REVENUE IMPACTS OF THE 2015 AVIAN INFLUENZA VIRUS OUTBREAK ON UNITED STATES TABLE EGG WHOLESALERS

A Thesis

by

MICHELLE RENEE PAUKETT

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Chair of Committee,	Senarath Dharmasena
Co-Chair of Committee,	David Bessler
Committee Member,	Craig Coufal
Head of Department,	C. Parr Rosson III

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ABSTRACT

From December 2014 to June 2015, the U.S. poultry industry experienced an outbreak of highly pathogenic avian influenza (HPAI), resulting in massive bird depopulations. Both turkey and egg producers were impacted and farms affected faced losses from costs of bird disposal and farm repopulation. This study isolates the table egg subsector of the poultry industry and looks at the revenue impact of the AI outbreak at the wholesale level. To determine this revenue impact, a vector error correction model (VECM) was defined and used to generate the counterfactual revenue during the time period the outbreak occurred. This counterfactual revenue was compared to the actual revenue observed during that time period and the difference is the revenue impact due to the outbreak, *ceteris paribus*. Additionally, machine learning algorithms, using residuals from the VECM, allowed us to determine causal relationships in contemporaneous time among the variables considered within the industry. The results from this study provide us with a better understanding of the table egg industry based on sound econometric modeling and provide a basis for conducting future revenue impact studies for similar events.

Our model was developed using eight variables defined by previous studies including the number of hens and eggs, egg price, feed input prices, retail pork and beef prices, and real disposable personal income. After rigorous testing using RATS software, the vector error correction model for forecasting was identified with one lag and two cointegrating vectors. When the counterfactual revenue was compared to the actual revenue from December 2014 to June 2015, a gain of about $676 million to wholesalers was determined to be attributed to the outbreak. Additionally, residual analysis of contemporaneous relationships, as shown by directed acyclic graphs, indicated that egg price is independent of direct production quantities, hens and eggs, but is impacted by production costs such as feed input costs. These results can be accounted for by various factors including the inelasticity of egg price and the imperfectly competitive behavior of the wholesalers. Future studies can use price transmission principles to expand this study and identify AI outbreak impacts at the consumer and producer levels.

DEDICATION

This thesis is dedicated to my family who have provided support throughout my pursuit of higher education and drive me to higher standards. Specifically, this document is dedicated to my following family members:

Parents: Donald and Diane Paukett

Grandparents: Lucille Giles and Eleanor Paukett

Sister: Rachel Paukett

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NOMENCLATURE

ADF	Augmented Dickey-Fuller
AI / HPAI	(Highly Pathogenic) Avian influenza
BIC	Bayesian Information Criterion
CATS	Cointegration Analysis for Time Series
CFI	Comparative Fit Index
CV	Coefficient of Variation
DF	Dickey-Fuller
GES	Greedy Equivalence Search
LR	Likelihood Ratio
PC	Peter-Clark Algorithm
RATS	Regression Analysis for Time Series
RDI	Real Disposable Personal Income
RMSEA	Root Mean Square Error of Approximation
SIC	Schwarz Information Criterion
TSA	Time Series Analysis
VAR	Vector Autoregressive Model
VECM	Vector Error Correction Model

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1. INTRODUCTION

1.1 Problem Statement and Justification

Starting in December 2014 and continuing through June 2015, the United States poultry industry experienced an outbreak of highly pathogenic avian influenza virus (HPAI). As the name suggests, this economically important poultry disease spreads easily and causes flu-like symptoms like lethargy and swelling in birds, while also presenting the hazard of being a zoonotic disease with the potential to spread to humans. This particular outbreak affected 211 commercial flocks comprised of egg, broiler, and turkey producers in 15 states throughout the western and central United States, including the largest and third largest egg producing states, Iowa and Indiana respectively. By the end of the outbreak over 50 million birds had been killed to control the spread of this virus, resulting in huge losses for the affected producers (USDA 2015). While broilers take merely six weeks to go from hatching to market, egg layers must be raised for an average of five months before they can produce eggs and, subsequently, the hens remain in the houses for about two years. Thus the extended time element involved in the layer industry means that individual egg producers may take longer to recover from the outbreak than a broiler farmer would. With the massive bird depopulation, egg production decreased and higher prices for table eggs were realized on the markets. These higher prices impact consumer purchasing decisions and disrupt desired trends such as the increasing per capita consumption of eggs. While costs are typically discussed surrounding outbreaks, it is also interesting to consider the revenue impacts of these events to determine if the price increases imposed are able to offset the loss in revenue that would otherwise be realized by a decrease in the number of eggs. By delving into this research question we will find ourselves identifying the driving forces within the industry along the way. Overall, the goal of this thesis is to develop an acceptable econometrical model for use in calculating the revenue impact of the 2015 avian influenza outbreak on United States table egg wholesalers.

Obtaining an estimate of revenue impact will be of interest to those reporting on the AI outbreak and industry leaders. Our results will also be of interest to data researchers, such as those with the United States Department of Agriculture Economic Research Service (USDA-ERS), who collect and interpret data about the table egg industry. Individuals interested in expanding on the results of our study or applying our methods to other relevant problems will want to build off or reference the model and methodology we implemented. For instance, researchers interested in the impacts of the 2015 AI outbreak at the consumer, retail, and producer levels can use our model and results as a basis for implementing price transmission techniques. Industry leaders also will benefit from our research by having a method to generate reliable egg price and quantity forecasts which will provide even more stability to the industry as uncertainty is minimized. Finally, we hope that this study will encourage future studies that utilize the vector autoregressive or vector error correction model in not only finding the revenue impact due to naturally occurring events, but also in policy analysis for both proposed policies and retrospective analysis.

1.2 Objective

The overarching goal of this thesis is to develop a sound econometric model that will generate a counterfactual revenue, or the revenue that would have been realized if the AI outbreak had not occurred, to which we can compare the actual reported revenue during the outbreak and obtain the revenue impact on US table egg wholesalers that is attributed to the AI outbreak, *ceteris paribus*. We outline four major objectives to ensure that we attain this goal and also obtain a clear understanding of relationships within the US table egg industry. The first objective is to identify general series characteristics for variables impacting the US table egg industry. This allows us to start identifying the specifications for a vector error correction model (VECM), or our second objective. The VECM is a widely accepted model for dealing with time series data and is useful for generating good forecasts, which is what we want to do to satisfy our third objective. Specifically, the third objective is essentially the primary goal of this thesis: to use our VECM to forecast the counterfactual revenue for US table egg wholesalers and compare this to their actual revenue received during the AI outbreak. This will provide us with the revenue impact on US table egg wholesalers due to the 2014-2015 AI outbreak, *ceteris paribus*. Our final objective is to derive additional information from our estimated model by analyzing the model's residuals, also known as innovations in time series literature, to determine contemporaneous causal relationships between variables in the US table egg industry. Altogether, satisfying these four objectives will provide us with an answer to our research question on what the impact of the AI outbreak on US table egg wholesaler revenue was.

1.3 Organization of Thesis

This thesis is organized into four major sections. Section 1 introduces the problem and outlines specific objectives that will guide our approach to answering our research question on the revenue impact of AI at the US table egg wholesaler level. Additionally, it offers justification as to why we decided to pursue this line of research. Section 2 provides background on the US table egg industry and avian influenza, while also reviewing previous studies related to our research. Section 3 then explains the conceptual framework and methodology used for our research. Section 4 starts by describing the data used in this study and then presents the results. These results are further analyzed and discussed in Section 5, where suggestions for future research and concluding remarks can also be found.

2. BACKGROUND

2.1 Brief Overview of the U.S. Layer Industry and Avian Influenza

Egg production can be found throughout the US, with the top five largest egg producing states in America being Iowa, Ohio, Indiana, Pennsylvania, and Texas, from first to fifth respectively. The majority of eggs produced in the US are also consumed in the US, although in 2014 over 350 million eggs were exported from the US ("The Egg Business" 2016). Eggs are an important part of the American diet, as evidenced by the increasing per capita consumption over the past seven years to 258 eggs in 2014, with a further increase to 266 eggs per person in 2016 expected (Watson 2014; "The Egg Business" 2016). In general, eggs are considered a necessary good with no clearly identified close substitutes and thus have an inelastic price, meaning that a one percent change in egg price will result in a less than one percent change in the quantity of eggs purchased.

Egg wholesalers are defined as an intermediary between egg producers and retailers who ultimately sell the eggs to consumers. These wholesalers may strictly focus on eggs, such as S&R Fresh Eggs in Wisconsin or CMC Farms in New Jersey, or be major wholesalers found throughout the US dealing with a wide variety of products like Kroger, Costco, and Walmart. Not all eggs pass through a wholesaler, as larger egg producing companies such as Cal-Maine Foods have enough market power to create direct agreements with retailers. Smaller farms, however, may use a wholesaler to send their eggs down the supply chain to consumers.

US egg production primarily takes place in large commercial houses, with flocks of 75,000 or more birds representing about 99% of all layer hens in the US. Currently about 5.5% of US egg production is considered “cage-free” and only 4.5% of producers identify as organic, together a total of around 30 million birds. Layers, or hens used in the production of eggs, take an average of five months to begin producing eggs and are typically kept in production for about two years. The average rate of lay per day in the industry is currently 77 eggs per 100 layers, with about 286 eggs laid per hen per year (American Egg Board 2016, “The Egg Business” 2016). Practices like forced molting[1] allow producers to extend the productive life of their birds if it is economically worthwhile to do so, although at lower productivity levels than these average laying rates. Egg producers unaffected by the AI outbreak may have implemented this practice in order to gain profit from the AI-inflated egg prices.

Highly pathogenic avian influenza (HPAI) virus is an economically important poultry disease that causes a variety of symptoms in poultry including lethargy, swelling, and sudden death in birds. Due to the highly infectious nature of the disease and its rare potential to spread to humans, once AI is detected on a farm all the birds must be killed and disposed of properly. This quickly leads to large losses of layers, as many commercial houses have an excess of 75,000 birds on site. Additional costs to producers include sanitizing houses, repopulating entire houses with birds, and the cost of having their facilities idle in the meantime.

The particular AI outbreak our research focuses on was first confirmed on US farms in December 2014 and quickly spread to a total of 211 commercial flocks and 21

[1] *Forced Molting: A practice where farmers can induce their birds to stop laying and lose their feathers for a brief time so that afterwards their laying period can be extended.*

backyard flocks until June 16th 2015 when the last detection was reported. States with reported cases include the #1 and #3 egg producing states, Iowa and Indiana respectively, as well as California, Oregon, Washington, Idaho, Montana, North and South Dakota, Nebraska, Kansas, Minnesota, Wisconsin, Missouri, and Arkansas. This outbreak impacted layer, turkey, and some broiler production and altogether over 50 million birds were culled (USDA 2015). To compensate these affected producers, the United States Department of Agriculture (USDA) paid out $190 million (McKenna 2015). Several cost estimates of losses from this outbreak can be found in extant literature such as Iowa alone having total economic damages of $957 million (Fry 2015). According to McKenna (2015), the cost of all the culled birds in the US was $1.57 billion and, when combined with costs to industries further down the supply chain like egg wholesalers and food service firms, this resulted in a total loss of $3.3 billion due to this particular AI outbreak. Since these authors don't clearly explain what these cost estimates include and do not describe how they are modeled, these estimates primarily serve to paint a general picture of the negative impact that the 2014-2015 AI outbreak had in the US.

2.2 Review of Previous Studies

As a major poultry industry event, many researchers are interested in the impacts of the 2014-2015 avian influenza outbreak. Many of these studies, such as those by Gao, Richardson, and Maisashvili (2016), look at the impacts to the whole poultry industry including broilers, layers, and other poultry products. The current research on this AI outbreak also focuses more on analyzing price changes, trade impacts, welfare analysis and regional impacts (Dobrowolska & Brown 2016; Seitzinger and Paarlberg 2016). This study will isolate table egg production, which was heavily impacted by the AI outbreak, and consider the revenue impact to US table egg wholesalers. By defining this smaller aspect of the industry, future studies will be able to expand on our model and results to answer larger questions about the impacts of AI on the poultry industry.

Estimates of the US wholesale table egg revenue impacts do not seem to be available in the extant literature, although McKenna (2015) implied that losses from these wholesalers contributed to the $3.3 billion in costs to the US poultry industry as a whole. As mentioned previously, this article is unclear on how this estimate was derived and specifically what it includes, but we can still compare it with our results to see if table egg wholesalers did realize a revenue loss due to the outbreak.

A paper published by Chavez and Johnson (1981) outlined a series of structural models that defined various aspects of the US egg industry from hatching to production and prices. Included was a wholesale egg price structural model with variables relevant to the industry today, such as feed prices and the number of hens and eggs, which we incorporated into the vector error correction model (VECM) we developed. We chose to find revenue impact using a VECM because this model tends to generate superior forecasts compared to structural models because of its ability to capture the dynamic effects of all the variables better than large structural models (Sims 1980). The VECM also has a history of being utilized as a tool to determine economic impacts of animal diseases in other studies, such as Costa, Bessler, and Rosson (2015), although this study forecasted price to analyze trade disruptions from the swine flu of 2005. Additionally, we use monthly data to more accurately measure the impacts of the AI outbreak throughout the time period it occurred, a suggestion offered by Chavez and Johnson (1981).

Overall, our review of the literature indicated a lack of emphasis on research regarding revenue impact due to the AI outbreak and supported the methodology we proposed to use in our study. From understanding the literature, we were able to define our objectives as first identifying series characteristics and then the specifications, such as the number of cointegrating vectors, required for the VECM model. Using the VECM we will estimate the revenue impact of the AI outbreak on US table egg wholesalers by generating a counterfactual forecast of revenue to compare to the actual observed revenue during the outbreak. Finally, using the residuals from the VECM, we will determine causal relationships with machine learning algorithms to better understand how the different industry variables interact in contemporaneous time.

3. METHODOLOGY

3.1 Conceptual Framework and Application[2]

Current evaluations of the 2014-2015 AI outbreak have focused on costs to the poultry industry, rather than revenue impacts, with reported estimates unclear as to what they encompass and how they were derived. Additionally, past approaches modeling the US wholesale table egg price did not implement time series techniques; for instance, Chavez and Johnson (1981) developed a structural model of this sector which, as stated by the authors themselves, is not ideal for forecasting. Thus a need for an updated, robust econometric model for wholesale table egg prices is another driving force behind this thesis document. We use observational data in this study, which recommends us to use a less structured model with relaxed dependency on the *ceteris paribus* assumption which is not as applicable to observed data, allowing us to generate better predictions of the real world. Therefore, this thesis focuses on using vector autoregressive (VAR) time series modelling techniques, specifically the VECM, to understand the effects of the 2014-2015 US avian influenza (AI) outbreak on US wholesaler revenue for table eggs. Additionally, this thesis will incorporate the concepts of innovation accounting and directed acyclic graphs (DAGs) to highlight variable interactions due to shocks like the AI outbreak and identify causal relationships in the US table egg industry in terms of the new information discovered for each variable.

This section on methodology opens with an introduction to the theoretical properties of time series modeling and a description of two widely accepted time series

[2]*This discussion follows Dharmasena (2003), Bessler & Yang (2003), and Dharmasena, Bessler, & Capps (2016).*

must be conducted to define a time series model, such as stationarity tests and tests for cointegration. Applications of the VAR and VECM in terms of forecasting, determining causal relationships between variables, and innovation accounting will conclude this section.

3.1.1 Introduction to Time Series

By definition, time series analysis (TSA) studies involve data reported at specific intervals over a defined timeframe, with the assumption that the order of observation within this timeframe matters. Therefore, the variable subscript t is used to indicate the chronological order of observations for TSA. Stationarity is another important stipulation of TSA, as it ensures a series has a finite and constant mean, variance, and covariance. This allows us to analyze the errors, or new information found from TSA modeling, without interference from variations in the historical mean. Before conducting time series modeling on a non-stationary series, the series must be converted to a stationary series by taking differences as described in Section 3.1.3.

The basic time series model is a univariate model that focuses on a single series of data and its movement through time. In this model, a random variable (X_t) is considered dependent only on past lagged values of itself, along with some error (e_t). In TSA, error is considered an innovation or new information that causes a variable in current time to deviate from its most recent value (X_{t-1}) in a way not necessarily tied to the historical mean value. Therefore, forecasting with the historical mean itself will not be as effective for generating a good forecasts. This simple model can be visualized as the following equation:

$$X_t = \mu + \beta_1 X_{t-1} + \beta_2 X_{t-2} + \ldots + \beta_k X_{t-k} + e_t \quad (1)$$

Where μ is a constant intercept term and the β's are unknown parameters. The uncorrelated error term, e_t, is assumed to have a mean of zero and a variance of σ_e^2. This equation represents an autoregressive model of order k, where k is the number of lags in the model. Lags refer to how many observations in the past (X_{t-k}) one must include in a model to define the variable's present value (X_t). For instance, if $k=3$ then the value of the variable in present time is considered a function of a constant (μ), the innovation term (e_t), and its values in the three periods preceding the current point in time (X_{t-1}, X_{t-2}, X_{t-3}). This univariate model provides the basis off of which we build our VAR, before transforming it in to a VECM to account for cointegrating vectors. These models will be discussed in the following section, Section 3.1.2.

3.1.2 Vector Autoregressive Model and Vector Error Correction Model

Expanding on the univariate model to account for the array of interacting variables found in the real world, multivariate vector autoregressive (VAR) models are useful in analyzing and summarizing the regularities in several series of observational data over time. The VAR is a non-structural model, allowing the researcher to choose variables relevant to his or her specific problem rather than being constrained by pre-determined models based on an overarching prior theory. The unrestricted VAR, with no constant, is shown below:

$$X_t = \sum_{k=1}^{k} \alpha(k) X_{t-k} + \delta_t \quad (2)$$

In this equation, X_t is an ($mx1$) matrix of variables, $\alpha(k)$ is an (mxm) matrix, and δ_t is an $(mx1)$ matrix with m being the number of variables in the model. The δ_t term represents innovations which are uncorrelated through time but often contemporaneously correlated, making them useful for determining contemporaneous causal relationships between variables. The unknown parameter to be estimated from the observed data in the model is α. Lag length, denoted as k in VAR analysis, is commonly derived using statistical loss functions where the lag with a minimum Schwartz Information Criteria (SIC) value is selected. This function seeks to identify a parsimonious model by considering the tradeoff between the number of variables in the model and the number of lags. SIC is calculated using the following equation:

$$\mathrm{SIC} = \log\left|\hat{\Sigma}_k\right| + (\log \mathrm{T})\, \mathrm{m}^2\mathrm{k}/\mathrm{T} \tag{3}$$

Here, $\left|\hat{\Sigma}_k\right|$ is the determinant of the residual variance-covariance matrix for the VAR(k) model, m is the number of variables, and T is the number of effective observations.

The VAR is converted to a vector error correction model if cointegration is found between series. Extra vectors accounting for the cointegrating relationships are added to the formula and the VAR portion is reduced to k-1 lags, while the error term remains untouched. As an equation, with an adjustment for seasonality, this would be:

$$\Delta \mathrm{X}_t = \Pi \mathrm{X}_{t-1} + \Psi \mathrm{S}_t + \sum_{i=1}^{k-1} \Gamma_i \Delta \mathrm{X}_{t-i} + \mathrm{e}_t \tag{4}$$

Where $\Delta X_t = (X_t - X_{t-1})$. In this equation, X_t is an ($mx1$) vector of variables, Γ_i is an (mxm) matrix of short run dynamics coefficients, and e_t is an ($mx1$) vector of innovations representing contemporaneous time. Ψ is an ($mx11$) matrix of coefficients for the S_t ($11x1$) vector of monthly dummy variables. Π is an ($mx[m+1]$) matrix of coefficients corresponding to an ($[m+1]x1$) vector of variables and a constant. $\Pi = \alpha\beta^{'}$ and the rank of Π is r, the number of cointegrating vectors. α is a coefficient matrix representing the short run adjustment to return to equilibrium after a shock to the system, whereas $\beta^{'}$ is the transposed cointegration matrix representing the long-run relationships between variables (Bessler & Yang 2003). Note that a VECM converted from a VAR with one lag would be lacking the $\sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i}$ portion of the model (Magee 2008). Overall, the VECM allows for some interesting analysis because the long run, short run, and contemporaneous structures can be isolated and further analyzed.

3.1.3 Tests of Nonstationary

By definition, a non-stationary series is comprised of data points that move away from their historical mean for extended periods of time. This results in a series with infinite variance that, when modeled, can lead to faulty conclusions from reported significance. For this reason, data series (X_t's) used in autoregressive models are expected to be stationary and differences should be taken until this condition is satisfied, with first differences represented as $\Delta X_t = (X_t - X_{t-1})$. If a non-stationary series is differenced once and is then stationary, it is said to be integrated to order 1, or $I(1)$. Therefore, a naturally stationary series is considered to be integrated to order 0, or $I(0)$.

A common test to determine if a series is stationary is the Dickey-Fuller (DF) test. In this test, $\Delta X_t = (X_t - X_{t-1})$, or first differences, are regressed on a constant (α_0) plus the non-differenced variable lagged one period ($\alpha_1 X_{t-1}$):

$$\Delta X_t = \alpha_0 + \alpha_1 X_{t-1} \tag{5}$$

The null hypothesis is that the series is non-stationary ($\alpha_1 = 0$). If the ordinary least squares estimate of α_1 in this equation has a t-statistic more negative than the t-statistic at the 5% level of -2.89, then this null hypothesis is rejected. For instance, if a calculated t-statistic value of -3.5 is found, based on the ratio between the estimated coefficient and the standard error of the estimated coefficient, then you can reject the null hypothesis and state that the series is stationary.

