A Strategy for Forecasting the Economic Impact of Alternative Meat

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Introduction

Over the past several years, growing consumer demand and technological advancement have led to the blossoming of a new field: alternative meat. Understanding the high environmental impact of animal agriculture on greenhouse gas emissions, a number of private companies and researchers have developed entirely plant-based alternatives for meat and other animal products. Companies such as Beyond Meat and Impossible Foods have seen great success among both vegetarian and meat-eating consumers with their plant-based offerings — particularly cow-free hamburger meat — as consumers look to ease their carbon footprint and technology allows for a product nearly indistinguishable from the real deal.

Looking forward, there are signs that alternative meat is only just beginning its ascent. Impossible Foods, for example, received a $500 million dollar investment this past March ("Impossible"), as its founder boldy strives to bring an end to animal agriculture by 2035 (Chiorando). Other companies continue to innovate with promising results, such as the Chilean company NotCo, whose AI-driven plant-based products earned them a $30 million dollar investment from groups such as Jeff Bezos' Bezos Expeditions ("The Not Company"). Perhaps even more striking is the burgeoning field of cultured meat, which aims to create real animal meat from the multiplication of cells outside an animal's body. Advocates for this field claim that these products can provide a healthier, safer, more eco-friendly alternative to conventional meats, and believe that given time to scale, they can become even more resource-efficient, and thus cost-competitive. While this was long viewed as a largely futuristic concept, several companies have produced cultured ground beef and sausage products, and companies like JUST have even announced shelf-ready cultured meat products currently undergoing the FDA approval process (Shanker). While the timeline for the release of these products is generally unknown or hidden from the public, it is likely there will be a push to release them sooner rather than later, as evidenced by the sudden expansion of companies like Berkeley's Memphis Meats, who received $161 million in funding this year ("Memphis Meats").

The introduction of these products to the marketplace will present a never-before seen economic phenomenon in the agricultural world — a direct substitute for animal meat that does not involve an animal. This throws a spoke into the work of those focusing on economic forecasts surrounding animal products, such as the Organization for Economic Cooperation and Development, who already struggle to incorporate in their forecasts the potential increase in consumer attitudes towards vegetarian alternatives (OECD).

Consumers, alt meat companies, and non-profit organizations like the Good Food Institute may be interested in understanding the effect of this unprecedented phenomenon on the total number of animals slaughtered. In the short term, the main focus of most cultured and plant-based meat manufacturers is developing alternatives to ground meats rather than full cuts, considering the structural difficulties that come with creating a viable alternative to, say, a ribeye steak or a chicken thigh (Shapiro, loc. 366). Beyond this, most companies are focused primarily on creating beef products due to their popularity and the fact that cows are responsible for the majority of greenhouse emissions of all animals farmed today (Shapiro loc. 2384).

The motivation of this project is to understand how to model the effect of cost-competitive direct alternatives to ground beef entering the market in the short term and how this can affect the number of cattle slaughtered each year. Ultimately, I will show an example of how one can use hard conditioning of a Bayesian vector autoregressive model to forecast cattle production given a reduction in demand for ground beef in the short term, while demand for other cuts of beef remains consistent.

Related Works

While the goals of this project are novel, previous work has been done along similar lines. Specifically, there have been two types of papers published which I found relevant to this task. The first type of paper describes how to model the effect that substitute product prices can have on beef demand, and the second type of paper describes how to create short-term economic forecasts conditioned on never before seen events (like the introduction of a direct substitute for ground beef).

Beef Substitute Studies

Several studies in the past have employed simple OLS regression to determine the relationship between quantities demanded of substitute goods (usually chicken, pork, or eggs) and the price or production of beef. A study by Wayne Purcell in 2000 found that when chicken and pork demand is high, beef prices tend to lower, indicating that chicken and pork are substitute goods for beef (Purcell). Additional studies from 1995 and 1997 use similar techniques and reinforce the idea that poultry and pork act as substitutes for beef;

however, studies from 2010 and 2011 have shown with more recent data that these can no longer be considered substitute goods (Tonsor). The world meat projections published by the OECD include forecasts of cattle production based on a large number of factors, and while they do not publish their methodology, they mention taking into account rising imports of pigmeat and poultry to Latin America as potentially impacting the demand for beef globally (OECD). While they take into account these substitutes, they are unable to account for the uncertain possible factor of vegetarian substitute products.

