The Performance of U.S. Futures Market in Hedging International Crude Oil

by

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Finally, I would like to dedicate this thesis to my dear parents and fiance.

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ABSTRACT

We study the effectiveness of U.S. futures markets in hedging price risks in the international crude oil spot market. Three international markets, Australia, Canada and Mexico are selected. We devote our attention to three hedging strategies: hedge a spot position that does not recognize native currency exchange rate fluctuations with a single commodity futures position; hedge a spot position that does recognize native currency exchange rate fluctuations with a single commodity futures position; hedge a spot position that does recognize native currency exchange rate fluctuations with both commodity and currency futures positions. Three base hedge ratio estimation models are developed based on these three hedging strategies. We compare the effectiveness of these hedging strategies over each of the three hedging horizons, one week, four weeks and twelve weeks for each country. Empirical hedge ratio estimation models are selected to deal with seasonality, autocorrelation and heteroscedasticity. Hedge effectiveness is properly estimated by comparing hedged and unhedged outcome variances of the autoregression-corrected and/or heteroscedasticity-corrected transformed data.

CHAPTER ONE: INTRODUCTION

The U.S. futures market, as the world's leading and most diverse derivatives marketplace, is important because of its performance in risk management as part of hedging strategies as practiced by domestic producers and processors. The Chicago Mercantile Exchange (CME Group), one of the largest futures exchange in the world, once used the slogan, "CME Group is where the world comes to manage risk". The essence of this thesis is a test of that claim as we will study the effectiveness of U.S. futures markets in hedging price risks in the international crude oil spot market. Three international markets, Australia, Canada and Mexico, will be selected to enhance the value of our conclusions.

One reason for choosing these three countries for investigation is that although Australia has its Australian Securities Exchange (ASX), Canada has its Montreal Exchange (MX) and Mexico has its Mexican Derivatives Exchange (MexDer), only a limited number of futures contracts are listed on these futures exchanges. Specifically, it is impossible for crude oil producers and processors from any of these three countries to hedge crude oil on their domestic exchanges as no crude oil futures contract or other relevant futures is available. U.S. futures market may be their first choice because of U.S. dollars being the world's primary currency. In brief, there is strong motivation for these international hedgers to come to the U.S. to manage risk.

On the other hand, Canada and Mexico are two of the largest exporters of crude oil to the

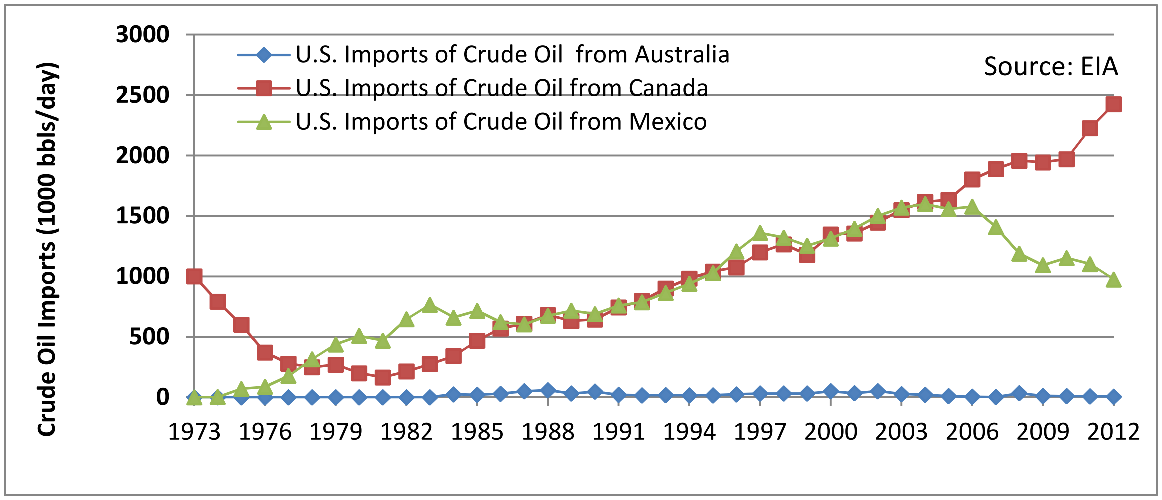


Figure 1.1 Crude Oil Imports (Thousand Barrels per Day)

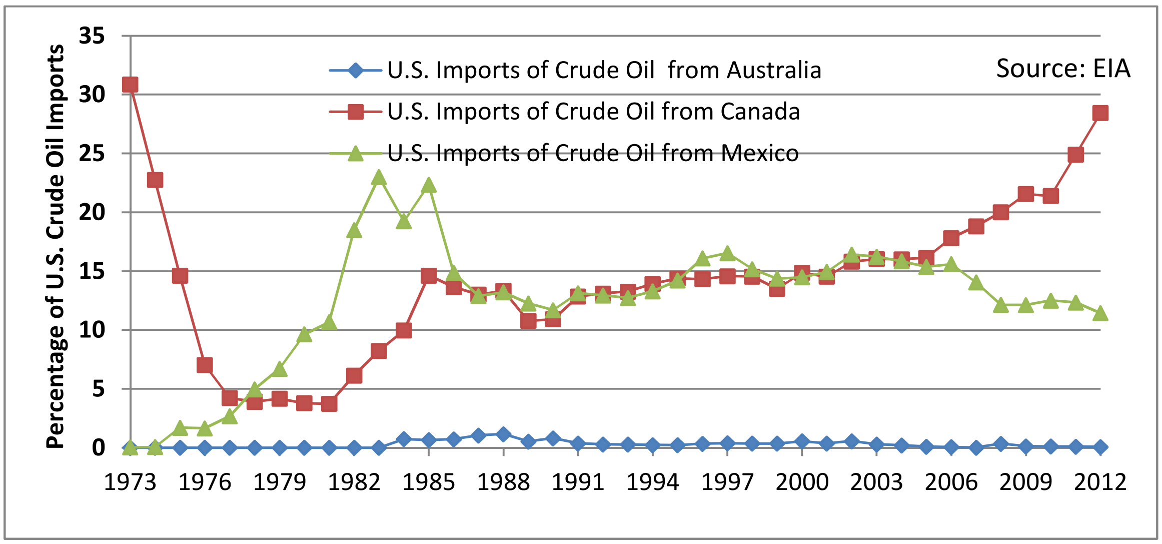


Figure 1.2 Percentage of U.S. Crude Oil Imports from Australia, Canada and Mexico

United States, while there is little crude oil trade between Australia and America (see figures 1.1 and 1.2).

We hypothesize that fluctuations in American crude oil futures market are related to fluctuations in Canadian and Mexican markets and a much smaller linkage between U.S. futures and Australian crude oil futures markets. As a result, the performance of U.S. futures market on these three international crude oil markets is unlikely to be identical.

Hedging effectiveness is anticipated to be lower in the case of Australia. We also anticipate that hedging Canadian and Mexican crude oil on U.S. futures markets will be very effective. Of greater interest will be the effectiveness comparison of hedging Australian, Canadian and Mexican crude oil in the U.S futures market.

When the spot commodity is valued in a currency different from the futures contract as happens in this thesis where the commodity is traded in an international market, we need to express the return of the hedge portfolio in a common currency. We will convert the international crude oil spot price to U.S. dollars. If the international currency exchange rate risk is ignored by an international hedger, then spot position return will be $c_0 s_1 - c_0 s_0 = c_0 \Delta s$. Otherwise, the spot position return will be $s_1 c_1 - s_0 c_0 = c_0 \Delta s + s_0 \Delta c + \Delta s \Delta c$. Hence, we will devote our attention to three hedging strategies: hedge a spot position that does not recognize native currency exchange rate fluctuations with a single commodity futures position; hedge a spot position that does recognize native currency exchange rate fluctuations with a single commodity futures position; hedge a spot position that does recognize native currency exchange rate fluctuations with both commodity and currency futures positions. Three base hedge ratio estimation models will be developed based on these three hedging strategies.

The empirical procedure will consist of applying these three theoretical scenarios to hedge price risk in crude oil markets in Australia, Canada and Mexico using the U.S. futures market. We will compare the effectiveness of these hedging strategies over each of the three hedging horizons, one week, four weeks and twelve weeks for each country.

The presence of seasonality, autocorrelation and heteroscedasticity will be entertained as part of the empirical hedge ratio estimation regression models, so estimation techniques to deal with autoregressive (AR) error, generalized autoregressive conditional heteroscedasticity (GARCH) error, or AR/GARCH error will be applied accordingly.

The remainder of the thesis has five chapters. Chapter two provides a review of the literature on hedge ratio and hedging effectiveness estimation. Chapter three introduces research design and analysis method. Chapter four describes the data used in empirical analysis and data manipulation. Chapter five reports the empirical results. The last chapter summarizes the findings and discusses future work.

CHAPTER TWO: LITERATURE REVIEW

2.1 Theory of Hedging

Hedging is an investment activity that allows sellers or buyers to offset potential loss in a spot market with an offsetting position in the futures market. The futures market allows hedgers to buy or sell contracts for future delivery of major commodities or intangible assets. The offsetting of spot market positions with futures contracts allows hedgers to reduce their price risk on the spot market positions. The price of any futures contract is the expected value of the corresponding specified asset at contract maturity, so it is natural for hedgers to anticipate the spot price and futures price will move together. Hence, taking a futures position that is opposite of the spot market position is typical hedging strategy. More specifically, a commodity owner can sell futures contracts to offset losses due to a spot price decrease, whereas purchasers can buy futures contracts to offset losses due to a spot price increase. One practical problem is to determine the hedge ratio that will minimize overall price risk as investment in futures market is also risky.

In traditional hedging theory, hedgers take futures positions that are equal to and opposite of their spot positions so the hedge ratio is simply minus one. However, Working (1953, p. 342) argued that "Hedging we found to be not primarily a sort of insurance, nor usually undertaken in the expectation that spot and futures prices would rise or fall equally. It is a form of arbitrage, undertaken most commonly in expectation of a favorable change in the relation between spot and futures prices."

Johnson (1960) used basic portfolio theory to model hedging, and Ederington (1979, p.169) concluded that "the decision to hedge a cash or forward market position in the futures market is no different from any other investment decision-investors hedge to obtain the best combination of risk and return." Ederington makes it clear that unlike other financial portfolio models, spot holdings are predetermined and the decision variable is the futures holdings that will constitute the hedge.