To account for possible autocorrelation in the estimated residuals, it is recommended that one also expands the DF test into an augmented Dickey-Fuller test (ADF) when testing if a series is stationary. The ADF test has the same null hypothesis and critical value at the 5% level as the DF test, but adds an additional term to the basic DF test formula:

$$\Delta X_t = \alpha_0 + \alpha_1 X_{t-1} + \sum_{i=1}^{k} \beta_i \Delta X_{t-i} \tag{6}$$

Where *k* is the lag length selected to "whiten" or remove the autocorrelation from the residuals. The ideal lag length can be found by minimizing Schwarz Information Criterion (SIC), as described in Section 3.1.2.

Likelihood ratio (LR) tests can also be used to test if a series is stationary using the following formula:

$$L(X) = \frac{p(H_0|X)}{p(H_1|X)} \tag{7}$$

Where *p* represents the probability of the hypothesis occurring. Unlike the DF test, the null hypothesis (H_0) is that a series is stationary. Therefore, H_1 represents the alternative hypothesis that the series tested is non-stationary. The statistic is distributed chi-squared under the null hypothesis with *p-r* degrees of freedom, where *r* is the rank of the cointegrating vector which will be discussed further in section 3.1.4. The chi-squared test statistic is calculated as:

$$C(X) = \Sigma \frac{(H_1 - H_0)^2}{H_0} \tag{8}$$

If the calculated chi-squared values are greater than the chi-square critical value at the 10% significance level, then the null hypothesis is rejected and the series would be considered non-stationary.

3.1.4 Cointegration and Rank of Π

If series are found to be *I(1)*, or non-stationary, there is a possibility that these *I(1)* series are co-integrated, meaning that they move together in a random walk. A random walk is where the best prediction of a variable's value tomorrow (X_{t+1}) is its value today, along with some white noise (e_{t+1}):

$$X_{t+1} = X_t + e_{t+1} \tag{9}$$

When cointegrating series are differenced from each other, the results will be stationary, or *I(0)*. Cointegration in a set of series requires one to develop a vector error correction model to avoid "spurious" regression and correlation.

Recall that Π with a rank of r cointegrating vectors is the product of the transposed matrix of cointegrating relationships (β') and the matrix of adjustment coefficients (α). If $r=0$ there is no Π matrix and a VAR in first differences can be modeled. If $r=m$, where m is the number of variables in the model, Π has full rank and there is no cointegration so a VAR in levels can be done. If Π has a reduced rank, where

$r<m$, cointegration exists and both α and β are (mxr) matrices with a rank of r. Therefore, there are at most $m-1$ cointegrating vectors.

Testing for cointegration is done using the Johansen (1991) trace test, which is a likelihood ratio test with a null hypothesis of $r=0$ and an alternative hypothesis of $r_0 < rank(\Pi) < m$. If this null hypothesis is rejected, then the test proceeds stepwise, such that the next null hypothesis is $r_0 + 1$ and the alternative hypothesis is $r_0 + 1 < rank(\Pi) < m$ (Dwyer 2015). The value of r at the first failure to reject the null hypothesis, using provided critical values, is the rank of Π. The trace test statistic is calculated as:

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{m} \ln(1 - \hat{\lambda}_i) \tag{10}$$

Where $\hat{\lambda}$ represents the estimated values of the characteristic roots obtained from the estimated Π and T represents the number of observations. The Johansen trace test is an accepted method for identifying the rank of Π, especially when working with data sets comprised of more than two variables.

3.1.5 Forecasting and Calculating Revenue Impact

Forecasting is a major application of the VAR and VECM models and forecasts for any $t+h$ horizon can be computed using the chain rule of forecasting. Based on a VAR(1) model, which has one lag, the h-step ahead forecast is equal to:

$$\hat{X}_{t+h|t} = \Phi_1^h X_t \tag{11}$$

Where Φ simply represents the estimated parameters and h is how far in the future you are forecasting. $\hat{X}_t$ represents an out-of-sample estimated value, or the forecast. Future errors are assumed to be zero, thus they are not shown here. The true observation for *t+h* for a VAR(1) model would be:

$$X_{t+h} = \Phi_1 X_{t+h-1} + (e_{t+h}) = \Phi_1^h X_t + (e_{t+h}) + \Phi_1 e_{t+h-1} \quad (12)$$

Since we want to avoid contamination in our forecasts from AI influenced data, we chose to do a 12-step ahead forecast for our counterfactual forecast. These forecasts were evaluated on their performance compared to a random walk using the Theil U statistic, calculated as:

$$U_t = RMS_t / RMSNCF_t \quad (13)$$

Where RMS is the root mean square error for our model forecasts and RMSNCF is the root mean square error for the no-change forecasts, or the random walk model. A Thiel U statistic less than one is an indication of good forecast performance, in which our model forecasts better than a random walk (Dharmasena 2003).

After developing and using the VECM to forecast counterfactual egg quantities and price over the time period that the AI outbreak occurred, a simple revenue calculation was done for both the counterfactual and actual data at each month during the outbreak by multiplying the price of eggs per dozen and the number of dozens of eggs. The difference between these two revenue amounts at each month of the outbreak represents revenue change due to the AI outbreak, *ceteris paribus*.

3.1.6 Contemporaneous Time Analysis

Since we are using observational data from a non-experimental setting, *ceteris paribus* does not hold true and we find ourselves in a system with many unknown, omitted variables and no specific economic theory to tell us the relationships among our variables. Thus enters the concept of DAGs, proposed by Pearl (1995), which possess the ability to find causal relationships among the variables in our model by simply using the correlation, or variance-covariance, matrix from the residuals of the VECM.

A directed graph is a comprised of an ordered triple, *<V,M,E>*, where *V* is a non-empty set of vertices, or variables, and *M* is a non-empty set of symbols attached to the end of undirected edges, such as an arrow. *E* is a set of ordered pairs and each member is an edge, with vertices connected by an edge being considered adjacent. A directed acyclic graph is a graph with an arrow on at least one edge of *E* and which contains no directed cyclic paths, where one vertex causes a variable than in turn causes the original vertex. Directed acyclic graphs represent conditional independence given by the recursive product decomposition:

$$\Pr(X_1, X_2, X_3,\ldots, X_n)=\prod_{i=1}^{n} \Pr(X_i \mid P_{ai}) \tag{14}$$

Where *Pr* is the joint probability of vertices $X_1, X_2, X_3, \ldots, X_n$ and P_{ai} is the realization of some subset of the variables that precede, in a causal sense, X_i in the order ($X_1, X_2, X_3, \ldots X_n$). If the DAGs are made so that the variables corresponding to P_{ai} are the direct causes, or parents of X_i, then the conditional independencies given by ΠPr can be derived from the graph using the concept of directional separation (d-separation). D-separation is defined as the blocking, or screening off, effect which allows us to determine the direction of causal flow in a set of variables.

There are several main causal relationships that can be described. For simplicity, consider three variables, *X*, *Y* and *Z*. A causal fork is where *X* is a common cause for both *Y* and *Z* such that $Y \leftarrow X \rightarrow Z$. If *X* is not considered when studying *Y* and *Z* you will find a non-zero correlation between *Y* and *Z*, meaning they are correlated and are directionally connected (d-connected). By introducing knowledge of *X*, the association between the joint effects will be d-separated and the correlation between *Y* and *Z* will be zero (Bessler & Lee 2002).

Another possibility is an inverted causal fork where *Y* and *Z* are joint causes of *X*, or $Y \rightarrow X \leftarrow Z$. Here the unconditional correlation between *Y* and *Z* is zero, and conditioning on *X* would cause their correlation to be non-zero. Therefore, common effects don't screen off association between their joint causes, but rather makes them d-connected. Expanding on this, if *X* is also the parent of a variable, *W*, then by conditioning on *W* rather than the collider *X* we will be able to d-connect *Y* and *Z*.

The final main scenario is a simple causal chain, which would be defined as *X* causing *Y* which causes *Z*, such as $X \rightarrow Y \rightarrow Z$. If we condition on *Y*, then we block the information flow between the endpoints and *X* and *Z* would have zero correlation. However, if only *X* and *Z* are considered, their unconditional association will be non-zero and these endpoints would be d-connected.

There are several computer algorithms one can use to build DAGs and we used the Peter-Clark (PC) Algorithm and Greedy Equivalence Search (GES) Algorithm in TETRAD V to identify causal relationships in our model. TETRAD software is freely provided by research workers at Carnegie Mellon University and only requires the correlation matrix, or the variance-covariance matrix, of the variables and the number of observations to build the DAGs. Knowledge of the problem area can be incorporated into the graphs by putting expected exogenous variables in the top tier of the knowledge structure and more endogenous variables in the lower tiers (Spirtes, Glymour, & Schenies 1993).

For the PC algorithm, the software starts with a completely undirected graph, where all variables are connected to all others with an edge with no arrow, and systematically uses correlation and conditional correlations to remove the edges between variables with significantly zero edges. All edges that pass this first test are then assigned arrows by applying the concept of d-separation, as described above.

The GES algorithm starts with a DAG with no edges, meaning all variables are independent, and begins to add edges between variables from equivalent classes, which are comprised of multiple DAGs that have the same probability distribution and independence constraints. It searches stepwise, scoring each graph with the Bayesian Information Criterion (BIC) metric which considers the tradeoff between model fit and parsimony:

$$B(G,D) = \ln p(D|\hat{\theta}, G^h) - \frac{d}{2} \ln m \tag{15}$$

Where d is the number of free parameters in graph G, $\hat{\theta}$ is the maximum-likelihood estimate of the unknown parameters, and m is the number of observations in the data D. $lnp(D|\hat{\theta}, G^h)$ represents model fit and the rest of the function represents model parsimony. The equivalence class that increases the score most is chosen for the next step in this first phase until no new replacement can increase the score. In the second phase of GES, single edges are deleted and the scores of DAGs in equivalence classes are repeatedly compared until a local maximum is reached, which is considered the optimal solution (Dharmasena, Bessler & Capps 2016).

The models generated by these algorithms in TETRAD V also are evaluated by several statistical measures including chi-squared testing, comparative fit index (CFI), and root mean square error of approximation (RMSEA). The chi square test assumes a minimized maximum likelihood function over the measured variables and has a null hypothesis that the population covariance matrix is equal to the estimated covariance matrix for all measured variables. A good fit is indicated by values close to zero. The degrees of freedom for this test are calculated as $m(m + 1) / (2 - d)$, where d is the number of linear coefficients, variance terms, and error covariance terms that are not fixed in the model.

The CFI statistic assumes that all latent variables are uncorrelated and compares the sample covariance matrix with this null model, while also adjusting for sample size. Values range from 0 to 1, with larger values indicating better fit. RMSEA is an indication of how well the model would fit the covariance matrix of the population and will favor a more parsimonious model. RMSEA also ranges from 0 to 1, however here a value closer to zero is an indication of good fit. As a note, goodness-of-fit is important to consider, however it doesn’t mean that a poor fitting model is necessarily bad or completely useless.

There are three main assumptions to consider when deciding on the edges of DAGs. The first is to assume there are no omitted variables that cause two or more of the variables in the algorithm, known as the causal sufficiency condition. The second is the causal Markov condition, where one only conditions on the parents of a variable to fully capture its joint probability distribution. In the case of the causal chain previously described, the underlying probability distribution under this condition would be *Pr(X,Y,Z)=Pr(X)Pr(Y|X)Pr(Z|Y)*. The last condition is the faithfulness condition which states that if there is zero or partial correlation between variables it is not due to cancellations of parameters in the model, but rather only occurs because their correlation is not significantly different from zero. Especially with observational data, these three conditions may not be met so care must be taken when interpreting the DAGs generated by TETRAD software, particularly if you want to apply the results to policy.

3.1.7 Innovation Accounting

The coefficients obtained from a VAR model are difficult to interpret and analyze on their own, so further analysis is often done based on the moving average representation of the VAR. The moving average matrix at lag zero contains information on the relationships between series in current time, t. However, the VAR can only tell us if series are contemporaneously correlated based on the i,j element of Σ, the variance-covariance matrix, and gives no insight on the direction of causal behaviors. To solve this problem, we utilize Bernanke factorization. For this, innovations are assumed orthogonal and can be written in matrix form as:

$$\begin{bmatrix} u_{1,t} \\ u_{2,t} \\ u_{3,t} \end{bmatrix} = \begin{bmatrix} 1 & a_{12} & a_{13} \\ a_{21} & 1 & a_{23} \\ a_{31} & a_{32} & 1 \end{bmatrix} \begin{bmatrix} e_{1,t} \\ e_{2,t} \\ e_{3,t} \end{bmatrix} \tag{16}$$

Where $e_{i,t}$ are observed innovations from the VAR and $u_{i,t}$ are orthogonal innovations. Lagged relationships are assumed unrestricted.

One benefit of using Bernanke factorization over alternative methods, such as Choleski factorization, is that we don’t need to know how to order the factorization.

Bernanke lets us arbitrarily impose a particular causal ordering on variables, allowing for a better view of unknown causal flows (Bessler 2015). We can use directed acyclic graphs to assign zeros to certain $a_{i,j\text{'s}}$ which allows us to identify causal relationships between series. Bernanke factorization can also be used to transform a VAR into:

$$AX_t=\Sigma_k A\Phi X_{t-k}+Au_t \tag{17}$$

Where *A* is the matrix of *a*'s from the previous equation. Using this equation, we can decompose each series into their historical shocks or look at their simulated responses to a particular shock over time. Analyzing these decompositions is a common form of VAR analysis known as "*innovation accounting*."

Impulse response functions show us how the *X* vector responds over time to a one-time shock in a single series, found in the error term (δ_t). For this we set the error of the shocked variable equal to one and all the other variable's errors to zero**,** so that we can focus on how X_{t+h} evolves throughout the periods following the shock. This equation is known as the "*impulse response function*:"

$$X_{t+h}= \theta(B)\delta_{t+h} \tag{18}$$

Where just the *i*th element of $\delta_{t+h}=1$ and all other elements are zero when $h=0$ and all elements are zero when $h\neq 0$. Once again, *h* represents the number of future periods being considered.

The $\theta(B)$ elements are derived from simulating the estimated VAR to a series of one time only shocks in each series' innovation term. Impulse responses are often shown as graphs and can indicate the elasticity of variables in the model; for instance, a variable the returns to its equilibrium level within a few periods after a shock would be considered inelastic. They also highlight relationships between variables, in terms of how much a series decreases or increases in response to a one-time shock to another variable.

Another form of innovation accounting are forecast error variance decompositions, which consider how much of the error variance of a series is caused by the error variance of specific variables in the VAR. Standing at time *t*, we fully expect all future innovations (δ_{t+h}) to equal zero. This means that when we take the difference of the expected ($\widehat{X}_{t+h}$) from the actual (X_{t+h}) to see the forecast error at horizon *h* we are left with these future innovations as the forecast error (FE_{t+h}):

$$\mathrm{FE}_{t+h} = \sum_{h=1}^{h} \theta_{h-1}\delta_{t+h} \tag{19}$$

Here θ_{h-1} is an (mxm) matrix that tells us how the forecast error in the future depends on innovation in the past and δ_{t+h} is a vector of the innovations at horizon *h* periods ahead. For any particular element of vector FE_{t+h}, its variance is composed of the corresponding elements of each θ matrix and each variance term. An example of the variance (V) of the forecast error (FE) at *h* steps ahead is:

$$\begin{aligned} \mathrm{V}(\mathrm{FE}_{t+h}) = \mathrm{V}(\delta_{1t+h}) + \theta_{11}^2(1)\mathrm{V}(\delta_{1t+h-1}) + \theta_{12}^2(1)\mathrm{V}(\delta_{2t+h-1}) + \ldots \\ \ldots + \theta_{11}^2(h+1)\mathrm{V}(\delta_{1t+1}) + \theta_{12}^2(h+1)\mathrm{V}(\delta_{2t+1}) \end{aligned} \tag{20}$$

This equation allows us to summarize the relative influence of each series on every other series in the VAR, including itself. By taking the variances associated with a particular series and dividing by the full variance of the forecast error we are able to obtain the percentage of variation in a series due to historical shocks in either its own series or shocks in another series (Franses, Djik, & Opschoor 2014).

4. ANALYSIS AND RESULTS

4.1 Description of Data

We considered both prior theory and previously developed models, like Chavez and Johnson's 1981 wholesale egg price model, and chose eight variables to use in our VECM. The number of table egg layers in the US are included because the premise of this study is that AI severely decreased the number of hens in the US and this lead to fewer eggs and higher egg prices. Since we plan to conduct innovation accounting and determine causal relationships within the industry, this is an important variable to include in our model even though it is not used for calculating revenue. The number of eggs produced in the US and the wholesale price of NYC Grade A Large Table Eggs are linchpins in our VECM, as they are used to calculate revenue. For the purposes of this study we assumed that all table eggs produced in the US pass through a wholesaler and the prices we used in our counterfactual forecast are actual monthly prices of Grade A Table eggs to volume buyers, store door delivery, in the NY metropolitan area. Soybean meal and cornmeal prices are included as value-adding input costs of producing eggs. To account for factors influencing egg demand, especially for causal analysis, we incorporated the retail prices of beef and pork as suggested by Chavas and Johnson (1981). These were adjusted using the non-seasonally adjusted Consumer Price Index for All Urban Consumers (CPI-U) since seasonality is accounted for in the model using dummy variables. Finally, the model's token macro variable is seasonally-adjusted real disposable personal income (RDI), as monthly data was not available for non-seasonally adjusted RDI. Altogether, our model is well-rounded by encompassing supply and demand-side variables, the crucial table egg industry variables, and a relevant macro variable.

Monthly data from March 1986 to May 2016 was collected for each variable from various government and online sources for a total of 363 observations. The VECM developed was identified using data from March 1986 to October 2014, providing a large sample size of 344 observations which strengthens the model and our confidence in the results. Truncating the full data set allows us to define a model that has not seen the effects of the 2014-2015 US AI outbreak, resulting in a counterfactual forecast that will better represent the revenue that would have been seen if the outbreak had not occurred.

The full data set is provided in Appendix C. This data was analyzed and the model estimated using Regression Analysis for Time Series software (RATS) and Cointegration Analysis for Time Series (CATS). Directed graphs were generated using TETRAD V software. Software input programs are located in Appendix D.

4.1.1 Summary Statistics

Summary statistics on the full data set and the truncated set for defining the VECM are shown in Table 1B. This information allows us to understand the historical characteristics of the data, which may need to be accounted for by the model. For instance, the mean provides an overall sense of the magnitude of different series values in relation to others. The amount of standard error, a form of standard deviation representing the accuracy of the sample compared to what is actually found in the industry, may be attributed to the evolution of the industry over the 30 year timeframe we summarized. For example, production methods in the 1980s may not have allowed for as many hens as there are on a commercial farm today, thus advancements and trends in the industry can correlate to a larger deviation in egg production. A useful descriptive statistic summarizing the mean and standard deviation of a series is the coefficient of variance (CV), a unit-less measure that represents the percent of dispersion around a series' mean. The higher the CV, the greater the dispersion; for instance, in both the estimated and full model data sets egg price had the highest CV at a 51% and 57% respectively, indicating more volatility in this series. Hens had the smallest CV (9%), followed by egg production (13%).

There is some skewness and kurtosis in the series, as expected from observed data, with both the estimated model series and the full data set returning similar results. However, there is a large, significant jump in kurtosis for egg price in the full data set, suggesting that the AI outbreak resulted in outliers that created a fat-tailed distribution for egg price. While normality is often favored in analysis, it is not a requirement for the VECM. Considering we have three decades of agricultural data, it is likely that these statistics represent structural changes in the industry due to shifts in demand and production. While it is important to acknowledge fat tails and deviations from normality, no adjustments were made to the data to account for these characteristics since they should not have a major impact on the model we are creating.

An analysis of the maximum and minimum data points and their corresponding dates was conducted to see if the results were within the relevant timeframe. Before the AI outbreak in 2015, the highest egg price at the wholesale level in the 30 year timespan had been in March of 2008 during the beginnings of the Great Recession. However, when looking at the full data set statistics, the highest egg price was realized in August 2015, or two months after the last reported AI case for this outbreak. Prior to the outbreak, the number of layers and egg production had both reached their 30 year maximum in December 2014. Overall, these summary statistics highlight some of the impacts the outbreak appears to have had on the variables in the model.

Graphs of the historical data, shown in Figures 4A and 5A, provide a visual analysis of trends in the various series. For example, both the number of hens and egg production trend upward before significantly dropping in 2015. These series also show signs of the seasonality expected in an agricultural production setting, which can be accounted for in the model using monthly dummy variables. Additionally, the plots of cornmeal and soybean meal price tend to move together, suggesting that we should test for possible cointegration. Finally, all series appear to have the potential for being non-stationary series which will be officially tested using DF and LR tests.

4.1.2 Stationary Tests and the Number of Lags

The Dickey-Fuller test and augmented Dickey-Fuller tests were initially used to determine if a series was stationary and the results are found in Table 2B. The DF test indicted that both the egg production and egg price series are stationary, although this result is not clear from the historical graphs. The ADF was run through 6 lags to see where SIC was minimized, with the results indicating that the number of hens, egg production, and egg price series require more lags to whiten their residuals, while the other supplementary variables require fewer. Based on the minimum SIC for each series, the ADF returned the same conclusion as the DF test, while also finding the number of hens series stationary.

Since the Dickey-Fuller tests did not agree and we want to consider cointegration in our model, we also conducted likelihood ratio tests on the series based on the rank of Π. When $r=2$, all series were non-stationary $I(1)$ series which is what we expect based on the length of time the data covers and the historical graphs plots (see Table 3B).

The number of lags for the VECM was selected based on comparing the SIC for scenarios including a levels VAR with a constant, trend or no trend, seasonality or no seasonality, and lags or no lags. Each scenario considered can be seen in Table 4B and we found that one lag will provide us with a parsimonious model ideal for forecasting, as SIC increases with additional lags.