While these previous models were able to show the impact of substitutes on the price and production of beef, their methods are insufficient for the means of this project for a few critical reasons. First is the lack of precedent with respect to the new alternative meat products, which are the first of their kind to truly serve as a *direct* substitute for beef. In economic literature, product B is said to be a substitute good for product A if a decrease in product B's price shifts the demand curve to the left for product A — that is, when product B gets cheaper, the demand for product A decreases, holding all other factors constant. A product is said to be a *direct* substitute if A and B are entirely interchangeable, whereas it is said to be an *indirect* substitute if there is a weak correlation between the two goods (Tonsor). Beef and pork could be thought of as indirect substitutes, since both provide animal protein as the main course of a meal, but clearly they are not identical products to most consumers. Even two competing beef products, such as steak and ribs, are more likely to be seen as indirect substitutes for one another, whereas products like the Impossible Burger and many cultured meats intend on acting as direct substitutes for ground beef. Since there is no good historical data as to how these products may affect beef in the marketplace like there have been for chicken and pork, the methods from the previous papers cannot apply.

Further, since this project focuses on ground beef rather than beef as an aggregate category, the problem becomes even more convoluted in that it requires that we look at the effect of a substitute on one specific beef product, assuming that this substitute does not affect the demand for other beef products. More granular data is required, and a more complicated modeling approach is required. Since the goal is to project cattle production, the modeling strategy must take into account the impact of demand of the many different cuts of meat which come from cows, and it must be able to show how sensitive cattle production is to changes in ground beef demand, given demand for other beef products is consistent with what we would expect otherwise.

Methods for Conditional Forecasting

Since we are without historical data on the impact of alternative meat, it is necessary to employ a modeling technique that allows for forecasts conditioned on beliefs about a future trend in an explanatory variable. Thankfully, economic researchers have studied forecasting methods that meet these requirements, specifically as they pertain to vector autoregression models.

Vector autoregression (also known as VAR) is a popular method for economic forecasting originally developed in the 1980s. VAR models improved upon previous econometric techniques in that they assume interdependent relationships between all covariates, making it simple to create long-term forecasts even when the causal variables themselves need to be forecasted (Allen). The stationary VAR model with lag p has the form:

$$\mathbf{Y}_t = \mathbf{c} + \mathbf{\Pi}_1 \mathbf{Y}_{t-1} + \ldots + \mathbf{\Pi}_p \mathbf{Y}_{t-p} + \epsilon_t$$

Where $\mathbf{Y}_t = (y_{1t}, \ldots, y_{nt})'$ is a vector of time series variables, $\mathbf{\Pi}_i$ are (nxn) covariate matrices, and ϵ_t is a vector of zero mean white noise vector processes that follow a time-invariant covariance matrix $\mathbf{\Sigma}$ (Zivot). In this model, the time series variables are assumed to be covariance stationary.

While estimation via OLS is often sufficient for VAR models, Bayesian vector autoregression (BVAR) has also become incredibly popular, especially in cases for which a large number of covariates are necessary. Due to the dense parameterization of VAR models, setting tight, informative priors on the model parameters has shown to greatly improve out-of-sample prediction accuracy by reducing estimation uncertainty (Giannone).

A VAR model can be forecasted using the following equation (Zivot):

$$\hat{\mathbf{Y}}_{t+h|t} = \hat{\mathbf{\Pi}}_1 \hat{\mathbf{Y}}_{t+h-1} + \ldots + \hat{\mathbf{\Pi}}_p \hat{\mathbf{Y}}_{t+h-p}$$

The forecast errors using this method are said to be asymptotically normally distributed, and for that reason, Monte Carlo simulation methods are often used to generate what is referred to as a *simulation-based forecast* of a VAR(p) model (Zivot). These simulation methods are frequently used to generate conditional forecasts, meaning forecasts for which the future path of one or more of the variables in the system are set to fixed values. This is used when future values are already known, or in the case of our study, when a researcher is interested in the effect of a potential future scenario. In 1999, Waggoner and Zha developed methods to compute the exact finite-sample distribution of a conditional VAR forecast using Bayesian methods (Waggoner). This methodology has been implemented in a number of statistical computing packages for R, notably the MSBVAR library and S+FinMetrics (Zivot, Brandt).

