FORECASTING MEAT PRICES USING THE FOOD DEMAND SURVEY (FooDS)

By

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FORECASTING MEAT PRICES USING THE FOOD

DEMAND SURVEY (FooDS)

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Abstract: Food price changes have important implications for agribusinesses, consumers, and policy makers. Better predictions of food prices should allow for more rapid and efficient adjustment to changing market conditions. This research seeks to determine whether a new source of data from a monthly, nationwide survey of food consumers, the Food Demand Survey (FooDS), is predictive of meat prices included in the food component of the Bureau of Labor Statistics Consumer Price Index (CPI). Unlike many previous efforts to forecast components of the CPI, this study relies on a direct measure of consumer preferences and their stated expectations about future prices and consumption. We compare the predictive performance of simple autoregressive models (where previous prices are used to predict future prices) to models that include data from FooDS. We find that, in most cases, the best fitting models are those that include consumer survey data from FooDS, suggesting that direct measures of consumer preferences and expectations can be used to better anticipate future price changes.

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CHAPTER I

INTRODUCTION

Classical welfare economics suggests that a necessary and sufficient condition for a distribution of scarce resources to be optimal (in the sense that no other distribution will make everyone better off in aggregate) is that the marginal rate of substitution between any two commodities be the same for every individual. Similarly, a necessary and sufficient condition for optimal production from given resources (in the sense that no other organization of production will yield greater quantities of every commodity) is that the marginal rate of transformation for every pair of commodities be the same for all firms in the economy (Arrow 1951). Prices, as revealed in market transactions, are the mechanism by which these marginal rates of substitution and transformation are equated. Stated differently, prices help allocate goods to their most valued use. Not only that, prices *reveal* and aggregate information unknown to any individual market participant or government official (Hayek, 1945). Hence, prices of commodities and goods affect which goods are produced and consumed, and the welfare of consumers and firms. For this reason, among others, changes in the prices for goods and services are measured and reported by many government agencies. One of the most common in the U.S. is the Consumer Price Index published by the Bureau of Labor Statistics.

Each month the Bureau of Labor Statistics (BLS) releases Consumer Price Index (CPI). A component of the CPI focuses on food. The United States Department of Agriculture (USDA) -

Economic Research Service (ERS) reports and attempts to forecast the food CPI for the next twelve to eighteen months. The CPI measures the average change over time in the prices paid by urban consumers for a representative market basket of consumer goods and services. Similarly, the CPI for food measures the changes in the retail prices of food items only and it is a component of the all-items CPI measurement of price changes for all consumer goods and services, including food (BLS Price Outlook Overview 2015).

According to the BLS, the CPI has three major uses: economic indicator, deflator of other economic series, and as a means of adjusting dollar values (BLS FAQ). As a matter of fact, the CPI is the most widely used measure of inflation and is sometimes viewed as an indicator of the effectiveness of government policy. The price change(s) information provided in CPI is used as a guide to making economic decisions by the U.S. government, businesses, and private citizens. Therefore, it should not be surprising that CPI is used to adjust consumers' income payments, such as social security, or to adjust income eligibility levels for government assistance. The BLS reports that the CPI currently affects the income of about 80 million persons as a result of statutory action: 48.4 million of whom are Social Security beneficiaries, roughly 19.8 million of whom are food stamp recipients, and an estimated 4.2 million military and federal Civil Service retirees and survivors. Additionally the cost of lunch for 26.5 million children who eat lunch at school is affected and determined partly by CPI (BLS CPI FAQ 2015).

Price indices are not only used to adjust government benefits. Specifically, many agribusinesses pay close attention to Food CPI. This is in large part due to the fact that price-cost planning for agribusinesses generally requires various statistical data that not only pertains to historical prices and costs, but also sales forecasts and assumptions about competitive behavior.

Accurate price data can help firms better plan and adjust to market conditions. For instance, public data and associated situation and outlook extension programs are argued often motivated by the belief that they provide more accurate price expectations, and in turn, improve producer and consumer welfare (Irwin, 1997; Freebairn, 1976, 1978; Lusk, 2013). The classic cob web model is used to describe the cyclical price fluctuations that arise when producers decide the quantity to produce before knowing the price (e.g., crops must be planted and harvested before they are sold and prices are realized). Therefore, the lag between production and consumption time periods can lead to an inefficiently supplied market. Better price expectations can help reduce these inefficiencies. Freebairn (1976) showed that the decrease in social welfare, associated with fluctuating cyclical prices in the cob web model, is directly related to the squared difference between producers' expected price and the actual, realized price. Moreover, Freebairn (1976) also found that improved Australian public agricultural price forecasts reduced social welfare losses by an amount approximately equal to 1% of the gross value of production.

Other studies have attempted to estimate the value of improved price expectations. Antonovitz and Roe (1986) estimated the value of adopting a rational expectations price forecast (using USDA data). It was found that the mean expected bimonthly value of information was $0.21 per hundredweight (cwt) live weight of fed cattle produced, or a total mean value of approximately $13.3 million per bimonth during the 1970 – 1980 time frame. Bradford and Kelejian (1978) also looked at the value of increased wheat crop forecast accuracy. It was found that perfectly accurate wheat supply information would be worth $64 million dollars to market participants, mainly due to better storage decisions. Therefore, a more accurate estimate of expected prices not only has a monetary benefit, but also helps increase market efficiency while improving social welfare. While most previous studies have focused on the value of improved price expectation accuracy at the farm level, downstream firms in the food supply chain might also benefit from improved information as well.

Arrow (1951) recognized that resources could be wasted by producing commodities which are left unsold. This waste can be avoided by setting the prices so that the supply of commodities offered by producers acting under the impulse of profit maximization equals the demand for commodities by utility maximizing consumers. Thus, perfect competition, combined with the equalization of supply and demand by suitable price adjustments, yields a social optimum. Agribusinesses generally allow for the cost of unsold goods within their budgets. Decreasing this cost of waste would ultimately lead to higher revenue and profit maximization, and in turn, improve social welfare.

It is apparent that reported CPI and CPI forecasts are important and widely followed by the government, firms, and citizens. Currently, the ERS forecasts food CPI by using an autoregressive moving average (ARMA) framework in which two lags are considered, a one month lag and one year lagged price. There have been other studies, however, that take similar but different approaches to forecast food prices of Food CPI. In 1997, a Principle Paper Session of the American Agricultural Economics Association Annual Meeting (AAEA) invited individuals involved with food price forecasting from the ERS, a private consulting firm (AUS), and the Food and Agricultural Policy Research Institute (FAPRI) at the University of Missouri to share their perspectives. Joutz (1997) compared the primary drivers of food prices used by each forecaster and the price forecasts for 1997 and 1998. During this time, the ERS used a Delphi approach in order to link farm prices and wholesale prices through price spreads (between the two prices) and economic forces going from the processor to the retail level with retail prices. However, analysts at the ERS had just begun using the univariate ARIMA and other time series models as forecasting tools still used today (see Denbaly et al. 1996). Researchers at FAPRI took a similar approach as the ERS in which economic factors, agricultural science, and biological processes were used to forecast CPI. The food price models estimated by FAPRI were estimated by an ordinary least squares (OLS) model in which the main explanatory variables were lagged prices for wheat, rice, sugar, soybeans, and high fructose corn syrup (important food processing inputs). Additionally, industry wage rates and producer price indexes (PPI) were used in several equations along with projections of livestock supplies and dairy product prices, respectively. Incorporated in the FAPRI model(s) were a time-series dynamic process(es) that have a cobweb-like model feature. Lastly, AUS used a structural econometric model to forecast agricultural supplies and demand to explain primary determinants of food price inflation. No feedback between the retail prices, or CPI, and the structural model existed. A model explaining the inverse of farm-to-retail price margin as a function of macroeconomic variables (such as hourly earnings of production workers) was also developed. Moreover, an interest rate explanatory variable was used in many of the AUS models. Each forecasting method used similar drivers to explain food price movements; however, the FAPRI model(s) appeared to have been the most sensitive to economic shock scenarios that were explored by all forecasters (Joutz 1997).

Aside from econometric forecasting models, futures markets allow for the trading of contracts that yield payments based on the outcome of uncertain events. There is evidence from studies that suggest futures markets can help produce forecasts of future outcomes with lower prediction errors than typical autoregressive forecasting methods. Specifically, futures prices in an efficient market provide forecasts of subsequent spot prices that are at least as accurate as any other forecast (Tomek 1997; Colino and Irwin 2009). In laymans terms, it should not be possible to "beat the market" in terms of forecast accuracy (Colino and Irwin 2010), as futures prices should reflect all available information. Colino and Irwin (2010) note that there have been numerous empirical studies that compare the accuracy of outlook forecasts and futures prices such as Just and Rausser (1981); Bessler and Brandt (1992); Irwin, Gerlow, and Liu (1994); Bowman and Husain (2004); Sanders and Manfredo (2004, 2005). Specifically, Colino and Irwin (2010) compare the accuracy of hog and cattle price forecasts from four outlook programs to the forecasts derived from futures markets. When estimating hog prices, outlook forecasts beat futures forecasts two out of eleven times and one out of seven times when estimating for cattle.

Moreover, futures forecasts were found not to encompass outlook in six of the eleven situations for hogs and three out of the seven cases for cattle.

While currently forecasted CPI measures have their benefits, they also have their downfalls. More accurate estimates would increase social welfare by reducing waste and increasing the speed at which markets reach equilibrium. However, existing food CPI forecasts by the USDA-ERS tend to have rather large confidence intervals. Moreover, while there are futures markets for some farm-level products such as live cattle, there are not futures markets for retail cuts of beef, like say rib-eye. Although live cattle futures market prices may help in estimating future retail beef prices it is unclear how accurate a forecast it can provide, especially considering the fact that the farmers' share of the total food dollar is about \$0.155 (i.e., about 84.5% of the cost of the retail product is comprised of goods beyond the agricultural commodity) (Canning 2013). In addition, there are many farm and retail products that are not traded or sold in futures markets (such as chicken).

Aside from historical retail prices or farm-commodity futures prices, are there other types of data which might prove useful in predicting retail meat prices? Might aggregate consumer expectations provide predictive insights? Surowiecki (2005) examines the idea that large groups are often smarter than any one expert, particularly in predicting the future. Likewise, Treynor (1987); Forsythe et al.(1992); Johnson (1998); and Maloney and Mulherin (2003) show that the aggregation of decentralized, independent factions with diversified opinions leads to optimal solutions and accurate predictions of the future.

These studies suggest that there is merit in the information that can be gathered and aggregated from independent individuals. Dr. Jayson Lusk began administering the Food Demand Survey (FoodS) in May of 2013, and has repeated the survey every month thereafter. However, to date it is not yet known whether the variables measured in this survey – consumer's willingness-to-pay, expected consumption, and expected prices for retail grocery products such as beef, pork, and chicken – are predictive of specific components of the food CPI.

Objectives

The primary objective of this research is to determine whether information on preferences, and expected price and consumption changes gathered from FooDS increase forecast accuracy of retail meat prices as compared to simple autoregressive price forecast models. A secondary objective is to determine which type of survey data – willingness-to-pay, expected price changes, or expected consumption changes, best predict future prices.

CHAPTER II

LITERATURE REVIEW

Agricultural economists began estimating consumer demand in the 1920's with hopes of forecasting agricultural prices and farm incomes. Beginning in the 1970's, agricultural economics literature began to focus on consumer behavior and consumer welfare. This literature contributed to estimation of demand models; thus, enabling the identification of changes in consumer preferences and the prediction of the impact policies would have on consumer welfare. Recently, new theories and methodologies have been formed relating to consumer choice studies as food products became more differentiated and as economic variables, such as price and income, have solely failed to fully explain consumer choice. As a result, survey and experimental auctions have been used in studies seeking to determine more accurate predictors of consumers' preferences (willingness-to-pay) and choices (Unnevehr et al. 2010). In this study, choice questions asked to respondents allow for the identification of aggregated willingness-to-pay for food products sold at the retail level. In turn, willingness-to-pay estimates are used as exogenous variables in order to predict future retail prices of the respective food products.

Due to an increase of concern regarding CPI, particularly the food component, and the state of knowledge regarding forecasting and explanation of the CPI for food was brought under extreme scrutiny in the early 1970's. Barr and Gale (1973) developed a model that relates retail food prices to prices received by farmers and to wage rates in food marketing industries to forecast the food price component of CPI published by the BLS. Retail values, similar to the USDA market basket, of farm foods is comprised of a farm value measuring the payment farmers received for raw materials (equivalent to food purchased by consumers) and a farm retail spread approximating the assembly, processing, transportation, and distribution costs associated with the respective farm food products. A constant quantity of different foods makes up the aforementioned market basket in order account for price variations in retail cost, farm value, and farm retail spread. A quasi-recursive system structured along the lines of the market basket was used to estimate farm values of the crop and livestock food groups. The estimates were then combined with equations estimating the farm retail spreads for the groups in order to estimate the food-at-home portion of CPI. Consequently, the all-food CPI is estimated. Equations were estimated by two-stage least squares (TSLS) and used quarterly data from the BLS. Thus, recursive and simultaneous relationships were used to describe the differences in markets for crop foods and livestock food products. Due to the wage-price control program enacted on August 15, 1971, the in-sample forecast estimates of the model were higher than realized prices, however, built in stabilizers helped estimate CPI for food at home and all food with an acceptable degree of accuracy.

As previously mentioned, the ERS switched CPI forecast estimation methods to a Delphi approach in order to better link farm prices and wholesale prices through price spreads (between the two prices) and economic forces going from the processor to the retail level with retail prices. In the late 1990’s, analysts at the ERS began using the univariate ARIMA and other time series models as forecasting tools that are still used today (see Denbaly et al. 1996).

Lamm and Westcott (1981) sought to determine the factors that explained a faster increase in retail food prices as opposed to nonfood prices. The major concern was the impact on consumers of changes in raw foodstuffs prices as well as the impact of changes in the cost of resources used in food processing and distribution. In this study, a small, quarterly, econometric model consisting of twenty linear equations served as the foundation. This model was tailored from Popkin's stage of processing model that requires prices be explained by stage of processing as functions of current and lagged resource prices along with excess demand variables. The principal argument made by Popkin, also adopted in their study, was that there are many theories of price determination, none of which can be demonstrated superior to the others. However, the aforementioned general price equations considering central theses of many theories are used as empirical approximations. Lamm and Westcott assume that retail food prices are determined by a general markup process in which a simultaneous structure including the prices of close substitutes and complements are considered in order to capture the inverse effect that a retail price increase in beef would have on the demand pull effect on pork and poultry prices, for example. Additionally, the relationship between output and input prices is captured in the markup model in which different output prices are jointly determined by expectations, current input prices, and lagged output prices. Exogenous price variables are expressed as quarterly percent changes in price. Moreover, seasonal dummy variables and a time trend variable are considered. The retail food prices are represented by the respective CPI, wage rates are represented by the BLS employment and earning series, farm-level prices for foodstuffs are represented by a prices received by farmers series from the USDA, and imported food and food input prices used in food processing and distributing are represented by producer price indices (PPI). Information for the fifteen retail food products used in the USDA-ERS Food-CPI for food consumed at home calculations were gathered in the aforementioned way and prices for each retail food product were estimated in the specified ordinary least squares (OLS) model. Statistically insignificant variables were dropped and the remaining statistically significant variables were used in a three-stage least squares model (under the assumption that stochastic errors were correlated across equations) to estimate the future retail food prices. Mean absolute percent errors (MAE) were then compared. Results from this study indicate that changes in nonfarm resource prices are important (even dominant) and affect consumers within two quarters of change. Moreover, the model is consistent with estimates that were put forth by the USDA.

Unsuspecting increases of commodity prices caused many economists and market analysts to re-evaluate the predictive power of commodity prices when estimating future consumer price inflation in the mid 1990's. Blomberg and Harris (1995) examine five major U.S. commodity indexes and three subgroups of commodities by using vector autoregression models (VARs) in order to determine whether commodity prices can predict subsequent movements in the finished goods producer price index (PPI) as well as non-food and non-energy CPI. They found no long-run relationship between commodity price and consumer price levels. However, results indicated that there is a co-integrating relationship between commodity price levels and the rate of consumer price inflation. The traditional commodity indexes showed some ability to predict short-run changes in core CPI inflation. Adding monetary variables and dollar exchange rates to models indicates that inflation signals seen from commodities are obscured by offsetting changes in exchange rates and monetary policy. Perhaps most important and relative to this study, Blomberg and Harris also found that commodities with sensitivity to major supply disruptions, namely food, retained more explanatory power than commodities primarily affected by input demands. Hence, food (and oil) were found to be good predictors of core CPI inflation. Therefore, more accurate forecast estimates of Food CPI will lead to more accurate predictions of CPI-U inflation.

Additional CPI Measures and Uses

The Conference Board's Consumer Confidence Index and the University of Michigan's Consumer Sentiment Index are the most widely followed measures of U.S. consumer confidence (Ludvigson 2004). In fact, much of the academic literature refers to the Michigan Index, probably due to the longevity of the time series information available. The Michigan Index began as an annual survey in the late 1940's, was administered on a quarterly basis beginning in 1952, and has been administered monthly since 1978. The Conference Board began nearly two decades later than the Michigan Index in 1967 and was measured on a bimonthly basis until it was administered on a monthly basis in 1977. Both the Michigan Index and the Conference Board measure the public's confidence in the economy. However, the questions are asked differently in each survey and contain different sample sizes and index formulations. It is important to note that in each survey, Michigan and Conference Board, two of the five main questions relate to present conditions while the remaining three pertain to consumer's expectations of the future. A present situation index and an expectations index are reported along with an overall index by each agency.

Although asked differently in FooDS, respondents are asked comparable questions in a similar fashion regarding future price expectations of beef, pork, and chicken as well as expected consumption of these goods. Specifics regarding the questions in FooDS are discussed in a later chapter (see Ludvigson 2004 for comparisons). The survey conducted by the University of Michigan is done so by phone throughout the month and is comprised of a sample size of about 500 respondents. Roughly two thirds of the goal sample size (500) is surveyed early in the month so that a preliminary "mid-month" report can be published. At the conclusion of the month when the sample size is complete, a final report is released. Conversely, the Conference Board sends out 5,000 mail surveys to respondents at the end of the previous month and usually receives 3,500 responses that comprise the effective sample size. It is important to note that the 5,000 respondents who receive the survey have agreed beforehand to participate in the survey process. The Conference Board also releases preliminary reports, but on the last Tuesday of the survey month when approximately 2,500 surveys have been collected. Final results from the survey are then released the following month with the preliminary report. FooDS is an online survey sent to at least 1,000 consumers, on the 10th of every month, in a panel maintained by Survey Sampling

Incorporated (SSI). If the 10th falls on a weekend, FooDS is sent out to respondents the following Monday. After completion of the survey each month, usually two or three days after the survey is sent to respondents, responses are weighted to match the U.S. population in terms of age, gender, education and region of residency and results are released. The use of an electronic survey allows for fast, timely responses and analyses; hence, the results from FooDS are analyzed and released two weeks before University of Michigan results and approximately a month before final Conference Board reports are released.

The Conference Board survey has a larger sample size, the overall response rate is unknown due to the unreported response rate of households who had been asked to take the survey (i.e.: only the response rate of households that had previously agreed to participate in the survey is reported). Increases in technology over the past 65 years should also be taken into consideration when talking about non-response error, specifically concerning the Michigan survey. The ability to screen unwanted calls and even the sharp decline in landline telephones in the U.S. should cause a significant increase in non-response error for both surveys. All surveys mentioned are subject to reporting, editing, and processing non-sampling sources of error.