4.1.3 Cointegration Results

$I(1)$ cointegration analysis using CATS in RATS shows Johansen trace test results which suggest that, at the 90% confidence level, there are three cointegrating vectors ($r=3$). However, the SIC value suggests the presence of one cointegrating vector (see Table 5B). Therefore, we assume there is a minimum of one and a maximum of 3 co-integrating vectors possible in this model. Since our objective is to forecast with our model, we generated forecast statistics for $r=1$, $r=2$, and $r=3$ to determine which forecasts best for both egg production and egg price, which are the variables for calculating revenue. When the model was run at each level, $r=2$ had the “best” forecasts, based on a Theil U statistic less than 1.0 at each step during the AI outbreak for both series. Selecting a rank of two ensures that we account for enough cointegration in the model to avoid spurious results, while also maintaining a parsimonious model ideal for forecasting.

Tests for variable exclusion and weak exogenetity were also conducted and the results for two cointegrating vectors can be seen in Table 6B and 7B, respectively. For the exclusion test, a decision to reject indicates that the series is part of the co-integrating space. In our case, all series except pork and beef price are in the co-integrating space at a 95% confidence level. The test of weak exogeneity given two cointegrating vectors shows that, except for RDI being weakly exogenous within the cointegration vector, all other series respond and make adjustments toward the estimated long run relationship (Bessler & Yang 2003). These tests provide insight into the composition of the cointegrating vector we are including in our model.

4.2 Estimated VECM

Based on the cointegration tests, we needed to develop a vector error correction model to account for the two cointegrating vectors in our data set. Since the LR test at $r=2$ indicated that the series were all non-stationary, we took the first differences of each series to make them stationary. The following variables are used in the model: number of hens (X_1), number of eggs (X_2), egg price (X_3), soybean meal price (X_4), corn meal price (X_5), retail beef price (X_6), retail pork price (X_7), and real disposable personal income (X_8). Seasonal dummy variables for January to November (D_1 *to* D_{11}) are also included in the model.

In the vector error correction model, lagged first differences are shown in the long-run series with the cointegrating vectors. Only one lag was included in the model, therefore the short run VAR portion, with *k-1* lags, becomes zero. This results in a simpler model with the following VECM equation:

$$\Delta X_t = \Pi X_{t-1} + \Psi S_t + e_t \tag{21}$$

With e_t representing innovations in contemporaneous time and the constant accounted for in the Π matrix. The results of this estimated VECM model are shown below:

$$\underset{(8\text{x}1)}{\begin{bmatrix} \Delta X_{1t} \\ \Delta X_{2t} \\ \Delta X_{3t} \\ \Delta X_{4t} \\ \Delta X_{5t} \\ \Delta X_{6t} \\ \Delta X_{7t} \\ \Delta X_{8t} \end{bmatrix}} = \underset{(8\text{x}11)\text{ Seasonal Matrix}}{\begin{bmatrix} -2638.54 & -2465.19 & -1800.58 & -512.35 & -55.26 & 544.70 & 1149.34 & 808.03 & -114.60 & -1970.69 & -1486 \\ -696.23 & -417.95 & -675.98 & -332.22 & -457.10 & -633.17 & -272.74 & -562.81 & -289.56 & -564.46 & -1040 \\ -13.04 & -13.31 & -3.86 & -2.15 & -1.58 & -4.69 & -5.38 & 6.01 & -2.431 & -9.65 & -7.528 \\ -12.07 & -3.22 & -4.02 & -9.15 & -21.86 & -17.12 & -19.73 & -10.20 & -10.36 & -16.56 & -14.43 \\ -12.89 & 1.03 & 14.44 & 7.08 & -1.57 & 3.26 & 12.36 & 8.67 & -6.89 & -18.93 & -0.17 \\ -1.26 & -1.63 & -2.23 & -2.60 & -1.88 & -3.39 & -1.50 & 0.78 & -2.43 & -3.91 & -2.072 \\ -1.58 & 1.54 & 1.69 & 2.18 & 1.08 & -0.53 & -0.90 & -1.63 & -1.18 & -0.96 & -0.64 \\ -298.883 & -23.40 & -240.66 & -145.68 & -207.95 & -272.77 & -173.01 & -185.23 & -3.97 & -353.21 & -201.70 \end{bmatrix}} \underset{(11\text{x}1)}{\begin{bmatrix} D_{1t} \\ D_{2t} \\ D_{3t} \\ D_{4t} \\ D_{5t} \\ D_{6t} \\ D_{7t} \\ D_{8t} \\ D_{9t} \\ D_{10t} \\ D_{11t} \end{bmatrix}}$$

$$+ \underset{(8\text{x}9\ \Pi\text{ matrix})}{\begin{bmatrix} -0.0459 & 2.2849 & 6.6781 & -0.7812 & -1.6748 & -2.6320 & 0.8017 & -0.0928 & 2231.0309 \\ 0.0054 & -0.2481 & -0.0988 & 0.2005 & 0.0195 & 0.1897 & -0.1925 & 0.0077 & -265.5907 \\ -0.0001 & -0.0010 & -0.2188 & -0.0396 & 0.0567 & 0.0343 & 0.0360 & 0.0008 & 7.0831 \\ -0.0003 & 0.0188 & 0.2026 & 0.0209 & -0.0521 & -0.0443 & -0.0183 & -0.0013 & 12.8084 \\ 0.0003 & 0.0074 & 0.7554 & 0.1331 & -0.1957 & -0.1210 & -0.1211 & -0.0030 & -20.1886 \\ 0.0000 & 0.0023 & 0.0356 & 0.0046 & -0.0092 & -0.0071 & -0.0041 & -0.0002 & 1.1276 \\ 0.0000 & 0.0016 & 0.0253 & 0.0033 & -0.0065 & -0.0050 & -0.0029 & -0.0001 & 0.7587 \\ -0.0068 & 0.3628 & 1.8844 & 0.0282 & -0.4796 & -0.5443 & -0.0115 & -0.0178 & 323.5059 \end{bmatrix}} \underset{(9\text{x}1)}{\begin{bmatrix} X_{1t-1} \\ X_{2t-1} \\ X_{3t-1} \\ X_{4t-1} \\ X_{5t-1} \\ X_{6t-1} \\ X_{7t-1} \\ X_{8t-1} \\ 1 \end{bmatrix}} + \underset{(8\text{x}1)}{\begin{bmatrix} E_{1t} \\ E_{2t} \\ E_{3t} \\ E_{4t} \\ E_{5t} \\ E_{6t} \\ E_{7t} \\ E_{8t} \end{bmatrix}}$$

Figure 1. Estimated VECM Model

In Figure 1, X_t is an (8x1) vector of variables, Π is a (9x8) vector of coefficients corresponding to a (9x1) vector of X_{t-1} lagged variables, which includes a constant. e_t is an (8x1) vector of innovations, which were found to be stationary and not autocorrelated. The t-statistic values and the components of Π, α and β' are shown in Figure 6A. Using e_t, innovation accounting is conducted to provide insight on what the model tells us about contemporaneous relationships.

4.2.1 Forecasts

We generated a 12-step ahead forecast for the number of eggs and egg price to avoid the influence of the AI outbreak on the counterfactual revenue. These are point forecasts, which are typically reported for major events, providing us with a definite amount of revenue change. These forecasts can be considered reliable because they are better than a random walk, as shown by Thiel U statistics less than one at each forecast step in Table 8B. Forecasts were calculated by first converting the number of eggs from millions of eggs to dozens of eggs using the equation $(X*10^6)/12$. The number of dozens of eggs was then multiplied by egg price, converted from cents per dozen to dollars per dozen using $(X/100)$, to obtain the revenue at each time period. This was done for both the actual data set values and the forecasts generated by the VECM from October 2014 to October 2015. This particular AI outbreak "officially" started in December 2014 and ended in June 2015 so the revenue for each month in this period was summed and the difference between the realized and counterfactual revenue was obtained (see Figure 7A and Table 9B). Our results showed that the realized revenue during the AI outbreak was higher, at \$6.76 billion, compared to the counterfactual revenue which was only about \$6.08 billion. Thus, *ceteris paribus*, the 2015 AI outbreak allowed wholesalers to gain about $676 million in revenue between December 2014 and June 2015. These results will be further discussed in Section 5.

4.2.2 Directed Acyclic Graphs

Both the GES and PC Algorithms were run in TETRAD V software using the estimated VECM residual covariance matrix and the number of observations as input. Knowledge for these graphs was given as income, soybean meal and cornmeal price in the top tier, pork and beef price in the second tier, eggs and hens in the third tier, and egg price in the fourth tier. The PC Algorithm was run with α=0.4 and the GES was run with a 0.15 penalty discount so that we could create a complete directed acyclic graph. The two models agreed on the contemporaneous relationships of the variables by finding the same edges. The graph we developed, shown in Figure 2, has a BIC score of 31.59, a CFI score of 0.57, and a RMSEA of 0.14, indicating that this is a fairly good fitting model.

The graph has no bi-directed edges, indicating that no major variables are missing in the model. We find that the number of eggs and egg price are endogenous variables in this system, while the number of hens are weakly exogenous. The significant edges, at the .05 level, in both graphs are found going from pork price to beef price, soybean meal price to egg price, and the number of hens to eggs (see Table 10B). Pork and beef are expected to have a causal relationship, as they are considered substitutes for each other. We found that a higher pork price yields a higher beef price, meaning that when the price of pork increases consumers switch to beef, pushing the beef demand curve rightward so that the same quantity they purchased of beef before now costs more.

Inputs like soybean meal add value to the number of eggs, which is manifested in their price. For example, a higher soybean meal price yields a higher egg price as the cost of the input is passed down the supply chain. Finally, eggs literally come from hens, so it would have been surprising if the DAG did not pick up on this positive relationship of an increase in the number of hens yielding a larger amount of eggs.

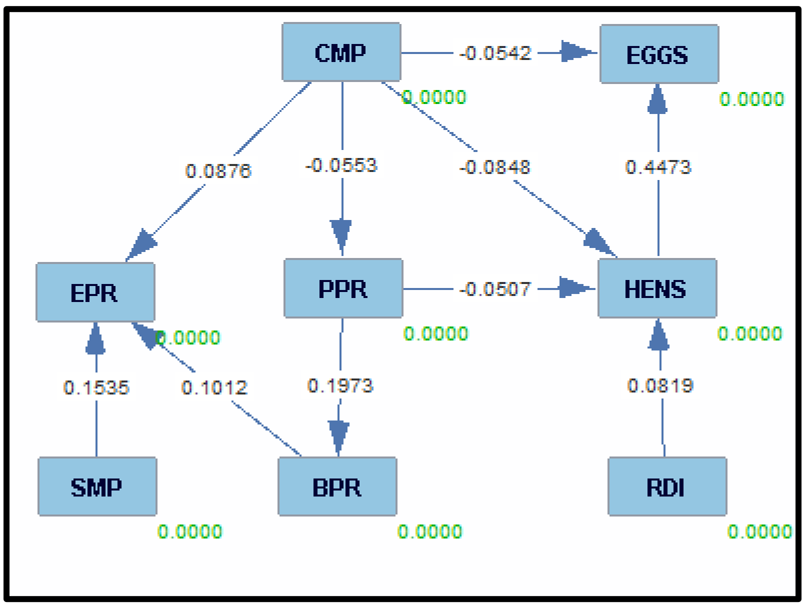

Figure 2. Directed Acyclic Graph Generated by Both the PC Algorithm and the Greedy Equivalence Search Algorithm

It is interesting to note is that neither the number of hens nor egg production is connected to egg price. Rather than these direct production factors impacting egg price, it appears from the DAG that cornmeal price is a common cause between the number of eggs and egg price, thus indirectly connecting them. Although cornmeal price has no significant relationships in the graph it does have the positive non-significant relationship with egg price and production we expect from an input, as well as having an indirect impact through pork and beef which require the same inputs as eggs production. Retail beef price is nearly significant with a significance of $p= 0.0569$, highlighting that the prices of commodities using similar inputs can appear causally related based on this common point. Unless otherwise noted, all of these results are for significant contemporaneous time relationships between the variables in the VECM we estimated.

4.2.3 Innovation Accounting

Impulse response functions, shown in Figures 8A and 9A, look at all the variable's responses to a one-time shock in one series. For the estimated model series, hens never really recovered from the shock, meaning they remained at the shocked amount even at two years following the shock. This is a logical result based on current production methods where layer houses are typically filled all at once and the hens remain there throughout their approximately two year productive cycle. As the DAGs indicate, a positive shock in hens elicits an increase in the number of eggs and, since the average rate of lay will not change drastically in the short run, the number of eggs is constant over the two years following a shock. Egg price decreases minimally following a shock in hens and levels out within about three months. This corroborates the economic theory of demand that the larger the quantity of a commodity for sale, in this case stemming from a supply shock in hens, the lower the price.

The supply of eggs decreases to a constant level higher than its original amount by about six months after a shock to itself, with the slope suggesting that the supply is inelastic. A shock in eggs also generates a positive response in hens that levels out around six months, or approximately the length of time it takes for a hen to start producing eggs, providing further evidence of the relationship between these two variables. The decrease in egg price due to a shock in the number of eggs is even smaller than it was for a shock in the number of hens, suggesting that egg price is relatively indifferent to shocks in these series. All other series estimated by the VECM have a positive response to shocks in the number of eggs and hens. These increases reflect that when there are more hens and eggs, more inputs are necessary for production which increases their prices. As these inputs are also used in beef and pork production, the retail prices for these commodities will absorb these costs and increase as well. As the prices of commodities increase, real personal disposable income should increase to cover the new norm. A shock in hens realizes smaller increases in these variables compared to a shock in eggs, as both the number of eggs and the other variables lie further on the demand side of the industry and thus interact and have a greater influence on each other than a supply variable like hens.

Approximately six months following a shock in egg price, egg prices level out at a higher level than where they started. The slope of egg price's response to a shock to itself suggests price inelasticity, which is expected of a necessary good and may explain some of its independence from its direct inputs: hens and eggs. The number of hens increase for a couple months before stabilizing following a shock in egg price, likely as an effort to generate a larger egg supply to benefit from the higher price. The number of eggs decrease slightly, possibly to due to the effects of changing production, then rise when hens stabilize. The egg price series also induces more positive responses from other series starting immediately after the shock, with cornmeal price having the largest response by stabilizing at 50% from its baseline by around six months. The responses from these other variables support the concept that prices are more sensitive and responsive to other price changes, rather than changes in production.

Forecast error variance decompositions, shown in Table 11B, consider what contributes to the variability in a series after a shock. Immediately after a shock, the variability in the number of hens is almost entirely due to itself and as time passes other variables, such as the number of eggs and input prices begin to have an impact on the variability in hens. Supporting the DAG's finding of hens causing eggs, a 20% influence of hens on eggs in the first period after a shock in eggs is observed. This influence increases to 45% over the period of two years as the contribution of eggs to itself falls to 30%. Feed input prices gradually impact the number of eggs more over time.

The variability in egg price is essentially independent of its direct inputs, eggs and hens, which have less than a 0.5% impact combined on egg price even after two years. In the first period after a shock, egg price itself contributes about 96% to its own variability with feed input prices explaining about 3% of the rest of the changes in egg price. By six months cornmeal price begins to have a large impact on egg price and this influence increases to 44% over two years as the contribution on egg price variability on itself decreases to 50%. A relationship between cornmeal price and egg price can also be seen in the DAG generated from the residuals of our model, which were discussed in Section 4.2.2.

5. DISCUSSION AND CONCLUSIONS

At the beginning of this paper we set an overarching goal to develop a sound econometric model that will allow us to obtain the revenue impact on US table egg wholesalers that is attributed to the 2014-2015 AI outbreak, *ceteris paribus*. The first objective in attaining this goal was to identify series characteristics for the model variables, which was done using summary statistics like CV and by plotting the historical values over the past 30 years to identify trends and possible cointegration. From this visual analysis we began to conduct tests to determine factors necessary for a VECM, such as identifying if series are stationary, how many lags to include in our model, and if cointegration is present. To satisfy our second objective of identifying a VECM, we were able to define an eight variable VECM for the US table egg industry with one lag and two cointegrating vectors. This was used to fulfill the third objective and primary goal of this research: to generate counterfactual point revenue forecasts over the time period the 2014-2015 AI outbreak occurred and compare these forecasts to actual revenue received to pinpoint revenue impact. This led us to a positive revenue impact of $676 million during this AI outbreak. Finally, we satisfied our fourth objective of determining contemporaneous relationships within the industry though DAGs, impulse response functions, and charts of forecast error variance decompositions.

Overall, our key finding is that while the 2014-2015 AI outbreak had a negative impact on many farms throughout the US, table egg wholesales were actually able to capture nearly $676 million in increased revenue from this event. This can be explained by looking at the revenue curves in Figure 3 for these wholesalers, who are operating in an imperfectly competitive market.

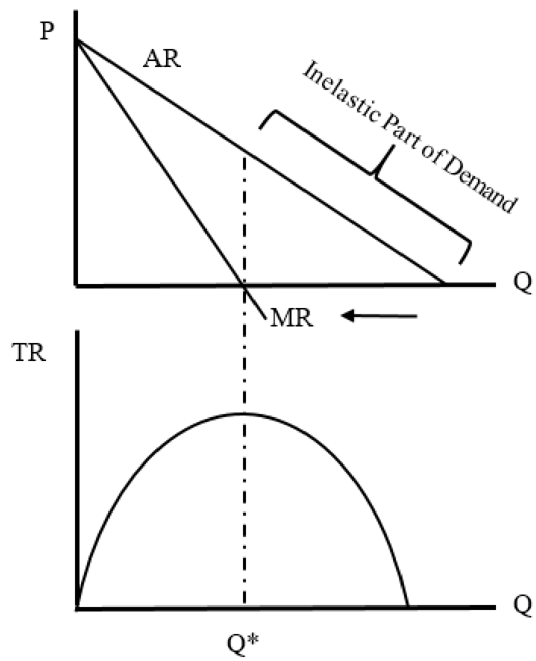

Figure 3. Marginal, Average and Total Revenue Graphs

In Figure 3, P and Q represent egg price and egg quantity, respectively. MR is marginal revenue, which when price equals zero is where total revenue (TR) is maximized. AR is average revenue, or the firm's demand curve, with the lower portion of the AR curve being inelastic where egg price would lie. Table egg wholesalers operate in this inelastic portion of their demand function, such that when the quantity of eggs decreases, their total revenue is actually increasing and a revenue gain of $676 million can be realized. Using similar logic, producers would be found operating in the left-hand portion of the TR curve so that they would have experienced a revenue loss during the outbreak. In this way, we can conceptualize how wholesalers can see a positive effect on revenue from the AI outbreak, while the general table egg industry can still be said to have faced heavy losses. Additional considerations on the wholesaler's ability to gain from the outbreak, include the fact that the direct impact of the AI outbreak was at the farm level and wholesalers did not face the costs associated with handling AI infected birds. Additionally, some of the burden of cost from the production level is often passed down the supply chain to the retail and consumer levels such that the wholesalers may not absorb much, if any, of the cost.

To summarize our findings on contemporaneous relationships within the industry, one interesting result was that egg price does not appear causally related to the supply of eggs or the number of hens. This may be the result of feed input prices, such as cornmeal price, being a causal fork d-separating the number of eggs and hens from the egg price. Additionally, results from innovation accounting support the relationship of egg price to the prices of feed inputs by indicating that variability in egg price following a shock, aside from itself, is largely due to cornmeal price. This does not mean that egg prices and the number of hens and eggs do not respond to shocks in the other's series, as our impulse response functions do show they respond to each other.

Based on our results, should another large-scale outbreak occur, one could consider implementing policies that allow for the revenue gains to be captured by those most effected by losses. This could possibly be done by ensuring that wholesalers share a certain amount of the cost burden that is passed down the supply chain. Additionally, because of the relationships input prices have with a host of other variables, policies regarding these commodities need to consider cross-industry impacts. These studies can consider revenue impacts using methods similar to those outlined in this thesis.

Future studies could try to regionalize the impacts of the AI outbreak, rather than looking at it from a U.S. macroeconomic standpoint. Exports and imports were also not considered in this study, but may be interesting to consider in future evaluations of AI outbreaks. Expanding on this study, one could use price transmission techniques to look at the consumer and retailer levels, or even the farm level revenue impact from the outbreak both on a macro or regionalized scale. Overall, we hope that this study will encourage the implementation of the VECM to calculate revenue loss and industry impacts due to either naturally occurring events, like the avian flu, or policies impacting an industry in future studies.

