Final Report on Predicting Hedged Exchange Rates

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March 19, 2019

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Executive Summary

New Zealand's largest export is dairy, which accounts for a quarter of total annual exports. The majority (84%) of dairy farmers in New Zealand supply milk to Fonterra, a large multinational dairy co-operative (Dowson, personal communication, 2019). Fonterra is responsible for auctioning the dairy internationally in U.S. Dollars and back paying the farmers in New Zealand Dollars at the end of each season. Fonterra's goal is to limit volatility in revenue brought back to the farmers caused by fluctuations in exchange rates. Fonterra's strategy for stabilizing revenue exchange is to *hedge* against exchange rate variability risk by securing a predetermined rate that they will exchange for at a future date – this is called a *hedge rate*. Our client, Oscar Dowson, runs the website DairyAnalytics (https://dairyanalytics.co.nz), which provides a free probabilistic forecast of expected price returns to help the New Zealand farmers maintain their budget.

During our analysis, we reconstructed the hedged exchange rate primarily using two models: the baseline model, which equally weighted the last 18 months of exchange rates to predict the following month, and a lasso regression model, which used a penalty function to limit the number of nonzero coefficients in the model. Although both models were highly predictive, we recommend our client to use the baseline model, since it fits better in the context of the problem. The baseline model is a simple rule, as Fonterra suggests they use in their public statements and can be easily implemented in our client's website (Dowson, personal communication, 2019). These predicted hedge rates can help dairy farmers in New Zealand understand the worth of their dairy products ahead of the auction.

Problem Statement

Fonterra sells dairy internationally, then at the end of each season, farmers are paid a "Farmgate Milk Price" for each kilogram of milk supplied during the preceding season (Dowson, personal communication, 2019). This "Farmgate Milk Price" is calculated by Fonterra after each season using:

1. The revenue earned by Fonterra
2. The exchange rate from USD to NZD
3. The processing costs

Because Fonterra controls such a large portion of New Zealand dairy exports, there is no market price set through competition (Fonterra 2019).

The Farmgate Milk Price is settled each September, and there is a great amount of uncertainty because the listed inputs have not yet occurred. The Farmgate Milk Price often fluctuates by nearly 50% of the initial price reported. Since Fonterra bases the Farmgate milk price on how much revenue they earn during that season, the New Zealand farmers bear the risk in the milk sale transaction. This makes it difficult for New Zealand farmers to budget their holdings.

Our goal is broken down into two parts. The first part of our goal was to find Fonterra's financial strategy for hedging the exchange rate, and provide statistical analysis to reconstruct their simple rule. The second part of our goal was to find if this strategy is effective in terms of reducing volatility and to protect the downside risk in a poor economy.

Currently, the DairyAnalytics model uses a set of previous milk prices to predict the next month's price. Our project focus is on Fonterra's financial strategy, specifically examining on the second of the three farmgate milk price inputs: the exchange rate at which Fonterra converts USD into NZD. Fonterra sells milk in US dollars but pays farmers in New Zealand dollars. Therefore, they are at risk of losing revenues due to currency fluctuations depending on when Fonterra returns the money to NZD to pay the farmers. To protect themselves against dramatic changes in the exchange rate, Fonterra *hedges* their exchange rates through a combination of futures and options contracts. "A futures contract is an agreement to exchange currency at a price agreed today at a set date in the future. An options contract is an option to exchange currency at a price agreed today at a set date in the future" (Investopedia). Fonterra's *hedge rate* is, therefore, the exchange rate from USD to NZD which is predetermined using a combination of futures and options contracts they use to convert their revenue and pay the farmers.

Problem Objective

Our two primary objectives were to complete the following:

1. Reconstruct Fonterra's strategy–a simple rule–for hedging USD-NZD exchange rate, consistent with their public statements. A method for better forecasting Fonterra's *hedged* exchange rate will consequently improve Farmgate Milk Price predictions made by Oscar on the DairyAnalytics website. We know Fonterra uses "futures" contracts to lock-in future exchange rates. Fonterra public reports suggest they use a simple rule and purchase such contracts months in advance.

2. Investigate whether this strategy is effective for Fonterra in reducing volatility in the Farmgate price and downside risk for the farmers.

Past Approaches to Solutions and Research into Problem

For this unique problem, there are no complete specific solutions that are publicly accessible. However, we know international companies have financial analysts who are responsible for strategizing exchange rate hedging strategies.

There are a few ways to protect against the risk of fluctuations in foreign exchange rates, in order to have a more consistent revenue stream.

1. Currency Forwards: a private contract between a buyer and seller to trade an asset at a future date. The price of the asset is set when the contract is drawn up (Phung). In this case, the "price" would be "price of currency", also known as an exchange rate
2. Currency Futures (Fonterra currently uses this strategy): similar to a forward agreement but marked-to-market, and is traded on an exchange, with financial intermediaries to lower risk (Phung).
3. Currency Options: the buyer has the right to buy or sell the underlying asset at a given price and date, *but don't have to use that price* (Picardo). So if Fonterra wanted to buy NZDs they could "call" the option and use the price in the contract, but only would if it's lower than the current market exchange rate.

This past year Fonterra used an average foreign exchange conversion rate of .7074 USD:NZD against an average spot rate of .7039 USD:NZD for the 2018 Season. This strategy "resulted in a decrease in the Farmgate Milk Price of 5 cents relative to translation at the spot exchange rate" (Fonterra 2018).

Compared to this year, in 2017, "hedging activities resulted in an increase in the Farmgate Milk Price of 28 cents relative to translation at the spot exchange rate" and in 2016, "hedging activities resulted in a decrease in the Farmgate Milk Price of 21 cents relative to translation at the spot exchange rate" (Fonterra 2018).

One of the goals of this project is to assess the effectiveness of Fonterra's hedging strategy. Therefore, it is important to have a firm understanding of the motivation for hedging in the dairy market and assess other hedging strategies executed by similar corporations within the industry.

Data Processing

Our data was comprised of publicly available financial data and Fonterra's quarterly earnings report. We were given the record of the United States national interest rate by month, and the New Zealand national interest rate every month that it changed. We were also given currency exchange rate data from USD to NZD by month. Both of these financial records were recorded from 2000 to 2018.

The rest of our data came from Fonterra's quarterly report which has been published four times a year since 2010. In these reports, the quarterly financial data is broken up into five three-month quarters. The fifth quarter of each year represents the same time period as the first quarter of the next year. The purpose of this overlap quarter is to distinguish the dairy being sold by whether is was produced in the previous year or the current year. Each financial year starts in September, and the first and last quarters cover months August-September-October. For example, in the 2009/2010 financial year, quarter 1 represents Aug. - Oct. of 2009, and quarter 5 represents Aug. - Oct. of 2010.

Fonterra's financial reports indicated that Fonterra "requires hedging of forecast cash receipts from sales for a period of up to 18 months." ("Farmgate Milk Price Statement", 6) Therefore, we paired each reported quarterly hedged exchange rate with the previous 18 months of relevant financial data (interest rates and currency exchange rate) to build a framework for a predictive model. This gave us 54 predictors and 45 recorded quarterly hedge rates. With more predictors than hedge rates, we would expect abundant overfitting on most model implementations. In order to reduce the number of predictors and the risk of overfitting while keeping the same amount of information, we paired USD and NZD monthly interest rates as a single factor in our model. To look at the relative difference of the economies we looked at US interest rate minus the NZ interest rate. This reduced the number of parameters for each quarterly hedge rate to 36 months of financial data.

