A MULTIVARIATE APPROACH TO FORECASTING DAIRY IMPORTS

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ABSTRACT

The global economy is becoming more connected with every passing year. Developing countries continue to lift themselves out of poverty and their markets are hungry for the opportunity to trade goods with nations all over the world. This is true in dairy markets, and it is a good time for domestic producers to set their sights on international markets. Domestic companies want to have a tool they can use to determine where the demand is not only strong today but will remain strong in the future. In this paper a model is developed to forecast demand in China, the world's top dairy importing nation. The accuracy of the model is checked. While forecasts will never be completely accurate the multivariate approach used in this paper shows promise for the helpfulness of such models to firms looking to evaluate foreign markets.

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LIST OF ABBREVIATIONS

AU .... Australasia

ADF .... Augmented Dickey-Fuller

AIC .... Akaike Information Criterion

AR.. Autoregressive

ARG .... Antibiotic Resistant Gene

ARIMA .... Autoregressive Integrated Moving Average

ARMA .... Autoregressive Moving Average

BIC.. Bayesian Information Criterion

BVAR .... Bayesian Vector Autoregression

DF.. Dickey-Fuller

DF-GLS .... Dickey-Fuller Generalized Least Squares

EU.. The European Union

FPLF .... Female Participation in the Labor Force

GDP .... Gross Domestic Product

LA/AIDS............................ Linear Approximation Almost Ideal Demand System

Lbs .... Pounds

LFPR... Labor Force Participation Rate

MA.. Moving Average

MAE .... Mean Absolute Error

MAPE .... Mean Absolute Percentage Error

MDM .... Modified Diebold-Mariano

RMSE .... Root Mean Square Error

SMP .... Skim Milk Powder

St. Dev .... Standard Deviation

Tonnes.. Metric Tonnes

US .... The United States of America

UW-WDM .... UW-Madison World Dairy Model

VAR.. Vector Autoregression

VECM.. Vector Error Correction Model

WMP.. Whole Milk Powder

CHAPTER 1. INTRODUCTION

World dairy demand has increased steadily in recent years (Smith, 2014). The United States has also continued to experience increasing dairy production due in part to the fact that the price of milk, while volatile, remains higher than the cost of production (Lawrence, 2008). The volatility dates back to the United States government discontinuing some of their practices for stabilizing dairy prices in the 1980s (Cropp, 1997). In recent years there have been record high and record low prices, but through it all production has increased (Farmers Weekly, 2013). As with any product, a high domestic price makes domestic products less competitive on the international level. The reason exports are expected to grow in spite of high domestic prices is that recent studies indicate that global dairy prices will continue to increase as well. This is not to say that dairy will necessarily become more profitable as the cost of feed and energy used in production of dairy products may also continue to rise, but only that it will remain at least somewhat profitable to export for years to come.

Problems in other dairy exporting countries have also contributed to the increasing competitiveness of US dairy products in international markets. Recent droughts in Australia, as well as the European Union and United Kingdom discontinuing many of their own dairy subsidies, have left a gap in world exports (Lawrence, 2008).

On the other hand the US has had a surplus of dairy for several decades (Bovard, 1991). The surplus was so large that at one point the government was paying dairy farmers to slaughter their cattle. During the same decade dozens of farmers were paid in excess of one million dollars each to discontinue their dairy operations for five years.

While there may be temporary production lags in some countries contributing to the demand for US dairy products, the main reason for the increase is a general increase in dairy demand, especially in Asia (Gee, 2014). As the population grows, and more of the population of the world lifts themselves out of poverty, more people can afford the luxury of consuming dairy products. Many of these developing nations in Asia have demand that far outpaces their domestic production because “The combination of unaccommodating climate, poor farming practices, unsuitable land and limited access to credit, creates a difficult environment for domestic producers and a great opportunity for exporters” (Song, 2014). Due to those characteristics and the high population density of some areas, such as many countries in Southeast Asia, they may never be able to meet their dairy demands domestically.

In recent years exports to Asian countries such as China and Vietnam have surged. With demand in the US remaining largely stagnant, overseas markets remain the best option for large producers looking to expand and sell off excess product (Gee, 2014). Total US dairy exports were up 8% in 2012 from 2011 (USDEC 2012). They were up 19% in volume in 2013 and were up 31% in value due to increasing prices. China has averaged an increase in milk powder imports of 33% since 2008 (Gee, 2014). Total dairy sales to China in 2013 rose by 70%, partially because of the adverse weather conditions in Europe, South America, and New Zealand that year which caused their production to go down. Drought on the western coast of the US may also play a role in increased demand for milk from other regions of the country.

While it is clear that times are good for expanding US dairy exports the question remains as to how and where these products should be exported. There are clear advantages to exporting milk powder, but increasingly powdered dairy products are viewed as inferior products in some markets including urban China (Fuller, 2006). The question as to where to export these products also poses a problem. While Southeast Asia seems to be one of the obvious answers it is a market already saturated with imports from top producers such as New Zealand and Australia.

China has also recently put in place regulations requiring foreign companies to register their products, storage facilities, and production facilities with the Chinese government before they can sell their products (Wong, 2014). They have also required companies to affix Chinese-language labels on products before they can be shipped into China. This has the joint purpose of promoting the sale of domestic products and limiting the ability of smaller unknown, and therefore less trusted, foreign companies from being able to import their products into China.

These regulations may slow the growing influence of foreign companies in China, but the Chinese people still strongly favor foreign brands with foreign brands claiming 60% of the infant formula market in the country (China Briefing, 2014). After the 2008 melamine scandal Chinese parents began to exhibit a stronger preference for foreign brands (China Briefing, 2014). Another concern is that locally raised livestock, including milk cattle, are being fed too many antibiotics (Guilford, 2013). While the United States uses antibiotics in people and livestock the numbers are nowhere near the levels China has reached. Chinese livestock is given four times as many antibiotics as livestock in the United States. A study showed that on a single pig farm in China there were a total of 149 unique antibiotic resistant genes (ARGs). The problem exists in pig farms and in human hospitals. Antibiotic use in China is not closely monitored. It can be expected to become a problem as large dairy farms in China become more common. The new ARGs found in manure could easily be washed into rivers, spread on fields, or seep into the ground where they could make people and livestock sick. They could also get into the milk from the cows and start another scandal and set demand for Chinese produced dairy products back even further.

While ARGs may make people sick and lose confidence in Chinese products, they may also damage livestock. In 2005 poultry producers were afflicted with birds suffering from the

H5N1 flu (Walsh, 2013). These officials found the flu to be almost impossible to accurately trace to its origins or to track its spreading. The recommended course of action was to just find and cull afflicted birds. This was nearly impossible in China because producers had dosed the birds with Tamiflu to prevent sick birds from showing symptoms. The sick animals were then unknowingly left with healthy birds, free to spread the flu. If the same situation arose amongst dairy producers it would cripple China's already limited ability to supply dairy products.

Once companies establish that there is indeed a market for them, in China or anywhere else, they need to determine how they want to enter that market. Some large companies have partnered with other producers to share markets. For a decade now Fonterra (of New Zealand) and Nestle (of Switzerland) have had a deal that has led to joint production ventures in several Central and South American countries (Astley, 2014). Fonterra is taking a particular interest in their operations in Brazil and Venezuela where they have recently taken majority control of their manufacturing operations.

More recently Fonterra has announced intent to buy a large portion of the shares for a Chinese company called Beingmate Baby and Child Food Company (Want China times, 2014). The deal is pending approval from the Chinese government. Fonterra's plans stem from their desire to find a Chinese based partner. They wanted their new partner to meet three criteria: "it should be a current client for New Zealand products, have the ambition to develop large-scale dairy farming in China and be willing to explore downstream markets with Fonterra Brands." Fonterra felt Beingmate met those criteria. Fonterra has also announced they have plans to build five ranches in China jointly with Abbott Laboratories, an American company. All of these developments will further connect Chinese and foreign companies and serve to increase competition for the growing market.

Fonterra is not the only company that has already bought or made plans to buy into Chinese dairy companies. Royal FrieslandCampina, a Dutch company, has plans to work with Huishan Dairy in China (Xinhua, 2014). The plan is to use Huishan's raw Chinese milk and Royal FrieslandCampina's technology and management to sell products in the Chinese market. The Dutch company is looking at this as a stepping stone towards establishing a second brand name in the Chinese market.

Even regional government sees the potential for dairy trade overseas. South Dakota governor Dennis Daugaard has gone on three trips to China. The most recent trip focused on trying to get South Dakota dairy products to China (Schmidt, 2014). People overseas want products they can trust, and the regulations in the US make our local products a good option on the international market.

While prices have been good for the last few years dairy prices have fallen throughout much of 2014 (The People's Daily, 2014). Production has remained strong in the world's main dairy producing and exporting regions. Too much of a good thing has led to bad news in global markets as the global market struggles to absorb the influx of dairy production. This struggle means that prices fell throughout much of 2014 and countries like China have slowed their international buying as they attempt to use up stocks purchased earlier in the year. The director of dairy research in New Zealand and Asia for one of the worlds top agribusiness banks, Rabobank, Hayley Moynihan, had good and bad news: "while a bottom appears to have been reached for New Zealand and Australian export prices, market rebalancing will be a slow process and price recovery looks some way off." While the recovery of dairy prices has started, producers can expect that a complete recovery of both prices and market balance is not going to be immediate.

New Zealand farmers have been warned to expect a rough year in the 2014-2015 markets (The People's Daily, 2014). Prices are expected to be profitable once again in the 2015-2016 year. This of course depends on many factors. Continued expansion in production could delay price recovery while droughts or other problems in any of the world's key dairy exporting areas could bolster prices.

However, there are those that believe this excess production is a trend. Goldman Sachs has predicted that over the next five years dairy production will outpace consumption by roughly two billion liters and serve to keep prices low (The People's Daily, 2014). On the other side of this argument are those who believe that unprecedented growth in demand in developing nations will mean that by the year 2018 dairies will find it hard if not impossible to meet demand (Rowan, 2014). They expect Chinese imports of milk, already strong, to double over the next ten years.

In China, United States companies so far have benefited the most from the growth in skim milk powder and whey imports to China (Cheese Reporter, 2014). Another fast-growing export is cheese imports from the US in China. Chinese imports of US cheese were up were up 44% January through May 2014 compared to the same numbers in January through May 2013. Cheese may become an important export to China for large US dairy companies. The increase in demand is expected to make China the second largest market for dairy products within a year. Currently Mexico is the largest market for US dairy products and Canada is the second largest.

The other negative impact on prices right now is the trade ban that Russia, the world's second largest importer of dairy products, has placed on western produce (Gray, 2014). The sanctions are a response to actions taken by governments who oppose Russia's recent actions in Ukraine. The ban prevents the import of dairy products from the European Union, the United

States, and Australia. New Zealand still has access to the Russian market, but they do not expect this access to give them a very big advantage as Russia is mostly going to be short cheese and butter while New Zealand has mostly skim milk powder available. This ban has meant an increase of inventory for many producers, and this is a particularly bad time since New Zealand and Australia have just entered their peak production period. The ban is currently set to last one year, but Russia could choose to extend the ban.

Now is a good time for any American dairy company to form a plan of action. Though prices are low now they are suffering only temporary lows caused by temporary lags in demand in China and Russia, the two largest dairy importers. If they wish to expand overseas they must choose where they want to expand. They must determine which products are most suitable for exporting. Companies must also determine how they wish to conduct their international trade. They have the option of finding domestic partners, international partners, or partnering with companies in the countries importing their goods. These decisions need to be made for any company separately based upon their own traits and preferences.

CHAPTER 2. LITERATURE REVIEW

The United States has not historically been a large dairy exporter, and in fact there was a point in time when it was questioned whether domestic producers could remain competitive domestically (Buxton, 1975). In 1975 it was determined that if the US adopted more liberal import policies that they would be unable to compete with imports from Australia and New Zealand. Even then, it was noted, however, that New Zealand and Australia are constrained by their capacity and would not be able to fill the entire US demand. In 1973 Australia and New Zealand accounted for 66% of world dairy exports, and only 4% of production. In 2009 that figure had dropped to only 38.9% of world exports and production, while higher than in 1973, had dropped to only 3% of world production (Blasko, 2009). The 1973 study concluded that free trade would lead to a decrease in domestic dairy production, claiming we would lose 4,200 dairy operations by 1980. While that may have been possible at that time, world demand has increased rapidly enough and production in more competitive countries, such as Australia and New Zealand, has increased slowly. The combination means that US dairy producers can be competitive domestically as well as internationally.

Section 2.1. Market Selection

The first stage in the analysis should be picking out a market to target. There are many factors that affect the attractiveness of conducting business in a foreign market. The need for this analysis has led to the creation of indices such as the World Bank’s ease of doing business rankings. Their ranking takes into account the ease of starting a business, taxes, registering property, protecting investors, trading across borders, and enforcing contracts. While some point out how these rankings help developing countries attract foreign direct investment (FDI), it is just as helpful to businesses in developed countries when trying to find new markets. It also showed that improving the quality of the rankings would on average increase FDI for a country (Jayasuriya, 2011).