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APPENDIX A

FIGURES

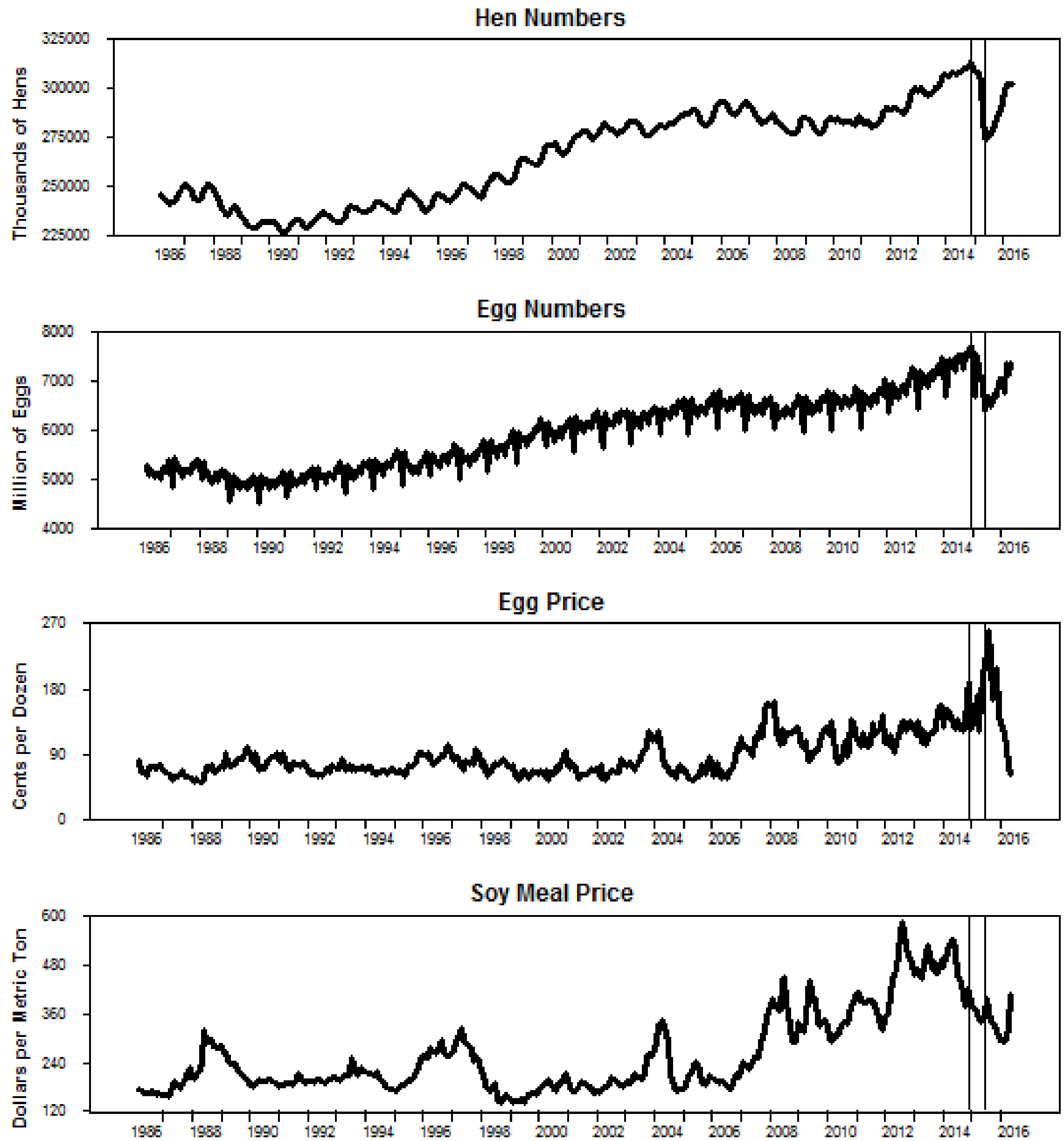

Figure 4A. Historical Charts for United States Hens, Eggs, Egg Price and Soybean Meal Price from March 1986 to May 2016[3]

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[3]Hen and egg numbers are quantities in thousands and millions, respectively. Egg prices are the wholesale price of NYC Grade A Large Table Eggs, expressed in cents per dozen. Soybean meal prices, in dollars per metric ton, represent Chicago soybean meal futures, first contract forward, for minimum 48% protein meal. All prices are in US currency. These graphs represent 30 years of series data.

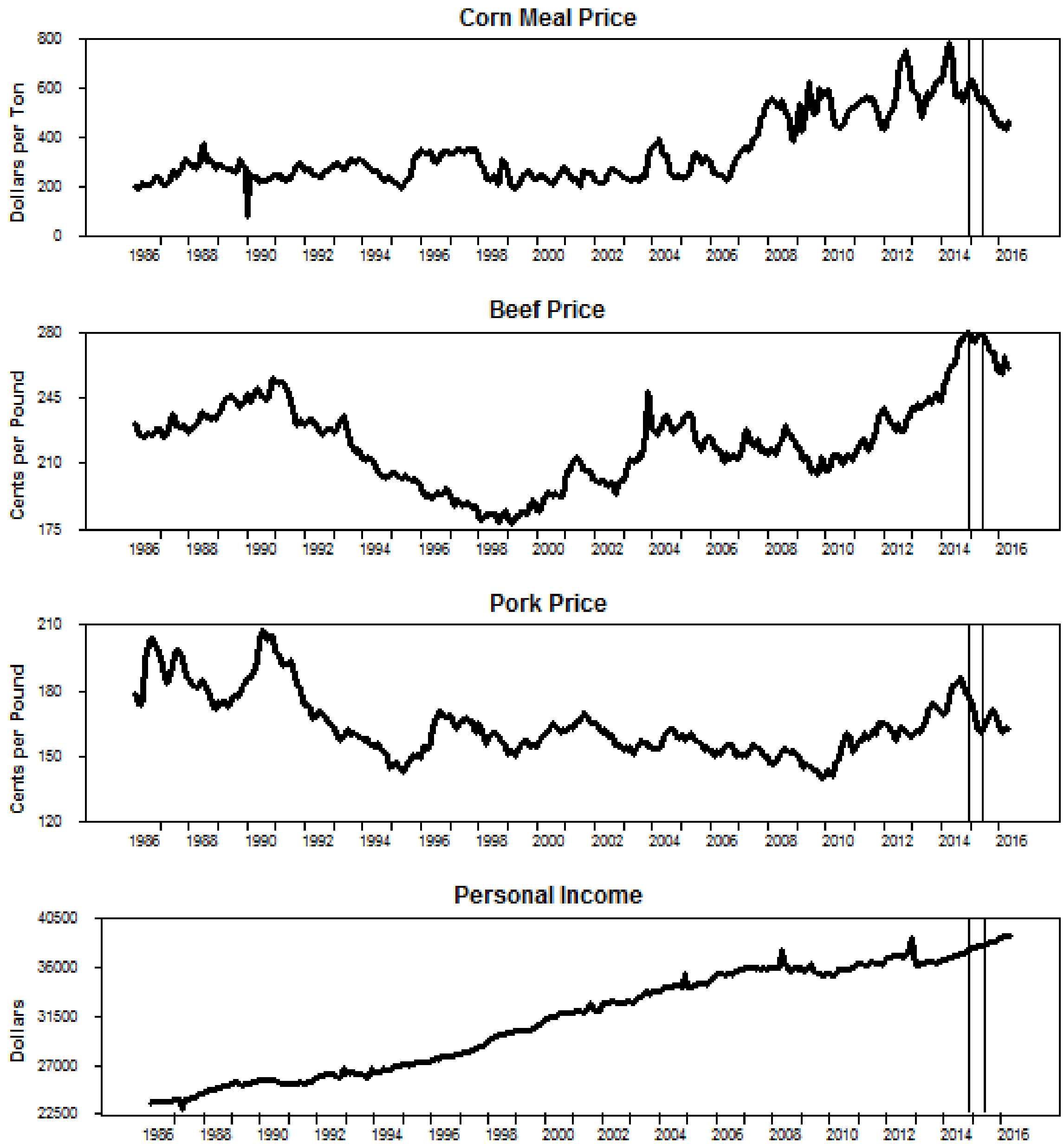

Figure 5A. Historical Charts for United States Cornmeal Price, Retail Beef & Pork Prices, and Real Personal Disposable Income from March 1986 to May 2016[4]

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[4] *Corn Meal Price represents the 60% protein corn gluten meal Midwestern US wholesale price, in dollars per ton. Both beef and pork price, in cents per pound for the retail weight equivalent, are retail prices adjusted using the non-seasonally adjusted consumer price index for all urban consumers (CPI-U), indexed at 1982-1984=100. Real disposable personal income per capita is the chained 2009 dollars seasonally adjusted annual rate. All series are in US currency. These graphs represent 30 years of series data.*

Transposed Beta (9x2) Matrix of Cointegrating Vectors for VECM

$$\begin{bmatrix} 0 & -0.005 & -0.071 & -0.009 & 0.018 & 0.014 & 0.008 & 0 & -2.677 \\ 0 & 0.014 & -0.018 & -0.015 & 0.005 & -0.007 & 0.014 & 0 & 15.332 \end{bmatrix}$$

Alpha (2x9) Matrix of Coefficients for VECM with t-values

Alpha Matrix Values

$$\begin{bmatrix} -124.084 & 123.847 \\ 5.435 & -16.373 \\ 2.825 & 0.955 \\ -2.915 & 0.326 \\ -9.819 & -3.031 \\ -0.495 & -0.013 \\ -0.351 & -0.012 \\ -30.278 & 15.813 \end{bmatrix}$$

Alpha Matrix t-values

$$\begin{bmatrix} -2.32 & 2.321 \\ 1.836 & -5.542 \\ 5.9 & 1.999 \\ -3.016 & 0.338 \\ -6.344 & -1.963 \\ -2.921 & -0.076 \\ -2.895 & -0.097 \\ -2.208 & 1.155 \end{bmatrix}$$

Π (8x9) Matrix of t-statistics for VECM*

$$\begin{bmatrix} -2.735 & 2.977 & 1.696 & -0.832 & -1.643 & -3.089 & 0.915 & -3.266 & 2.686 \\ 5.796 & -5.837 & -0.453 & 3.856 & 0.345 & 4.021 & -3.970 & 4.924 & -5.776 \\ -0.791 & -0.145 & -6.206 & -4.702 & 6.214 & 4.489 & 4.593 & 3.315 & 0.952 \\ -0.929 & 1.352 & 2.847 & 1.230 & -2.826 & -2.874 & -1.156 & -2.554 & 0.853 \\ 0.668 & 0.332 & 6.629 & 4.895 & -6.635 & -4.907 & -4.775 & -3.683 & -0.840 \\ -0.504 & 0.930 & 2.853 & 1.540 & -2.841 & -2.611 & -1.474 & -2.218 & 0.428 \\ -0.478 & 0.901 & 2.833 & 1.545 & -2.822 & -2.579 & -1.480 & -2.184 & 0.403 \\ -1.570 & 1.843 & 1.866 & 0.117 & -1.835 & -2.490 & -0.051 & -2.443 & 1.519 \end{bmatrix}$$

Seasonal Dummy (8x11) Matrix of t-statistics for VECM*

$$\begin{bmatrix} -4.847 & -6.018 & -3.700 & -1.345 & -0.110 & 1.069 & 2.923 & 1.538 & -0.261 & -3.495 & -2.961 \\ -23.101 & -18.427 & -25.085 & -15.748 & -16.412 & -22.434 & -12.525 & -19.347 & -11.892 & -18.082 & -37.423 \\ -2.675 & -3.627 & -0.885 & -0.631 & -0.350 & -1.026 & -1.527 & 1.278 & -0.617 & -1.912 & -1.676 \\ -1.227 & -0.435 & -0.457 & -1.328 & -2.405 & -1.858 & -2.776 & -1.074 & -1.303 & -1.625 & -1.591 \\ -0.818 & 0.087 & 1.025 & 0.642 & -0.107 & 0.221 & 1.086 & 0.570 & -0.541 & -1.160 & -0.012 \\ -0.727 & -1.255 & -1.443 & -2.154 & -1.180 & -2.094 & -1.200 & 0.466 & -1.740 & -2.184 & -1.302 \\ -1.276 & 1.661 & 1.530 & 2.518 & 0.943 & -0.459 & -1.007 & -1.367 & -1.181 & -0.752 & -0.562 \\ -2.141 & -0.223 & -1.928 & -1.491 & -1.612 & -2.086 & -1.715 & -1.375 & -0.035 & -2.443 & -1.567 \end{bmatrix}$$

*See Figure 1 for actual Π and seasonal dummy matrix values

Figure 6A. VECM Matrices and test-statistics[5]

[5]*Our 8 variable VECM has a Π matrix of 2 cointegrating vectors lagged one period, generated by multiplying the transposed beta matrix with the alpha matrix, and a matrix for the 11 seasonal dummy variables in current time with December as the intercept. The constant is held within the cointegrating vector. t-statistics are reported at the α=0.05 level based on the critical value of 1.960 with ∞ degrees of freedom for a two-tailed test. See Figure 1 for actual Π and seasonal dummy matrix values.*

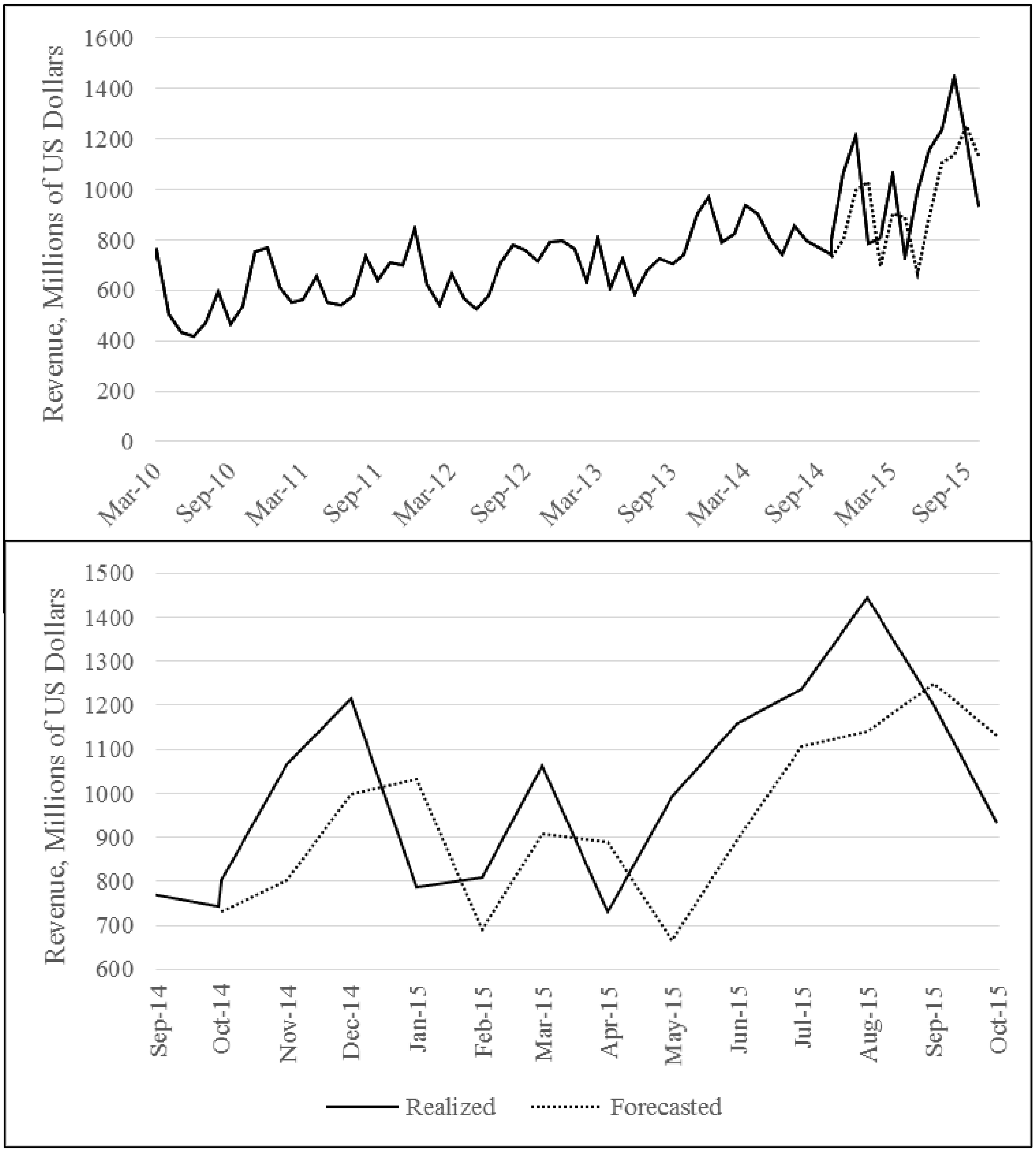

Figure 7A. Realized and Counterfactual Forecast for United States Wholesale Table Egg Revenue 2010-2015[6]

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[6] *The counterfactual revenue forecast generated from the VECM, which we would have expected to see if the AI outbreak had not occurred, is shown as the dotted line. This was calculated by forecasting a 12-step ahead forecast of the egg price and number of eggs separately, then using these values to calculate revenue from December 2014 to June 2015 when outbreak officially started and ended.*

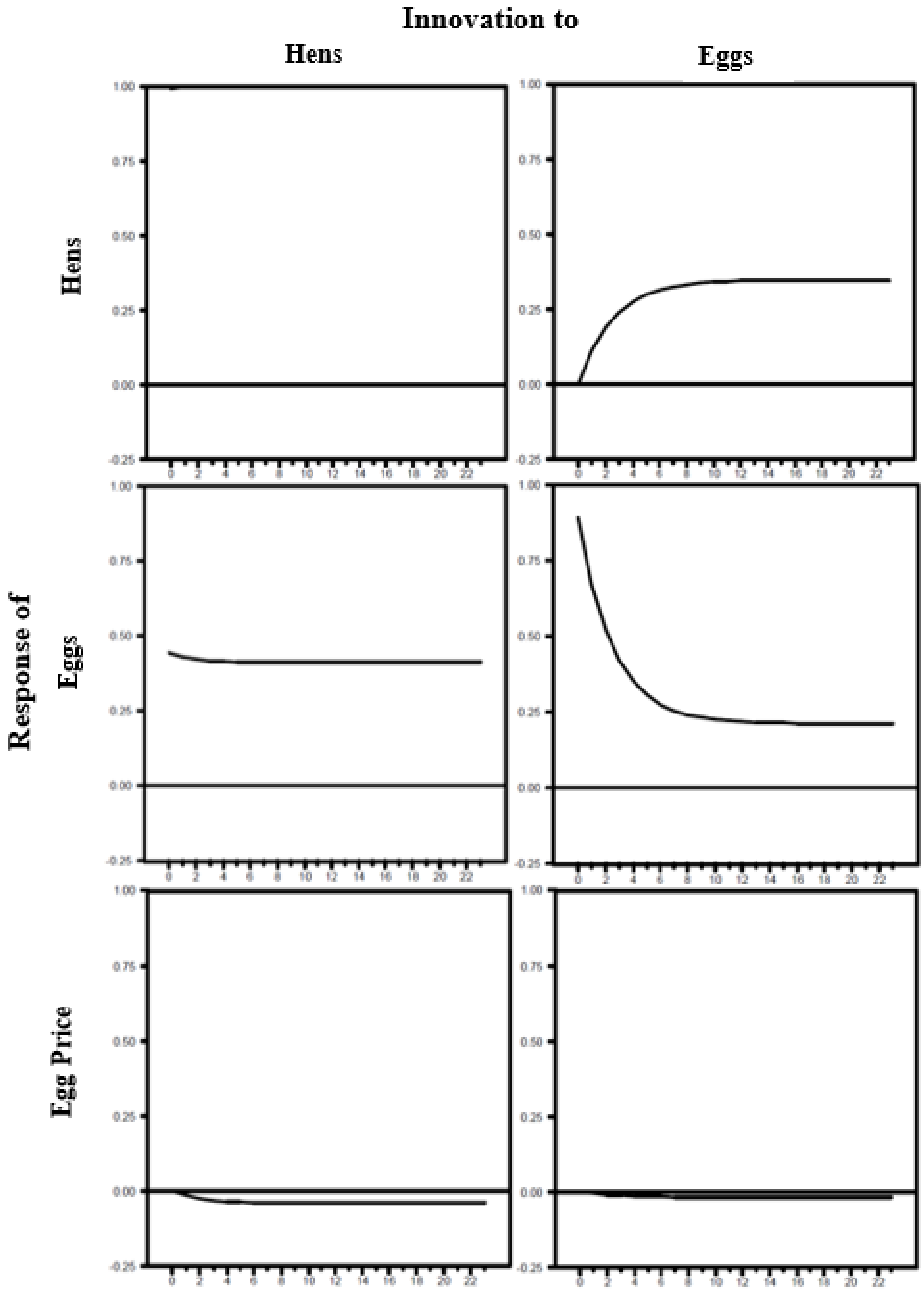

Figure 8A. Impulse Response Functions to Innovations in Eggs and Hens[7]

[7]*The graphs represent the responses of series to a one time shock in the innovation series. The horizontal axis represents the number of months after a shock, during which a series is trying to recover or stabilize, set to 24 months or 2 years in this case. The vertical axis represents the magnitude and direction of a shock, from -0.25 to 1.0. Series are wholesale egg price and the number of hens and eggs in the US.*

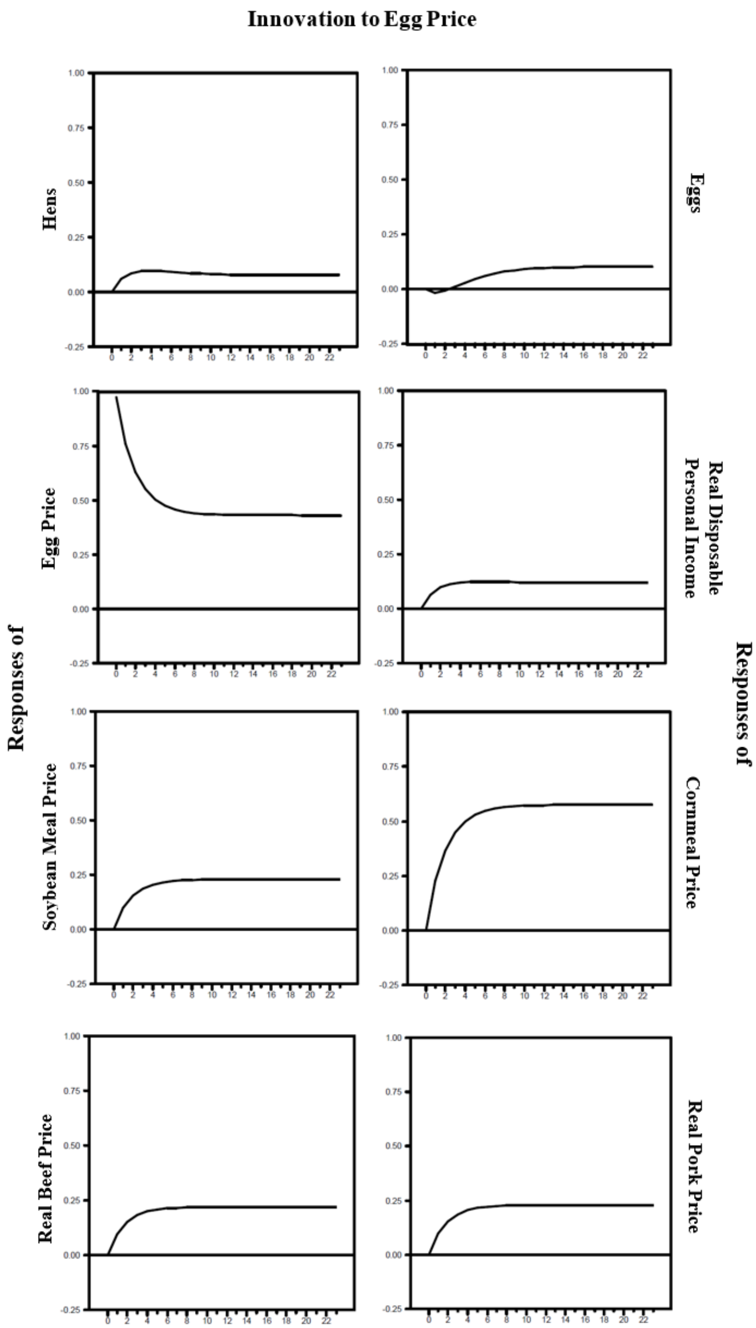

Figure 9A. Impulse Response Functions to Innovations in Egg Price[8]

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[8]The graphs represent the responses of series to a one time shock in the innovation series. The horizontal axis represents the number of months after a shock, during which a series is trying to recover or stabilize, set to 24 months or 2 years in this case. The vertical axis represents the magnitude and direction of a shock, from -0.25 to 1.0. Series are US wholesale egg price, number of hens and eggs, cornmeal price, soybean meal price, retail beef price, retail pork price, and real disposable personal income.