Ludvigson (2004) seeks to determine how well consumer confidence surveys can forecast the growth of various categories of personal consumption expenditure. This study follows Bram and Ludvigson (1998) when measuring the effect of consumer attitudes on the five categories that make up household personal consumption expenditure (total expenditure, motor vehicle expenditure, expenditure on goods – excluding motor vehicles, expenditure on services, and expenditures on durable goods – excluding motor vehicles). The largest span of time in which data for both indices is available is from 1968 – 2002. The independent variables in the model were described as “lags of consumer confidence over the previous four quarters,” and dummy variables to control for the 1990 – 1991 recession. Adjusted R-squared values and p-values for the joint marginal significance of the lags of each variable were the statistics of interest.

Considering these statistics, results indicated that measures of consumer attitudes alone have statistically and economically significant predictive power when estimating quarterly consumption growth in a variety of expenditure categories. Fifteen percent of the one-quarter-ahead variation in total personal consumption expenditure growth was explained by overall CPI lagged values from the Michigan and Conference Board surveys alike. Additionally, the measured expectations component for the indices measured by the Michigan and Conference Board surveys exhibited greater predictive power than overall CPI lagged values. Notably, twenty percent of the variation in the next quarter total consumer expenditure growth was explained by the Conference Board's expectations index while the expectation index measured in the Michigan Survey explains nineteen percent of the variation in next quarter's expenditures on goods (excluding motor vehicles). Ludvigson (2004) was also interested in finding out if confidence measures contain predictive information that is not already contained in a standard set of baseline indicators. The baseline indicators that are common in the works of Carrol, Fuhrer and Wilcox (1994) and Bran and Ludvigson (1998) and their examination of predictive power of consumer confidence surveys were used. These indicators are lagged values of the dependent variable, labor income growth, the log of the first difference between the real stock price, and the first difference of the three-month Treasury bill rate (Ludvigson 2004). These variables are lagged four periods for the benchmark regression. Results indicated that the lagged consumption growth in every category of consumer expenditure mentioned is positively related to consumption growth. Conversely, a negative relationship existed between lagged interest rates and future consumption. Moreover, including consumption and interest rate variables reduced the statistical significance of the income and stock market variables when forecasting consumer expenditure growth on services, durable goods – excluding motor vehicles, and all goods – excluding motor vehicles. A measure of consumer confidence from the Michigan or Conference Board surveys (overall or expectations index) was included to the baseline regression in order to determine whether consumer sentiment contains additional information about future spending. As with the other model(s), a dummy variable was created to correct for the 1990 – 1991 recession. Differences in the adjusted R-squared values from these models and the baseline models were recorded and compared. Results indicate that the inclusion of overall indices measured by the Michigan and Conference Board survey increase forecasting power of total personal consumer expenditure growth. Although, greater predictive power was gained by considering the last four quarters of data from the Conference Board overall confidence index in the baseline equation than when considering the lagged values of consumer sentiment measured in the Michigan Survey. Moreover, considering the indices measured in both surveys increased the baseline adjusted R-squared value by 10%. It is important to note that while the expectations index calculated from each survey did increase predictive power in the baseline model, it did not exhibit as much predictive power as the overall indices from each survey when forecasting total expenditure growth, however. Therefore, index measures from both surveys added predictive power to simple autoregressive models when forecasting future personal consumption expenditures, but it cannot be determined that one index is greater than the other overall.

Ang, Bekaert, and Wei (2006) examine the forecasting power of alternative methods to forecast future (out-of-sample) U.S. inflation rates. All out-of-sample forecasts estimated annual inflation (rates). The methods explored in this study that are of interest to the current study are time-series ARIMA models and survey based measures. As previously mentioned, the USDA-ERS currently uses ARIMA (simple autoregressive) models in order to forecast Food CPI. Ang, Bekaert, and Wei (2006) use two ARMA(p,q) models. The first is an ARMA(1, 1) model that is estimated by maximum likelihood (conditional on a zero initial residual) and a pure autoregressive model with p number of lags, AR(p) where the optimal lag length is recursively selected by considering the Schwartz criterion (BIC) from the in-sample data.

The Livingston survey, the survey of professional forecasters (SPF), and the Michigan Survey (all inflation expectation surveys) are used in their study. Economists from industry, government, and academia are polled twice a year (June and December) in the Livingston survey. Not adjusted for seasonality, six and twelve month CPI level forecasts of the polled economists are usually recorded in the middle of the month that they are asked. Due to the fact that respondents are not asked to forecast an inflation rate, Ang, Bekaert, and Wei (2006) follow Thomas (1999) and Mehra (2002) when adjusting the raw Livingston forecasts. The raw data is adjusted by a 12/14 factor in order to obtain the annual inflation forecast. Opposite of the Livingston Survey, respondents of the SPF and Michigan Surveys forecast inflation rates. SPF Survey participants are usually business professionals and are asked in the middle of each quarter to forecast the changes in the quarterly average of seasonally adjusted CPI-U levels. As mentioned earlier, the Michigan Survey asks households, or consumers, on a monthly basis to estimate expected price changes during the twelve months that proceed. The forecasts from the Michigan and SPF surveys are directly used to represent forecasts of future U.S. annual inflation. Ang, Bekaert, and Wei adjust the surveys to correct for bias because studies by Thomas (1999), Mehra (2002) and Souleles (2004) find that there is bias within survey forecasts.

The RSME associated with each forecast model is used to determine the accuracy of each forecast model. The ARMA(1,1) model is used as the benchmark to all RMSE's for a ratio that is also created to measure forecast accuracy. The out-of-sample forecast accuracy is determined in the same way as Stock and Watson (1999).

Additionally, different methods pertaining to the combination of forecasts are explored. Mean and median combination methods are used in which the overall means and medians for different forecast models are considered. The forecasts are weighted equally when these combination methods are used due to studies by Bates and Granger (1969) and Stock and Watson (2003). Additionally, OLS, equal-weight prior, and unit-weight prior forecast combination methods are used (see Ang, Bekaert, Wei 2007).

Results indicate that surveys outperform all forecasting methods explored in this study – time-series ARIMA models, regressions using real activity measures motivated from the Phillips curve, and term structure models (including linear, non-linear, and arbitrage-free specifications). This aligns with the results from Grant and Thomas (1999), Thomas (1999), and Mehra (2002) that indicate simple time-series benchmarks for forecasting inflation are out-performed by survey information. Specifically, the median forecasts were found to be the best survey forecasts, however, little to no change was seen forecast performance when mean values were used. Also, forecast accuracy was improved when linear combinations of forecasts with weights based on past performance and prior information were evaluated. Additionally, it is important to mention that the participants in the Michigan survey (consumers and not experts) produce accurate out-of-sample forecasts. Moreover, when forecasts were combined, the data placed the highest weights on survey information consistently. Ultimately, there was little evidence to suggest that combining forecasts resulted in a superior forecast to survey information alone.

After the sharp decline in the University's Index Consumer Sentiment (ICS) in 1990, Carrol, Fuhrer, Wilcox (1994) were interested in whether an index of consumer sentiment has any predictive power for future changes in consumption spending and whether it contains information about future changes in consumer spending aside from the information contained in other available indicators.

In order to determine the predictive power associated with ICS, R-squared values from a model in which the log difference between starting and ending period values of the indicated category of real household spending was regressed by quarterly ICS values lagged four periods. Results indicate that lagged values of the ICS explain roughly fourteen percent of the variation in the growth of total real personal consumption expenditures. Therefore, consumer sentiment alone has predictive power when estimating future changes in consumption (household) spending. In order to explain the predictive power associated with ICS, the modification of the pure life-cycle/permanent – income hypothesis and framework put forth by Campbell and Mankiw (1989, 1990, 1991) were followed. It is assumed that there are two types of consumers, one that spends strictly according to a standard life-cycle/permanent-income model and the other that spends the amount of income received. In this scenario, the lagged ICS is used as an instrument for current growth of income; hence, ICS is not a variable but rather used to calculate the "growth of income" variable(s). The predictive power associated with ICS was not explained even after testing a simple model considering that consumers are precautionary savers as well as a model considering the idea that consumers are habitual. Due to these results, it is mentioned that a model incorporating habits formed by consumers and precautionary consumer saving motives may be able to explain the predictive power associated with ICS.

A vector of variables was added to the aforementioned autoregressive model in order to control for economic information not captured by ICS. These control variables include: growth of real labor income lagged four periods. All variables in this model, including ICS values, were deflated by the implicit deflator for total personal consumption expenditures. Through comparisons of adjusted R-squared values, it was determined that not all of the information contained in ICS is held in common with the control variables. This study makes the conclusion that ICS has a small amount of incremental predictive power relative to some other economic indicators related to spending growth. Moreover, it was concluded in their study that ICS "probably" contains information about future changes in consumer spending independent of information contained in other available indicators.

In a study by Zakrzewicz, Brorsen, and Briggeman (2012), the hypothesis that land value estimates from the Quarterly Tenth District Survey of Agricultural Credit Conditions administered by the Federal Reserve Bank of Kansas City are leading indicators of land value estimates from the Annual USDA Survey published in the USDA Annual Report is tested. The survey administered by the Federal Reserve asks agricultural bankers about current farmland values in the Federal Reserve Tenth District on a quarterly basis while the Annual USDA Survey is an area-based survey asking agricultural producers about the fair market values of farmland in their area. Therefore, agricultural bankers', or "experts", future land value estimates are examined and compared to reported land value estimates. Just as the USDA National Agricultural Statistics Service (NASS) has traditionally been the gold standard for land valuation (Zakrzewicz, Brorsen, Briggeman (2012), the BLS has traditionally been the gold standard regarding macroeconomic reports, specifically Food CPI, by gaining public trust through using statistical sampling methods.

In order to determine if the USDA and Federal Reserve surveys are leading indicators of each other, a granger causality test is used. The causality model is useful in exploring the linear linkages between two economic series and determining if they are indicators of one another (Zakrzewicz, Brorsen, Briggeman 2012; Sanders et al., 2003). If the dependent variable is better predicted using lagged values of the dependent variable as well as another independent variable as opposed to only the dependent variable lagged, the independent variable is said to Granger cause the dependent variable. Therefore, the yearly percentage change in USDA land price estimates are regressed by the summation of annual lagged percentage changes in USDA and Federal Reserve land value estimates alike. This model was run four separate times in order to account for the differing survey administration times (USDA is administered annually while the Federal Reserve is administered quarterly). Each regression uses the annual percentage change in Federal Reserve land value estimates for each of the four quarters. Moreover, the yearly percentage change in Federal Reserve land price estimates were regressed by the same variables while accounting for the differences in survey administration in order to determine the lead lag relationship between USDA and Federal Reserve land value estimates. Results from the granger causality tests indicate that Federal Reserve land value estimates are leading indicators of USDA land value estimates. Not only is this study important to consider from a theoretical standpoint, but it also indicates that even the “gold standard” can be predicted through survey results.

The surveys administered by the Federal Reserve are qualitative in nature, as are parts of the FooDS Survey used in this study. Bankers participating in the Federal Reserve Survey are asked whether they expect the (farm)land values to be higher, lower, or not to change in the following three months. Questions regarding expectations of future prices and consumption of meat products are asked in a similar fashion to consumers in the FooDS Survey. Zakrzewicz, Brorsen, and Briggeman (2013) examine the ability of respondents who participate in the Quarterly Tenth District Survey of Agricultural Credit Conditions to forecast land value movements. The survey forecast estimates are compared with realized changes in land values by three different methods using both aggregated and disaggregated data.

The first method uses contingency tables in order to determine the average prediction accuracy for each banker considered. Within the contingency tables, relative frequency of each directional price movement within the sampling period and forecast likelihood are reported. From this information the forecast accuracy is measured using overall bias (or miscalculation in expectations of future land value movement), proportion of correct forecasts out of the total number of forecasts for each category, proportion of correctly predicted outcomes given a specific outcome (probability of detection) , and the proportion of correctly forecasted estimates out of all forecasts made. Pearson’s chi-squared test is then used in order to test independence between banker’s forecasts and the actual prices.

The aggregation of directional forecasts allows for proportional calculations. These proportions are often interpreted as predictions of the probability of a movement in the given direction and called probability forecasts (Zakrzewicz, Brorsen, and Briggeman 2013; Diebold and Lopez 1996). The Federal Reserve Survey data are conducive to using Brier’s probability score and

Yates' decomposition to assess the forecasting ability of bankers (Zakrzewicz, Brorsen, and Briggeman 2013; Bessler and Ruffley, 2006). Following Covey (1999a, 1999b), Zakrzewicz, Brorsen, and Briggeman (2013) use Brier's mean probability scores (Brier 1950) to analyze aggregated land value data from the Federal Reserve Survey. This mean probability score allows the total forecast accuracy for all directional forecasts over all sample periods to be measured. Moreover, a decomposition of the mean probability score was derived by Yates (1982), also known as the covariance decomposition. The framework of Yates' covariance decomposition was used to calculate an additional probability forecast. These two probability forecasts, Yates and Brier, are measured against a uniform model in which the probability of directional movement is equal across all possible outcomes. Additionally, the probability forecasts are measured against a relative frequency model (calculated in-sample) in which the relative frequency of actual outcomes is assigned by the model.

Additionally, Zakrzewicz, Brorsen, and Briggeman (2013) convert the qualitative forecasts of the bankers by regressing percentage changes in land values against the proportion of bankers who forecasted increased land values and the proportion of banks who forecasted decreases in land values. These forecast estimates are compared to naïve no-change land value forecast estimates, which, in turn, help determine if bankers provide forward looking forecasts. Errors associated with each forecast were evaluated using RMSE.

Methods of using disaggregated data from the survey used in the study indicate that bankers in the Tenth District of the Federal Reserve were able to accurately forecast movements in land prices. Likewise, the methods using aggregated data also indicate there was predictive power in aggregated survey data. Moreover, forecast models considering aggregated directional predictions were more accurate than the naïve no-change forecast model. Ultimately, this study shows that using the expectations of survey respondents results in accurate forecasts of future prices.

Similar to Zakrzewicz, Brorsen, and Briggeman (2012, 2013), Tsuchiya (2013) seeks to determine whether directional forecasts of Gross Domestic Product (GDP) by corporate executives are "useful" or even "valuable" to users. While many studies have investigated the use of information provided by businesses (Klein and Ozumucur 2010; Claveria et al. 2007), government (Zakrzewicz, Brorsen, and Briggeman 2012, 2013), and international organizations (Artis 1996; Ash et al. 1998; Ashiya 2003; Baghestani 2011; Joutz and Stekler 2000; Pons 2000, 2001, Sinclair et al. 2010) surveys to improve forecast accuracy, few (Tsuchiya 2012a; Pesaran and Timmermann 1992) have paid attention to directional analyses of business survey indices. Tsuchiya (2013) uses directional analysis methodologies and results from the Annual Survey of Corporate Behavior (ASCB), the Business and Investment Survey of Incorporated Enterprises (BISIE), and the Business Outlook Survey (BOS) in order to determine whether the economic predictions of the economy from business executives are useful predictors of real Japanese GDP. Results from the Tankan Survey (a business survey administered in Japan) are compared with results from the BOS. Not only is the most recent historical data used in directional forecasts, but initially published real-time data is also used.

Tsuchiya (2013) uses Fisher's Exact Test (FE test), the chi-squared test, and Pesaran and Timmermann's (1992) test in order to predict the directional change of real Japanese GDP. The FE and chi-squared tests indicate if the sign of the predicted change in Japanese GDP is statistically independent of the sign of the actual change by use of a contingency table. When the null hypothesis following Schnader and Stekler (1990) is rejected, it is implied that corporate executive forecasts are useful predictors of change in real Japanese GDP and differ significantly from a naïve, directional prediction model. The non-parametric test (PT test) of predictive failure (Pesaran and Timmerman 1992) is then used when the null hypothesis of predictive failure is rejected.

Results indicate that surveys including real-time data, such as the Tankan survey, are not useful when considering historical data to forecast future changes in Japanese GDP. This could be due to false real-time signals of directional change within the economy. As seen in Maloney and Mulherin (2003) and the study of the effects of a space shuttle crash on the stock market, initial shocks due to breaking information may not always remain. That is, stock markets are extremely volatile, especially when viewed in real-time, and do not always exhibit the overall direction of the stock market or economy. Additionally, it was found that when forecast horizons of one to fourteen months were useful, especially when combining results from different surveys. Slightly consistent with Easaw and Heravi (2004) and Easaw et al. (2005), the further into the future models try to predict changes, the worse the forecast accuracy. Moreover, results do indicate that business professionals look relatively far into the future due to the fact that investment decisions made by business professionals and future impacts must be considered. Therefore, business professionals tend to be forward looking. Thus, all the surveys examined in this study pertain to expectations from forward looking individuals. In turn, forward looking expectations were proven valuable and useful.

Investor sentiment, or Gross National Happiness (GNH), is used by Karabulut (2013) in order to predict changes in daily returns and trading volume within the U.S. stock market. As argued by Baker and Wurgler (2006), "Now, the question is no longer, as it was a few decades ago, whether investor sentiment affects stock prices, but rather how to measure investor sentiment and quantify its effects," (Karabulut 2013). A measure of GNH is calculated by Karabulut (2013) by using the textual analysis of emotion words posted by more than 160 million users on Facebook. Vector autoregressive models are used to examine the relationship between the calculated GNH and daily stock market activity. Results indicate that this index, GNH, is statistically significant and economically meaningful in the sense that it can predict future stock market returns regardless of whether past stock market volatility, daily economic conditions, or turn-of-the-year effects are controlled for. However, under the same conditions, there seems to be no predictive power behind GNH when forecasting short run macroeconomic conditions. Additionally, out-of-sample forecasts are run in order to determine whether GNH measures can predict stock market returns and trading returns in U.S. as well as international markets (UK and Germany). Following the previously discussed results, the GNH index proves to be a predictor of future stock market activity throughout all markets tested. In order to validate the results that indicate that the GNH index is a proxy for investor sentiment, Karabulut (2013) follows Baker, Wurgler, and Yuan (2011) in the examination of the effects of differential GNH on the relative price deviations of dual-listed companies. Results indicate that relative price deviations of the twin companies are positively associated with the relative GNH values within the respective markets, even when non-synchronous trading and exchange rate fluctuations are accounted and controlled for. Hence, country-specific sentiment is shown to explain in part the disparities in twin company pricing (Froot and Dabora, 1999), further indicating that GNH is a reflection of investor sentiment. This study is important in the fact that the GNH index is a direct measure of well-being calculated from an indirect survey of independent, non-experts in the field of stock market speculation.

Capps (2009) states that determining the factors influencing demand for food products through applying newly developed theoretical and empirical models, coupled with the help of information technology, forecast accuracy of consumption of food products and respective prices will be increased. These results will aid market development, marketing strategies, and decision making in retail management and operations (Capps 2009; Capps and Love 2002). The identification of nonconventional determinants of price spreads between prices before and after an economic shock such as food recalls or BSE outbreaks, will lead to a greater understanding of price spreads, or marketing margins (Capps 2009; Capps and Senauer 1986).

Shifts in the demand curve affect prices. Therefore, by measuring consumer willingness-to-pay (the underlying preferences that dictate the shape of the demand curve), and exploring how WTP changes over time, it might be possible to predict price changes.