2.2 Optimal Hedge Ratio and Hedging Effectiveness

Conventional Method of Futures Hedging

Johnson (1960) and Ederington (1979) did pioneering work in this area and estimated the optimal hedge ratio for minimizing the variance of the hedged portfolio return. They determined that the optimal hedge ratio is the ratio of the covariance of the period-to-period change in the spot and futures prices relative to the variance of the period-to-period change in the futures price. Equally important is that they defined hedging effectiveness as the proportionate reduction in the variance of hedged portfolio return relative to the variance of unhedged spot position return. The measure of hedging effectiveness is the coefficient of determination, denoted as R^2, obtained from a simple ordinary least square (OLS) regression model where the dependent variable is the spot price change and the explanatory variable is the futures price change.

Similarly, Carter and Loyns (1985) performed an OLS regression of the cash price changes of cattle fed in Canada on the price changes of U.S. cattle futures and reported the coefficient of determination as hedging effectiveness. Brown (1985) modified Johnson's and Ederington's approach and compared the two approaches with Friday closing spot and futures prices of wheat, corn and soybeans, regressing spot returns on futures returns, where returns are defined as the percentage change in price from period to period. He compared the optimal hedge ratio and hedging effectiveness with regression results based on price changes and concluded that better estimates were obtained from his reformulation of the portfolio model.

Myers and Thompson (1989) provided a framework for generalized optimal hedge ratio estimation. They claimed initially that none of the three frequently used simple regression approaches (price levels, percentage returns or price changes) are appropriate to estimate optimal hedge ratio except under special conditions. They then proposed a single-equation estimation method that can be used for evaluating the appropriateness of simple regression methods. Their results indicated that a simple regression with price changes did provide reasonable estimates.

Dahlgran (2008) has pointed out that the R^2 of OLS regression structure overestimates the hedging effectiveness and any systematic effects like seasonality, day-of-the-week effects or autocorrelation should be included in the regression model and also included when determining the variance of the unhedged outcome.

Other Methods of Futures Hedging

Concerns about the efficiency of OLS hedge ratio arise when the spot and futures price changes as time series violate the assumptions of an OLS regression model.

Anderson (1985) found that price volatility is time-varying and efficient hedge ratio estimation require correction for when it is present.

Myers (1991) provided a method for estimating time-varying optimal hedge ratios after he had indicated (1989) that time variation should be allowed for in hedge ratio estimation. He applied the generalized autoregressive conditional heteroscedasticity (GARCH) model introduced by Engle (1982) and developed by Bollerslev (1986). According to his argument, a bivariate GARCH model has significant theoretical advantages by allowing for time-varying volatility in assets prices. The application of the bivariate GARCH model resulted in only slightly better estimates than were obtained from a simple regression model.

Holmes (1996) stated that in terms of the variance minimizing hedge ratio and variance reduction (hedging effectiveness), OLS estimates performs marginally better than ECM model and GARCH model. After further examination of the stability of hedge ratios over time, he also concluded that hedge ratios are fairly stationary. Although his results showed that hedge ratios do vary over time, it seems that they are drawn from one distribution with constant mean and variance. He also suggested that the additional costs of frequently adjusting hedge ratios must be borne by hedgers even if a dynamic hedging scenario might seem optimal.

Kroner and Sultan (1993) estimated a bivariate error correction model (ECM) of spot and futures price changes with a GARCH error structure. They found that a GARCH(1,1) model could perform at least as well as other GARCH models with respect to hedge ratio estimation. Their variance comparisons of within-sample hedging effectiveness after accounting for transactions costs shows that their proposed model only marginally outperforms a conventional hedge strategy.

2.3 "Weekend Effect" in Markets

The term "weekend effect", also known as "the Monday effect", epitomizes a phenomenon in financial market that returns on Monday are typically lower than the previous Friday. Keim and Stambaugh (1984) gave strong evidence of a weekend effect in the U.S. stock market. Penman (1987) has found that bad news is more likely to be distributed on Mondays and Fridays than on other weekdays and the research done by Fishe and his colleagues (1993) also supports Penman's claim.

CHAPTER THREE: METHODOLOGY

3.1 Framework

Background

The research is a case study of hedging Australian, Canadian and Mexican crude oil spot price risk in U.S. futures market. These three international markets were selected to enhance the value of our conclusions. Canada and Mexico are two of the largest exporters of crude oil to the United States, so we hypothesize that there is a higher correlation between their native crude oil price and U.S. crude oil futures price than between Australian crude oil price and U.S. crude oil futures price because there is little crude oil trade between Australia and America. Canadian and Mexican crude oil price fluctuations should affect the spot price in the United States and hence the crude oil futures price, and vice versa. In other words, fluctuations in American crude oil futures market are expected to be related to fluctuations in these two international markets. For an isolated market (Australia), hedging effectiveness should be low. Thus, we will compare the effectiveness of hedging Australian, Canadian and Mexican crude oil in U.S futures market.

The literature reviewed in Chapter two indicates that advanced hedge ratio determination methods are not clearly superior to the more basic methods. However, there is no harm in following the conventional methods and making adjustments as warranted.

We designate the return on an unhedged position of x_s units from time t_0 to time t_1 as $\pi_u = x_s(s_1 - s_0) = x_s\Delta s$, where s_0 and s_1 are spot prices at times t_0 and t_1. Correspondingly the return on a hedged position of x_f futures market units is $\pi_h = x_s(s_1 - s_0) + x_f(f_1 - f_0) = x_s\Delta s + x_f\Delta f$, where f_0 and f_1 are futures prices at times t_0 and t_1 respectively. The risk of the hedged return can be represented in terms of its variance,

$$\mathrm{var}(\pi_h) = \mathrm{var}(x_s\Delta s + x_f\Delta f) = x_s^2\mathrm{var}(\Delta s) + x_f^2\mathrm{var}(\Delta f) + 2x_s x_f\mathrm{cov}(\Delta s, \Delta f).$$

The minimum variance optimal hedge ratio is obtained by setting $\partial\mathrm{var}(\pi_h)/\ \partial x_f$ to zero. This gives $2x_f\mathrm{var}(\Delta f) + 2x_s\mathrm{cov}(\Delta s, \Delta f) = 0$.

Solving for x_f gives $x_f^* = -x_s\mathrm{cov}(\Delta s, \Delta f)/\mathrm{var}(\Delta f)$. Hence, the optimal hedge ratio is $x_f^*/x_s = -\mathrm{cov}(\Delta s, \Delta f)/\mathrm{var}(\Delta f)$. The negative sign implies a futures position opposite to the spot position. For simpler interpretation, we can assume x_s to be one in our study thus x_f will be equivalent to the hedge ratio denoted as h and the portfolio return can be expressed as $\pi_h = \Delta s + h\Delta f$.

When the spot commodity and the futures contracts are in different currencies as happens in our case where the commodity is traded in an international market, we need to express the return of the hedge portfolio in a common currency. Since U.S. futures markets are the subject of this study, f is in dollars. The spot price, s, is in international currency. We can either convert the U.S. futures price to the international currency where the revalued futures price change will be $f_1c_1 - f_0c_0 = c_0\Delta f + f_0\Delta c + \Delta f\Delta c$ or convert the international spot price to U.S. dollars where the spot price change will be $s_1c_1 -$

$s_0c_0 = c_0\Delta s + s_0\Delta c + \Delta s\Delta c$, where c denotes the international currency price of U.S. dollars in the former expression or dollar price of the international currency in the latter expression. Expressing U.S. futures prices in a foreign currency as in the first method, the hedge ratio becomes $\mathrm{cov}(\Delta s, c_0\Delta f + f_0\Delta c + \Delta f\Delta c)/\mathrm{var}(c_0\Delta f + f_0\Delta c + \Delta f\Delta c)$. On the other hand, the hedge ratio for expressing international spot prices in dollars turns to be

$$\frac{\mathrm{cov}(c_0\Delta s + s_0\Delta c + \Delta s\Delta c, \Delta f)}{\mathrm{var}(\Delta f)} = \frac{c_0\mathrm{cov}(\Delta s,\ \Delta f)}{\mathrm{var}(\Delta f)} + \frac{s_0\mathrm{cov}(\Delta c,\ \Delta f)}{\mathrm{var}(\Delta f)} + \frac{\mathrm{cov}(\Delta s\Delta c,\ \Delta f)}{\mathrm{var}(\Delta f)}.$$

This method of expressing the hedge portfolio return in a common currency gives the more elegant hedge ratio as its denominator is simpler.

If international currency exchange rate risk is ignored by an international hedger, then the portfolio return will be $\pi_h = (c_0s_1 - c_0s_0) + h(f_1 - f_0) = c_0\Delta s + h\Delta f$. The conventional risk minimizing hedge ratio is $(c_0\ \mathrm{cov}(\Delta s,\ \Delta f))/\mathrm{var}(\Delta f)$, first of the three components in the expansion of $\mathrm{cov}(c_0\ \Delta s + s_0\ \Delta c + \Delta s\Delta c, \Delta f)/\mathrm{var}(\Delta f)$. This is also the slope coefficient in the regression model

$$c_0\ \Delta s = \alpha + \beta_f\Delta f + \varepsilon_t.$$

We can anticipate that such hedge strategy will be less effective than a more inclusive strategy.

