334	283	84.73	334	271	81.14
Thailand						
No Crisis	318	284	89.31	318	305	95.91
Crisis	16	11	68.75	16	8	50.00
Sum	334	295	88.32	334	313	93.71
Indonesia						
No Crisis	317	297	93.69	317	292	92.11
Crisis	17	10	58.82	17	11	64.71
Sum	334	307	91.92	334	303	90.72
Singapore						
No Crisis	314	267	85.03	314	291	92.68
Crisis	20	10	50.00	20	14	70.00
Sum	334	277	82.93	334	305	91.32
Philippines						
No Crisis	320	269	84.06	320	262	81.88
Crisis	14	10	71.43	14	13	92.86
Sum	334	279	83.53	334	275	82.34

3.7 The Multinomial Logit Estimation

3.7.1 Methodology

The Binary Logit/Probit regressions have been widely used to examine currency crises. Such are referred to as the discrete-dependent-variable approaches. In these approaches, it normally involves converting the exchange market pressure index (which is used as the currency crises indicator) into a binary variable. Currency crisis is occurring when market pressure is bigger than a threshold value, which is often defined as the mean of market pressure plus *a* times it's standard deviation. Thus the binary dependent variable Y_t is often defined as:

$$Y_t = \begin{cases} 1 & \text{if } MP_t > mean(MP) + a * Std(MP) \\ 0 & \text{otherwise} \end{cases}$$

The crisis index Y_t is explained by a set of independent variable X_t includes fundamental variables like RM2, RER, and GDC, Risk, etc. The aim of the model is to estimate the impact of the indicators X_t on the probability of experiencing a crisis.

The logit model is defined using a logistic distribution:

$$prob(Y_t = 1) = \frac{\exp(X_t \beta)}{1 + \exp(X_t \beta)} = \Lambda(\beta' X_t) \qquad (3.54)$$

Where $\Lambda(.)$ indicates the logistic cumulative distribution function.

The link function follows a linear regression:

$$Y_t = \beta' X + \varepsilon_t \tag{3.52}$$

In our study, it can be written as

$$\begin{aligned} Y_t = \beta_0 + \underset{(+)or(-)}{\beta_1 RM2_{t-1}} + \underset{(+)or(-)}{\beta_2 RER_{t-1}} + \underset{(+)}{\beta_3 GDC_{t-1}} + \underset{(+)}{\beta_4 Risk_{t-1}} \\ + \underset{(+)or(-)}{\beta_5 DRM2_t} + \underset{(+)or(-)}{\beta_6 DRER_t} + \underset{(+)}{\beta_7 DGDC_t} + \underset{(+)}{\beta_8 DRisk_t} + \varepsilon_t \end{aligned} \tag{3.53}$$

The probit model is defined as

$$prob(Y_t = 1) = \phi(\beta' X_t) \tag{3.55}$$

$\phi(.)$ the cumulative distribution function of the standard normal distribution

There are some defects of the Binary Logit/Probit models. One drawback is that, using the above settings, they can only detect if there is currency crisis triggered by currency depreciation. However, as we claimed earlier, the 2 regimes Markov Switching models in our study can be used to detect not only the depreciation but also the appreciation currency attacks. To overcome this obvious shortcoming of Binary Logit/Probit models, Multinomial models are used to study the MP and compared with the estimation results from the Markov Switching models.

The Multinomial Logit model is used rather than the Multinomial Probit models because it is more appropriate for our data. Hahn and Soyer (2005) suggest that Logit provides a better fit in the presence of extreme independent variable levels and conversely that Probit better fit random effects models with moderate data sets. Finney (1952) suggests using the Logit over the Probit transformation when data are not normally distributed. Maddala (1992) shows that in the case of disproportionate sampling in two binary groups, i.e., very few response ($Y_t = 1, Y_t$ defined below) or very few non-response ($Y_t = 0$), the Logit coefficients model is not affected. However, Probit model is not valid in estimating the disproportionate sample. In our case, there are very few observations where $Y_t = 1$, Logit mode is a proper choice.

The Multinomial Logit (Mlogit) model is a straightforward extension of the Binary Logit model. Suppose dependent variable has *M+1* categories. One value (typically the first, the last or the value with the highest frequency of the dependent variable) is designated as the reference category. The probability of membership in other categories is compared to the probability of membership in the reference category.

For a dependent variable with *M+1* categories, this requires the calculation of *M* equations, or for each category relative to the reference category, to describe the relationship between dependent variable and the independent variables.

Hence, if the first category is the reference, then, for m= 1, …, M

$$In \frac{P(Y_i = m)}{P(Y_i = 0)} = a_m + \sum_{k=1}^{K} b_{mk} X_{ik} = Z_{mi} \qquad (3.56)$$

Hence, for each category, there will be M predicted log odds, one for each category relative to the reference category. The probability is a little more complicated than it was in logistic regression. For m=1,…,M

$$\Pr(Y_i = m) = \frac{\exp(Z_{mi})}{1 + \sum_{h=1}^{M} \exp(Z_{hi})} \tag{3.57}$$

For the reference category

$$\Pr(Y_i = 0) = \frac{1}{1 + \sum_{h=1}^{M} \exp(Z_{hi})} \tag{3.58}$$

For our estimation of currency crises, we assume there are three categories, namely, the stable state, depreciation state and appreciation state. The stable state is used as the reference/base state, and the other two states are in a volatile state as defined in the Markov Switching models.

Hence the Mlogit model can be written as

$$Y_{i,t} = \begin{cases} 1 & \text{if } MP_t > mean(MP_t) + a * std(MP_t) \\ 2 & \text{if } MP_t < mean(MP_t) - a * std(MP_t) \\ 0 & \text{otherwise} \end{cases} \tag{3.59}$$

The probabilities for each category is

$$\Pr(Y_{i,t} = 0) = \frac{1}{1 + e^{(\alpha_1 + X_t \beta_1)} + e^{(\alpha_2 + X_t \beta_2)}} \tag{3.60}$$

$$\Pr(Y_{i,t} = 1) = \frac{e^{(\alpha_1 + X_t \beta_1)}}{1 + e^{(\alpha_1 + X_t \beta_1)} + e^{(\alpha_2 + X_t \beta_2)}} \tag{3.61}$$

$$\Pr(Y_{i,t} = 2) = \frac{e^{(\alpha_2 + X_t \beta_2)}}{1 + e^{(\alpha_1 + X_t \beta_1)} + e^{(\alpha_2 + X_t \beta_2)}} \tag{3.62}$$

3.7.2 Estimation results for Multinomial Logit Models

The Multinomial Logit models estimation results, when *a=1.5*, are reported in Table 3.26. The estimation results for Mlogit models when *a=1* and *a=1.5* are available upon request. For the multinomial estimations of the six countries, we find that more than half the estimated parameters are statistically not significantly different from zero, for all the six countries; and signs on the GDC, DGDC, Risk and DRisk variables are not always matching anticipation. Nonetheless, we find the Mlogit model with these fundamental and risk factors as explanatory variables can describe the market pressure and detecting crisis well, as shown below.

One objective is to evaluate the ability of the Logit model in predicting a crisis correctly based on a specified prediction rule. Here we use the conventional cut-off rule of a probability of 0.5 or 50%. The "correct" predictions of state 1, the high market pressure (i.e. the depreciation currency attacks/crisis) are obtained when the predicted probability $prob(\breve{Y}_t = 1) = \Lambda(\hat{\beta}' X_t)$ is larger than 0.5 and the observed $Y_t = 1$. Similar, the "correct" predictions for state 2, (i.e., the appreciation currency attacks/crisis) are obtained when the predicted probability $prob(\breve{Y}_t = 2) = \Lambda(\hat{\beta}' X_t)$ is larger than 0.5 and the observed $Y_t = 2$. The "correct" predictions for State 0, or stable non-crisis state, follow the same mechanism. These are reported in Table 3.26 (1) to (3), for *a=1.5, 1 and 2* respectively. Comparing with the results obtained from Markov Switching models in Table 3.25 (1) to (3), we can observe that the Mlogit model gives overall better prediction for the market pressures than the Markov switching models. Our results do not provide evidence that 2 regimes switching models are better for the modelling currency crisis than the Logit models, as claimed in other literature (e.g. Ford, et al 2007). One argument is that we use 3 states in the Logit model but only 2 in the Markov Switching model. Using 3 regimes in the Markov Switching model may improve the results.

Figure 3.20 (1) to (6) charts the predicated probabilities and market pressure dummies. The upper halves of the graphs are the predicted probabilities of a crisis generated by the Mlogit model, and the lower halves graph the timing of crises according to the market pressure dummy. When the upper halves graphs the predicted probability of being in state 1 (predicated occurrence of depreciation crises), the lower halves of the figures mark the timing of the depreciation crisis, i.e., $MP_t > mean(mp) + 1.5 * Std(MP)$. When the upper halves graphs the predicted probability of being in state 2 (predicated occurrence of appreciation crises), the lower halves of the figures mark the timing of the depreciation crisis, i.e., $MP_t < mean(mp) - 1.5 * Std(MP)$. From the figure for the four countries, we can conclude the Mlogit model does provide a good explanation of cause and timing of the crises, especially for the depreciating currency crises. When come to explaining the appreciating market pressures, the model do not give as good results as explaining the depreciating currency attacks.

