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Prediction Accuracy of Futures Contracts Traded in Thailand Futures Exchange (TFEX)

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Abstract

This paper examines prediction accuracy of future spot price by a futures price, a random walk model and an ARMA model. The study covers SET50 stock index, gold price and thirty single stocks which serve as underlying assets for single stock futures contracts. The prediction accuracy is measured by Mean Error (ME), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Root Mean Square Percentage Error (RMSPE) and Theil's inequality coefficient. The data cover daily prices from 2006 to 2010.

In term of predicting SET50 stock index, ARMA model has the lowest RMSPE for short term forecast (less than one month), whereas random walk model has the lowest errors for medium to long term forecast (one month to one year). Futures price performs nearly as well as random walk model in the short term, and clearly beat ARMA model in the long term. In term of predicting gold price, futures price performs as well as the other two predictors in both short and long term. Lastly, in case of single stock price prediction, there is no clear winner between a futures price and a random walk model.

We also find that futures prices tend to under predict future spot prices since mean errors are normally negative. This would imply that on average it is profitable to long futures contracts and wait until maturity to make a profit.

Keywords: Futures, prediction accuracy, SET50
JEL Classification Codes: G13, G14, G17

1. Introduction

According to market efficiency theory, futures prices reflect all relevant information (including historical data and expectation of future events) in forecasting subsequent spot prices. As such, futures price should be an unbiased and accurate predictor of future spot price (Kolb & Overdahl, 2007). This paper set up a horse race among various predictors to examine futures price prediction performance when compared to other methods, namely a random walk model and an ARMA model.

The contracts examined are traded at the Thailand Futures Exchange (TFEX). The exchange, established in 2004, currently has eight types of futures contracts, namely, SET50 stock index futures, single stock futures, gold futures, silver futures, interest rate futures, bond futures, oil futures, and currency futures. This study covers the top three most liquid futures contracts which are SET50 stock index futures, single stock futures and gold futures. The data cover daily prices from 2006 to 2010.

The prediction accuracy is measured by Mean Error (ME), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Root Mean Square Percentage Error (RMSPE) and Theil's inequality coefficient. Furthermore, Theil's inequality coefficient is decomposed into a bias proportion (Um) a variance proportion (Us), and a covariance proportion (Uc). They are useful as a mean of breaking the forecasting errors into specific sources.

In term of predicting SET50 stock index, ARMA model has the lowest RMSPE for short term forecast (one week to three weeks), whereas random walk model has the lowest errors for medium to long term forecast (one month to one year). Futures price performs nearly as well as random walk model in the short term, and clearly beat ARMA model in the long term. In term of predicting gold price, futures price performs as well as the other two predictors in both short and long term. Lastly, in case of single stock price prediction, there is no clear winner between a futures price and a random walk model. The Theil's inequality covariance proportion dominates prediction errors, implying that errors are random.

This paper expands on previous studies by including stock and stock index futures. Prior research focuses mostly just on prediction accuracy of commodities futures. Only a few cover financial futures and almost none on stock or stock index futures.

This paper is organized as follows. Section 2 provides literature review for both theories and prior empirical studies. Section 3 and 4 discuss methodology and data respectively. Section 5 provides statistical results. Lastly, section 6 concludes.

2. Previous Research

2.1. Theories

2.1.1. Unbiasedness Hypothesis

A market is efficient (in the informational sense) if the prices of the assets traded on that market reflect all relevant information. When applied to futures prices, market efficiency would imply that futures prices should reflect all relevant information of the underlying asset's prices at the maturity date. As such, a futures price should be an unbiased predictor of a spot price at maturity.

Unbiasedness hypothesis suggests that the current futures price should equal the spot price expected to prevail at maturity. If market participants had access to additional information to predict the spot price expected to prevail at maturity, they would profit by buying or selling a futures contract if the current futures price was not equal to the expected spot price at maturity. Such buying and selling should ensure that equality is established. This idea can be formulated as the following equation.

$$F_{t,T} = E_t(S_T)$$

$F_{t,T}$ is the futures price at time t for a maturity date at time T and $E_t(S_T)$ is the expectation at time t of the spot price to prevail at time T. We can also write the above equation in terms of the following statistical model.

$$S_T = F_{t,T} + \varepsilon_T$$

S_T is the spot price at futures contract expiration and ε_T is a zero-mean error term.

2.1.2. Cost of Carry Model

The cost of carry model, which is based on the assumption of perfect markets and deterministic interest rates, states that the futures prices depend on the spot price and the cost of storing an underlying asset from now to a maturity date. It is based on the concept of arbitrage between a spot price and a futures price. An arbitrage should ensure that the difference between the current asset price and the futures contract price is the net cost of carrying the asset, which involves a dividend yield and an interest cost. The cost of carry formula, which gives a fair price of the futures contract, can be written as follows.

$$F_{t,T} = S_t\, e^{(r-d)(T-t)}$$

S_t is a spot price at time t. r is the continuous risk free interest rate and d is the continuous dividend yield of an underlying asset. (T - t) is the time to maturity of the futures contract.

2.2. Empirical Studies

The prediction accuracy of futures price has been studied extensively. Previous studies include various types of underlying assets such as oil, bank bill, exchange rate, energy, base metals, and agricultural commodities. This study classifies previous literature into two major groups: (1) evaluation of forecasting performance and (2) testing of an unbiasedness hypothesis.

2.2.1. Predictive Power of Futures Prices

In terms of forecasting power, most studies find that futures prices beat other predictors. This section classifies previous studies based on underlying assets: Interest Rate, Exchange Rate and Commodities. It is noteworthy that there is no previous study on the predictive power of stock index futures.

Interest Rate

Krippner (1998) tests the predictive power of New Zealand bank bill futures rates. He used futures data from 1989 to 1997. The result is that a futures price outperforms a random walk model on all horizons.

Exchange Rate

Laws and Thompson (2004) examine forecasting performance of futures exchange rates of Euro, Pound Sterling and Yen against dollars over forecasting horizons of one, two and three months, using data during the year 1987 to 2000. They use three predictors for comparison: (a) an ARIMA model, (b) a random walk model and (c) a VECM model. The criteria used to assess the forecasting accuracy are Mean Error (ME), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Theil's inequality coefficient and Correct Direction Index (CDI). Their paper finds that for all forecasting horizons, exchange rate futures price tends to provide a superior forecast of the subsequent spot price when compared to other predictors except the yen futures contract.

Commodities

Abosedra (2006) evaluates whether futures prices of U.S. natural gas accurately predict subsequent spot prices. This study assesses forecasting performances over one, three, six, nine, and twelve month horizons. The data cover from year 1993 to 2004. The results suggest that futures prices outperform corresponding naive forecasts across all forecasting horizons. In addition, results from Theil's inequality coefficients suggest that the one month-ahead contracts has the lowest errors.

Hoffman, Irwin, and Toasa (2007) study forecasting performance of corn, soybeans, and wheat futures contracts. Their paper assesses forecasting ability based on MAE, MAPE (Mean Absolute Percentage Error), and RMSPE (Root Mean Square Percentage Error). The forecasting period covers year 1980 to 2005. Their paper finds that futures forecasts from corn, soybeans, and wheat contract have lower RMSPE than those of World Agricultural Supply and Demand Estimates (WASDE) projections, though not for all horizons

Chinn and Coibion (2010) examine relationships between spot and futures prices for a broad range of commodities, including energy, precious and base metals, and agricultural commodities. In particular, they investigate whether a futures price is an unbiased and accurate predictor of a subsequent spot price. Their study also compares forecasting abilities of a futures price, a random walk and an ARIMA model based on RMSE and MAE. Their data cover year 2003 to 2009. They find that for an oil market, futures prices outperform a random walk model at three month horizon. For precious metals and agricultural commodities, futures prices outperform a random walk model at most horizons. For base metals, a random walk model modestly outperforms futures prices at all horizons.