Technological Impacts on Demand

In 1896 Gustave LeBon introduced a theory to explain the "hypnotic influence" that a crowd has, such that the anonymity of a large group of people can ignite emotionally charged or irrational behavior. When the behavior of people change after an interaction with another person or group, oftentimes attributed to increased awareness, social learning, or the desire to adhere to perceived norms through a process of relating, a fad, or social contagion, arises (Latane 2000; Van den Bulte, and Wuyts 2007; Rapp et al. 2013). As found in many managerial research studies (Burt 1987; Contractor and Eisenberg 1990), contagion is supported by communication networks exposing people to information, attitudes, behaviors, and beliefs of others in the network. Increased exposure to network outlets relaying various types of information to a population leads to a higher likelihood that the exposed faction will adopt similar characteristics. Frequency, strength, and asymmetry of communication can increase or diminish the aforementioned contagion effects (Erickson 1988). The Federal Communications Commission (FCC) reports that the number of connections with downstream speeds of at least 10 Mbps increased by 104% from December 2012 to December 2013, to 122 million connections, comprised of 64 million fixed connections and 58 million mobile connections. Moreover, growth in mobile internet subscriptions has increased significantly. The number of mobile subscriptions with speeds over 200 kpbs in at least one direction grew to 197 million from December 2012 to December 2013, up by 16%. Fixed-location connections at speeds over 200 kbps in at least one direction increased by 4% to 96 million during the same time frame. The FCC also reports that residential fixed-location internet access connections over 200 kpbs in at least one direction increased by 4% to 88 million from December 2012 to December 2013 (U.S. FCC). With access to networks increasing at a rapid rate, rapid changes in consumer demand should be expected; thus, having a more pronounced effect on food prices than in the past.

Wisdom in Crowds

More likely than not, everyone has had a teacher at some point in their elementary education (maybe even at an advanced degree level) ask the class to guess how many jelly-beans are in a jar. Jack Treynor (1987) describes a “bean jar” experiment in which observers are asked to guess the number of beans filling a jar. The overall goal is to determine how accurate the mean of the guesses is compared to the average guess. The experiment was conducted in his investment course amongst the students. Of the two classes taught and tested in the experiment, only two of the forty-six students enrolled in the first class were more accurate than the class’s mean estimate and only one of the fifty-six students enrolled in the second class were more accurate in their estimate than the class’s mean estimate. These results suggest that in a situation where participants have not been schooled in a proper approach, the majority of the errors associated with the estimates will be independent. People are unique in their history and experiences, personalities, and evaluation methods. Therefore, independence is essential when referring to “wisdom of crowds”.

Norman Johnson (1998) conducted a study in order to gain extended insight to the dynamics of collective decision making relative to decisions made by individuals absent to the complexities associated with shared learning, cooperation and competition; thus, retaining independence. Agents, as participants are referred to in this study, were placed in a maze for a learning phase in which they are asked to find their way to the exit of the maze. The next phase in the study was called the application phase. The agents were sent back into the same maze in order to apply what they had learned in the learning phase to find their way to the exit of the maze. As expected, the agents were able to find their way to the exit of the maze in less steps during the application phase than in the learning phase. Additionally, individual agents were randomly placed into "ensembles" in order to determine a collective solution for finding the exit of the maze. In each ensemble, say comprised of five agents from a population of one hundred, the paths were combined and decisions made at each "node" or intersection were used in order to determine the ensemble's optimal path, noted as the ensemble's collective solution. Moreover, the average collective solution steps taken out of a population of one hundred agents were less than the number of steps by the individual agents in the application phase when considering a population of one hundred agents. The collective solution was deemed the optimal solution, as there was no possible way to get to the exit of the maze in less steps than what was outlined in the path taken by the collective solution. Therefore, the knowledge and information gained from a collective group of independent individuals was proven to be better than that of any single individual, even after a learning phase. This suggests that there is knowledge associated with a group of independent individuals who have differing experiences, personalities, and evaluation methods. It is important to note that the information available to an agent at a decision point, or node, is independent of the path they took to get there, the same problems were solved by all agents, individuals had identical capabilities and identical assessments of information, and individuals were (most importantly) independent of each other (even in the collective phase).

Maloney and Mulherin (2003) study the crash of the space shuttle, Challenger, and the accuracy of price discovery associated with the crash by looking at stock returns and trading volume. The launching of Challenger was nationally televised, and consequently, the explosion. There were four main manufacturing firms involved with the shuttle project, all of whom were initially blamed. Within twenty-one minutes of the space shuttle crash, stocks of Martin had declined 5.05%, stocks of Martin Marietta had declined 2.83%, and Rockwell had declined 6.12%. With the resumption of trading (fifty-one minutes after the crash) for Morton Thiokol, the fourth manufacturing firm, stocks had declined 6%. Interestingly, by the end of the day Martin, Martin

Marietta, and Rockwell stocks had bounced back close to the opening prices on the day of the crash; however, Morton Thiokol continued to decline throughout the remainder of trading. This decline was maintained in subsequent months while the other three manufacturing firms continued to outperform Morton Thiokol. This suggests that the stock market believed Morton Thiokol to be the party to blame for the crash of the space shuttle, Challenger. The sitting president, President Reagan, appointed a blue-ribbon panel (headed by former Secretary of State, William Rogers) to investigate the crash. Several months of testimony and deliberation later, the commission concluded that the cause of the crash was due to the lack of resiliency at low temperatures in the seals of the shuttle's booster rockets supplied by none other than Morton Thiokol. To put this into perspective, by the end of the day without any scientific evidence or expert knowledge regarding space shuttles or the crash, the stock market had identified the company responsible for the space shuttle crash. Maloney and Mulherin looked at records of insider trades to see if Thiokol executives or Thiokol competitors had dumped or sold stock short; however, there was no evidence to support any of the claims. Additionally, none of the other three manufacturing firms had made suspicious moves in the stock market. The decline in the guilty firm's stock was solely related to uninformed buyers and traders. Therefore the conditions for a wise crowd were satisfied that day: diversity of opinion, independence, decentralization, and aggregation; ultimately, resulting in the perfect forecast.

Another example in which a well-established method of predicting future behavior can be observed is in polling for presidential elections. Quite simply, if knowledge of future voting behavior is desired, the best way to determine said behavior is to ask those voting who they plan to vote for at the voting booth. Although much statistics is involved, polling tends to be quite accurate. There is another method, however, in which economists can predict the outcome of an election. There are stock markets in which traders can sell portfolios of shares in candidates to buyers. The investment/payoff rule adopted in these markets provides a direct translation of market prices into estimates of vote shares; thus, offering a prediction of the election winner as well as the margin by which they will win. In order to determine how well markets work as aggregators of information, Forsythe, et al. (1992) analyzed results from the 1988 Iowa Political Stock Market. The popular vote and the share of the popular vote for the candidates were compared to the predicted shares of the vote based on the market prices on the eve of the election. Results indicate that the market under-valued the loser by a penny and over-valued the combined strength of all third-party candidates by a penny. Nonetheless, the market was extremely accurate in predicting election outcome. Results from this study seem to support the Hayek hypothesis – markets work even when participants know very little about the environment or about other participants. Traders have many different talents, interests and abilities. Additionally they interpret information differently and are ultimately independent of each other; hence, wisdom in crowds.

CHAPTER III

CONCEPTUAL FRAMEWORK AND HYPOTHESES

This section will outline the hypotheses associated with this study and briefly discuss additional, literature relevant to the hypotheses. The first hypothesis is as follows:

H1: BLS beef, pork, and chicken prices are positively correlated with consumer price expectations, consumption expectations, and willingness-to-pay measured in FooDS.

Consumer confidence indices and consumer sentiment indices have been calculated and considered in economic analyses for over fifty-eight years. Consumer confidence interacts with consumer behavior as well as other economic factors, and is commonly used as a forecasting tool by many economists (Merkle, Langer, and Sussman 2003). As consumer expectations and confidence fluctuate, so should consumer demands. Hence, consumer confidence (and sentiment), or expectations, are key economic indicators explaining market and product consumption changes alike.

Moreover, we also hypothesize:

H2: Stated consumer preferences (willingness-to-pay) and consumer price and consumption expectations gathered from the Food Demand Survey (FooDS) will improve price forecast accuracy of retail meat prices as opposed to models strictly using past prices of the same good (simple autoregressive models).

As seen in Lusk, Chang, Norwood (2009); Loureiro, McCluskey, and Mittelhammer (2003); Brooks and Lusk (2010); stated consumer preferences are effective in predicting actual market behavior. Thus, increased knowledge of consumer preferences will lead to increased predictions of revealed preferences (observed consumer behavior), or willingness-to-pay, and predictions of actual market prices associated with these products.

The third hypothesis is as follows:

H3: Willingness-to-pay is a better predictor of future retail beef, pork, and chicken prices than price and consumption expectations measured in FooDS.

CHAPTER IV

METHODS AND PROCEDURES

This chapter will discuss the consumer survey data from the Food Demand Survey (FooDS), including information on how the data are collected and how measures of WTP, price expectations, and consumption expectations are derived. Then, retail price data from BLS will be discussed. Finally, this chapter will discuss the econometric methods used to study forecast accuracy.

Consumer Survey Data from FooDS

FooDS is a monthly, online survey sent out to at least 1,000 consumers each month. The first FooDS survey was administered in May of 2013 and is issued consistently each month. FooDS is sent out to respondents on the 10th of every month unless the 10th falls on Saturday or Sunday. If the 10th falls on a weekend, FooDS is sent out to respondents the following Monday.

The survey is sent to a sample of consumers in a panel maintained by Survey Sampling Incorporated (SSI). After completion of the survey each month, responses are weighted to match the U.S. population in terms of age, gender, education, and region of residency.

We make use of aggregate results from the FooDS from the month it began in May 2013. Our econometric models use data through December 2014, which means we have 20 monthly observations. In addition, we use results from the January, February, and March 2015 surveys to explore out-of-sample forecasts.

Willingness to Pay

Each respondent is presented with several choice questions asking consumers to select which of nine options they are most likely to purchase at the grocery store to prepare a meal for them or their household (see Lusk 2013 for more detail). The nine-options include two beef (steak and hamburger), two pork (chop and deli ham), two chicken (breast and wing), two non-meat (spaghetti and rice and beans), and a "no purchase" option. Each option (except "no purchase") has a price, and consumers must select which they'd be most likely to purchase. After their initial choice, consumers answer eight additional choice questions that are identical to the first, except the prices vary.

To assign prices to options, a main-effects orthogonal design was constructed. A perfectly orthogonal design requiring the prices of each choice alternative to be uncorrelated with each other called for twenty-seven choices. The twenty-seven choices were allocated to three blocks with nine choices (questions) in each block. Each respondent is randomly assigned to one block. The order of appearance of each food item varies by block.

For each option, the price took one of three levels. Hamburger prices in each block ranged between \$2 and \$5; beef steak prices ranged between \$5 and \$8; pork chop prices ranged between \$2.25 and \$5.25; deli ham prices ranged between \$1.15 and \$4.15; chicken breast prices ranged between \$1.75 and \$4.75; chicken wing prices ranged between \$0.25 and \$3.25; rice and beans ranged between \$0.50 and \$3.50; and tomato-pasta prices ranged between \$2.50 and \$5.50, all in dollars per pound. The midpoint of the price ranges constituted as the third price level in each block. Figure 1 depicts a portion of the choice questions presented to respondents.

Figure 1. FooDS Choice Options

To determine willingness-to-pay in time *t*, the choices were analyzed by a multinomial logit model with alternative-specific brand and price effects. Individual respondent *i* was assumed to derive utility U_{ijt} from the choice of option *j* in time period *t*:

$$U_{ijt} = V_{ijt} + \varepsilon_{ijt}$$

where respondent utility, V_{ijt} is derived from described attributes (price and brand) of choice option *j* and the unobserved stochastic factor ε_{ijt}. Therefore, V_{ijt} is defined:

$$V_{ijt} = B_{jt} + \alpha_{jt}(Price)_{ij}$$

where utility for food type *j* in time *t* is denoted as β_{jt}, and α_{jt} denotes the marginal utility of price for alternative *j* in time t. $Price_{ij}$ is the price presented to respondent *i* for meal option j. It is important to note the utility of the option not to purchase any of the available meal options was normalized to zero; thus, utility gained from purchasing meal option *j* is relative to not purchasing a meal. Hence, the probability of respondent *i* purchasing alternative *j* in time *t* can be determined:

$$Prob[V_{ij} + e_{ij} \geq V_{ik} + \varepsilon_{ik} \forall k \in C_i]$$

where the choice set for respondent *i* is $C_i = (1,2, \ldots ,9)$. The nine choice options consist of the eight meal options mentioned above along with the option not to purchase any of the meal options. If the random errors ε_{ijt} are independently and identically distributed across individuals and alternatives with type I extreme value distribution, we have the probability of consumer *i* choosing alternative *j* in time *t*:

$$\pi_{ijt} = Prob(j\ is\ chosen) = \frac{exp^{V_{ijt}}}{\sum_{k\in C} exp^{V_{ijt}}}$$

Willingness-to-pay (WTP) for meal option *j* in time period *t* was estimated by determining the price at which the individual respondent becomes indifferent to purchasing the respective meal option and not purchasing a meal. WTP for meal option *j* in time period *t* can be expressed as:

$$WTP_{jt} = -\frac{\beta_{jt}}{a_{jt}}$$

Price and Consumption Expectations

Respondents were asked to what degree they planned to purchase more beef, chicken, pork, or eat out more in the next two weeks as opposed to the previous two weeks. Likewise, respondents were asked whether they expected the price of beef, pork, and chicken to be higher during the compared time frame. The manner in which respondents were asked about price and consumption expectations can be seen in Figure 2.

To derive an aggregate measure of price expectations in each month *t*, we calculated the proportion of respondents who agreed that prices would increase and subtracted it from the proportion of respondents who agreed that prices would decrease. Formally, price expectations (PE) for meat type *j* in month *t* was calculated as:

$$PE_{jt} = \frac{\sum_{i=1}^{nt} AGREE_{ijt}}{n_t} - \frac{\sum_{i=1}^{nt} DISAGREE_{ijt}}{n_t}$$

To what extent do you agree or disagree with the following statements regarding your purchases in the next two weeks as compared to the previous two weeks?

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
I plan to buy more beef	○	○	○	○	○
I plan to buy more chicken	○	○	○	○	○
I plan to buy more pork	○	○	○	○	○
I plan to eat out more	○	○	○	○	○
I expect the price of beef to be higher	○	○	○	○	○
I expect the price of pork to be higher	○	○	○	○	○
I expect the price of chicken to be higher	○	○	○	○	○

Figure 2. Consumer Expectation Questions

where PE_{jt} is the consumer price expectation for meat *j* in each time period (month) *t*, $j = 1,2,3$ where 1 denotes beef, 2 denotes chicken, and 3 denotes pork, $t = 1, \dots, 20$, *n* is the total number of respondents in time period *t*. $AGREE_{ijt}$, is a 0/1 dummy variable indicating whether respondent *i* either strongly agreed or agreed that the price of meat type *j* would increase in the coming weeks. $DISAGREE_{ijt}$, is a 0/1 dummy variable indicating whether a respondent either strongly disagreed or disagreed that the price of meat type *j* would increase in the coming weeks.

Similarly, the consumer consumption or quantity expectation (QE) is calculated as:

$$QE_{jt} = \frac{\sum_{i=1}^{nt} AGREE_{ijt}}{n_t} - \frac{\sum_{i=1}^{nt} DISAGREE_{ijt}}{n_t}$$

where QE_{jt} is the consumer consumption expectation for meat *j* in each time period (month) *t*, $j = 1,2,3$ where 1 denotes beef, 2 denotes chicken, and 3 denotes pork, $t = 1, \dots, 20$, *n* is the total number of respondents in time period *t*. $AGREE_{ijt}$, is a 0/1 dummy variable indicating whether respondent *i* either strongly agreed or agreed that the quantity consumed of meat type *j* would increase in the coming weeks. $DISAGREE_{ijt}$, is a 0/1 dummy variable indicating whether a respondent either strongly disagreed or disagreed that the quantity consumed of meat type *j* would increase in the coming weeks. Table 1 shows PE and QE for each month from May 2013 – March 2015.

Table 1. Willingness-to-Pay, Price and Consumption Expectations from FooDS

	Willingness-to-Pay							Price Expectation			Consumption Expectation		
Month	Ground Beef	Beef Steak	Pork Chop	Deli Ham	Chicken Breast	Chicken Wing	Beans & Rice	Beef	Pork	Chicken	Beef	Pork	Chicken
May 2013	$4.21	$7.03	$3.91	$2.28	$5.03	$2.07	$1.92	0.27	0.19	0.17	0.00	-0.09	0.32
June 2013	$4.03	$6.88	$3.63	$2.21	$4.89	$2.27	$2.26	0.34	0.18	0.20	-0.10	-0.14	0.31
July 2013	$4.14	$6.20	$3.47	$2.47	$4.98	$2.13	$2.30	0.28	0.18	0.14	-0.08	-0.13	0.30
August 2013	$4.11	$6.60	$3.85	$2.57	$4.90	$2.40	$2.29	0.29	0.20	0.17	-0.12	-0.14	0.30
September 2013	$4.16	$7.16	$3.68	$2.40	$5.11	$2.11	$2.36	0.24	0.13	0.11	-0.07	-0.14	0.28
October 2013	$3.92	$6.74	$3.80	$2.26	$4.91	$2.12	$2.18	0.22	0.16	0.13	-0.07	-0.09	0.29
November 2013	$3.96	$6.72	$3.75	$2.59	$5.03	$2.37	$2.22	0.26	0.20	0.13	-0.06	-0.12	0.27
December 2013	$4.20	$6.41	$3.61	$2.21	$4.52	$1.93	$1.97	0.26	0.14	0.15	-0.01	-0.07	0.27
January 2014	$4.06	$6.88	$3.47	$1.97	$5.03	$2.52	$2.04	0.27	0.19	0.16	-0.06	-0.10	0.27
February 2014	$4.06	$6.88	$3.47	$1.97	$5.03	$2.52	$2.04	0.32	0.20	0.16	-0.03	-0.11	0.33
March 2014	$4.28	$6.59	$3.55	$2.20	$4.85	$2.02	$1.57	0.27	0.22	0.16	-0.08	-0.13	0.24
April 2014	$4.17	$6.87	$3.76	$2.42	$4.97	$2.27	$2.19	0.37	0.27	0.19	-0.07	-0.14	0.24
May 2014	$4.06	$6.35	$3.51	$2.29	$4.63	$2.01	$2.08	0.41	0.30	0.25	-0.09	-0.13	0.29
June 2014	$4.50	$7.52	$4.14	$2.89	$5.35	$2.73	$2.62	0.45	0.29	0.26	-0.06	-0.12	0.28
July 2014	$4.30	$7.00	$3.71	$2.48	$5.00	$2.18	$1.80	0.34	0.26	0.22	-0.04	-0.13	0.29
August 2014	$4.32	$7.01	$4.16	$2.68	$5.05	$2.10	$2.08	0.39	0.27	0.22	0.01	-0.09	0.31
September 2014	$4.48	$7.18	$4.01	$2.44	$5.06	$2.10	$1.90	0.38	0.28	0.24	-0.07	-0.09	0.23
October 2014	$4.25	$7.05	$3.69	$2.37	$4.88	$2.21	$2.11	0.36	0.24	0.23	-0.04	-0.07	0.28
November 2014	$4.62	$7.00	$4.02	$2.56	$5.16	$2.42	$2.20	0.33	0.21	0.20	-0.05	-0.10	0.32
December 2014	$4.49	$7.80	$4.08	$2.67	$5.02	$2.52	$2.35	0.33	0.21	0.20	-0.05	-0.10	0.32
January 2015	$4.14	$7.28	$4.04	$2.41	$5.09	$2.55	$2.33	0.33	0.20	0.18	-0.04	-0.08	0.31
February 2015	$4.54	$7.92	$3.81	$2.78	$5.05	$2.23	$2.31	0.34	0.20	0.19	0.03	-0.04	0.33
March 2015	$4.61	$7.89	$4.25	$2.79	$5.47	$2.29	$2.82	0.31	0.16	0.12	-0.01	-0.04	0.32

Retail Prices

The Bureau of Labor Statistics (BLS) publishes average U.S. city prices of various consumer products on a monthly basis. Due to processing time, the monthly prices reported by the BLS are released two to three weeks following the month in question (BLS 2014). For example, the average prices in May are not released until mid-June. Average U.S. city prices for uncooked ground beef (APU0000FC1101), uncooked beef steak (APU0000FC3101), boneless chicken breast (APU0000FF1101), and all pork chops (APU0000FD3101) for May 2013 to December 2014 were collected from the BLS website. The BLS does not report average U.S. city prices for deli ham, chicken wings, or beans and rice together. However, in order to provide a point of comparison with the FooDS data, food product prices were gathered in order to represent absent deli ham, chicken wing, and beans and rice prices. These products are represented by BLS boneless ham excluding canned (APU0000704312), bone-in chicken leg (APU0000706212), and a combined average all sizes dried beans (APU0000714233) and average white, long grain, uncooked rice (APU0000701312) prices, respectively. Average dry beans prices were added to average rice prices to represent beans and rice prices as they are represented in the FooDS Survey; thus, a combined price reflects the retail price of these two products as if they were purchased by a consumer in a retail setting. These prices can be seen on the next page in Table 2.