APPENDIX B

TABLES

Table 1B. Series Summary Statistics[9]

	Series	Mean	Std. Error	CV[10]	S	K	Max Min	Date[11]
Estimated Model: 344 Observations 3/1986 To 10/2014	Hens Numbers (Thousands)	264854	23287	0.088	-0.039	**-1.378**	**313019** 226283	Oct 2014
	Egg Production (Millions)	5897	724	0.126	0.155	**-1.090**	**7539** 4495	Oct 2014
	Egg Price (Cents/Dozen)	85	25	0.512	**1.061**	0.339	**162** 51	Mar 2008
	Soybean Meal (Dollars/Metric Ton)	257	99	0.457	**1.273**	**0.742**	**586** 143	Aug 2012
	Corn Meal (Dollars/Ton)	341	135	0.450	**1.206**	0.504	**784** 81	Apr 2014
	Retail Beef Price (Cents/Pound)	219	20	0.176	0.004	-0.451	**276** 178	Sep 2014
	Retail Pork Price (Cents/Pound)	164	15	0.205	**1.031**	0.502	208 **140**	Dec 2009
	Real Disposable Personal Income, Per Capita (Chained 2009$, seasonally adjusted annual rate)	30866	4568	0.149	-0.095	**-1.550**	**38639** 23015	Dec 2012
Full Data Set: 363 Observations 3/1986 To 5/2016	Hens Numbers (Thousands)	266423	23820	0.089	-0.070	**-1.324**	**313019** 226283	Dec 2014
	Egg Production (Millions)	5956	753	0.130	0.130	**-1.076**	**7731** 4495	Dec 2014
	Egg Price (Cents/Dozen)	89	32	0.568	**1.794**	**4.433**	**261** 51	Aug 2015
	Soybean Meal (Dollars/Metric Ton)	262	99	0.449	**1.122**	0.380	**586** 143	Aug 2012
	Corn Meal (Dollars/Ton)	351	139	0.449	**1.015**	-0.048	**784** 81	Apr 2014
	Retail Beef Price (Cents/Pound)	221	23	0.188	**0.308**	-0.168	**280** 178	Dec 2014
	Retail Pork Price (Cents/Pound)	164	14	0.198	**1.014**	**0.573**	208 **140**	Dec 2009
	Real Disposable Personal Income, Per Capita (Chained 2009$, seasonally adjusted annual rate)	31250	4739	0.152	-0.128	**-1.504**	**38849** 23015	May 2016

[9] *Bold values indicate significance at the .05 level for skewness (S) and kurtosis (K). Bold values in the Max/Min column are for max and min values in the series that occurred in the past decade, or since 2006. The full data set includes the raw data from when the AI outbreak occurred, whereas the model was estimated using data that stops before the outbreak to avoid AI contaminated values from influencing the counterfactual forecast.*
[10] *Coefficient of Variance, standard deviation divided by mean, is a measure of the volatility of a series.*
[11] *Date corresponds to the date of the bold value for max/min for that series.*

Table 2B. Dickey-Fuller and Augmented Dickey-Fuller Tests for Stationarity[12]

	Dickey-Fuller Test		Augmented Dickey-Fuller Test			
Series	**t-stat.**	**Order of Integration**	**Lag (k)**	**Schwarz Information Criteria (SIC) Value**	**t-stat.**	**Order of Integration**
Hens	0.647	I(1)	6	13.742[13]	**-5.520**	I(0)
Egg Production	**-3.535**	I(0)	6	10.550	**-3.936**	I(0)
Egg Price	**-4.111**	I(0)	6	4.802[14]	**-4.634**	I(0)
Soybean Meal Price	-1.666	I(1)	1	5.909	**4.389**	I(1)
Corn Meal Price	**-1.999**	I(1)	1	6.944	1.857	I(1)
Retail Beef Price	-0.263	I(1)	1	2.472	**3.744**	I(1)
Retail Pork Price	-1.400	I(1)	1	1.665	**4.524**	I(1)
Real Disposable Personal Income	-0.798	I(1)	3	11.133	**-2.830**	I(1)

[12]The null hypothesis for both tests is that a series is non-stationary. If the t-statistic value is less than the 5% level critical value of -2.89, then the null hypothesis is rejected. Bold values indicate significance at the α=.05 level. The Augmented Dickey-Fuller test is used to correct for autocorrelation in the estimated residuals by adding lags, selected by minimizing the SIC value, to "whiten" the errors. For the ADF test, the t-statistic and SIC values are associated with the particular lag listed, which had the smallest SIC value. For the order of integration, I(0) represents a stationary series and I(1) represents a non-stationary series.

[13]SIC values decreased to lag 4 (2nd lowest SIC, I(0) here), increased for lag 5, then was lowest at lag 6.

[14]SIC values increased from the first lag (2nd lowest SIC, I(0) here), then fluctuated up and down with lag 6 having the lowest SIC.

Table 3B. Likelihood Ratio Test for Stationarity Based on a Rank of Π of Two[15]

Series	Chi-Value r=2	p-value	Decision
Hens	46.05	0.000	R
Egg Production	45.76	0.000	R
Egg Price	45.52	0.000	R
Soybean Meal Price	46.14	0.000	R
Corn Meal Price	44.63	0.000	R
Retail Beef Price	48.54	0.000	R
Retail Pork Price	47.63	0.000	R
Real Disposable Personal Income	45.69	0.000	R

[15]*The null hypothesis for this test is that a series is stationary. This test uses a chi-squared test statistic, with 14.07 being the critical value based on seven degrees of freedom. The p-values correspond with the chi-values given a 95% confidence interval. The Decision column represents the decision to reject (R) or fail to reject (F) the null hypothesis.*

Table 4B. Model Lag Determination Using Schwarz Information Criteria (SIC)[16]

Lags	Nothing	Seasonals Only	Seasonals & Lags	Seasonals, Trend, & Lags	Lags Only	Trend & Lags
0	76.47	75.39	-------	-------	-------	-------
1	-------	-------	55.42	**55.25**	57.99	57.93
2	-------	-------	55.57	55.50	57.62	57.51
3	-------	-------	56.19	56.14	58.10	57.91
4	-------	-------	56.90	56.88	58.69	58.50
5	-------	-------	57.66	57.67	59.19	59.15
6	-------	-------	58.43	58.41	59.80	59.72

[16]*Schwarz Information Criteria evaluates the trade-off between the number of variables in a model and the number of lags, in an attempt to find the most parsimonious model. This table shows the SIC results for different scenarios of a levels VAR with a constant, with the bold value being where SIC is minimized.*

Table 5B. Trace Tests for Model Rank and Cointegration[17]

r	T	C(10%)	Decision	SIC
=0	294.70	159.74	R	55.44
$\leq$1	180.85	126.71	R	**55.02**
$\leq$2	113.96	97.17	R	55.06
$\leq$3	62.51	71.66	F#	55.11
$\leq$4	34.79	49.92	F	55.20
$\leq$5	19.15	31.88	F	55.29
$\leq$6	7.41	17.79	F	55.36
$\leq$7	2.62	7.50	F	55.42

[17] *Trace tests for determining the rank of Π were described by Johansen (1991) and have a null hypothesis of r cointegrating relations, shown in the first column. This test is done in a step-wise fashion starting from the top of the table and ends at the first failure to reject (F#), which is where the trace test indicates the rank of Π is at. The decision column indicates the decision to reject (R) or fail (F) the null hypothesis at the 90% confidence level. Results are associated with a constant in the co-integrating space. T is the calculated test statistic and C(10%) is the chi-squared critical value at the 90% confidence interval. The minimum Schwarz Information Criteria value from the residual analysis is in bold.*

Table 6B. Exclusion Test Results for Two Cointegrating Vectors[18]

Series	Chi-Value r=2	p-value	D
Hens	15.72	0.000	R
Egg Production	20.43	0.000	R
Egg Price	47.39	0.000	R
Soybean Meal Price	8.80	0.012	R
Corn Meal Price	30.45	0.000	R
Retail Beef Price	5.74	0.057	F
Retail Pork Price	1.89	0.389	F
Real Disposable Personal Income	21.23	0.000	R
Constant	13.00	0.002	R

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[18] *The null hypothesis for the exclusion test is that the series is not in the co-integrating space. This test uses a chi-squared test statistic, with 5.99 being the critical value based on two degrees of freedom. The p-values correspond with the given chi-values given a 95% confidence interval. The D column represents the decision to reject (R) or fail to reject (F) the null hypothesis.*

Table 7B. Weak Exogeneity Test Results for Two Cointegrating Vectors[19]

Series	**Chi-Value r=2**	**p-value**	**Decision**
Hens	6.87	0.032	R
Egg Production	11.91	0.003	R
Egg Price	26.17	0.000	R
Soybean Meal Price	8.57	0.014	R
Corn Meal Price	24.87	0.000	R
Retail Beef Price	7.89	0.019	R
Retail Pork Price	8.25	0.016	R
Real Disposable Personal Income	5.74	0.057	F

[19]*The null hypothesis for this test is that the series is weakly exogenous with respect to perturbations in the co-integrating vector. This test uses a chi-squared test statistic, with 5.99 being the critical value based on two degrees of freedom. The p-values correspond with the given chi-values given a 95% confidence interval. The Decision column represents the decision to reject (R) or fail to reject (F) the null hypothesis.*

Table 8B. Theil U-Statistic to Evaluate Forecast Performance[20]

Step	Number of Eggs (Millions)	Egg Price (Cents/Dozen)	Number of Observations
1	0.370	0.939	13
2	0.504	0.958	13
3	0.547	1.009	13
4	0.589	0.935	13
5	0.686	0.929	13
6	0.674	0.934	13
7	0.750	0.907	13
8	0.758	0.905	13
9	0.769	0.901	12
10	0.752	0.918	11
11	0.714	0.945	10
12	0.805	0.943	9

[20]*Theil's U-statistic is the ratio between the vector error correction model's forecast root mean square error and a random walk's forecast root mean square error. A value less than 1.0 indicates a model that forecasts better than a random walk. The step column is the number of steps ahead the model forecasts and the number of observations are those available for each step ahead forecast.*

Table 9B. Revenue Calculations[21]

Date	Realized Revenue	Counterfactual Revenue
2014-12-01	1,215,184,350	998,313,465
2015-01-01	787,607,333	1,032,262,106
2015-02-01	809,219,250	691,581,641
2015-03-01	1,061,901,533	907,501,990
2015-04-01	732,096,583	890,371,289
2015-05-01	993,284,500	666,604,645
2015-06-01	1,158,175,150	894,403,187
Sum Total	6,757,468,700	6,081,038,323
Difference	676,430,377	

[21] *A 12-step ahead forecast was generated for the number of eggs and the egg price using a vector error correction model with one lag, two cointegrating vectors, and seasonal dummies. From the forecasted values, the counterfactual revenue was calculated and compared to the realized revenue, or the revenue that was reported by the industry. Both the realized and counterfactual revenue was calculated and summed over the official months the outbreak occurred, from December 2014 to June 2015. The difference of the counterfactual revenue taken from the realized revenue is in the Difference row and represents the revenue impact the avian influenza outbreak had on the industry at the wholesale level, ceteris paribus.*

Table 10B. Greedy Equivalence Search (GES) and PC Algorithm (PC) Machine Learning Edge Statistics[22]

Edge	Edge Coefficient	t-statistic	P
PPR —> BPR	0.1973	3.7160	0.0002
RDI —> HENS	0.0819	1.5194	0.1296
PPR —> HENS	-0.0507	-0.9397	0.3480
HENS —> EGGS	0.4473	9.2297	0.0000
SMP —> EPR	0.1535	2.5952	0.0099
CMP —> PPR	-0.0553	-1.0232	0.3069
BPR —> EPR	0.1012	1.9105	0.0569
CMP —> HENS	-0.0848	-1.572	0.1169
CMP —> EPR	0.0876	1.4804	0.1397
CMP —> EGGS	-0.0542	-1.1182	0.2643

[22] *The t-statistic and p-value are for a null hypothesis that the edge is zero. The PC Algorithm was run with α=0.55 and the GES was run with a 0.1 penalty discount. The PC algorithm starts with a completely undirected graph and tests edges to remove those with significantly zero edges. The GES algorithm starts with no edges at all and scores graphs with the Bayesian Information Criterion (BIC) metric. Any edges found have an edge coefficient, with its significance shown with a t-statistic and associated p-value. Both searches generated the same results.*

Table 11B. Percent Forecast Error Variance Decomposition for Hens, Eggs, and Egg Price[23]

	Month	HENS	EGGS	EPR	SMP	CMP	BPR	PPR	RDI
Number of Hens	1	98.40	0.00	0.00	0.00	0.67	0.00	0.26	0.67
	6	92.74	4.11	0.57	0.07	2.07	0.00	0.21	0.23
	12	89.91	6.78	0.59	0.20	2.19	0.01	0.19	0.14
	18	88.83	7.87	0.56	0.27	2.18	0.01	0.18	0.10
	24	88.29	8.43	0.54	0.31	2.17	0.01	0.18	0.09
Number of Eggs	Month	HENS	EGGS	EPR	SMP	CMP	BPR	PPR	RDI
	1	19.68	79.30	0.00	0.00	0.83	0.00	0.05	0.13
	6	33.57	59.29	0.11	3.86	1.22	0.07	0.21	1.67
	12	40.32	43.29	0.84	9.79	2.41	0.17	0.34	2.84
	18	43.15	34.99	1.44	13.20	3.20	0.22	0.41	3.39
	24	44.71	30.23	1.81	15.18	3.68	0.25	0.45	3.70
Egg Price	Month	HENS	EGGS	EPR	SMP	CMP	BPR	PPR	RDI
	1	0.00	0.00	95.82	2.38	0.76	1.00	0.04	0.00
	6	0.13	0.02	74.83	1.45	21.95	1.19	0.18	0.26
	12	0.22	0.04	59.99	2.36	35.51	1.19	0.25	0.45
	18	0.26	0.04	53.62	2.80	41.29	1.18	0.27	0.54
	24	0.28	0.05	50.21	3.04	44.38	1.18	0.29	0.58

[23]*Forecast error variance decompositions are found by taking the forecast error variances associated with one series and dividing by the full forecast error variance. From this we can see how much of the error variance in a shocked series is due to itself and other series over time, in months, after a one-time shock. The 8 series considered are number of hens (HENS), number of eggs (EGGS), egg price (EPR), soybean meal price (SMP), cornmeal price (CMP), retail beef price (BPR), retail pork price (PPR), and real disposable personal income (RDI).*

APPENDIX C

INPUT DATA

1C. Data for Regression Analysis for Time Series (RATS) Software[24]

Date	Number of Hens	Number of Eggs	Egg Price	Soybean Meal Price	Cornmeal Price	Retail Beef Price	Retail Pork Price	Real Disposable Personal Income
Mar-86	246348	5287	80.8	175.93	198.75	231.26	179.18	23571
Apr-86	244527	5057	65.7	169.15	192.90	226.27	174.04	23649
May-86	242831	5182	65.2	165.23	210.60	224.70	173.10	23661
Jun-86	241247	5016	59.2	164.13	216.90	223.82	177.04	23631
Jul-86	241323	5116	73.0	167.45	211.50	223.72	194.23	23742
Aug-86	242073	5125	72.8	167.67	206.25	225.85	200.94	23760
Sep-86	243398	4997	72.6	168.41	208.00	225.52	204.25	23765
Oct-86	246548	5222	69.6	163.29	222.50	225.05	204.16	23731
Nov-86	248396	5162	77.2	165.29	230.60	227.08	201.25	23732
Dec-86	249569	5377	75.5	158.84	241.50	227.84	199.80	23760
Jan-87	250796	5331	67.1	159.03	232.20	228.26	195.30	23812
Feb-87	250549	4809	65.2	159.00	206.25	224.22	191.76	23925
Mar-87	249689	5409	62.0	155.27	208.50	223.78	186.95	23934
Apr-87	246853	5191	62.4	166.05	213.10	225.80	183.59	23015
May-87	244570	5226	55.6	184.11	226.40	231.43	187.96	23930
Jun-87	243234	5010	58.7	194.45	267.80	236.45	191.40	23878
Jul-87	243612	5173	59.1	186.47	268.75	234.39	196.76	23929
Aug-87	245226	5183	63.2	177.45	240.60	230.81	198.64	24012
Sep-87	247812	5088	68.3	189.72	259.50	229.81	198.40	23992
Oct-87	250079	5325	60.2	196.54	278.75	229.34	195.32	24122
Nov-87	251051	5217	60.5	218.22	305.60	230.20	190.10	24196
Dec-87	250074	5400	56.9	227.64	313.50	228.96	186.48	24398
Jan-88	248302	5348	55.9	206.32	309.40	226.35	185.83	24436
Feb-88	246878	5004	52.7	201.56	283.75	228.40	182.75	24557
Mar-88	244283	5346	56.4	208.33	287.00	229.61	182.27	24637
Apr-88	241899	5086	52.1	218.75	275.60	230.03	181.02	24707
May-88	239098	5142	50.9	245.04	278.75	231.97	181.03	24725
Jun-88	235807	4908	56.8	320.55	355.50	237.45	184.76	24799
Jul-88	235184	5054	73.7	292.11	380.00	236.46	183.92	24878
Aug-88	236703	5089	69.5	294.76	310.00	234.63	181.72	24930
Sep-88	238647	4945	75.6	295.28	309.40	235.73	180.63	24943
Oct-88	240214	5169	66.0	281.67	313.75	233.12	176.76	25060
Nov-88	239442	5040	65.3	277.51	293.00	234.86	172.77	25052
Dec-88	236540	5154	70.4	276.26	277.50	233.85	171.72	25174

1C. Continued

Date	Number of Hens	Number of Eggs	Egg Price	Soybean Meal Price	Cornmeal Price	Retail Beef Price	Retail Pork Price	Real Disposable Personal Income
Jan-89	235016	5062	72.0	280.23	281.00	236.50	174.82	25273
Feb-89	234336	4538	71.1	263.39	288.10	236.23	173.56	25338
Mar-89	232357	5060	92.2	264.55	280.60	243.29	174.75	25450
Apr-89	230448	4864	76.6	247.61	275.60	244.29	174.87	25298
May-89	229449	4968	73.7	238.93	272.00	244.90	172.06	25161
Jun-89	229446	4793	75.2	233.79	270.63	245.57	173.05	25208
Jul-89	229337	4926	76.5	236.36	271.25	246.30	176.62	25285
Aug-89	229473	4900	84.2	216.78	257.00	244.48	178.04	25324
Sep-89	230677	4777	83.8	216.57	267.00	241.56	177.04	25365
Oct-89	231885	4969	84.8	206.34	313.00	240.25	178.22	25458
Nov-89	232455	4878	93.4	203.73	298.75	241.30	181.70	25465
Dec-89	232234	5066	99.5	200.26	280.00	243.80	183.07	25453
Jan-90	231888	4984	92.4	191.31	81.00	246.76	185.63	25593
Feb-90	231752	4495	79.6	182.27	260.90	242.83	186.29	25639
Mar-90	231827	5065	91.5	184.33	238.75	243.09	185.93	25611
Apr-90	230881	4895	82.4	191.06	238.10	246.58	188.60	25735
May-90	228826	4968	67.9	199.97	240.50	250.75	192.89	25651
Jun-90	226779	4773	73.6	192.49	215.60	248.55	203.30	25679
Jul-90	226283	4931	70.9	193.97	222.00	245.96	206.58	25741
Aug-90	227475	4961	80.3	192.70	223.75	245.28	207.99	25558
Sep-90	228640	4811	82.2	198.24	229.40	244.00	203.14	25524
Oct-90	230229	5038	86.5	200.76	232.00	245.19	204.81	25291
Nov-90	231702	4958	86.5	192.01	231.90	252.69	204.36	25269
Dec-90	232810	5141	92.5	189.54	240.60	255.89	204.63	25383
Jan-91	233428	5102	87.6	180.40	247.00	254.88	197.61	25274
Feb-91	233135	4610	78.3	183.51	239.40	252.16	196.55	25290
Mar-91	231574	5135	91.8	184.07	247.50	253.56	194.25	25309
Apr-91	229598	4876	74.9	190.37	236.70	253.71	191.27	25369
May-91	229379	4973	67.0	189.32	226.90	252.00	192.06	25341
Jun-91	230072	4849	69.0	190.08	230.00	247.80	192.41	25443
Jul-91	230745	5045	79.6	184.68	236.20	243.38	194.37	25361
Aug-91	231833	5076	76.3	199.19	254.60	239.83	190.44	25377
Sep-91	233435	4917	75.5	212.96	269.40	233.81	187.14	25420
Oct-91	235449	5121	74.5	203.19	292.50	230.62	182.82	25431
Nov-91	236313	5019	75.8	198.68	296.25	233.58	180.38	25454
Dec-91	236940	5232	80.0	191.53	287.50	231.87	176.39	25662
Jan-92	235933	5135	66.6	193.36	267.50	230.14	173.60	25913
Feb-92	235175	4788	61.7	192.56	275.60	232.32	173.84	26019
Mar-92	235064	5209	63.1	194.94	272.00	233.52	171.46	26029
Apr-92	233550	5017	65.0	192.28	247.50	233.63	166.91	26077