If international currency exchange risk is not ignored, then the full spot price return will be $s_1c_1 - s_0c_0 = c_0\Delta s + s_0\Delta c + \Delta s\Delta c$, and the corresponding portfolio return hedged with a single futures position in the underlying commodity will be $\pi_h = (c_0\Delta s + s_0\Delta c + \Delta s\Delta c) + h\Delta f$. In this case, the optimal hedge ratio $\mathrm{cov}(c_0\ \Delta s + s_0\ \Delta c +$

$\Delta s\Delta c, \Delta f)/\mathrm{var}(\Delta f)$ can be obtained from estimating

$$c_0\,\Delta s + s_0\,\Delta c + \Delta s\Delta c = \alpha + \beta_f\Delta f + \varepsilon_t.$$

It is certainly feasible to hedge the international currency exchange rate as well. In this case, the portfolio return is $\pi_h = (c_0\Delta s + s_0\Delta c + \Delta s\Delta c) + h_f\Delta f + h_e\Delta e$ where Δe is foreign currency futures price change from time t_0 to time t_1. Furthermore, an imperfect but reasonable hedge ratio estimation model will be

$$c_0\,\Delta s + s_0\,\Delta c + \Delta s\Delta c = \alpha + \beta_f\Delta f + \beta_e\Delta e + \varepsilon_t.$$

Research Design

We will devote our attention to three hedging strategies:

1. Hedge via a single commodity futures position without taking into account fluctuations in native currency exchange rate with respect to U.S. dollars. The corresponding base hedge ratio estimation model is

$$c_0\,\Delta s = \alpha + \beta_f\Delta f + \varepsilon_t.$$

2. Hedge via a single commodity futures position while including fluctuations in native currency exchange rate. The corresponding base hedge ratio estimation model is

$$c_0\,\Delta s + s_0\,\Delta c + \Delta s\Delta c = \alpha + \beta_f\Delta f + \varepsilon_t.$$

3. Hedge via both commodity futures and foreign currency futures positions while taking into account fluctuations in native currency exchange rate. The corresponding base hedge ratio estimation model is

$$c_0\,\Delta s + s_0\,\Delta c + \Delta s\Delta c = \alpha + \beta_f\Delta f + \beta_e\Delta e + \varepsilon_t.$$

The empirical procedure will consist of applying these three theoretical scenarios to hedge price risk in crude oil markets in Australia, Canada and Mexico using the U.S.

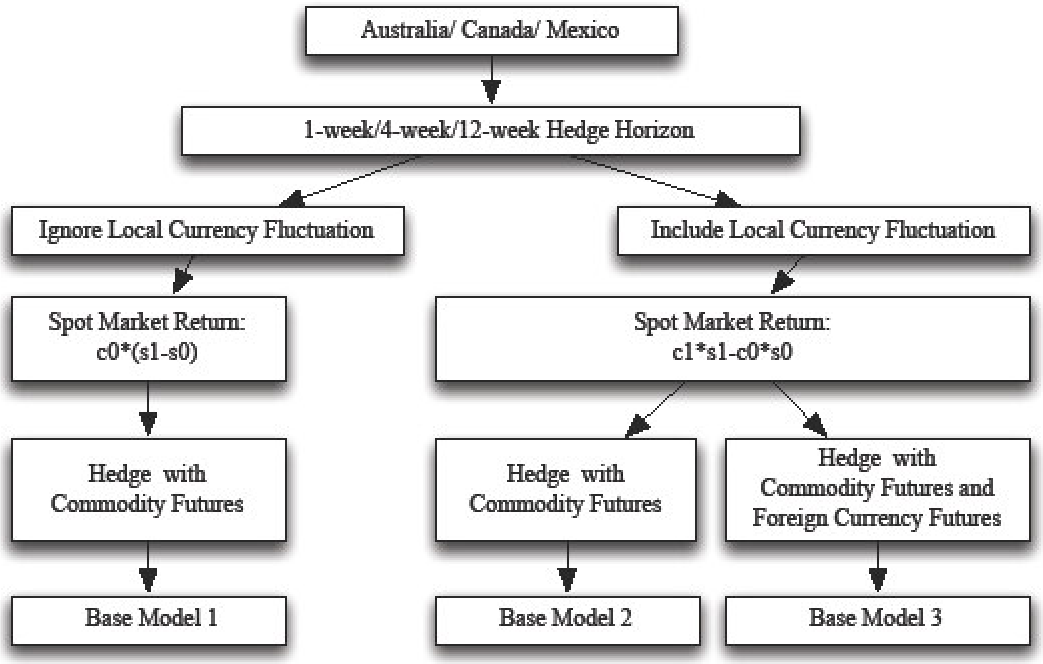


Figure 3.1 Process Diagram of Research Design

futures market. We will compare the effectiveness of these different hedging strategies over each of three hedging horizons, one week, four weeks and twelve weeks for each country (see figure 3.1).

Our data consist of daily observations on the native currency exchange rate and crude oil spot prices for Australia, Canada and Mexico. Our data also include foreign currency futures prices for each of the relevant currencies and crude oil futures prices in U.S. futures market. More details of data are in the next chapter. Each futures contract has multiple maturities trading each day. Over time contracts mature, but it is important to insure that only one contract maturity is involved in generating each futures price change. When the hedge portfolio includes the crude oil and currency futures positions, the maturities of both the commodity futures contract and the foreign currency futures contract are required to be the same. To avoid the weekend effect, we use Wednesday prices only in analysis. 1-week, 4-week and 12-week hedge horizons will be applied. Then each price change is calculated as the change in prices between every two, four or twelve Wednesdays.

3.2 Empirical Hedge Ratio Estimation Model

Seasonal effects should be accounted for to properly evaluate hedging effectiveness according to Dahlgran (2008). Setting the first quarter as default, three dummy variables respectively indicating each of the remaining three quarters are created. Insignificant quarterly dummy variables will be omitted to save degree of freedom after a preliminary estimation of each hedge ratio model, listed in the section 3.2. The two dependent variables of interest are $c_0 \Delta s$ and $c_0 \Delta s + s_0 \Delta c + \Delta s \Delta c$. Regressors consist of Δf and/or Δe according to different hedging strategies.

We start by analyzing autocorrelation and/or heteroscedasticity in the residuals of the hedge ratio estimation models. The commonly employed regression procedure that assumes fixed x's and autoregressive (AR) error is appropriate for correcting for autocorrelation in our cases (Durbin 1960). As for dealing with heteroscedasticity, the error variance at different times is unknown and must be estimated from the data. The regression model with generalized autoregressive conditional heteroscedasticity

(GARCH) error can be used to model the changing error variance (Bollerslev 1986). Based on the research of Kroner and Sultan (1993), a GARCH(1,1) model (where the first parameter is the order of the GARCH terms and the second parameter is the order of the ARCH terms) is generally sufficient. Furthermore, we can combine the autoregressive error model with GARCH error model if there is also an issue of heteroscedasticity after the autocorrelation in OLS residuals has been corrected (Ruppert 2011). More details of the three models, AR error regression model, GARCH error regression model and AR/GARCH error regression model, will be given below. If there is neither autocorrelation nor heteroscedasticity, OLS regression model will be applied.

The Regression Model with AR(m) Error (Durbin 1960)

The general autoregressive error model is

$$y_t = x_t'\beta + v_t,$$

$$v_t = \varphi_1 v_{t-1} + \varphi_2 v_{t-2} + \cdots + \varphi_m v_{t-m} + \varepsilon_t,$$

$$\varepsilon_t \sim \text{i.i.d.}\, N(0, \sigma^2).$$

Using polynomials in the lag operator where

$$\varphi(L) = 1 - \varphi_1 L - \varphi_2 L^2 - \cdots - \varphi_m L^m,$$

the AR model for the error can be written as

$$\varphi(L) v_t = \varepsilon_t.$$

Hence, we can write the regression model as

$$y_t = x_t'\beta + \frac{\varepsilon_t}{\varphi(L)},$$

and then by multiplying each side by $\varphi(L)$ we have

$$\varphi(L)y_t = \varphi(L)x_t'\beta + \varepsilon_t.$$

After correcting for autoregressive errors, the adjusted slope coefficients can be estimated from

$$y_t^* = x_t^{*\prime}\beta + \varepsilon_t,$$

where $y_t^* = \varphi(L)y_t$ and $x_t^* = \varphi(L)x_t$.

The Regression Model with GARCH(1,1) Error (Bollerslev 1986)

The general GARCH(1,1) regression model is

$$y_t = x_t'\beta + v_t,$$

$$v_t = \sqrt{h_t}\varepsilon_t,$$

$$h_t = w + \alpha v_{t-1}^2 + \gamma h_{t-1},$$

$$\varepsilon_t \sim \text{i.i.d.}\, N(0,1).$$

u_{t-1}^2 is the ARCH term and h_{t-1} is the GARCH term. If $\gamma = 0$, the model is reduced to ARCH(1) regression model. In ARCH(1) model, next period's volatility in h_t is only conditional on last period's squared residual v_{t-1}^2. In GARCH(1,1) model, our next period forecast of variance is a mixture of our last period forecast h_{t-1} and last period's squared residual v_{t-1}^2 (Reider 2009, p.5). The ARCH(1) error model is a short memory process in which only last period's information is used to estimate the current variance, whereas the GARCH(1,1) error model is a long memory process in that all the past squared residuals are used to estimate the changing variance (SAS Institute Inc. 2013, p.326).

We can re-estimate the regression model using weighted least squares after we have obtained all $\widehat{h_t}'s$ from the data, the estimated conditional error variance series.

The Regression Model with AR(m)/GARCH(1,1) Error (Ruppert 2011)

The general AR(m)/GARCH(1,1) regression model is

$$y_t = x_t'\beta + v_t,$$

$$v_t = \varphi_1 v_{t-1} + \varphi_2 v_{t-2} + \cdots + \varphi_m v_{t-m} + u_t,$$

$$u_t = \sqrt{h_t}\varepsilon_t,$$

$$h_t = w + \alpha u_{t-1}^2 + \gamma h_{t-1},$$

$$\varepsilon_t \sim \mathrm{i.i.d.}\, N(0,1).$$

SAS can fit the linear regression model with AR/GARCH disturbances in one step. Transformed variables corrected for autoregressive error can be calculated using estimated parameters in the autoregressive part as in dealing with regression model with autoregressive error only. Weighted least square is applied to the transformed variable by setting weights equal to the reciprocals of the estimated conditional error variances.

The OLS Regression Model

The general OLS regression model is

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

$$\varepsilon_t \sim \mathrm{i.i.d.}\, N(0,\sigma^2).$$

Hedging effectiveness can be estimated directly from this model.

3.3 Empirical Hedge Ratio Estimation Model Selection

For each dataset, the most appropriate estimation technique of these four models mentioned above will be selected for estimation.

The PROC AUTOREG procedure in SAS is used to find statistically significant seasonal dummies. Insignificant seasonal dummies are omitted in further analysis. Then autocorrelation of the first, second, third and fourth orders in the OLS residuals are checked using Durbin-Watson test after fitting the base model including significant seasonal dummy variable(s). We conclude that autocorrelation will be significant if one of the tests is significant for the hypothesis of no autocorrelation of that order. Stepwise autoregression available in the AUTOREG SAS procedure is used to select the order of the autoregressive error model. Initially the first five autoregressive lags are included. Insignificant lags are removed sequentially until only significant lags remain. We then test for heteroscedasticity using the Lagrange multiplier (LM) tests. When autocorrelation is present, the residuals of the AR error regression model are tested for heteroscedasticity. On the other hand, if autocorrelation is insignificant, then the OLS residuals are tested for heteroscedasticity. In either case, the final model for a given dataset is based on whether or not the null hypothesis of homoscedasticity is rejected. Figure 3.2 summarizes this process.