Methods

In this section, I will describe generally a method to forecast the impact of lowered ground beef demand on cattle output using conditional VAR forecasting. First, I will outline the method, and then I will run through an implementation of this method using a naive model.

Method Description

Assume that time series data exists such that

$$\mathbf{Y}_t = (q_{\text{ground beef},t}, q_{\text{round roast},t}, q_{\text{other beef cuts},t}, s_t, \ldots)'$$

where $\mathbf{q}_{\text{ground beef}}$ represents the time series of quantity demanded of ground beef, and $\mathbf{q}_{\text{round roast}}$, $\mathbf{q}_{\text{other beef cuts}}$ follow as well and are included in the model in addition to time series for any other cut of beef for which data is available. Say as well that s (for *supply*) is the time series of the quantity of cattle produced in a given time interval. Including these variables in a VAR model alongside other possible predictors will allow for forecasts of future cattle production given historical data on its relationship with demand for each cut of beef in the marketplace.

After fitting a sufficient VAR model, the values $\hat{\mathbf{Y}}_{t+1}, \ldots, \hat{\mathbf{Y}}_{t+h}$ can be forecasted unconditionally. From these results we can construct the vector of unconditional forecasts:

$$\hat{\mathbf{q}}_{\text{ground beef}} = (\hat{q}_{\text{ground beef},t+1}, \ldots, \hat{q}_{\text{ground beef},t+h})'$$

and similar vectors $\hat{\mathbf{q}}_{\text{round roast}}$, $\hat{\mathbf{q}}_{\text{other beef cuts}}$, and $\hat{\mathrm{s}}$ of unconditional forecasts.

VAR models operate such that when conditioned on the result of an unconditional forecast, holding out one variable, the held-out variable's conditional prediction will be equal to its unconditional forecast. This property is a result of the law of conditional probability, as shown below with the probability distribution of the future values of s:

$$p(\mathbf{s}_{t+1,\ldots,t+h|t} | \hat{\mathbf{q}}_{\text{ground beef}}, \hat{\mathbf{q}}_{\text{round roast}}, \hat{\mathbf{q}}_{\text{other beef cuts}}) \propto p(\mathbf{s}_{t+1,\ldots,t+h|t}, \hat{\mathbf{q}}_{\text{ground beef}}, \hat{\mathbf{q}}_{\text{round roast}}, \hat{\mathbf{q}}_{\text{other beef cuts}})$$

In the above equation, the value of $\mathbf{s}_{t+1,\ldots,t+h|t}$ which optimizes the unconditional forecast (right hand side) is $\hat{\mathrm{s}}$. Due to proportionality with the left hand side and the axioms of probability ensuring no negative probabilities, we know that $\hat{\mathrm{s}}$ is also the value optimizing the conditional probability on the left hand side. So conditioning a forecast of s on the unconditional forecast results of all other variables in the system yields the same unconditional forecast result.

For this reason, we are able to test the sensitivity of our forecasts on s. Say we have an effective model showing how the demand curve for ground beef will change over the next five years due to a substitute good entering the market. We can apply this belief to our unconditional forecast $\hat{\mathbf{q}}_{\text{ground beef}}$, preserving that forecast's dependencies on other variables in the system while also showing the effects of the shifted demand curve. We generate a new, demand shifted vector of forecasts for $\mathbf{q}_{\text{ground beef}}$ which we will call $\hat{\mathbf{q}}^*_{\text{ground beef}}$.

Since we have shown that a forecast of s conditioned on $\hat{\mathbf{q}}_{\text{ground beef}}, \hat{\mathbf{q}}_{\text{round roast}}$, and $\hat{\mathbf{q}}_{\text{other beef cuts}}$ is equivalent to $\hat{\mathrm{s}}$, it would be reasonable to compare this value to the forecast of s conditioned on $\hat{\mathbf{q}}^*_{\text{ground beef}}, \hat{\mathbf{q}}_{\text{round roast}}$, and $\hat{\mathbf{q}}_{\text{other beef cuts}}$, using our demand-shifted version of the unconditional ground beef forecast. This forecast, which we can call $\hat{\mathrm{s}}^*$, will show how sensitive cattle production is to our proposed change in ground beef demand when compared with $\hat{\mathrm{s}}$. This method allows us to test the scenario in which demand for ground beef changes independently of demand for other cuts of beef, which is what we would expect to happen in any scenario for which ground beef substitutes enter the market while other cuts like steaks and ribs have no such competitor.