1C. Continued

Date	Number of Hens	Number of Eggs	Egg Price	Soybean Meal Price	Cornmeal Price	Retail Beef Price	Retail Pork Price	Real Disposable Personal Income
May-92	231931	5069	58.9	199.53	246.25	230.86	167.84	26178
Jun-92	231721	4889	62.0	201.30	248.50	231.35	168.04	26259
Jul-92	232041	5095	58.6	192.64	243.75	228.14	170.61	26207
Aug-92	232548	5125	64.6	190.18	242.75	224.80	170.16	26262
Sep-92	235496	5004	70.5	194.99	266.00	227.28	168.94	26099
Oct-92	238442	5246	65.3	199.87	269.40	227.39	167.12	25901
Nov-92	239781	5132	75.3	199.12	266.90	228.04	165.04	25886
Dec-92	239916	5340	73.6	204.84	287.00	227.84	164.70	26776
Jan-93	238913	5237	71.7	203.32	283.10	226.37	162.77	26250
Feb-93	238669	4701	69.9	195.97	294.40	228.52	160.27	26317
Mar-93	238155	5260	85.2	199.39	295.50	229.60	159.40	26205
Apr-93	237533	5065	77.8	204.27	284.40	232.04	157.10	26299
May-93	237030	5172	67.6	211.56	276.90	235.45	159.52	26227
Jun-93	236919	5003	74.7	210.53	276.50	229.33	160.04	26146
Jul-93	237742	5171	68.9	250.73	300.60	227.53	162.43	26178
Aug-93	238635	5209	72.8	239.49	314.50	221.05	159.75	26185
Sep-93	239883	5096	67.2	219.99	305.60	217.33	160.73	26088
Oct-93	241321	5331	70.9	211.49	296.20	216.10	159.45	25919
Nov-93	241964	5244	71.5	227.76	305.75	217.49	159.81	25967
Dec-93	241985	5407	72.2	223.82	316.25	215.40	159.02	26827
Jan-94	240692	5292	68.0	217.13	309.40	213.08	158.15	26307
Feb-94	240293	4774	72.1	215.25	296.25	211.35	156.89	26344
Mar-94	240633	5404	74.4	213.48	288.50	213.56	157.84	26403
Apr-94	239634	5176	65.0	207.52	278.10	212.35	155.49	26384
May-94	238184	5248	61.9	210.81	263.50	212.46	155.11	26676
Jun-94	237376	5084	62.9	216.99	263.75	208.31	154.81	26597
Jul-94	237097	5268	66.2	199.92	263.75	205.65	155.75	26591
Aug-94	239256	5336	68.0	192.50	252.30	203.81	154.21	26600
Sep-94	242496	5218	66.7	186.32	235.60	204.08	152.15	26682
Oct-94	244495	5445	63.8	179.34	226.90	202.26	151.92	26901
Nov-94	246380	5371	68.5	175.45	232.50	203.34	149.72	26867
Dec-94	247818	5584	69.3	173.45	239.40	202.61	144.54	26967
Jan-95	246655	5443	65.2	172.51	230.50	204.63	146.63	27056
Feb-95	245556	4884	64.3	170.29	221.25	205.12	144.96	27094
Mar-95	244886	5530	66.2	177.20	215.60	204.38	146.97	27137
Apr-95	243500	5283	66.7	184.07	206.25	203.37	144.56	26904
May-95	241421	5326	59.5	185.63	196.50	202.00	144.65	27142
Jun-95	239040	5115	64.8	189.85	208.10	202.14	142.63	27196
Jul-95	237331	5240	75.6	199.36	218.75	204.56	144.13	27221
Aug-95	237361	5246	72.8	194.64	232.00	201.85	148.15	27213

1C. Continued

Date	Number of Hens	Number of Eggs	Egg Price	Soybean Meal Price	Cornmeal Price	Retail Beef Price	Retail Pork Price	Real Disposable Personal Income
Sep-95	238910	5106	77.1	209.81	250.00	200.64	148.25	27270
Oct-95	240992	5338	79.4	219.23	290.50	201.20	151.01	27273
Nov-95	244478	5331	91.1	230.54	326.90	201.69	149.61	27321
Dec-95	246272	5565	91.8	249.43	331.90	200.21	150.76	27331
Jan-96	245921	5431	91.3	258.36	351.00	197.41	149.20	27353
Feb-96	245247	5049	85.7	253.71	342.50	194.83	153.93	27542
Mar-96	245382	5523	91.8	251.40	341.25	192.06	154.50	27608
Apr-96	244673	5309	85.6	274.40	336.50	193.96	153.26	27424
May-96	242827	5367	76.5	271.62	343.10	191.82	156.72	27747
Jun-96	242335	5229	79.4	264.25	315.00	191.34	163.02	27884
Jul-96	244133	5478	81.0	272.55	308.50	192.24	165.37	27780
Aug-96	245653	5487	86.9	281.53	295.00	194.13	169.08	27816
Sep-96	246860	5319	90.0	294.05	329.40	193.45	170.77	27851
Oct-96	248909	5561	86.7	260.90	344.00	193.48	169.19	27817
Nov-96	250580	5487	102.5	255.55	340.00	196.09	168.06	27862
Dec-96	251044	5706	100.9	258.24	342.50	197.05	167.77	27935
Jan-97	249923	5577	86.3	260.66	336.25	192.68	168.40	28003
Feb-97	249435	4997	82.0	273.45	335.60	189.91	166.81	28062
Mar-97	249343	5595	86.3	301.17	340.00	187.57	164.52	28165
Apr-97	248055	5350	75.6	309.33	342.50	189.28	162.58	28157
May-97	246382	5475	72.3	324.99	355.75	190.03	164.26	28245
Jun-97	245069	5285	68.4	300.66	349.40	187.57	167.06	28305
Jul-97	244569	5434	81.9	284.33	337.00	188.14	165.90	28387
Aug-97	245694	5489	74.7	279.81	345.60	188.59	167.58	28500
Sep-97	249095	5374	82.4	277.95	355.00	189.42	166.21	28546
Oct-97	251689	5630	77.0	245.04	343.75	186.62	166.24	28650
Nov-97	254381	5576	97.4	259.68	351.25	185.70	163.47	28800
Dec-97	255919	5802	90.3	241.42	350.50	187.64	160.29	28936
Jan-98	255085	5724	72.5	217.84	321.90	183.17	165.28	29174
Feb-98	255991	5154	81.5	207.11	295.00	180.25	164.41	29341
Mar-98	256720	5801	71.6	188.89	270.50	180.38	158.78	29487
Apr-98	254152	5559	60.5	176.48	238.10	183.15	155.10	29555
May-98	251887	5588	67.3	171.40	236.25	182.26	158.08	29647
Jun-98	252014	5437	73.3	178.42	225.60	182.75	159.41	29785
Jul-98	251881	5677	77.7	188.04	252.50	182.62	160.72	29808
Aug-98	252291	5658	77.0	152.85	245.00	182.73	160.24	29873
Sep-98	254787	5484	78.9	143.22	210.00	178.98	159.73	29933
Oct-98	258578	5759	83.6	151.25	227.50	178.92	157.58	29953
Nov-98	262410	5715	82.7	160.32	313.10	182.29	156.90	30047
Dec-98	264187	5989	75.8	160.90	291.50	184.76	155.11	30071

1C. Continued

Date	Number of Hens	Number of Eggs	Egg Price	Soybean Meal Price	Cornmeal Price	Retail Beef Price	Retail Pork Price	Real Disposable Personal Income
Jan-99	264211	5917	69.6	150.15	257.50	180.76	151.17	30162
Feb-99	264382	5312	75.5	143.06	222.50	179.47	152.94	30238
Mar-99	263708	5963	60.2	144.45	198.00	177.84	152.28	30248
Apr-99	262589	5731	59.3	146.51	192.50	181.64	150.22	30162
May-99	261960	5848	54.9	145.24	201.25	180.84	152.75	30195
Jun-99	261611	5673	68.7	150.37	209.50	183.28	153.92	30267
Jul-99	261289	5819	67.4	143.26	241.25	184.27	155.61	30268
Aug-99	262371	5897	62.4	154.13	252.50	183.73	156.90	30364
Sep-99	264984	5816	56.9	161.68	258.13	183.37	157.25	30310
Oct-99	268182	6059	67.2	166.01	265.00	186.61	154.58	30468
Nov-99	270902	5987	65.4	164.45	250.00	189.16	154.27	30655
Dec-99	271295	6218	65.6	161.50	234.00	190.26	155.17	30879
Jan-00	271006	6092	62.2	172.43	236.25	185.25	154.42	31111
Feb-00	271776	5655	67.1	180.47	248.50	183.98	157.25	31208
Mar-00	272078	6133	60.7	185.63	243.13	186.17	158.01	31260
Apr-00	269758	5933	68.5	187.86	246.25	190.63	159.49	31363
May-00	267250	5993	53.5	200.98	240.00	192.87	160.05	31454
Jun-00	266759	5745	64.2	191.49	223.75	194.35	162.39	31498
Jul-00	267605	5977	61.9	175.93	218.75	193.14	163.42	31635
Aug-00	268837	6042	72.5	171.07	211.00	192.74	165.20	31776
Sep-00	270736	5843	67.1	188.03	225.00	194.18	164.39	31747
Oct-00	273196	6087	73.0	186.00	247.00	192.96	162.22	31770
Nov-00	275636	6014	81.4	194.33	263.75	192.12	160.55	31722
Dec-00	276204	6234	94.9	211.81	273.13	192.23	162.77	31735
Jan-01	276471	6157	76.2	197.59	284.50	198.86	161.26	31886
Feb-01	277703	5543	71.5	178.71	267.50	206.43	161.54	31928
Mar-01	278639	6252	79.6	169.52	253.75	206.11	163.64	32004
Apr-01	278780	6043	74.4	169.02	228.75	211.20	162.05	31907
May-01	276503	6143	58.1	178.07	231.00	211.19	163.97	31814
Jun-01	274532	5936	57.3	185.04	237.50	213.28	166.19	31789
Jul-01	274414	6126	59.8	194.23	205.50	211.64	165.73	32239
Aug-01	275772	6170	62.8	189.10	263.75	207.67	169.11	32771
Sep-01	278442	6028	61.5	183.94	268.13	206.37	169.98	32502
Oct-01	280490	6306	66.1	177.63	260.00	206.08	168.55	31968
Nov-01	281479	6204	71.3	177.99	258.13	205.87	165.40	32019
Dec-01	282339	6391	67.1	166.50	257.50	201.54	165.62	32074
Jan-02	281179	6210	69.7	169.58	236.00	201.33	164.79	32733
Feb-02	279727	5619	60.7	165.45	221.88	200.89	165.18	32744
Mar-02	279236	6354	76.9	174.29	219.38	199.86	163.82	32707
Apr-02	277842	6057	55.8	175.93	217.00	200.66	160.46	32776

1C. Continued

Date	Number of Hens	Number of Eggs	Egg Price	Soybean Meal Price	Cornmeal Price	Retail Beef Price	Retail Pork Price	Real Disposable Personal Income
May-02	276403	6197	53.3	179.90	217.38	200.69	162.38	32821
Jun-02	276848	6075	66.1	185.83	230.00	198.53	160.42	32866
Jul-02	278323	6296	64.6	204.24	254.00	197.27	158.47	32736
Aug-02	279556	6314	67.3	201.12	275.00	200.18	159.55	32681
Sep-02	281501	6145	64.0	200.25	272.50	196.17	155.83	32670
Oct-02	282959	6394	65.2	185.35	268.50	193.71	155.14	32716
Nov-02	283412	6259	84.0	183.88	256.25	198.48	153.97	32765
Dec-02	283325	6406	77.1	181.98	255.90	200.69	154.84	32837
Jan-03	282983	6322	77.4	184.87	239.75	201.27	152.94	32828
Feb-03	281983	5691	74.1	192.42	234.00	204.92	154.66	32739
Mar-03	280697	6333	80.0	191.36	230.40	208.39	152.94	32832
Apr-03	278805	6121	77.1	200.26	226.20	212.96	154.03	33019
May-03	276767	6220	67.7	214.18	235.00	210.72	150.71	33249
Jun-03	276027	6046	76.9	210.61	230.40	212.04	153.38	33335
Jul-03	276475	6337	81.0	200.44	223.50	211.45	154.13	33682
Aug-03	277520	6318	93.8	199.30	226.90	216.13	156.62	33861
Sep-03	277883	6118	94.9	218.14	246.90	213.50	156.94	33442
Oct-03	279104	6403	100.0	245.71	239.48	226.04	155.44	33557
Nov-03	281735	6319	122.9	262.96	321.88	247.97	156.33	33778
Dec-03	281659	6487	109.3	255.64	337.50	243.85	154.03	33814
Jan-04	279983	6320	114.3	278.48	360.63	228.74	153.79	33830
Feb-04	280283	5894	107.5	286.39	371.25	226.90	153.04	33880
Mar-04	282021	6451	122.9	331.41	383.00	225.36	153.01	33979
Apr-04	282720	6280	89.6	343.71	390.38	229.32	153.38	34065
May-04	282532	6393	73.5	331.65	344.10	228.19	155.45	34214
Jun-04	283497	6223	75.9	311.68	332.50	234.43	158.97	34188
Jul-04	284372	6484	69.8	291.01	332.50	235.43	160.42	34213
Aug-04	285182	6472	63.4	212.15	267.50	231.72	162.56	34284
Sep-04	286172	6304	65.3	182.69	256.88	228.95	162.51	34255
Oct-04	287013	6588	57.9	171.44	241.25	226.26	162.48	34257
Nov-04	286869	6447	71.1	170.13	238.00	228.70	158.46	34149
Dec-04	287630	6647	75.1	175.72	253.63	230.93	157.71	35370
Jan-05	289304	6538	64.9	175.18	245.63	230.64	160.01	34164
Feb-05	289802	5925	67.8	178.55	232.50	232.15	159.73	34156
Mar-05	288013	6626	60.9	207.64	240.50	235.69	157.25	34240
Apr-05	284738	6333	56.2	210.27	246.25	236.66	158.46	34282
May-05	283103	6462	54.6	218.01	274.60	236.98	160.88	34398
Jun-05	281823	6273	56.8	241.22	322.13	232.59	159.00	34469
Jul-05	281001	6468	63.7	238.80	334.25	221.72	157.71	34527
Aug-05	282032	6450	60.1	217.60	327.70	220.89	156.12	34548

1C. Continued

Date	Number of Hens	Number of Eggs	Egg Price	Soybean Meal Price	Cornmeal Price	Retail Beef Price	Retail Pork Price	Real Disposable Personal Income
Sep-05	284135	6302	76.1	193.57	294.75	216.81	156.13	34341
Oct-05	286265	6587	62.8	186.58	300.00	219.30	154.02	34477
Nov-05	289160	6478	76.8	192.15	319.00	221.66	152.79	34686
Dec-05	292077	6736	85.5	209.58	319.75	224.45	154.01	34844
Jan-06	293010	6674	75.6	201.96	303.75	223.95	152.06	35286
Feb-06	293200	6030	59.0	198.43	259.38	221.67	152.72	35412
Mar-06	293688	6784	79.6	192.43	263.75	217.76	150.00	35451
Apr-06	292290	6519	65.9	190.55	250.63	218.74	152.13	35379
May-06	289261	6575	56.4	193.25	251.70	215.33	150.74	35321
Jun-06	287482	6393	65.8	196.26	250.00	213.47	152.38	35370
Jul-06	286523	6609	56.6	187.27	240.00	210.87	154.55	35330
Aug-06	286950	6616	68.0	175.91	229.25	215.38	154.39	35292
Sep-06	289003	6438	67.3	177.59	237.50	212.00	155.62	35476
Oct-06	290701	6662	71.4	194.12	272.20	213.34	154.93	35650
Nov-06	292414	6561	100.0	214.23	306.25	214.80	151.50	35747
Dec-06	292908	6740	95.7	205.69	314.31	212.74	150.20	35813
Jan-07	291592	6594	113.9	221.79	333.00	212.72	151.32	35819
Feb-07	290851	5973	100.2	244.10	346.88	217.49	150.23	35887
Mar-07	289892	6706	102.0	239.53	361.50	223.27	150.73	35970
Apr-07	287262	6400	93.9	221.75	363.33	227.91	149.65	35936
May-07	284035	6510	95.6	227.67	344.00	227.26	151.96	35891
Jun-07	282107	6300	86.4	249.16	352.75	222.18	153.34	35820
Jul-07	282434	6495	115.2	252.57	398.50	218.73	155.04	35870
Aug-07	283385	6497	112.3	251.83	404.38	219.47	154.69	35859
Sep-07	283744	6329	129.9	288.78	414.38	222.59	153.03	35918
Oct-07	285303	6628	113.8	300.43	472.50	216.33	153.45	35822
Nov-07	286884	6481	148.7	315.25	495.63	217.75	149.92	35759
Dec-07	285930	6664	160.6	351.22	540.79	216.13	150.26	35883
Jan-08	283595	6492	157.4	376.33	545.00	215.01	149.74	35961
Feb-08	281931	6028	157.3	396.71	543.13	218.26	147.30	35999
Mar-08	280925	6512	161.8	379.70	561.88	217.54	146.57	36049
Apr-08	279705	6251	123.4	375.32	547.00	214.38	146.89	35887
May-08	279114	6407	103.8	369.37	529.00	218.18	149.35	37585
Jun-08	278647	6258	124.9	436.91	524.38	220.85	150.77	36564
Jul-08	277289	6470	105.4	452.19	554.50	222.11	151.57	35958
Aug-08	277057	6434	119.0	388.40	505.00	230.43	153.62	35640
Sep-08	277321	6274	119.1	363.78	495.50	226.79	152.22	35650
Oct-08	278499	6547	119.2	290.84	464.13	226.47	151.45	35799
Nov-08	282330	6458	123.8	292.76	406.25	224.34	151.95	36022
Dec-08	285167	6723	124.8	292.94	389.00	223.13	152.70	35867

1C. Continued

Date	Number of Hens	Number of Eggs	Egg Price	Soybean Meal Price	Cornmeal Price	Retail Beef Price	Retail Pork Price	Real Disposable Personal Income
Jan-09	285120	6618	126.9	338.50	469.38	217.86	151.10	35993
Feb-09	284368	5932	100.7	320.89	539.38	219.32	149.03	35646
Mar-09	284268	6663	101.5	315.37	424.38	215.02	147.27	35624
Apr-09	283652	6436	107.7	349.57	443.13	211.85	144.61	35795
May-09	280815	6534	80.7	408.05	564.38	213.51	145.88	36326
Jun-09	277630	6315	80.6	441.78	630.00	210.57	145.58	35683
Jul-09	276960	6521	91.3	385.85	532.50	204.85	145.32	35531
Aug-09	277737	6541	96.9	397.30	495.00	206.96	143.88	35415
Sep-09	279430	6373	96.2	342.18	508.50	204.03	143.22	35433
Oct-09	281628	6662	105.4	328.54	606.25	205.42	142.72	35260
Nov-09	283863	6576	123.5	337.63	595.00	213.61	139.84	35317
Dec-09	285232	6804	124.2	345.58	573.50	212.14	139.74	35416
Jan-10	283998	6657	126.8	325.85	582.50	206.14	142.17	35331
Feb-10	283428	5971	116.4	303.66	594.94	205.68	143.35	35246
Mar-10	284913	6769	134.9	292.60	541.70	209.58	141.92	35303
Apr-10	283896	6536	92.5	308.05	492.13	214.63	141.22	35544
May-10	282226	6644	78.3	305.74	455.63	214.31	146.34	35761
Jun-10	282999	6450	77.6	314.32	445.00	214.62	148.96	35753
Jul-10	282896	6637	85.4	335.09	441.25	211.95	152.92	35758
Aug-10	283576	6685	107.4	339.14	451.50	209.34	155.43	35842
Sep-10	282914	6482	86.6	334.06	464.38	211.89	158.26	35772
Oct-10	280880	6639	97.2	353.75	501.88	214.30	160.94	35834
Nov-10	283352	6556	138.4	376.04	518.00	213.55	157.95	35915
Dec-10	286323	6866	134.2	387.51	520.00	210.94	151.80	36145
Jan-11	285012	6756	108.4	412.07	524.06	214.20	153.56	36312
Feb-11	282713	6046	109.4	410.16	533.75	216.49	155.09	36394
Mar-11	283457	6765	99.6	393.93	543.30	221.26	157.24	36321
Apr-11	283099	6559	120.0	388.22	556.25	223.18	157.18	36205
May-11	280041	6673	99.2	388.26	556.00	223.29	160.83	36165
Jun-11	280087	6464	100.5	391.54	567.50	218.46	159.09	36297
Jul-11	281585	6700	104.3	389.29	556.25	216.70	157.57	36418
Aug-11	282760	6715	131.9	393.80	559.00	222.19	160.29	36367
Sep-11	284823	6564	116.9	381.85	550.63	224.32	162.79	36236
Oct-11	286485	6836	124.4	347.45	524.38	227.54	160.14	36244
Nov-11	289155	6709	125.3	329.09	487.00	234.82	165.27	36185
Dec-11	290239	7035	144.0	320.68	441.25	237.29	164.62	36441
Jan-12	289631	6912	108.2	347.60	433.50	239.41	165.53	36673
Feb-12	289746	6361	102.5	364.49	448.75	236.02	164.69	36857
Mar-12	290722	6934	115.6	405.23	487.50	235.72	164.07	36933
Apr-12	290214	6690	102.1	440.62	498.75	231.77	162.23	37011