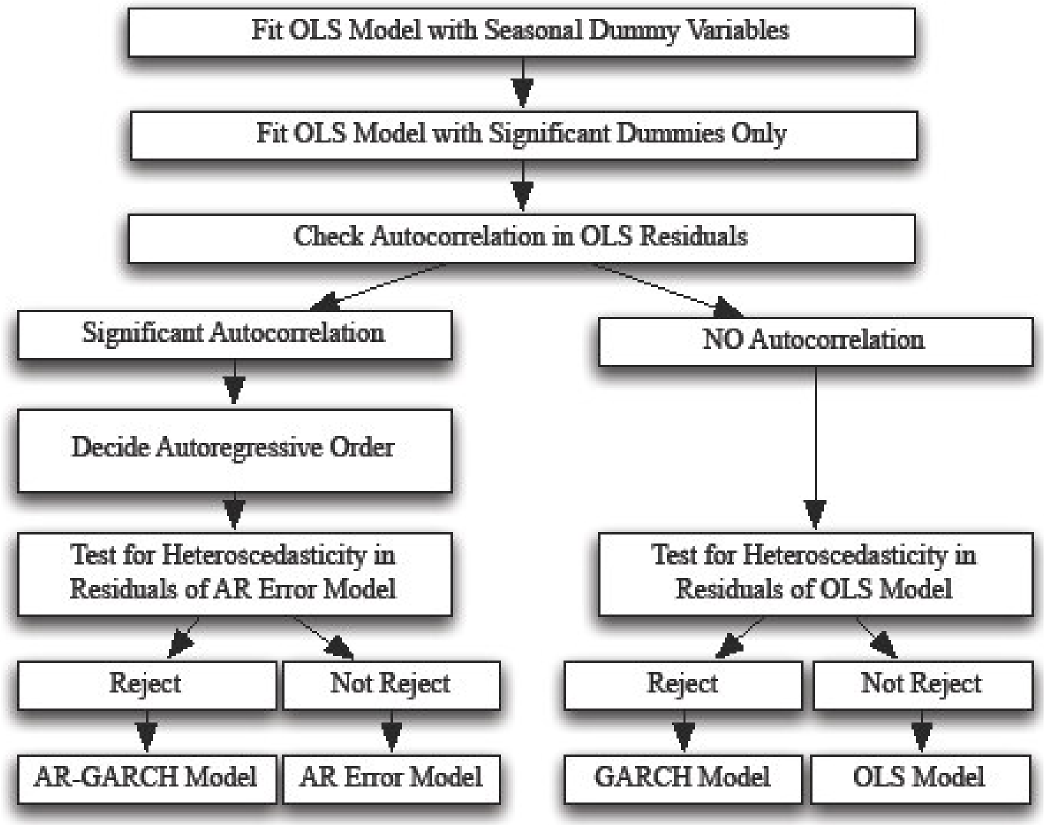


Figure 3.2 Process Diagram of Model Selection

3.4 Hedging Effectiveness Estimation Method

For AR error regression model, hedge effectiveness is estimated from the model using the transformed data after correcting for autoregressive errors. For the GARCH error regression model, effectiveness is estimated from the weighted least squares (WLS) model using the transformed data that is weighted by the reciprocals of the estimated conditional error variances. For AR/GARCH error regression model, hedge effectiveness is estimated from the WLS model using transformed data that has been corrected for autocorrelation and weighed by the reciprocals of the estimated conditional error variances. For the OLS regression model, hedge effectiveness is estimated directly from the unweighted data. In each case, hedging effectiveness can be obtained through a transformation of the F statistic that tests the linear hypothesis that the hedge ratios are zero.

For the hedge portfolios with a single commodity futures, F statistics are obtained by testing the null hypothesis that $\beta_f = 0$ in the appropriately adjusted version of each empirical model. For the hedge portfolios including both commodity and currency futures positions, the F statistics are obtained by testing the null hypothesis of $\beta_f = \beta_e = 0$ in the appropriately adjusted version of each empirical model. Let

$$F = \frac{(RSS_R - RSS_{UR})/(df_{UR} - df_R)}{RSS_{UR}/df_{UR}},$$

where RSS_R is the residual sum of squared errors without hedging (i.e. $\beta_f = 0$ or $\beta_f = \beta_e = 0$), RSS_{UR} is the residual sum of squared errors with hedging (i.e. β_f unrestricted or β_f and β_e unrestricted), and df_R and df_{UR} are degree of freedom corresponding to the respective RSS.

$$F * \frac{RSS_{UR}}{df_{UR}} = \frac{RSS_R - RSS_{UR}}{df_{UR} - df_R},$$

$$RSS_R = \left(1 + \frac{F(df_{UR} - df_R)}{df_{UR}}\right) RSS_{UR},$$

$$\text{Hedging Effectiveness} = \frac{VAR(\pi_u) - VAR(\pi_h)}{VAR(\pi_u)} * 100(\%) = \frac{RSS_R - RSS_{UR}}{RSS_R} * 100\%$$
$$= \frac{F(df_{UR} - df_R)}{df_{UR} + F(df_{UR} - df_R)} * 100(\%).$$

If a hedge strategy with a single futures is applied, then $df_{UR} - df_R = 1$. If a hedge strategy with two futures is applied, then $df_{UR} - df_R = 2$.

CHAPTER FOUR: DATA DESCRIPTION

4.1 Data Sources and Manipulation

The commodity of interest in this study is crude oil in each of the three countries, Australia, Canada and Mexico. Crude oil prices and native currency exchange rates in terms of U.S. dollars (USD) for each country were obtained from the Bloomberg Terminal. Australian Cossack, Canadian Edmonton Syncrude Sweet and Mexican Mixed crude oil spot prices are used.

Historical daily crude oil futures prices and prices of the three relevant foreign currency futures for Australian dollars (AUD), Canadian dollars (CAD) and Mexican Pesos (MQD) in the U.S. market, were obtained from barchart.com.

The availability of crude oil price data dictates the time span of our investigation Australian, Canadian and Mexican data is from November 1, 1995, March 29, 2006 and July 17, 2000 respectively to the end of 2012. (See table 4.1)

To avoid weekend effects, we use Wednesday's prices. These data still contain some missing values and present a maturity selection problem as futures contracts may expire while the hedge is in place. We will deal with this shortly.

It is impossible to use prices of a single futures contract underlying crude oil or international currency because of contract maturity, but we select data so as to ensure that the futures price change over the hedging horizon applies a single maturity. This maturity selection process applies to both commodity and foreign currency futures. Furthermore, there are twelve crude oil futures maturities per year, but only March, June, September and December contracts for the three currency futures. Thus, we match currency and crude oil futures maturities. Although currency futures positions are not included in two of the three hedge strategies considered, when currency futures are used we select a crude oil futures maturity that matches the currency futures maturity.

After discarding observations for which the last trading day is less than 30 days beyond the hedge termination date, we use the nearby futures contract as the hedge vehicle. This one-month maturity buffer avoids a potential price volatility increase as a contract approaches maturity.

Table 4.1 Data Sources and Descriptions

Australian Crude Oil - Spot	Australian Cossack crude oil, AUD/bbl, daily. Nov 1, 1995 to the end of 2012. Source: Bloomberg Terminal
Australian Dollars - Spot	$/AUD, daily. Source: Bloomberg Terminal
Australian Dollars - Futures	CME, Mar, Jun, Sep, Dec contracts, $/AUD, daily. Source: barchart.com
Canadian Crude Oil - Spot	Canadian Edmonton Syncrude Sweet, CAD/bbl, daily. Mar 29, 2006 to the end of 2012 Source: Bloomberg Terminal
Canadian Dollars - Spot	$/CAD, daily. Source: Bloomberg Terminal
Canadian Dollars - Futures	CME, Mar, Jun, Sep, Dec contracts, $/CAD, daily. Source: barchart.com
Mexican Crude Oil - Spot	Mexican Mixed, MQD/bbl, daily. Jul 17, 2000 to the end of 2012. Source: Bloomberg Terminal
Mexican Pesos - Spot	$/MQD, daily. Source: Bloomberg Terminal
Mexican Pesos - Futures	CME, Mar, Jun, Sep, Dec contracts, $/MQD, daily. Source: barchart.com
Crude oil - Futures	NYM, 12 maturities/year, $/bbl, daily. Nov 1, 1995 to the end of 2012. Source: barchart.com

The same data selection method is applied to both the crude oil spot price and the native currency spot exchange rate with respect to U.S. dollars. A more complex filtering process is required for futures prices.

1. Missing Values in the crude oil and native currency exchange rate data were treated as follows.

We first construct a simple dataset containing non weekend date and price. This dataset contains missing values. Since our analysis seeks to model Wednesday transactions, missing values for Wednesdays are replaced as follows: Thursday's price is the first option, then Friday's price, then Tuesday's price, and finally Monday's price.

2. Missing records for commodity and currency futures prices were treated with the following procedure.

Many different maturities of each futures contract are traded each weekday except for holidays, when the futures market is closed. There is nothing to indicate holidays in the raw data, but a complete calendar for each contract maturity shows blank rows on these dates. Missing values for Wednesdays are replaced in the manner described above where only one maturity is missing.

Final Datasets Used in Future Analysis

For each country, we join the datasets of the Wednesday's crude oil spot price, international currency spot exchange rate, crude oil futures price and currency futures price after missing values have been handled. Based on the hedging horizon, we generate a new dataset containing Wednesday-to-Wednesday price changes for one week, four weeks or twelve week intervals. In each case we ensure that the futures price change applies to the nearby maturity for both commodity and currency futures and there is only one observation per day. Ultimately, we have three datasets corresponding to each of the three different hedge horizons for each of the three countries. The number of observations is reduced as longer hedging horizons are applied (see table 4.2). Australian data ranges over fifteen years, Canadian data ranges over five years and Mexican data ranges over ten years.