Modeling Example

This section will show a walkthrough of how this modeling technique can be applied to understand how cattle production responds to changes in demand for ground beef in the short term.

Data

A substantial challenge in this modeling task is finding effective data sources at the level of granularity needed. Jason Lusk, a food and agriculture economist from Purdue University, has emphasized the difficulties in finding data representing consumer demand for specific cuts of beef, rather than the aggregated beef-as-a-category data used in the majority of studies (Lusk). He suggests that grocery store data, such as the commercial Nielsen Total Food View, is not sufficient, since those datasets do not include information on product weights, making it impossible to accurately estimate customer demand. Instead, Lusk opts for conducting consumer surveys to determine demand for different cuts of meat.

For the sake of this study, I am taking a somewhat naive approach to generating demand variables for cuts of beef. The U.S. Bureau of Labor Statistics offers monthly time series data on the average retail prices of various food categories, some of which date back to the early 1980s ("Average"). For this project, I extracted price data for the categories "All uncooked ground beef, per lb.," "All uncooked beef roasts, per lb.," "All uncooked beef steaks, per lb.," and "All other uncooked beef (excluding veal) per lb." These categories, while aggregations of many more specific cuts of beef, provide more granular data on price history of different categories, one of which is ground beef, one of the key variables of interest in our study. Data from these four categories date back to 1998, providing 265 months of price data.

The other important variable of interest is the number of cattle slaughtered each month. I downloaded this data from the U.S. Department of Agriculture's Livestock and Meat Domestic Data database ("Livestock").

Price data of beef products cannot be used in and of itself as a "demand" variable to predict cattle supply. Since price is set by both supply and demand, this type of model would suffer from a simultaneity bias, which, in regression, refers to the case when an explanatory variable is correlated with the regression error term (Floyd). In simple terms, this means that since supply is one of the drivers of price, price should not be used to predict supply. In econometrics, this issue is frequently referred to as an identification problem and is dealt with via a process called instrumental variable identification (MacKay). In our case, to estimate demand from price and supply, we would need to look for an external variable (or variables) for each of our price variables which can be shown to have a relationship with the price variable, but not with the supply variable. This is called estimating the demand curve via a supply-side instrument. A limitation of the model presented in this section is that I was unable to identify a supply-side instrument for the price of each individual cut of meat, so the demand curve was instead estimated using the following naive method:

1. Adjust price data for inflation by matching to CPI ("Consumer").
2. Assume that price at time t is set by demand at time t and supply at time t, and that we can model this relationship as $\mathrm{price}_t = f(\mathrm{demand}_t) + g(\mathrm{supply}_t) + \epsilon$. This allows us to rearrange and find an estimate of the demand curve as $f(\mathrm{demand}_t) + \epsilon = \mathrm{price}_t - g(\mathrm{supply}_t)$.
3. Assume the true relationship between price and supply is linear. Estimate $g(\mathrm{supply}_t)$ by regressing price on supply, using all our data.
4. The residuals of this regression should estimate $f(\mathrm{demand}_t)$.

An initial analysis of this method shows that the estimated demand variable serves its purpose effectively: to extract the information from price unrelated to supply. Figure 1 shows cattle production, demand for ground beef, and inflation-adjusted price for ground beef plotted on the same axes after applying a min-max scaler. It can be seen that when price is high and supply is low, demand is high, and when price is low and supply is high, demand is low. This demonstrates the law of supply and demand as expected.

VAR Model

The next step towards the conditional forecasting model is to fit an appropriate VAR model. To ensure that a VAR model is an effective modeling strategy for our data, we need to check the following assumptions and conditions:

1. Check the Granger causality of all possible combinations of variables in the system. Ensuring that a relationship exists between each variable in the system is an important assessment of whether a VAR model is appropriate for a task (Prabhakar).
2. Determine the stationarity of each time series variable. The stationary VAR model assumes each variable in the system is a stationary time series, meaning its properties such as mean and variance are stable across time (Hyndman). If this is not the case, stationarity can be achieved by differencing each value in the series by the value just before it, and repeating this process until stationarity is achieved. Stationarity can be assessed via the Augmented Dickey-Fuller test.
3. Determine the optimal lag-order of the model. This can be determined by fitting a number of models with different lag values and choosing the optimal model as indicated by a criterion such as AIC or BIC.
4. Assess out-of-sample model accuracy by holding out data, fitting a model on the training data and evaluating it on the held-out validation set.