Forecasting Models

Our base prediction model, which does not rely on FooDS data, is a distribution lag model, like the following:

$$Price_{j,t} = \beta_0 + \beta_1 Price_{j,t-1} + \beta_2 Price_{j,t-2} + \beta_3 Price_{j,t-3} + \varepsilon_{j,t}$$

Table 2. BLS Prices

Month	Ground Beef	Beef Steak	Pork Chop	Deli Ham	Chicken Breast	Chicken Wing	Beans and Rice
May 2013	$3.75	$6.37	$3.55	$3.94	$3.43	$1.61	$2.09
June 2013	$3.76	$6.42	$3.39	$4.11	$3.53	$1.65	$2.12
July 2013	$3.79	$6.43	$3.51	$4.07	$3.55	$1.65	$2.14
August 2013	$3.83	$6.34	$3.53	$4.17	$3.60	$1.65	$2.17
September 2013	$3.82	$6.40	$3.61	$4.18	$3.61	$1.66	$2.17
October 2013	$3.82	$6.36	$3.58	$4.17	$3.65	$1.68	$2.15
November 2013	$3.89	$6.33	$3.68	$4.10	$3.45	$1.58	$2.19
December 2013	$3.90	$6.34	$3.73	$4.06	$3.46	$1.59	$2.19
January 2014	$3.90	$6.34	$3.72	$4.11	$3.43	$1.54	$2.20
February 2014	$4.04	$6.56	$3.66	$4.11	$3.38	$1.58	$2.22
March 2014	$4.13	$6.73	$3.82	$4.21	$3.47	$1.55	$2.21
April 2014	$4.23	$6.97	$4.04	$4.13	$3.39	$1.54	$2.23
May 2014	$4.21	$6.94	$4.11	$4.20	$3.47	$1.56	$2.20
June 2014	$4.24	$6.97	$4.02	$4.28	$3.50	$1.55	$2.22
July 2014	$4.22	$7.00	$4.01	$4.37	$3.44	$1.55	$2.24
August 2014	$4.36	$7.36	$4.17	$4.50	$3.48	$1.56	$2.21
September 2014	$4.50	$7.40	$4.17	$4.63	$3.48	$1.58	$2.24
October 2014	$4.57	$7.40	$4.17	$4.64	$3.49	$1.62	$2.18
November 2014	$4.59	$7.47	$4.10	$4.48	$3.53	$1.63	$2.18
December 2014	$4.60	$7.54	$4.06	$4.35	$3.48	$1.61	$2.18
January 2015	$4.68	$7.53	$3.99	$4.41	$3.44	$1.58	$2.14
February 2015	$4.71	$7.57	$3.96	$4.43	$3.51	$1.58	$2.17

where $Price_{j,t}$ represents the actual retail price (gathered from the BLS) of food product *j* in time period *t*. Aside from the general model above, we also consider more restrictive models with $\beta_3 = 0$ or $\beta_2 = \beta_3 = 0$. The model with the lowest Akaike Information Criterion (AIC) for product *j* is used as the basis of comparison. Because we consider models with up to three lags and because FooDS didn't begin until May 2013, the estimation data series begins with August 2013 (meaning we have 17 observations).

To determine the predictive power of the FooDS data, the best fitting auto-regressive model from above, is compared against the best-fitting model using the FooDS data. The most general model specification incorporating FooDS data is:

$$\begin{aligned} Price_{j,t} = \beta_0 + \beta_1 Price_{j,t-1} + \beta_2 Price_{j,t-2} + \beta_3 Price_{j,t-3} + \beta_4 WTP_{j,t-1} + \beta_5 WTP_{j,t-2} \\ + \beta_6 WTP_{j,t-3} + \beta_7 EQ_{j,t-1} + \beta_8 EQ_{j,t-2} + \beta_9 EQ_{j,t-3} + \beta_{10} EP_{j,t-1} + \beta_{11} EP_{j,t-2} \\ + \beta_{12} EP_{j,t-3} + \varepsilon_{j,t} \end{aligned}$$

where $Price_{j,t}$ represents the realized price (gathered from the BLS) of food product *j* in time period *t*, $WTP_{j,t}$ represents willingness-to-pay of food product *j* in time period *t*, $EP_{j,t}$ represents quantity or consumption expectations measured in FooDS for food product *j* in time period *t*, $EP_{j,t}$ represents price expectations measured in FooDS for food product *j* in time period *t*.

To determine the best fitting model, each type of data, past prices, WTP, EP, and EQ were sequentially added to the model and AIC values were recorded. We can then determine whether the inclusion of the FooDS data improves prediction accuracy. Nested versions the model specified above were created by considering all possible combinations of variables for each lag period. For example, when considering only the variables lagged one period all combination possibilities including at least $Price_{j,t-1}$ (except for Beans and Rice) were as follows: (1) $Price_{j,t-1}$, $WTP_{j,t-1}$, $EQ_{j,t-1}$, $EP_{j,t-1}$; (2) $Price_{j,t-1}$, $WTP_{j,t-1}$, $EQ_{j,t-1}$; (3) $Price_{j,t-1}$,

$WTP_{j,t-1}$, $EP_{j,t-1}$; (4) $Price_{j,t-1}$, $EQ_{j,t-1}$, $EP_{j,t-1}$; (5) $Price_{j,t-1}$, $WTP_{j,t-1}$; (6) $Price_{j,t-1}$, $EQ_{j,t-1}$; and (7) $Price_{j,t-1}$, $EP_{j,t-1}$. Therefore, each lagged period has a total of seven possible combinations considering the variables used in the regressions. Ultimately, twenty-one regressions were run for each meat *j* (excluding Beans and Rice) in time period *t* and sorted by AIC values. This allowed for the comparison of forecast accuracy associated with models including realized past prices and FooDS information to the forecast accuracy of models strictly considering past prices.

Out-of-sample forecasts were conducted using the aforementioned models to predict prices for food option *j* during the months of January and February 2015. Moreover, this will allow for an assessment of the forecast accuracy for each type of model, simple autoregressive and the model(s) considering all available information (FooDS and BLS).

CHAPTER V

RESULTS

This chapter will first evaluate the correlations between BLS prices and FooDS variables. Next, results from each model tested will be outlined and the diagnostic statistics from the most accurate autoregressive and FooDS models will be discussed. Furthermore, implications of these results as they pertain to the aforementioned hypotheses will be evaluated. Lastly, out-of-sample predictions are mentioned.

Correlations Between BLS Prices and FooDS Variables

Table 3 shows that beef prices (ground beef and beef steak) are positively related to consumer price expectations and willingness-to-pay measured in FooDS. No statistically significant relationship exists between consumption expectations and beef prices. Therefore, we fail to reject H1 and conclude that a positive relationship exists between BLS beef prices and consumer price expectations as well as willingness-to-pay. However, we fail to reject H1 because no statistically significant relationship exists between BLS beef prices (ground beef and beef steak) and consumer consumption expectations. Additionally, pork chop and deli ham prices are positively related to consumer price expectations. However, a positive relationship exists between pork chop prices and willingness-to-pay for pork chops while no statistically significant relationship exists between consumers' willingness-to-pay for deli ham and the actual price of deli ham. Therefore, we fail to reject H1 and conclude that a positive relationship exists between pork chop prices and

Table 3. Correlations Between BLS Prices and FooDS Variables

		Actual Price	EP	WTP	EQ
Ground Beef	Actual Price	1.00			
	EP	0.67***	1.00		
	WTP	0.79***	0.54**	1.00	
	EQ	0.26	0.16	0.24	1.00
Beef Steak	Actual Price	1.00			
	EP	0.70***	1.00		
	WTP	0.56***	0.36	1.00	
	EQ	0.28	0.16	0.20	1.00
Pork Chop	Actual Price	1.00			
	EP	0.79***	1.00		
	WTP	0.46*	0.35	1.00	
	EQ	0.27	-0.16	0.20	1.00
Deli Ham	Actual Price	1.00			
	EP	0.5**	1.00		
	WTP	0.40	0.42*	1.00	
	EQ	0.43*	-0.16	-0.12	1.00
Chicken Breast	Actual Price	1.00			
	EP	-0.24	1.00		
	WTP	0.08	0.15	1.00	
	EQ	0.18	0.04	0.19	1.00
Chicken Wing	Actual Price	1.00			
	EP	-0.40	1.00		
	WTP	-0.11	0.12	1.00	
	EQ	0.37	0.04	0.39	1.00

Note: Asterisks represent levels of significance. One asterisk (*) represents significance at the 90% confidence level, two asterisks at the 95% level, and three asterisks at the 99% level.

willingness-to-pay as well as consumer price expectations. Moreover, H1 is rejected because no statistically significant relationship exists between pork chop prices and expected pork chop consumption. A positive relationship is observed between consumers' expected deli ham consumption and deli prices while no statistically significant relationship exists between pork chop prices and expected consumption. Therefore, we fail to reject H1 and state that deli ham prices are positively related to expected prices as well as consumption. Additionally, H1 is rejected because no statistically significant relationship exists between deli ham prices and willingness-to-pay. Table 3 also indicates that a no statistically significant relationship exists between the price of chicken breast (BLS) and consumers' expected price, expected consumption, or willingness-to-pay for chicken breast as measured in FooDS; hence, H1 is rejected. Moreover, no statistically significant relationship exists between the actual price of chicken wings (BLS) and the expected price, expected consumption, or willingness-to-pay for chicken wing (measured in FooDS); thus, resulting in the rejection of H1. A graphical representation of the relationships between actual price, willingness-to-pay, and expected price for each food option can be seen in Figures 3-8.

Regression Results

We now consider the regression results for each food option, starting with the simple autoregressive models shown in Table 4. Tables 5-11 then show more detailed regression results incorporating FooDS data for ground beef, steak, pork chop, deli ham, chicken breast, chicken wings, and beans and rice, respectively. In each table, separate models are assigned a number (shown in the column heading) to ease the exposition in what follows.

Ground Beef

The best performing autoregressive forecast model for predicting the price of hamburger, or uncooked ground beef, was lagged one period and had an AIC value of -95.3. Model 1, as seen in Table 4, is significant at the 99% confidence level.

As seen in Table 5, seven of the model combination possibilities lagged one period considering past ground beef prices as well as FooDS data, there were two models that had lower AIC values than Model 1 in Table 4, Models 23 and 27.

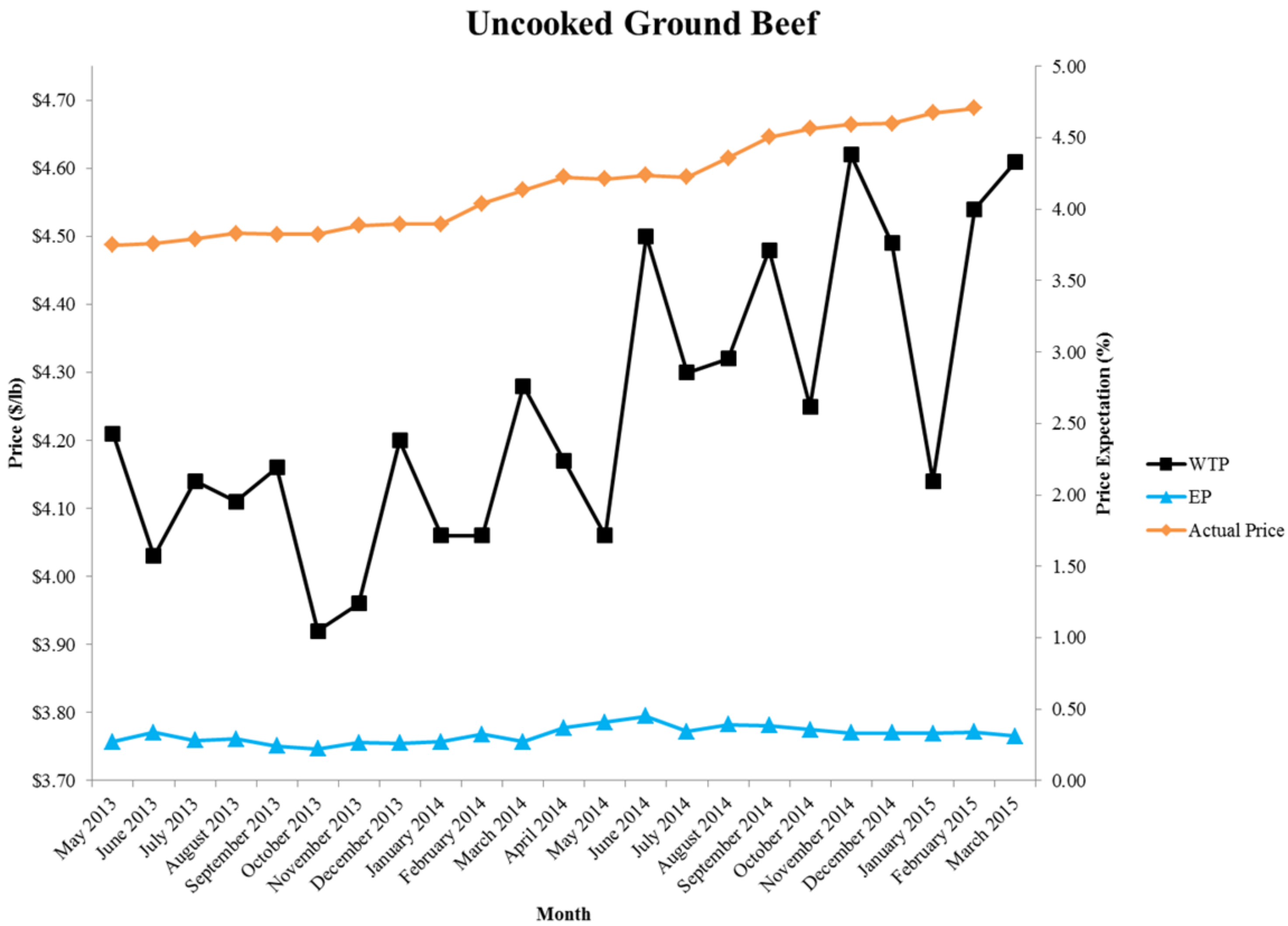

Figure 3. Uncooked Ground Beef Actual Prices, Price Expectations, and Willingness-to-Pay