Table 4.2 Number of Observations in Each Dataset

	Australia	Canada	Mexico
1-week Horizon	891	347	645
4-week Horizon	222	86	161
12-week Horizon	74	28	53

4.2 Descriptive Statistics of Primary Variables

Our three base hedge ratio estimation models from section 3.2 are:

$$c_0\,\Delta s = \alpha + \beta_f \Delta f + \varepsilon_t$$

$$c_0\,\Delta s + s_0\,\Delta c + \Delta s \Delta c = \alpha + \beta_f \Delta f + \varepsilon_t$$

$$c_0\,\Delta s + s_0\,\Delta c + \Delta s \Delta c = \alpha + \beta_f \Delta f + \beta_e \Delta e + \varepsilon_t$$

where c_0 is one of the three international currencies (Australian dollars (AUD), Canadian dollars (CAD) and Mexican Peso (MQD)) priced in U.S. dollars at time t_0; Δs is the price change of Australian, Canadian or Mexican crude oil from time t_0 to time t_1; Δf is the crude oil futures price change and Δe is the corresponding foreign currency futures price change in U.S. futures market.

To simplify, let $y_1 = c_0\,\Delta s$ and $y_2 = c_0\,\Delta s + s_0\,\Delta c + \Delta s \Delta c$.

Descriptive statistics of the variables Δf, Δe, y_1 and y_2, are shown for each country (see tables 4.3, 4.4 and 4.5). Not surprisingly, the standard deviation of each variable increases with the length of the hedge. In most cases, the standard deviation of futures price change is larger than that of the incomplete spot price change measured in U.S. dollars, $y_1 = c_0\,\Delta s$, as fluctuations in the spot currency exchange rate are ignored. As expected, the variance of the complete spot price change priced in U.S. dollars, $y_2 = c_0\,\Delta s + s_0\,\Delta c + \Delta s \Delta c$, is always larger than that of incomplete spot price change.

The standard deviation of Δf, y_1 or y_2 representing four-week change is around twice that of one-week change, which coincides with the theory of variance ratio for prices (Cohen 1996). The theory also applies to volatility in twelve-week change, since each standard deviation in the category related to 12-week horizon is approximately the square root of twelve times the standard deviation of the 1-week horizon. This relationship is consistent across all the tables.

Table 4.3 Descriptive Statistics of Australian Data

		Maximum	Minimum	Mean	*Std*
1-week Horizon	Δf	14.47	-13.55	0.06	*2.60*
	Δe	0.06	-0.11	0.00	*0.01*
	y_1	11.95	-10.33	0.09	*2.30*
	y_2	12.48	-14.18	0.10	*2.59*
4-week Horizon	Δf	19.38	-22.07	0.27	*5.00*
	Δe	0.06	-0.13	0.00	*0.03*
	y_1	13.92	-17.30	0.33	*4.53*
	y_2	15.03	-23.52	0.41	*5.43*
12-week Horizon	Δf	32.40	-49.18	1.00	*10.40*
	Δe	0.13	-0.14	0.01	*0.05*
	y_1	25.53	-46.39	0.85	*9.21*
	y_2	29.56	-53.92	1.23	*11.54*

Table 4.4 Descriptive Statistics of Canadian Data

		Maximum	Minimum	Mean	*Std*
1-week Horizon	Δf	14.47	-13.55	-0.07	*3.80*
	Δe	0.05	-0.05	0.00	*0.01*
	y_1	23.39	-14.06	0.02	*4.43*
	y_2	22.99	-14.47	0.05	*4.87*
4-week Horizon	Δf	19.38	-22.07	-0.21	*7.42*
	Δe	0.06	-0.09	0.00	*0.03*
	y_1	21.48	-20.52	0.03	*8.41*
	y_2	23.94	-28.58	0.13	*9.50*
12-week Horizon	Δf	24.63	-51.00	-0.18	*16.45*
	Δe	0.09	-0.14	0.01	*0.05*
	y_1	27.14	-40.77	1.09	*15.46*
	y_2	30.80	-53.82	1.62	*18.36*

Table 4.5 Descriptive Statistics of Mexican Data

		Maximum	Minimum	Mean	*Std*
1-week Horizon	Δf	14.30	-13.55	0.02	*3.03*
	Δe	0.01	-0.01	0.00	*0.00*
	y_1	15.14	-16.27	0.14	*2.73*
	y_2	13.71	-20.25	0.11	*2.90*
4-week Horizon	Δf	15.17	-30.01	0.16	*6.14*
	Δe	0.00	-0.02	0.00	*0.00*
	y_1	13.60	-23.85	0.51	*5.20*
	y_2	14.18	-33.51	0.41	*5.82*
12-week Horizon	Δf	25.65	-50.97	0.64	*10.82*
	Δe	0.01	-0.02	0.00	*0.00*
	y_1	17.03	-38.91	1.63	*8.96*
	y_2	19.78	-55.01	1.40	*10.74*

4.3 Graphic Interpretation

The data are illustrated graphically for each country based on 1-week hedging horizon. Figures 4.1, 4.2 and 4.3 show us the exchange rates of the three international currencies (Australian dollars (AUD), Canadian dollars (CAD) and Mexican Peso (MQD)) with respect to the U.S. dollars (USD). Figures 4.4, 4.5 and 4.6 present crude oil spot prices in the native currency and in dollars for each country. The impacts of the 2008 financial crisis on crude oil spot and currency markets in all three countries are clearly revealed on these graphs. Currency fluctuations can also been seen in the divergence between the native currency spot prices and the dollar denominated spot price. The currency exchange rates were relatively stable during some periods, resulting in many nearly parallel segments in figures 4.4, 4.5 or 4.6. With currency depreciation or appreciation, the distance between the two price lines expands or contracts. Figures 4.7, 4.8 and 4.9 show the change in crude oil spot price measured in an international currency (upper series in each figure) and change in spot dollar price (lower series in each figure). Both series seem to move in the same direction. In other words, the sign of price change valued in native currency of a country over one hedging horizon, $s_1 - s_0$, always remains the same as that of dollar price change, $c_1 s_1 - c_0 s_0 = c_0\,\Delta s + s_0\,\Delta c + \Delta s \Delta c = c_0\,\Delta s + s_1\,\Delta c$. $c_0\,\Delta s$ generally dominates $s_1\,\Delta c$.