Table 3. 26 Parameter Estimates and Related Statistics for Multinomial Logit models

	Korea			Indonesia		
	Coefficient	Std.Error	t-prob	Coefficient	Std.Error	t-prob
State (1)						
β_1	-20.9376	17.6300	0.2360	-14.0711	5.4460	0.0100
β_2	9.2472	11.8000	0.4340	6.9461	2.1260	0.0010
β_3	-77.7059	73.0000	0.2880	15.7203	7.2640	0.0310
β_4	-1.1779	23.9700	0.9610	12.6292	4.9330	0.0110
β_5	-207.4140	125.0000	0.0980	-45.1566	15.2200	0.0030
β_6	134.2930	62.4700	0.0320	20.5874	10.6200	0.0530
β_7	-8.9432	33.9600	0.7920	-5.2047	4.2510	0.2220
β_8	-18.9671	36.5700	0.6040	-13.1312	7.3510	0.0750
State (2)						
β_1	-2.3140	11.0800	0.8350	-11.1159	5.1710	0.0320
β_2	0.1317	6.5350	0.9840	0.5990	1.9530	0.7590
β_3	146.1340	117.8000	0.2160	-3.3944	7.2200	0.6390
β_4	39.5459	40.6600	0.3320	1.9444	3.6030	0.5900
β_5	461.4340	246.0000	0.0620	93.7569	23.6800	0.0000
β_6	-235.5530	106.7000	0.0280	-46.0423	11.7300	0.0000
β_7	-85.3047	64.8800	0.1890	-2.9408	6.1790	0.6340
β_8	42.5171	26.4000	0.1080	10.5506	5.0160	0.0360
log-likelihood	-16.4044			-64.8263		
zeroline log-lik	-71.7509			-130.9684		
Test: Chi^2(16)	110.69			132.28		
AIC	68.8087			165.6525		
AIC/T	0.2036			0.4901		

Note: The critical value for $\chi^2(16) = 26.30$

Table 3.26 continued:

	Thailand			Malaysia		
	Coefficient	Std.Error	t-prob	Coefficient	Std.Error	t-prob
State (1)						
β_1	-89.8642	44.3600	0.0440	-36.7083	8.4250	0.0000
β_2	-1.93463	9.3220	0.8360	16.6959	7.6000	0.0290
β_3	-52.6395	90.7700	0.5620	-34.3530	26.8700	0.2020
β_4	30.4145	31.2800	0.3320	-2.0497	10.9400	0.8510
β_5	-163.0070	146.0000	0.2650	-201.6810	61.7100	0.0010
β_6	627.2510	331.3000	0.0590	195.3750	50.1600	0.0000
β_7	-202.4310	136.4000	0.1390	0.5644	22.0800	0.9800
β_8	-20.0897	34.0900	0.5560	-6.3652	16.0200	0.6910
State (2)						
β_1	-33.4229	6.3580	0.0000	-30.6169	7.3970	0.0000
β_2	-19.4058	8.6420	0.0250	-10.3613	7.3920	0.1620
β_3	-100.7980	51.8600	0.0530	-5.5259	15.1900	0.7160
β_4	-7.9427	16.9600	0.6400	-37.3219	22.5700	0.0990
β_5	38.4748	52.4200	0.4640	-0.0312	56.4200	1.0000
β_6	-175.1770	46.2100	0.0000	-73.6461	42.3100	0.0830
β_7	39.1766	42.5800	0.3580	2.0332	9.6160	0.8330
β_8	15.3195	18.8600	0.4170	147.9890	54.4700	0.0070
log-likelihood	-26.6217			-33.6451		
zeroline log-lik	-371.3310			-371.3310		
Test: Chi^2(16)	689.42			675.37		
AIC	85.2434			99.2901		
AIC/T	0.2522			0.2938		

Note: The critical value for $\chi^2(16) = 26.30$

Table 3.26 continued:

	Singapore			Philippines		
	Coefficient	Std.Error	t-prob	Coefficient	Std.Error	t-prob
State (1)						
β_1	-21.3109	7.9050	0.0070	-29.5624	6.7710	0.0000
β_2	45.5617	18.4300	0.0140	-0.2455	5.7820	0.9660
β_3	-26.2597	40.3000	0.5150	-28.2019	25.3800	0.2670
β_4	120.3760	59.7000	0.0450	24.5317	10.4200	0.0190
β_5	-49.4505	72.1500	0.4940	54.0947	31.3800	0.0860
β_6	447.7180	180.4000	0.0140	155.0430	43.4600	0.0000
β_7	-14.4528	18.8400	0.4440	-2.0390	17.4900	0.9070
β_8	-135.0380	55.6400	0.0160	-27.3876	10.7000	0.0110
State (2)						
β_1	-6.6467	1.1870	0.0000	-21.0370	4.3300	0.0000
β_2	-9.4092	5.9310	0.1140	-14.2625	5.6460	0.0120
β_3	-4.4800	16.8100	0.7900	4.4503	23.0400	0.8470
β_4	-52.2844	21.9700	0.0180	73.3318	23.0800	0.0020
β_5	64.9997	32.6900	0.0480	20.6464	26.8300	0.4420
β_6	-262.4630	56.9500	0.0000	-206.5900	54.5900	0.0000
β_7	16.5257	14.8800	0.2670	5.7050	22.6000	0.8010
β_8	43.9516	26.7900	0.1020	-48.5689	17.0900	0.0050
log-likelihood	-37.8523			-33.5652		
zeroline log-lik	-371.3310			-371.3310		
Test: Chi^2(16)	666.96			675.53		
AIC	107.7047			99.1305		
AIC/T	0.3187			0.2933		

Note: The critical value for $\chi^2(16) = 26.30$

Table 3. 27 Crisis Prediction Evaluation for Multinomial Logit Models

(1) *a=1.5*

Korea					
	State 0	State 1	State 2	Sum actual	correct prob
State 0	322	0	1	323	0.9969
State 1	2	5	0	7	0.7143
State 2	2	0	6	8	0.7500
Sum pred	326	5	7	338	0.9852
Indonesia					
	State 0	State 1	State 2	Sum actual	correct prob
State 0	300	2	3	305	0.9836
State 1	8	8	0	16	0.5000
State 2	9	0	8	17	0.4706
Sum pred	317	10	11	338	0.9349
Thailand					
	State 0	State 1	State 2	Sum actual	correct prob
State 0	314	1	1	316	0.9937
State 1	1	12	0	13	0.9231
State 2	3	0	6	9	0.6667
Sum pred	318	13	7	338	0.9822
Malaysia					
	State 0	State 1	State 2	Sum actual	correct prob
State 0	310	3	1	314	0.9873
State 1	5	12	0	17	0.7059
State 2	3	0	4	7	0.5714
Sum pred	318	15	5	338	0.9645
Singapore					
	State 0	State 1	State 2	Sum actual	correct prob
State 0	294	2	3	299	0.9833
State 1	3	15	0	18	0.8333
State 2	8	0	13	21	0.6190
Sum pred	305	17	16	338	0.9527
Philippines					
	State 0	State 1	State 2	Sum actual	correct prob
State 0	311	4	4	319	0.9749
State 1	3	10	0	13	0.7692
State 2	3	0	3	6	0.5000
Sum pred	317	14	7	338	0.9586

(2) *a=1*

	State 0	State 1	State 2	Sum actual	correct prob
			Korea		
	State 0	State 1	State 2	Sum actual	correct prob
State 0	286	2	10	298	0.9597
State 1	7	11	0	18	0.6111
State 2	10	0	12	22	0.5455
Sum pred	303	13	22	338	0.9142
			Indonesia		
	State 0	State 1	State 2	Sum actual	correct prob
State 0	268	4	5	277	0.9675
State 1	12	21	0	33	0.6364
State 2	11	0	17	28	0.6071
Sum pred	291	25	22	338	0.9053
			Thailand		
	State 0	State 1	State 2	Sum actual	correct prob
State 0	283	2	3	288	0.9826
State 1	6	16	0	22	0.7273
State 2	17	0	11	28	0.3929
Sum pred	306	18	14	338	0.9172
			Malaysia		
	State 0	State 1	State 2	Sum actual	correct prob
State 0	281	3	7	291	0.9656
State 1	3	22	0	25	0.8800
State 2	12	0	10	22	0.4545
Sum pred	296	25	17	338	0.9260
			Singapore		
	State 0	State 1	State 2	Sum actual	correct prob
State 0	248	6	6	260	0.9538
State 1	14	24	0	38	0.6316
State 2	16	0	24	40	0.6000
Sum pred	278	30	30	338	0.8757
			Philippines		
	State 0	State 1	State 2	Sum actual	correct prob
State 0	290	4	6	300	0.9667
State 1	6	13	1	20	0.6500
State 2	14	0	4	18	0.2222
Sum pred	310	17	11	338	0.9083

(3) *a=2*

Korea					
	State 0	State 1	State 2	Sum actual	correct prob
State 0	329	0	0	329	1.0000
State 1	1	4	0	5	0.8000
State 2	1	0	3	4	0.7500
Sum pred	331	4	3	338	0.9941

Indonesia					
	State 0	State 1	State 2	Sum actual	correct prob
State 0	318	1	2	321	0.9907
State 1	6	5	0	11	0.4545
State 2	3	0	3	6	0.5000
Sum pred	327	6	5	338	0.9645

Thailand					
	State 0	State 1	State 2	Sum actual	correct prob
State 0	320	1	1	322	0.9938
State 1	1	9	0	10	0.9000
State 2	1	0	5	6	0.8333
Sum pred	322	10	6	338	0.9882

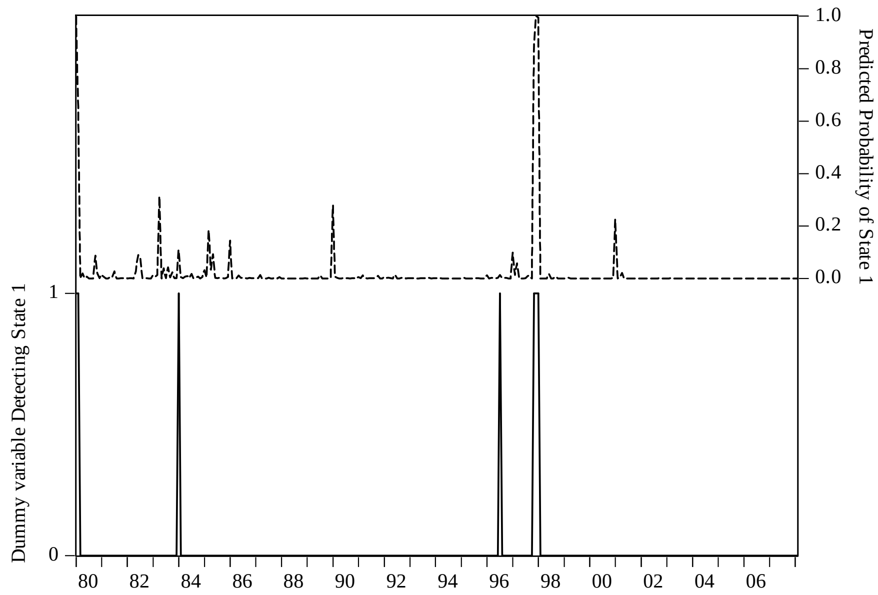
Malaysia					
	State 0	State 1	State 2	Sum actual	correct prob
State 0	326	1	0	327	0.9969
State 1	3	5	0	8	0.6250
State 2	1	0	2	3	0.6667
Sum pred	330	6	2	338	0.9852