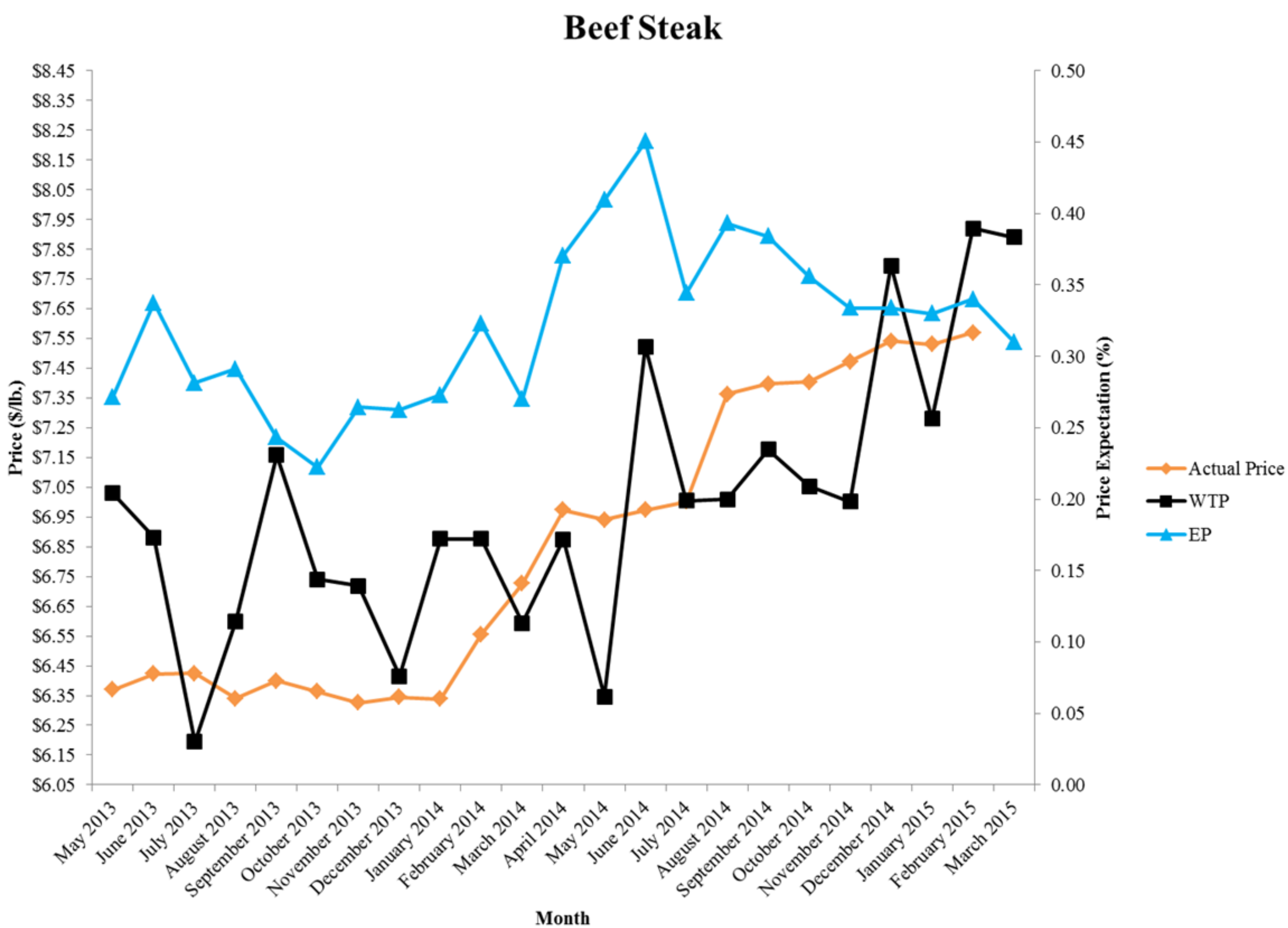

Figure 4. Beef Steak Actual Prices, Price Expectations, and Willingness-to-Pay

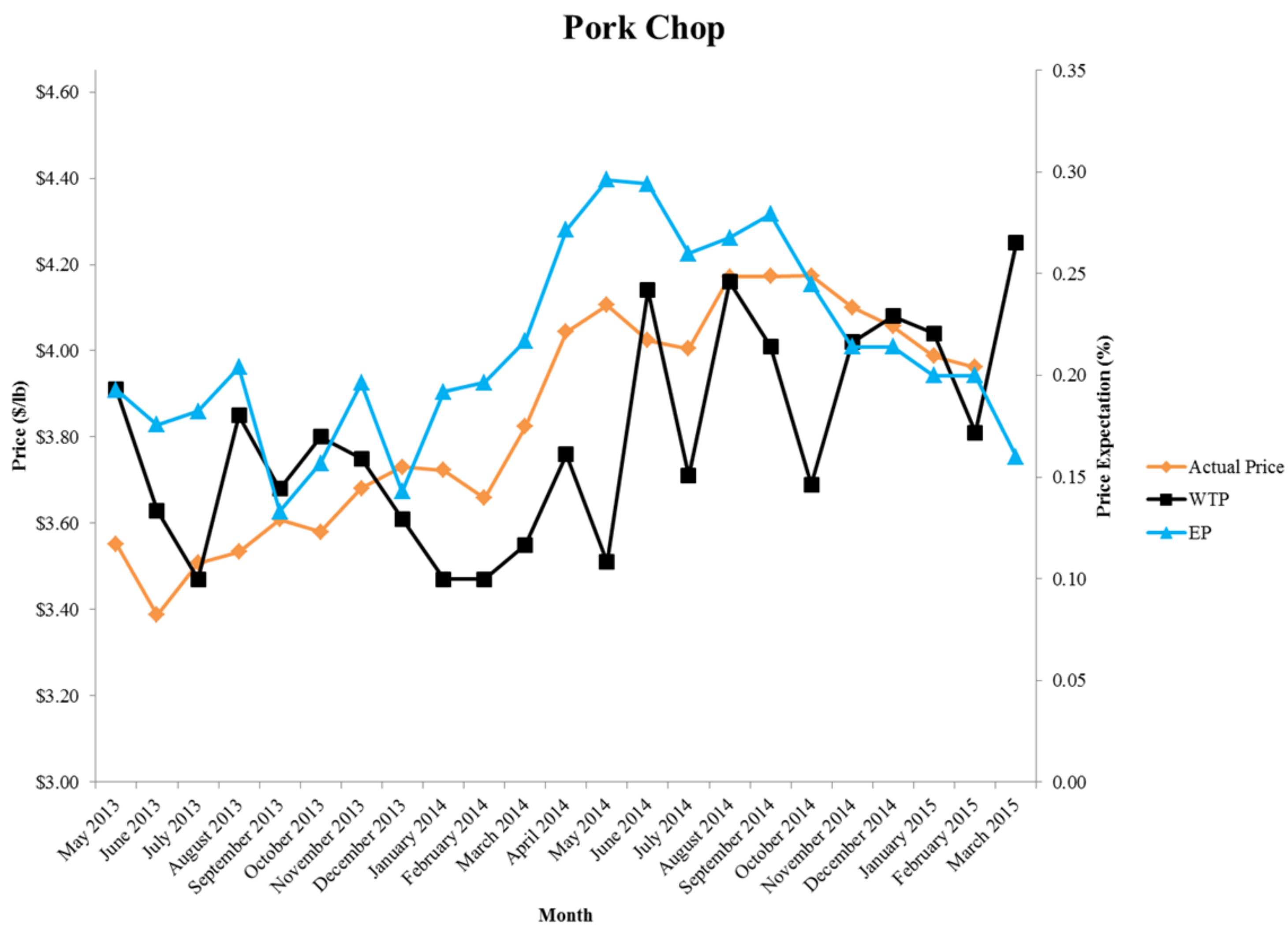

Figure 5. Pork Chop Actual Prices, Price Expectations, and Willingness-to-Pay

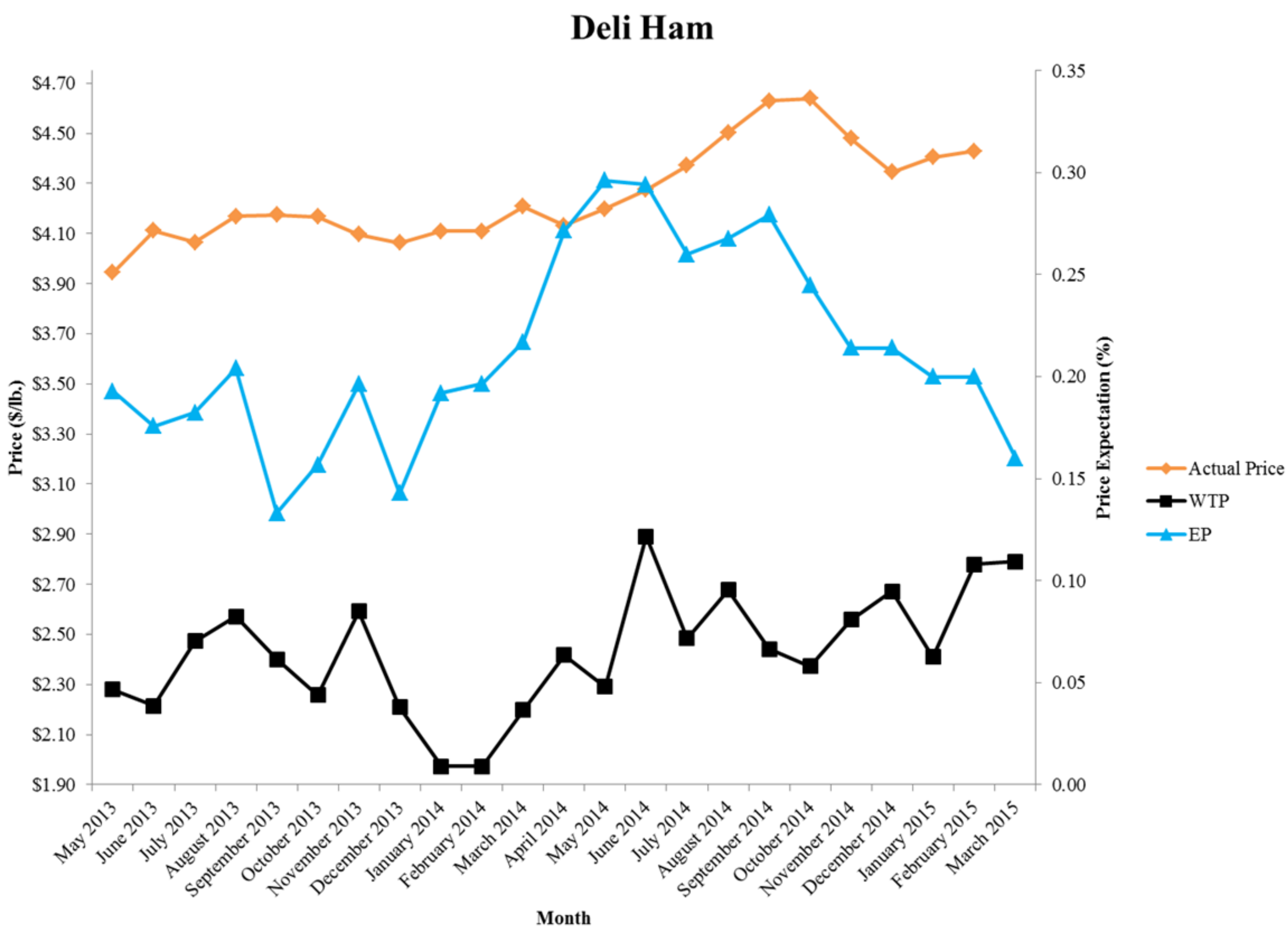

Figure 6. Deli Ham Actual Prices, Price Expectations, and Willingness-to-Pay

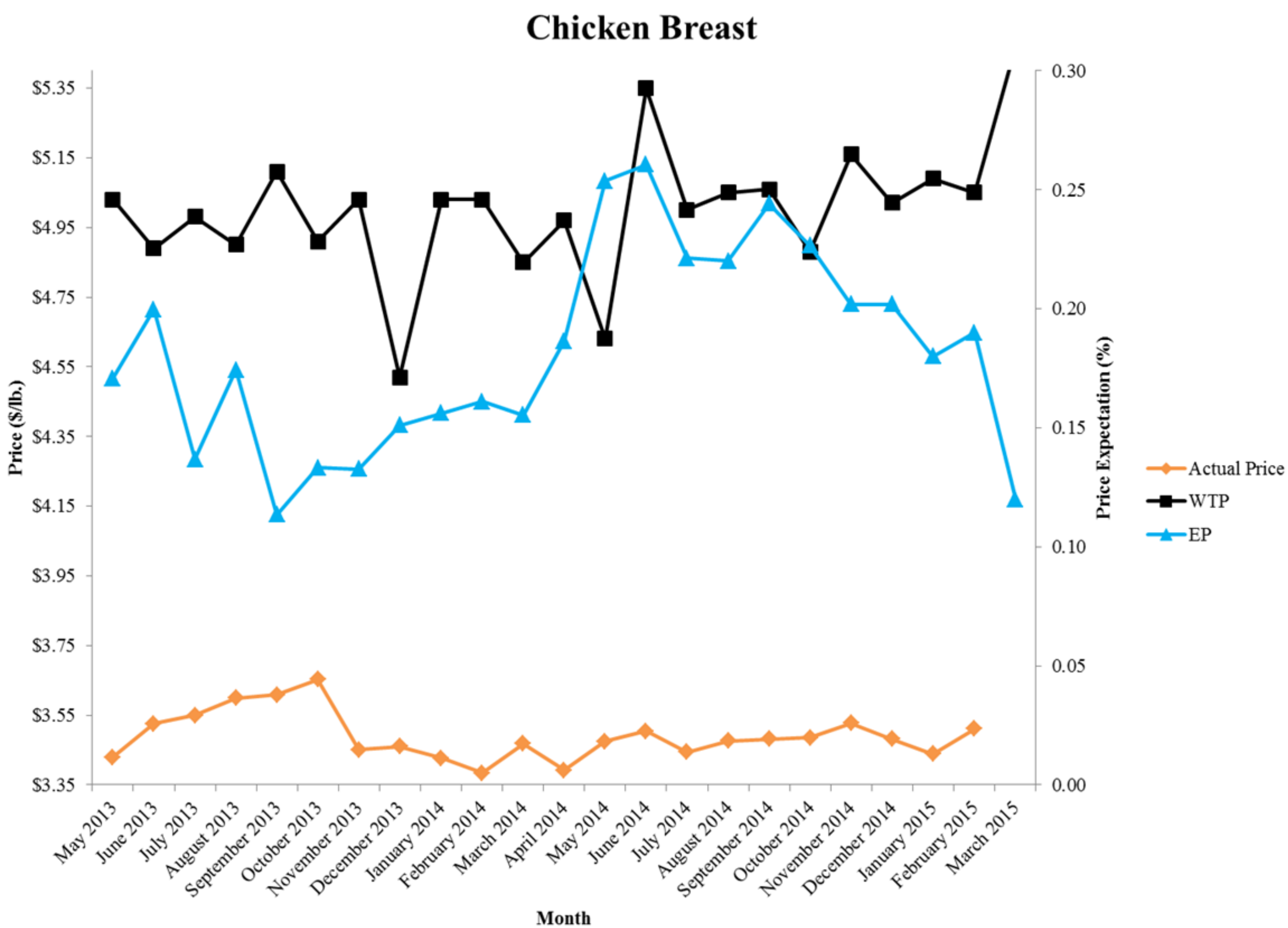

Figure 7. Chicken Breast Actual Prices, Price Expectations, and Willingness-to-Pay

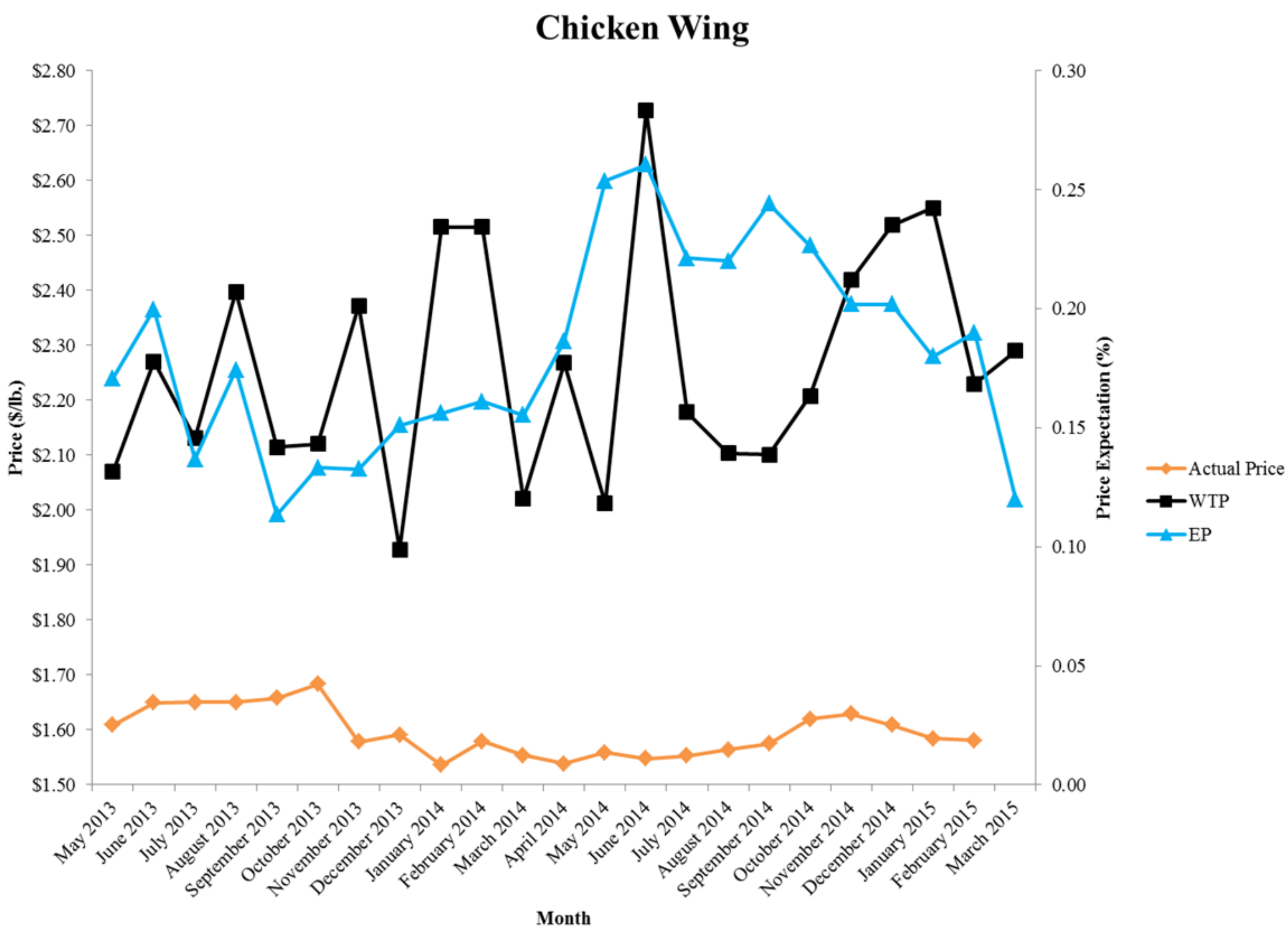

Figure 8. Chicken Wing Actual Prices, Price Expectations, and Willingness-to-Pay

Table 4. BLS Autoregressive Forecast Models

	Ground Beef			Beef Steak			Pork Chop		
Variables	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)	Model (9)
Constant	-0.01	0.23	-0.07	-0.10	-0.05	-0.06	0.49	0.49	0.38
	(0.22)	(1.24)	(0.26)	(0.47)	(0.52)	(0.59)	(0.34)	(0.35)	(0.36)
Price lagged 1 period	1.01	0.27	1.29	1.02	1.09	1.09	0.88	1.02	1.03
	(0.05)	-(0.25)	(0.27)	(0.07)	(0.27)	(0.28)	(0.09)	(0.27)	(0.26)
Price lagged 2 periods		0.29	-0.58		-0.07	-0.08		-0.14	-0.39
			(0.42)		(0.29)	(0.41)		(0.25)	(0.33)
Price lagged 3 periods			0.33			0.01			0.26
			(0.30)			(0.30)			(0.23)
Diagnostic Statistics									
R-Squared	0.96	0.96	0.97	0.93	0.94	0.94	0.87	0.87	0.88
AIC	-95.30	-94.17	-93.62	-69.85	-67.92	-65.93	-81.04	-79.41	-79.00
MAE	0.05	0.04	0.04	0.09	0.09	0.09	0.06	0.06	0.07
F-Test			124.68***			62.54***			32.67***

Note: Standard errors are in parentheses. One asterisk (*) represents significance at the 90% confidence level, two asterisks at the 95% level, and three asterisks at the 99% confidence level (for diagnostic statistics only).

Table 4 continued. BLS Autoregressive Forecast Models

	Deli Ham			Chicken Breast		
Variables	Model (10)	Model (11)	Model (12)	Model (13)	Model (14)	Model (15)
Constant	0.59	0.84	1.17	1.60	1.36	1.72
	(0.48)	(0.46)	(0.48)	(0.74)	(0.85)	(0.92)
Price lagged 1 period	0.87	1.32	1.28	0.54	0.45	0.48
	(0.11)	(0.25)	(0.23)	(0.21)	(0.26)	(0.26)
Price lagged 2 periods		-0.51	-0.09		0.16	0.28
		(0.25)	(0.35)		(0.26)	(0.29)
Price lagged 3 periods			-0.46			-0.25
			(0.28)			(0.25)
Diagnostic Statistics						
R-Squared	0.79	0.84	0.87	0.31	0.32	0.37
AIC	-80.84	-83.21	-84.37	-92.44	-90.87	-90.15
MAE	0.07	0.06	0.06	0.05	0.05	0.05
F-Test			28.45***			2.56*

Note: Standard errors are in parentheses. One asterisk (*) represents significance at the 90% confidence level, two asterisks at the 95% level, and three asterisks at the 99% confidence level (for diagnostic statistics only).

Table 4 continued. BLS Autoregressive Forecast Models

	Chicken Wing			Beans and Rice		
Variables	Model (16)	Model (17)	Model (18)	Model (19)	Model (20)	Model (21)
Constant	0.54	0.45	0.57	1.07	0.91	0.92
	(0.28)	(0.31)	(0.31)	(0.42)	(0.41)	(0.44)
Price lagged 1 period	0.66	0.49	0.55	0.52	0.27	0.27
	(0.18)	(0.26)	(0.26)	(0.19)	(0.25)	(0.28)
Price lagged 2 periods		0.23	0.40		0.31	0.31
		(0.25)	(0.28)		(0.21)	(0.27)
Price lagged 3 periods			-0.31			0.01
			(0.25)			(0.23)
Diagnostic Statistics						
R-Squared	0.47	0.43	0.56	0.33	0.42	0.42
AIC	-113.69	-112.67	-112.61	-126.56	-126.96	-124.97
MAE	0.02	0.02	0.02	0.02	0.02	0.02
F-Test			5.45**			3.12*

Note: Standard errors are in parentheses. One asterisk (*) represents significance at the 90% confidence level, two asterisks at the 95% level, and three asterisks at the 99% confidence level (for diagnostic statistics only).