No one indicator alone can determine the best option for a specific industry or company. Some of the eastern and southern Asian countries, such as Bangladesh and Sri Lanka, did not even manage to crack the top half of the 2014 (doingbusiness.org, 2014). China managed to make the top half with the 90th spot out of 189. However, dairy exporting nations should not dismiss these countries as they have some of the highest forecasted growth in milk consumption and imports (Gee, 2014).

In 2001 the volatility of dairy prices was thirty times higher than in 1981 (Thraen, 2002). That volatility was the result of the US backing off on their price stabilizing practices. This increased volatility makes it more important than ever to create accurate forecasting models. Even countries with relatively stable economies and dairy markets are troublesome places in which to get ahead. When companies plan to expand into developing countries they are moving into unknown conditions.

On a domestic level it has been shown that decreasing price volatility means higher prices (O'Connor, 2009). In this study a GARCH model is used to show that the European Union's efforts to stabilize prices was successful in lowering volatility by using price floors and trade restrictions. The article concludes that when the EU government senses extreme volatilities it will simply employ their risk management policies. However, their policy choice may be limited in the future as new world trade organization policies go into effect.

It has also been shown that international volatility can affect a country's domestic prices (Tadesse, 2013). This same study concluded that when it came to general food price volatility demand-side shocks have a greater effect than market or supply-side shocks. One of the conclusions drawn is that excessive speculation can contribute to price volatility in food markets. To solve this problem it is suggested that people could either put a cap on trading or tax food commodity futures (Tadesse, 2013). One problem that arises for producers expanding into developing countries is that even during times of stable international prices a developing nation may suffer from high price volatility (FAO, 2011). This happens because developing nations often lack the ability to adequately absorb any domestic shocks that may occur. In this way even if a country has used policy to insulate their prices from international effects they may still suffer from homegrown volatility issues.

There have been other papers addressing the needs to forecast dairy demand. However, many of these papers focus on domestic demand (Schmit, 2006). In one study a similar approach to the one that will be laid out in this paper is used to forecast dairy demand in Mexico (Tanyeri-Abur, 1996). In this case the author uses only domestic variables. While the effects of the North American free trade agreement are discussed they do not include variables pertaining to price, production, or export values for the US and Canada or any other country.

Section 2.2. Forecasting Foreign Demand

The general idea remains the same when a domestic company wants to forecast demand in a foreign country. In the United States there is already a strong dairy consuming culture, so the changes in demand are primarily driven by changes in population demographics (Schmit, 2006). Demographics may not be as relevant in developing nations, but the other major component of change in retail demand for dairy in the US is change in consumers' food-spending habits which is extremely relevant in developing nations. In developing nations the population has higher incomes and more choices available to them than they had just a few decades ago. The retail supply side modeling is a function of retail price, wholesale price, a price index for energy, a time trend as proxy for change in retailing, seasonal dummy variables, and lagged retail supply to represent constraints on capacity (Schmit, 2006). The wholesale supply equation had similar constraints. The retail demand model used was a function of retail prices, real per capita disposable income, percentage of US population identifying as Asian or Hispanic, real per capita expenditures on food eaten away from home, seasonal dummy variables, and national branded and generic cheese advertising expenditures.

The supply side model represents in this case a partial equilibrium model of the US dairy sector and divides it into the retail, wholesale, and farm markets (Schmit, 2006). While the retail and wholesale functions are similar, the farm market function is very different. It is a function of the all-milk price, the ration price, the slaughter-cow price, a time trend as proxy for change in dairy production, seasonal dummy variables, intercept shifters for periods when dairy termination program was in effect, and lagged farm supply. The all-milk price is a weighted average of the prices for the different classes of milk.

The retail demand model accounts for the effects of economic, demographic, and advertising on per capita demand. The authors also tracked the change in effects of generic advertising (Schmit, 2006). The theory there is that as demographics change the effectiveness of advertising will also change. The authors discovered branded advertising does not seem to help, at least in the US. Branded advertising aims to steal business away from competitors, so it does not necessarily increase overall dairy spending. Generic advertising, however, was a significant variable when it came to dairy demand. The authors then used root mean square error (RMSE) to test the accuracy of their model compared to actualized values for 2002-2005. The RMSE for all prediction statistics is below 3%, which is a promising indicator that the model is successful. The biggest drawback of this approach is that only domestic variables were considered. In an increasingly international market it is important to consider changes happening in key importing and exporting nations. A study like this would miss the effect of rising demand in China, the Russian embargo, or any production fluctuation in Australasia.

Dairy industries have been described as one of the more distorted sectors in agriculture (Peng, 2006). Peng categorizes the dairy policies of the top producers and consumers in Asia. The policies are divided into three categories. “Amber Box” policies are policies that distort international trade the most and also affect production. Developed countries took account of the policies in the late 1980s and agreed to tone them down in the interest of promoting international trade. “Green Box” policies have little to no effect on international trade and countries are permitted by the WTO to use these as liberally as they wish. “Blue Box” policies are between the former two in the severity of their effects, while they are currently not regulated by the WTO they reserve the right to revisit the regulation of “Blue Box” policies in the future should countries abuse their use. Currently only Japan uses the Green policies, but China is a potential user of these policies in the near future. Japan and Korea are the only two countries that cannot use any Amber policies. They do however choose to employ Blue policies.

Korea uses “Blue Box” policies and still has relatively high barriers to trade for dairy products (Lee, 2006). So a study was conducted to illustrate what would happen to the dairy markets in Korea if restrictions were further lifted. Korea has a well-developed dairy production sector, which was created in its modern form when dairy cows were imported from the west in 1962 (Lee, 2006). The production per cow has increased at an average of two percent a year and the average production of a Korean milk cow is 83% of the average production for a cow in the US. This production level has steadily driven down costs of production and over the same time period Korean consumption of dairy products also increased. However, it is uncertain if these

Korean dairy farmers could compete with competition. The government sets prices above production cost to guarantee farmers make a net profit. It is possible that even if Korea allows more dairy imports and lowers tariffs that they may still set a high raw milk price. The study showed that the various reform options lead to a wide array of outcomes; for example, under this scenario the price for nonfat milk is projected anywhere from the same price as before reforms to a decrease of thirty cents (Lee,2006). This is a good example of trade policy contributing to price uncertainty and volatility.

The UW-Madison World Dairy Model (UW-WDM) is an interregional competition model that splits the world into 21 regions (Peng, 2006). This model includes domestic and trade policies that will affect the production in the other regions. Peng adds to this model by including additional foreign trade policy including the US-Australian free trade agreement. This model shows the importance of taking into account the domestic and foreign policies of key importing and exporting nations. The overall findings are that Asian countries (mainly Japan and Korea) will lose producer surplus with addition trade liberalization. Overall world trade liberalization will lower dairy prices and therefore increase consumer surpluses.

There have also been attempts to forecast in dairy futures markets (Sanders, 2004). Attempts to forecast agricultural markets using their respective futures markets has had mixed results. Sanders worked to show that “the accepted mean square error is not enough and may lead to low power against the null hypothesis of forecast efficiency” (Sanders, 2004). While this kind of modeling is helpful where futures markets exist and are well established, they will not be directly relevant in markets without a futures market. Sanders used time series to analyze the data and then he used a modified Diebold-Mariano (MDM) test to interpret the results. The time series models were then able to forecast one to three quarters ahead. The forecasts were tested using RMSE, and then the MDM to test for differences in the forecast accuracy.

Even though futures market analysis may prove useful in some cases, it appears as though it is not the most efficient route for the dairy market (Sanders, 2004). The prior studies that Sanders compared findings to were more accurate than the use of futures markets. Though, it is noted that the futures market predictions are the most accurate when looking at predicting only one quarter into the future.

Dairy products are known as the most complete food and that fact makes them an important commodity to study (Mohtashami, 2009). Mohtashami focuses on comparing the performance of alternative time series equations for predicting future consumption. The paper uses standard measures to compare the different time series models; these include mean absolute potential error (MAPE) and RMSE. There are a plethora of time series forecasting models that have been developed to forecast consumption. Those methods can rather plainly be divided into single- and multivariate methods.

CHAPTER 3. THEORY AND METHODOLOGY

Section 3.1. Theory

When looking at future values one needs to understand the inputs involved and the reasons for choosing certain inputs. Studies of expectations have revealed that generally the average of the expectations within an industry will be a more accurate predictor than a single model, and people underestimate changes that do occur (Muth, 1961). This occurs because a rational expectation of an individual is using prior knowledge to deduce what will happen in the future. However, rational expectations will not account for shocks. The main point to take away from the rational thought theory is that if you can come up with a model that better predicts future values then you have an advantage over the competition. The rationality of individuals is also unreliable in many cases. If an individual relies only on their own rationality they may forget certain details, succumb to a personal bias, or any number of things.

Section 3.2. Regression Methods

In single variable methods the future of a variable is modeled based on its past behavior (Mohtashami, 2009). So, for example, dairy consumption in a given period is determined by consumption in the previous time periods. The first single variate time series method is the autoregressive integrated moving average (ARIMA) model. In the ARIMA model the future value of the variable is a linear combination of errors and values from previous periods. An ARIMA equation takes the form:

$$X_t = \theta_0 + \varphi_p X_{t-1} + \cdots + \varphi_p X_{t-p} + et - \theta_1 e_{t-1} - \cdots - \theta$$

In that model X_t is the actual value and e_t is the random error at time *t*. θ and φ are model parameters, and p and q are integers and often referred to as moving average polynomials. It is assumed the random error is independently and identically distributed with constant variance and zero mean. The ARIMA has three identifiable phases: model identification, parameters estimation, diagnostic checking. The other single-variable time series method is double exponential smoothing. Double exponential smoothing is useful when your data has a linear trend. The series that is smoothed is expressed in the equations:

$$F_t = \alpha D_{t-1} + (1-\alpha)(F_{t-1} + T_{t-1})$$

$$T_t = \beta(F_t + F_{t-1}) \quad + (1-\beta)T_{t-1}$$

$$F_{1+t} = F_t + T_t$$

In this case F_t is the forecasted measure at time t whereas D_t is the actual amount at time t. T is the trend variable, α is the smoothing constant, and β is the parameter for trend smoothing.

There are three multivariate methods used as well. The first one is the vector autoregressive (VAR) model. The VAR model can be used to examine the effects that random shocks have on the system of variables. VAR can be modeled as:

$$Q_t = \psi(B)Q_t + \alpha Z_t + \mu_t$$

Where Q_t is the vector of endogenous variables; $\psi(B)$ is a matrix of polynomials in lag operator, B; and Z_t is a vector of exogenous variables that include a constant and the dummy variables. The VAR model uses OLS and the results will vary depending on which variables you choose to include and the chosen lag length. The second method is autoregressive distributed lag (ARDL) model. Values found in ARDL depend on both the previous values of the variable in question and the past and present values of independent variables in the model. ARDL in equation form is:

$$Y(L,P) = \sum_{i=1}^{k} \beta_i(L, q_i)X_{it} + \delta'^{W_t} + \varepsilon_t$$

$$Y(L,P) = 1 - \varphi_1 L + \varphi_2 L^2 - \cdots - \varphi_P L^P$$

$$\beta_i(L, q_i) = \beta_{i0} - \beta_{i1}L + \cdots + \beta_{iq_i}L^{q_i}$$

Where Y_t is the dependent variable, X_{it} is vector of explanatory variables, k number of explanatory variables in the model, $(q_1$,...., $q_t)$ is number of optimal lags of each explanatory variable, p number of optimal lags of dependent variable and W_t is the vector of exogenous variables such as constant, trend and the dummy variables. In ARDL Y_t is the dependent variable, X_{it} is the explanatory variables, and k is the number of explanatory variables in the model.

The last model is the vector error correction model (VECM). A VECM is a restricted VAR model which means that it has co-integration restrictions. VECM uses a maximum likelihood approach. The unrestricted VAR version:

$$y_t = \delta + \Gamma_1 y_{t-1} + \Gamma_2 y_{t-2} + \cdots + \Gamma_p y_{t-p} + u_t$$

The VAR model can be re-parameterized to give the VECM:

$$\Delta y_t = \delta + \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + u_t$$

In VECM Δy_t is a vector, δ is the intercept, the matrix Γ shows the short run relationship between y_t and the matrix Π shows the long run relationship.

When determining which method was the most appropriate for the data there were three measures used (Mohtashami, 2009). The measures were mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean square error (RMSE). The more accurate a forecast is the lower the value of the statistics. An augmented Dicky-Fuller (ADF) test is used to determine the integrated order of the series of data. The conclusion is that VECM outperformed all other models and gave the best estimation for the forecasting of milk consumption.

Another approach that has been taken is the Bayesian VAR (BVAR). The BVAR is able to account for cyclical economic occurrences, and it is able to provide conditional forecasts on the relevant variables (Thraen, 2002). The reason this is the chosen method in this case study is that the author desired a model that did not require one to assume any particular relationship between the variables but it will still reveal relevant properties of the data. Thraen et al shows that the cheese and milk prices are significantly related using the BVAR.