Using Python code adapted from Selva Prabhakaran's Machine Learning Plus blog, I was able to check these assumptions on our data. Table 1 shows the p-values of a Granger causality test between all pairs of variables in the system. A small p-value of a Granger causality test between A and B indicates that we can reject the hypothesis that A has no causal effect on B. Since all p-values besides one are below a threshold of 0.05, the Granger causality test shows that the variables are well-suited for VAR modeling.

	$\mathbf{D}_{\text{beef roasts}}$	$\mathbf{D}_{\text{beef steaks}}$	$\mathbf{D}_{\text{ground beef}}$	$\mathbf{D}_{\text{other beef}}$	**S**
$\mathbf{D}_{\text{beef roasts}}$	1.0	2.473866e-03	0.0	1.588954e-02	0.0
$\mathbf{D}_{\text{beef steaks}}$	0.000411	1.0	0.0	1.462158e-03	0.0
$\mathbf{D}_{\text{ground beef}}$	0.090667	1.148151e-03	1.0	2.162131e-02	0.0
$\mathbf{D}_{\text{other beef}}$	0.000002	1.632000e-07	0.0	1.0	0.0
S	0.000000	8.200000e-09	0.0	1.662000e-07	1.0

Table 1: Granger causality test p-values for all variables in the system.

Table 2 shows the results of an Augmented Dickey-Fuller test on each time series variable to determine its stationarity. Each value in the table is a p-value, and a low value indicates a series is stationary. The first row represents the data with no differencing, and the second row represents the data with one difference. Differencing one time led to a stationary series for every variable.

Difference	$\mathbf{D}_{\text{beef roasts}}$	$\mathbf{D}_{\text{beef steaks}}$	$\mathbf{D}_{\text{ground beef}}$	$\mathbf{D}_{\text{other beef}}$	**S**
0	0.0793	0.1103	0.4707	0.6733	0.1889
1	0.015	0.0259	0.0104	0.0001	0.0322

Table 2: p-values of an Augmented Dickey-Fuller test for stationary of each variable.

Next, models were fit with lags ranging from 1 to 25, and the model with lowest AIC determined the optimal lag of 15. For the sake of this section, we are fitting the conventional stationary VAR model using OLS.

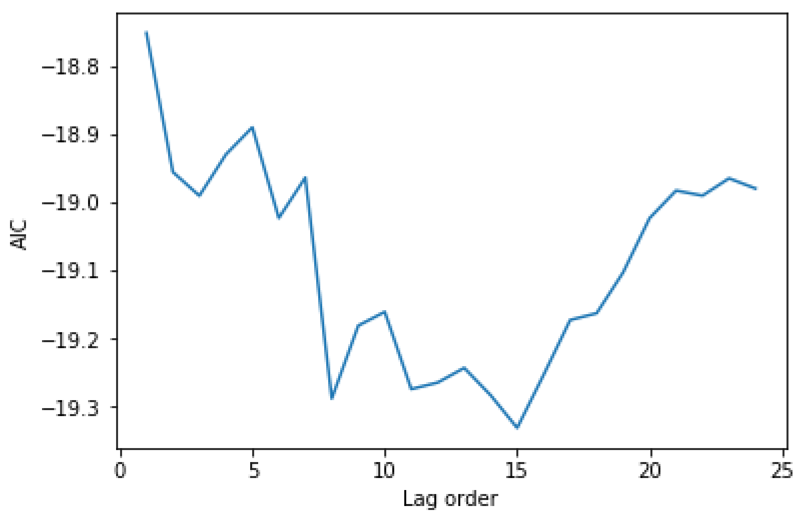

Figure 2: Plot showing AIC as a function of lag order.

After this I performed a Durbin-Watson test, which determines if there exists a serial correlation of errors. Values far from 2 indicate a high serial correlation, and as shown in Table 3, all values were close to 2, so this is not a cause for concern.