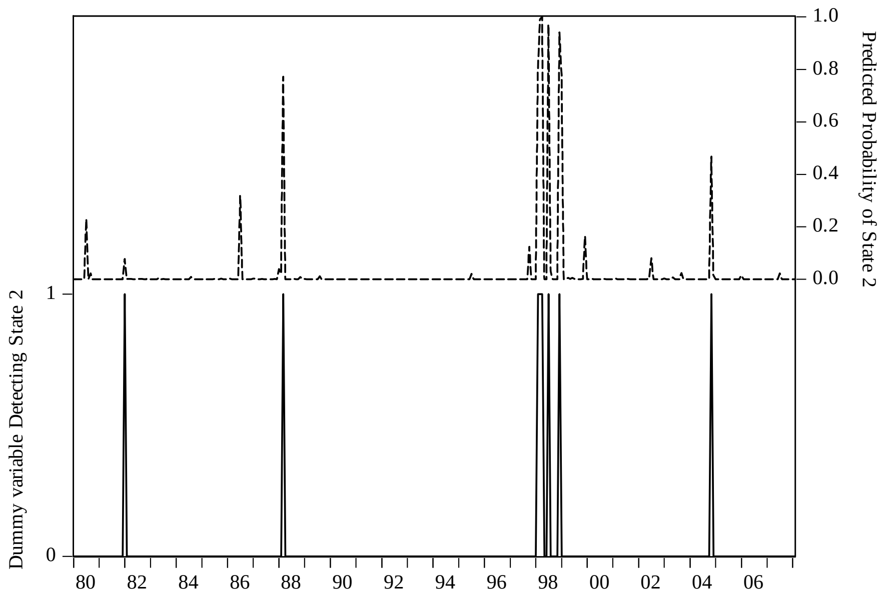
Singapore					
	State 0	State 1	State 2	Sum actual	correct prob
State 0	313	1	3	317	0.9874
State 1	1	8	0	9	0.8889
State 2	4	0	8	12	0.6667
Sum pred	318	9	11	338	0.9734

Philippines					
	State 0	State 1	State 2	Sum actual	correct prob
State 0	319	3	2	324	0.9846
State 1	1	10	0	11	0.9091
State 2	3	0	0	3	0.0000
Sum pred	323	13	2	338	0.9734

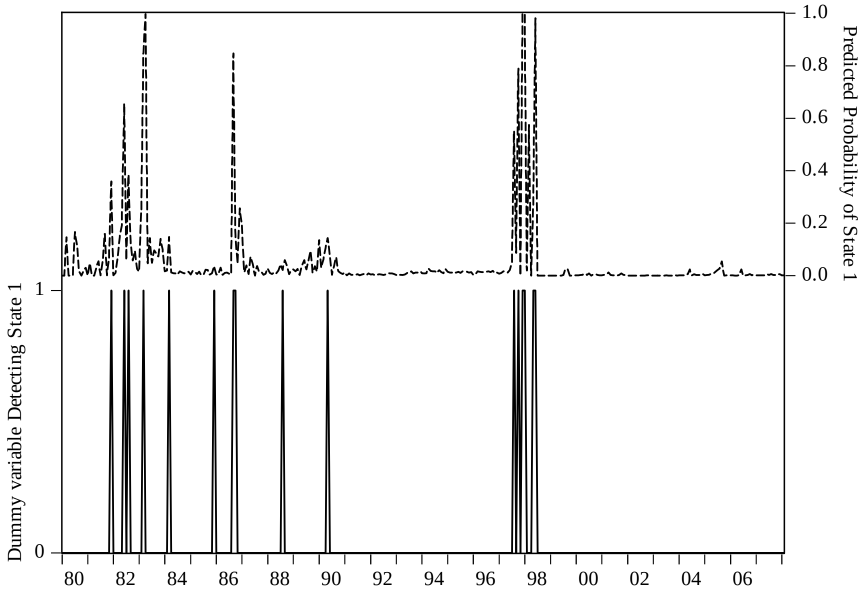
Figure 3. 20 Multinomial Logit models: Market pressure and Probability of Crisis

(1) Korea

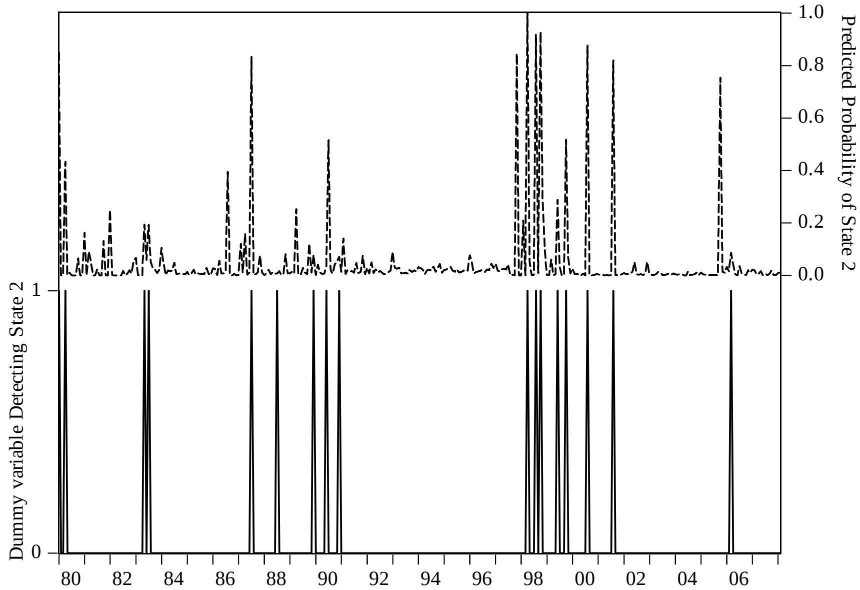




(2) Indonesia



Predicted Probability of State 1
Dummy variable Detecting State 1
1.0
0.8
0.6
0.4
0.2
0.0
1
0
80 82 84 86 88 90 92 94 96 98 00 02 04 06



Predicted Probability of State 2
Dummy variable Detecting State 2
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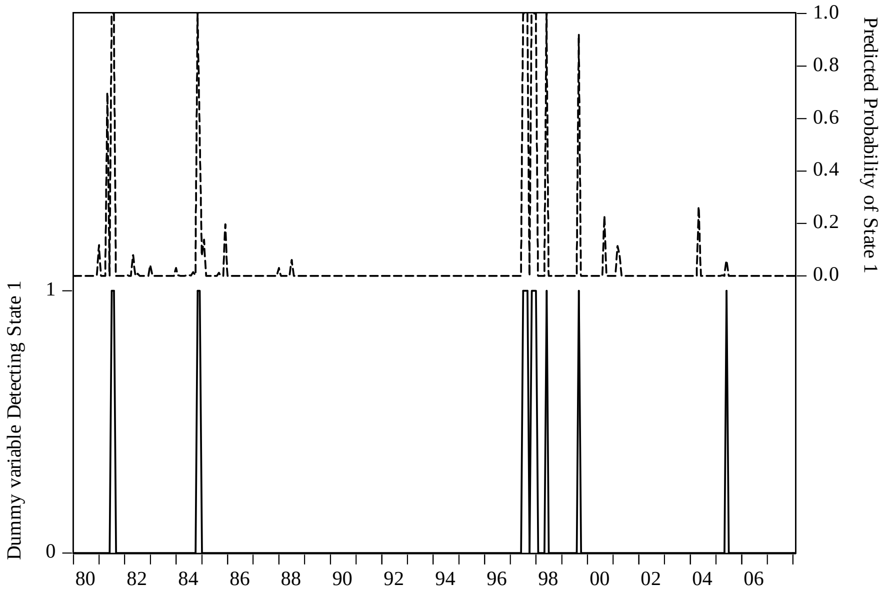
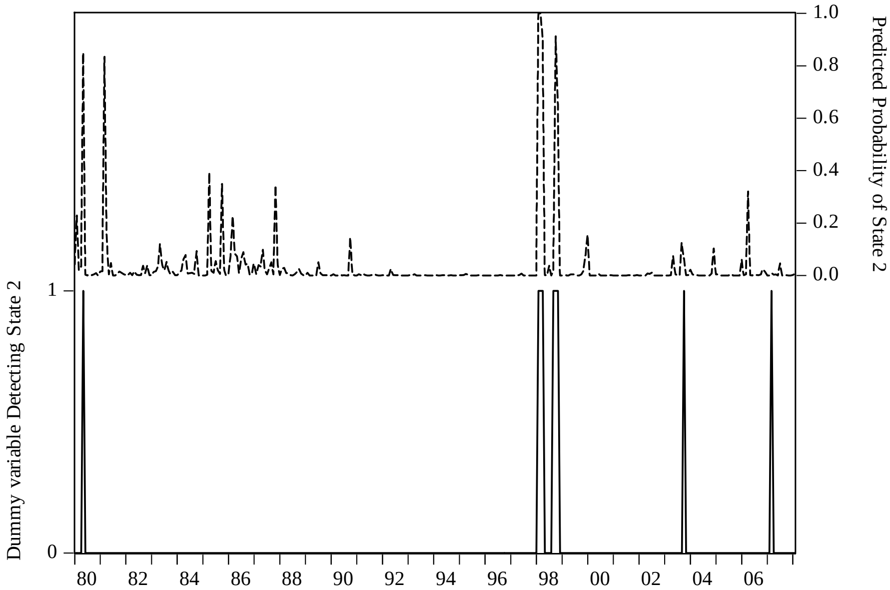
0.6
0.4
0.2
0.0
1
0
80 82 84 86 88 90 92 94 96 98 00 02 04 06

(3) Thailand



1.0
0.8
0.6
0.4
0.2
0.0
Predicted Probability of State 1
1
0
Dummy variable Detecting State 1
80
82
84
86
88
90
92
94
96
98
00
02
04
06