Potatoes are another US crop that experience price volatility, and it is believed that expanding exports could provide price stability (Lin, 1992). In 1989 over half of all US frozen potato exports were sent to Japan, and over the course of the 1980s over 80% of all Japanese frozen potato imports were from the US. This increasing demand in Japan is due to several things: greater economic prosperity, increased female participation in the work force, and the westernization of the Japanese diet. Over this same decade fast food restaurants tripled in numbers in Japan, and they accounted for over 80% of the usage of frozen potatoes. Frozen potatoes are less popular at home in Japan in part due to limited freezer space in many Japanese residences.

When modeling for frozen potato imports in Japan a very important factor is Australian beef and Japanese beef import policies (Lin, 1992). This is because of the high correlation between the consumption of beef and frozen potatoes at fast food restaurants and the fact that most beef consumed in Japan is imported Australian beef. That means that Japanese beef import quotas and beef tariffs are important to importers and exporters of frozen potato products.

The aim of the frozen potato study was not only to examine an under-studied market but was also to forecast future import demand (Lin, 1992). In the study they presume that frozen potato imports are affected by its own historical price, prices of related import commodities, and other demand shifters (such is import quotas or tariffs). Lagged total imports of frozen potatoes was also included in the model in an attempt to account for changing consumer preferences. The second stage of this particular problem is to use the prices from exporting nations to determine where the origins of Japanese imports will be (Lin, 1992). This was modeled using the linear approximate almost ideal demand system (LA/AIDS).

The model was estimated and the coefficients and standard errors were found (Lin, 1992). These estimated models are then used to forecast future potato imports. The future potato imports are affected by the future values of exogenous variables. These values are uncertain and so sensitivity analyses were performed. To make the forecasts they make a few assumptions about future conditions. Then these assumptions are modified to do the sensitivity analysis and show the different possible outcomes. The results showed that imports would continue to be largely determined by hamburger prices and people's changing habits.

Section 3.3. VAR and VECM

The method used in this endeavor will be a multivariate approach. Both multivariate and single-variable methods use past values to predict future values, but multivariate approaches also take into account other independent variables in the model. There are two models that will be used and then it will be determined which is the most accurate model to use. These multivariate approaches are the unrestricted VAR model and the VECM model.

A vector autoregression is a nonstructural model. A structural model is formed under the idea that all of the relationships between variables can all be explained by economic theories. Nonstructural models are helpful when economic theory is insufficient. Economic theory may be insufficient for a variety of reasons such as there being more than one possible structure or the theory could be too complicated to be able to find the exact specifications of a model. The nonstructured model is determined by the data. The only part of the model that needs to be specified to run a VAR model is to declare exogenous and endogenous variables and the number of lags to include to capture the effects of the past values of endogenous variables.

When selecting the number of lags it is important to not pick a number that is too high or too low. For each lag there is another parameter that must be estimated. For each parameter there is one additional degree of freedom lost, the same as there would be for adding another exogenous variable. At the same time using too few lags will mean that the effects of previous values of endogenous values will not be accounted for.

To test the appropriateness of the model a corrected R squared or an Akaike information criterion (AIC) test can be used:

$$AIC = \log\left(\frac{\sum \hat{\varepsilon}_i^2}{N}\right) + \frac{2k}{N}$$

Here k is the number of parameters, N is the number of data points, and ε is the maximized value of the likelihood function for the model. AIC can also be used to determine the optimal number of lags.

Section 3.4. Preparing Data

Before any model can be created the variables need to be tested for unit roots and random walks. This can be accomplished using a Dickey-Fuller test, or by using a modified Dickey-Fuller test known as the DF-GLS test, where GLS stands for generalized least squares. The DF-GLS test is preferable because it is capable of testing 1 to k lags, where k is any number the executor of the test chooses. The difference between how an augmented Dickey-Fuller (ADF) test and a DF-GLS test are performed is that when the DF-GLS test is performed the time series data is transformed by a generalized least squares (GLS) regression before the test is run.

It is important to test for unit roots because a regression performed on data with unit roots will lead to a spurious regression. Spurious regression occurs when two or more variables are correlated related due to correlation with another variable. This means that two random variables might seem to be related when regressed on each other, but when an additional variable is added to the regression there is no longer any correlation. The problem can occur in stationary time series, but it can be solved by including a time trend in the regression.

The need to test for random walks is very similar. Random walks can also lead to spurious regressions. A random walk is when effects from shocks to a variable are permanent and do not go away over time. Detrending will not get rid of the random walk but first-differencing will.

The ADF test fits regressions of the form:

$$\Delta y_t = \alpha + \beta y_{t-1} + \delta t + \vartheta_1 \Delta y_{t-1} + \vartheta_2 \Delta y_{t-2} + \cdots + \vartheta_k \Delta y_{t-k} + \varepsilon_t$$

with a null hypothesis that β equals zero. In this equation t represents the time period, k is the number of lags, α is a constant term, ε is the error term, and the δ is the time trend. The DF-GLS is performed the same way but uses GLS-detrended data. The DF-GLS then gives us the unit root and how many lags need to be used to detrend or smooth the original data.

The DF-GLS is considered more powerful than the standard ADF test. This is because the ADF is based on OLS regression instead of GLS like the DF-GLS test (Kapetanios, 2003). OLS detrending has been showed to significantly decrease the accuracy of the tests it is used in.

A time series is said to be stationary when it has a constant mean, variance, and autocorrelation. Stationary series do not have trends and they are not seasonal. There are several methods that can be used to make a time series stationary: differencing, smoothing, detrending by using residuals after fitting data to a curve, or taking a logarithm or square root. The first method examined here is differencing. Differencing is simple and effective, but it does cause a lot of loss of information about long-run relationships between variables in the regression.

Differencing can be used to obtain a stationary mean and variance. To take the first difference of a variable, *x*, at time, *t*, the following can be used:

$$Dif(1) = x_t - x_{t-1}.$$

The first difference is the change between consecutive observations of the time series. If a time series is stationary after one difference then we say the original series was integrated of order one, or I(1). I(1) indicates a series has one unit root, and I(0) indicates there are no unit roots and the series is stationary. In some cases more than one difference is required. In this case a second difference was needed for several variables. The second difference is produced using:

$$Dif(2) = (x_t - x_{t-1}) - (x_{t-1} - x_{t-2}).$$

The second difference is the change in the change between consecutive variables. Second differences are a relatively rare tool to use. Many avoid it because it will cause you to lose an additional degree of freedom. Differencing beyond order two would be possible, but it is almost never used.

In some cases differencing may not be an effective method to create a stationary time series, if that is the case smoothing techniques can be applied to produce a stationary time series. Smoothing is more appropriate than differencing when data points in the times series are auto correlated with earlier data points in the same time series (Nau, 2014). Smoothing can be accomplished by using a moving average filter. This will create a new series of data where each data point is the average of nearby values in the original series of data. Moving average filters are of the form

$$\hat{x}_t = \frac{\sum_{i=-l}^{f} w_i x_t + i}{\sum_{i=-l}^{f} w_i}$$

where $\hat{x}_t$ is the moving average, x_t is the original data set that needs to be smoothed, w_i are the weights being applied to the terms put through the filter, l is the longest lag in the span of the filter, and f is the longest lead in the span of the filter. Once the data is smoothed it is ready to be used in a model.

Once differencing or smoothing is performed on all non-stationary series the DF-GLS test can be run again. It should show no unit roots if all data was properly differenced.

After that is done it is time to look at the VAR and VECM models. The good thing about these models is that only one of them will be appropriate for any set of data. VAR is appropriate to be used when data is not cointegrated, and VECM is an appropriate approach if they are cointegrated. This means that the first step is to test the data for cointegration. This can be accomplished using the Johansen test, the Johansen test is a good option because it allows for multiple cointegrating relationships.

Using the Johansen test in STATA applies three methods for finding the number of cointegrating equations in a VECM. The first method is Johansen's "trace" statistic method, Johansen's "maximum eigenvalue" method, and the third chooses a number of VECM cointegrating equations to minimize an information criterion (which is the measure of the goodness of fit of a selected statistical model for the data in question). All three models are based on Johansen's maximum likelihood estimators.

The null hypothesis of a Johansen test is that there are no more than *r* cointegrating relationships. For each number 0 through *r* a trace statistic is derived using

$$-T\sum_{i=r+1}^{k}\ln(1-\hat{\lambda}_i)$$

where T is the number of observations and $\hat{\lambda}_i$ are the eigenvalues. If your trace statistic is smaller than your critical value for any given number *r* or less, it means that there are fewer cointegrated equations than that value. This means that if the trace statistic is less than the critical value for maximum rank equals zero, then there is no cointegration present.

The basic VECM is:

$$\Delta y_t = \alpha\beta' y_{t-1} + \sum_{t=1}^{p-1}\Gamma_i \Delta y_{t-i} + \varepsilon_t$$

where *y* is a (*K* x 1) vector of I(1) variables, α and β are (*K x r*) parameter matrices of rank $r<K$. $\Gamma_1, \dots, \Gamma_{p-1}$ are *(K x K)* matrices of parameters, and ε_t is a (*K x 1*) vector of normally distributed errors that is serially uncorrelated but has but has a contemporaneous covariance matrix Ω.

If there is no cointegration present then VECM can be ruled out as an appropriate model. This means that VAR will be an appropriate model to use. A VAR model has *K* variables which are described as linear functions of *p* of their own lags, *p* lags of the other *K*-1 variables, and possibly additional exogenous variables. A *p*-order VAR model, written VAR(*p*), is shown as:

$$y_t = v + A_1 y_{t-1} + \cdots + A_p y_{t-p} + B_0 y_t + B_1 y_{t-1} + \cdots + B_s y_{t-s} + u_t, \qquad t \in \{-\infty, \infty\}$$

where $y_t = (y_{1t}, \dots, y_{Kt})'$ is a $K \times 1$ random vector, $A_1 - A_p$ are $K \times K$ matrices of parameters, x_t is an $M \times 1$ vector of parameters, and u_t is assumed to be white noise. That means $E(u_t) = 0,\ E(u_t u_t') = \Sigma,$ and $E(u_t u_s') = 0$ for $t \neq s$. Σ is a covariance matrix.

Section 3.5. Endogenous Variables

When the model is fit there can be multiple endogenous variables chosen. This allows for the lagged values of all variables chosen as endogenous values to be used in the predictions of the model. Endogenous variables should be any variable whose lagged values are relevant to the current value of the variable being predicted. In this case the goal is to model Chinese imports. Therefore Chinese imports is an endogenous variable. US Exports and Australasia Exports are also included as endogenous variables. Russian imports were not included as an endogenous variable since there are no strong dairy import/export ties between Russia and China.

This method of using multiple endogenous variables creates a system of equations. For each endogenous variable there is an equation. All of the equations have the same independent variables, both the exogenous and the lagged endogenous variables. The dependent variables are the only things that change from equation to equation.

When running a regression it must be considered whether or not any of the variables need to have a logarithm taken. The natural logarithm can be denoted several ways, but a popular form in econometrics is simply:

$$Y = \log(X)$$

The actual equation to find the natural logarithm of X, Y, is:

$$X = e^{Y}.$$

This transformation of a variable is useful in examining time series that have a constant or near constant rate of growth. Things like price or GDP often grow continuously (Michener, 2003). The logarithm of a variable growing at a constant rate is effectively growing as a function of time while the variable itself is growing exponentially. If the variable was growing at a near constant rate over time it would be expected that the logarithm values would appear near linear when plotted, and any deviations from the line fit to the data can show significant data. The deviations show any abnormal periods or shocks that have occurred over time.

Once a model has been fit to the properly lagged data forecasts can be made. The data from the initial forecast can be used to test the significance of each variable. Performing a simple *t* test will show whether each variable is significant enough to bother including it in the model. A simple *t* test is:

$$t = \frac{\bar{x} - \mu}{S_{\bar{x}}} \sqrt{n}$$

where $\bar{x}$ is the sample mean, μ is the population mean, *n* is the sample size, and $S_{\bar{x}}$ is the sample standard deviation. Along with *t* tests *F* tests must also be run to test whether variables that are insignificant on their own are jointly significant. A basic *F* test is

$$F = \frac{MS_{factors}}{MS_{errors}}$$

where MS stands for mean squares.

This is important because excluding relevant variables will create an omitted variable bias. Omitted variable bias can cause inaccuracies in the relationship modeled between the endogenous and exogenous variables and affect the overall accuracy of the model. The omitted variable bias can cause an upward or downward bias, either of which can be serious problems. It is more important how large the bias is than whether it is up or downward.

Leaving in unnecessary variables can also have undesirable side effects. Additional variables mean the number of degrees of freedom you have will drop. Overspecifying the model can also cause a larger standard error. Overspecification may also cause a larger variance amongst the variables' coefficients.

The model found using differenced variables will have a relatively low R-square. This lower R-square can be attributed to the fact that differencing causes a loss of information in the data.

Section 3.6. Exogenous Variables

Once a VAR model is created we must find forecasted values for the exogenous variables so we can apply the VAR model and use it for forecasting. This can be done by fitting each variable to a time series distribution. The distribution is then used to create univariate forecasts, or unconditional forecasts, for the individual variables which can then be fed into the VAR model. This is necessary for any variable for which future values are unknown, and for most economic variables the precise future values are unknown.