$\mathbf{D}_{\text{beef roasts}}$	$\mathbf{D}_{\text{beef steaks}}$	$\mathbf{D}_{\text{ground beef}}$	$\mathbf{D}_{\text{other beef}}$	**S**
1.96	1.97	1.98	1.98	1.93

Table 3: Durbin-Watson statistics for all variables in the system.

The next step was to generate a hold-out validation set, and test the forecast performance of the model on that set. The performance was good, with a mean absolute percent error of 0.0389 when trained on the first 241 data points and evaluated on the final 24 data points (last two years of data) for cattle supply. The forecast fit of this naive model is shown in Figure 3.

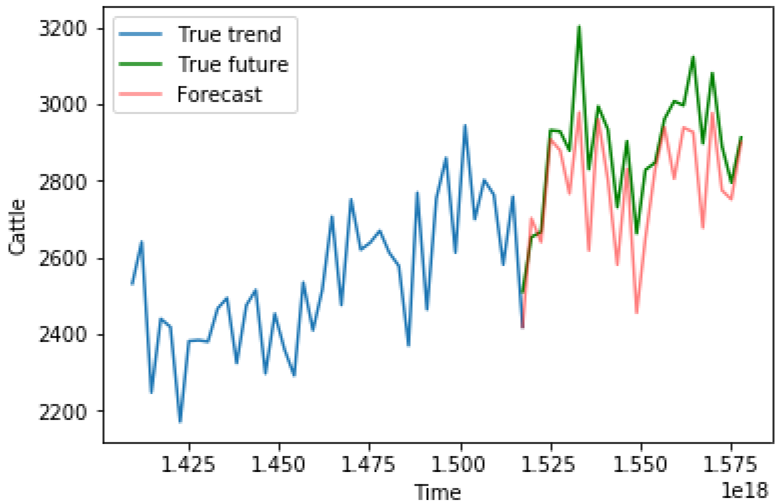

Figure 3: Forecasting results of naive model on held-out validation set.

Bayesian Conditional Forecasting

After completing the preliminary data analysis, it was determined that once-differenced data and a lag of 15 produced effective VAR results out-of-sample. Next steps in developing our conditional VAR forecasts are:

1. Train an adequate Bayesian VAR model.
2. Find unconditional forecasts for all variables in the system.
3. Modify the unconditional forecast on ground beef demand to show a potential demand shift as a result of substitute goods entering the market.
4. Generate hard conditional forecasts, conditioned on the unconditional forecasts for all variables besides cattle produced and ground beef demanded. Condition also on the modified ground beef demand forecast.

Due to its convenient implementation of hard conditional forecasting, I chose to model using the MSBVAR package in R. Using this package, I fit a Sims-Zha Bayesian VAR model with parameters set as $\lambda_0 = 1, \lambda_1 = 1, \lambda_3 = 1, \lambda_4 = 1, \lambda_5 = 0, \mu_5 = 0, \mu_6 = 0,$ and $\nu = 0$ using a flat-flat prior. The authors of the package suggest these parameters as a flat prior (Brendt). In many cases, it is not advised to use flat priors, since out-of-sample forecasting tends to be inaccurate (Giannone). Often, modelers will instead choose priors which optimize out-of-sample forecast accuracy or in-sample fit. In our case, a flat prior will suffice, since it ensures that the posterior distribution of VAR coefficients are centered at the OLS solution, which we have shown in our example above performs well out-of-sample for this task.

Figure 4 shows some of the unconditional forecast results, specifically on cattle production and ground beef demand. With these forecasts in hand, the next step is to model the effect of a new competitor for ground beef entering the market. This part of the modeling process requires much more information than is currently available to the public about the commercial future of cultured and plant-based meats, mostly dependent on FDA regulation as well as scaling and distribution. For the sake of demonstration, I imagine that a product enters the market, and over the next 30 months, sees a linear decrease in price as production costs gradually decrease. The result of this would be to continuously shift the demand curve for ground beef left. Figure 5 shows a representation of how this might look, subtracting $0.007 * h$ from ground beef demand for each time interval h past the current time t.