With our 36 predictors and 45 quarterly hedge rates, we performed a stepwise regression analysis to further analyze which predictors were most impactful. Stepwise regression analysis exclusively suggested using a combination of exchange rates for prediction (see Appendix A for source code). We used this rationale to further cut down our data consideration for models to the 18 previous exchange rates. With these insights, we began our financial analysis.

Goal One: Results of Data Analysis

The primary metric we chose to compare models with was R^2. Whenever testing the model "in-sample" (testing and training on the same data), we used an adjusted R^2 to account for overfitting. Whenever possible, our R^2 values are cross-validated out of sample to mitigate risks of overfitting, as we were not training and testing on the same data. We started our financial analysis by creating a model in AMPL that provided insight regarding the amount of revenue Fonterra brought back to NZD per month.

Spot Rate Model

The spot rate is used as a baseline indication of how well the hedge rate is performing. Creating a spot rate model gave us a preliminary understanding of how Fonterra brings back revenue from USD to NZD based on their published spot rates is important to understand. We created a quadratic program that minimized the total squared error between the Fonterra's published spot rate and our model's prediction. We found Fonterra's revenue was brought back according to the model's parameters outlined below in Figure 1.

Input Data

Y: Set of years

Q: Set of quarters

M: Set of months (corresponds to the 1st, 2nd, or 3rd quarter of each month)

A_q^y: Fonterra's calculated spot rate for quarter q in year y

E_{mq}^y: Exchange rate in month m of quarter q in year y

Decision Variables

X_{mq}: Weight placed on month m of quarter q

S_q^y: Estimated spot rate for quarter q in year y

$$\text{minimize} \sum_{q \in Q} \sum_{y \in Y} (A_q^y - S_q^y)^2$$

subject to:

$$\sum_{m \in M} X_{mq} = 1 \qquad \forall\, q \in Q$$

$$\sum_{m \in M} E_{mq}^y X_{mq} = S_q^y \qquad \forall\, q \in Q, \forall\, y \in Y$$

$$X_{mq} \geq 0 \qquad \forall\, q \in Q, \forall\, m \in M$$

$$X_{mq} \leq 1 \qquad \forall\, q \in Q, \forall\, m \in M$$

$$S_q^y \geq 0 \qquad \forall\, q \in Q, \forall\, y \in Y$$

Figure 1: Spot Rate Model Inputs and Constraints

The constraints in Figure 1 gave us the weights for each month of revenue brought back for each quarter. These weights are shown in Figure 2.

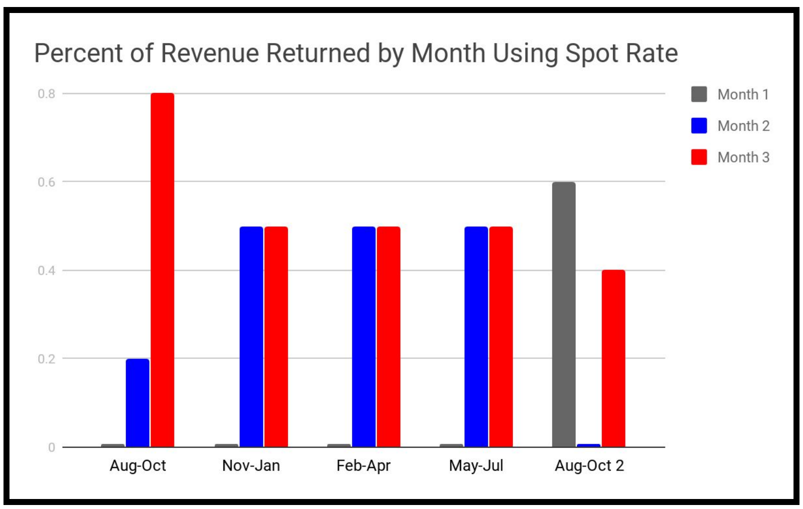

Figure 2: Revenue Returned by Month

From Figure 2, we observe that Fonterra brings back their revenue from USD to NZD equally in the second and third months of the middle of the year- namely the second, third, and fourth quarters. In the first quarter, the revenue brought back is greatest for the third month. In the fifth quarter, the revenue brought back is greatest for the first month of that quarter. This shows a clear picture of Fonterra's revenue exchange strategy and provides context for future predictions and analysis of what Fonterra's published spot price will be based on observed market exchange rates.

The quadratic spot rate model had an adjusted R^2 of 0.96, which suggests the spot rate variability can be largely explained by the exchange rate. To confirm, we observe the spot rate residuals vs. order plot in Figure 3.

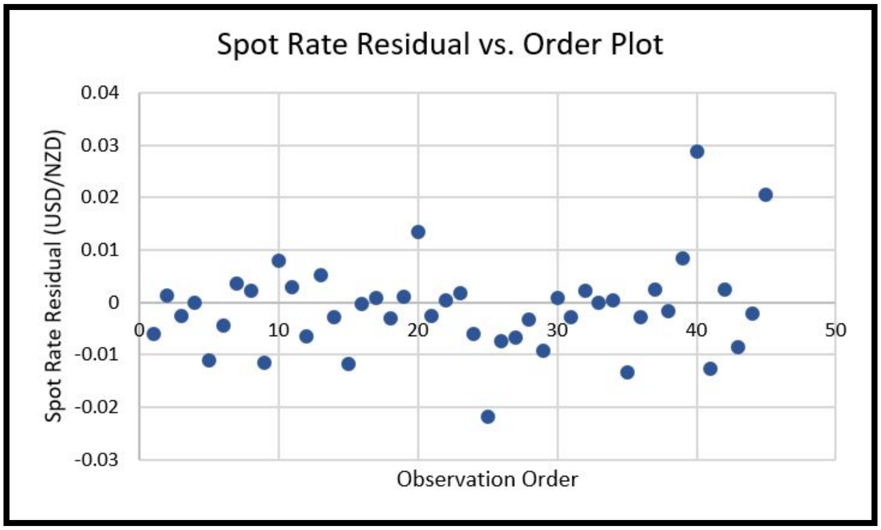

Figure 3: Spot Rate Residuals Order Plot

The residual versus order plot does not have a clear pattern. This suggests there is no correlation between error terms near each other in the sequence and further confirms the R^2 value and power of the spot rate model.

Lasso Model

LASSO stands for *Least Absolute Shrinkage and Selection Operator*. This method uses a loss function to select only certain variables to avoid overfitting, and makes the rest have a 0 coefficient. It involves a lambda value which is the tuning parameter for an accuracy-simplicity tradeoff.

The lasso model run on the 18 months of exchange rate data leading up to each quarter has the highest prediction power of any model we investigated. Lasso regressions work best when there is a large number of predictors compared to a relatively small number of total observations. We chose to implement a lasso regression once we modeled a basic linear regression to the small data set and experienced overfitting. Reducing the number of coefficients in our model with the lasso could help reduce some of the effects of overfitting on our data set. The goal of lasso was to obtain the subset of predictors that minimizes prediction error of the quantitative response variable, Fonterra's quarterly hedged exchange rate. The lasso model created this subset of nonzero coefficients by imposing a constraint on the model parameters that caused the regression coefficients for some variables to shrink toward zero. This process of shrinking the coefficients on our predictors allowed us to adjust our model to avoid too much overfitting when training. As seen in Figure 4, we determined the optimal lambda value for our lasso regression by finding the maximum cross-validated test R^2 when we set the lambda value of our lasso model between 10^{-1} to 10^{-7}. The optimal lambda value is shown in Figure 4: we obtained an optimal value of 0.00066, which we used in our final lasso model that had a mean cross-validated R^2 of 0.955, with a standard deviation of 0.016.