Reichsfeld and Roache (2011) assess the forecasting performance of ten commodity futures: aluminum, copper, corn, cotton, crude oil, gasoline, gold, natural gas, soy and wheat futures. Their study compares RMSE of a futures price, a random walk model and an ARIMA model for 91, 182, 364 and 728 day horizon. Their sample of spot and futures prices covers year 1990 to 2011. The result is that futures prices perform at least as well as a random walk model for most commodities and over most horizons.

Though most studies find that a futures price can reasonably predict a future spot price, some recent studies find the opposite. One such study is Yun (2006). He examines the relative forecasting performance of futures prices compared to expert forecasts from The Energy Information Administration (EIA) and four other econometric models. This study uses spot and futures prices of WTI crude oil for the period of 1998 to 2004 and analyses one to six month forecasting horizons. The result is that forecasts based on econometric models outperform forecasts based on EIA and futures prices.

2.2.2. Testing the Unbiasedness Hypothesis of Futures Price

Most studies found that a futures price is not an unbiased predictor. This section groups previous studies by types of underlying assets: stock index, exchange rate and commodity.

Stock Index

Antoniou and Holmes (1996) investigate the joint hypothesis of market efficiency and unbiasedness of futures prices for the FTSE-100 stock index futures. Their analysis covers all future contracts with expiry dates between September 1984 to June 1993. They test both a long run and a short-run efficiency, using a cointegration and an error correction model. They find that a futures price is not an unbiased predictor of a subsequent spot price at least up to a three month forecasting horizon. However, they become unbiased predictors for four or five month forecasting horizons.

Kenourgios (2005) tests both market efficiency and unbiasedness hypothesis of the FTSE/ASE-20 stock index futures contract in the Greek futures market. The data consist of minute-by-minute spot values of the FTSE/ASE-20 stock index and the FTSE/ASE-20 futures contract prices from March 2000 to March 2002. The Johansen cointegration procedure reveals that the FTSE/ASE-20 futures market is inefficient and a futures price is not an unbiased predictor of a subsequent spot price at least for a one-month horizon.

Commodity

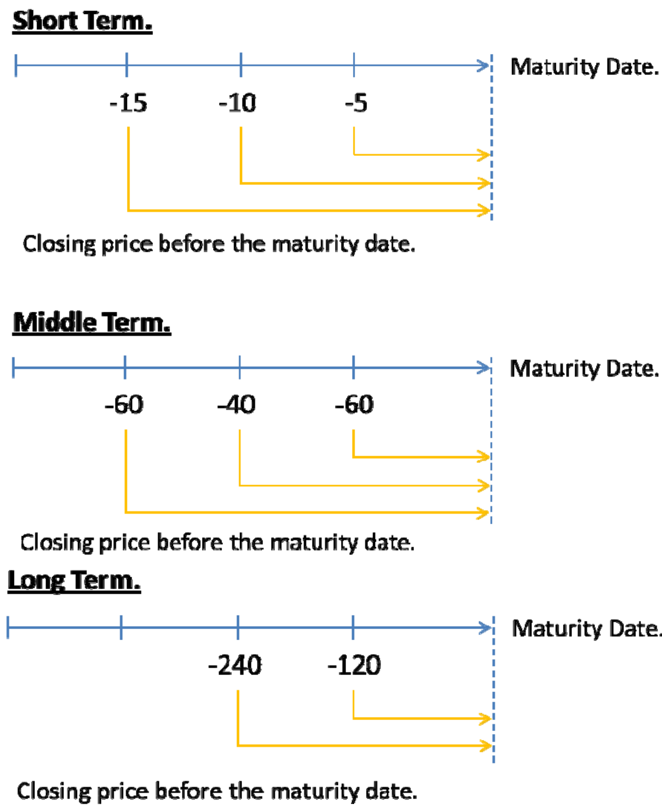
Liu (2009) tests market efficiency of crude palm oil futures. The goal is to investigate crude palm oil (CPO) futures market efficiency of Bursa Malaysia (BMD). Both Johansen cointegration test and VECM are conducted to test long-run and short-run efficiency test for the European spot market and four different futures forecasting horizons, namely one week, two weeks, one month and two months. The data cover year 2001 to year 2007. He finds that the hypothesis of unbiasedness cannot be rejected for most tested samples at least in the long term.

3. Methodology

3.1. Forecasting Horizons

The study separates forecasting horizons into three periods: Short term, Medium term and Long term as defined in Figure 1. We assign a maturity date as day "0" and one day before the maturity date as day "-1" and two days before the maturity date as day "-2", and so on.

Figure 1: Forecasting horizons



3.2. Forecasting Methods

There are numerous methods in predicting future spot prices. We evaluate which methods are most accurate. The unbiasedness hypothesis suggests that a futures price should equal to an expected spot price at maturity. Therefore, we hypothesize that a futures price would be one of the most accurate predictor. In this research, we set up a horse race among three forecasting methods.

1) Futures Forecast

Theoretically, if the market is efficient, a futures price should be an unbiased predictor of the future spot price.

$$F_{t,T} = E_t\,(S_T)$$

2) Random Walk Forecast

If a spot price follows a random walk model, then the best predictor of a future spot price is the current spot price. A random walk model can be written as the following equation.

$$S_T = S_{t,} + \varepsilon_T$$

T is the maturity date, S_T is a spot price at time T, S_t is a current spot price at time t and ε_T is an error term with a zero mean.

3) ARMA Forecast

Autoregressive moving average (ARMA) model is a useful statistical tools to examine the dynamical characteristics of time-series data. We model returns as an ARMA process as returns are stationary. In particular, we use an ARMA (1, 1). The model is applied to returns of SET50 and Gold but not to returns of single stocks because of limited observations. ARMA (1, 1) has the following form.

$$r_t = a_0 + a_1 r_{t-1} + \varepsilon_t + \beta_1 \varepsilon_{t-1}$$

r_t is a log return of an underlying asset. ε_t is a white noise error with a zero mean and a constant variance. We use the summation of predicted returns of each series to calculate a forecast of subsequent spot price from the following equation.

$$S_{t,T}^{f} = S_t . e \sum_{i=1}^{n} (y_{t+i})$$

$S_{t,T}{}^{f}$ represents the forecasting price at time t of the price expected at time T. y_t is the predicted return from the ARMA model. The ARMA forecast is based on a rolling estimation of data from date t to t-240. The estimation and forecasting periods are shown in Figure 2.

Figure 2: The estimation and forecasting periods

3.3. Measurement of Prediction Accuracy

For measurement of predictive power, this paper use five statistics: (1) Mean Error (ME), (2) Mean Absolute Error (MAE), (3) Root Mean Square Error (RMSE), (4) Root Mean Square Percentage Error (RMSPE), and (5) Theil's inequality coefficient.

Mean Error (ME)

The mean error is used to measure a bias of the predicted values. It is calculated from the difference between the simulated value and the values actually observed. It can be either positive or negative. Positive number would imply over prediction, whereas negative number would imply under prediction.

$$ME = \frac{1}{N}\sum_{T=1}^{N}(S_T^f - S_T^a)$$

S_T^f is a predictor of spot price expected to prevailed at time T. S_T^a is an actual spot price at time T. T is an index of an expiry date of a futures contract. N is the number of a futures contract that already expired within the sample.