1.0
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0.6
0.4
0.2
0.0
Predicted Probability of State 2
1
0
Dummy variable Detecting State 2
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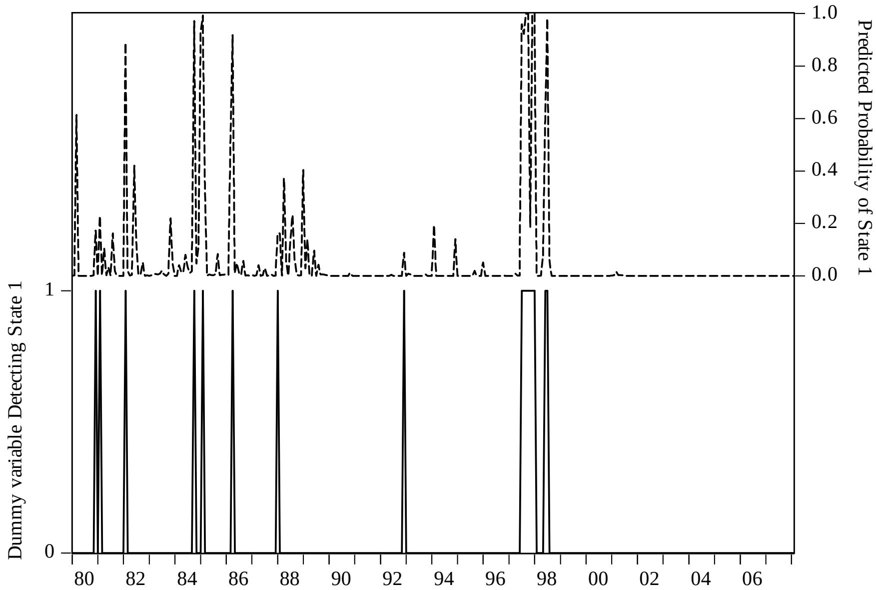
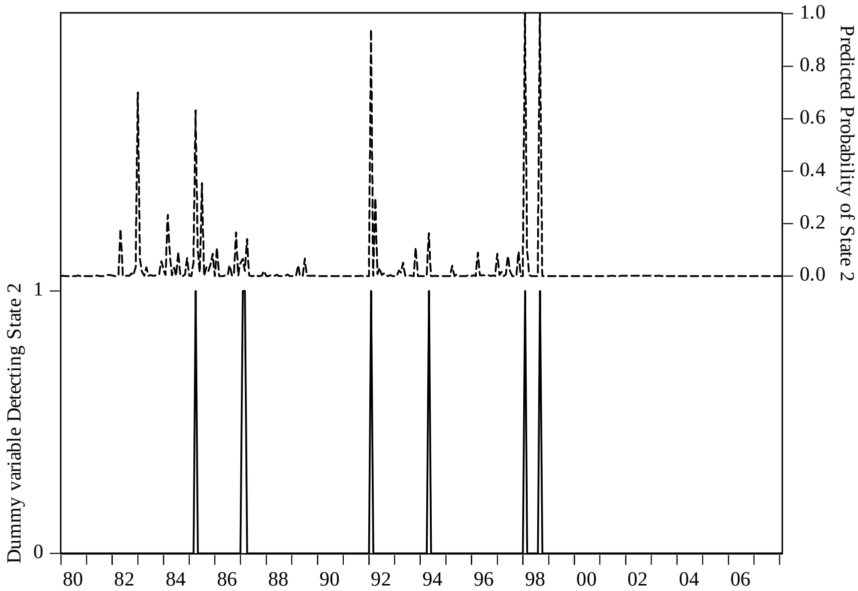
82
84
86
88
90
92
94
96
98
00
02
04
06

(4) Malaysia

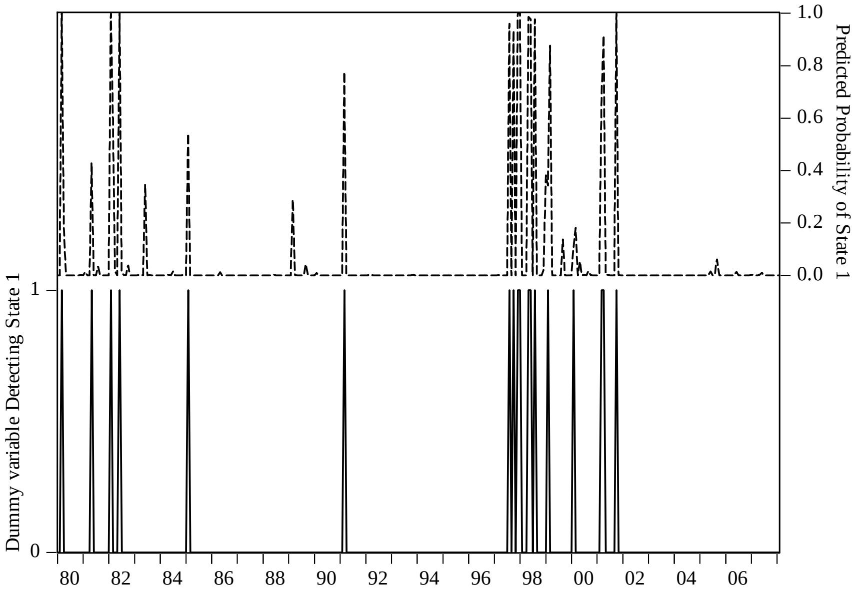


1.0
0.8
0.6
0.4
0.2
0.0
Predicted Probability of State 1
1
0
Dummy variable Detecting State 1
80 82 84 86 88 90 92 94 96 98 00 02 04 06



1.0
0.8
0.6
0.4
0.2
0.0
Predicted Probability of State 2
1
0
Dummy variable Detecting State 2
80 82 84 86 88 90 92 94 96 98 00 02 04 06

(5) Singapore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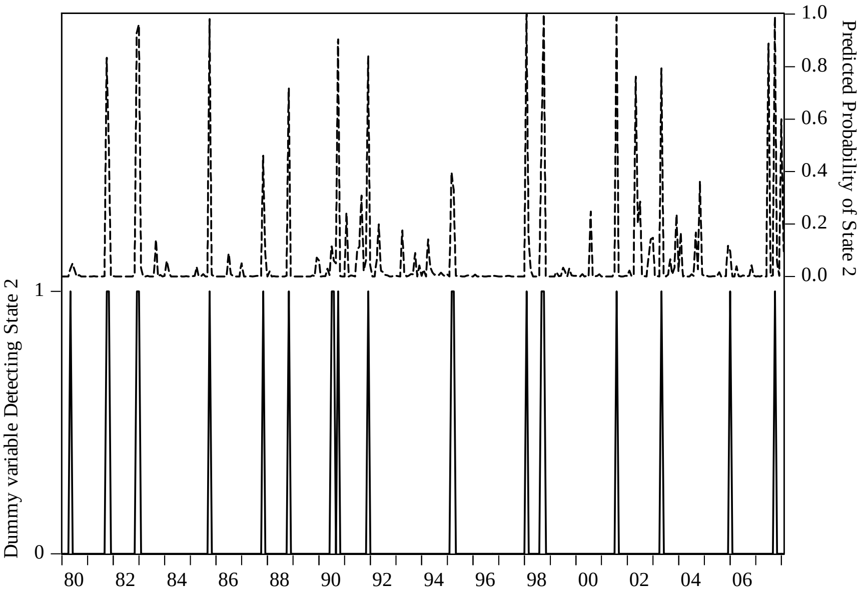
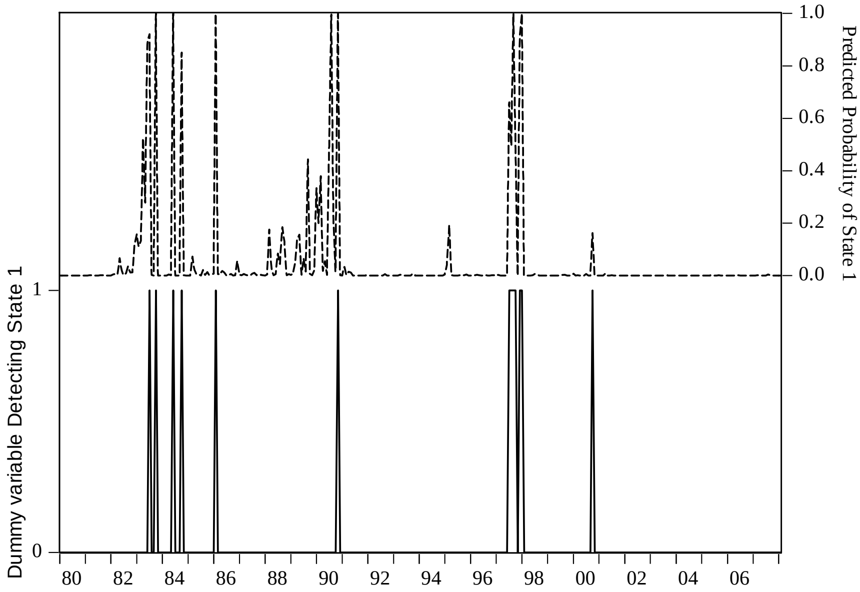
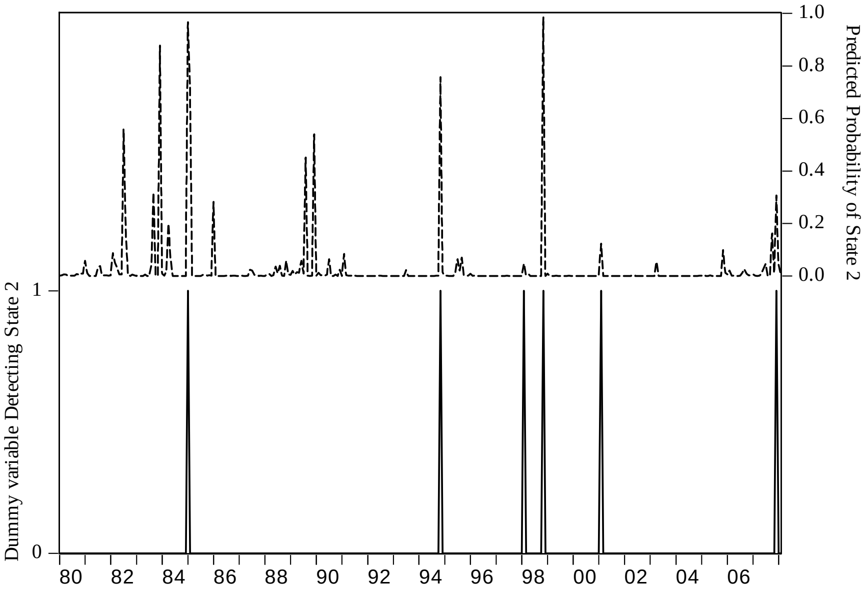
0.8
0.6
0.4
0.2
0.0
Predicted Probability of State 1
1
0
Dummy variable Detecting State 1
80
82
84
86
88
90
92
94
96
98
00
02
04
06


1.0
0.8
0.6
0.4
0.2
0.0
Predicted Probability of State 2
1
0
Dummy variable Detecting State 2
80
82
84
86
88
90
92
94
96
98
00
02
04
06

(6) Philippines





3.8 Conclusion

3.8.1 Summary of results

This study examines the power of the conventional macroeconomic factors to explain the 1997-98 Asia currency crises in six countries, namely, Korea, Malaysia, Thailand, Indonesia, Singapore and Philippines, based on the Markov Switching models. Two types of Markov switching modelling specifications were examined. One is to assume that the conditional variance of market pressure follows an asymmetric GARCH process. The other one is to assume the conditional variance of market pressure is constant. We can conclude that the Markov Switching specifications have several advantages: (1) they can explain the appreciating currency attacks as well as depreciating currency attacks; (2) by allowing regression parameters to switch between different regimes, they mimic the existence of multiple equilibria relations, (3) not like Logit/Probit models which require an ex-ante definition of a threshold value to distinguish stable and volatile state, they can supply us with such information.