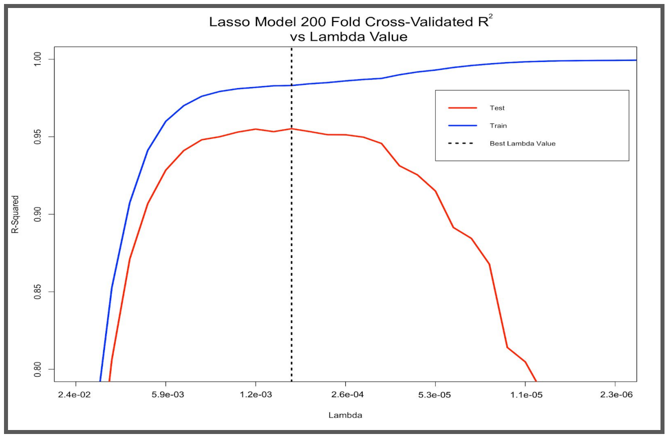

Figure 4: Lambda Selection

Ascending and Descending Models

Through communications with Fonterra and using their financial statements, Oscar Dowson found that Fonterra has a relatively simple rule they use to hedge their foreign exchange rates. We used this assumption throughout our analysis since it was explicitly given to us from our client.

In further investigating Fonterra's hedging strategy, we took a simple average of different combinations of exchange rates and analyzed its predictive power on random subsets of the data. This is analogous to cross-validating on out-of-sample data, but not quite the same because the model is not fit by any data, and therefore there is no actual in-sample or out-of-sample data. Using subsets makes the results more comparable to the analysis performed on the linear and lasso models. Another benefit of using the average models is that there is no risk of overfitting the model to our limited data point sets because the fit is not determined by the data.

Fonterra notes in their annual Farmgate Milk Price Statement that their policy is to hedge 100% of "net recognized foreign currency trade receivables and payable" ("Farmgate Milk Price Statement", 6). They also require "hedging of forecast cash receipts from sales for a period of up to 18 months within limits approved by Fonterra's Board" ("Farmgate Milk Price Statement", 6). Fonterra indicates they use a period of 18 months prior to the hedge rate; it is unclear exactly which 18 month period this is, so we begin with an analysis of the exchange rates of the 18 months immediately before the quarter's hedge rate. We first consider the predictive power of just the most recent month's exchange rate, and then consecutively include an average month from two, three, four, etc. up to including and averaging all of the previous 18 months. We also perform this in reverse; first considering the oldest month, and consecutively adding more recent months. The 95% confidence intervals for R^2 values from 100 randomly selected subsets of the hedge rates are shown below for the ascending and descending models.

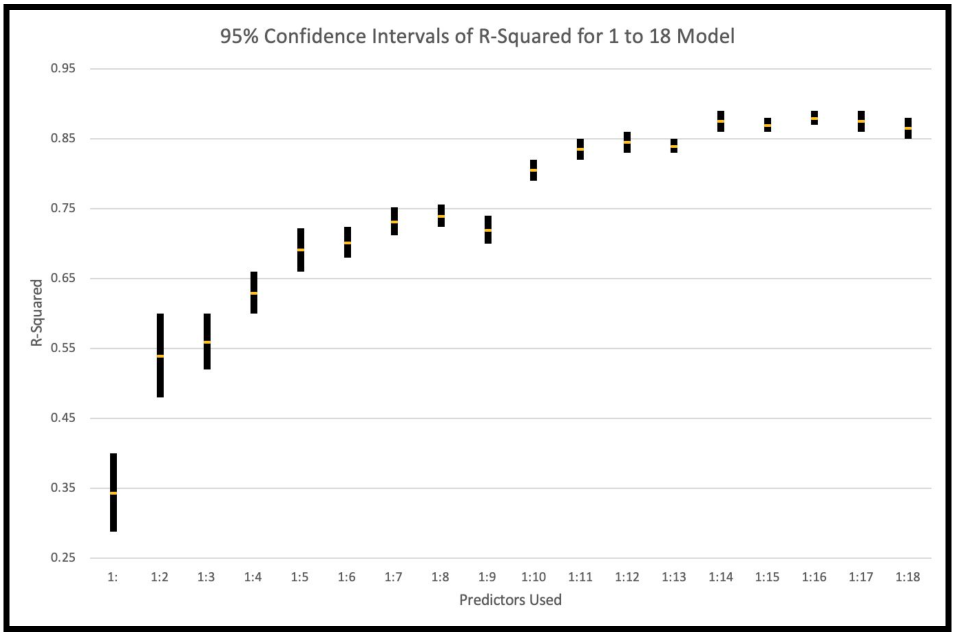

Figure 5: Ascending Average Model

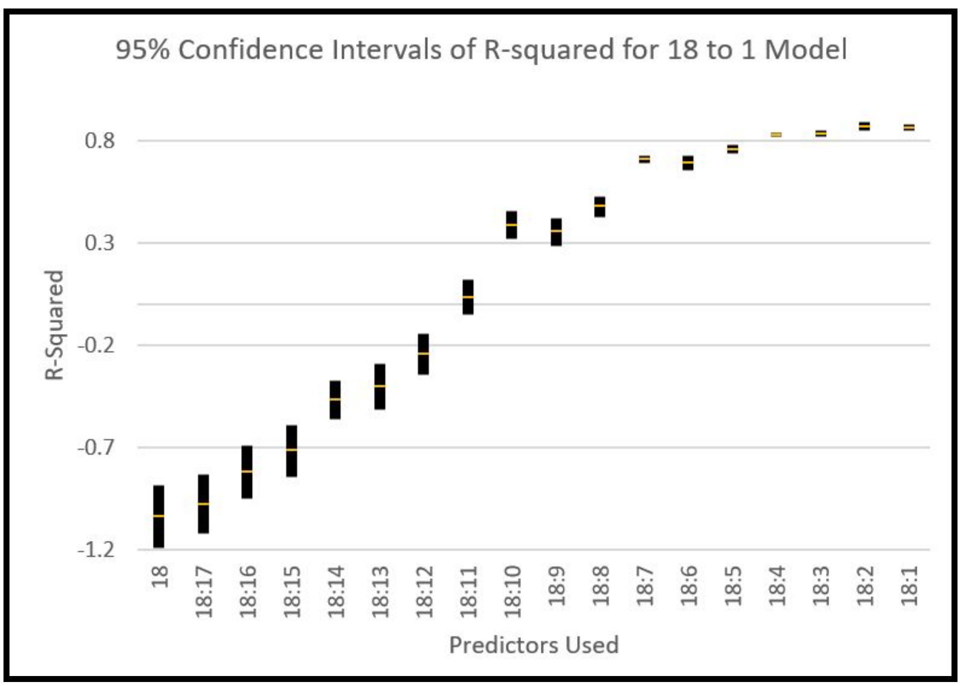

Figure 6: Descending Average Model

In Figures 5 and 6, we found the 95% confidence interval and average R^2 value using each of the predictors labeled on the x-axis. These models showed us that the predictive power of the most recent months is much higher than the oldest months. The most recent 6 months have higher average R^2 values, as well as much smaller confidence intervals, compared the models using the 6 oldest months. The more predictors used, the better the average value and tighter the confidence interval. Both of these equal weights models have the highest R^2 when using all 18 prior months.

Linear Models

An additional consideration was the performance of our equal weights baseline model versus a linear regression model developed over the same set of predictors. We trained our linear models on a random sample of two-thirds of the data and obtained our out-of-sample R^2 from the remaining data. We then used the same test data set to find an R^2 for the equal weights model that is comparable. This was cross-validated 100 times. A set that demonstrates the linear model's comparable performance to the equal weights models is shown below.