1C. Continued

Date	Number of Hens	Number of Eggs	Egg Price	Soybean Meal Price	Cornmeal Price	Retail Beef Price	Retail Pork Price	Real Disposable Personal Income
May-12	289203	6852	92.0	459.42	533.00	230.14	159.36	37028
Jun-12	288308	6622	105.0	464.02	579.00	226.89	157.49	37087
Jul-12	287696	6832	125.1	552.54	629.00	231.15	159.48	36962
Aug-12	289250	6922	135.5	585.75	718.75	227.69	163.39	36869
Sep-12	291763	6727	135.2	559.56	721.88	227.48	162.40	37016
Oct-12	295347	7046	121.7	519.91	753.50	231.46	161.18	37209
Nov-12	299793	7022	135.1	490.60	716.25	236.17	160.79	37679
Dec-12	300166	7263	131.7	489.69	673.34	235.13	158.68	38639
Jan-13	298678	7160	128.3	456.81	599.50	240.24	159.27	36139
Feb-13	299686	6437	117.8	469.16	584.38	238.95	161.06	36185
Mar-13	300399	7198	134.4	467.95	581.88	241.85	161.61	36230
Apr-13	298071	6954	104.8	446.36	540.50	239.62	160.86	36242
May-13	296590	7124	122.6	476.74	480.63	239.53	162.83	36399
Jun-13	296942	6878	102.4	503.56	550.00	241.98	165.92	36448
Jul-13	297353	7085	115.0	528.34	591.00	244.53	169.52	36416
Aug-13	299442	7186	121.6	470.99	565.63	245.09	172.11	36489
Sep-13	300095	7028	120.4	490.19	573.75	242.37	173.60	36554
Oct-13	301104	7300	121.8	460.83	601.25	244.83	174.17	36401
Nov-13	304497	7172	151.2	461.65	631.25	247.19	172.58	36490
Dec-13	307126	7471	156.1	495.00	638.13	244.57	171.61	36492
Jan-14	307221	7417	128.1	473.75	625.00	242.74	170.63	36608
Feb-14	306665	6667	148.5	499.36	668.13	251.93	168.40	36774
Mar-14	307713	7449	151.3	506.69	744.38	255.97	171.41	36879
Apr-14	308303	7256	150.0	533.63	784.00	261.05	175.63	36899
May-14	307596	7433	130.0	542.78	761.25	261.69	181.41	36934
Jun-14	307037	7185	123.9	519.27	694.50	262.13	182.33	37042
Jul-14	308198	7501	137.1	451.02	574.00	263.43	182.67	37048
Aug-14	309581	7497	127.7	447.82	572.88	275.43	185.38	37160
Sep-14	310357	7230	123.3	409.10	587.50	275.74	185.80	37167
Oct-14	310740	7539	128.0	378.82	549.38	275.62	183.22	37279
Nov-14	312700	7465	171.5	423.25	581.88	278.61	179.63	37477
Dec-14	313019	7731	188.6	418.09	613.50	279.60	176.86	37654
Jan-15	309465	7504	126.0	379.04	632.50	279.40	176.01	37774
Feb-15	308069	6685	145.3	374.25	631.25	275.40	173.11	37820
Mar-15	308050	7517	169.5	364.86	613.00	275.02	168.89	37708
Apr-15	303568	7198	122.1	349.71	575.63	278.23	163.82	37881
May-15	286793	6942	171.7	340.47	549.38	279.00	160.82	37946
Jun-15	274176	6402	217.1	353.90	571.60	279.17	161.38	38014
Jul-15	275146	6630	223.7	394.64	560.00	277.82	164.53	38086
Aug-15	276561	6656	260.7	370.41	550.63	274.68	166.43	38178

1C. Continued

Date	Number of Hens	Number of Eggs	Egg Price	Soybean Meal Price	Cornmeal Price	Retail Beef Price	Retail Pork Price	Real Disposable Personal Income
Sep-15	278923	6467	222.7	342.96	525.00	269.23	169.37	38232
Oct-15	281677	6744	166.0	338.21	509.38	269.36	171.74	38324
Nov-15	285491	6673	209.1	320.34	477.50	269.86	170.15	38370
Dec-15	289726	6986	147.2	303.86	482.25	260.09	167.50	38495
Jan-16	293069	7024	133.5	297.18	452.50	259.47	164.71	38645
Feb-16	298555	6759	130.6	291.37	457.50	257.83	161.01	38702
Mar-16	302464	7363	100.6	296.18	445.50	267.34	161.53	38791
Apr-16	302374	7095	75.3	327.70	434.00	262.55	163.38	38843
May-16	301963	7361	63.4	407.50	464.10	261.05	162.31	38849

[24] *The vector error correction model was estimated using the data from above the double-black line, ending in October 2014; the altosdata.txt file for the RATS programs provided. The highlighted portion indicates the period of time that the flu occurred. In the RATS programs, this full data set is beef&pork.txt.*

2C. TETRAD V Input Data

/covariance							
343	Observations						
HENS	EGGS	EPR	SMP	CMP	BPR	PPR	RDI
1.000							
0.452	1.000						
0.026	0.011	1.000					
-0.058	-0.023	0.196	1.000				
-0.082	-0.091	0.151	0.446	1.000			
0.001	-0.003	0.102	0.034	-0.046	1.000		
-0.046	-0.052	0.026	-0.018	-0.055	0.197	1.000	
0.082	0.068	-0.037	-0.004	0.003	-0.033	-0.005	1.000

APPENDIX D

REGRESSION ANALYSIS FOR TIME SERIES (RATS) INPUT PROGRAMS

1D. Summary Statistics for the Estimated Model: March 1986 to October 2014[25]

```
calendar 1986 1 12
allocate 500 2016:6
eqv 1 to 8
 hens eggs eggprice soymealp cornmealp beefprice prkprice inc
*********
open data altosdata.txt
data(format=free,org=obs) 1986:3 2014:10 1 to 8
**********************************************

Table

EXTREMUM(print) hens 1986:3 2014:10
EXTREMUM(print) eggs 1986:3 2014:10
EXTREMUM(print) eggprice 1986:3 2014:10
EXTREMUM(print) soymealp 1986:3 2014:10
EXTREMUM(print) cornmealp 1986:3 2014:10
EXTREMUM(print) beefprice 1986:3 2014:10
EXTREMUM(print) prkprice 1986:3 2014:10
EXTREMUM(print) inc 1986:3 2014:10

STATISTICS(print) hens 1986:3 2014:10
STATISTICS(print) eggs 1986:3 2014:10
STATISTICS(print) eggprice 1986:3 2014:10
STATISTICS(print) soymealp 1986:3 2014:10
STATISTICS(print) cornmealp 1986:3 2014:10
STATISTICS(print) beefprice 1986:3 2014:10
STATISTICS(print) prkprice 1986:3 2014:10
STATISTICS(print) inc 1986:3 2014:10

End
```

[25] *For the full data set, all 2014:10 dates are replaced with 2016:5 and the data file is changed to beef&pork.txt.*

2D. Plots of Data for the Estimated Model Data Set[26]

```
calendar 1986 1 12
allocate 500 2016:12

eqv 1 to 8
 hens eggs eggp smp cmp beefp porkp inc
open data altosdata.txt
data(format=free,org=obs) 1986:3 2014:10 1 to 8

compute neqn = 8
Compute nlags = 1
compute nsteps = 24

DECLARE RECT PATTERN(8,8)
compute p=8
declare rect A
declare rect[series] impblk(neqn,neqn)
declare vect[series] scaled(neqn)
declare vect[labels] implabel(neqn)
declare vect[strings] mplabel(neqn)

seasonal seas 1986:1 2016:12 12 1986:12

system 1 to 8
vars 1 to 8
lags 1 to 1
det constant seas{0 to 10}
end(system)

estimate(noprint,ftests,outsigma=v) 1986:4 2014:10  21
vcv(matrix=v) 1986:4 2014:10
#  21 22 23 24 25 26 27 28

Input implabel
  hens eggs eggp smp cmp bp pp inc

list ieqn = 1 to neqn
smpl 1 nsteps
do I=1,neqn
   impulse(noprint) neqn nsteps I V
   Cards ieqn impblk(ieqn,I) 1 ieqn
   Display(store=header) "Plot of responses to" implabel(I)
    Do J=1,neqn
     set scaled(J) = (impblk(J,I))/sqrt(v(J,J))
     Labels scaled(J)
     # implabel(J)
   End do J
   Graph(header=header, key=right, number=0) neqn
   cards scaled(ieqn)
End do I
*******************************************
```

```
Do I=1,neqn
  Display(store=header) 'Plot of responses of' implabel(I)
  Do J=1,neqn
    labels impblk(I,J)
    # implabel(J)
  end do J
  Graph(header=header, key=right, number=0) neqn
  cards impblk(I,ieqn)
End do I

 open plot grfeggplots.rgf

 spgraph(vfields=4,hfields=2)

 set grid 2014:12 2014:12 = (T==2014:12)
set grid 2015:6 2015:6 = (T==2015:6)

 graph(patterns,header=" Hen Numbers", grid=grid, VLABEL="Thousands of Hens",VTICKS=4) 1
 # 1 1986:3 2014:10
 graph(patterns,header=" Egg Numbers",grid=grid, VLABEL="Million of Eggs",VTICKS=4) 1
 # 2 1986:3 2014:10
 graph(patterns,header=" Egg Price",grid=grid,VLABEL="Cents per Dozen",VTICKS=4) 1
 # 3 1986:3 2014:10
 graph(patterns,header=" Soy Meal Price", grid=grid, VLABEL="Dollars per Metric Ton",VTICKS=4) 1
 # 4 1986:3 2014:10
 graph(patterns,header=" Corn Meal Price", grid=grid, VLABEL="Dollars per Ton",VTICKS=4) 1
 # 5 1986:3 2014:10
graph(patterns,header=" Beef Price",grid=grid, VLABEL="Cents per Pound",VTICKS=4) 1
 # 6 1986:3 2014:10
 graph(patterns,header=" Pork Price", grid=grid, VLABEL="Cents per Pound",VTICKS=4) 1
 # 7 1986:3 2014:10
 graph(patterns,header=" Personal Income", grid=grid, VLABEL="Dollars",VTICKS=4) 1
 # 8 1986:3 2014:10

spgraph(done)

ERRORS(impulses) 8 24 v
# 1 * * 1
# 2 * * 2
# 3 * * 3
# 4 * * 4
# 5 * * 5
# 6 * * 6
# 7 * * 7
# 8 * * 8

End
```

[26] *For the full data set, all 2014:10 dates are replaced with 2016:5 and the data file is changed to beef&pork.txt.*

3D. Generating Impulse Graphs

```
calendar 1986 1 12
allocate 100 2018:12

eqv 1 to 8
 hens eggs eggprice soymealp $
 cornmealp beefprice prkprice inc

open data altosdata.txt
data(format=free,org=obs) 1986:3 2014:10 1 to 8

***p is no of series
compute p=8
***def by hui
dec rect pi
dec rect const
dec rect a1

dec rect ta1 tc1
dec vect[vect] coeflag1(p)

dec vect[vect] c1(p)
dec vect[vect] coef(p)

dec vect sd
dec symmetric sd2 corr
dec rect v(p,p)
**********
DECLARE RECT PATTERN(p,p)
declare rect A
declare rect[series] impblk(p,p)
declare vect[series] scaled(p)
declare vect[labels] implabel(p)
declare vect[strings] mplabel(p)

source(noecho) c:\rats\bernanke.src

compute pi=$
     ||-0.0459404, 2.2848594, 6.6781304, -0.7811818, -1.6747604, -2.6320198, 0.8016778, -0.0927614| $
       0.0053911, -0.2480674, -0.0988423, 0.2005225, 0.0194677, 0.1897341, -0.1925349, 0.0077431| $
      -0.0001190, -0.0009969, -0.2188126, -0.0395529, 0.0567087, 0.0342552, 0.0360228, 0.0008431| $
      -0.0002821, 0.0187640, 0.2025944, 0.0208862, -0.0520625, -0.0442718, -0.0183082, -0.0013111| $
       0.0003245, 0.0073714, 0.7554459, 0.1330897, -0.1956881, -0.1210308, -0.1210543, -0.0030277| $
      -0.0000268, 0.0022636, 0.0356298, 0.0045872, -0.0091818, -0.0070566, -0.0040937, -0.0001998| $
      -0.0000182, 0.0015685, 0.0252950, 0.0032906, -0.0065195, -0.0049827, -0.0029388, -0.0001407| $
      -0.0067638, 0.3628017, 1.8843918, 0.0282192, -0.4795738, -0.5442817, -0.0115259, -0.0177925||

compute const= $
||2231.0308989|-265.5906547|7.0830910|12.8083881|-20.1885862|1.1276006|0.7586982|323.5058842||

compute A1=%identity(p)+pi
```

```
*write 'A1' a1
compute ta1=tr(a1)
compute tc1=tr(const)

do i=1,p
 overlay ta1(1,i) with coeflag1 (i) (p)

 overlay tc1(1,i) with c1 (i) (1)
 end do i

*write 'coeflag1' coeflag1
*write 'c1' c1

do i=1,p
 compute coef(i) = ||coeflag1 (i) (1),coeflag1 (i) (2), $
 coeflag1 (i) (3), coeflag1 (i) (4), coeflag1 (i) (5), $
 coeflag1 (i) (6), coeflag1 (i) (7), coeflag1 (i) (8), $
 c1 (i) (1)||
 write 'coef(i)' coef(i)
 end do i

system 1 to p
do i=1,p
 equation i i
 # 1{1} 2{1} 3{1} 4{1} 5{1} 6{1} 7{1} 8{1}  $
   constant
 associate i coef(i)
 end do i
end(system)

compute sd= $
||990.411219,54.837581,8.868870,17.902268,28.666248,3.141017,2.245612,254.012694||

compute %nobs= 243

compute sd2= sd*tr(sd)
*write 'sd2' sd2

compute corr= $
 || 1.000000 | $
  0.451690,  1.000000 | $
  0.025955,  0.011419,  1.000000 | $
 -0.057876, -0.023389,  0.195906,  1.000000 | $
 -0.081763, -0.090757,  0.151336,  0.445795,  1.000000 | $
  0.000559, -0.002518,  0.102352,  0.033568, -0.046054,  1.000000 | $
 -0.046389, -0.052483,  0.026267, -0.017751, -0.055323,  0.197276,  1.000000 | $
  0.081827,  0.067730, -0.037270, -0.003514,  0.003150, -0.033081, -0.004596,  1.000000||

dec rect v(p,p)
ewise v(i,j)=sd2(i,j)*corr(i,j)
write 'v' v
```

```
INPUT PATTERN
1 0 0 0 1 0 1 1
1 1 0 0 1 0 0 0
0 0 1 1 1 1 0 0
0 0 0 1 0 0 0 0
0 0 0 0 1 0 0 0
0 0 0 0 0 1 1 0
0 0 0 0 1 0 1 0
0 0 0 0 0 0 0 1

nonlin A23 A35 A36
*declare rect A
compute A23=-.1, A35=-.1, A36=-.1

compute A=%Identity(p)
find min -2*log(%det(A))+%sum(%log(%mqformdiag(v,TR(A)))) {
 compute A(2,3)=A23, $
        A(3,5)=A35, $
        A(3,6)=A36
                 }
  end find

@BERNANKE(initial=A,TEST,PRINT) v pattern factor
ERRORS(DECOMP=FACTOR,Impulses) 8 24
# 1
# 2
# 3
# 4
# 5
# 6
# 7
# 8

 compute neqn = 8
compute implabel=||'Hens','Eggs','Egg Price','Soybean Meal Price','Cornmeal Price','Beef Price','Pork
Price','Income'||
list ieqn = 1 to 8
compute mplabel=||'Hens','Eggs','Egg Price','Soybean Meal Price','Cornmeal Price','Beef Price','Pork
Price','Income'||

 impluse(noprint,decomp=factor) 8 24 1
 card ieqn impblk(ieqn,1) 1 ieqn

  set scaled(1) = (impblk(1,1))/sqrt(v(1,1))
  set g11 = scaled(1)
  labels scaled(1)
  #implabel(1)

  set scaled(2) = (impblk(2,1))/sqrt(v(2,2))
  set g21 = scaled(2)
  labels scaled(2)
  #implabel(2)
```

```
 set scaled(3) = (impblk(3,1))/sqrt(v(3,3))
 set g31 = scaled(3)
 labels scaled(3)
 #implabel(3)

 set scaled(4) = (impblk(4,1))/sqrt(v(4,4))
 set g41 = scaled(4)
 labels scaled(4)
 #implabel(4)

 set scaled(5) = (impblk(5,1))/sqrt(v(5,5))
 set g51 = scaled(5)
 labels scaled(5)
 #implabel(5)

 set scaled(6) = (impblk(6,1))/sqrt(v(6,6))
 set g61 = scaled(6)
 labels scaled(6)
 #implabel(6)

 set scaled(7) = (impblk(7,1))/sqrt(v(7,7))
 set g71 = scaled(7)
 labels scaled(7)
 #implabel(7)

 set scaled(8) = (impblk(8,1))/sqrt(v(8,8))
 set g81 = scaled(8)
 labels scaled(8)
 #implabel(8)

impluse(noprint,decomp=factor) 8 24 2
card ieqn impblk(ieqn,2) 1 ieqn

 set scaled(1) = (impblk(1,2))/sqrt(v(1,1))
 set g12 = scaled(1)
 labels scaled(1)
 #implabel(1)

 set scaled(2) = (impblk(2,2))/sqrt(v(2,2))
 set g22 = scaled(2)
 labels scaled(2)
 #implabel(2)

 set scaled(3) = (impblk(3,2))/sqrt(v(3,3))
 set g32 = scaled(3)
 labels scaled(3)
 #implabel(3)

 set scaled(4) = (impblk(4,2))/sqrt(v(4,4))
 set g42 = scaled(4)
 labels scaled(4)
 #implabel(4)
```

```
 set scaled(5) = (impblk(5,2))/sqrt(v(5,5))
 set g52 = scaled(5)
 labels scaled(5)
 #implabel(5)

 set scaled(6) = (impblk(6,2))/sqrt(v(6,6))
 set g62 = scaled(6)
 labels scaled(6)
 #implabel(6)

 set scaled(7) = (impblk(7,2))/sqrt(v(7,7))
 set g72 = scaled(7)
 labels scaled(7)
 #implabel(7)

 set scaled(8) = (impblk(8,2))/sqrt(v(8,8))
 set g82 = scaled(8)
 labels scaled(8)
 #implabel(8)

impluse(noprint,decomp=factor) 8 24 3
card ieqn impblk(ieqn,3) 1 ieqn

 set scaled(1) = (impblk(1,3))/sqrt(v(1,1))
 set g13 = scaled(1)
 labels scaled(1)
 #implabel(1)

 set scaled(2) = (impblk(2,3))/sqrt(v(2,2))
 set g23 = scaled(2)
 labels scaled(2)
 #implabel(2)

 set scaled(3) = (impblk(3,3))/sqrt(v(3,3))
 set g33 = scaled(3)
 labels scaled(3)
 #implabel(3)

 set scaled(4) = (impblk(4,3))/sqrt(v(4,4))
 set g43 = scaled(4)
 labels scaled(4)
 #implabel(4)

 set scaled(5) = (impblk(5,3))/sqrt(v(5,5))
 set g53 = scaled(5)
 labels scaled(5)
 #implabel(5)

 set scaled(6) = (impblk(6,3))/sqrt(v(6,6))
 set g63 = scaled(6)
 labels scaled(6)
 #implabel(6)
```

```
 set scaled(7) = (impblk(7,3))/sqrt(v(7,7))
 set g73 = scaled(7)
 labels scaled(7)
 #implabel(7)

 set scaled(8) = (impblk(8,3))/sqrt(v(8,8))
 set g83 = scaled(8)
 labels scaled(8)
 #implabel(8)

 impluse(noprint,decomp=factor) 8 24 4
card ieqn impblk(ieqn,4) 1 ieqn

 set scaled(1) = (impblk(1,4))/sqrt(v(1,1))
 set g14 = scaled(1)
 labels scaled(1)
 #implabel(1)

 set scaled(2) = (impblk(2,4))/sqrt(v(2,2))
 set g24 = scaled(2)
 labels scaled(2)
 #implabel(2)

 set scaled(3) = (impblk(3,4))/sqrt(v(3,3))
 set g34 = scaled(3)
 labels scaled(3)
 #implabel(3)

 set scaled(4) = (impblk(4,4))/sqrt(v(4,4))
 set g44 = scaled(4)
 labels scaled(4)
 #implabel(4)

 set scaled(5) = (impblk(5,4))/sqrt(v(5,5))
 set g54 = scaled(5)
 labels scaled(5)
 #implabel(5)

 set scaled(6) = (impblk(6,4))/sqrt(v(6,6))
 set g64 = scaled(6)
 labels scaled(6)
 #implabel(6)

 set scaled(7) = (impblk(7,4))/sqrt(v(7,7))
 set g74 = scaled(7)
 labels scaled(7)
 #implabel(7)

 set scaled(8) = (impblk(8,4))/sqrt(v(8,8))
 set g84 = scaled(8)
 labels scaled(8)
 #implabel(8)
```

```
impluse(noprint,decomp=factor) 8 24 5
card ieqn impblk(ieqn,5) 1 ieqn

set scaled(1) = (impblk(1,5))/sqrt(v(1,1))
set g15 = scaled(1)
labels scaled(1)
#implabel(1)

set scaled(2) = (impblk(2,5))/sqrt(v(2,2))
set g25 = scaled(2)
labels scaled(2)
#implabel(2)

set scaled(3) = (impblk(3,5))/sqrt(v(3,3))
set g35 = scaled(3)
labels scaled(3)
#implabel(3)

set scaled(4) = (impblk(4,5))/sqrt(v(4,4))
set g45 = scaled(4)
labels scaled(4)
#implabel(4)

set scaled(5) = (impblk(5,5))/sqrt(v(5,5))
set g55 = scaled(5)
labels scaled(5)
#implabel(5)

set scaled(6) = (impblk(6,5))/sqrt(v(6,6))
set g65 = scaled(6)
labels scaled(6)
#implabel(6)

set scaled(7) = (impblk(7,5))/sqrt(v(7,7))
set g75 = scaled(7)
labels scaled(7)
#implabel(7)

set scaled(8) = (impblk(8,5))/sqrt(v(8,8))
set g85 = scaled(8)
labels scaled(8)
#implabel(8)

impluse(noprint,decomp=factor) 8 24 6
card ieqn impblk(ieqn,6) 1 ieqn

set scaled(1) = (impblk(1,6))/sqrt(v(1,1))
set g16 = scaled(1)
labels scaled(1)
#implabel(1)

set scaled(2) = (impblk(2,6))/sqrt(v(2,2))
set g26 = scaled(2)
```

```
labels scaled(2)
#implabel(2)

set scaled(3) = (impblk(3,6))/sqrt(v(3,3))
set g36 = scaled(3)
labels scaled(3)
#implabel(3)

set scaled(4) = (impblk(4,6))/sqrt(v(4,4))
set g46 = scaled(4)
labels scaled(4)
#implabel(4)

set scaled(5) = (impblk(5,6))/sqrt(v(5,5))
set g56 = scaled(5)
labels scaled(5)
#implabel(5)

set scaled(6) = (impblk(6,6))/sqrt(v(6,6))
set g66 = scaled(6)
labels scaled(6)
#implabel(6)

set scaled(7) = (impblk(7,6))/sqrt(v(7,7))
set g76 = scaled(7)
labels scaled(7)
#implabel(7)

set scaled(8) = (impblk(8,6))/sqrt(v(8,8))
set g86 = scaled(8)
labels scaled(8)
#implabel(8)

impluse(noprint,decomp=factor) 8 24 7
card ieqn impblk(ieqn,7) 1 ieqn

set scaled(1) = (impblk(1,7))/sqrt(v(1,1))
set g17 = scaled(1)
labels scaled(1)
#implabel(1)

set scaled(2) = (impblk(2,7))/sqrt(v(2,2))
set g27 = scaled(2)
labels scaled(2)
#implabel(2)

set scaled(3) = (impblk(3,7))/sqrt(v(3,3))
set g37 = scaled(3)
labels scaled(3)
#implabel(3)

set scaled(4) = (impblk(4,7))/sqrt(v(4,4))
set g47 = scaled(4)
```

```
labels scaled(4)
#implabel(4)

set scaled(5) = (impblk(5,7))/sqrt(v(5,5))
set g57 = scaled(5)
labels scaled(5)
#implabel(5)

set scaled(6) = (impblk(6,7))/sqrt(v(6,6))
set g67 = scaled(6)
labels scaled(6)
#implabel(6)

set scaled(7) = (impblk(7,7))/sqrt(v(7,7))
set g77 = scaled(7)
labels scaled(7)
#implabel(7)

set scaled(8) = (impblk(8,7))/sqrt(v(8,8))
set g87 = scaled(8)
labels scaled(8)
#implabel(8)

impluse(noprint,decomp=factor) 8 24 8
card ieqn impblk(ieqn,8) 1 ieqn

set scaled(1) = (impblk(1,8))/sqrt(v(1,1))
set g18 = scaled(1)
labels scaled(1)
#implabel(1)

set scaled(2) = (impblk(2,8))/sqrt(v(2,2))
set g28 = scaled(2)
labels scaled(2)
#implabel(2)

set scaled(3) = (impblk(3,8))/sqrt(v(3,3))
set g38 = scaled(3)
labels scaled(3)
#implabel(3)

set scaled(4) = (impblk(4,8))/sqrt(v(4,4))
set g48 = scaled(4)
labels scaled(4)
#implabel(4)

set scaled(5) = (impblk(5,8))/sqrt(v(5,5))
set g58 = scaled(5)
labels scaled(5)
#implabel(5)

set scaled(6) = (impblk(6,8))/sqrt(v(6,6))
set g68 = scaled(6)
```

```
  labels scaled(6)
  #implabel(6)

  set scaled(7) = (impblk(7,8))/sqrt(v(7,7))
  set g78 = scaled(7)
  labels scaled(7)
  #implabel(7)

  set scaled(8) = (impblk(8,8))/sqrt(v(8,8))
  set g88 = scaled(8)
  labels scaled(8)
  #implabel(8)

grparm(nobold,font='time new roman') hlabel 8 matrixlabels 8 $
                              header * vlabel *
spgraph(vfields=p,hfields=p,header='Innovation to',$
       xlabels=mplabel,ylabels=mplabel,vlabel='Response of',$
       xpos=both,ypos=both)


dofor i = g11 g21 g31 g41 g51 g61 g71 g81 $
        g12 g22 g32 g42 g52 g62 g72 g82 $
        g13 g23 g33 g43 g53 g63 g73 g83 $
        g14 g24 g34 g44 g54 g64 g74 g84 $
        g15 g25 g35 g45 g55 g65 g75 g85 $
        g16 g26 g36 g46 g56 g66 g76 g86 $
        g17 g27 g37 g47 g57 g67 g77 g87 $
        g18 g28 g38 g48 g58 g68 g78 g88

   open plot grf2.rgf

   graph(number=0,min=-0.250,max=1.00) 1
    # i

end dofor
spgraph(done)

END
```