The variables first need to be transformed into a stationary series and then they can be fit to a distribution. Some common distributions are the Autoregressive, Moving Average, Autoregressive moving average:

$$AR(1)\colon X_k \;=\; \rho_1 X_{k-1} \qquad k = \; 0, \pm 1, \pm 2, \ldots$$

$$AR(2)\colon X_k \;=\; \rho_1 X_{k-1} + \rho_2 X_{k-2} \qquad k = \; 0, \pm 1, \pm 2, \ldots$$

$$MA(1)\colon X_k \;=\; \mu + \rho_k \;+\; \rho_1 W_{k-1} \qquad k = \; 0, \pm 1, \pm 2, \ldots$$

$$MA(2)\colon X_k \;=\; \mu + \rho_k \;+\; \rho_1 W_{k-1} + \rho_2 W_{k-2} \qquad k = \; 0, \pm 1, \pm 2, \ldots$$

$$ARMA\colon X_k \;=\; \rho_1 X_{k-1} + \rho_k - W_1 \;\; \rho_{k-1} \qquad k = \; 0, \pm 1, \pm 2, \ldots$$

X_k represents the data set being fit to a distribution, μ is the intercept, ρ is the lag weight, and W is a white noise error term. These techniques can be used to model univariate forecasts. These distributions are chosen for each variable based on the AIC and Bayesian information criterion (BIC) criteria. No time series is going to fit any distribution perfectly so it is important to weigh pros and cons of all before selecting one to fit your data and predict future values.

An alternative to univariate forecasting is to analyze different scenarios. This can account for external shocks that a model may not anticipate. A prime example is the recent Russian sanctions on top dairy producers. Instead of creating a univariate forecast we can assume that the import amounts will remain low and substitute in those numbers, or a scenario can be created where the numbers go back up before the sanctions are scheduled to be lifted to compare the effects of the sanctions lasting for longer or shorter periods of time. Similar techniques could be applied to any variable.

CHAPTER 4. DATA

When setting up a multivariate regression the selection of variables is important to the accuracy of the model. It is important not to leave out relevant variables. At the same time including unnecessary variables will decrease the degrees of freedom the model has and the accuracy of the model.

The data in this case is time series data. The main characteristic that distinguishes time series data from cross-sectional data is that it follows a chronological order instead of being a random sample from within a larger population. Time series variables are still viewed as random variables since their future values are uncertain, it is impossible to guarantee how many gallons of milk the United States will produce in the next year. People can speculate, make an educated guess, or forecast the value but there is no certainty.

Section 4.1. Data Sources

The data for this project includes several series of prices, import quantities, export quantities, and some social indicators. The objective of this project is to determine the best multivariate forecasting method to use on dairy imports. The imports being forecast is the Chinese import quantity for skim milk powders (SMP). Chinese price data is difficult to find and the series being used is the compiled price of milk powders, solid milk, and cheese. This time series and the way it fluctuates will serve as a proxy for the Chinese SMP price.

Skim milk powder was the chosen commodity for several reasons. It is a common export from key dairy exporting nations, which means that the data is readily available on exports and prices from most major dairy producers. The imports of SMP have risen steadily in China as Chinese dairy consumption grows and changes. SMP has also been one of the most common dairy exports from the US to China.

It is important when discussing a particular product to be precise and accurate. It is important to note that while the terms “skim” and “non-fat” are often used interchangeably when discussing dairy product non-fat dry milk and skim milk powder are not the same thing. Nonfat dry milk and skimmed milk powder are similar; both are manufactured by removing water from pasteurized skim milk, contain 5% or less moisture by weight, and they contain 1.5% or less milkfat by weight (U.S. Dairy Council). The difference between the two is that skimmed milk powder has a minimum milk protein content of 34% and nonfat dry milk has no standard protein level.

Skimmed milk powder is classified for use as ingredients according to the heat treatment used in their manufacture (U.S. Dairy Council). The trade and price data for SMP that has been collected is for SMP in general and does not focus on any particular level of heat treatment. SMP is commonly used as a relatively inexpensive source of nonfat dairy solids. High-heat SMP is used to obtain higher volume in bread loaves. Low-heat SMP is important for optimizing sensory properties in dairy foods and beverages. However, the main appeal of SMP is that it is easier to transport and store than most dairy products, a characteristic that makes it ideal for being shipped long distances and to destinations without readily available refrigeration.

By far the most difficult data to locate was the Chinese data. The source for Chinese imports and prices was Bloomberg, and Bloomberg’s source for the data was China Customs Statistics. There was information on Comtrade and several sites, this information could not be used because the data ends at December 2012. The reports from the United States Department of Agriculture Foreign Agricultural Service stop after 2012 as well. China was chosen as the importing country to look at because they are both the largest importer of dairy products in the world, but they also have a demand that is still projected to grow for years to come.

The production for the US was collected from the USDA website. Production data shows the amount of SMP produced in the US for that particular month in thousands of pounds. Production data is important when working with exports and prices. As production, or supply, fluctuates so must the prices and export quantities in order for the market to find a short-term equilibrium.

The price data for the US came from the University of Wisconsin Dairy Marketing and Risk Management Program (University of Wisconsin). These prices are in US dollars and are the per pound prices. US prices are important due to the importance of US exports in the world market. US prices are also important to US producers because they determine how competitive US products are on the world market.

The export quantities for the US were found on Comtrade (Comtrade). Export quantities from Comtrade are given in kilograms, which were then converted into thousands of pounds to match the production quantities. The quantities of exports from the United States are important as the United States is a large exporter of dairy products. The US also has growing potential for production and stagnant demand, implying that their presence on the international market will only grow in the years to come.

The Australasia data for prices and exports were found on Comtrade, the data is for Australia and New Zealand only (Comtrade). Australasia technically includes Papua New Guinea and several smaller islands as well, but their production is small enough it was decided to exclude them. The price and exports from Australasia are included in the determination of Chinese imports because Australasia is the largest exporter of dairy products in the world. This means that their prices and supply have a large effect on prices and imports in other countries around the world.

The world price data was found using Comtrade. Comtrade compiles data from all reporting nations in both monthly and annual formats. The world price determines the competitiveness of import and export prices of countries around the world. It is also a benchmark for determining how well the global market is doing.

The world and Chinese production data was gathered from the USDA. The USDA only had annual production so those numbers were divided out over twelve months; the percent attributed to each month of the year was based on the average percentage of yearly production from 2000 to 2014 in the US production numbers. World production is important to show how strong supply and demand are. The world production is a factor in exports, imports, and prices around the world. Chinese production is also extremely important as it determines the domestic supply available and therefore determines the amount of foreign imports that are needed to meet domestic demand.

Due to the recent upheaval regarding Russian dairy imports the Russian import quantities of skim milk powder were also included in the study. Russia is the second largest dairy importer in the world and any sudden changes in their import quantities could have significant impact on Chinese imports as well as prices around the world. The import data from Russia was obtained from Comtrade. Large fluctuations in Russian imports, either in general or from specific importers, will affect the exports of large exporters and in turn the prices. Russia has stopped imports from Australia and the United States, this will cause a lag in demand and in turn is likely to impact world prices which have already been depressed for a good part of the year.

The last price variable included was the skim milk powder global price index. This information was found on the Global Dairy Trade website. Some months had two values listed, one for the beginning of the month and one for the middle of the month. The value at the beginning of each month was the value used (Global dairy Trade). Price indices are calculated and used because they avoid biases that can show up in normal averaged prices. The biases in prices occur because of the change in quantities sold in different periods.

For US dairy export quantities Comtrade only had reports through May 2014. The value for June 2014 was taken from the U.S. Dairy Export Council. US exports are important to import quantities and prices in major trade partners. Since this paper focuses on Chinese imports from the perspective of current or potential US exporters it is important to include the US export numbers in the analysis.

China GDP growth is also included in the model. GDP is a good proxy for measuring the size of the economy as a whole. As GDP grows other things tend to grow as well. GDP growth can indicate income growth which will in turn lead to people have more money, which means they spend more money. Dairy products are generally considered a luxury good, and many dairy products require special storage whether it is refrigeration or kept cool and dry like milk powders. As GDP grows so does the consumption, and by extension the imports, of dairy products.

China female participation in the labor force (FPLF) is also included in the examination of Chinese imports. The FPLF shows what percent of working-aged women in a country are active in the work force. The FPLF is important as the increase in women working means that women are increasing their families' total income and therefore the amount of income that can be allotted to purchasing higher end food products or even products like refrigerators. A woman participating in the labor force also gives her a larger role in determining how the household money is spent (Lim, 2002).

The Chinese urban population is the last variable. The urban population is included for several reasons. People in urban areas cannot produce their own food. As more people live in cities more people need to shop at grocery stores and have storage within their living area for food. This shift makes grocery stores more common which exposes people to a wider variety of food choices. Urbanization also means more land is covered by urban sprawl and less can be used in the production of food (Chen, 2007). This urbanization will make it more difficult for China to feed themselves and play a large role in the amount of food products, including dairy, that need to be imported to feed their growing population.

Section 4.2. Summary Statistics

Table 1 shows the summary statistics for all of the variables in the raw data and Table 2 shows the summary statistics for all of the variables edited for the regression. The mean shows the average value of each variable. The standard deviation shows the degree of variation from the actual values to the mean value. Skewness shows whether the distribution is symmetric around the mean or if most of the values fall above or below the mean. Kurtosis looks at the thickness of the tails of a distribution. Skewness and kurtosis both deal with the shape of the distribution of values.

Table 1: Data Summary Statistics

Variable	Units	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
World Price Index	-	1310.907	271.8987	924	1952	.668	2.3419
World Price	US Dollars	1.6308	0.2283	1.06	2.0956	.1814	2.5055
World Production	1000 tonnes	682.4935	112.7108	457.441	880.084	-.2071	2.1631
Chinese Imports	1000 lbs	121362.6	69913.96	33437.2	350692	1.4447	4.6776
Chinese Production	1000 lbs	10.2871	1.4765	7.2695	12.5947	-.4791	2.1081
Chinese Price	US Dollars	1.7245	0.2964	1.2355	2.3157	.8122	2.5323
US Price	US Dollars	1.4836	0.2779	1.0459	2.1007	.492	2.3843
US Production	1000 lbs	134136	26778.01	74026	194828	.0777	2.7545
US Exports	1000 lbs	143318.6	65821.32	21471.6	282121	.4648	2.5236
AU Price	US Dollars	1.7395	0.371	0.8987	2.8496	.7961	3.9882
AU Imports	1000s lbs	89560.45	31259.23	28854.6	173582	.3905	3.1693
Ch GDP Growth	Percentage	8.8519	0.9956	7.6526	10.447	.0926	1.4367
China LFPR	Percentage	69.6621	0.1859	69.2942	70	-.0176	1.9902
Chinese Urban Pop.	1 Person	6.85E+08	2.70E+07	6.39E+08	7.31E+08	.0089	1.8151
Russian Imports	Lbs	12582.71	6054.388	3512.158	27695.49	.4617	2.8326

Table 2: Variable Summary Statistics

Variable	Units	Mean	St. Dev.	Variance	Skewness	Kurtosis
WPI1Dif	-	8.5228	125.7445	15811.67	1.2861	7.7789
World Price	US Dollars	1.6366	0.2307	0.0532	0.1177	2.475
World Production	1000 tonnes	683.8675	114.6651	13148.08	-0.2394	2.1103
ChIm2Dif	1000 lbs	3311.225	52327.84	2740000000	0.1254	3.0791
China Production	1000 lbs	10.2936	1.5046	2.2638	-0.4836	2.0412
ChP1Dif	US Dollars	0.016	0.0701	0.0049	0.471	3.4801
USP1Dif	US Dollars	0.0107	0.0711	0.0051	-0.4243	2.6748
US Production	1000 lbs	134556.9	27187.33	739000000	0.0347	2.6897
USEx1Dif	1000 lbs	4669.585	26084.32	680000000	0.7504	5.7639
Australasia Price	US Dollars	1.7442	0.3769	0.1421	0.755	3.851
Australasia Exports	1000s lbs	89993.3	31587.1	998000000	0.3673	3.1252
ChGDPGrowth1Dif	Percentage	-0.0191	0.1007	0.0101	0.2185	1.4769
FemaleLFPR	Percentage	69.6594	0.1882	0.0354	0.0155	1.9593
ChUrbanPop1Dif	1 Person	1731334	38164.16	1460000000	1.1655	3.6621
RusIm1Dif	lbs	-24729.3	2745893	7.54E+12	-0.0666	4.2473

One of the interesting things that can be seen is the difference between the maximum and minimum. Among the prices it is a rather large difference of over a dollar for all four prices represented. There were also several variables with large standard deviations. Chinese imports, US exports, and Russian imports have about the highest variation proportionally, but AU imports also have a rather large deviation. These large deviations are most likely due to the fact that these variables are both on a general upwards trend and experience a seasonality factor.