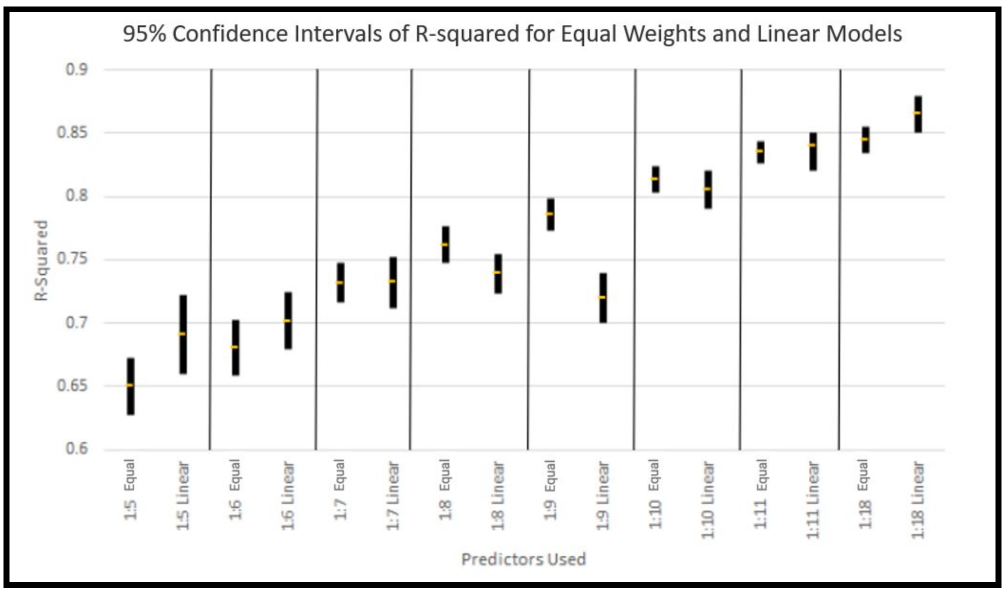

Figure 7: Linear Model compared to Equal Weights Model

We observe in Figure 7 the linear models performing comparably better in some instances and worse in others. We also ran many more linear models not shown in Figure 6, which consisted of random groupings of predictors, and varied number of predictors used. These other linear models showed similar results compared to the results above, but were not as simple as the baseline equal weights model nor as predictive as the lasso.

Ultimately we determined that with our extremely limited data set, the linear model's marginally better performances do not responsibly justify using it rather than using the simpler rule of equal weights or the better performing lasso model. These insights led us to concluding that the lasso model and baseline models have the most predictive power with our limited dataset.

Goal Two: Assess the Effectiveness of Fonterra's Strategy

After the construction and analysis of our spot and hedge exchange rate models, we tackled our second objective of evaluating the efficacy of Fonterra's hedging practices. Fonterra's goal is to reduce the variability in its revenues and by extension the prices paid out to its farmers. More specifically, Fonterra may be more willing to sacrifice profits when the New Zealand economy is prosperous in order to limit the downside risk when the New Zealand economy is in a downturn.

We begin by comparing Fonterra's actual revenue, which they earned through their use of hedging, to what their revenues would have been in the case that Fonterra had not hedged. These were calculated by converting Fonterra's revenues from USD to NZD using their published quarterly hedge and spot exchange rates respectively. The average revenue earned by Fonterra is statistically significantly higher when hedging. However, the variance in revenue is not statistically different when converting revenue using the hedge rate or the spot rate. These analyses were performed using a T-Test and F-Test using a 0.05 significance level. See Appendix D for detailed analysis results. This suggests that Fonterra's hedging strategy not effective in reducing volatility in its revenues.

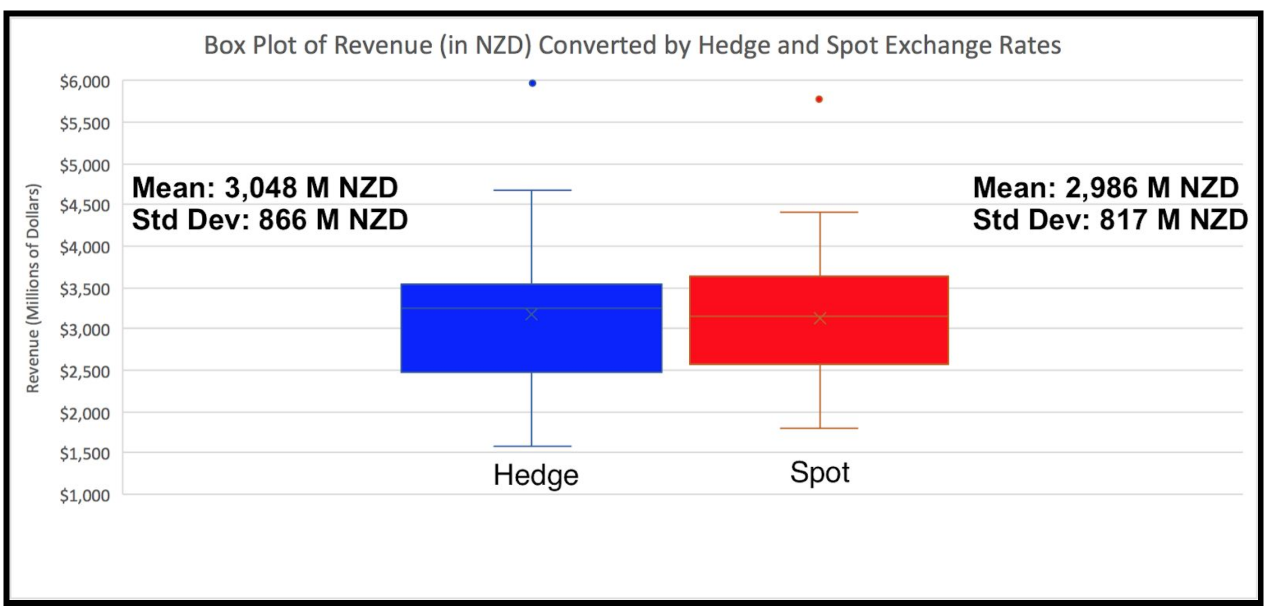

Figure 8: Fonterra's Quarterly Revenues

With this in mind, we attempted to determine the underlying reasons why Fonterra's hedging strategy is not effective. Fonterra is in a unique position because it's such a large player that large changes in exports may cause changes in the exchange rate. From 2013 to 2014, China purchased increasingly large amounts of dairy product from New Zealand, driving dairy prices and revenues up; however, changes in international tariffs resulted in a precipitous drop in the amount of dairy exported to China as well as dairy prices and revenues (Dickrell). With dairy playing such a large role in the New Zealand economy, the decrease in dairy exports had a significant negative impact on the economy. Over the same time, the USD-NZD exchange rate dropped significantly as seen in the graph below.