In this study, we model the economy having two regimes, namely, stable state and volatile state. Different from other studies using Markov switching framework in modelling currency crises, we provide tests to congregate which regime relate to which state. The tests we employ include the quadratic probability score (QPS) test, the log probability score (LPS) test and the Global squared bias (GSB) tests. These statistics measures the accuracy of the probabilities in forecasting the current state. Although the state of a regime can be readily identified in a 2-regime model through graphing the inferred probability of being in a certain state against MP, it is not the case where there are more than two regimes. These statistics can then be very helpful for detecting regimes in those situations.

Another distinct feature of our study is that we use a more reliable statistics to test for the number of regimes (1 regime versus 2 regimes). The convention likelihood ratio test for the same purpose is argued to be questionable because of the problems poised by the presence of nuisance parameters and the parameter boundary problem. The Neyman's $C(\alpha)$ test we employed, however, is design to rectify such problems. Moreover, we test 1 versus more than 1 regimes by accessing whether the residuals from one regime models estimation are non-normally distributed which may result from the distortion of the existence of other regimes. Bootstrapping methods are used for such purpose.

The empirical estimates from Markov Switching models give credence to the view that fundamental variables can still explain the market pressure on the behaviour of the exchange rate and the Asian currency crises. In these models, the majority of those macroeconomic fundamental variables are significant at 5% significant level. Thus we believe the crises are not purely self-fulfilling phenomena; detrimental of economic fundamentals do have some impact on the trigging of currency crises. Different from previously studies on Asian financial crises, we find that the real growth of domestic credit is not a powerful indicator for currency crises in Asia. The inferred probabilities for the presence of a volatile state that estimated from the Markov switching models have substantial informative content in explaining the Asian currency crises in 1997. We can observe that at, or close to, the time of the currency crises attacks, the filtered probability increase significantly.

Our results show that, although Markov Regime Switching TGARCH model is by and large more favourable than the Markov Regime Switching constant model, it is not necessary always the case. Multinomial Logit model is also examined for its ability to predict currency crisis. We find that the Mlogit model performs better in predicting depreciating currency attacks than in predicting the appreciating ones.

3.8.2 Further Research

This study may be extended in two ways. First, this study is based on the first and second generation currency crises theory. It may be extended by including factors that capture the deficiencies of banking and financial sectors — the “third generation” currency crisis model. Financial deregulations, inadequate supervisory, together with credit market imperfections or distortions that take the form of explicit or implicit government bailout guarantees can create moral hazard. Such financial instability raise largely through a bank channel mechanism might create or encourage a currency crisis. Example indicators for the possible role of the bank lending channel and financial fragility include: the ratio of foreign currency denominated assets to total assets, the ratio of foreign currency denominated liabilities to total liabilities, the ratio of non-performing banking loans to total credit grant.

Another extension can be made by assuming three regimes. As we mentioned before, extreme high exchange market pressure and extreme low exchange market pressure can both trigger currency attacks and currency crisis. Instead of using two regimes Markov Switching model, we can experiment with three regimes Markov Switching model to capture the three possible states in exchange market: an appreciating regime (possible "speculative"), a stable regime, and a depreciating regime (possible "speculative"). The latter would be regarded as a text book currency attack, but the first regime could also be observed in the market.

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Appendix 3.A Data Analysis and Descriptive Statistics for MP and it's determinants