Some of the variables also had notably small deviations. Even though the price variables had a large difference between their min and max they have small standard deviations. The Chinese female labor force participation rate and the Chinese urban population both have a small standard deviation. This is because the Chinese female LFPR changed very little over the period. The urban population changed by a relatively large amount, but it was a steady climb without any signs of seasonality or large shocks.

All the variables have multiple data points that create a time series. A time series can be fit to a certain type of series. The types used for the variables in my data were the Autoregressive, Moving Average, Autoregressive moving average, and Block Matrix-based Multiple Regularization (BMMR) method. They can also be used to identify a series with a nonstationary mean or variance. The SMP world price index, China Imports, US price, and US exports all follow a moving a first degree moving average model. US production follows a second degree moving average model. World production, Chinese production, and Australasia production all follow a second degree autoregressive model. Chinese price, Chinese GDP growth, and Chinese female work force participation rate all follow the ARMA(1,1) model. The ARMA is a combination of moving average and autoregressive methods. World price, Australasian exports, Chinese urban population, and Russian imports all follow the BMMR method.

Below are graphs of the variables over the analyzed period. The first graph shows the changes in the SMP world price index. Below it is a graph showing the change in the US price, Australasian price, Chinese price and the world price. It is clear to see that the prices tend to move together. While they are not generally the same they are close to one another and move the same direction most periods.

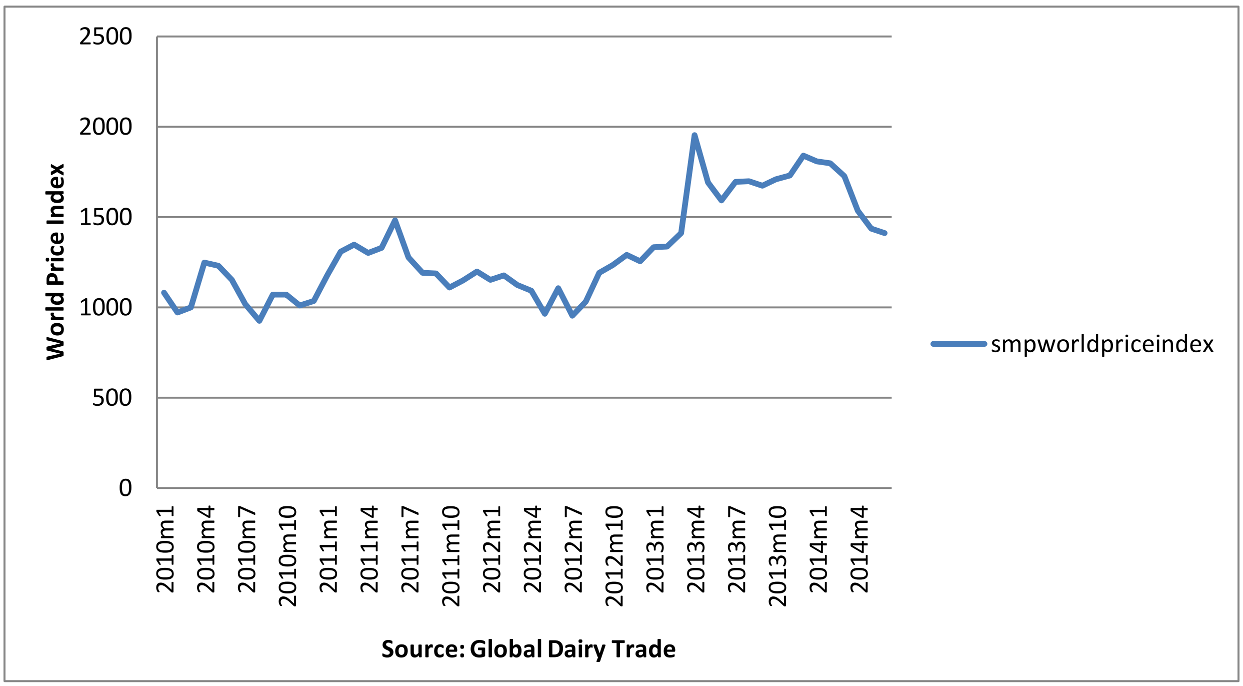

Figure 1: SMP World Price Index

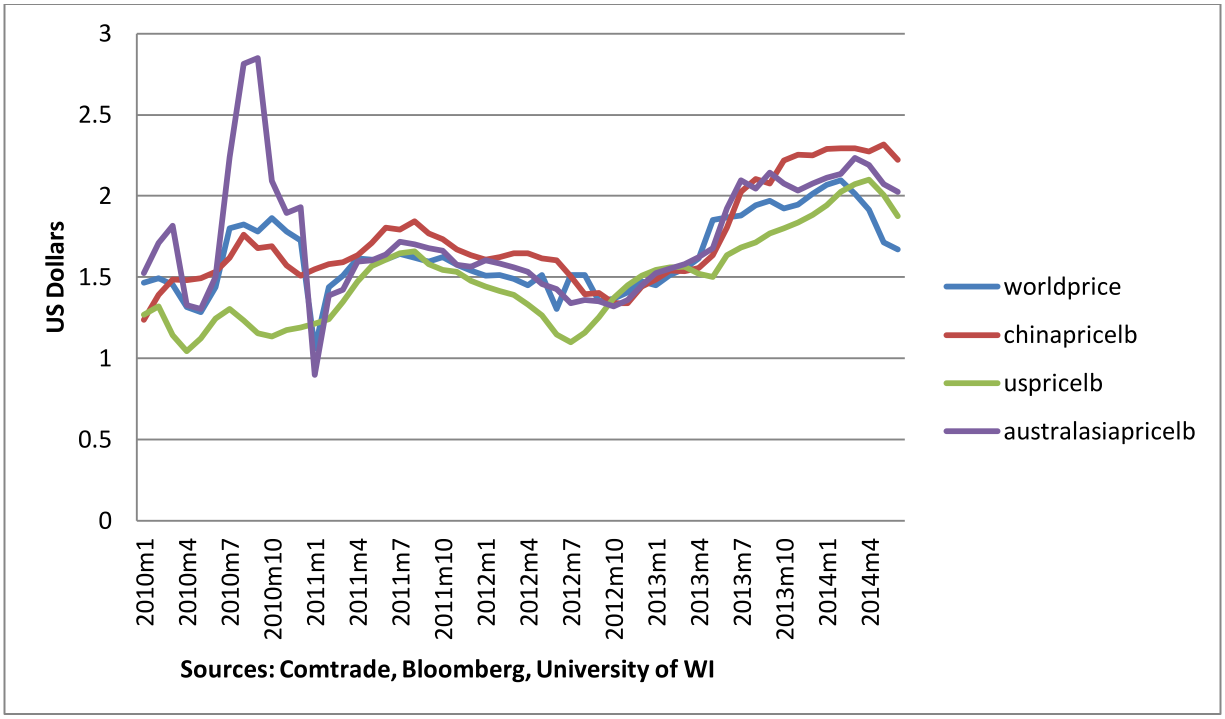

Figure 2: SMP Price per Pound

The graph below prices divides the world price index to a level where its fluctuations can easily be compared to those of the raw prices. This further illustrates how the world price index and various prices all tend to move together. This view also shows when there may have a shock to one data set. For example, it is clear that Australasian prices suffered a shock causing prices to spike in the second half of 2010.

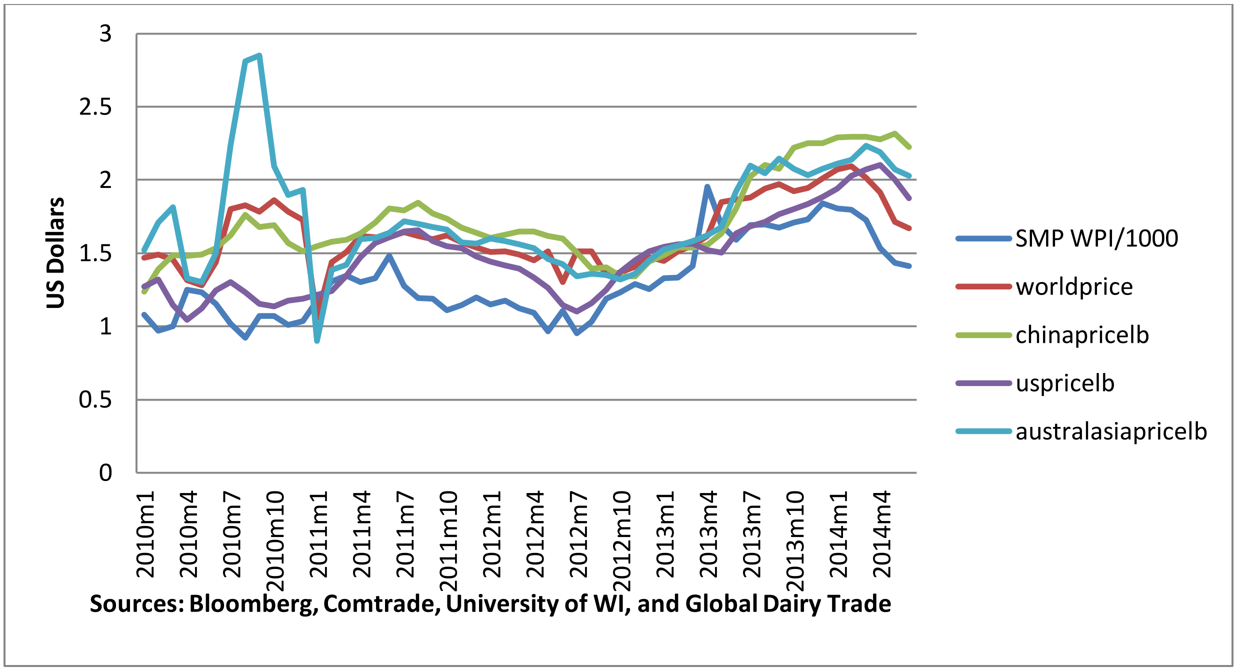

Figure 3: Prices and World Price Index

The graphs of production also show some key things. The first thing to notice is that there is seasonality production. For the US, for example, it is clear that the peak in yearly production happens around May of each year. Production in China also tends to peak around the month of May. This is not surprising since both countries have similar climate and seasons play a role in the quantity of production.

Looking at the graphs it also becomes clear that several of the variables are following an upward trend. US exports have been growing steadily over the period, but they experienced a relatively large jump in late 2013. The two are probably related. Also related would be the fact that the growth in US exports was during the months when Dairy production in the US was on the upswing.