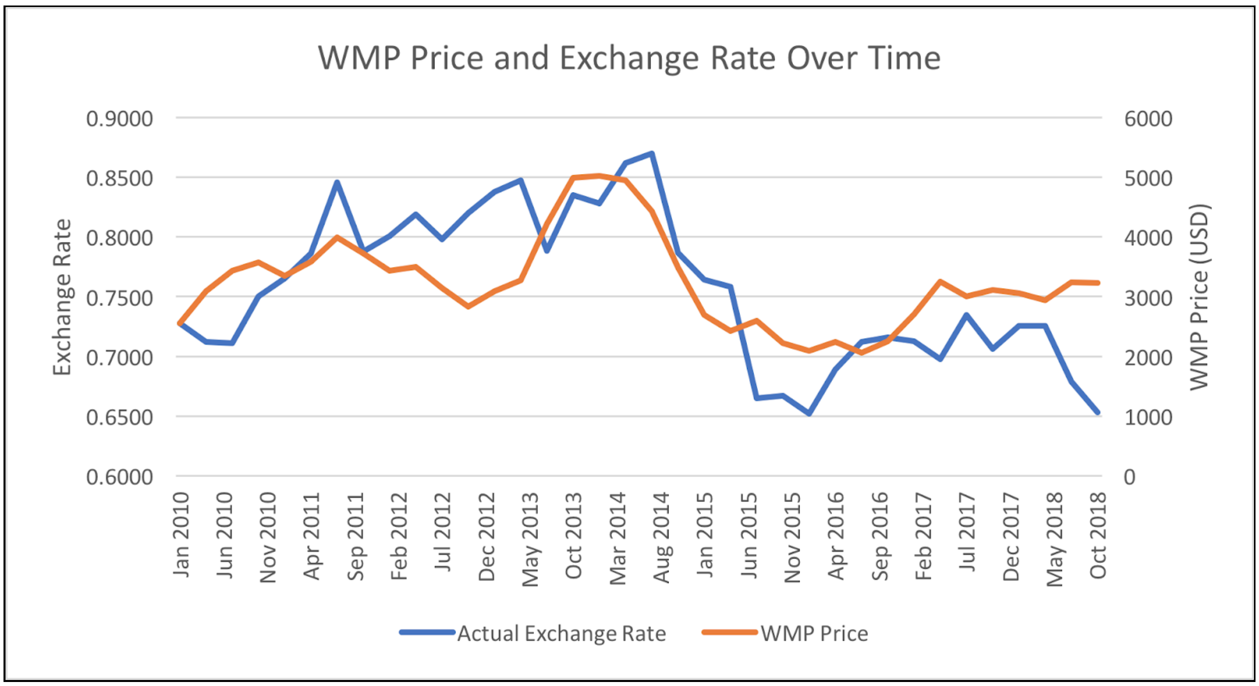

Figure 9: Price Index and Exchange Rate Over Time

Fonterra's hedging strategy should protect them from losing revenue due to the volatility of the exchange rate. In this scenario, an effective strategy would ensure that the hedged exchange rate at which Fonterra converts its revenue from USD-NZD was lower than or equal to the low spot exchange rate. This does not seem to be the case according to the following graph of Fonterra's hedged and spot exchange rates over time.

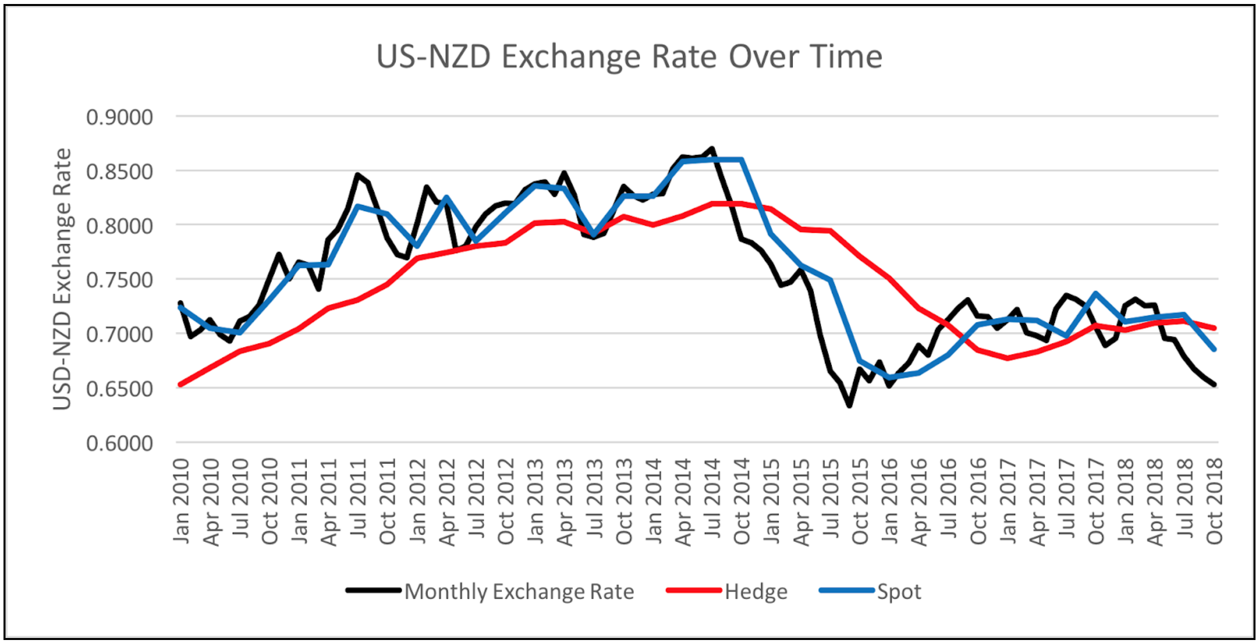

Figure 10: Exchange Rate Over Time Using Different Models

As seen above, Fonterra typically has a lower hedge than spot exchange rates, but when the New Zealand economy is at its worst, hedged rates are above spot rates. This trend is corroborated by graphing the difference between hedge and spot rates against Fonterra's revenue in the following graph.

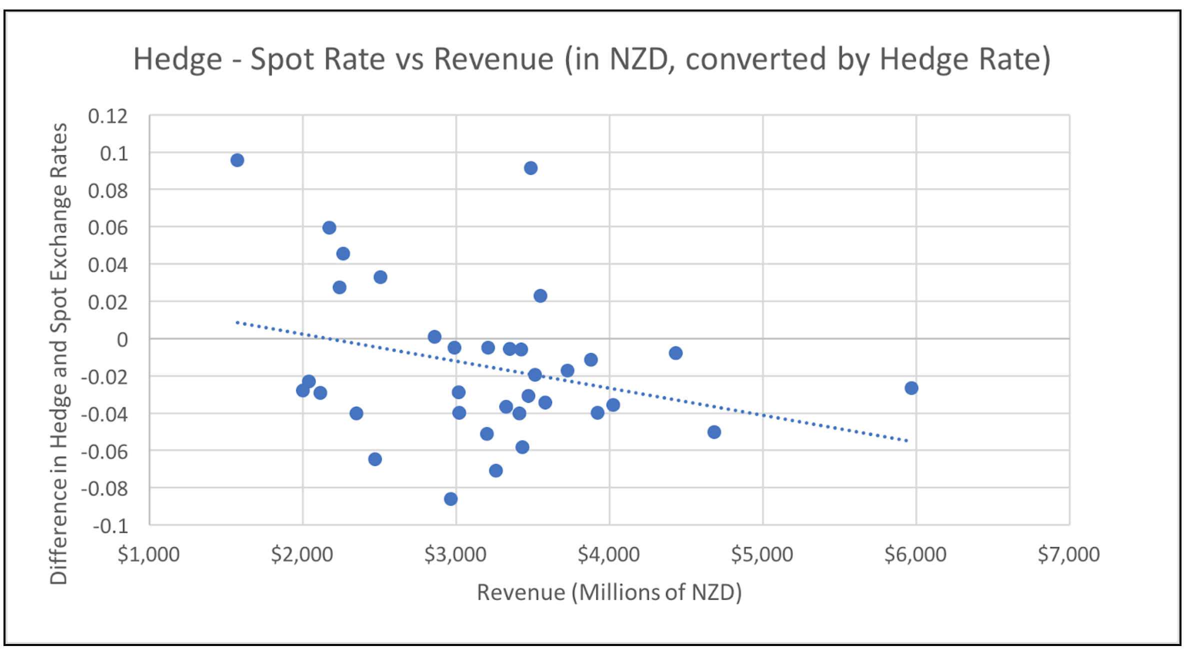

Figure 11: Performance of Current Strategy

A negative trend can be seen above, such that Fonterra's hedge performs worst when its revenue is low. Fonterra's ideal strategy would see the trend reversed; its hedging should be most effective when revenues are low.