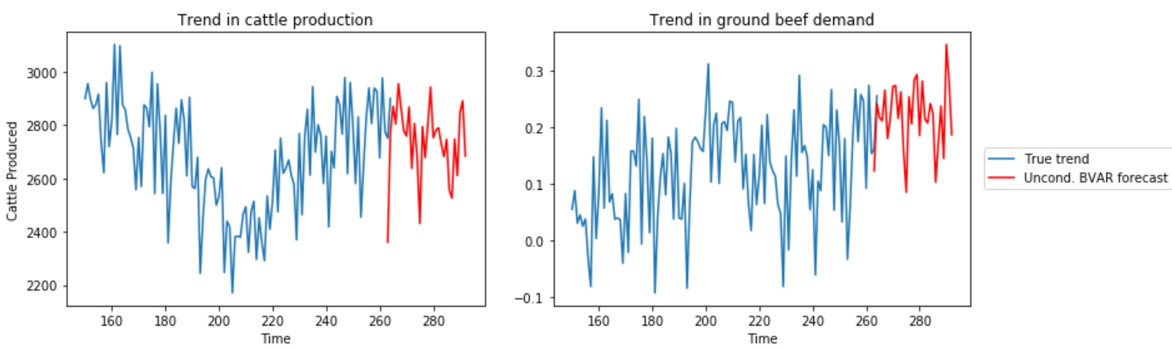

Figure 4: Unconditional forecasts for cattle production and ground beef demand. Time starts at t=0; these plots show later values only to emphasize recent trends.

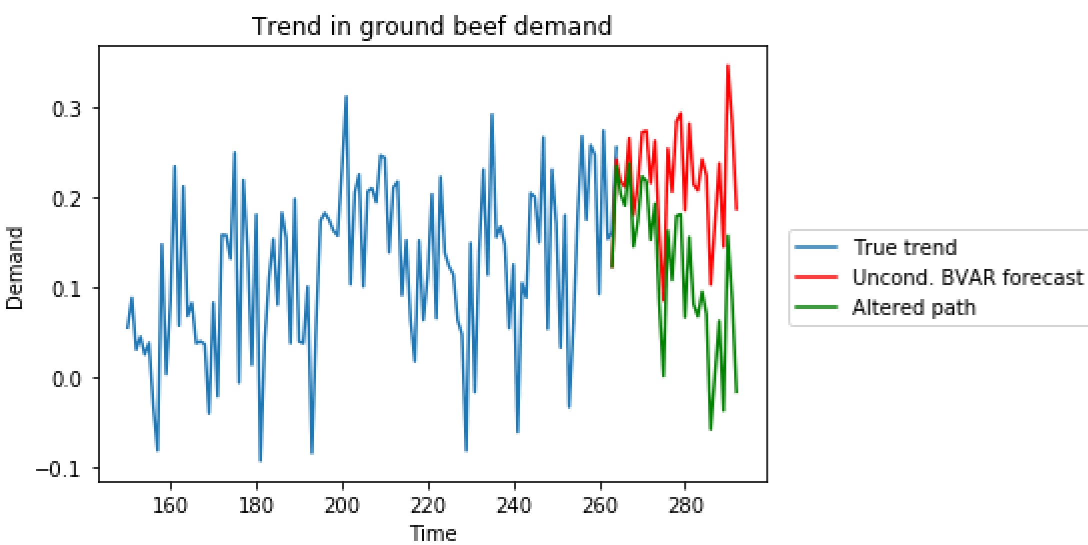

Figure 5: Graph showing a possible future path of ground beef demand based on a naive model for the effect of substitute goods.

With the new altered forecast for ground beef demand, we are able now to forecast conditionally on the unconditional forecasts of demand for beef steaks, beef roasts, and other beef cuts as well as on the altered forecast for ground beef demand. Figure 6 shows the results of this unconditional forecast on the forecast of cattle production, and also, interestingly, the forecast on ground beef demand. Two things are immediately clear from the results: the forecast on cattle production seems identical to the unconditional forecast, and the forecast of ground beef demand looks much more like its unconditional forecast than its altered path, upon which we conditioned. This was a very puzzling result, since hard conditional forecasting in theory should retain the conditioned paths exactly. In other tests of the MSBVAR hard conditional forecasting function, this was the behavior, yet not in this instance. The authors of the package write, of the method: “The forecast densities are estimated as the posterior sample for the VAR model using Markov Chain Monte Carlo with data augmentation to account for the uncertainty of the forecasts and the parameters. This function DOES account for parameter uncertainty in the MCMC algorithm” (Brendt). My belief is that the forecasting method is ineffective for the specific example used here, due to high uncertainty surrounding the forecast results, leading to conditional forecasts which look much more like unconditional forecast estimates.