Table 5. Ground Beef Estimates

	1 Lag							2 Lags							3 Lags						
	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model
Variables	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)	(31)	(32)	(33)	(34)	(35)	(36)	(37)	(38)	(39)	(40)	(41)	(42)
Constant	0.30	0.34	0.10	0.12	0.15	0.16	-0.06	0.60	0.005	-0.07	0.61	-0.51	0.44	0.14	0.64	-0.25	-0.40	0.70	-0.43	0.36	-0.10
	(0.35)	(0.31)	(0.36)	(0.26)	(0.32)	(0.22)	(0.25)	(0.42)	(0.35)	(0.66)	(0.23)	(0.47)	(0.20)	(0.28)	(1.19)	(0.47)	(1.31)	(0.39)	(0.65)	(0.25)	(0.38)
Price lagged 1 period	1.04	1.03	1.07	1.00	1.05	0.98	1.04	1.05	0.94	1.44	0.99	1.29	0.87	1.41	1.40	0.83	1.80	0.81	1.38	0.82	1.53
	(0.09)	(0.08)	(0.10)	(0.07)	(0.08)	(0.05)	(0.08)	(0.20)	(0.20)	(0.30)	(0.24)	(0.25)	(0.23)	(0.29)	(0.46)	(0.29)	(0.35)	(0.38)	(0.29)	(0.29)	(0.32)
Price lagged 2 periods								-0.19	-0.08	-0.51	-0.13	-0.40	0.06	-0.45	-0.36	-0.17	-1.55	-0.08	-0.81	-0.16	-0.96
								(0.20)	(0.21)	(0.31)	(0.24)	(0.28)	(0.23)	(0.32)	(0.70)	(0.40)	(0.58)	(0.52)	(0.46)	(0.38)	(0.55)
Price lagged 3 periods															0.22	0.18	0.89	0.11	0.40	0.30	0.48
															(0.43)	(0.30)	(0.42)	(0.35)	(0.34)	(0.29)	(0.40)
WTP lagged 1 period	-0.08	-0.09	-0.08		-0.08			-0.11	-0.02	-0.08		0.00			-0.15	-0.02	-0.11		-0.03		
	(0.11)	(0.11)	(0.12)		-(0.08)			(0.08)	(0.08)	(0.14)		(0.11)			(0.14)	(0.09)	(0.17)		(0.12)		
WTP lagged 2 periods								0.11	0.19	0.16		0.23			0.07	0.20	0.21		0.22		
								(0.09)	(0.08)	(0.15)		(0.12)			(0.20)	(0.09)	(0.23)		(0.13)		
WTP lagged 3 periods															0.29	0.08	-0.10		-0.04		
															(0.13)	(0.11)	(0.15)		(0.14)		
EP lagged 1 period	-0.10		-0.13	-0.11			-0.14	-0.10		-0.30	-0.12			-0.37	-0.21		-0.60	-0.12			-0.56
	(0.31)		(0.33)	(0.30)			(0.32)	(0.23)		(0.37)	(0.26)			(0.36)	(0.35)		(0.41)	(0.32)			(0.39)
EP lagged 2 periods								0.53		0.47	0.48			0.51	0.56		0.71	0.31			0.56
								(0.27)		(0.45)	(0.26)			(0.37)	(0.36)		(0.45)	(0.32)			(0.41)
EP lagged 3 periods															0.12		-0.48	0.34			-0.04
															(0.58)		(0.58)	(0.34)			(0.41)
EQ lagged 1 period	0.86	0.87		0.85		0.86		0.77	0.71		0.74		0.71		0.55	0.53		0.52		0.46	
	(0.48)	(0.47)		(0.48)		(0.46)		(0.30)	(0.33)		(0.36)		(0.38)		(0.45)	(0.42)		(0.46)		(0.47)	
EQ lagged 2 periods								1.15	1.08		1.19		1.19		1.28	1.28		1.44		1.35	
								(0.33)	(0.36)		(0.40)		(0.41)		(0.57)	(0.43)		(0.49)		(0.46)	
EQ lagged 3 periods															0.07	0.15		0.31		0.26	
															(0.48)	(0.39)		(0.46)		(0.46)	
Diagnostic Statistics																					
R-Squared	0.97	0.97	0.96	0.97	0.96	0.97	0.96	0.99	0.99	0.98	0.99	0.97	0.98	0.97	0.99	0.99	0.99	0.99	0.98	0.98	0.97
AIC	-94.03	-95.89	-92.04	-95.24	-93.85	-97.06	-93.52	-110.29	-106.83	-93.08	-103.87	-95.19	-102.69	-92.98	-107.72	-104.75	95.47	-102.00	-93.45	-100.48	-92.02
MAE	0.04	0.04	0.05	0.04	0.05	0.04	0.05	0.02	0.02	0.03	0.02	0.04	0.03	0.04	0.02	0.02	0.03	0.02	0.03	0.03	0.04
F-Test															65.23 ***						
F-Test for all BLS Prices															14.59 **						
F-Test for all FooDS															2.49						
F-Test for all WTP															1.32						
F-Test for all EQ															2.57						
F-Test for all EP															0.93						

Note: Standard errors are in parentheses. One asterisk (*) represents significance at the 90% confidence level, two asterisks at the 95% level, and three asterisks at the 99% confidence level (for diagnostic statistics only).

Moreover, four out of the seven combination models considering all information available lagged two periods had lower AIC values than Model 1 (Table 4). These models, Model 29, 30, 32, and 34 are described in Table 5. Lastly, of the seven possible combination models lagged three periods, Models 36, 37, 38, 39, and 41 (Table 5) performed better than Model 1 (Table 4). The most accurate model in forecasting hamburger, or uncooked ground beef, was Model 29 (Table 5), and had an AIC value of -110.29.

Diagnostic statistics in Table 4 and Table 5 indicate that both the autoregressive approach and the approach considering FooDS data produce statistically significant regression models. As seen in the previously mentioned tables, Model 29 (Table 5) has the lowest AIC value than Model 1 (Table 4). Additionally, Model 29 is associated with a lower MAE than Model 1 (Tables 4 and 5, respectively). Therefore, we fail to reject H2 because of these diagnostic measurements. It is important to note that the F-test results in Table 5 indicate that FooDS data is not statistically significant, however, the aforementioned measurement value (AIC) indicates that FooDS does increase predictive power.

Moreover, the F-test results in Table 5 show that neither WTP, EQ, nor EP are statistically different from zero. Thus, there is not sufficient evidence to suggest that WTP is a better predictor of future ground beef prices than EP or EQ; consequently, H3 is rejected.

Beef Steak

The autoregressive model that forecasts the price of beef steaks with the greatest accuracy is lagged one period with an AIC value of -69.85. This model, Model 4 (Table 4), is significant at the 99% level.

As seen in Table 6, none of the seven historical price, willingness-to-pay, and expected prices or expected consumption combination possibilities lagged one period used to estimate future prices of beef steak outperformed Model 4 (Table 4). However, Model 53 (Table 6), considering

Table 6. Uncooked Beef Steak Estimates

	1 Lag							2 Lags							3 Lags						
	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model
Variables	(43)	(44)	(45)	(46)	(47)	(48)	(49)	(50)	(51)	(52)	(53)	(54)	(55)	(56)	(57)	(58)	(59)	(60)	(61)	(62)	(63)
Constant	-0.25	-0.14	-0.40	-0.04	-0.29	0.03	-0.18	0.39	-0.71	-0.15	1.09	-1.01	0.41	0.40	1.04	1.21	0.52	0.60	-0.11	0.10	0.51
	(0.90)	(0.75)	(0.80)	(0.65)	(0.67)	(0.53)	(0.58)	(1.22)	(1.09)	(1.15)	(0.67)	(0.95)	(0.57)	(0.64)	(1.84)	(1.45)	(2.04)	(0.95)	(1.50)	(0.67)	(0.88)
Price lagged 1 period	1.02	1.00	1.03	1.03	1.01	1.01	1.04	1.07	0.99	1.15	1.11	1.01	0.97	1.23	1.53	1.49	1.16	1.43	1.11	1.14	1.20
	(0.12)	(0.09)	(0.12)	(0.12)	(0.08)	(0.08)	(0.11)	(0.33)	(0.32)	(0.33)	(0.30)	(0.28)	(0.31)	(0.27)	(0.41)	(0.36)	(0.44)	(0.44)	(0.33)	(0.36)	(0.34)
Price lagged 2 periods								-0.32	-0.10	-0.28	-0.30	-0.08	0.00	-0.32	-1.93	-1.31	-0.18	-1.24	-0.11	-0.54	-0.25
								(0.34)	(0.34)	(0.33)	(0.31)	(0.29)	(0.32)	(0.30)	(0.85)	(0.68)	(0.59)	(0.77)	(0.47)	(0.65)	(0.49)
Price lagged 3 periods															1.30	0.96	-0.09	0.69	0.00	0.41	-0.06
															(0.59)	(0.48)	(0.44)	(0.51)	(0.36)	(0.45)	(0.36)
WTP lagged 1 period	0.04	0.04	0.05		0.04			0.07	0.10	0.06		0.08			-0.11	-0.11	0.03		0.04		
	(0.12)	(0.11)	(0.11)		(0.11)			(0.11)	(0.12)	(0.12)		(0.11)			(0.13)	(0.13)	(0.18)		(0.15)		
WTP lagged 2 periods								0.08	0.14	0.07		0.14			0.18	0.07	0.04		0.09		
								(0.15)	(0.12)	(0.15)		(0.11)			(0.16)	(0.12)	(0.19)		(0.13)		
WTP lagged 3 periods															-0.17	-0.24	-0.07		-0.11		
															(0.13)	(0.12)	(0.17)		(0.13)		
EP lagged 1 period	-0.19		-0.22	-0.15			0.18	-0.16		-0.45	-0.45			-0.71	0.93		-0.49	-0.29			-0.71
	(0.78)		(0.75)	(0.74)			(0.72)	(0.96)		(1.03)	(0.69)			(0.74)	(0.96)		(1.22)	(0.72)			(0.81)
EP lagged 2 periods								1.39		1.25	1.61			1.46	0.88		1.00	1.87			1.40
								(0.87)		(0.95)	(0.71)			(0.78)	(0.87)		(1.28)	(0.82)			(0.90)
EP lagged 3 periods															-0.14		0.32	-0.43			0.20
															(1.01)		(1.24)	(1.00)			(0.99)
EQ lagged 1 period	0.52	0.55		0.59		0.61		-0.35	-0.43		0.06		0.34		-3.67	-2.33		-1.71		-0.77	
	(1.18)	(1.13)		(1.12)		(1.08)		(1.34)	(1.39)		(1.09)		(1.22)		(2.05)	(1.74)		(1.70)		(1.75)	
EQ lagged 2 periods								2.09	1.76		2.04		1.74		4.97	3.95		3.36		2.55	
								(1.04)	(1.07)		(0.96)		(1.04)		(1.46)	(1.37)		(1.37)		(1.42)	
EQ lagged 3 periods															-0.16	-0.13		-0.44		-0.37	
															(0.91)	(0.88)		(0.97)		(1.00)	
Diagnostic Statistics																					
R-Squared	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.97	0.96	0.95	0.97	0.94	0.95	0.95	0.99	0.98	0.95	0.97	0.95	0.95	0.95
AIC	-64.45	-66.37	-66.17	-66.28	-68.06	-68.23	-67.92	-67.97	-66.22	-64.98	-70.90	-66.09	-67.81	-68.38	-77.14	-70.94	-59.57	-69.69	-63.29	-65.56	-64.46
MAE	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.07	0.08	0.08	0.07	0.09	0.07	0.08	0.04	0.05	0.08	0.06	0.08	0.07	0.08
F-Test															28.4 **						
F-Test for all BLS Prices															9.46 **						
F-Test for all FooDS															2.03						
F-Test for all WTP															1.61						
F-Test for all EQ															4.00						
F-Test for all EP															1.40						

Note: Standard errors are in parentheses. One asterisk (*) represents significance at the 90% confidence level, two asterisks at the 95% level, and three asterisks at the 99% confidence level (for diagnostic statistics only).

historical prices and FooDS results lagged two periods exhibited greater forecast accuracy than Model 4 (Table 4). Similarly, Table 6 shows that two of the seven possible combination models lagged three periods, Models 57 and 58, showed greater forecast accuracy than Model 4 (Table 4).

Model 57 in Table 6, lagged three periods, best estimates future beef steak prices and recorded an AIC value of -77.14. Model 57 is statistically significant at the 95% level. Additionally, the MAE associated with Model 57 is 0.04 as compared to the higher MAE (0.09) for Model 4 in Table 4. We fail to reject H2 because of these diagnostic statistics (AIC and MAE), and conclude that FooDS data increases the predictive power of autoregressive models when estimating future beef steak prices.

F-Tests for WTP, EP, and EQ, as seen in Table 6, are not statistically different from zero, however. Therefore, it should be said that although FooDS data is not statistically significant, it does add predictive power when estimating future beef steak prices. Moreover, because neither WTP, EP, nor EQ are statistically different from zero (Table 6), it cannot be determined which of the FooDS variables is the best predictor. Hence, H3 is rejected.

Pork Chops

The autoregressive model with the greatest forecast accuracy, Model 7 (Table 4), considers pork prices from one period before the estimated price and is associated with an AIC value of -81. Additionally, Model 7 is significant at the 99% level.

Results indicate that of the fourteen possible historical pork prices, willingness-to-pay, consumer consumption and price expectations combination possibilities lagged either one or two periods, seen in Table 7, none forecasted pork chop prices as accurately as the aforementioned autoregressive forecast model (Model 7 in Table 4). However, out of the seven possible models considering a combination of historical prices and FooDS results, there were two lagged three

Table 7. Pork Chop Estimates

	1 Lag							2 Lags							3 Lags						
Variables	Model (64)	Model (65)	Model (66)	Model (67)	Model (68)	Model (69)	Model (70)	Model (71)	Model (72)	Model (73)	Model (74)	Model (75)	Model (76)	Model (77)	Model (78)	Model (79)	Model (80)	Model (81)	Model (82)	Model (83)	Model (84)
Constant	0.70	0.30	0.86	0.67	0.52	0.29	0.83	1.23	0.40	0.90	1.17	0.59	0.34	0.86	1.74	1.99	0.74	-0.27	1.03	0.20	0.55
	(0.70)	(0.49)	(0.54)	(0.76)	(0.42)	(0.41)	(0.47)	(1.73)	(0.69)	(0.78)	(1.44)	(0.55)	(0.47)	(0.58)	(2.07)	(0.85)	(0.90)	(2.31)	(0.50)	(0.51)	(0.68)
Price lagged 1 period	0.79	0.91	0.76	0.79	0.89	0.91	0.75	0.88	1.00	0.87	0.87	1.02	1.00	0.87	0.67	0.99	0.96	0.91	0.98	0.99	0.87
	(0.23)	(0.11)	(0.16)	(0.22)	(0.11)	(0.09)	(0.15)	(0.41)	(0.32)	(0.35)	(0.36)	(0.29)	(0.29)	(0.32)	(0.29)	(0.25)	(0.32)	(0.41)	(0.24)	(0.30)	(0.32)
Price lagged 2 periods								-0.22	-0.09	-0.13	-0.22	-0.12	-0.09	-0.13	-0.48	-0.63	-0.49	-0.31	-0.49	-0.32	-0.40
								(0.47)	(0.32)	(0.31)	(0.41)	(0.28)	(0.28)	(0.28)	(0.38)	(0.35)	(0.35)	(0.51)	(0.30)	(0.40)	(0.36)
Price lagged 3 periods															0.67	0.62	0.58	0.48	0.50	0.27	0.37
															(0.35)	(0.28)	(0.31)	(0.53)	(0.23)	(0.28)	(0.29)
WTP lagged 1 period	-0.01	0.00	-0.02		-0.01			0.00	0.00	-0.01		-0.01			0.29	0.14	0.09		0.07		
	(0.12)	(0.12)	(0.11)		(0.11)			(0.15)	(0.14)	(0.13)		(0.12)			(0.16)	(0.15)	(0.14)		(0.11)		
WTP lagged 2 periods								-0.02	-0.02	-0.01		-0.04			0.09	-0.10	-0.03		-0.07		
								(0.16)	(0.14)	(0.15)		(0.12)			(0.16)	(0.13)	(0.13)		(0.10)		
WTP lagged 3 periods															-0.58	-0.48	-0.28		-0.26		
															(0.17)	(0.17)	(0.14)		(0.11)		
EP lagged 1 period	0.60		0.77	0.59			0.76	0.71		0.67	0.75			0.70	1.78		0.39	0.71			0.93
	(1.03)		(0.75)	(0.99)			(0.72)	(1.32)		(0.97)	(1.15)			(0.82)	(0.96)		(0.93)	(1.29)			(0.85)
EP lagged 2 periods								0.52		0.16	0.45			0.13	-1.74		-0.70	-0.65			-0.08
								(1.62)		(1.01)	(1.36)			(0.88)	(1.53)		(1.00)	(1.83)			(0.96)
EP lagged 3 periods															0.19		-0.08	-0.66			-0.38
															(1.10)		(1.01)	(1.53)			(0.89)
EQ lagged 1 period	-0.34	-0.88		-0.36		-0.88		0.00	-0.86		-0.02		-0.90		2.97	2.45		-0.52		-0.96	
	(1.40)	(1.03)		(1.34)		(0.99)		(2.06)	(1.35)		(1.83)		(1.21)		(1.99)	(1.69)		(2.11)		(1.29)	
EQ lagged 2 periods								0.71	0.28		0.66		0.27		-2.02	-0.75		-0.85		0.06	
								(1.83)	(1.33)		(1.58)		(1.17)		(1.81)	(1.09)		(2.44)		(1.27)	
EQ lagged 3 periods															2.76	0.54		0.00		0.14	
															(1.85)	(1.52)		(1.70)		(1.26)	
Diagnostic Statistics																					
R-Squared	0.88	0.88	0.88	0.88	0.87	0.88	0.88	0.88	0.88	0.88	0.88	0.87	0.88	0.88	0.97	0.95	0.93	0.90	0.93	0.89	0.90
AIC	-76.46	-77.99	-78.38	-78.45	-79.06	-79.98	-80.35	-69.00	-72.23	-72.69	-72.97	-75.56	-76.17	-76.67	-87.16	-80.92	-76.77	-69.58	-81.41	-74.00	-75.21
MAE	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.03	0.04	0.05	0.06	0.05	0.06	0.06
F-Test															12.93 **						
F-Test for all BLS Prices															2.62						
F-Test for all FooDS															1.63						
F-Test for all WTP															4.01						
F-Test for all EQ															2.16						
F-Test for all EP															1.41						

Note: Standard errors are in parentheses. One asterisk (*) represents significance at the 90% confidence level, two asterisks at the 95% level, and three asterisks at the 99% confidence level (for diagnostic statistics only).

periods that exhibited greater forecast accuracy than Model 7 (Table 4). The most accurate, Model 78 (Table 7), reported an AIC value of -87.2 and is significant at the 95% level. Additionally, Model 78 reports a MAE of 0.03 (Table 7) and Model 7 reports a MAE of 0.06 (Table 4). These diagnostic statistics indicate that Model 78 is more accurate than Model 7, and consequently, we fail to reject H2. While Model 78 is statistically significant, F-Test results indicate that neither past prices, WTP, EP, nor EQ are statistically different from zero when tested independently. Therefore, no statistical significance is associated with FooDS data, let alone WTP, and it cannot be determined which of the FooDS variables is a better predictor of future pork chop prices. Thus, H3 is rejected.

Deli Ham

When estimating future prices of deli ham, the best autoregressive forecast model consisted of ham prices lagged three periods, or months. This model, Model 12 (Table 4), was associated with an AIC value of -84.37 and is statistically significant at the 99% confidence level.

Model 91 (Table 8), consisting of historical ham prices and expected deli ham prices estimated in FooDS lagged one period, proved to have a lower AIC value when estimating future deli ham prices than Model 12 (Table 4). Similarly, as seen in Table 8, Models 94 and 98 outperformed Model 12 (Table 4) when considering historical ham prices and variables estimated in FooDS lagged two periods.