In order to determine if this was a consistent pattern in the performance of Fonterra's hedging strategy, we created a forecast of Fonterra's hedge and spot exchange rate values using the past exchange rate data from 1999 to 2009.

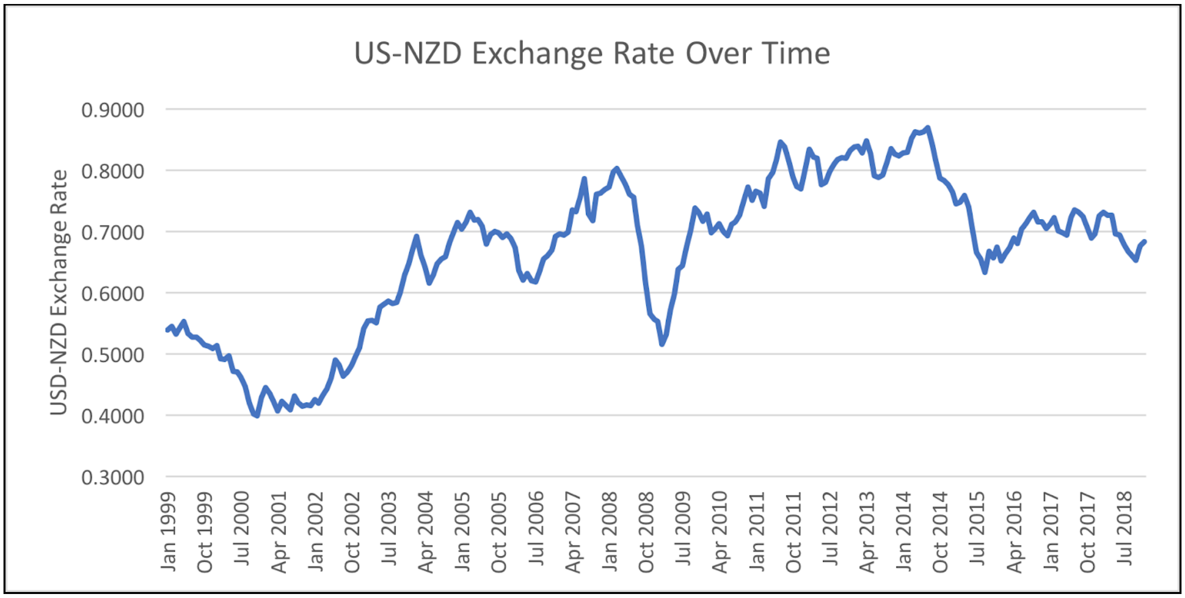

Figure 12: Backwards Forecasted Exchange Rate

After examining the graph of the USD-NZD exchange rate over time, we noticed a drastic drop in the exchange rate in 2008, similar to 2014. In our forecast, we would expect a similar pattern of the larger hedge than spot rates to occur in 2008. The forecasted values of the hedge rate were calculated using our best predictors of Fonterra's hedging rule: the lasso and 1/18th baseline model. Similarly, the forecasted spot rates were calculated using the values found in our spot rate model.

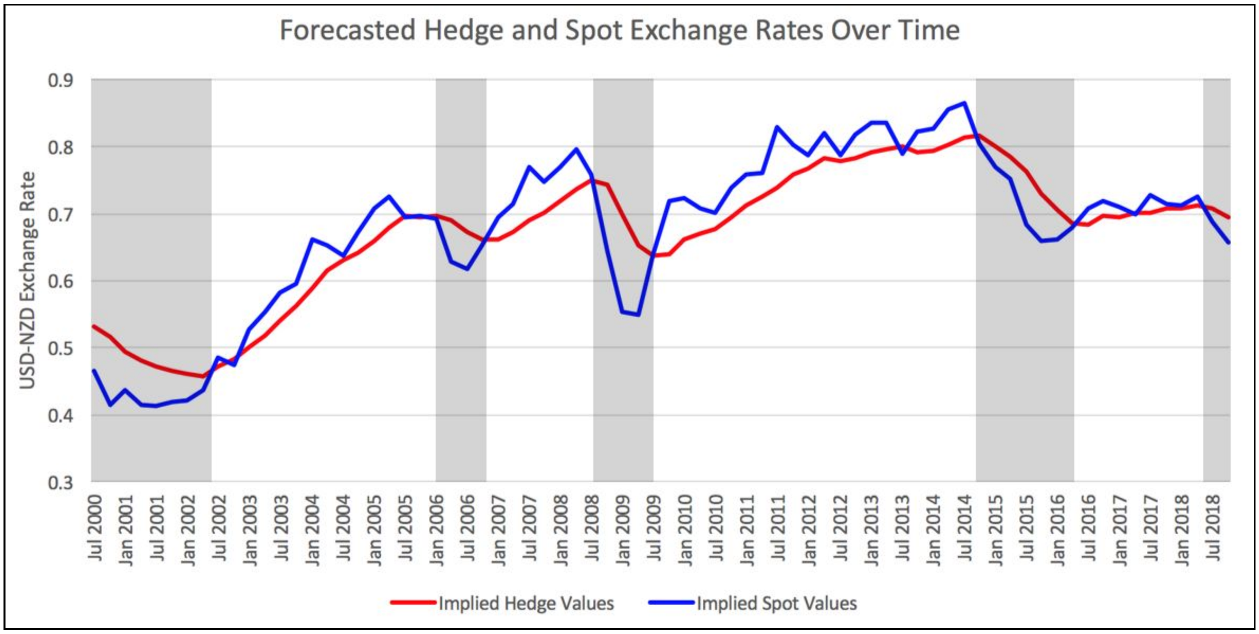

Figure 13: Performance during Economic Downturns

Our forecast suggests that Fonterra's performance would have been consistent with their results in recent years, had they used their current hedging strategy from 1999-2009. Ultimately, the forecast not only suggests that Fonterra's strategy would not have effectively hedged against exchange rate fluctuations seen in 2008, but also that they would have had similar incidences in 2000 and 2006. During the 2014 event, ineffective hedging resulted in Fonterra collecting 1.17 billion NZD less in revenue compared with the revenue they would have collected if they converted their revenue at the spot value. Based on our forecast, Fonterra would have benefitted by approximately 1.08 billion NZD during the 2008 event if they had used the spot. Given the above findings, it can be concluded that Fonterra's hedging strategy is not consistent with its goal of reducing volatility in its revenues and prices paid out to farmers.

Limitations

While we are confident in our analysis and recommendations given to our client, there were some limitations that may have affected our analysis and findings. As mentioned in the Data Processing section, Fonterra implemented their hedging strategy relatively recently and reports its hedge exchange rates on a quarterly basis; only 45 hedge exchange rates have been reported as of the time of completion of our project. This small sample size limited the number of predictors that we were able to use in our models. Additionally, Fonterra's financial statements are particularly vague with respect to describing their hedging strategy. As a result of Fonterra's lack of transparency, there are not many valuable insights from their published documentation regarding the methodology Fonterra uses to hedge.

Recommendations

According to Oscar Dowson, the equal weights model over the last 18 months is the baseline predictive model he has been using for his website, DairyAnalytics. Our recommendation is to continue using this model for DairyAnalytics, since it is an accurate simple rule that we found to have a comparable predictive power compared to that of our lasso model. Since our first goal was to incorporate Fonterra's hedged exchange rate strategy using a simple rule, the equal weights model was chosen as the policy DairyAnalytics should use for the website.