Mean Absolute Error (MAE)

The Mean Absolute Error (MAE) is the average of the absolute value of the residuals (error). The MAE is very similar to the ME, but with absolute values instead. It is less sensitive to large errors compared to RMSE. The MAE measures the average magnitude of the errors in a set of forecasts, without considering their directions. The MAE is the average over the sample of the absolute values of the difference between the forecasted value and the actual value.

$$MAE = \frac{1}{N}\sum_{T=1}^{N}\left|S_T^f - S_T^a\right|$$

Root Mean Square Error (RMSE)

The Root Mean Square Error is the Square root of the average of the sum of the squared difference between the actual and forecast value. The lower RMSE would mean better and more accurate forecasts.

$$RMSE = \sqrt{\frac{1}{N}\sum_{T=1}^{N}(S_T^f - S_T^a)^2}$$

Root mean Square Percentage Error (RMSPE)

The root mean square percentage error is another measure of prediction accuracy. It is a measure of the percentage deviation of the predictor and its actual value.

$$RMSPE = \sqrt{\frac{1}{N}\sum_{T=1}^{N}\left(\frac{S_T^f - S_T^a}{S_T^a}\right)^2}$$

Theil's Inequality Coefficient

Theil's inequality coefficient is defined as the following.

$$U = \frac{\sqrt{\frac{1}{N}\sum_{T=1}^{N}(S_T^f - S_T^a)^2}}{\sqrt{\frac{1}{N}\sum_{T=1}^{N}(S_T^f)^2} + \sqrt{\frac{1}{N}\sum_{T=1}^{N}(S_T^a)^2}}$$

This coefficient will be between zero (perfect accuracy) and one. It can be decomposed into different proportions: U^m, U^s and U^c called respectively the bias, the variance, and the covariance proportion. U^m is an indication of systematic error that should be close to zero. U^s is an indication of the ability of a model to replicate a degree of variability. U^c is the covariance proportion which measures unsystematic error. The sum of all these proportion would always be one. Ideally, distribution of error over these three source should be $U^m = U^s = 0$,$U^c = 1$. The formulae for these proportions are the following.

$$U^m = \frac{(S^f - \overline{s^a})^2}{(1/N)\sum_{T=1}^{N}(S_T^f - S_T^a)} \qquad U^s = \frac{(\sigma_f - \sigma_a)^2}{(1/N)\sum_{T=1}^{N}(S_T^f - S_T^a)} \qquad U^c = \frac{2(1-\rho)\sigma_f\sigma_a}{(1/N)\sum_{T=1}^{N}(S_T^f - S_T^a)}$$

4. Data

This section discusses data issues of SET50 index, index futures, Gold price, Gold futures, and thirty single stocks futures, in turns.

4.1) SET50 index was launched in 1995. It is the first large-cap stock index in Thailand, providing a benchmark of investment in the Stock Exchange of Thailand (SET). It is calculated from stock prices of the top 50 listed companies in terms of market capitalization and liquidity. SET50 index data in this paper cover from April 3rd, 2006 to December 29th, 2011. It is obtained from SET Market analysis and reporting tool (www.setsmart.com). The data collected are daily closing prices. The prices are dividends adjusted.

4.2) SET50 Index Futures is the first product to be traded on Thailand Futures Exchange (TFEX). It was launched on 28 April 2006. This paper uses daily closing futures price[1] as a futures price predictor. If there is no daily closing price on that day, we will use settlement prices[2] instead. We prefer closing prices (if available) to settlement prices because closing price reflect more closely the market value of the underlying asset. The data cover from April 3rd, 2006 to December 29th, 2011. It includes twenty three maturity dates. The futures contract has four different maturity dates per year: at the end of March (H), June (M), September (U), and December (Z). The first contract of SET50 index futures is S50M07 with maturity on April 28th 2006. The last contract used in this study is S50Z11 with maturity on December 30th 2011.

4.3) Gold spot prices are collected from www.goldtraders.or.th/goldprice of gold trader associate of Thailand. In Thailand, the standard for gold purity is 96.5% not 99.99%. The reason is that 99.99% purity does not fit operating conditions in Thailand since gold will lose its shape. The gold closing spot prices are collected daily. In this research, we collect data of Gold spot price from February 1st, 2006 to December 30th, 2011.

4.4) Gold futures data are collected daily from February 2nd, 2010 to December 29th, 2011. If there are no daily closing prices in any given day, we will use settlement price instead. TFEX offers two types of gold future: (1) “Fifty Baht Gold Futures (GF50)”, launched on February 2nd 2010 and (2) “Ten Baht Gold Futures (GF10)”, launched on August 2nd 2011. The number of observations for GF50 is eighteen and that of GF10 is nine. The final settlement price is calculated on the basis of the London Gold AM pricing. The gold price is announced by London Gold Market Fixing Limited. The exchange rate for conversion of gold price in US dollars into Thai baht is announced by TFEX on the last trading day. The final gold futures settlement price[3] is calculated after adjustments for weight and purity.

4.5) TFEX has thirty single stock futures contracts. Single stock futures was first launched on November 24th 2008. Initially, TFEX launched three futures contracts based on the following shares: ADVANC, PTT and PTTEP. The numbers of observation vary from three to thirteen. The reason is that each contract was launched on different dates. The underlying single stock’s closing prices were

1 The closing price is the executed price of the last trade on that particular day.

2 The Settlement price is the official price established by the clearinghouse at the end of each day for use in the daily settlement. Typically, the settlement price is set by calculating the weighted average price over a certain period of trading shortly before the close of the market.

3 The formula for its calculation is as follows: final settlement price = London Gold AM Fixing x (15.244/31.1035) x (0.965/0.995) x (THB/USD) troy ounce = 31.1035 grams, 1 Thai Gold Baht = 15.244 grams, London Gold AM Fixing is based on gold with 99.5% purity, An underlying of the gold futures contract is gold with 96.5% purity, Price per one baht-weight of gold (rounded to 2 decimal points)

collected also from www.setsmart.com. Data were collected since November 24th 2008 to December 29th 2011.

5. Empirical Results

Results of the predictive power in this paper are separated into three parts. In the first part, we show results from the SET50 index as an underlying asset. In the second part, gold is an underlying asset. In the last part, we present results from single stock futures contracts.

5.1. SET50 Stock Index Futures

In this part, we measure a prediction accuracy of SET50 futures. The results are presented in Table 1. It presents the five measures of prediction accuracy: ME, MAE, RMSE, RMSPE and Theil's inequality coefficient. All measures give the same conclusion that prediction errors increase with the forecasting horizons.

The ARMA model is the best predictor for a short term horizon (5 to 20 trading days). For the medium to long term horizon (40 to 240 trading days), the best predictor is a random walk (RW). A futures price has never been the best predictor in any horizon, though its performance is closely matched that of a random walk (RW) in the medium to long term horizon. Interestingly, futures prices always have negative mean errors. This means, on average, futures prices tend to underestimate subsequent spot prices.

In term of Theil's inequality coefficient, we find that the proportions Um for all predictors are close to zero which means there are no systematic biased. Almost all errors belong to Uc. This suggests that most errors are unsystematic.

The futures price in a short term has more power in forecasting SET50 index than the futures price in a long term. Figure 3-5 show SET50 index prices at maturity dates compared to SET50 futures prices on five, twenty, and one-hundred-twenty trading days before maturity dates, respectively.

5.2. Gold Futures

Results from GF50 and GF10 are reported in the Table 2 and 3, respectively. For GF50, we find that futures price is the best predictor, in terms of smallest RMSPE, for most horizons. However, an ARMA model beats a futures price on fifteen and twenty trading day forecasting horizons. A random walk (RW) is the worst predictor. For all predictors, errors increase with the forecasting horizons. Figure 6-8 show gold prices at maturity dates compared to gold futures prices on five, twenty, and one-hundred-twenty trading days before maturity dates, respectively.

Table 3 presents results from GF10. It reveals that futures price is the best predictor, in terms of smallest RMSPE, for most horizons. It performs almost as well as a random walk (RW) for five and fifteen trading day horizons. An ARMA model beats a futures price only for twenty trading day horizon.