Figure 4.1 Price of AUD in USD on Wednesdays

Figure 4.2 Price of CAD in USD on Wednesdays

Figure 4.3 Price of MQD in USD on Wednesdays

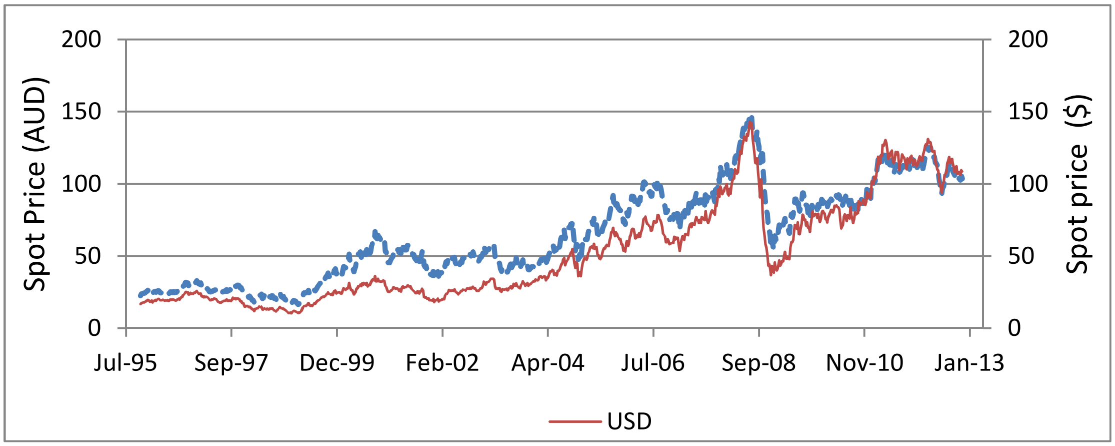


Figure 4.4 Australian Crude Oil Price in AUD and USD Respectively

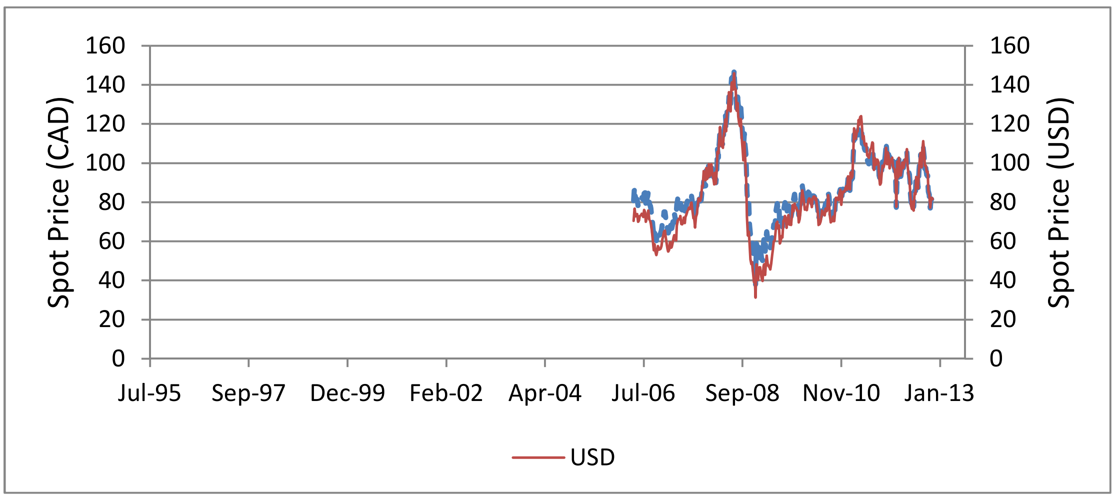


Figure 4.5 Canadian Crude Oil Price in CAD and USD Respectively

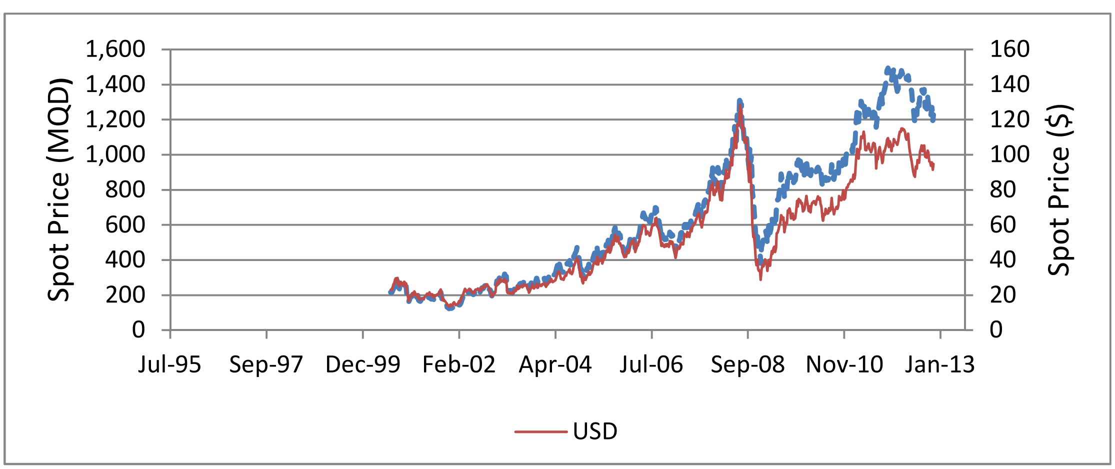


Figure 4.6 Mexican Crude Oil Price in MQD and USD Respectively

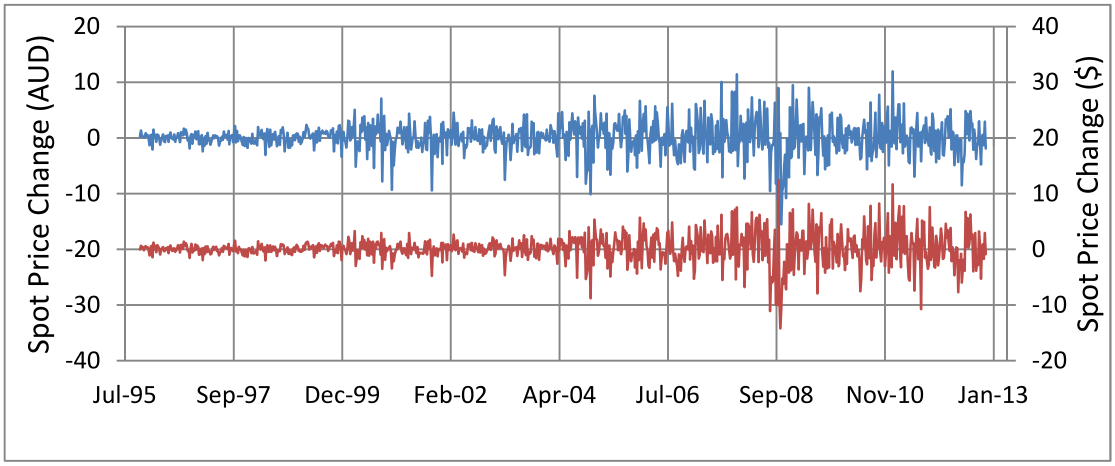


Figure 4.7 Australian Crude Oil Price Change in AUD and USD Respectively

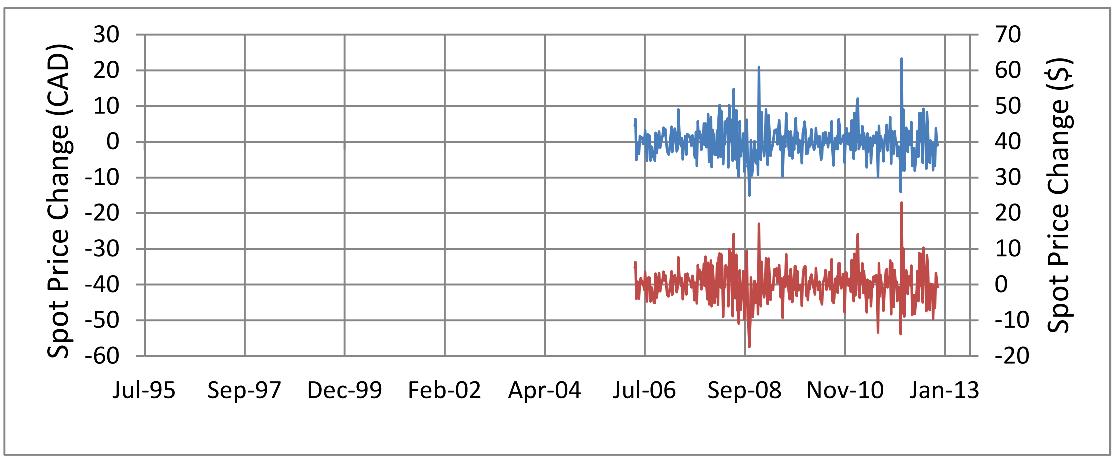


Figure 4.8 Canadian Crude Oil Price Change in CAD and USD Respectively

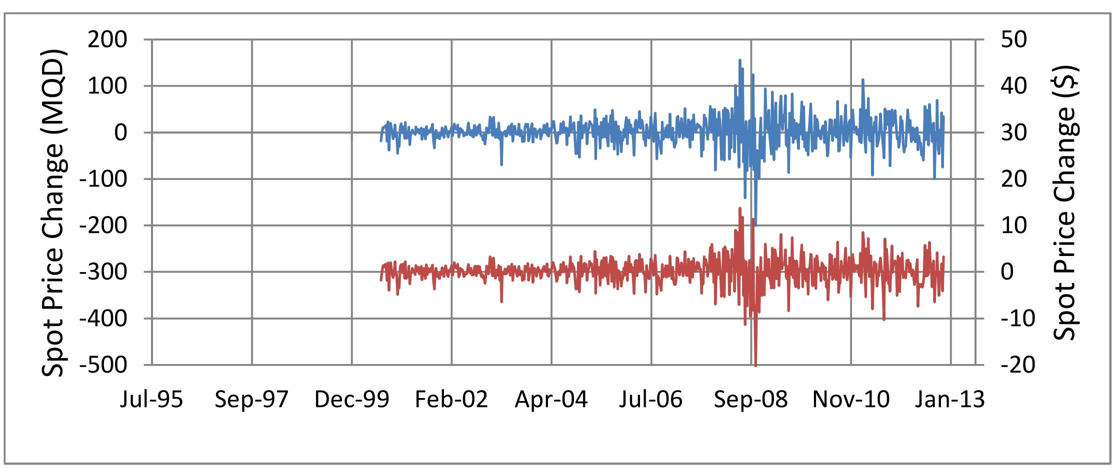


Figure 4.9 Mexican Crude Oil Price Change in MQD and USD Respectively

CHAPTER FIVE: RESULTS

5.1 Model Selection

We will present results for each of the three hedging strategies discussed in Chapter 3. These strategies are:

1. Hedge a spot position that ignores native currency exchange rate fluctuations with a single commodity futures position. The corresponding base hedge ratio estimation model is

$$\text{base model 1 (BM1): } c_0\,\Delta s = \alpha + \beta_f \Delta f + \varepsilon_t.$$

2. Hedge a spot position that recognizes native currency exchange rate fluctuations with a single commodity futures position. The corresponding base hedge ratio estimation model is

$$\text{base model 2 (BM2): } c_0\,\Delta s + s_0\,\Delta c + \Delta s \Delta c = \alpha + \beta_f \Delta f + \varepsilon_t.$$

3. Hedge a spot position that recognizes native currency exchange rate fluctuations with both commodity futures and foreign currency futures positions. The corresponding base hedge ratio estimation model is

$$\text{base model 3 (BM3): } c_0\,\Delta s + s_0\,\Delta c + \Delta s \Delta c = \alpha + \beta_f \Delta f + \beta_e \Delta e + \varepsilon_t.$$

Autocorrelation and/or heteroscedasticity are possible in base models 1 through 3. We consider these possibilities and select the most appropriate one from the following four specifications for each dataset described in the third chapter based on seasonality, autocorrelation and heteroscedasticity tests.

(1) The OLS Regression Model

The general OLS regression model is

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

$$\varepsilon_t \sim \text{i.i.d.}\, N(0, \sigma^2)$$

(2) The Regression Model with AR(m) Error (Durbin 1960)

The general autoregressive error model is

$$y_t = x_t'\beta + v_t,$$

$$v_t = \varphi_1 v_{t-1} + \varphi_2 v_{t-2} + \cdots + \varphi_m v_{t-m} + \varepsilon_t,$$

$$\varepsilon_t \sim \text{i.i.d.}\, N(0, \sigma^2)$$

(3) The Regression Model with GARCH(1,1) Error (Bollerslev 1986)

The general GARCH(1,1) regression model is

$$y_t = x_t'\beta + v_t,$$

$$v_t = \sqrt{h_t}\varepsilon_t,$$

$$h_t = w + \alpha v_{t-1}^2 + \gamma h_{t-1},$$

$$\varepsilon_t \sim \text{i.i.d.}\, N(0,1).$$

If $\gamma = 0$, then this model is reduced to an ARCH(1) regression model.

(4) The Regression Model with AR(m)/GARCH(1,1) Error (Ruppert 2011)

The general AR(m)/GARCH(1,1) regression model is

$$y_t = x_t'\beta + v_t,$$

$$v_t = \varphi_1 v_{t-1} + \varphi_2 v_{t-2} + \cdots + \varphi_m v_{t-m} + u_t,$$

$$u_t = \sqrt{h_t}\varepsilon_t,$$

$$h_t = w + \alpha u_{t-1}^2 + \gamma h_{t-1},$$

$$\varepsilon_t \sim i.i.d.\, N(0,1).$$

If $\gamma = 0$, then this model is reduced to AR(m)/ARCH(1) model. u_{t-1}^2 is the ARCH term and h_{t-1} is the GARCH term.

We follow the model selection process shown in figure 3.2 to decide the most appropriate specification for each of the nine cases for each country.

Test for Seasonality

Setting the first quarter as default, we create three dummy variables to indicate the remaining three quarters. These dummies are included in a base hedge ratio estimation model which was fit using OLS. We test the null hypothesis that all dummy variable coefficients equal zero or there is no seasonality. The two dummies representing the second and third quarters are statistically insignificant for every dataset estimated from the OLS model. Table 5.1 summarizes our findings.