In terms of our second goal, determining whether Fonterra's financial strategy is effective, we found that their hedging exchange rate strategy is not as effective as they might hope. Since their hedging strategy sometimes amplifies the volatility of the exchange rate, we also recommend that Fonterra use options instead of futures. Options will allow Fonterra some flexibility in their hedging strategy, and hopefully when they are experiencing a downturn, they are not forced by the future to exchange at a higher rate, and can instead use the option to exchange their revenue at the spot exchange rate.

We modeled the reconstruction of the hedged exchange rate based off of Fonterra's annual reports, where it explicitly said that the hedged exchange rate was a simple rule using the prior 18 months of data. The skepticism surrounding the company and its financial reports are clearly stated in the Otago Daily Times: "the lack of accountability of Fonterra, as a company and from the people involved in its running, has been appalling. An analysis of the financial accounts shows Fonterra continuing to underperform financially. Fonterra has struggled to put financial returns on the board." (Accountability) This excerpt clearly demonstrates the uncertainty of the assumptions we built our model off of to help reconstruct the strategy. We recommend that Fonterra be more clear and upfront with their stakeholders.

Conclusions About Effectiveness and Economic Value of Solution

The DairyAnalytics website is widely used by many dairy farmers across New Zealand to predict how much their earnings will be for the 2018/2019 year. Dairy is 3.5% of New Zealand's GDP, with Fonterra capturing 90% of the accounting for 90 percent of the NZ milk supply (NZIER). Our forecasting helps the farmers understand how much the farmers will receive from the dairy products by reconstructing Fonterra's hedged exchange rate for Oscar to use on the DairyAnalytics website. DairyAnalytics can share these insights with its users who, aided by this analysis, can raise concerns to Fonterra about their hedging policy and potentially prompt a change in strategy.

While our group does not work with Fonterra directly, it's helpful to note that our analysis suggests Fonterra's hedging rule does not seem consistent with the claim that much of their hedging is performed upwards of 12 months in advance. This is seen in the fact our most predictive models relied heavily on more recent data. Furthermore, Fonterra's current hedging strategy is inconsistent with goal of reducing volatility in revenue and prices paid to farmers. DairyAnalytics has a vested interested in the farmers well-being, so they can communicate these findings to both Fonterra and the farmers in hopes of improving the hedging strategy.

Implementation Plan

Our recommendation is for Oscar Dowson to implement the hedging model using the last 18 months of exchange rates weighted equally to predict the current month's hedge rate. This is according to the simple rule baseline model that we suggested in section 7. In order to implement this solution, Oscar may feed in the most recent 18 months of exchange rates monthly to his online platform to assist New Zealand dairy farmers in their budget planning.

Oscar should also keep track of these exchange rates and price of dairy by month so that he can keep measuring the effectiveness of this solution. This can be measured by calculating the R^2 each month when he predicts the hedge rate, to make sure the 18-month average still is an appropriate model. As he adds each of these months to the data set, the amount of data will grow, and perhaps in the future, another data analysis team can revisit this hedged exchange rate model to improve its accuracy.

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Appendix A

Stepwise

```
#run this command once to get glmnet--->"install.packages("glmnet", repos =
"http://cran.us.r-project.org")"
library(glmnet);
#Read and clean up csv file
farm<- read.csv("Farmgate by month.csv");
farm[6:26]<-NULL;
farm[6]<-1:240;
#--------------------------------------------------------------------------------
---#
#create new data frame for analysis using last 18 months of data to predict
hedge
x<- data.frame("hedge"=farm[5])
x[2:37]<-1
for (i in 128:236){
  for (j in 1:18){
    j
    x[i,2*j]<- farm[i-j,2]
    x[i,2*j+1]<-farm$NZ.Interest.Rate[i-j]-farm$Federal.Interest.Rate[i-j]
    #x[i,3*j+2]<-farm$Federal.Interest.Rate[i-j]
  }
}
#Clean up new data frame and name columns
x<-x[-c(1:127), ]
names(x) <- c("Hedge", "Exchange 1","NZ Interest-US Interest 1","Exchange
2","NZ Interest-US Interest 2","Exchange 3","NZ Interest-US Interest
3","Exchange 4","NZ Interest-US Interest 4","Exchange 5","NZ Interest-US
Interest 5","Exchange 6","NZ Interest-US Interest 6","Exchange 7","NZ
Interest-US Interest 7","Exchange 8","NZ Interest-US Interest 8","Exchange
9","NZ Interest-US Interest 9","Exchange 10","NZ Interest-US Interest
10","Exchange 11","NZ Interest-US Interest 11","Exchange 12","NZ Interest-US
Interest 12","Exchange 13","NZ Interest-US Interest 13","Exchange 14","NZ
Interest-US Interest 14","Exchange 15","NZ Interest-US Interest 15","Exchange
16","NZ Interest-US Interest 16","Exchange 17","NZ Interest-US Interest
17","Exchange 18","NZ Interest-US Interest 18")

#Only keep rows with hedge data
new_DF <- x[!is.na(x$Hedge)>0,]
```

Appendix B

Spot Rate Model AMPL Program

<u>.mod file</u>

```
# years
set Y;
# quarters
set Q;
# months
set M;

# monthly exchange rates
param E{m in M, y in Y};

# quartlery spot rates
param A{q in Q, y in Y};

# weight
var x{m in M} >= 0;

# estimated spot by quarter and year
var s{q in Q, y in Y};


minimize square: sum{q in Q, y in Y} (A[q,y] - s[q,y])^2;

subject to sum1: x[1] + x[2] + x[3]    = 1;
subject to sum2: x[4] + x[5] + x[6]    = 1;
subject to sum3: x[7] + x[8] + x[9]    = 1;
subject to sum4: x[10] + x[11] + x[12] = 1;
subject to sum5: x[13] + x[14] + x[15] = 1;


subject to quart1 {y in Y}: E[1,y]*x[1] + E[2,y]*x[2] + E[3,y]*x[3]       =
s[1,y];
subject to quart2 {y in Y}: E[4,y]*x[4] + E[5,y]*x[5] + E[6,y]*x[6]       =
s[2,y];
subject to quart3 {y in Y}: E[7,y]*x[7] + E[8,y]*x[8] + E[9,y]*x[9]       =
s[3,y];
subject to quart4 {y in Y}: E[10,y]*x[10] + E[11,y]*x[11] + E[12,y]*x[12] =
s[4,y];
subject to quart5 {y in Y}: E[13,y]*x[13] + E[14,y]*x[14] + E[15,y]*x[15] =
s[5,y];


set M := 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15;
```

```
set Y := 1 2 3 4 5 6 7 8 9;
set Q := 1 2 3 4 5;
```

.dat file

```
# actual hedge rate for each month and year
param E: 1 2 3 4 5 6 7 8 9 :=
1  0.6754   0.71540.83840.80980.79220.84350.65490.72290.7311
2 0.7024    0.72590.81430.81740.81250.81660.63340.73090.7246
3 0.7383    0.75010.78790.81980.83490.78690.66700.71580.7062
4 0.7309    0.77270.77280.81920.82650.78320.65670.71530.6888
5 0.7162    0.75040.76970.83180.82280.77640.67370.70480.6953
6 0.7277    0.76530.80070.83750.82820.76400.65200.71260.7255
7 0.6974    0.76230.83430.83890.82870.74440.66330.72200.7312
8 0.7032    0.74080.82080.82780.85170.74730.67330.70090.7257
9 0.7123    0.78590.81900.84730.86200.75830.68920.69750.7258
10 0.6992   0.79580.77620.82660.86090.73940.68030.69370.6953
11 0.6928   0.81500.78010.79080.86210.69900.70340.72250.6941
12 0.7111   0.84550.79820.78840.86970.66520.71230.73490.6788
13 0.7154   0.83840.80980.79220.84350.65490.72290.73110.6671
14 0.7259   0.81430.81740.81250.81660.63340.73090.72460.6595
15 0.7501   0.78790.81980.83490.78690.66700.71580.70620.6530;

# actual spot rate for each quarter and year
param A: 1 2 3 4 5 6 7 8 9 :=
1      0.72580.744 0.79560.81910.82830.78480.65810.71560.6968
2      0.72390.76230.78050.83570.82630.76280.66370.71170.7147
3      0.70470.763 0.82530.83340.858 0.74880.68030.69780.7172
4      0.70070.81690.78520.79090.85950.67490.70780.73640.6853
5      0.71780.82690.80190.82210.79980.66030.70690.75040.68212;
```