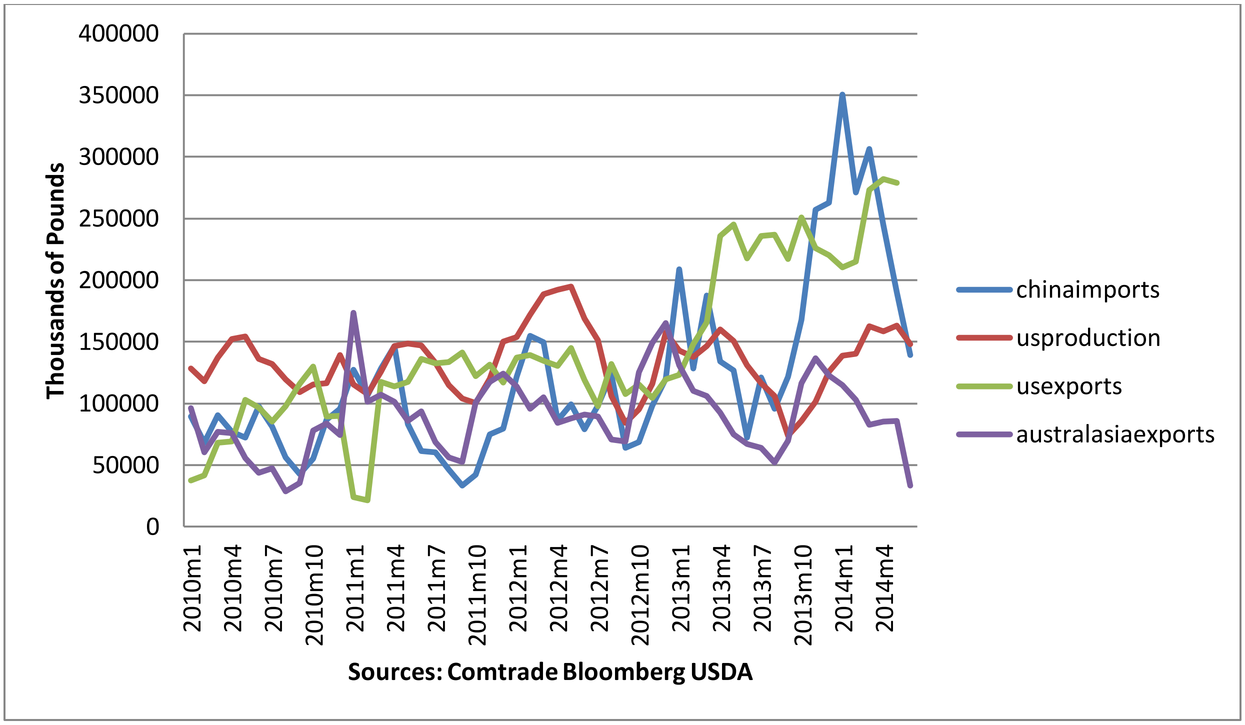

Figure 4: SMP Exports, Imports, Production

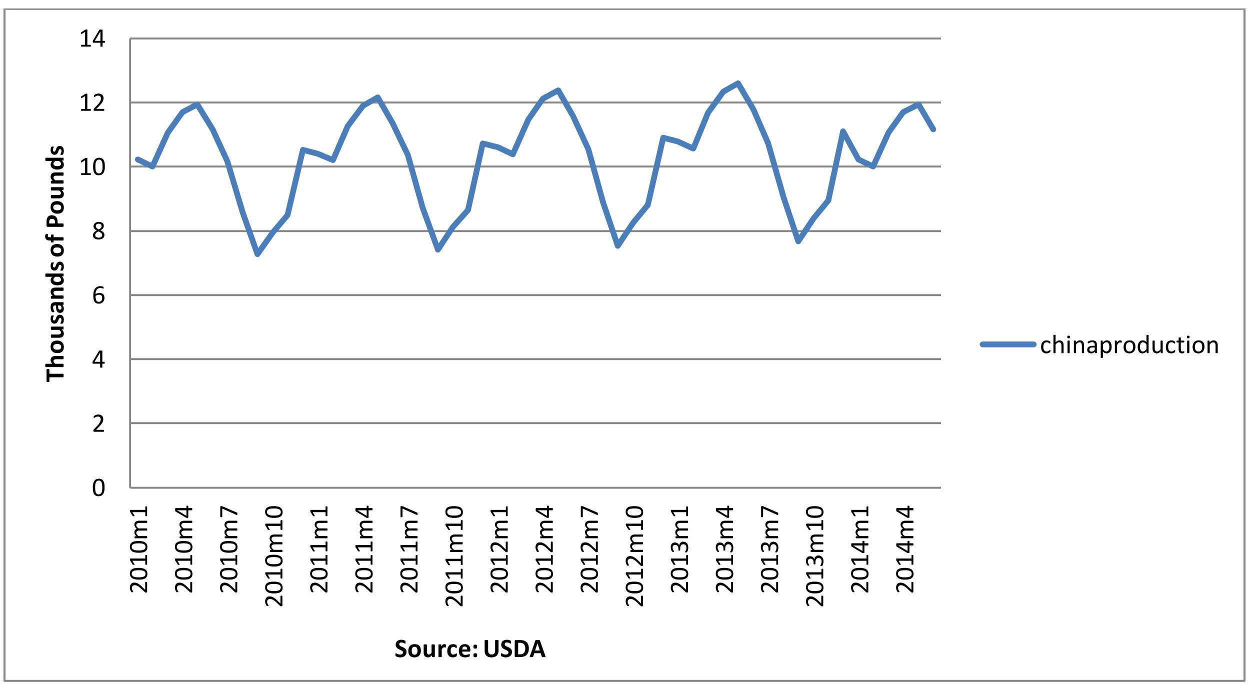

Figure 5: China SMP Production

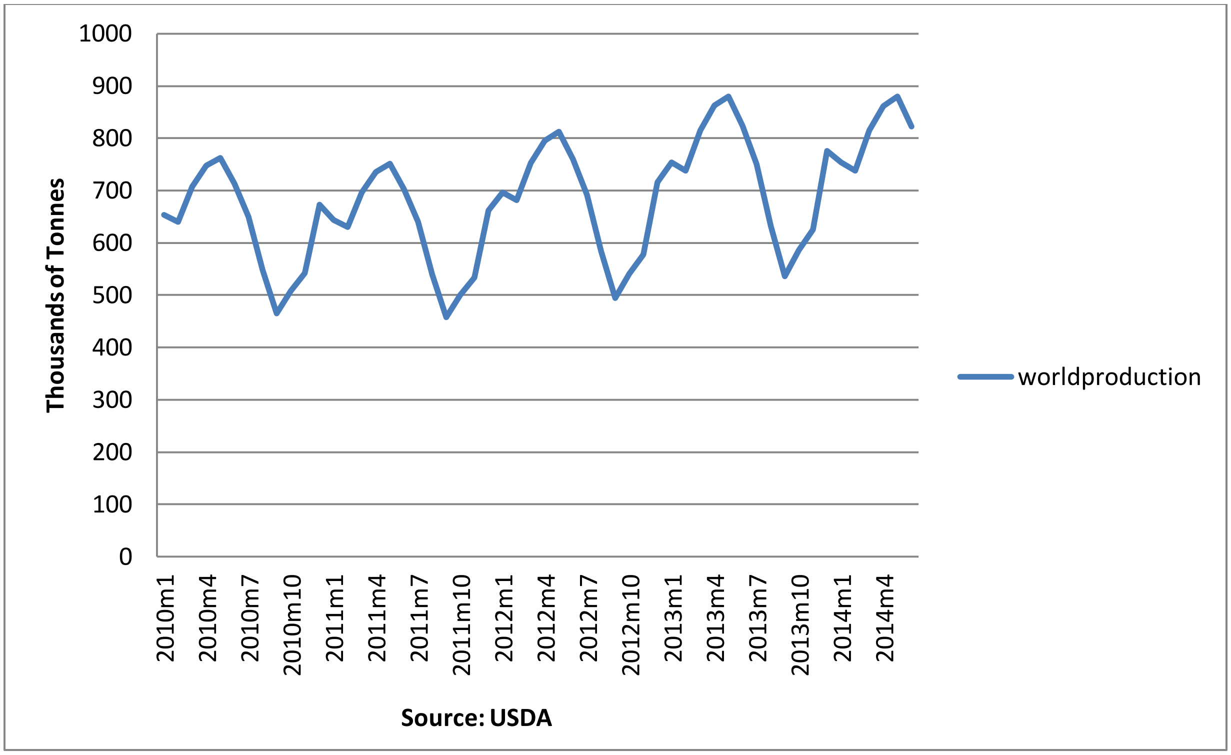

Figure 6: World SMP Production

Below is a graph of Russian imports. Russian imports grew over the last two years but were quite low in 2011. These numbers will most likely drop once again for the last quarter of 2014 and the beginning of 2015. The Russian embargo on dairy products from many of the top dairy producers will cause them to struggle to meet demand. They are still willing to accept foodstuffs from New Zealand which is where much of their trade can be expected to come from.

China is still a developing country. For this reason the GDP growth rate, urban population, and female labor force participation rate are important in shaping the consumption patterns of the population of the entire country. Dairy is considered a luxury item and is more costly than many food sources. The GDP growth rate of China illustrates how quickly the income of the country is changing. While the growth rate fluctuates from year to year it has been going up steadily over the observed period. Increased income means increased spending on luxury items like dairy products.

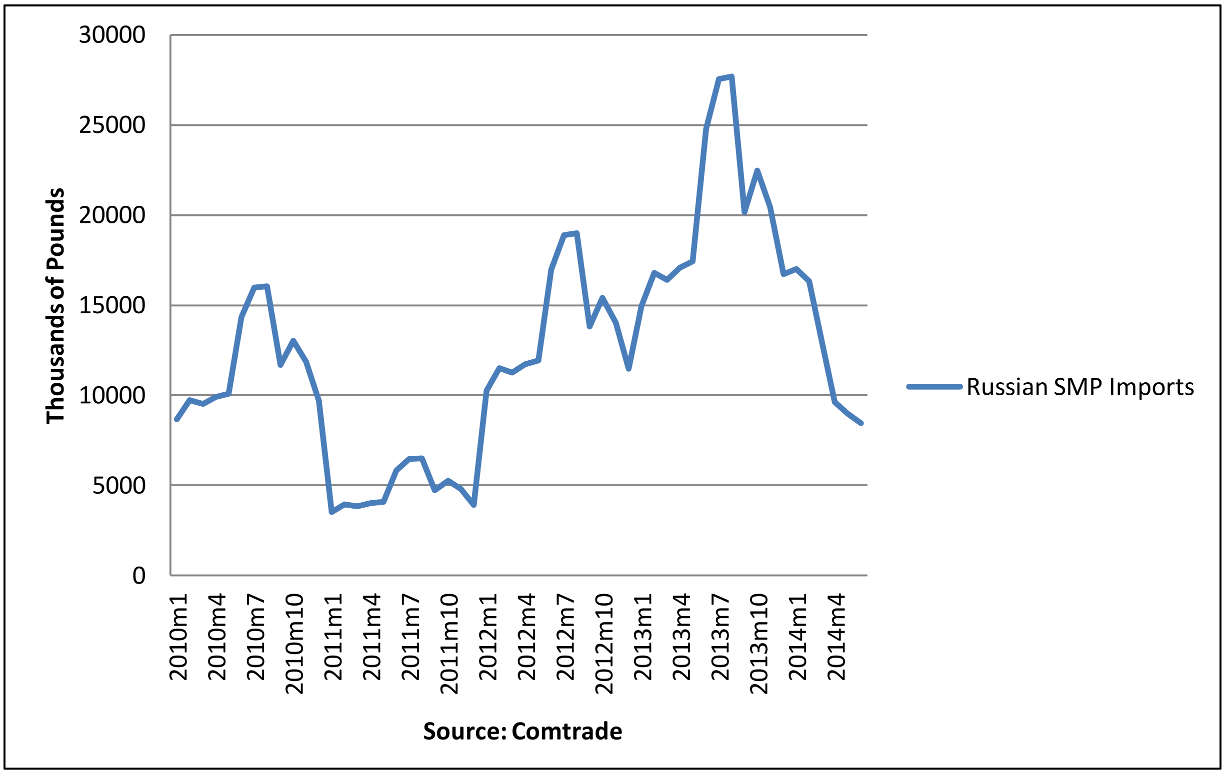

Figure 7: Russian SMP Imports

Urban population and the female labor force participation rate represent changing demographics that influence purchasing patterns. As urban areas grow the access to refrigeration grows, and the number of people who can produce their own food dwindles. This means people will have a greater demand for store-bought, refrigerated products. The female labor force participation rate has gone up and down in recent years, but at over 69 percent it is probably not going to grow much higher.