Figure 3.A 1 MP and its components for Korea

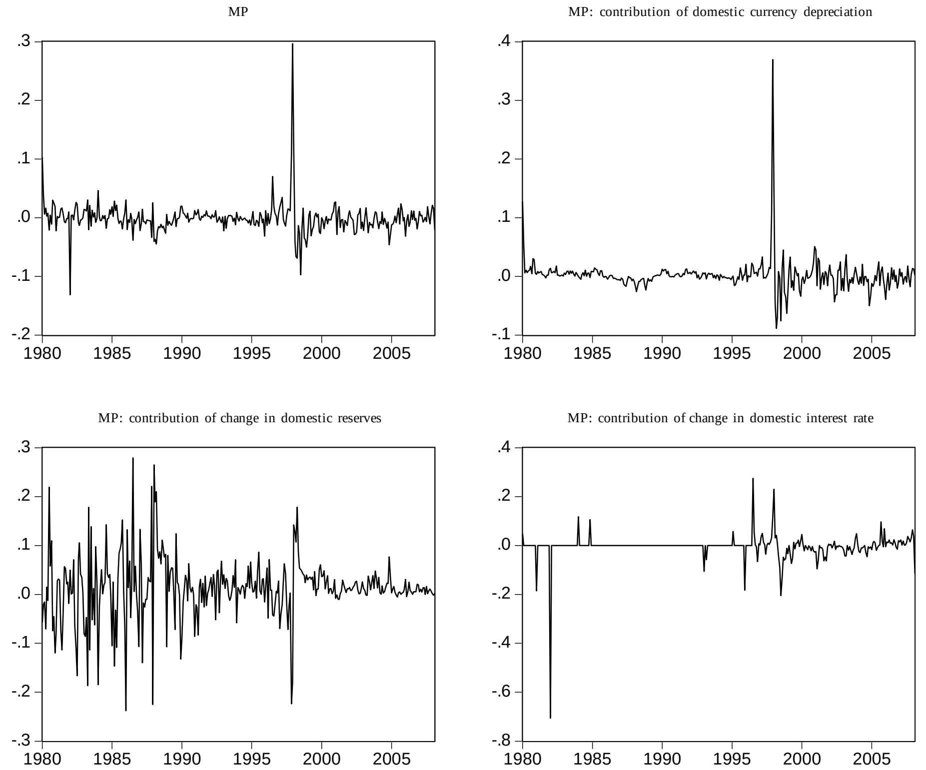

Figure 3.A 2 MP and its components for Indonesia

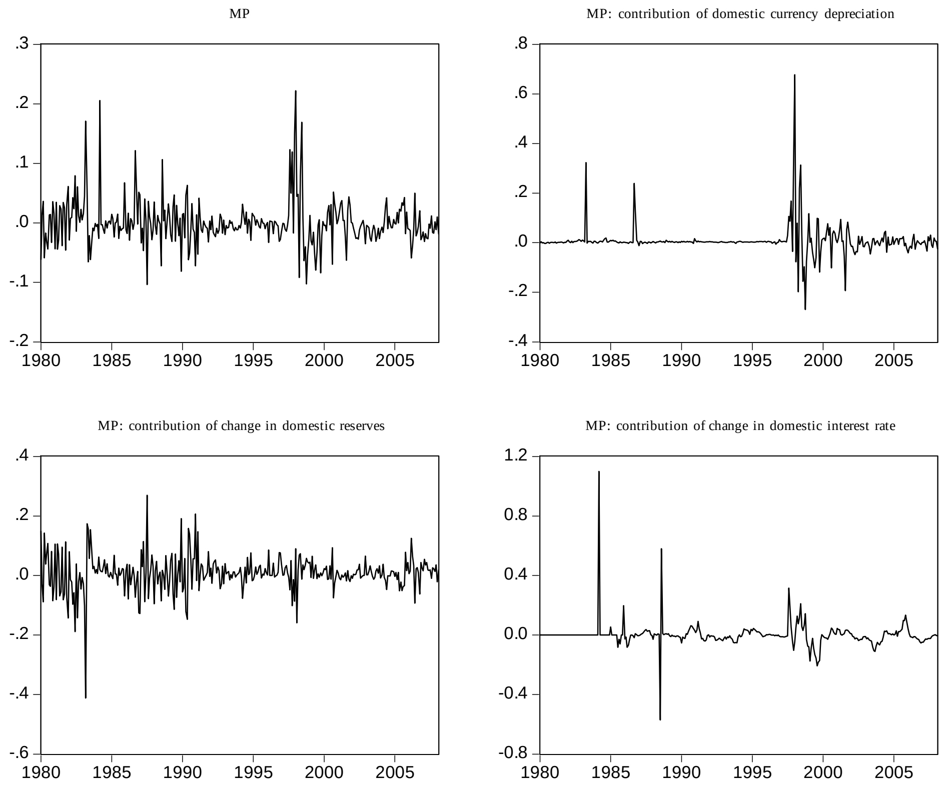

Figure 3.A 3 MP and its components for Thailand

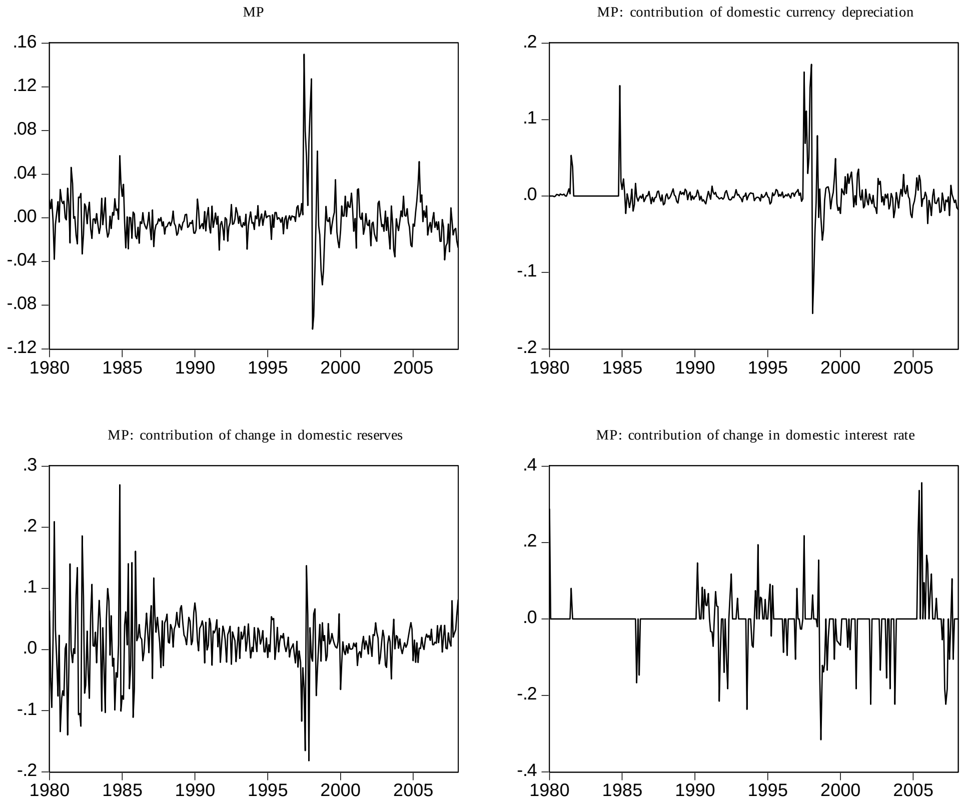

Figure 3.A 4 MP and its components for Malaysia

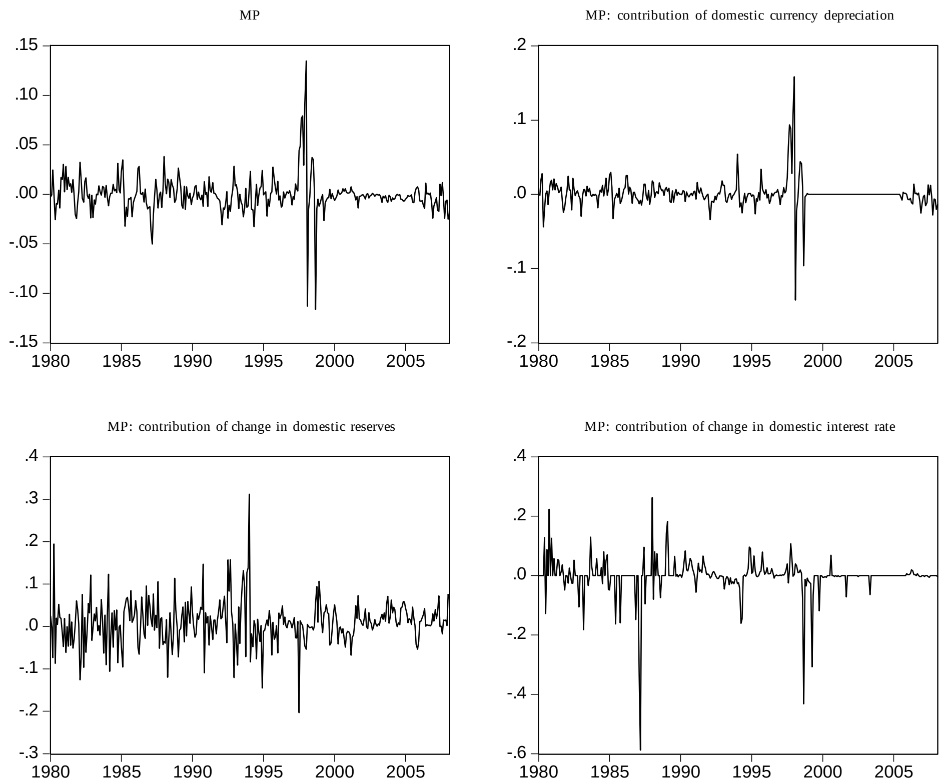

Figure 3.A 5 MP and its components for Singapore

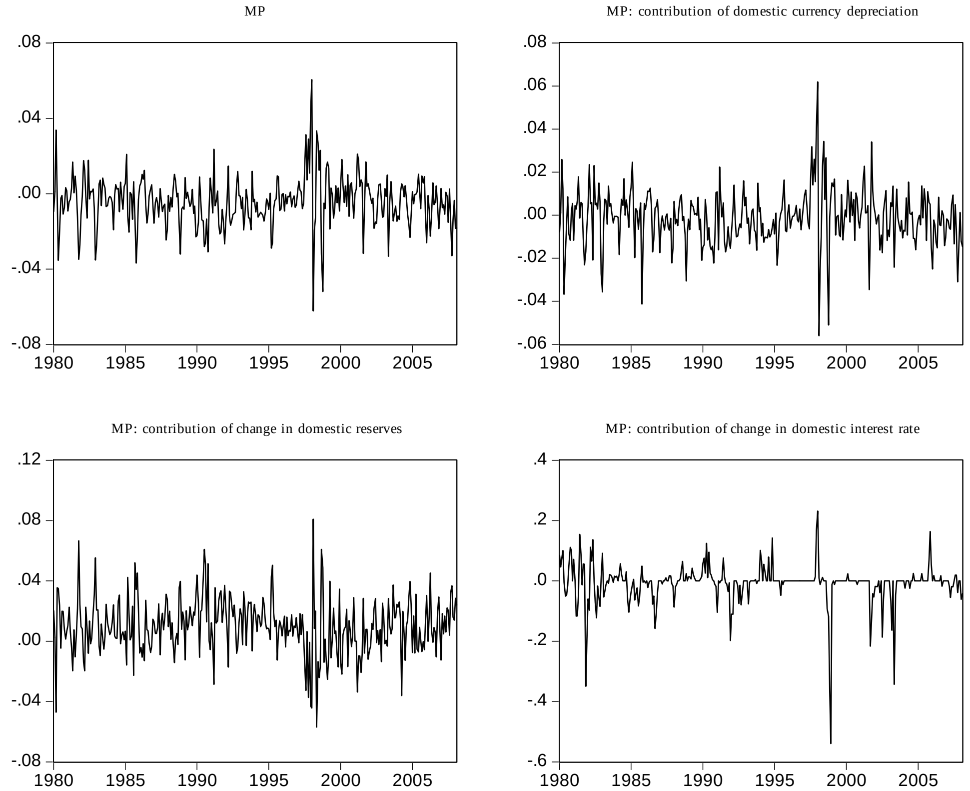

Figure 3.A 6 MP and its components for Philippines

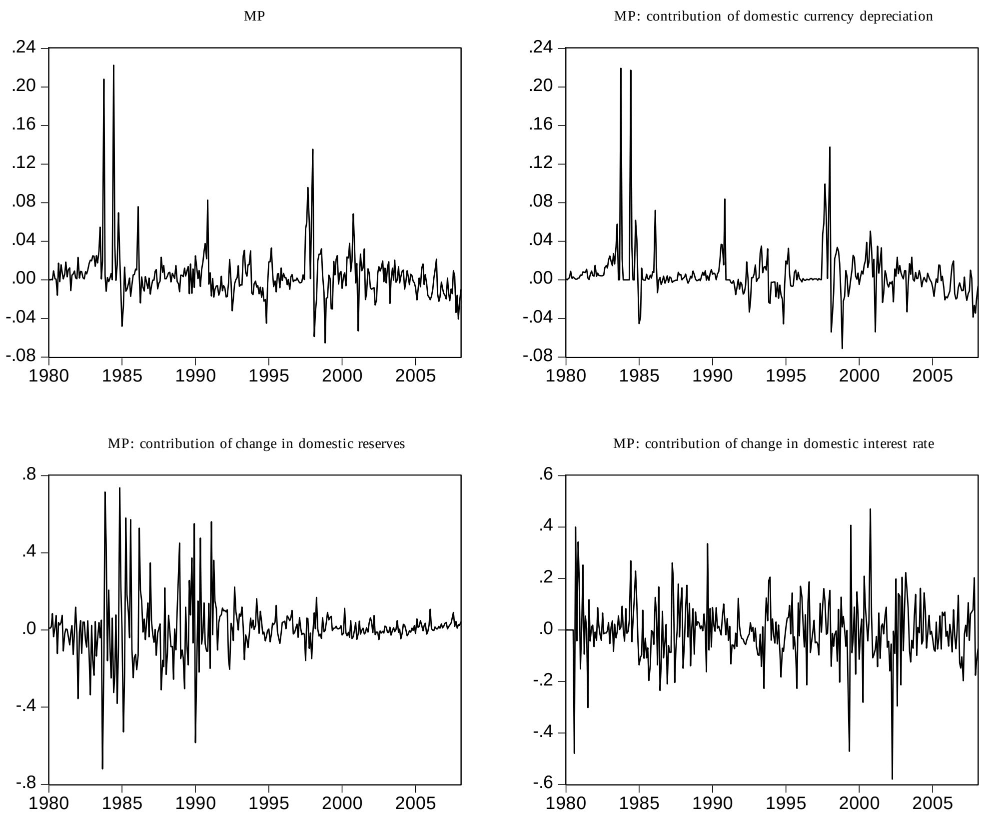

Table 3.A 1 Descriptive Statistics of MP and its determinants for Korea

	MP	RM2	RER	GDC	RISK	DRM2	DRER	DGDC	DRISK
Mean	-0.0010	0.1997	0.0064	0.0085	-0.0232	0.0008	0.0002	0.0000	-0.0003
Median	-0.0016	0.1639	0.0078	0.0083	-0.0250	0.0011	-0.0004	0.0020	-0.0005
Maximum	0.2965	0.4158	0.6395	0.0920	0.3190	0.0373	0.3379	0.0589	0.2309
Minimum	-0.1314	0.0660	-0.2009	-0.0358	-0.2746	-0.0380	-0.1019	-0.0983	-0.4956
Std. Dev.	0.0265	0.0990	0.1120	0.0147	0.0420	0.0092	0.0271	0.0209	0.0435
Skewness	4.2794	0.6368	1.5846	0.6229	0.8056	0.0377	5.7596	-0.8073	-4.1564
Kurtosis	53.3446	2.2499	9.3565	6.5914	20.4000	5.5499	76.0838	5.0795	58.1133
ADF	-11.3045	0.4326	-2.7161	-18.5105	-7.3707	-17.6239	-12.6155	-12.8100	-12.3886
KPSS	0.1258	1.8239	0.2201	0.2235	0.3773	0.3255	0.0333	0.0835	0.1543

Note: Critical value for ADF test: 1% level, -3.45; 5% level, -2.87 and 10% level, -2.57

Critical value for KPSS test: 1% level, 0.739; 5% level, 0.463 and 10% level, 0.347.