.run file

```
reset;
model spot.mod;
data spot.dat;
option solver CPLEX;
solve;
```

Appendix C

Lasso Model Lambda Calculation

```
#run this command once to get glmnet--->"install.packages("glmnet", repos =
"http://cran.us.r-project.org")"
library(glmnet);
#Read and clean up csv file
new_DF<-read.csv("FarmgateByQuarter.csv")
# Generate data
set.seed(19875)  # Set seed for reproducibility
n <- 45  # Number of observations
p <- 36  # Number of predictors included in model
real_p <- 4  # Number of true predictors

x=model.matrix(Hedge~.-Quarter,new_DF)[,-1]
y=new_DF$Hedge
grid = 10^seq(-1,-7,length = 45)

# Split data into train (2/3) and test (1/3) sets
#train_rows <- sample(1:n, .66*n)
#x.train <- x[train_rows, ]
#x.test <- x[-train_rows, ]

#y.train <- y[train_rows]
#y.test <- y[-train_rows]


#base<-c(1:29)
#base[1:29]=mean(y.train)
#traintss=sum((y.train-base)^2)
#basetest<-c(1:16)
#basetest[1:16]=mean(y.test)
#testtss=sum((y.test-basetest)^2)

trainrsq<-c(1:45)
testrsq<-c(1:45)
testrsqsd<-c(1:45)
trainmse<-c(1:45)
testmse<-c(1:45)
for (i in 1:45){
  train.cvrsq=c(1:200)
  test.cvrsq=c(1:200)
  train.cvmse=c(1:200)
  test.cvmse=c(1:200)
  for(jj in 1:200){
    train_rows <- sample(1:n, .66*n)
```

```
    x.train <- x[train_rows, ]
    x.test <- x[-train_rows, ]
    y.train <- y[train_rows]
    y.test <- y[-train_rows]
    print(grid[i])

    testtss=sum((y.test-mean(y.test))^2)
    traintss=sum((y.train-mean(y.train))^2)

    lasso.mod = glmnet(x.train,y.train,alpha = 1, lambda=grid[i])
    lasso.train.pred=predict(lasso.mod,lambda=grid[i], newx=x.train)
    lasso.test.pred=predict(lasso.mod,lambda=grid[i], newx=x.test)

    test.rss=sum((y.test-lasso.test.pred)^2)
    train.rss=sum((y.train-lasso.train.pred)^2)

    train.mse=mean((y.train-lasso.train.pred)^2)
    test.mse=mean((y.test-lasso.test.pred)^2)

    test.rsq=1-(test.rss/testtss)
    train.rsq=1-(train.rss/traintss)

    train.cvrsq[jj]=train.rsq
    test.cvrsq[jj]=test.rsq
    train.cvmse[jj]=train.mse
    test.cvmse[jj]=test.mse
    print(test.cvrsq)
  }
  trainrsq[i]=mean(train.cvrsq)
  testrsq[i]=mean(test.cvrsq)
  testrsqsd[i]=sd(test.cvrsq)
  trainmse[i]=mean(train.cvmse)
  testmse[i]=mean(test.cvmse)
}
plot(trainrsq,xlab="Lambda",ylab="R-Squared",lwd=3, xlim=c(5,35),ylim=c(.8,1),
col="blue", type="l", main="R-Squared", lables=FALSE)
text(grid, labels=grid)
lines(testrsq,xlab="Lambda",ylab="R-Squared", lwd=3, ylim=c(.8,1), col="red")

legend(25, .98, legend=c('Test', 'Train','Best Lambda Value'),
       col=c("red", "blue","black"), lwd=3,lty=c(1,1,3), cex=0.8)

best=max(testrsq)
bestind=match(best,testrsq)
abline(v=bestind,lwd=3,lty=3)

plot(trainmse,xlab="Lambda",ylab="Mean Squared Error",
xlim=c(5,35),ylim=c(0,.001),lwd=3, col="blue", type="l", main="Error")
```

```
lines(testmse,xlab="Lambda",ylab="Mean Squared Error", lwd=3,ylim=c(0,.0001),
col="red")

legend(10, .0007, legend=c('Test', 'Train'),
     lwd=3,col=c("red", "blue"), lty=1:1, cex=0.8)
```

Lasso Model

```
#run this command once to get glmnet--->"install.packages("glmnet", repos =
"http://cran.us.r-project.org")"
library(glmnet);
#Read and clean up csv file
new_DF<-read.csv("FarmgateByQuarter.csv")
new_DF<-new_DF[,-c(4,6,8,10,12,14,16,18,20,22,24,26,28,30,32,34,36,38)]
# Generate data
set.seed(19875)  # Set seed for reproducibility
n <- 45
x=model.matrix(Hedge~.-Quarter,new_DF)[,-1]
y=new_DF$Hedge
rsq=c(1:100)

cv.out = cv.glmnet(x,y,alpha = 1)
bestlam = cv.out$lambda.min

for(i in 1:100){
  train_rows <- sample(1:n, .66*n)
  x.train=x[train_rows,]
  y.train=y[train_rows]
  x.test=x[-train_rows,]
  y.test=y[-train_rows]
  out= glmnet(x.train,y.train,family="gaussian",alpha = 1, lambda=bestlam)
  lasso.pred = predict(out, lambda= bestlam, newx = x.test)
  tss=sum((y.test-mean(y.test))^2)
  sse=sum((lasso.pred-y.test)^2)
  r2=1-(sse/tss)
  rsq[i]=r2
}


mean(rsq)
avg = mean(rsq)
z = 1.96
s = sd(rsq)
n = 100
CI_upper = avg + z*s/sqrt(n)
CI_lower = avg - z*s/sqrt(n)
```

```
min(rsq)
max(rsq)
avg
CI_lower
CI_upper
s


cv.out = cv.glmnet(x,y,alpha = 1)
bestlam = cv.out$lambda.min
out= glmnet(x,y,alpha = 1, lambda=bestlam)
lasso.coef = predict(out, type = "coefficients", lambda= bestlam)[1:19,]
lasso.coef[lasso.coef != 0]
```

Appendix D

T-Test and F-Test output

<u>F-Test Output</u>

```
> var.test(hedge,spot,altenative="two.sided")

        F test to compare two variances

data:  hedge and spot
F = 1.1239, num df = 34, denom df = 34, p-value = 0.7354
alternative hypothesis: true ratio of variances is not equal to 1
95 percent confidence interval:
 0.5673029 2.2265695
sample estimates:
ratio of variances
          1.123895
```

<u>T-Test Output</u>

```
> t.test(hedge,spot,paired=TRUE)

        Paired t-test

data:  hedge and spot
t = 2.3181, df = 34, p-value = 0.02659
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
   7788052 118507127
sample estimates:
mean of the differences
               63147590
```