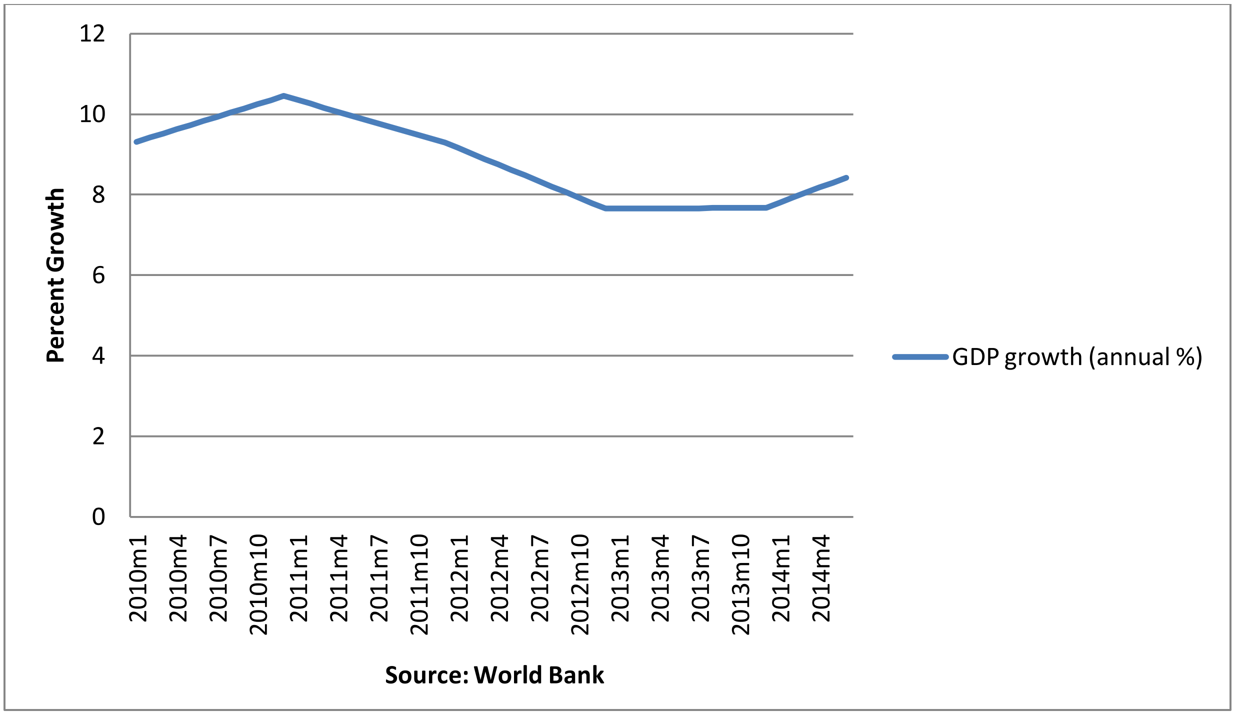

Figure 8: China GDP Growth

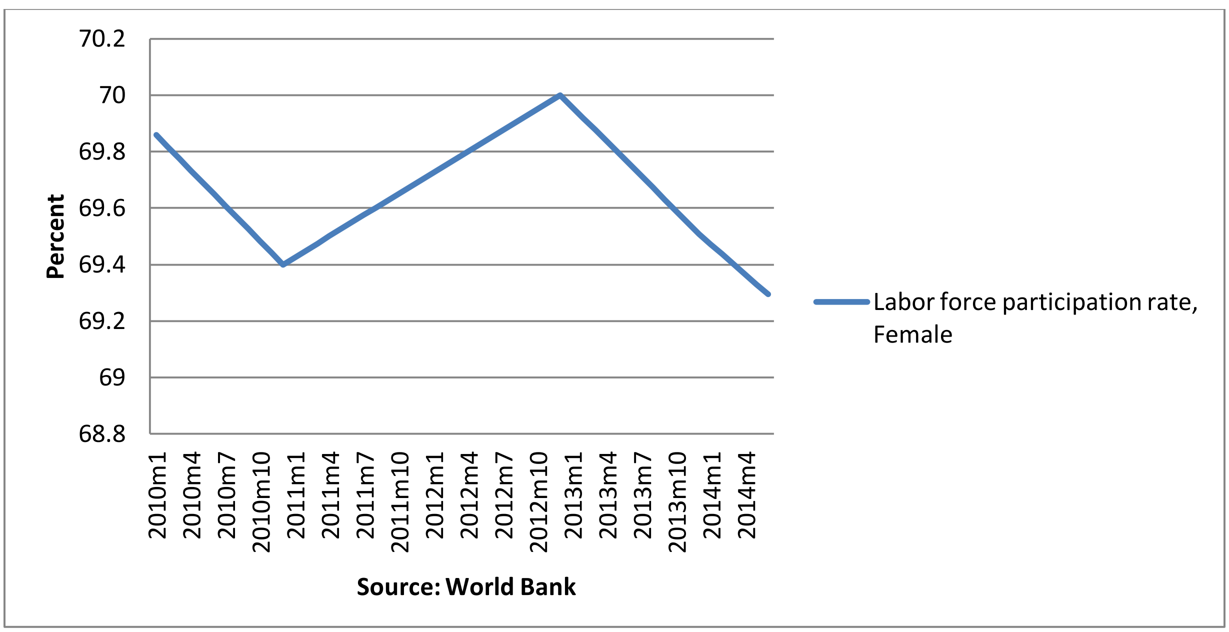

Figure 9: China, Female Labor Force Participation Rate

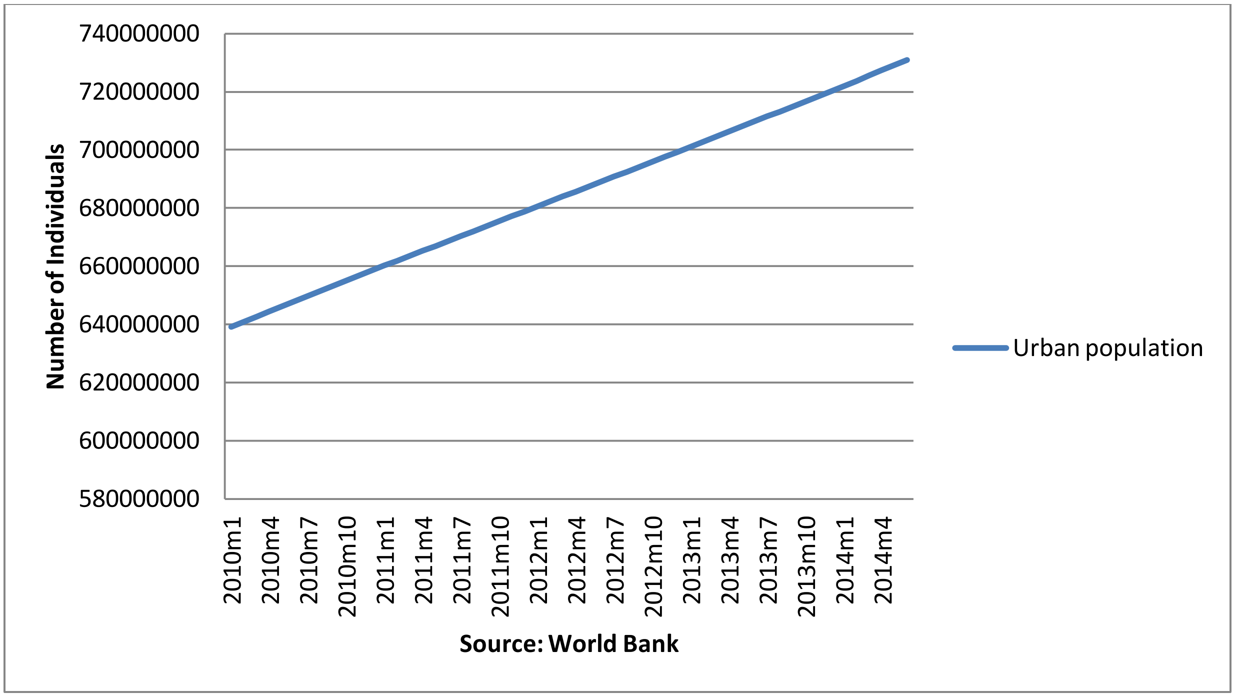

Figure 10: Chinese Urban Population

Section 4.3. Preparing Data for Regression

Nonstationarity in a time series can decrease the accuracy of any regression that is run. In this case all of the data was either stationary or required only first or second differencing. First differencing is when you subtract $W_k - W_{k-1}$, second differencing is $W_k - W_{k-2}$, etc. For each level of differencing a data point must be discarded. Since first differencing was required one data point was lost. Some of the other originally nonstationary variables were stationary after taking the natural logarithm.

There were a few variables that were stationary without any manipulation. China production, US production, Australasian exports, and the female labor force participation rate were all stationary without any transformation. Taking the natural logarithm of world price and Australasian price was enough for stationary means. The SMP world price index, world production, Chinese imports, US exports, Chinese GDP growth, Chinese urban population, and

Russian imports all had a stationary mean after undergoing first differencing. US prices and China prices are the last two variables; they both required first differencing and taking the natural logarithm to find a stationary mean.

CHAPTER 5. RESULTS

Section 5.1. Cointegration Results

The first step in estimating a multivariate model was determining which type of model the data fit. The Johansen test for cointegration showed that there was no cointegration and that a VAR model would be appropriate for modeling skim milk powder imports and exports. These results can be found in Table 3.

Table 3: Johansen Cointegration Results

Maximum Rank	Parms	LL	Eigen Value	Trace Statistic	5% Critical Value
0	156	-2700.57	.	592.4092*	.
1	179	-2638.44	0.91672	468.1328	277.71
2	200	-2588.56	0.86398	368.3854	233.13
3	219	-2548.71	0.7969	288.6815	192.89
4	236	-2514.1	0.74957	219.4531	156
5	251	-2487.13	0.65989	165.5291	124.24
6	264	-2462.51	0.62657	116.2779	94.15
7	275	-2440.91	0.57847	73.0847	68.52
8	284	-2422.36	0.52393	35.9749	47.21
9	291	-2413.09	0.3096	17.4509	29.68
10	296	-2407.78	0.19149	6.8228	15.41
11	299	-2404.37	0.12746	0.0053	3.76
12	300	-2404.37	0.00011		

Note: The asterisk is next to the trace statistic of the value r at which all variables are stationary.

Section 5.2. VAR Results

STATA statistical modeling software was used to fit the data to an appropriate VAR model. Chinese Imports, US Exports, and Australasia Exports of skim milk powder were all included as endogenous variables. Russian imports were not chosen as an endogenous variable, this is because the main focus was on finding Chinese imports of SMP. China and Russia are both mostly importers of SMP. This means that there is relatively little trade between the two nations and therefore the lagged values of Russian imports will not have the same effect as the lagged effects of US and AU exports.

The lagged values of Chinese imports and US and AU exports then became exogenous variables. The coefficients, standard errors and the significance level are all indicated in Table 4. The coefficients' values can be found in Table 4. The coefficients complete the system of equations. The regression found that most of the variables were significant at the 10% level or higher for at least one of the equations in the system of equations.

Some variables that were not found significant were still left in the model. While this uses up degrees of freedom there were some variables that common sense tells us are relevant even if they were not within the ten percent significance level. For example, the Chinese imports equation shows Chinese production and prices as being insignificant at the ten percent level. They are left in for two reasons. The first reason is that Chinese production and Chinese and Australasian prices are all significant in at least one of the other equations. The other reason is that even if they were not significant at a certain level, common sense tells us that they should have at least a small effect. Chinese production will dictate how much of its demand is met domestically and how much will need to be imported.

Similar to Chinese Imports, US exports shows that US production and multiple prices are not significant at the ten percent level. Again, US production is important because it will dictate how much stock there is that can be exported. The prices are either significant in other equations or they can similarly be argued for. US price for example is important as it determines how competitive US exports are on the world market and therefore how many US exports there will be.

The Australasian exports equation is interesting for several reasons. It was the only equation that found any price variables significant at the ten percent level. It was also the only equation that did not at least one lag of all three endogenous variables to be significant at the ten percent level. In this equation neither the first nor second lag for US exports or Chinese imports was significant.

The data was run using China Imports, Australian Exports, and United States Exports as endogenous variables. This means that all three were found using the first and second lagged value of itself and the other two endogenous variables to help improve the accuracy of the model. This method produces the following system of equations:

$ChIm1Dif =$

$I + C_1(ChIm1Dif1L) - C_2(ChIm1Dif2L) + C_3(USEx1Dif1L) + C_4(USEx1Dif2L) +$

$C_5(OcEx1L) + C_6(OcEx2L) + C_7(WPI1Dif) + C_8(WProd) + C_9(ChProd) +$

$C_{10}(ChP1Dif) + C_{11}(USP1dif) + C_{12}(USProd) + C_{13}(OcP) + C_{14}(ChGDPGr1Dif) +$

$C_{15}(ChFemLFPR) + C_{16}(ChUrbanPop1Dif) + C_{17}(RusIm1Dif)$

Table 4: Regression Results for Chinese Imports, United States Exports, and Australasian Exports of Skim Milk Powder

	Chinese Imports		US Exports		Australasia Exports	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
ChinaImDif1L1	-0.3001**	0.13	-0.2629***	0.0839	0.0345	0.0665
ChinaImDif1L2	0.3148**	0.1367	-0.2048**	0.0882	0.0419	0.0699
UsExDif1L1	0.0779	0.1763	-0.2667**	0.1137	0.0867	0.0901
UsExDif1L2	-0.7529***	0.1881	-0.1957	0.1213	-0.0463	0.0962
AUExL1	0.4539**	0.2176	-0.2114***	0.1404	0.2933***	0.1113
AUExL2	-0.4725**	0.2329	0.5917**	0.1503	-0.0067	0.1191
WPI1Dif	2.0404	38.9171	64.1122**	25.1111	9.8496	19.8999
WProdDif1	133.5835*	75.2706	96.2379**	48.5681	259.2753***	38.489
ChProd	-6287.26	8213.046	-2075.65	5299.44	-7751.43*	4199.667
UsProd	0.1083	0.4126	0.2136	0.2662	-0.1421	0.211
GDPGrowthChDif1	149963.9	115301.6	115439	74397.95	-159528***	58958.42
ChFemaleLFPR	27713.6	29516.21	18437.72	19045.23	-19153.7	15092.85
ChUrbanPopDif1	-0.375	0.2589	-0.2639	0.167	0.3744***	0.1324
RussiaImDif1	0.0038**	0.001841	0.0006	0.0012	0.000001	0.0009
lnWorldP	114952.1	76552.43	32221.66	49395.2	49865.22	39144.4
lnChinaPDif1	-57232.1	132417.8	-43932	85442.13	253158.7***	67710.64
lnUsPDif1	110882.9	114641.4	95063.14	73972	-75899.6	58620.87
lnAUP	-52958.9	62285.98	31074.57	40189.82	-98750.7***	31849.38
Intercept	-1250838	2090257	-892591	1348731	871752.8	1068834

Note: Asterisks indicate statistical significance at the 10% (*), 5% (**), and 1% (***) level, respectively.

$$USEX1Dif = I + U_1(ChIm1Dif1L) - U_2(ChIm1Dif2L) + U_3(USEx1Dif1L) + U_4(USEx1Dif2L) + U_5(OcEx1L) + U_6(OcEx2L) + U_7(WPI1Dif) + U_8(WProd) + U_9(ChProd) + U_{10}(ChP1Dif) + U_{11}(USP1dif) + U_{12}(USProd) + U_{13}(OcP) + U_{14}(ChGDPGr1Dif) + U_{15}(ChFemLFPR) + U_{16}(ChUrbanPop1Dif) + U_{17}(RusIm1Dif)$$

$$AUEX = I + A_1(ChIm1Dif1L) - A_2(ChIm1Dif2L) + A_3(USEx1Dif1L) + A_4(USEx1Dif2L) + A_5(OcEx1L) + A_6(OcEx2L) + A_7(WPI1Dif) + A_8(WProd) + A_9(ChProd) + A_{10}(ChP1Dif) + A_{11}(USP1dif) + A_{12}(USProd) + A_{13}(OcP) + A_{14}(ChGDPGr1Dif) + A_{15}(ChFemLFPR) + A_{16}(ChUrbanPop1Dif) + A_{17}(RusIm1Dif)$$

The next things to look at are the graphs of the impulse response functions (IRFs). These can also be generated in STATA. An IRF shows the effect of a shock to an endogenous variable on itself or on another endogenous variable. Since this particular VAR model has three endogenous variables there are nine IRFs.