Table 3.A 2 Correlation of MP and its determinants for Korea

	MP	RM2	RER	GDC	RISK	DRM2	DRER	DGDC	DRISK
MP	1.0000	-0.0942	0.2125	0.0942	0.0466	-0.1044	0.8491	-0.0538	-0.5102
RM2	-0.0942	1.0000	-0.3319	-0.0965	-0.0208	0.1132	-0.0153	0.0029	0.0027
RER	0.2125	-0.3319	1.0000	0.0585	-0.2119	0.0456	0.1168	-0.0330	-0.1417
GDC	0.0942	-0.0965	0.0585	1.0000	0.2123	-0.3428	0.0879	0.7098	0.0977
RISK	0.0466	-0.0208	-0.2119	0.2123	1.0000	-0.2332	0.0857	0.1693	0.5002
DRM2	-0.1044	0.1132	0.0456	-0.3428	-0.2332	1.0000	0.1491	-0.2170	-0.3370
DRER	0.8491	-0.0153	0.1168	0.0879	0.0857	0.1491	1.0000	-0.0818	-0.5376
DGDC	-0.0538	0.0029	-0.0330	0.7098	0.1693	-0.2170	-0.0818	1.0000	0.2395
DRISK	-0.5102	0.0027	-0.1417	0.0977	0.5002	-0.3370	-0.5376	0.2395	1.0000

Table 3.A 3 Descriptive Statistics of MP and its determinants for Indonesia

	MP	RM2	RER	GDC	RISK	DRM2	DRER	DGDC	DRISK
Mean	0.0001	0.2632	0.0565	0.0088	-0.0786	-0.0005	-0.0009	0.0002	-0.0003
Median	-0.0032	0.2636	0.0120	0.0099	-0.0880	-0.0006	-0.0028	0.0026	0.0003
Maximum	0.2220	0.5392	1.2151	0.7021	0.6183	0.2019	0.5949	0.7669	0.5855
Minimum	-0.1038	0.1038	-0.2330	-0.7415	-0.7674	-0.1030	-0.2885	-0.6789	-0.9617
Std. Dev.	0.0387	0.0920	0.1895	0.0758	0.1175	0.0236	0.0612	0.1099	0.0970
Skewness	1.7532	0.6485	2.8719	-0.8686	-0.4439	1.8271	2.8448	0.1699	-2.5652
Kurtosis	10.8483	3.1072	15.0488	51.9259	11.6911	21.6090	36.7608	23.2127	40.5175
ADF	-15.1216	-3.2887	-3.6416	-23.6077	-3.0494	-20.2153	-15.2654	-15.2388	-15.6839
KPSS	0.1323	0.3595	0.3440	0.2211	0.6376	0.3126	0.0214	0.2492	0.0382

Table 3.A 4 Correlation of MP and its determinants for Indonesia

	MP	RM2	RER	GDC	RISK	DRM2	DRER	DGDC	DRISK
MP	1.0000	-0.0236	0.2928	0.1890	0.1272	0.0089	0.6133	0.0878	-0.3773
RM2	-0.0236	1.0000	0.1868	-0.0926	0.1218	0.0952	-0.0029	0.0093	-0.1325
RER	0.2928	0.1868	1.0000	-0.0269	-0.2428	0.1724	0.1616	-0.0037	-0.2496
GDC	0.1890	-0.0926	-0.0269	1.0000	0.0382	0.0138	0.2057	0.7239	-0.1423
RISK	0.1272	0.1218	-0.2428	0.0382	1.0000	-0.0400	0.1547	-0.0299	0.4096
DRM2	0.0089	0.0952	0.1724	0.0138	-0.0400	1.0000	0.6109	0.0256	-0.5230
DRER	0.6133	-0.0029	0.1616	0.2057	0.1547	0.6109	1.0000	0.1242	-0.5685
DGDC	0.0878	0.0093	-0.0037	0.7239	-0.0299	0.0256	0.1242	1.0000	-0.1377
DRISK	-0.3773	-0.1325	-0.2496	-0.1423	0.4096	-0.5230	-0.5685	-0.1377	1.0000

Table 3.A 5 Descriptive Statistics of MP and its determinants for Thailand

	MP	RM2	RER	GDC	RISK	DRM2	DRER	DGDC	DRISK
Mean	-0.0015	0.1961	0.0209	0.0062	-0.0183	0.0006	-0.0004	0.0000	-0.0002
Median	-0.0030	0.2268	-0.0059	0.0064	-0.0227	0.0007	-0.0016	0.0011	-0.0002
Maximum	0.1500	0.3523	0.6209	0.0529	0.1809	0.0408	0.1579	0.0512	0.2188
Minimum	-0.1021	0.0677	-0.1460	-0.0598	-0.3060	-0.0692	-0.1772	-0.0738	-0.3965
Std. Dev.	0.0216	0.0680	0.0937	0.0131	0.0436	0.0096	0.0252	0.0150	0.0381
Skewness	1.7607	-0.5218	2.0435	-0.3377	-0.1443	-0.7235	1.1823	-0.4433	-2.8708
Kurtosis	16.9902	1.9823	10.4908	6.0193	10.2268	14.5148	25.5016	6.0031	43.4154
ADF	-11.8306	-0.1717	-3.1336	-1.6501	-3.4408	-9.2239	-13.7019	-13.4081	-15.8925
KPSS	0.1100	1.7540	0.1700	0.9714	0.4196	0.3190	0.0657	0.1630	0.0795

Table 3.A 6 Correlation of MP and its determinants for Thailand

	MP	RM2	RER	GDC	RISK	DRM2	DRER	DGDC	DRISK
MP	1.0000	-0.0263	0.2601	0.2572	0.0869	0.1418	0.8299	0.1144	-0.5033
RM2	-0.0263	1.0000	-0.2350	-0.1737	-0.0196	0.1240	0.0180	0.0071	-0.0618
RER	0.2601	-0.2350	1.0000	-0.1182	-0.1603	0.0050	0.1517	-0.0300	-0.1825
GDC	0.2572	-0.1737	-0.1182	1.0000	-0.2055	0.1023	0.3898	0.5716	-0.2197
RISK	0.0869	-0.0196	-0.1603	-0.2055	1.0000	-0.0131	0.0841	0.0718	0.4331
DRM2	0.1418	0.1240	0.0050	0.1023	-0.0131	1.0000	0.4768	0.1441	-0.4869
DRER	0.8299	0.0180	0.1517	0.3898	0.0841	0.4768	1.0000	0.2252	-0.5803
DGDC	0.1144	0.0071	-0.0300	0.5716	0.0718	0.1441	0.2252	1.0000	-0.1080
DRISK	-0.5033	-0.0618	-0.1825	-0.2197	0.4331	-0.4869	-0.5803	-0.1080	1.0000

Table 3.A 7 Descriptive Statistics of MP and its determinants for Malaysia

	MP	RM2	RER	GDC	RISK	DRM2	DRER	DGDC	DRISK
Mean	-0.0003	0.2557	0.0356	0.0073	0.0072	0.0013	-0.0004	0.0000	-0.0002
Median	-0.0009	0.2437	0.0211	0.0072	0.0050	0.0004	-0.0013	0.0001	0.0001
Maximum	0.1347	0.5143	0.5085	0.4540	0.1367	0.2509	0.1401	0.6604	0.2064
Minimum	-0.1163	0.1001	-0.1106	-0.6549	-0.2530	-0.0998	-0.1698	-0.6701	-0.3774
Std. Dev.	0.0187	0.0977	0.0805	0.0508	0.0376	0.0222	0.0199	0.0746	0.0308
Skewness	0.6617	0.5172	1.9649	-4.6567	-0.5661	5.3373	-0.3116	0.6054	-4.4402
Kurtosis	21.0253	2.4031	9.5510	108.3365	10.2824	59.1347	30.6218	53.7530	75.6270
ADF	-13.0690	-1.0708	-2.5567	-19.7787	-3.5531	-17.1921	-14.7237	-11.9792	-14.4153
KPSS	0.1151	1.2591	0.1625	0.1432	0.6398	0.1132	0.0708	0.1696	0.0222

Table 3.A 8 Correlation of MP and its determinants for Malaysia

	MP	RM2	RER	GDC	RISK	DRM2	DRER	DGDC	DRISK
MP	1.0000	-0.1008	0.2598	0.0574	0.0834	-0.0375	0.8711	0.0411	-0.5541
RM2	-0.1008	1.0000	-0.3125	-0.0714	-0.2057	0.0942	-0.0377	0.0005	-0.0146
RER	0.2598	-0.3125	1.0000	-0.0631	0.0550	0.0362	0.1432	0.0004	-0.1462
GDC	0.0574	-0.0714	-0.0631	1.0000	-0.0411	-0.3973	0.0203	0.7339	-0.0581
RISK	0.0834	-0.2057	0.0550	-0.0411	1.0000	0.0280	0.0257	-0.0069	0.4018
DRM2	-0.0375	0.0942	0.0362	-0.3973	0.0280	1.0000	0.1990	-0.2687	-0.1042
DRER	0.8711	-0.0377	0.1432	0.0203	0.0257	0.1990	1.0000	0.0128	-0.5730
DGDC	0.0411	0.0005	0.0004	0.7339	-0.0069	-0.2687	0.0128	1.0000	-0.0476
DRISK	-0.5541	-0.0146	-0.1462	-0.0581	0.4018	-0.1042	-0.5730	-0.0476	1.0000