4D. Dickey Fuller & Augmented Dickey Fuller Test

```
calendar 1986 1 12
allocate 500 2016:6
eqv 1 to 16
 hens eggs eggprice soymealp cornmealp beefprice prkprice inc $
 HEN PDXN EPR SMP CMP BPR PPR RDI
************************************************
open data altosdata.txt
data(format=free,org=obs) 1986:3 2014:10 1 to 8
*************************************************

do i=1,8
diff i 1986:4 2014:10 i+8 1986:4
end do i

do i=9,16
linreg i 1986:5 2014:10
# constant (i-8){1}
**************************************
compute schwarz = log(%seesq) + ((%nreg))*log(%nobs)/%nobs
compute akaike = log(%seesq) + 2*((%nreg)*8)/%nobs
compute phi = log(%seesq) + ((%nreg))*2.1*log(log(%nobs))/%nobs
display @10 ##### %nreg schwarz @+10 ####.#### phi @+10 #####.#### akaike @+10 #####.####
**************************************
end do i

do i=9,16
do j=1,12
linreg i 1987:5 2014:10
# constant (i-8){1} i{1 to j}
*********************************************************
compute schwarz = log(%seesq) + ((%nreg))*log(%nobs)/%nobs
compute akaike = log(%seesq) + 2*((%nreg)*8)/%nobs
compute phi = log(%seesq) + ((%nreg))*2.1*log(log(%nobs))/%nobs
display @10 ##### %nreg schwarz @+10 ####.#### phi @+10 #####.#### akaike @+10 #####.####

end do j
end do i

end
```

5D. Stationarity, Weak Exogeneity, and Exclusion Tests

```
calendar 1986 1 12
allocate 500 2016:6
eqv 1 to 8
 hens eggs eggprice soymealp cornmealp beefprice prkprice inc
***********************************************
open data altosdata.txt
data(format=free,org=obs) 1986:3 2014:10 1 to 8
************************************************
set ser1 = hens
set ser2 = eggs
set ser3 = eggprice
set ser4 = soymealp
set ser5 = cornmealp
set ser6 = beefprice
set ser7 = prkprice
set ser8 = inc

open copy upCIres.tsp.txt
source CATS\CATSMAIN.SRC

@CATS(proc=tsprop,season=12,lags=1,dettrend=cimean) 1986:3 2014:10
# hens eggs eggprice soymealp cornmealp beefprice prkprice inc

end
```

6D. Determining the Presence of Cointegration and Residual Analysis for the Estimated Model

```
calendar 1986 1 12
allocate 500 2016:6
eqv 1 to 8
 hens eggs eggprice soymealp cornmealp beefprice prkprice inc
*************************************************
open data altosdata.txt
data(format=free,org=obs) 1986:3 2014:10 1 to 8
**************************************************
set ser1 = hens
set ser2 = eggs
set ser3 = eggprice
set ser4 = soymealp
set ser5 = cornmealp
set ser6 = beefprice
set ser7 = prkprice
set ser8 = inc

open copy upci1.txt
source CATS\CATSMAIN.SRC

@CATS(proc=i1, season=12, lags=1,dettrend=cimean) 1986:3 2014:10
# hens eggs eggprice soymealp cornmealp beefprice prkprice inc

End
```

7D. Determining the Number of Lags in the VAR Estimated Model

```
calendar 1986 1 12
allocate 500 2016:6

eqv 1 to 8
 hens eggs eggprice soymealp cornmealp beefprice prkprice inc
open data altosdata.txt
data(format=free,org=obs) 1986:3 2014:10 1 to 8

DECLARE RECT PATTERN(8,8)
compute p=8
declare rect A
declare rect[series] impblk(p,p)
declare vect[series] scaled(p)
declare vect[labels] implabel(p)
declare vect[strings] mplabel(p)

seasonal seas 1986:1 2016:12 12 1986:12
set trend 1986:1 2016:1 = t

display @10 "levels VAR constant and  no lags, no seasonals, no trend "
system 1 to 8
variables   1 2 3 4 5 6 7 8
det constant
end(system)
estimate(noprint,noftests,outsigma=vsigma) 1987:6 2014:10
compute schwarz = log(%det(vsigma)) + ((%nreg)*8)*log(%nobs)/%nobs
compute akaike = log(%det(vsigma)) + 2*((%nreg)*8)/%nobs
compute phi =  log(%det(vsigma)) + ((%nreg)*8)*(2.01)*log(log(%nobs))/%nobs
display @10 ####.#### schwarz @20 ####.#### phi @30 ####.#### akaike

display @10 "levels VAR constant and seasonals, no lags "
system 1 to 8
variables   1 2 3 4 5 6 7 8
det constant seas{0 to 10}
end(system)
estimate(noprint,noftests,outsigma=vsigma) 1987:6 2014:10
compute schwarz = log(%det(vsigma)) + ((%nreg)*8)*log(%nobs)/%nobs
compute akaike = log(%det(vsigma)) + 2*((%nreg)*8)/%nobs
compute phi =  log(%det(vsigma)) + ((%nreg)*8)*(2.01)*log(log(%nobs))/%nobs
display @10 ####.#### schwarz @20 ####.#### phi @30 ####.#### akaike

display @10 "levels VAR constant, seasonals and lags "
do i=1,6
system 1 to 8
variables   1 2 3 4 5 6 7 8
lags 1 to i
det constant seas{0 to 10}
end(system)
estimate(noprint,noftests,outsigma=vsigma) 1987:6 2014:10
compute schwarz = log(%det(vsigma)) + ((%nreg)*8)*log(%nobs)/%nobs
```

```
compute akaike = log(%det(vsigma)) + 2*((%nreg)*8)/%nobs
compute phi =  log(%det(vsigma)) + ((%nreg)*8)*(2.01)*log(log(%nobs))/%nobs
display @10 ####.#### schwarz @20 ####.#### phi @30 ####.#### akaike
end do i

display @10 "levels VAR constant,  seasonals and lags and trend "
do i=1,6
system 1 to 8
variables   1 2 3 4 5 6 7 8
lags 1 to i
det constant seas{0 to 10} trend
end(system)
estimate(noprint,noftests,outsigma=vsigma) 1987:6 2014:10
compute schwarz = log(%det(vsigma)) + ((%nreg)*8)*log(%nobs)/%nobs
compute akaike = log(%det(vsigma)) + 2*((%nreg)*8)/%nobs
compute phi =  log(%det(vsigma)) + ((%nreg)*8)*(2.01)*log(log(%nobs))/%nobs
display @10 ####.#### schwarz @20 ####.#### phi @30 ####.#### akaike
end do i

display @10 "levels VAR constant, no seasonals, no trend  and lags "
do i=1,6
system 1 to 8
variables   1 2 3 4 5 6 7 8
lags 1 to i
det constant
end(system)
estimate(noprint,noftests,outsigma=vsigma) 1987:6 2014:10
compute schwarz = log(%det(vsigma)) + ((%nreg)*8)*log(%nobs)/%nobs
compute akaike = log(%det(vsigma)) + 2*((%nreg)*8)/%nobs
compute phi =  log(%det(vsigma)) + ((%nreg)*8)*(2.01)*log(log(%nobs))/%nobs
display @10 ####.#### schwarz @20 ####.#### phi @30 ####.#### akaike
end do i

display @10 "levels VAR constant,  lags and trend "
do i=1,6
system 1 to 8
variables   1 2 3 4 5 6 7 8
lags 1 to i
det constant  trend
end(system)
estimate(noprint,noftests,outsigma=vsigma) 1987:6 2014:10
compute schwarz = log(%det(vsigma)) + ((%nreg)*8)*log(%nobs)/%nobs
compute akaike = log(%det(vsigma)) + 2*((%nreg)*8)/%nobs
compute phi =  log(%det(vsigma)) + ((%nreg)*8)*(2.01)*log(log(%nobs))/%nobs
display @10 ####.#### schwarz @20 ####.#### phi @30 ####.#### akaike
end do i

end
```

8D. Forecasting with the Model[27]

```
calendar 1986 1 12
allocate 100 2018:12

eqv 1 to 16
 hens eggs eggprice soymealp $
 cornmealp beefprice prkprice inc $
 dHEN dPDXN dEPR dSMP dCMP dBPR dPPR dRDI

open data beef&pork.txt
data(format=free,org=obs) 1986:3 2016:5 1 to 8

*print 1986:3 2016:5 1 2 3 4 5 6 7 8

do i=1,8
diff i 1986:4 2016:5 i+8 1986:4
end do i

*print 1986:3 2016:5 9 10 11 12 13 14 15 16
seasonal seas 1986:1 2018:12 12 1986:12

dec sym M00 M11 Mkk S00 Skk iM11 MM
dec rect M01 M0K S0k Sk0
dec rect alfa beta pi tpi
dec rect ms st VV
dec vect test(i) Lmax(i) trace(i)

dec rect GAMMA tGAMMA
dec vect[vect] iGAMMA(i)

dec vect[vect] ipi(i)

dec rect piXt1 tpiXt1
dec vect[vect] coefXt1(i)
dec vect[vect] COEF(i)

Theil(setup) 16 12 2016:5
# 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16

do date = 2013:10,2014:10

make(trans) DZ0 1986:6 date N p0
#  9 10 11 12 13 14 15 16
make(trans) DDZ1 1986:6 date N p1
# seas{-10 to 0}
make(trans) Zk 1986:6 date N pk
# 1{1} 2{1} 3{1} 4{1} 5{1} 6{1} 7{1} 8{1} constant

compute [integer] r = 2
*** set the rank of cointegrating space ***
compute [integer] N1 = N
compute [real] invN = 1.0/N1
```

```
compute [integer] p = pk
**************************************************
compute M00 = (DZ0*tr(DZ0))*invN
compute M01 = (DZ0*tr(DDZ1))*invN
compute M0k = (DZ0*tr(Zk))*invN
compute M11 = (DDZ1*tr(DDZ1))*invN
compute M1k = (DDZ1*tr(Zk))*invN
compute Mkk = (Zk*tr(Zk))*invN
compute iM11 = inv(M11)
*write 'iM11' iM11
compute S00 = M00 - M01*iM11*tr(M01)
compute S0k = M0k - M01*iM11*M1k
compute Sk0 = tr(S0k)
compute Skk = Mkk - tr(M1k)*iM11*M1k
compute ms = %decomp(Skk)
compute st = inv(ms)
compute MM = st*Sk0*inv(S00)*S0k*tr(st)
eigen MM D V

******** CALCULATE LAMDAMAX AND TRACE TESTS ********
compute sld = 0.0
    do i=p0,1,-1
**************************************************
    compute test(i) = D(i)
    compute Lmax(i) = - N1*(log(1-D(i)))
    compute trace(i) = sld + Lmax(i)
    compute sld = trace(i)
*      write 'test(i)' test(i)
*      write 'Lmax(i)' Lmax(i)
*       write 'trace(i)' trace(i)
    end do i

******** CALCULATE ALFA BETA PI AND GAMMA ********
overlay V(1,1) with beta(pk,r)
compute VV = tr(st)*V
compute beta = tr(st)*beta
compute alfa = S0k*beta
compute pi = alfa*tr(beta)
compute GAMMA = (M01 - pi*tr(M1k))*iM11

 *write '#OBS' N
 *write 'EIGENVALUE' D
 *write 'EIGENVECTORS' VV
 *write 'BETA' beta
 *write 'ALFA' alfa
 *write 'PI' pi
**write 'GAMMA' GAMMA

******** CALCULATE AND STORE COEFF'S FOR FORECASTING ********
*compute tp+i = tr(pi)
*write 'PI TRANSPOSED' tpi
**************************
compute [rect] BBB = ||1,0,0,0,0,0,0,0,0|$
```

```
                    0,1,0,0,0,0,0,0,0,0|$
                    0,0,1,0,0,0,0,0,0,0|$
                    0,0,0,1,0,0,0,0,0,0|$
                    0,0,0,0,1,0,0,0,0,0|$
                    0,0,0,0,0,1,0,0,0,0|$
                    0,0,0,0,0,0,1,0,0,0|$
                    0,0,0,0,0,0,0,0,1,0||

compute piXt1 = pi + BBB
*compute piXt1 = pi + %identity(p0)
compute tpiXt1 = tr(piXt1)

  do i=1,p0
*************************************************
  overlay tpiXt1(1,i) with coefXt1(i)(pk)
  *write 'COEFFICIENTS ON X(t-1)' coefXt1(i)
  end do i

 compute tGAMMA = tr(GAMMA)
 *write 'GAMMA' GAMMA
 **write 'GAMMA TRANSPOSED' tGAMMA

    do i=1,p0
 *************************************************
    overlay tGAMMA(1,i) with iGAMMA(i)(p1)
    *write 'GAMMA(i)' iGAMMA(i)
    end do i

   do i=1,p0
 *************************************************
   compute COEF(i) = ||coefXt1(i)(1),coefXt1(i)(2), coefxt1(i)(3),coefxt1(i)(4),coefxt1(i)(5), $
        coefxt1(i)(6),coefxt1(i)(7),coefxt1(i)(8), coefxt1(i)(9), $
        iGAMMA(i)(1),iGAMMA(i)(2),  igamma(i)(3),igamma(i)(4),  igamma(i)(5),igamma(i)(6), $
        igamma(i)(7),igamma(i)(8),  igamma(i)(9),igamma(i)(10), igamma(i)(11) ||

*** each element between ',' in ||.,.,|| must be a singleton****
*write 'COEF(i)' COEF(i)
 end do i

  equation 1 1
  # 1{1}  2{1}  3{1}  4{1} 5{1}  6{1}  7{1}  8{1} constant $
    seas{-10 to 0}
  associate 1 COEF(1)

 equation 2 2
  # 1{1}  2{1}  3{1}  4{1} 5{1}  6{1}  7{1}  8{1} constant $
             seas{-10 to 0}
 associate 2 coef(2)

equation 3 3
  # 1{1}  2{1}  3{1}  4{1} 5{1}  6{1}  7{1}  8{1} constant $
    seas{-10 to 0}
  associate 3 COEF(3)
```

```
 equation 4 4
  # 1{1}  2{1}  3{1}  4{1} 5{1}  6{1}  7{1}  8{1} constant $
    seas{-10 to 0}
 associate 4 coef(4)

equation 5 5
 # 1{1}  2{1}  3{1}  4{1} 5{1}  6{1}  7{1}  8{1} constant $
 seas{-10 to 0}
associate 5 COEF(5)

equation 6 6
 # 1{1}  2{1}  3{1}  4{1}  5{1}  6{1}  7{1}  8{1} constant $
             seas{-10 to 0}
 associate 6 coef(6)

equation 7 7
 # 1{1}  2{1}  3{1}  4{1}  5{1}  6{1}  7{1}  8{1} constant $
 seas{-10 to 0}
associate 7 COEF(7)

equation 8 8
 # 1{1}  2{1}  3{1}  4{1}  5{1}  6{1}  7{1}  8{1} constant $
   seas{-10 to 0}
 associate 8 coef(8)

equation 9 9
 # 1 1{1}
 associate 9
 # 1 -1

equation 10 10
 # 2 2{1}
 associate 10
 # 1 -1

equation 11 11
 # 3 3{1}
 associate 11
 # 1 -1

equation 12 12
 # 4 4{1}
 associate 12
 # 1 -1

equation 13 13
 # 5 5{1}
 associate 13
 # 1 -1


equation 14 14
```

```
 # 6 6{1}
 associate 14
 # 1 -1

equation 15 15
 # 7 7{1}
 associate 15
 # 1 -1

equation 16 16
 # 8 8{1}
 associate 16
 # 1 -1

system 1 to 16
end(system)

 forecast 16 12 date+12
 # 1  31
 # 2  32
 # 3  33
 # 4  34
 # 5  35
 # 6  36
 # 7  37
 # 8  38
 # 9  39
 # 10  40
 # 11  41
 # 12  42
 # 13  43
 # 14  44
 # 15  45
 # 16  46

 Theil date+12
 end do date

 Theil(dump)

print 2014:10  2015:10  31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46


end
```

[27]*This program was adapted from the original RATS program written by former Texas A&M graduate student Thanapat Chaisantikul.*