Table 1: SET50 index forecast

Trading day horizons		5	10	15	20	40	60	120	240
Observation		23	23	23	23	22	22	21	19
Mean Error	Futures	-5	-5	-3	-10	-15	-14	-22	-49
(Baht)	RW	-5	-4	-2	-7	-8	-13	**-19**	-47
	ARMA	**-3**	**-2**	**1**	**-3**	**1**	**5**	24	**42**
Mean Absolute Error	Futures	13	18	28	36	51	51	92	148
(Baht)	RW	13	18	26	34	**48**	**51**	**89**	**148**
	ARMA	**12**	**16**	**24**	**32**	52	62	120	227
RMSE	Futures	18	26	36	41	59	69	112	169
(Baht)	RW	17	26	34	40	**57**	**68**	**109**	**167**
	ARMA	**16**	**24**	**32**	**38**	67	78	140	264

Table 1: SET50 index forecast - continued

RMSPE (Percent)	Futures	3.0%	4.4%	6.8%	7.9%	10.6%	14.0%	24.9%	**38.9%**
	RW	2.8%	4.5%	6.5%	**7.4%**	**10.1%**	**13.9%**	**24.6%**	39.1%
	ARMA	**2.7%**	**4.2%**	**6.5%**	7.5%	12.4%	14.8%	27.9%	60.3%
Theil's inequality coefficient	Futures	0.02	0.02	0.03	0.04	0.05	0.06	0.10	0.15
	Um	0.09	0.03	0.01	0.05	0.06	0.04	0.04	0.07
	Us	0.01	0.00	0.03	0.02	0.06	0.00	0.00	0.02
	Uc	0.91	0.96	0.96	0.92	0.88	0.96	0.96	0.91
Theil's inequality coefficient	RW	0.01	0.02	0.03	0.04	**0.05**	**0.06**	**0.10**	0.15
	Um	0.07	0.02	0.00	0.03	0.02	0.04	0.03	0.04
	Us	0.00	0.00	0.02	0.01	0.04	0.00	0.00	0.00
	Uc	0.92	0.97	0.98	0.96	**0.94**	**0.96**	**0.97**	0.96
Theil's inequality coefficient	ARMA	**0.01**	**0.02**	**0.03**	**0.03**	0.06	0.07	0.12	0.21
	Um	0.05	0.01	0.00	0.01	0.00	0.00	0.03	0.03
	Us	0.00	0.01	0.10	0.08	0.20	0.13	0.22	0.26
	Uc	**0.95**	**0.98**	**0.90**	**0.91**	0.79	0.87	0.75	0.71

Bold letters denote minimum errors.

Figure 3: SET50 Index Prices at maturity and SET50 Futures Price 5 days before maturity of each contract.

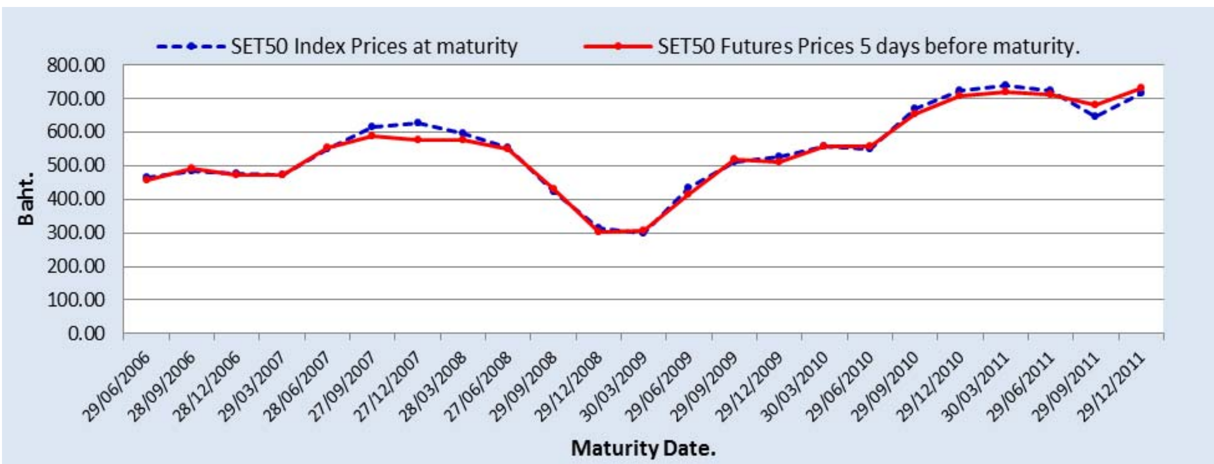


Figure 4: SET50 Index Prices at maturity and SET50 Futures Price 20 days before maturity of each contract.

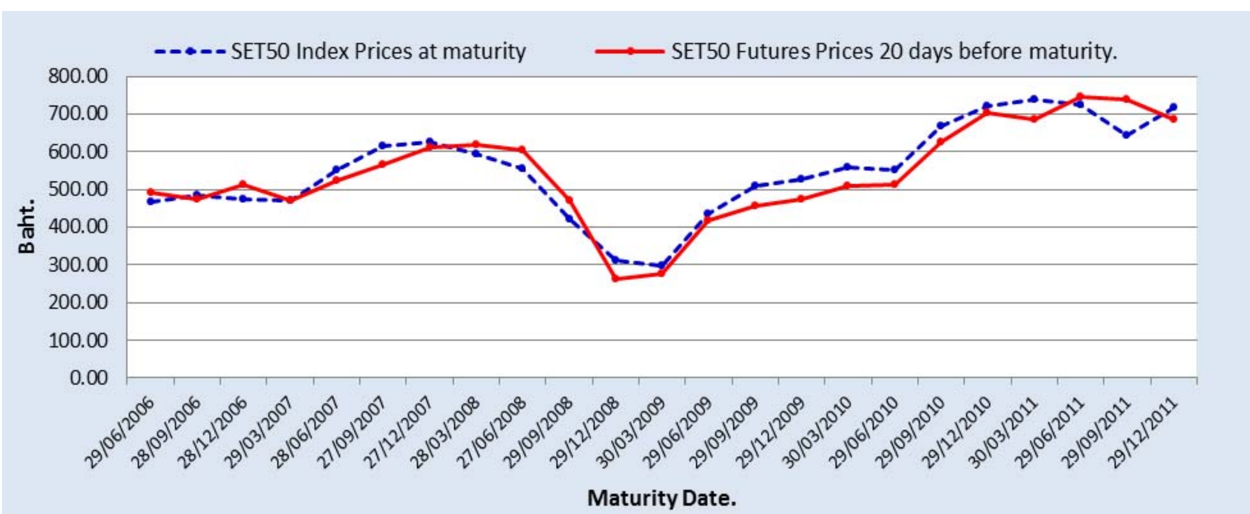


Figure 5: SET50 Index Prices at maturity and SET50 Futures Price 120 days before maturity of each contract.