Table 5.1 Model Selection Criteria

Horizon		Australia			Canada			Mexico		
		BM1[c]	BM2[d]	BM3[e]	BM1	BM2	BM3	BM1	BM2	BM3
1-wk	Seasonality[a]	Y	Y	Y	N	N	N	N	Y	Y
	Autocorrelation	(2)	(3)	(3)	(1)	(4)	(4)	(2)	(5)	(5)
	Heteroscedasticity[b]	(1)-(12)***	(1)-(12)***	(1)-(12)***	(1)-(12)***	(1)-(12)***	(1)-(12)***	(1)-(12)***	(1)-(12)**	(1)-(12)**
	EHREM[f,g,h,i]	***AR-GARCH***	***AR-GARCH***	***AR-GARCH***	***AR-GARCH***	***AR-GARCH***	***AR-GARCH***	***AR-GARCH***	***AR-GARCH***	***AR-GARCH***
4-wk	Seasonality	Y	Y	Y	N	N	N	N	Y	Y
	Autocorrelation	(4)	N	N	N	N	N	(1)	(1)	(1)
	Heteroscedasticity	(1)-(12)***	(1)-(12)***	(1)-(12)***	N	N	N	(1)-(12)*	(2)-(12)*	N
	EHREM	***AR-GARCH***	***GARCH***	***GARCH***	***OLS***	***OLS***	***OLS***	***AR-ARCH***	***AR-GARCH***	***AR***
12-wk	Seasonality	Y	Y	Y	N	N	N	N	N	N
	Autocorrelation	(1)	N	N	N	N	N	N	N	N
	Heteroscedasticity	(9)-(12)***	(2)-(12)*	(9)-(12)***	N	N	N	N	N	N
	EHREM	***AR-GARCH***	***GARCH***	***ARCH***	***OLS***	***OLS***	***OLS***	***OLS***	***OLS***	***OLS***

[a] "Y" denotes "YES". "N" denotes "NO".

[b] LM Statistics. Significance level: * significant at 0.05, ** significant at 0.01, *** significant at 0.0001.

[c] Base Hedge Ratio Estimation Model 1 (BM1): $c_0\ \Delta s = \alpha + \beta_f \Delta f + \varepsilon_t$

[d] Base Hedge Ratio Estimation Model 2 (BM2): $c_0\ \Delta s + s_0\ \Delta c + \Delta s \Delta c = \alpha + \beta_f \Delta f + \varepsilon_t$

[e] Base Hedge Ratio Estimation Model 3 (BM3): $c_0\ \Delta s + s_0\ \Delta c + \Delta s \Delta c = \alpha + \beta_f \Delta f + \beta_e \Delta e + \varepsilon_t$

[f] Empirical Hedge Ratio Estimation Model (EHREM).

[g] AR-GARCH represents AR(m)-GARCH(1,1) regression model where (m) can be seen from the item of Autocorrelation.

[h] ARCH represents ARCH(1) regression model.

[i] AR represents AR(m) regression model where (m) can be seen from the item of Autocorrelation.

A “Y” in the seasonality row indicates that the null hypothesis that all three dummy variable coefficients are equal to zero is rejected. More specifically, there is a significant negative seasonal effect in the fourth quarter, so the corresponding dummy variable for that quarter is included in all subsequent tests and analyses. Some researchers also found similar seasonality for crude oil prices using spot prices for West Texas Intermediate (WTI) Cushing, Oklahoma crude oil from the beginning of 1986 to April 2011 (The CXO Advisory Group 2012).

An “N” in the seasonality row of table 5.1 indicates there is no statistical significant seasonality present in a dataset which is interpreted as no need to keep quarterly dummies in the indicated model. Table 5.1 indicates that significant seasonality is present in all the nine cases for Australia. To the contrary, seasonality does not exist in the datasets for Canada. As for Mexican data, seasonality shows up in base hedge ratio estimation model 2 and 3 with 1-week or 4-week hedge horizon.

Test for Autocorrelation

Next we fit the OLS base hedge ratio estimation models including only significant seasonal effects and test for autocorrelation of the residuals in each OLS model via Durbin-Watson tests. Insignificant autocorrelation is indicated with an “N” in the autocorrelation row of table 5.1; otherwise, the order of significant autoregressive errors is given in parentheses. This is the value of m in AR(m). For a 1-week hedge horizon, autocorrelation exists across all three base models (BM1, BM2 and BM3) for each country, and base models 2 and 3 present higher orders of autocorrelation than base model 1. As the hedge horizon increases, we can see that in general the autocorrelation disappears or the order of autocorrelation decreases. This is not surprising, because the current spot price is more likely to depend on recent events and new information rather than historical data. Particularly noteworthy, base models 2 and 3 show exactly the same results in terms of seasonality and autocorrelation. It seems the statistical characteristics of models 1 and 2 differ substantially while the statistical characteristics of models 2 and 3 are very similar.

Test for Heteroscedasticity

We next test for heteroscedasticity using the Lagrange multiplier (LM) test. When autocorrelation is present, the residuals of the AR error regression model are tested for heteroscedasticity. On the other hand, if autocorrelation is insignificant, the OLS residuals are tested for heteroscedasticity. Engle (1982) proposed a Lagrange multiplier test, LM(q), for the qth order ARCH process. Lee (1991) showed that Engle's method can also be used to test for the GARCH alternative.

LM(1) to LM(12) are tested for each dataset. If the LM statistics are statistically insignificant through the first order to the twelfth, we conclude that heteroscedasticity does not exist and enter an "N" in the heteroscedasticity row of table 5.1. Otherwise, the order of significant LM statistics is given and asterisks are used to represent significance level. When a 1-week hedge horizon is assumed, the twelve LM statistics are all significant at a 0.01 level for each of the three hedge strategies for every country. Heteroscedasticity exists in all the nine cases of Australia. Heteroscedasticity is not a problem in Canadian datasets when longer hedge horizons are used. Mexican data do not display heteroscedasticity in the case of a 12-week hedge horizon. The 17-year time span of the Australian data (1995 to 2012) is responsible for its greater tendency toward heteroscedasticity.

Empirical Hedge Ratio Estimation Model (EHREM)

When the twelve LM statistics are significant at beyond the 0.01 level, the GARCH(1,1) regression model is selected for further analysis if both the ARCH term and GARCH terms are significant. In other cases (based on significance), we first apply GARCH(1,1) regression model to the residuals. If the GARCH term is not significant at 0.05 level, the ARCH(1) regression model is selected. When a 1-week hedge horizon is assumed, AR(m)-GARCH(1,1) regression model is always selected regardless of model and country because of the presence of autocorrelation (order m is indicated in the autocorrelation row) and heteroscedasticity. In the case of 4-week hedge horizon, for Australia, AR(4)/GARCH(1,1) regression model is selected for base model 1 and GARCH(1,1) models are selected for the other two base models; for Canada, OLS models are used for all three base models; for Mexico, AR(1)/ARCH(1), AR(1)/GARCH(1,1) and AR(1) regression models are selected for base models 1, 2, and 3 respectively. When 12-week hedge horizon is applied, OLS regression models are chosen for all Canadian and Mexican datasets; for Australia, AR(1)-GARCH(1,1), GARCH(1,1) and ARCH(1) regression models are selected for the three base models respectively.

5.2 Hedge Ratio Estimation

Hedge ratios are estimated from the models selected in section 5.1. These hedge ratios are the coefficients on the futures price change variables. In table 5.2, β_f is the hedge ratio for the commodity futures position and β_e is the hedge ratio for the currency futures position.

Compare the hedge ratios for base model 1 and 2 in each row. The value in the second column is greater than the value in the first column. This means that if we hedge a spot position and recognize native currency exchange rate fluctuation with a single commodity futures position, then more commodity futures contracts are needed to hedge this position than if we hedge a spot position without taking into account fluctuations in native currency exchange rate. Comparing the values of β_f from base models 2 and 3 in each row, we can see that they are very similar to each other in all the nine rows. Although we expected to see a monotone relationship between the hedge ratio and hedge length, this simple relationship is not indicated by table 5.2.

The coefficient estimates of β_e (base model 3) behave unexpectedly. Unlike all the estimates of β_f which are significant at the level beyond the 0.0001, none of the estimates of β_e are statistically significantly different from zero in the case of Australia and Canada. This result leads one to question the necessity of including currency futures position in the hedge portfolio. However, it seems that Mexican hedgers need to hedge via both commodity and futures positions especially when shorter horizons are considered.

Table 5.2 Hedge Ratio

	Base Model:	1	2	3	
	Hedge Ratio:	β_f	β_f	β_f	β_e
Australia	1-week Horizon	0.64***	0.78***	0.78***	4.49
	4-week Horizon	0.72***	0.90***	0.90***	4.87
	12-week Horizon	0.80***	0.98***	0.97***	7.50
Canada	1-week Horizon	0.85***	1.03***	1.03***	-1.16
	4-week Horizon	0.98***	1.16***	1.13***	17.70
	12-week Horizon	0.88***	1.06***	0.96***	48.43
Mexico	1-week Horizon	0.80***	0.87***	0.87***	64.65**
	4-week Horizon	0.77***	0.88***	0.86***	162.07*
	12-week Horizon	0.73***	0.91***	0.84***	289.07

Significance level: * significant at 0.05, ** significant at 0.01, *** significant at 0.0001

5.3 Hedge Effectiveness Estimation

When autoregression is present, hedge effectiveness is properly estimated by comparing hedged and unhedged outcome variances of the autoregression-corrected transformed data. Similarly, when heteroscedasticity is present, effectiveness is properly estimated by comparing hedged and unhedged outcome variances of the heteroscedasticity-corrected transformed data. For a GARCH specification, the data transformations are the reciprocals of the estimated conditional error variances. By extension, for an AR/GARCH error model, hedge effectiveness is properly estimated by comparing the hedged and unhedged outcome variances of the transformed data. In this case, the transformation includes correction for autocorrelation and weighting by the reciprocals of the estimated conditional error variances. And of course when autoregression and heteroscedasticity are not present, hedge effectiveness can also be estimated from the original data. Hedging effectiveness can be obtained by transformation of the F test statistic used to test the linear hypothesis that hedge ratios are zero. As developed in section 3.4, hedging effectiveness is

$$\frac{\mathrm{F}(\mathrm{df_{UR}} - \mathrm{df_R})}{\mathrm{df_{UR}} + \mathrm{F}(\mathrm{df_{UR}} - \mathrm{df_R})} * 100(\%).$$

The values of F statistics (F), degree of freedom $\mathrm{df_{UR}}$ ($\mathrm{df_e}$) and hedging effectiveness (HE) are listed in table 5.3. Of greatest interest is the comparison of hedging effectiveness by country and by hedging strategy as hedge length increases.