The IRF names consist of three things: IRF name, impulse variable, response variable. The line shows the response to the shock, and the gray area around it shows the 95% confidence interval for the impulse response. Since the series are all stationary the effects of a shock are not persistent and they all die out in time. This trend can be observed in all nine graphs as the IRF becomes flatter and the 95% confidence interval gets smaller.

Section 5.3. Interpreting Results

Comparing the impulse response functions it is immediately obvious that Australasian exports have a smaller response to all of the IRFs where they are the response variable. Chinese imports as the response variable experience the greatest changes in the impulse function showing wild swings up and down and is still noticeably not at equilibrium after the eight periods shown in the graph. US exports as the response variable show a larger response in the IRFs than the AU exports, but it does come closer to equilibrium than the IRFs where Chinese imports are the response variable.

Table 5 demonstrates how effective the model is for forecasting. Table 5 compares the actual values of Chinese imports and AU and US exports to the values predicted by the model. The third section shows the residuals, the residuals are merely the difference between the actual value and the predicted value. These values can also be used to find the RMSE. The RMSE is very low US exports. The RMSE is not quite as low for Chinese imports relative to the actual values of Chinese imports. The RMSE was almost 40% of the actual value of Australasian exports in their month with the lowest exports. This looks bad, but it is somewhat deceiving since the variation in export amounts was very high over the examined period.

Since this variation over the time period can cause the RMSE to look bad in some periods the error for each individual point can be examined. Table 7 does just this by showing the error as a percentage of the actual value.

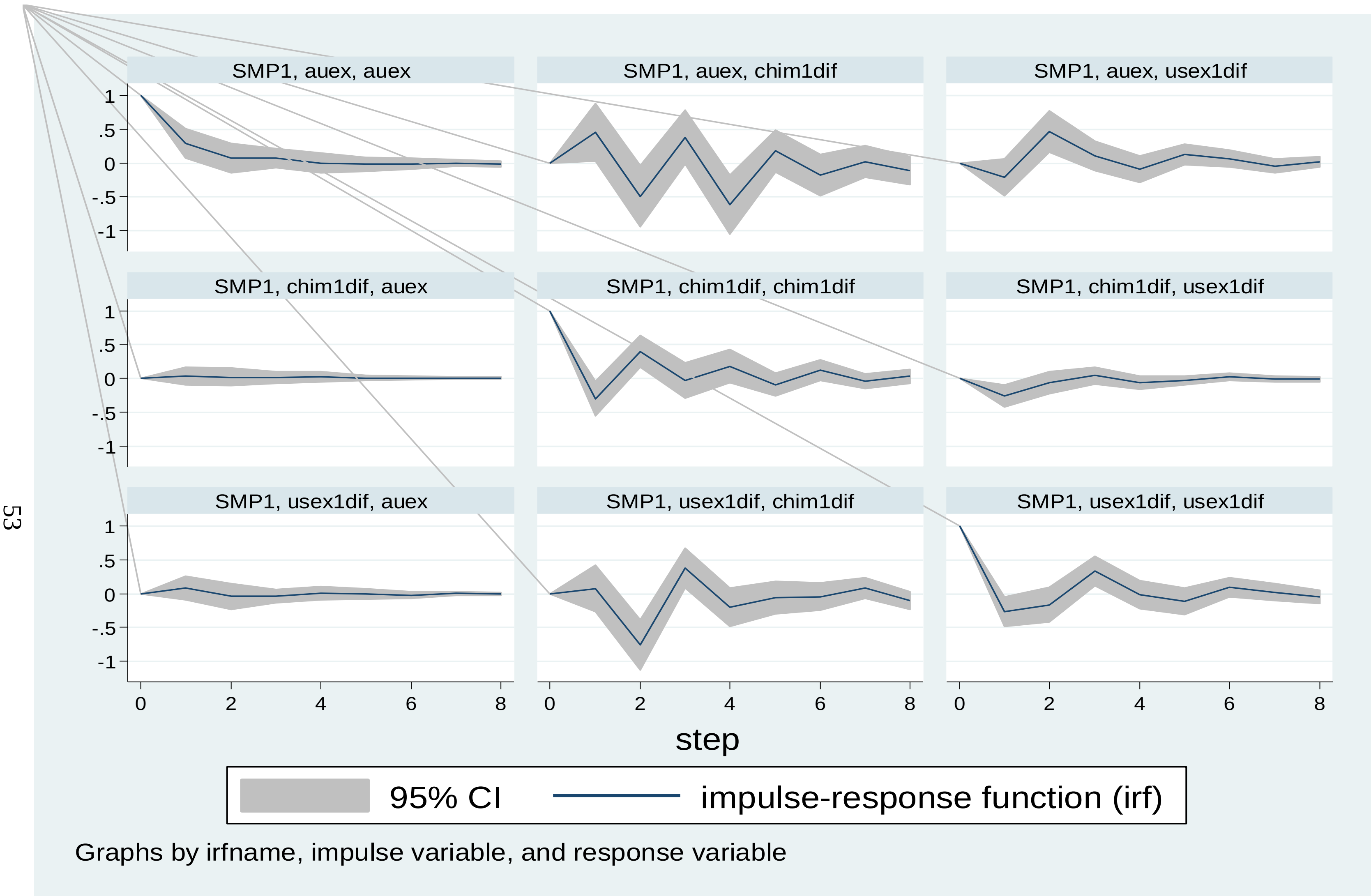

Figure 11: Impulse Response Functions

Table 5: Comparing VAR Modeling to Actual Value

	Residuals			Fcast Values			Actual Values		
Date	AUEx	USEx	ChIm	AUEx	USEx	ChIm	AUEx	USEx	ChIm
14-Jan	13984.8	-27491	45645.3	100867	237663	305047	114852	210172	350692
14-Feb	7074.79	-30904	-14142	95684.2	245769	285153	102759	214865	271011
14-Mar	-15779	-6407.1	-25502	98685.5	279542	331966	82906.7	273135	306464
14-Apr	5991.97	1069.07	-21762	79224	281052	266303	85216	282121	244541
14-May	8361.23	11444.6	-28718	77280.2	267327	218909	85641.4	278772	190191
14-Jun	-19409	11992.5	-26817	52876.6	280637	166335	33467.9	292629	139518

Table 6: RMSE Measurements

	AUEx	USEx	ChIm
Largest Value	114852	292629	350692
Smallest Value	33467.9	210172	139518
RMSE	12761.45	18383.9	28726.6
RMSE per LG value	0.1111	0.0628	0.0819
RMSE per SM value	0.3813	0.0874	0.2059

Table 7: Residual as a Percentage of Actual Value

	ChIm	USEx	AUEx
Jan-14	0.1301	-.1308	0.1217
Feb-14	-0.0521	-.1438	0.0688
Mar-14	-0.0832	-.0234	-0.1903
Apr-14	-0.0889	0.0037	0.0703
May-14	-.1509	0.0410	0.0976
Jun-14	-0.1922	0.0409	-0.5799
Average	-0.0729	-0.0353	-0.0686
StDev	0.1019	0.0755	0.2511

Table 7 further simplifies the information in Table 5. Table 7 finds the percentage difference between the actual value and the value predicted from the VAR output. The average difference and standard deviation over the six months analyzed is also included. US exports had the smallest average difference as well as the smallest standard deviation. Chinese imports had the highest average difference, on average predicting values 7% below the actual value. However, Chinese imports had a relatively low standard deviation at just over 10%. Australasian exports had the second lowest average difference, but they also had the largest standard deviation by a wide margin.

Overall it appears that the model forecasts generally conservative estimates for all three endogenous variables. The Australasian forecasts are problematic due to the high standard deviation. The US exports and Chinese imports forecasts are very close to the actual values with small standard deviations. The model provides useful information if there are quality estimates for exogenous variables.

This model can also be used to make forecasts for variables under theoretical conditions. Table 8 illustrates what would happen to the endogenous variables if Russian imports over the modeled period were suddenly cut in half. The results showed that the impact on US exports turned out to be rather small. On the other hand, the change in Russian imports caused a drastic change in the amount of SMP the Australasia exported. The effects on Chinese imports also proved to be quite small, this is probably because they are both primarily importers of dairy products and the decline in Russian imports would have minimal direct impact on Chinese imports. In the long run though a decline in Russian imports would be expected to cause a decline in prices and therefore potentially increase Chinese demand or decrease US supply on the world market.

Table 8: The Effects of Low Volume Russian Imports

	Decline in Russian Imports			Fcast Values			Difference From Fcast Values			Difference as Percentage of Fcast Values		
Month	AUEx	USEx	ChIM	AUEx	USEx	ChIm	AUEx	USEx	ChIm	AUEx	USEx	ChIm
14-Jan	136313	237581	304511	100867	237663	305047	35446	-81.697	-536.13	0.3514	-0.0003	-0.0018
14-Feb	125164	245886	285918	95684.2	245769	285153	29479.3	116.624	765.334	0.3081	0.0005	0.0027
14-Mar	107072	280641	339180	98685.5	279542	331966	8386.51	1099.34	7214.36	0.0850	0.0039	0.0217
14-Apr	60224.6	283128	279929	79224	281052	266303	-18999	2076.29	13625.5	-0.2398	0.0074	0.0511
14-May	71434.8	269592	233766	77280.2	267327	218909	-5845.4	2264.01	14857.4	-0.0756	0.0084	0.0679
14-Jun	12702.7	283054	182202	52876.6	280637	166335	-40174	2417.78	15866.5	-0.7598	0.0086	0.0954

CHAPTER 6. CONCLUSIONS

The market for dairy products is growing. While demand may remain largely stagnant in the United States and other developed countries it is becoming obvious that developing nations are where the future growth in dairy consumption will be. This makes it important for private firms in top dairy producing nation to have tools they can use to identify key growth centers.

The largest dairy producing regions in the world are also well developed areas. New Zealand and Australia have consistently been the leading exporters in the world. The United States, the European Union, and Great Britain are also large producers. It is not a coincidence that these regions are both prolific dairy producers and developed. Developed nations have more technology and a more educated work force. As former "third-world" countries continue to develop they will not only have growing demands for dairy but growing production capacity as they invest in infrastructure and education. Producers in developed countries need to act quickly to establish themselves before new producers in developing nations do.

While much of Southeast Asia will likely never be self-sufficient as far as dairy production is concerned, there are other developing nations that could be. China has invested in growing their domestic milk production. Other countries with hospitable weather and lower population densities may also one day become self-sufficient or even become a new major international competitor.

This study was unique in that it applied data from multiple importing and exporting nations to create a better picture of dairy imports. In an increasingly international market it is important to take account for influences from third party countries. Trade between the US and China can be affected by price changes in Russia or production changes in Australasia. Using

VAR modelling allows an econometrician to see how these variables affect one another without requiring them to make any assumptions.

When looking at the results the impulse response functions are very interesting. These showed that changes in Australasian exports greatly affected US exports and Chinese imports. Whereas, US exports and Chinese imports both had minimal effects on Australasian exports.

The actual regression also showed some interesting things. While Chinese imports and US exports both seemed to be mostly determined by lagged endogenous variables the Australasian exports were primarily affected by exogenous variables. It was also interesting to note that the Chinese economic factors affected Australasian exports to a greater degree than Chinese imports.

Looking at the RMSE the effectiveness of the model can be seen. The RMSE is used in models that wish to forecast out of sample values. In this case the RMSE was a very good fit for US exports and good for Chinese imports. The accuracy on Australasian exports was mediocre, this can likely be attributed to the fact that the actual value of Australasian exports sees a much larger variation over the months tested.

The results show that when forecasting skim milk powder imports and exports the vector autoregression model is effective and relatively accurate. No forecast is going to be completely accurate. The accuracy of any forecasts will also depend on the accuracy of exogenous variable forecasts used in the system of equations. Overall this method is effective and has produced good results.

This method could also be applied to testing for theoretical future situations. Currently, for example, there is a lot of uncertainty pertaining to Russian imports. The forecasted values for future Russian imports could be replaced with values picked by the econometrician. Knowing that Russian imports are likely to remain lower than normal until their embargo ends means that there is known information that the model does not know. While the results showed that merely lowering Russian imports did not have a large effect on Chinese imports or US exports there would need to be additional tests run to determine how the effects may be further reaching. If Russian imports were lowered one could assume that world prices would be affected. Possibly the rest of the world would experience a slump in price while Russia and the countries it is willing to trade with experienced price spikes.

While politics may create an extraordinary situation, generally a VAR model will prove to be a useful tool for predicting future imports and exports. While no model is completely accurate, this model will help those using it to get a general picture of where demand is moving. This model will give those using it an advantage if it is more precise than the rational expectations of the competition within the industry.

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