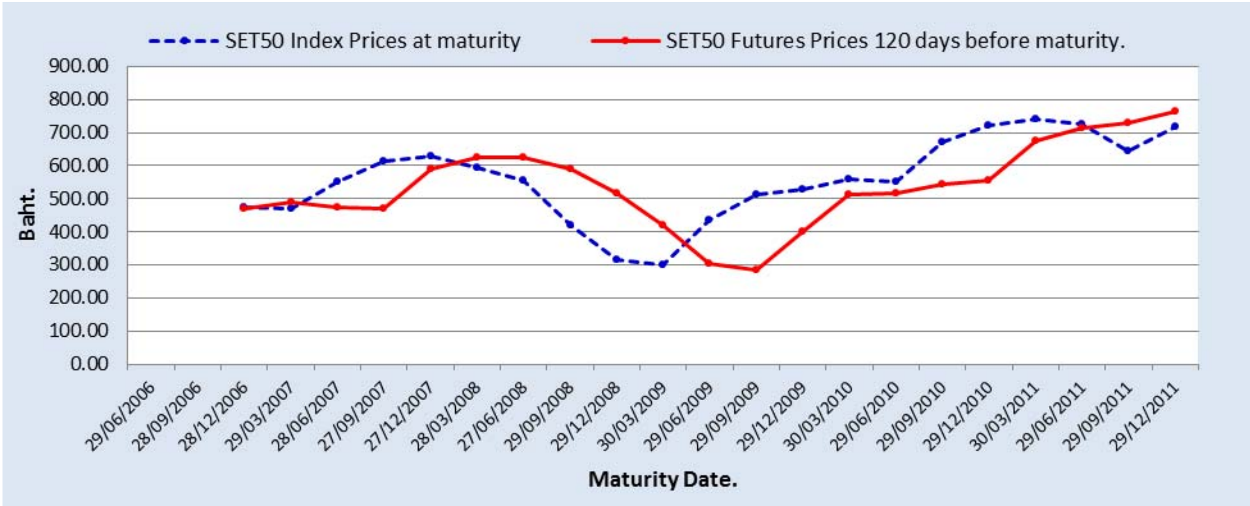


Table 2: Gold spot (GF50) price forecast

Trading day horizons		5	10	15	20	40	60	120
Observation		**18**	**18**	**18**	**18**	**17**	**16**	**11**
Mean Error	Futures	23	-76	35	-145	**-232**	-628	-1,856
	RW	**-14**	-153	-69	-259	-415	-825	-2,132
	ARMA	-1,070	**-38**	**27**	**21**	491	**-72**	**-399**
Mean Absolute Error	Futures	**312**	**246**	628	738	**871**	1,226	**1,856**
	RW	314	269	592	741	915	1,288	2,132
	ARMA	2,725	308	**429**	**703**	980	**1,106**	2,256
RMSE	Futures	455	**312**	827	1,024	**1,143**	**1,381**	**2,168**
	RW	**454**	345	810	1,010	1,186	1,482	2,426
	ARMA	3,552	372	**618**	**937**	1,569	1,569	3,182
RMSPE	Futures	**1.9%**	**1.6%**	4.2%	4.7%	**5.2%**	**6.6%**	**9.8%**
	RW	2.0%	1.7%	4.0%	4.6%	5.5%	7.0%	11.0%
	ARMA	18.2%	1.9%	**3.1%**	**4.5%**	6.8%	6.8%	13.4%
Theil's inequality coefficient	**Futures**	**0.01**	**0.01**	0.02	0.03	**0.03**	**0.04**	**0.06**
	Um	0.00	0.06	0.00	0.02	0.04	0.21	**0.73**
	Us	0.06	0.05	0.00	0.05	0.00	0.06	0.07
	Uc	**0.94**	**0.89**	1.00	0.93	**0.96**	**0.73**	0.20
Theil's inequality coefficient	**RW**	0.01	0.01	0.02	0.03	0.03	0.04	0.07
	Um	0.00	0.20	0.01	0.07	0.12	0.31	0.77
	Us	0.05	0.06	0.01	0.06	0.00	0.08	0.07
	Uc	0.95	0.74	0.99	0.87	0.88	0.61	0.16
Theil's inequality coefficient	**ARMA**	0.09	0.01	**0.02**	**0.02**	0.04	0.04	0.08
	Um	0.09	0.01	0.00	0.01	0.09	0.00	0.02
	Us	0.00	0.01	0.04	0.02	0.19	0.03	0.00
	Uc	0.91	0.98	**0.96**	**0.97**	0.72	0.97	0.98

Bold letters denote minimum errors.

Table 3: Gold spot (GF10) price forecast

Trading day horizons		5	10	15	20	40	60	120
Observation		**9**	**9**	**9**	**8**	**8**	**8**	**5**
Mean Error	Futures	87	-121	-84	-399	**-321**	-1,050	-2,496
	RW	**33**	-211	-217	-531	-569	-1,294	-2,850
	ARMA	-1,519	**-37**	**78**	**-98**	620	**-289**	**-1,720**
Mean Absolute Error	Futures	473	**303**	671	1,011	**1,109**	**1,423**	**2,496**

Table 3: Gold spot (GF10) price forecast - continued

	RW	**467**	344	672	1,019	1,144	1,556	2,850
	ARMA	2,995	374	**501**	**944**	1,522	1,540	3,491
RMSE	Futures	617	**356**	**902**	1,350	**1,450**	**1,594**	**2,825**
	RW	**609**	415	902	1,342	1,491	1,746	3,124
	ARMA	4,025	431	737	**1,196**	2,198	2,049	4,433
RMSPE	Futures	2.5%	**1.6%**	3.9%	5.6%	**6.0%**	**6.8%**	**11.6%**
	RW	**2.5%**	1.9%	**3.9%**	5.6%	6.1%	7.5%	12.9%
	ARMA	17.0%	2.0%	3.2%	**5.1%**	9.1%	8.4%	17.8%
Theil's inequality coefficient	**Futures**	0.01	**0.01**	0.02	0.03	**0.03**	**0.04**	**0.06**
	Um	0.02	0.12	0.01	0.09	0.05	0.43	**0.78**
	Us	0.08	0.07	0.00	0.00	0.06	0.00	0.03
	Uc	0.90	**0.82**	0.99	0.91	**0.89**	**0.57**	0.19
Theil's inequality coefficient	**RW**	**0.01**	0.01	0.02	0.03	0.03	0.04	0.07
	Um	0.00	0.26	0.06	0.16	0.15	0.55	0.83
	Us	0.08	0.07	0.00	0.00	0.03	0.00	0.03
	Uc	**0.92**	0.67	0.94	0.84	0.83	0.45	0.14
Theil's inequality coefficient	**ARMA**	0.10	0.01	**0.02**	**0.03**	0.05	0.05	0.10
	Um	0.14	0.01	0.01	0.01	0.08	0.02	0.15
	Us	0.01	0.01	0.06	0.01	0.34	0.18	0.11
	Uc	0.85	0.98	**0.93**	**0.98**	0.58	0.80	0.74

Bold letters denote minimum errors.

Figure 6: Gold Spot Prices at maturity and Gold Futures Price 5 days before maturity of each contract.(GF50)

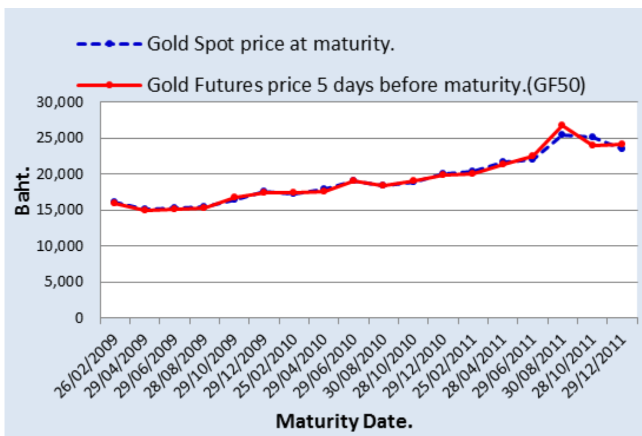


Figure 7: Gold Spot Prices at maturity and Gold Futures Price 20 days before maturity of each contract.(GF50)

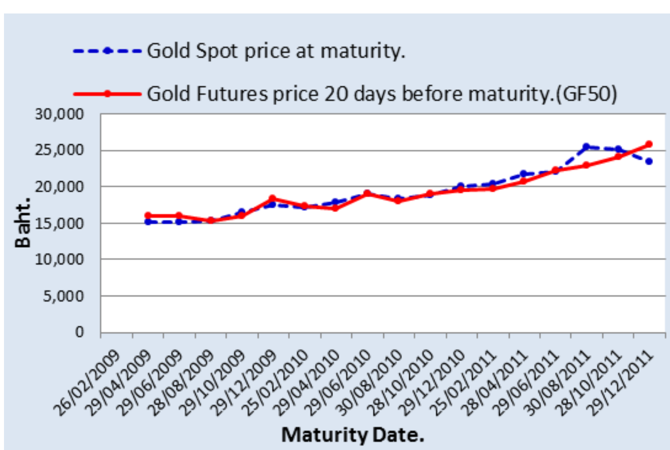


Figure 8: Gold Spot Prices at maturity and Gold Futures Price 120 days before maturity of each contract.(GF50)