Table 5.3 Hedging Effectiveness

		BM1[a]			BM2[b]			BM3[c]		
		F[d]	df_e	*HE(%)*	F[e]	df_e	*HE(%)*	F[f]	df_e	*HE(%)*
Australia	1-week Horizon	680.79	888	*43*	1225.07	888	***58***	618.12	887	*58*
	4-week Horizon	304.13	219	*58*	549.85	220	***71***	269.35	218	*71*
	12-week Horizon	329.55	71	*82*	433.18	72	***86***	195.85	71	*85*
Canada	1-week Horizon	725.13	345	*68*	1416.37	345	***80***	705.37	344	*80*
	4-week Horizon	249.43	84	*75*	390.23	84	***82***	194.84	83	*82*
	12-week Horizon	185.17	26	*88*	245.93	26	***90***	130.84	25	*91*
Mexico	1-week Horizon	2521.51	643	*80*	4493.86	642	***87***	2241.56	641	*87*
	4-week Horizon	710.81	159	*82*	1353.27	158	***90***	693.05	157	*90*
	12-week Horizon	175.22	51	*77*	288.1	51	***85***	154.57	50	*86*

[a] Base Hedge Ratio Estimation Model 1 (BM1): $c_0\,\Delta s = \alpha + \beta_f \Delta f + \varepsilon_t$

[b] Base Hedge Ratio Estimation Model 2 (BM2): $c_0\,\Delta s + s_0\,\Delta c + \Delta s \Delta c = \alpha + \beta_f \Delta f + \varepsilon_t$

[c] Base Hedge Ratio Estimation Model 3 (BM3): $c_0\,\Delta s + s_0\,\Delta c + \Delta s \Delta c = \alpha + \beta_f \Delta f + \beta_e \Delta e + \varepsilon_t$

[d] $H_0: \beta_f = 0$

[e] $H_0: \beta_f = 0$

[f] $H_0: \beta_f = \beta_e = 0$

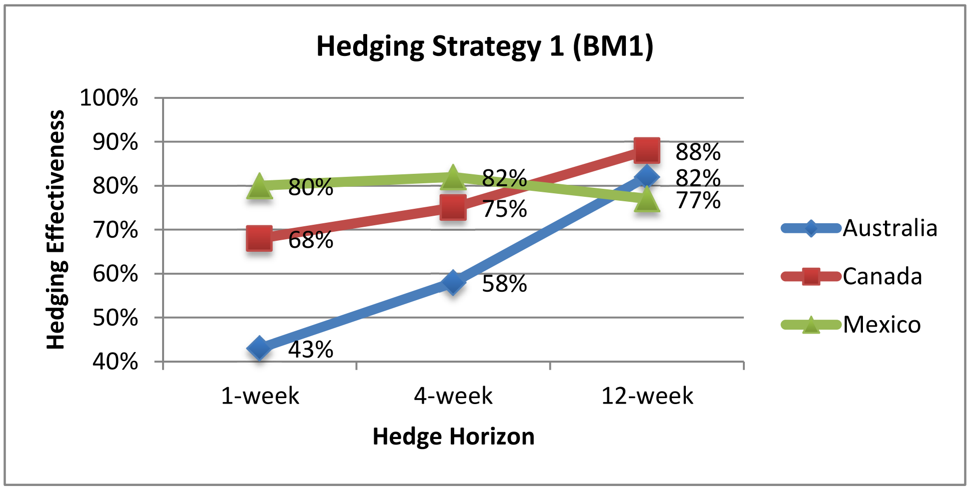
First, we see from figure 5.1 that the pattern of improvement of hedging effectiveness for Australia as hedge horizon increases is similar to that for Canada across all three hedging strategies. The link between hedge length and hedging effectiveness is monotone increasing regardless of hedging strategy. This is in contrast to what occurs in the case of Mexico, where hedging effectiveness increases when 4-week hedge horizon is applied and then declines when the horizon is increased to 12 weeks.

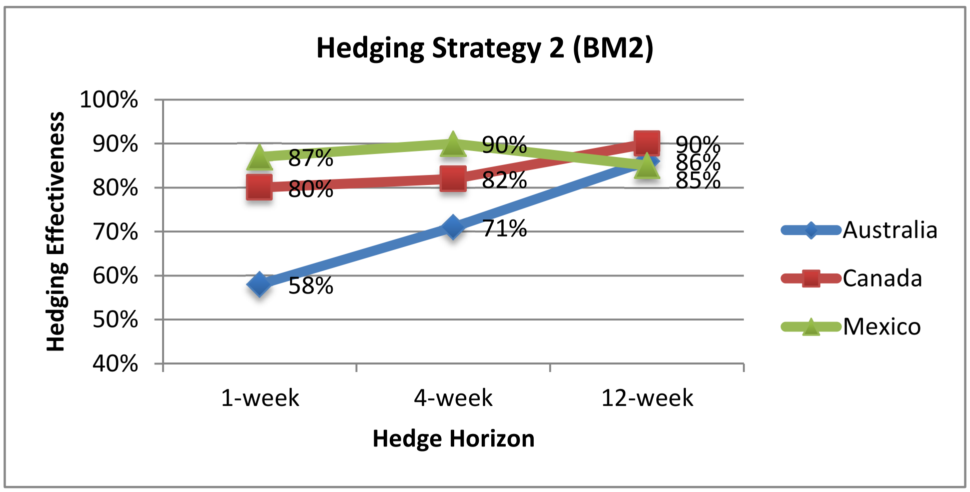
Second, the effectiveness of hedging with a single commodity futures position without taking into account fluctuations in native currency exchange rate (shown in the first part of figure 5.1) is less than the effectiveness of the other two hedge strategies which recognize fluctuations in native currency exchange rate. This is true especially when shorter hedge horizons are considered.

Third, it appears that the performances of the two hedge strategies that recognize native currency exchange rate fluctuations are almost identical in terms of hedging effectiveness. This relationship also suggests a currency futures position contributes little to the hedge performance as indicated by hedge ratio estimates.

In addition, the difference of effectiveness among countries shrinks as hedging horizon lengthens.

Last but not least, in general, hedging effectiveness for Canadian and Mexican producers and processors in U.S. futures markets is greater than the hedging effectiveness for Australian hedgers as we initially expected.





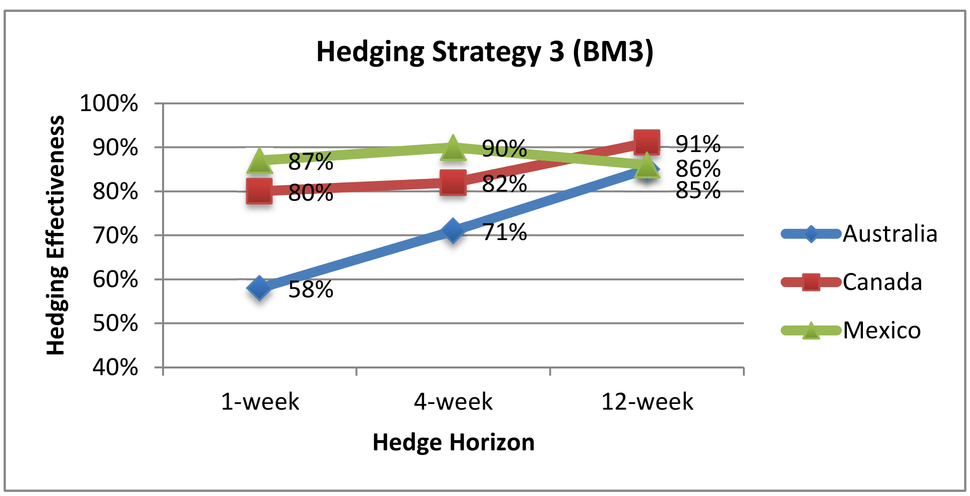


Figure 5.1 Graphic Interpretation of Table 5.3

CHAPTER SIX: CONCLUSION

The objective of this thesis was to explore the performance of U.S. futures market in providing price risk protection for international crude oil dealers. In a larger sense, we were interested in the performance of U.S. futures market on the world stage, so we conducted this case study to determine how these markets perform. Australia, Canada and Mexico were selected as international markets to provide comparisons and offer conclusions. Three hedging strategies, hedge via a single commodity futures position without recognizing native currency exchange rate fluctuations, hedge via a single commodity futures position while taking into account fluctuations in the native currency exchange rate, and hedge recognizing native currency exchange rate fluctuations with both commodity and currency futures positions, were designed. For each strategy, a base hedge ratio estimation model was developed and 1-week, 4-week and 12-week hedge horizons were studied. We compared hedge effectiveness across different countries, length of hedge and hedge strategies.

After checking seasonality, autocorrelation and heteroscedasticity, we selected the most appropriate specification from four empirical hedge ratio estimation models presented in section 3.2 in order to estimate the hedge ratio. Then we obtained hedging effectiveness using transformed or original data accordingly via a transformation of the F statistic.

Hedging effectiveness appears to increase when currency exchange rate fluctuations are recognized in hedge. However, the results of both hedge ratio and hedging effectiveness estimates indicate little benefit in hedging via currency futures contract position as well for Australian and Canadian hedgers. Although significant hedge ratio estimates are present for Mexican data, hedging effectiveness does not increase when we hedge via both commodity and currency futures positions. Considering the cost of holding two futures positions, little benefit in hedging via an extra currency futures position is found for Mexico either. In a word, the performance of U.S. market in hedging Australian, Canadian and Mexican crude oil is not improved by hedging with both commodity and currency futures positions.

It seems that U.S. futures market is not an ideal place for Australian crude oil processors and producers to hedge their price risks when the hedge horizon is short but these futures markets perform fairly well for Canadian and Mexican hedgers. The main reason behind this claim is the fact that Canada and Mexico are two of the largest exporters of crude oil to the United States, while there is little crude oil trade between Australia and the United States. Canadian and Mexican crude oil markets interact with U.S. markets much more than Australia. Thus, the results are not surprising.

To sum up, first, fluctuations in native currency exchange rate should be taken into account when international hedgers use U.S. futures market; second, these hedgers will determine whether a position in currency futures is necessary; third, hedge will be more effective if there is interaction between the international market and the U.S. spot market; and the longer the hedge horizon, the more effective hedging will be.

Some areas of futures study that might lead to greater hedging effectiveness are a determination of hedge horizon and the liquidity risk of the margin account while holding a futures position.

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