Additionally, as seen in Table 8, Models 99, 101, 102, and 105 exhibited greater forecast accuracy than Model 12 (Table 4). Of the aforementioned (four) models in Table 8, Model 99 was the best performing model and is statistically significant at the 95% level. An AIC value of -88.74 is associated with Model 99. As compared to the MAE associated with Model 12, 0.06, (seen in Table 4) Model 99 reported a MAE of 0.02 (Table 8). These diagnostic statistics lead us to fail to reject H2 and conclude that FooDS data increases forecast accuracy of autoregressive

Table 8. Deli Ham Estimates

	1 Lag							2 Lags							3 Lags						
Variables	Model (85)	Model (86)	Model (87)	Model (88)	Model (89)	Model (90)	Model (91)	Model (92)	Model (93)	Model (94)	Model (95)	Model (96)	Model (97)	Model (98)	Model (99)	Model (100)	Model (101)	Model (102)	Model (103)	Model (104)	Model (105)
Constant	1.00	0.29	0.95	0.97	0.53	0.22	1.00	1.52	0.60	1.35	1.53	0.77	0.41	1.49	2.03	1.35	1.95	2.77	1.09	0.92	1.98
	(0.68)	(0.63)	(0.48)	(0.66)	(0.49)	(0.61)	(0.45)	(0.87)	(0.74)	(0.53)	(0.79)	(0.46)	(0.65)	(0.48)	(1.15)	(1.00)	(0.63)	(1.02)	(0.51)	(0.83)	(0.55)
Price lagged 1 period	0.69	0.87	0.71	0.72	0.82	0.92	0.72	0.84	1.22	0.87	0.91	1.22	1.27	0.96	0.73	1.27	0.62	0.73	1.18	1.28	0.86
	(0.17)	(0.15)	(0.12)	(0.15)	(0.12)	(0.13)	(0.12)	(0.32)	(0.29)	(0.29)	(0.28)	(0.26)	(0.26)	(0.25)	(0.34)	(0.30)	(0.30)	(0.31)	(0.27)	(0.29)	(0.26)
Price lagged 2 periods								-0.31	-0.44	-0.31	-0.33	-0.49	-0.40	-0.37	-0.07	-0.38	0.22	0.13	-0.07	-0.13	0.01
								(0.31)	(0.31)	(0.26)	(0.27)	(0.26)	(0.28)	(0.23)	(0.45)	(0.51)	(0.35)	(0.39)	(0.38)	(0.44)	(0.31)
Price lagged 3 periods															-0.41	-0.34	-0.49	-0.58	-0.45	-0.37	-0.41
															(0.36)	(0.42)	(0.26)	(0.32)	(0.31)	(0.37)	(0.24)
WTP lagged 1 period	0.05	0.07	0.04		0.10			0.02	0.07	0.01		0.09			0.07	0.16	-0.05		0.06		
	(0.10)	(0.11)	(0.09)		(0.10)			(0.11)	(0.12)	(0.09)		(0.09)			(0.13)	(0.14)	(0.09)		(0.09)		
WTP lagged 2 periods								0.08	0.06	0.09		0.07			0.25	0.16	0.11		0.09		
								(0.11)	(0.11)	(0.10)		(0.10)			(0.15)	(0.13)	(0.10)		(0.10)		
WTP lagged 3 periods															0.14	0.02	0.11		-0.03		
															(0.15)	(0.17)	(0.10)		(0.10)		
EP lagged 1 period	1.01		0.99	1.04			1.05	0.63		0.54	0.43			0.27	1.36		0.87	0.38			0.27
	(0.53)		(0.47)	(1.07)			(0.43)	(0.76)		(0.66)	(0.62)			(0.54)	(0.84)		(0.64)	(0.61)			(0.51)
EP lagged 2 periods								0.69		0.68	0.92			1.01	-0.01		0.74	1.06			0.77
								(0.83)		(0.72)	(0.72)			(0.61)	(1.03)		(0.72)	(0.77)			(0.60)
EP lagged 3 periods															0.12		0.07	0.40			0.47
															(0.77)		(0.70)	(0.73)			(0.62)
EQ lagged 1 period	0.13	-0.74		-0.06		-1.07		0.62	-0.16		0.62		-0.30		-0.19	-0.30		1.25		-0.05	
	(1.17)	(1.19)		(1.07)		(1.05)		(1.19)	(1.24)		(1.07)		(1.09)		(1.64)	(1.89)		(1.17)		(1.21)	
EQ lagged 2 periods								-0.29	-0.36		-0.56		-0.90		0.39	0.44		0.29		-0.62	
								(1.20)	(1.27)		(1.01)		(1.04)		(1.16)	(1.35)		(1.12)		(1.15)	
EQ lagged 3 periods															2.21	1.87		-0.34		0.25	
															(1.89)	(1.74)		(1.04)		(1.13)	
Diagnostic Statistics																					
R-Squared	0.86	0.81	0.86	0.86	0.81	0.81	0.86	0.91	0.86	0.91	0.90	0.86	0.85	0.90	0.96	0.91	0.95	0.94	0.89	0.87	0.93
AIC	-81.14	-78.60	-83.12	-82.82	-80.10	-80.04	-84.82	-81.07	-77.96	-84.46	-83.79	-81.76	-80.74	-86.97	-88.74	-78.20	-87.76	-85.25	-81.11	-78.89	-88.32
MAE	0.06	0.07	0.06	0.06	0.07	0.07	0.06	0.04	0.06	0.04	0.04	0.06	0.06	0.05	0.02	0.05	0.04	0.04	0.05	0.05	0.04
F-Test															9.07 **						
F-Test for all BLS Prices															2.63						
F-Test for all FooDS															1.21						
F-Test for all WTP															1.00						
F-Test for all EQ															0.68						
F-Test for all EP															2.19						

Note: Standard errors are in parentheses. One asterisk (*) represents significance at the 90% confidence level, two asterisks at the 95% level, and three asterisks at the 99% confidence level (for diagnostic statistics only).

models when estimating future prices of deli ham. Although Model 99 is statistically significant (Table 8), F-Tests indicate that none of the variables, neither past prices, WTP, EQ, nor EP, are statistically different from zero. Therefore, there is not sufficient evidence to say that WTP is a better predictor of future pork chop retail prices than any of the other FooDS variables used and H3 is rejected.

Chicken Breast

The model that best estimates future prices of chicken breast is an autoregressive model lagged one period. This model, Model 13 (Table 4 continued), recorded an AIC value of -92.44.

It is important to point out that while Model 13 (Table 4 continued) was indeed the most accurate (statistically significant at the 95% level) when estimating future prices for chicken breast, Model 111 (Table 9) has a minimally higher AIC value (-91.12). It should also be mentioned that Table 4 shows that Model 13 reported a MAE of 0.05 while Table 9 indicates a MAE of 0.05 is associated with Model 111. These diagnostic statistics lead us to reject H2 and conclude that FooDS data does not increase the forecast accuracy of the autoregressive model, Model 13 (Table 4). F-Test results in Table 9 indicate that WTP is not statistically different from zero, as is the case for EP and EQ. Therefore, H3 is rejected because there is not sufficient evidence to suggest WTP is a better predictor of future chicken prices than EP or EQ.

Chicken Wings

Similar to the estimation results of chicken breast prices, an autoregressive forecast model lagged one period, Model 16 (Table 4 continued), was the most accurate in estimating future chicken wing prices. Model 16 had an AIC value of -113.69, and as seen in Table 4 (continued), is significant at the 95% level. However, there was also a model considering historical chicken wing prices and expected chicken wing prices that exhibited similar predictive power as Model

Table 9. Uncooked Chicken Breast Estimates

	1 Lag							2 Lags							3 Lags						
	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model
Variables	(106)	(107)	(108)	(109)	(110)	(111)	(112)	(113)	(114)	(115)	(116)	(117)	(118)	(119)	(120)	(121)	(122)	(123)	(124)	(125)	(126)
Constant	1.57	1.57	1.53	1.60	1.52	1.60	1.59	1.52	1.00	1.58	1.39	1.09	1.30	1.36	1.17	2.33	2.82	0.88	2.17	1.86	1.60
	(0.93)	(0.86)	(0.91)	(0.83)	(0.84)	(0.75)	(0.81)	(1.42)	(1.25)	(1.27)	(1.09)	(1.10)	(0.90)	(1.03)	(2.86)	(1.69)	(2.30)	(1.27)	(1.45)	(0.89)	(1.31)
Price lagged 1 period	0.50	0.51	0.54	0.51	0.54	0.51	0.54	0.43	0.47	0.41	0.49	0.45	0.45	0.44	0.47	0.40	0.43	0.50	0.46	0.45	0.48
	(0.25)	(0.23)	(0.24)	(0.24)	(0.22)	(0.22)	(0.23)	(0.37)	(0.34)	(0.29)	(0.31)	(0.28)	(0.30)	(0.27)	(0.44)	(0.35)	(0.35)	(0.30)	(0.29)	(0.27)	(0.31)
Price lagged 2 periods								0.23	0.14	0.26	0.13	0.14	0.17	0.15	0.22	0.34	0.57	0.03	0.49	0.12	0.21
								(0.45)	(0.32)	(0.37)	(0.33)	(0.29)	(0.28)	(0.30)	(0.77)	(0.59)	(0.52)	(0.33)	(0.40)	(0.30)	(0.35)
Price lagged 3 periods															-0.26	-0.46	-0.44	-0.07	-0.49	-0.26	-0.16
															(0.63)	(0.52)	(0.44)	(0.30)	(0.39)	(0.24)	(0.32)
WTP lagged 1 period	0.01	0.01	0.02		0.02			-0.07	0.03	-0.09		0.02			-0.07	-0.09	-0.20		-0.10		
	(0.09)	(0.09)	(0.09)		(0.09)			(0.19)	(0.12)	(0.15)		(0.10)			(0.30)	(0.21)	(0.21)		(0.14)		
WTP lagged 2 periods								-0.01	0.05	-0.02		0.05			0.04	0.01	-0.03		0.05		
								(0.14)	(0.11)	(0.12)		(0.10)			(0.25)	(0.13)	(0.21)		(0.11)		
WTP lagged 3 periods															0.02	0.00	-0.04		-0.01		
															(0.17)	(0.12)	(0.14)				
EP lagged 1 period	-0.01		-0.01	0.44			0.00	-0.46		-0.40	-0.49			-0.34	0.39		-0.45	0.44			-0.30
	(0.39)		(0.38)	(0.61)			(0.36)	(0.76)		(0.63)	(0.69)			(0.59)	(1.06)		(0.76)	(0.79)			(0.65)
EP lagged 2 periods								0.80		0.83	0.66			0.58	0.72		0.80	0.69			0.54
								(0.77)		(0.71)	(0.61)			(0.53)	(0.88)		(0.82)	(0.66)			(0.71)
EP lagged 3 periods															-0.90		0.07	-0.88			-0.12
															(1.24)		(0.97)	(0.69)			(0.62)
EQ lagged 1 period	0.43	0.43		-0.01		0.44		0.28	0.31		0.17		0.39		1.35	0.99		1.26		0.86	
	(0.64)	(0.61)		(0.37)		(0.58)		(0.83)	(0.75)		(0.70)		(0.64)		(1.16)	(0.86)		(0.82)		(0.63)	
EQ lagged 2 periods								-0.33	-0.35		-0.52		-0.26		0.37	0.06		0.34		-0.06	
								(0.76)	(0.82)		(0.78)		(0.69)		(1.19)	(0.84)		(0.84)		(0.65)	
EQ lagged 3 periods															1.41	0.86		1.68		1.09	
															(1.27)	(0.90)		(0.83)		(0.62)	
Diagnostic Statistics																					
R-Squared	0.33	0.33	0.31	0.33	0.31	0.33	0.31	0.45	0.37	0.42	0.43	0.33	0.36	0.39	0.68	0.57	0.50	0.66	0.43	0.56	0.41
AIC	-87.13	-89.13	-88.49	-89.12	-90.49	-91.12	-90.44	-82.28	-84.13	-85.41	-85.83	-87.17	-87.83	-88.66	-83.43	-84.79	-82.16	-88.72	-85.83	-90.22	-85.20
MAE	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.04	0.05	0.04	0.05	0.05	0.05	0.03	0.03	0.04	0.03	0.04	0.03	0.05
F-Test															0.7						
F-Test for all BLS Prices															0.81						
F-Test for all FooDS															0.42						
F-Test for all WTP															0.06						
F-Test for all EQ															0.71						
F-Test for all EP															0.42						

Note: Standard errors are in parentheses. One asterisk (*) represents significance at the 90% confidence level, two asterisks at the 95% level, and three asterisks at the 99% confidence level (for diagnostic statistics only).

16 (Table 4 continued), Model 140 (Table 10). As seen in Table 10, Model 140 is associated with an AIC value that is equal to Model 16's AIC value, at -113.69.

Additionally, it can be seen in Table 10 that Model 140 is statistically significant at the 95% confidence level and has a MAE equal to 0.02. Moreover, Table 4 reports a MAE equal to 0.02 for Model 16. Therefore, the accuracy of Model 16 (Table 4) was not increased when including FooDS results in Model 140 (Table 10) and H2 is rejected. Moreover, F-Test results in Table 10 indicate that WTP, EP, and EQ are not statistically different from zero. Sufficient evidence is not available to suggest that WTP is a better predictor of future chicken wing prices than EP or EQ; hence, H3 is rejected.

Beans and Rice

The best beans and rice autoregressive model, Model 20 (Table 4 continued), is statistically significant at the 95% confidence level. This model is associated with an AIC value of -126.96. As seen in Table 4 (continued), there were seven historical beans and rice price, willingness-to-pay, consumer consumption and price expectation combination possibilities for each number of periods lagged, a minimum of one and maximum of three, estimated.

None of the twenty-one forecast models considering all of the available information from BLS and FooDS were as accurate as Model 20 when predicting the future prices of beans and rice. However, Model 148 is associated with an AIC value of -124.76, as seen in Table 11.

Summary

Although only the most accurate forecast model considering willingness-to-pay, expected consumption, and expected prices measured in FooDS was emphasized, it is important to note that there were additional forecast models considering FooDS variables that exhibited greater forecast accuracy than the autoregressive models, as previously mentioned. A summary of the

Table 10. Chicken Wing Estimates

	1 Lag							2 Lags							3 Lags						
	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model
Variables	(127)	(128)	(129)	(130)	(131)	(132)	(133)	(134)	(135)	(136)	(137)	(138)	(139)	(140)	(141)	(142)	(143)	(144)	(145)	(146)	(147)
Constant	0.40	0.42	0.38	0.52	0.44	0.56	0.47	0.43	0.34	0.55	0.19	0.47	0.45	0.20	0.99	0.99	1.09	0.13	0.86	0.64	0.20
	(0.38)	(0.32)	(0.38)	(0.36)	(0.32)	(0.29)	(0.35)	(0.64)	(0.43)	(0.57)	(0.44)	(0.40)	(0.32)	(0.40)	(1.59)	(0.61)	(1.21)	(0.60)	(0.53)	(0.34)	(0.55)
Price lagged 1 period	0.73	0.72	0.71	0.70	0.68	0.68	0.69	0.53	0.61	0.46	0.45	0.55	0.51	0.42	0.38	0.46	0.36	0.46	0.53	0.50	0.45
	(0.21)	(0.18)	(0.21)	(0.21)	(0.18)	(0.18)	(0.21)	(0.30)	(0.31)	(0.27)	(0.26)	(0.29)	(0.27)	(0.24)	(0.47)	(0.33)	(0.40)	(0.34)	(0.30)	(0.28)	(0.32)
Price lagged 2 periods								0.21	0.04	0.24	0.40	0.16	0.23	0.42	0.31	0.45	0.23	0.50	0.40	0.44	0.41
									(0.05)	(0.35)	(0.30)	(0.28)	(0.27)	(0.28)	(0.58)	(0.36)	(0.42)	(0.35)	(0.34)	(0.30)	(0.32)
Price lagged 3 periods															-0.24	-0.52	-0.08	-0.19	-0.34	-0.41	-0.03
															(0.56)	(0.33)	(0.43)	(0.40)	(0.28)	(0.28)	(0.34)
WTP lagged 1 period	0.04	0.04	0.03		0.03			0.01	0.04	-0.01		0.01			-0.01	0.01	-0.02		-0.01		
	(0.04)	(0.04)	(0.04)		(0.04)			(0.05)	(0.05)	(0.04)		(0.05)			(0.08)	(0.06)	(0.06)		(0.05)		
WTP lagged 2 periods								-0.04	-0.01	-0.05		-0.02			-0.07	-0.04	-0.08		-0.04		
								(0.06)	(0.05)	(0.05)		(0.05)			(0.13)	(0.06)	(0.08)		(0.05)		
WTP lagged 3 periods															-0.06	-0.07	-0.05		-0.04		
															(0.11)		(0.08)		(0.05)		
EP lagged 1 period	0.02		0.07	0.05			0.08	-0.25		-0.30	-0.06			-0.07	-0.27		-0.46	0.13			-0.05
	(0.21)		(0.21)	(0.21)			(0.21)	(0.43)		(0.39)	(0.33)			(0.31)	(0.81)		(0.56)	(0.41)			(0.35)
EP lagged 2 periods								0.51		0.55	0.41			0.42	0.36		0.46	0.45			0.44
								(0.34)		(0.30)	(0.27)			(0.25)	(0.57)		(0.46)	(0.36)			(0.34)
EP lagged 3 periods															0.10		0.15	-0.24			-0.07
															(0.69)		(0.48)	(0.39)			(0.32)
EQ lagged 1 period	-0.22	-0.23		-0.17		-0.18		-0.10	-0.22		-0.14		-0.19		0.06	0.07		0.07		-0.03	
	(0.21)	(0.20)		(0.20)		(0.19)		(0.24)	(0.24)		(0.19)		(0.20)		(0.37)	(0.29)		(0.28)		(0.23)	
EQ lagged 2 periods								0.14	0.10		0.08		0.04		0.11	0.04		-0.04		-0.04	
								(0.22)	(0.23)		(0.20)		(0.20)		(0.37)	(0.25)		(0.24)		(0.22)	
EQ lagged 3 periods															0.45	0.64		0.60		0.46	
															(0.70)	(0.47)		(0.51)		(0.41)	
Diagnostic Statistics																					
R-Squared	0.54	0.54	0.50	0.51	0.49	0.51	0.48	0.69	0.57	0.66	0.66	0.52	0.54	0.63	0.75	0.71	0.68	0.71	0.59	0.63	0.63
AIC	-110.06	-112.04	-110.46	-110.82	-112.33	-112.76	-111.85	-108.48	-107.15	-111.26	-110.99	-109.34	-110.00	-113.69	-104.13	-107.62	-106.16	-108.09	-108.12	-109.75	-109.79
MAE	0.02	0.02	0.03	0.02	0.02	0.02	0.03	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
F-Test															0.98						
F-Test for all BLS Prices															0.44						
F-Test for all FooDS															0.33						
F-Test for all WTP															0.17						
F-Test for all EQ															0.35						
F-Test for all EP															0.21						

Note: Standard errors are in parentheses. One asterisk (*) represents significance at the 90% confidence level, two asterisks at the 95% level, and three asterisks at the 99% confidence level (for diagnostic statistics only).

Table 11. Beans and Rice Estimates

Variables	1 Lag Model (148)	2 Lags Model (149)	3 Lags Model (150)
Constant	1.17	0.98	0.86
	(0.50)	(0.66)	(0.72)
Price lagged 1 period	0.48	0.27	0.25
	(0.21)	(0.27)	(0.32)
Price lagged 2 periods		0.29	0.28
		(0.26)	(0.33)
Price lagged 3 periods			0.06
			(0.28)
WTP lagged 1 period	-0.01	-0.002	-0.01
	(0.03)	(0.03)	(0.03)
WTP lagged 2 periods		-0.0050	0.0001
		(0.03)	(0.03)
WTP lagged 3 periods			0.03
			(0.03)
Diagnostic Statistics			
R-Squared	0.34	0.42	0.47
AIC	-124.76	-123.00	-120.61
MAE	0.02	0.02	0.02
F-Test			1.49
F-Test for all BLS Prices			1.56
F-Test for all WTP			0.34

Note: Standard errors are in parentheses. One asterisk (*) represents significance at the 90% confidence level, two asterisks at the 95% level, and three asterisks at the 99% confidence level (for diagnostic statistics only).

number of forecast models considering FooDS information that outperformed the most accurate autoregressive forecast models for each food option (in terms of AIC values) can be seen in Table 12.