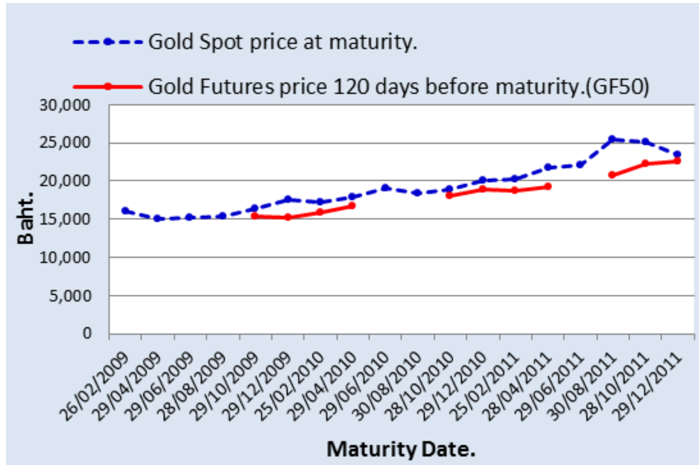


Figure 9: Gold Spot Prices at maturity and Gold Futures Price 5 days before maturity of each contract.(GF10)

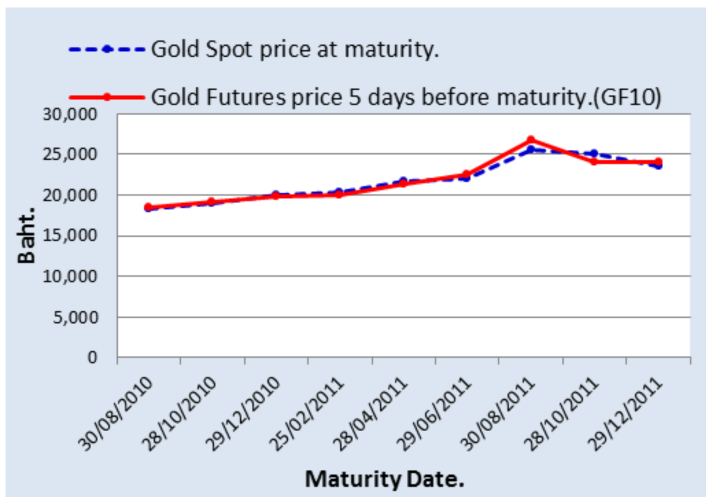


Figure 10: Gold Spot Prices at maturity and Gold Futures Price 20 days before maturity of each contract.(GF10)

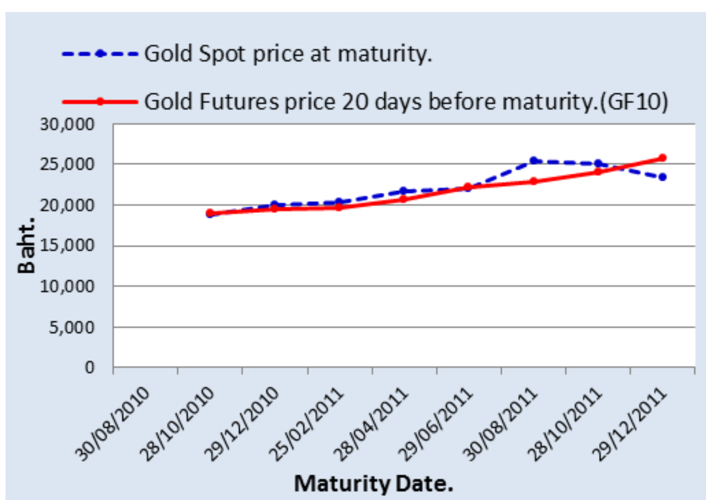
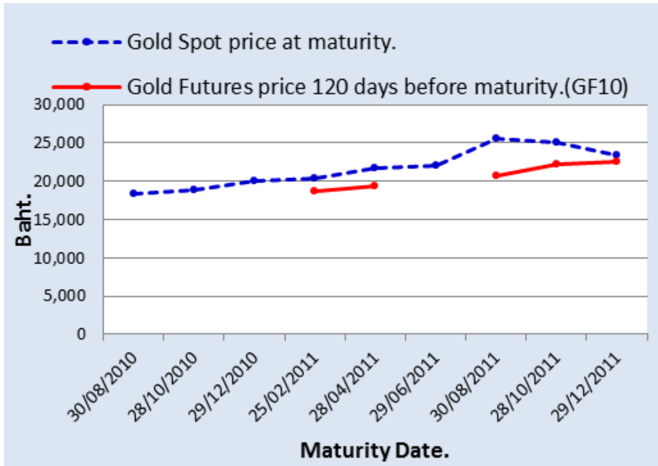


Figure 11: Gold Spot Prices at maturity and Gold Futures Price 120 days before maturity of each contract.(GF10)



5.3. Thirty Single Stock Futures

The results of thirty single stock futures are reported in table 4. We find that the best predictor changes when we change a single stock or a horizon. However, for most single stocks and in most horizons, a random walk (RW) performs better or very close (based on RMSPE) to a futures price. Interestingly, a random walk (RW) even beat a futures price in the medium to long term forecast (20 to 240 trading days), where we would expect a futures price to perform better. This may result from a lack of liquidity for a single stock futures. It is noteworthy that the sample size of each single stock futures is not large. The largest sample size is only thirteen. This fact limits our inference.

Figure 12-17 show graphs of futures prices and spot prices of the underlying assets at the maturity dates on different forecasting horizons. Normally, a futures price becomes a better predictor near a maturity date. The selected single stocks are ADVANC and PTTEP, the most liquid single stock futures contracts.

6. Conclusions

This paper assesses the forecasting performance of futures contracts at various horizons up to one year. Futures contracts studied include SET50 stock index futures, gold futures, and thirty single stock futures.

The result from SET50 stock index can be summarized as follows. For short term horizons (less than one month), an ARMA can accurately predict future spot prices better than other models. For medium to long term horizons (one month to one year), a random walk can predict subsequent spot prices better than other models. Surprisingly, SET50 stock index futures has never been the best predictor in any horizon. Although SET50 future is not the best predictor in any horizon, its mean error is close to those of ARMA or random walk model. It is noteworthy that mean error of futures prices are always negative, implying an under prediction in any horizon. Therefore, Investor can make a profit on average by holding futures contracts to maturity.

In case of gold, futures price performs as well as the other two predictors in both short and long term. This is surprising given the fact that an underlying of the gold futures contracts is a gold bullion traded in London, not a domestic gold. In case of single stocks, we find that for most single stocks and in most horizons, a random walk (RW) performs better or very close to a futures price. However, we cannot draw too much inferences because of limited observations.