Table 3.A 9 Descriptive Statistics of MP and its determinants for Singapore

	MP	RM2	RER	GDC	RISK	DRM2	DRER	DGDC	DRISK
Mean	-0.0042	0.8513	0.0087	0.0082	0.0271	-0.0006	-0.0004	-0.0001	-0.0001
Median	-0.0036	0.8362	0.0088	0.0038	0.0258	0.0004	-0.0004	0.0002	0.0002
Maximum	0.0605	0.9829	0.2084	0.3211	0.1046	0.0685	0.0628	0.3813	0.0713
Minimum	-0.0622	0.6936	-0.1280	-0.2799	-0.0765	-0.1420	-0.0591	-0.5895	-0.1365
Std. Dev.	0.0132	0.0720	0.0608	0.0433	0.0238	0.0158	0.0137	0.0688	0.0211
Skewness	0.1100	0.3118	0.3287	2.2684	0.0108	-2.1425	-0.1837	-1.0767	-0.9229
Kurtosis	6.3546	1.8222	2.9382	26.5659	4.0086	22.5291	5.5891	26.6642	10.1559
ADF	-13.0103	-2.1963	-1.9920	-23.9051	-6.7115	-19.3411	-15.2183	-10.9883	-11.8471
KPSS	0.1898	0.1303	0.1814	0.3241	0.5036	0.0703	0.1481	0.3241	0.2577

Table 3.A 10 Correlation of MP and its determinants for Singapore

	MP	RM2	RER	GDC	RISK	DRM2	DRER	DGDC	DRISK
MP	1.0000	0.0750	0.3248	-0.0684	0.0836	-0.0519	0.8575	-0.0205	-0.5380
RM2	0.0750	1.0000	-0.0346	-0.0337	-0.1958	0.0964	0.1413	-0.0096	0.0033
RER	0.3248	-0.0346	1.0000	-0.0098	0.0841	-0.1021	0.1463	0.0094	-0.1079
GDC	-0.0684	-0.0337	-0.0098	1.0000	0.0746	-0.4197	-0.0028	0.7930	0.0460
RISK	0.0836	-0.1958	0.0841	0.0746	1.0000	-0.1085	0.0458	-0.0173	0.4399
DRM2	-0.0519	0.0964	-0.1021	-0.4197	-0.1085	1.0000	0.0657	-0.2947	-0.0752
DRER	0.8575	0.1413	0.1463	-0.0028	0.0458	0.0657	1.0000	0.0378	-0.4408
DGDC	-0.0205	-0.0096	0.0094	0.7930	-0.0173	-0.2947	0.0378	1.0000	0.0125
DRISK	-0.5380	0.0033	-0.1079	0.0460	0.4399	-0.0752	-0.4408	0.0125	1.0000

Table 3.A 11 Descriptive Statistics of MP and its determinants for Philippines

	MP	RM2	RER	GDC	RISK	DRM2	DRER	DGDC	DRISK
Mean	0.0043	0.2176	0.0173	0.0029	-0.0404	0.0001	-0.0001	-0.0005	0.0000
Median	0.0017	0.2259	0.0103	0.0020	-0.0354	-0.0012	0.0024	-0.0004	0.0011
Maximum	0.2225	0.3911	0.3826	0.5931	0.2010	0.0814	0.5755	0.2026	0.2454
Minimum	-0.0655	0.0344	-0.2399	-0.1158	-0.2976	-0.0725	-0.5059	-0.0962	-0.2929
Std. Dev.	0.0263	0.0968	0.1052	0.0446	0.0553	0.0176	0.0564	0.0257	0.0478
Skewness	3.7091	-0.3548	0.5276	6.9150	-0.2408	0.2593	0.6871	2.1832	-0.6991
Kurtosis	28.8064	1.8972	3.4734	92.6242	6.2559	5.5831	53.1439	20.4435	15.0530
ADF	-13.7940	-1.6144	-2.2286	-14.9181	-4.1427	-17.5814	-15.2912	-13.7276	-16.7823
KPSS	0.4408	1.0274	0.1734	0.1967	0.2533	0.2846	0.1534	0.1467	0.1488

Table 3.A 12 Correlation of MP and its determinants for Philippines

	MP	RM2	RER	GDC	RISK	DRM2	DRER	DGDC	DRISK
MP	1.0000	-0.2103	0.4009	0.1726	-0.0095	-0.1159	0.0065	0.8589	-0.5812
RM2	-0.2103	1.0000	-0.1956	0.0258	0.3193	0.0962	0.0095	-0.0410	0.0252
RER	0.4009	-0.1956	1.0000	-0.1134	-0.1150	0.0040	-0.0342	0.1541	-0.1540
GDC	0.1726	0.0258	-0.1134	1.0000	0.1266	-0.1683	0.6318	0.2600	-0.0770
RISK	-0.0095	0.3193	-0.1150	0.1266	1.0000	-0.2105	0.0212	0.0712	0.4319
DRM2	-0.1159	0.0962	0.0040	-0.1683	-0.2105	1.0000	-0.0673	-0.0263	-0.1098
DRER	0.0065	0.0095	-0.0342	0.6318	0.0212	-0.0673	1.0000	0.0582	-0.0336
DGDC	0.8589	-0.0410	0.1541	0.2600	0.0712	-0.0263	0.0582	1.0000	-0.5191
DRISK	-0.5812	0.0252	-0.1540	-0.0770	0.4319	-0.1098	-0.0336	-0.5191	1.0000

Appendix 3.B Neyman's $C(\alpha)$ test

The $C(\alpha)$ tests were designed to deal with hypothesis testing of a parameter of primary interest in the presence of nuisance parameter. In particular, Neyman dispenses with the maximum likelihood estimates and utilizes only $\sqrt{n}$ -consistent estimates that are relatively easy to find. Another attractive feature of the optimal $C(\alpha)$ tests statistics is that by design it satisfies a certain optimality principle; it maximizes the slope of the limiting power function under "local alternative" to the null hypothesis.

Assume that there are n independent observations, $y_1, y_2, \ldots y_n$ with identical density function $f(y;\theta)$ where θ is a $p \times 1$ parameter vector with $\theta \in \Theta \subset \mathbb{R}^p$. The log-likelihood function, score function, and the information matrix are then defined, respectively, as

$$l(\theta) = \sum_{i=1}^{n} \ln f(y_i, \theta) \tag{3.B.1}$$

$$s(\theta) = \frac{\partial l(\theta)}{\partial \theta} \tag{3.B.2}$$

and

$$\psi(\theta) = -E\left[\frac{\partial^2 l(\theta)}{\partial \theta \cdot \partial \theta'}\right] \tag{3.B.3}$$

Suppose that $\theta = (\zeta', \eta')'$ and interest centers on testing the null hypothesis $H_0 : \zeta = \zeta_0$ which in practice requires knowledge of the parameter η. The parameter

ζ is the parameter of primary interest while the parameter η is the nuisance parameter.

Let $s_\zeta(\zeta,\eta)=\partial l(\zeta,\eta)/\partial\zeta$ and $s_\eta(\zeta,\eta)=\partial l(\zeta,\eta)/\partial\eta$. Denote the part of information matrix that corresponds to ζ by $\psi_{\zeta\zeta}(\zeta,\eta)$ and the notation $\psi_{\eta\eta}(\zeta,\eta)$ $\psi_{\zeta\eta}(\zeta,\eta)$ and $\psi_{\eta\zeta}(\zeta,\eta)$ have analogous meanings. Neyman's (1959) finding is that asymptotic optimality in the sense mentioned above suggests that hypothesis testing should be based on the statistic

$$\begin{aligned} C(\alpha) = &\left[s_\zeta(\zeta_0,\eta) - \psi_{\zeta\eta}(\zeta_0,\eta)\psi_{\eta\eta}(\zeta_0,\eta)^{-1} s_\eta(\zeta_0,\eta) \right]' \\ &\times\left[\psi_{\zeta\zeta}(\zeta_0,\eta) - \psi_{\zeta\eta}(\zeta_0,\eta)\psi_{\eta\eta}(\zeta_0,\eta)^{-1}\psi_{\eta\zeta}(\zeta_0,\eta) \right]^{-1} \\ &\times\left[s_\zeta(\zeta_0,\eta) - \psi_{\zeta\eta}(\zeta_0,\eta)\psi_{\eta\eta}(\zeta_0,\eta)^{-1} s_\eta(\zeta_0,\eta) \right] \end{aligned} \tag{3.B.4}$$

with all the score and information quantities evaluated at the null value of ζ, ζ_0 and η replaced by a $\sqrt{n}$-consistent estimator.

Apart from its relatively easy method of calculation, the matrix algebra expression itself can be prove difficult to use because the information matrix (essentially the second derivatives of the likelihood function) would not have zero elements, but would be singular. Therefore, its generalized inverse would have to be used; but the key matrix then, that of the eigenvalues, might also be found to be singular. That means that the generalized inverse of the information matrix have to be obtained which make the process become one of the infinite regress.

A welcome feature of the $C(\alpha)$ test statistic is that it can be readily obtained from an artificial regression. Breusch and Pagan (1980) suggested one type of artificial calculation. With some algebraic manipulation, Equation (3.B.4) can be written as

$$C(\alpha) = s(\zeta_0,\eta)'\psi(\zeta_0,\eta)^{-1}s(\zeta_0,\eta) - s_\eta(\zeta_0,\eta)'\psi_{\eta\eta}^{-1}s_\eta(\zeta_0,\eta) \qquad (3.B.5)$$

Let $S(\theta)$ be a $n \times p$ matrix with $\partial \ln f(y_i,\theta)/\partial\theta_j$ as its typical $(i,j)th$ element. Note that the first r columns correspond to the parameters of primary interest[56] and the last $(p-r)$ to the nuisance parameters[57] .

We use $S_{\zeta_0}^+$ to denote the $n \times r$ submatrix of $S(\theta)$ with parameters of primary interest (denoted as $S(\zeta_0)$) , while S_η^+ to denote the matrix of $S(\zeta_0,\eta)$ with the parameters of primary interest and the nuisance parameters. The statistics can be obtained in two steps. First, regress $S_{\zeta_0}^+$ and S_η^+ on residuals obtained from estimates considering the primary interest only, respectively. Save the two R^2s from the each regression. Second, calculate the $C(\alpha)$ test statistics as n times the difference of two R^2 obtained from regress. The critical values for the $C(\alpha)$ test can be obtained from a χ_γ^2 distribution, with γ being the number of restrictions, when one regime is excluded.

[56] In our study of the Markov Regime Switching models, these are the parameters from the single regime estimation.
[57] These are the additional parameters when estimating using 2 regimes Markov Switching model.