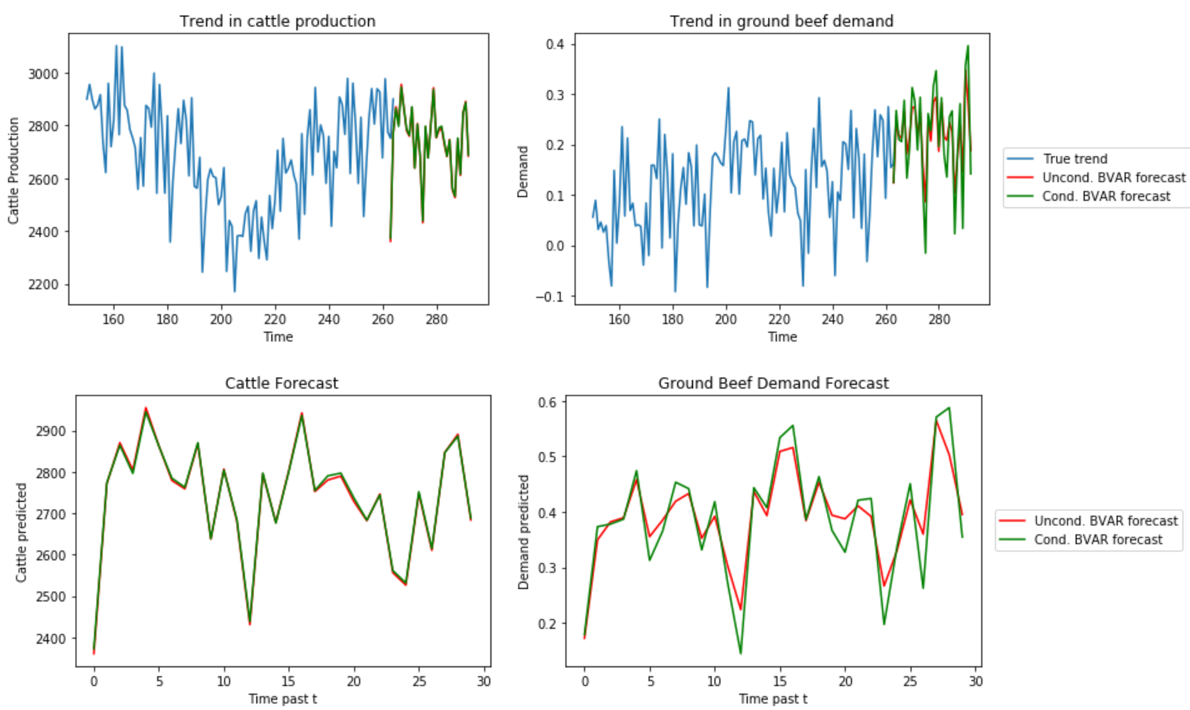

Figure 6: Results of conditional forecasting. Top plots include true trend, from 150 months past t = 0. Bottom row plots isolate the future forecasted values.

Conclusion

The example in the previous section has shown that, in a naive model, this modeling strategy proved ineffective at showing the sensitivity of cattle production to changes in ground beef demand. Of course, it would not be fair to dismiss the modeling strategy as a whole because of this one result. For one, the BVAR model implementation lends itself to high uncertainty, given it oversimplifies the task of forecasting cattle production by limiting its possible drivers to a small number of demand variables. In most VAR forecasts created by econometricians, an incredibly large number of possible factors are included in each model with hopes of capturing all possible causal effects (Allen). OECD, for example, in their report on beef projections, describes over the course of several pages a number of the complex and multifaceted drivers used in their model (OECD). Further, as explained in the data section, our demand variables are based on an oversimplified model for demand, and in a model with the goals of predictive accuracy and low uncertainty, other, presumably more accurate surrogates for demand will be required, whether they be direct measurements of demand or generated using a supply-side instrument. The model created in the above section, while showing underwhelming results, was intended for demonstration, not accuracy, and lends itself to expanded future research. Other future directions may include implementing hard conditional forecasting algorithms intended to demonstrate hypothetical changes in an unconditional forecast, such that their corrections for uncertainty are not so dramatic as to obfuscate the results.

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