Table 4: Single stock price forecast

RMSPE (Percent)	Horizons	5	10	15	20	40	60	120	240
ADVANC Futures	Futures	**2.81%**	3.92%	**5.81%**	**7.01%**	8.85%	9.21%	16.52%	20.40%
	RW	2.95%	**3.55%**	6.06%	7.21%	**8.53%**	**7.48%**	**14.08%**	**17.14%**
	Number of observation	13	13	13	13	12	12	11	8
BANPU Futures	Futures	4.98%	7.00%	7.94%	9.56%	16.85%	17.92%	**26.28%**	**29.17%**
	RW	**4.29%**	**6.48%**	**7.92%**	**9.15%**	**15.10%**	**17.77%**	26.74%	34.38%
	Number of observation	11	10	10	10	10	10	9	6
BAY Futures	Futures	4.98%	8.91%	**9.62%**	11.73%	13.96%	**16.58%**	**19.01%**	21.98%
	RW	**4.29%**	**7.60%**	10.15%	**10.98%**	**13.65%**	19.09%	20.39%	**21.55%**
	Number of observation	11	10			10	10	9	7
BBL Futures	Futures	8.88%	8.98%	9.70%	10.20%	12.51%	13.28%	17.38%	25.83%
	RW	**3.05%**	**5.39%**	**6.35%**	**7.68%**	**10.50%**	**12.27%**	**12.39%**	**17.59%**
	Number of observation	11	10	10	10	10	10	9	7
BTS Futures	Futures	3.47%	7.74%	**6.02%**	8.38%	19.05%	17.07%	21.81%	
	RW	3.47%	**7.23%**	5.89%	**7.89%**	**16.18%**	**15.94%**	**17.71%**	
	Number of observation	4	3	3	3	3	3	2	0
CPALL Futures	Futures	2.36%	**2.05%**	**3.85%**	**5.25%**	6.55%	**10.30%**	**11.55%**	
	RW	**1.62%**	3.51%	4.26%	5.32%	**6.34%**	10.33%	11.97%	
	Number of observation	3	3	3	3	3	3	2	0
CPF Futures	Futures	**3.26%**	7.66%	9.17%	8.80%	**13.09%**	16.92%	**5.77%**	
	RW	3.57%	**7.14%**	**8.73%**	**8.73%**	14.41%	**16.60%**	7.27%	
	Number of observation	4	3	3	3	3	3	2	0
DTAC Futures	Futures	**12.04%**	**11.08%**	8.20%	**8.72%**	**8.43%**	17.22%	30.83%	
	RW	12.14%	11.13%	**7.35%**	9.06%	9.20%	**16.49%**	**29.19%**	
	Number of observation	4	3	3	3	3	3	2	0
HMPRO Futures	Futures	11.59%	13.30%	14.01%	14.01%	13.09%	**7.57%**	14.96%	
	RW	**4.64%**	**6.67%**	**7.29%**	**9.81%**	**10.85%**	13.54%	**14.21%**	
	Number of observation	4	3	3	3	3	3	2	0
IRPC Futures	Futures	9.87%	17.25%	**20.35%**	**20.80%**	36.66%	37.13%	**50.42%**	
	RW	**9.76%**	**17.08%**	21.05%	21.62%	**36.04%**	**35.99%**	51.96%	
	Number of observation	4	3	3	3	3	3	2	0
ITD Futures	Futures	**6.38%**	**11.26%**	14.82%	16.78%	22.43%	24.76%	31.31%	**27.60%**
	RW	6.39%	11.44%	**14.39%**	**16.60%**	**21.90%**	**23.98%**	**29.66%**	27.94%
	Number of observation	11	10	10	10	10	10	9	7
IVL Futures	Futures	3.39%	**11.59%**	**19.04%**	17.81%	37.63%	42.00%	72.80%	
	RW	**2.84%**	12.01%	19.19%	**17.79%**	**36.13%**	**41.16%**	**71.79%**	
	Number of observation	4	3	3	3	3	3	2	0
KBANK Futures	Futures	4.77%	6.40%	**5.92%**	7.03%	10.40%	10.90%	15.73%	25.21%
	RW	**2.55%**	**5.10%**	6.03%	**3.58%**	**5.43%**	**4.78%**	**15.54%**	**23.55%**
	Number of observation	11	10	10	10	10	10	9	7
KTB Futures	Futures	5.06%	**7.41%**	9.76%	7.46%	10.90%	9.66%	23.46%	34.79%
	RW	**4.75%**	7.50%	**9.73%**	**7.27%**	**10.76%**	**9.28%**	**22.84%**	**33.13%**
	Number of observation	10	9	9	9	9	9	8	6
LH Futures	Futures	5.90%	**7.24%**	8.35%	9.91%	13.69%	**15.05%**	14.80%	10.07%
	RW	**5.89%**	7.49%	**8.31%**	**9.89%**	**13.62%**	15.16%	**14.13%**	**9.07%**
	Number of observation	11	10	10	10	10	10	9	7
MINT Futures	Futures	9.59%	15.52%	14.21%	16.17%	20.93%	12.96%	17.56%	
	RW	**6.93%**	**10.30%**	**13.07%**	**14.57%**	**18.44%**	**11.96%**	**11.94%**	
	Number of observation	4	3	3	3	3	3	2	0
PS Futures	Futures	14.44%	14.11%	**16.51%**	17.02%	**20.48%**	24.08%	**57.42%**	
	RW	**9.78%**	**12.96%**	19.32%	**16.95%**	21.18%	**23.27%**	58.36%	
	Number of observation	4	3	3	3	3	3	2	0
PTT Futures	Futures	5.13%	6.69%	**9.13%**	**10.18%**	30.48%	**32.03%**	21.13%	23.92%
	RW	**5.06%**	**6.62%**	9.31%	10.25%	**30.37%**	32.06%	**20.75%**	**21.60%**
	Number of observation	13	13	13	13	12	12	11	9
PTTEP Futures	Futures	**3.23%**	**5.23%**	7.00%	10.22%	11.19%	**12.16%**	16.28%	16.73%
	RW	3.36%	5.28%	**6.80%**	**10.13%**	**11.14%**	12.34%	**16.20%**	**16.12%**
	Number of observation	13	13	13	13	12	12	11	9
QH Futures	Futures	4.48%	7.08%	**9.10%**	10.99%	**17.96%**	22.63%	**27.55%**	42.08%
	RW	**4.34%**	**7.03%**	9.25%	**10.74%**	18.38%	**22.28%**	28.65%	**36.30%**
	Number of observation	11	10	10	10	10	10	9	7
SCB Futures	Futures	5.30%	7.48%	8.23%	8.60%	11.37%	12.83%	12.64%	18.72%
	RW	**3.26%**	**5.05%**	**6.06%**	**6.82%**	**9.77%**	**11.51%**	**11.19%**	**16.01%**
	Number of observation	11	10	10	10	10	10	9	7
SCC Futures	Futures	**5.25%**	7.97%	**8.70%**	13.41%	17.04%	19.58%	**20.24%**	30.15%
	RW	5.55%	**6.97%**	9.33%	**11.46%**	**16.75%**	**19.09%**	21.98%	**28.87%**
	Number of observation	11	10	10	10	10	10	9	7
STA Futures	Futures	5.18%	22.95%	32.01%	**30.83%**	54.70%	54.70%	66.15%	
	RW	**4.24%**	**22.87%**	**30.78%**	31.74%	**54.38%**	**54.38%**	**63.44%**	
	Number of observation	4	3	3	3	3	3	2	0

Table 4: Single stock price forecast - continue

TCAP Futures	Futures	4.81%	5.87%	**8.44%**	10.11%	**8.17%**	10.89%	18.64%	
	RW	**4.49%**	5.87%	9.08%	**9.92%**	8.73%	**10.04%**	**16.36%**	
	Number of observation	4	3	3	3	3	3	2	0
THAI Futures	Futures	8.51%	**13.03%**	20.03%	23.29%	31.62%	35.61%	70.61%	
	RW	**6.67%**	14.06%	**18.22%**	**20.78%**	**31.14%**	**33.14%**	**69.81%**	
	Number of observation	4	3	3	3	3	3	2	0
TMB Futures	Futures	**6.69%**	12.01%	10.73%	13.90%	26.29%	29.36%	54.63%	
	RW	7.00%	**10.92%**	**10.40%**	**13.48%**	**25.06%**	**27.89%**	**48.51%**	
	Number of observation	4	3	3	3	3	3	2	0
TOP Futures	Futures	**4.31%**	14.09%	**17.64%**	17.89%	**29.93%**	**31.30%**	50.50%	
	RW	4.49%	**13.80%**	19.38%	**17.83%**	30.94%	31.51%	**49.64%**	
	Number of observation	4	3	3	3	3	3	2	0
TRUE Futures	Futures	11.01%	16.49%	18.00%	17.56%	**25.46%**	38.62%	**56.97%**	
	RW	**10.50%**	**11.76%**	**16.60%**	**16.54%**	25.51%	**35.94%**	57.46%	
	Number of observation	4	3	3	3	3	3	2	0
TTA Futures	Futures	**5.45%**	**9.50%**	10.96%	13.15%	17.72%	17.47%	18.94%	**27.48%**
	RW	5.92%	9.52%	**10.55%**	13.15%	17.72%	**16.84%**	**18.48%**	31.73%
	Number of observation	11	10	10	10	10	10	9	7
TUF Futures	Futures	4.32%	5.38%	**5.38%**	5.48%	**8.62%**	**8.59%**	14.94%	
	RW	**2.31%**	**4.44%**	5.61%	**4.26%**	8.81%	9.62%	**10.90%**	
	Number of observation	4	3	3	3	3	3	2	0

Bold letters denote minimum errors.

Figure 12: ADVANC Spot Prices at maturity and ADVANC Futures Price 5 days before maturity of each contract.

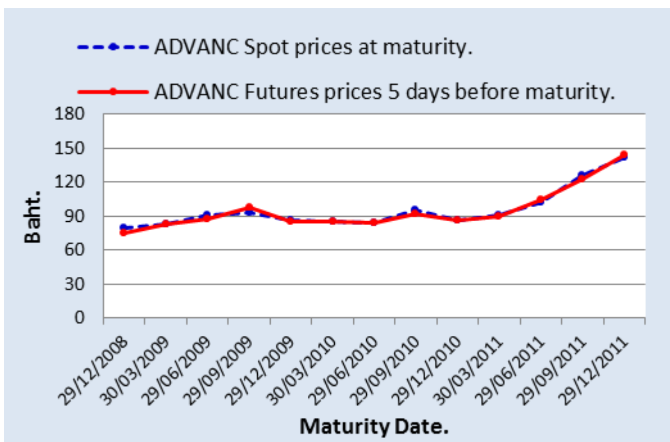


Figure 13: ADVANC Spot Prices at maturity and ADVANC Futures Price 20 days before maturity of each contract.

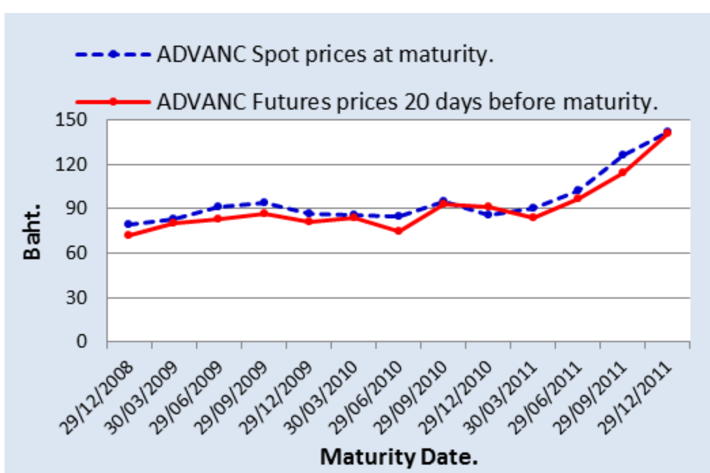


Figure 14: ADVANC Spot Prices at maturity and ADVANC Futures Price 120 days before maturity of each contract.

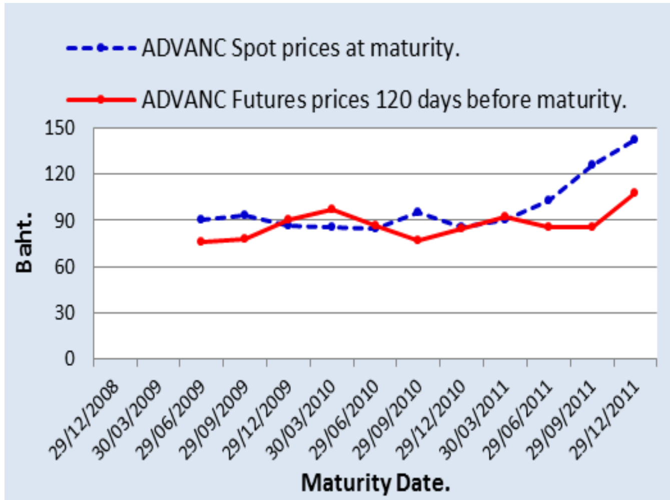


Figure 15: PTTEP Spot Prices at maturity and PTTEP Futures Price 5 days before maturity of each contract.

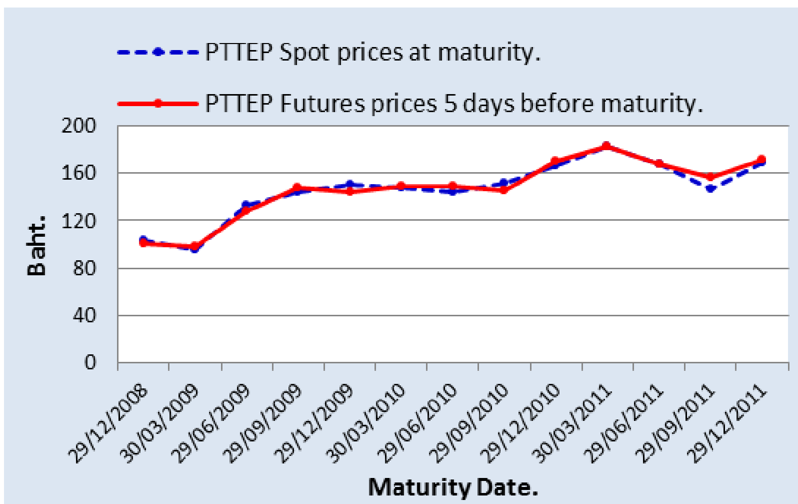


Figure 16: PTTEP Spot Prices at maturity and PTTEP Futures Price 20 days before maturity of each contract.

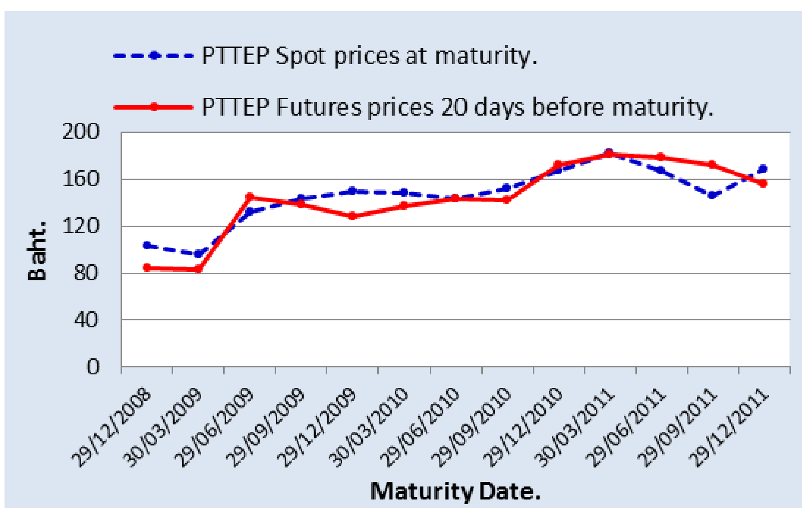
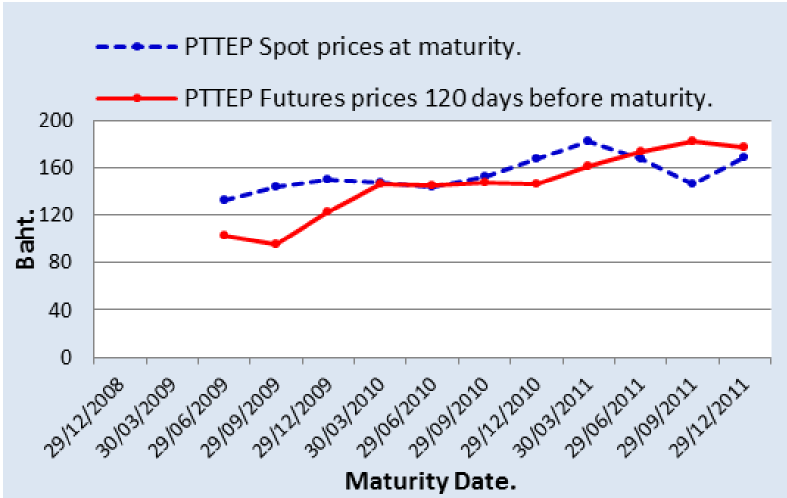


Figure 17: PTTEP Spot Prices at maturity and PTTEP Futures Price 120 days before maturity of each contract



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