Out-of-Sample Predictions

This portion of the results section will report and compare the out-of-sample price estimates for each food option. Results are summarized in Table 13.

Table 12. Number of FooDS Models That Outperform Autoregressive Models

	Number of Periods Lagged				
FooDS Model	1 Period	2 Period	3 Period	Total	Percent
Ground Beef	2	4	5	11	52.38%
Beef Steak	0	1	2	3	14.29%
Pork Chop	0	0	2	2	9.52%
Deli Ham	1	2	4	7	33.33%
Chicken Breast	0	0	0	0	0.00%
Chicken Wing	0	0	0	0	0.00%
Beans and Rice	0	0	0	0	0.00%

Table 13. Actual Prices, In-Sample and Out-of-Sample Forecasts

	Retail Price							FooDS Prediction						
Month	Ground Beef	Beef Steak	Pork Chop	Deli Ham	Chicken Breast	Chicken Wing	Beans and Rice	Ground Beef Model (29)	Beef Steak Model (57)	Pork Chop Model (78)	Deli Ham Model (99)	Chicken Breast Model (111)	Chicken Wing Model (140)	Beans & Rice Model (148)
August 2013	$3.83	$6.34	$3.53	$4.17	$3.60	$1.65	$2.17	$3.83	$6.45	$3.60	$4.18	$3.54	$1.70	$2.17
September 2013	$3.82	$6.40	$3.61	$4.18	$3.61	$1.66	$2.17	$3.84	$6.42	$3.55	$4.17	$3.57	$1.69	$2.19
October 2013	$3.82	$6.36	$3.58	$4.17	$3.65	$1.68	$2.15	$3.82	$6.43	$3.63	$4.15	$3.56	$1.69	$2.19
November 2013	$3.89	$6.33	$3.68	$4.10	$3.45	$1.58	$2.19	$3.89	$6.40	$3.68	$4.07	$3.59	$1.70	$2.18
December 2013	$3.90	$6.34	$3.73	$4.06	$3.46	$1.59	$2.19	$3.91	$6.32	$3.75	$4.06	$3.48	$1.67	$2.20
January 2014	$3.90	$6.34	$3.72	$4.11	$3.43	$1.54	$2.20	$3.96	$6.34	$3.76	$4.10	$3.48	$1.63	$2.20
February 2014	$4.04	$6.56	$3.66	$4.11	$3.38	$1.58	$2.22	$4.02	$6.59	$3.73	$4.13	$3.46	$1.61	$2.21
March 2014	$4.13	$6.73	$3.82	$4.21	$3.47	$1.55	$2.21	$4.12	$6.80	$3.83	$4.12	$3.47	$1.60	$2.21
April 2014	$4.23	$6.97	$4.04	$4.13	$3.39	$1.54	$2.23	$4.20	$6.92	$4.03	$4.13	$3.47	$1.64	$2.22
May 2014	$4.21	$6.94	$4.11	$4.20	$3.47	$1.56	$2.20	$4.22	$6.93	$4.14	$4.18	$3.44	$1.58	$2.22
June 2014	$4.24	$6.97	$4.02	$4.28	$3.50	$1.55	$2.22	$4.24	$7.02	$4.04	$4.27	$3.50	$1.58	$2.20
July 2014	$4.22	$7.00	$4.01	$4.37	$3.44	$1.55	$2.24	$4.23	$7.02	$4.09	$4.37	$3.51	$1.61	$2.21
August 2014	$4.36	$7.36	$4.17	$4.50	$3.48	$1.56	$2.21	$4.36	$7.35	$4.17	$4.49	$3.48	$1.60	$2.22
September 2014	$4.50	$7.40	$4.17	$4.63	$3.48	$1.58	$2.24	$4.48	$7.46	$4.19	$4.56	$3.51	$1.61	$2.21
October 2014	$4.57	$7.40	$4.17	$4.64	$3.49	$1.62	$2.18	$4.62	$7.50	$4.22	$4.60	$3.48	$1.63	$2.23
November 2014	$4.59	$7.47	$4.10	$4.48	$3.53	$1.63	$2.18	$4.62	$7.43	$4.08	$4.55	$3.50	$1.62	$2.20
December 2014	$4.60	$7.54	$4.06	$4.35	$3.48	$1.61	$2.18	$4.58	$7.63	$4.07	$4.29	$3.54	$1.66	$2.19
January 2015	$4.68	$7.53	$3.99	$4.41	$3.44	$1.58	$2.14	$4.60	$7.61	$4.46	$4.24	$3.55	$1.69	$2.20
February 2015	$4.71	$7.57	$3.96	$4.43	$3.51	$1.58	$2.17	$4.65	$7.72	$4.45	$4.24	$3.55	$1.70	$2.20
March 2015	-	-	-	-	-	-	-	$4.66	$7.49	$4.45	$4.24	$3.55	$1.68	$2.20
Diagnostic Statistics														
Mean Absolute Error								$0.07	$0.11	$0.48	$0.18	$0.07	$0.11	$0.04

Note: This table displays in-sample and out-of-sample forecasts. January, February, and March 2015 are out-of-sample price estimates.

Table 13 continued. Actual Prices, In-Sample and Out-of-Sample Forecasts

	Retail Price							BLS Autoregressive Prediction						
Month	Ground Beef	Beef Steak	Pork Chop	Deli Ham	Chicken Breast	Chicken Wing	Beans and Rice	Ground Beef Model (1)	Beef Steak Model (4)	Pork Chop Model (7)	Deli Ham Model (12)	Chicken Breast Model (13)	Chicken Wing Model (16)	Beans & Rice Model (20)
August 2013	\$3.83	\$6.34	\$3.53	\$4.17	\$3.60	\$1.65	\$2.17	\$3.82	\$6.46	\$3.58	\$4.15	\$3.52	\$1.63	\$2.15
September 2013	\$3.82	\$6.40	\$3.61	\$4.18	\$3.61	\$1.66	\$2.17	\$3.86	\$6.37	\$3.60	\$4.21	\$3.54	\$1.63	\$2.16
October 2013	\$3.82	\$6.36	\$3.58	\$4.17	\$3.65	\$1.68	\$2.15	\$3.85	\$6.43	\$3.67	\$4.23	\$3.55	\$1.63	\$2.17
November 2013	\$3.89	\$6.33	\$3.68	\$4.10	\$3.45	\$1.58	\$2.19	\$3.85	\$6.39	\$3.64	\$4.17	\$3.57	\$1.65	\$2.16
December 2013	\$3.90	\$6.34	\$3.73	\$4.06	\$3.46	\$1.59	\$2.19	\$3.92	\$6.35	\$3.73	\$4.08	\$3.46	\$1.58	\$2.17
January 2014	\$3.90	\$6.34	\$3.72	\$4.11	\$3.43	\$1.54	\$2.20	\$3.93	\$6.37	\$3.77	\$4.04	\$3.47	\$1.59	\$2.18
February 2014	\$4.04	\$6.56	\$3.66	\$4.11	\$3.38	\$1.58	\$2.22	\$3.93	\$6.37	\$3.77	\$4.14	\$3.45	\$1.55	\$2.18
March 2014	\$4.13	\$6.73	\$3.82	\$4.21	\$3.47	\$1.55	\$2.21	\$4.07	\$6.59	\$3.71	\$4.15	\$3.43	\$1.58	\$2.19
April 2014	\$4.23	\$6.97	\$4.04	\$4.13	\$3.39	\$1.54	\$2.23	\$4.17	\$6.76	\$3.86	\$4.25	\$3.47	\$1.57	\$2.20
May 2014	\$4.21	\$6.94	\$4.11	\$4.20	\$3.47	\$1.56	\$2.20	\$4.26	\$7.02	\$4.05	\$4.15	\$3.43	\$1.56	\$2.20
June 2014	\$4.24	\$6.97	\$4.02	\$4.28	\$3.50	\$1.55	\$2.22	\$4.25	\$6.98	\$4.10	\$4.19	\$3.48	\$1.57	\$2.19
July 2014	\$4.22	\$7.00	\$4.01	\$4.37	\$3.44	\$1.55	\$2.24	\$4.27	\$7.02	\$4.03	\$4.32	\$3.49	\$1.56	\$2.19
August 2014	\$4.36	\$7.36	\$4.17	\$4.50	\$3.48	\$1.56	\$2.21	\$4.26	\$7.04	\$4.01	\$4.41	\$3.46	\$1.56	\$2.20
September 2014	\$4.50	\$7.40	\$4.17	\$4.63	\$3.48	\$1.58	\$2.24	\$4.39	\$7.41	\$4.16	\$4.53	\$3.48	\$1.57	\$2.20
October 2014	\$4.57	\$7.40	\$4.17	\$4.64	\$3.49	\$1.62	\$2.18	\$4.54	\$7.45	\$4.16	\$4.63	\$3.48	\$1.58	\$2.20
November 2014	\$4.59	\$7.47	\$4.10	\$4.48	\$3.53	\$1.63	\$2.18	\$4.60	\$7.45	\$4.16	\$4.57	\$3.48	\$1.61	\$2.19
December 2014	\$4.60	\$7.54	\$4.06	\$4.35	\$3.48	\$1.61	\$2.18	\$4.63	\$7.52	\$4.10	\$4.31	\$3.50	\$1.62	\$2.18
January 2015	\$4.68	\$7.53	\$3.99	\$4.41	\$3.44	\$1.58	\$2.14	\$4.67	\$7.58	\$4.10	\$4.11	\$3.49	\$1.61	\$2.17
February 2015	\$4.71	\$7.57	\$3.96	\$4.43	\$3.51	\$1.58	\$2.17	\$4.71	\$7.63	\$4.09	\$3.93	\$3.49	\$1.60	\$2.17
March 2015	-	-	-	-	-	-	-	\$4.75	\$7.69	\$4.09	\$3.73	\$3.48	\$1.60	\$2.16
Diagnostic Statistics														
Mean Absolute Error								\$0.003	\$0.05	\$0.12	\$0.40	\$0.04	\$0.02	\$0.02

Note: This table displays in-sample and out-of-sample forecasts. January, February, and March 2015 are out-of-sample

Ground Beef

Model 1 from Table 4 estimated the average U.S. City price of hamburgers to be $4.67 per pound in January, $4.71 per pound in February, and $4.75 in March 2015. Additionally, Model 29 from Table 5 estimates a price of $4.59, $4.64, $4.68 per pound for hamburger in January, February, and March 2015, respectively. Realized hamburger prices are depicted along with estimated hamburger prices in Figure 9 to graphically depict forecast accuracy during the aforementioned time frame.

Beef Steak

Average U.S. city beef steak prices are estimated to be $7.58 and $7.63 per pound for the months of January and February 2015, respectively, according to Model 4 (Table 4). Also, the price of beef steak for March 2015 is estimated to be $7.69 per pound by Model 4. Likewise, Model 57 (Table 6) estimates U.S. city average beef steak prices to be $7.82 per pound in January, $7.80 per pound in February, and $7.18 per pound in March 2015. Figure 10 presents a graphical depiction of estimated and realized beef steak prices.

Pork Chop

Model 7 (Table 4) estimates average U.S. city pork chop prices to be $4.10 in January 2015. February and March 2015 average pork prices are estimated to be $4.09 per pound. Moreover, Model 78 in Table 7 estimates average U.S. city pork chop prices to be $4.50 and $4.46 per pound for the months of January and February 2015, respectively. March 2015 prices are estimated to be $4.22 per pound. A graphical representation of the aforementioned estimations along with realized, historical prices can be seen in Figure 11.

Deli Ham

Average U.S. city deli ham prices are estimated to be $4.10 per pound in January and $3.89 in

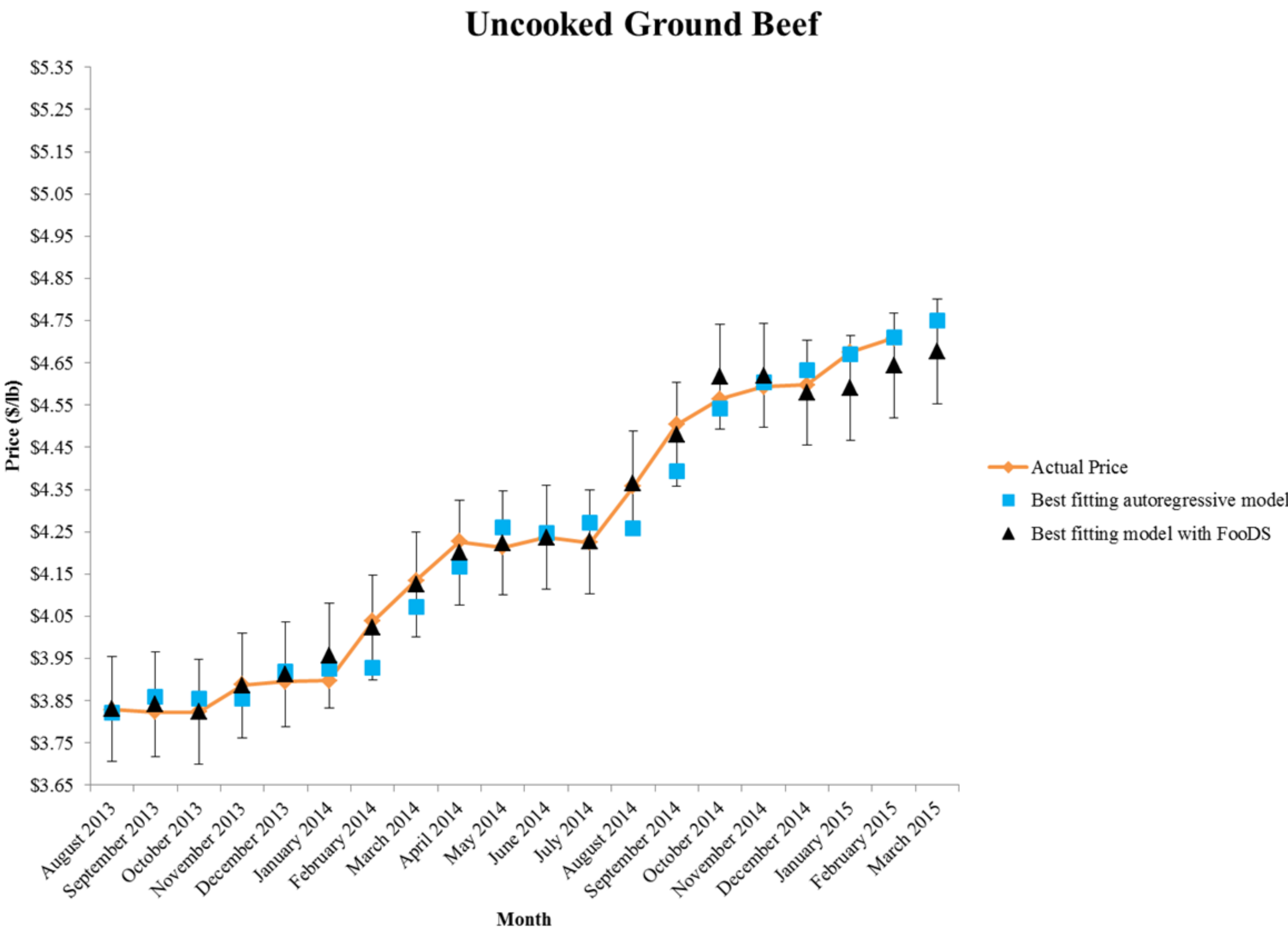

Figure 9. Uncooked Ground Beef Price Estimate

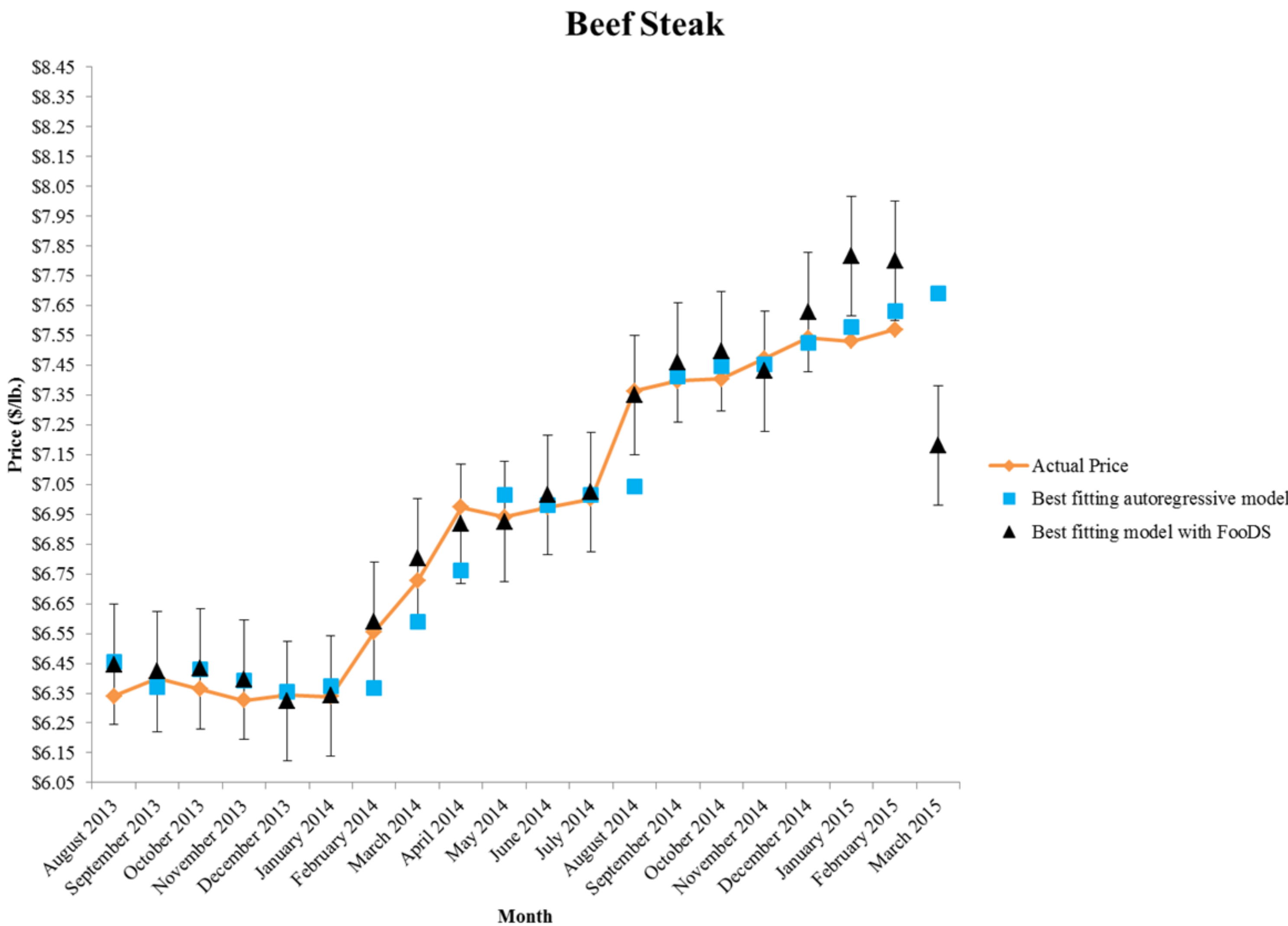

Figure 10. Uncooked Beef Steak Price Estimates

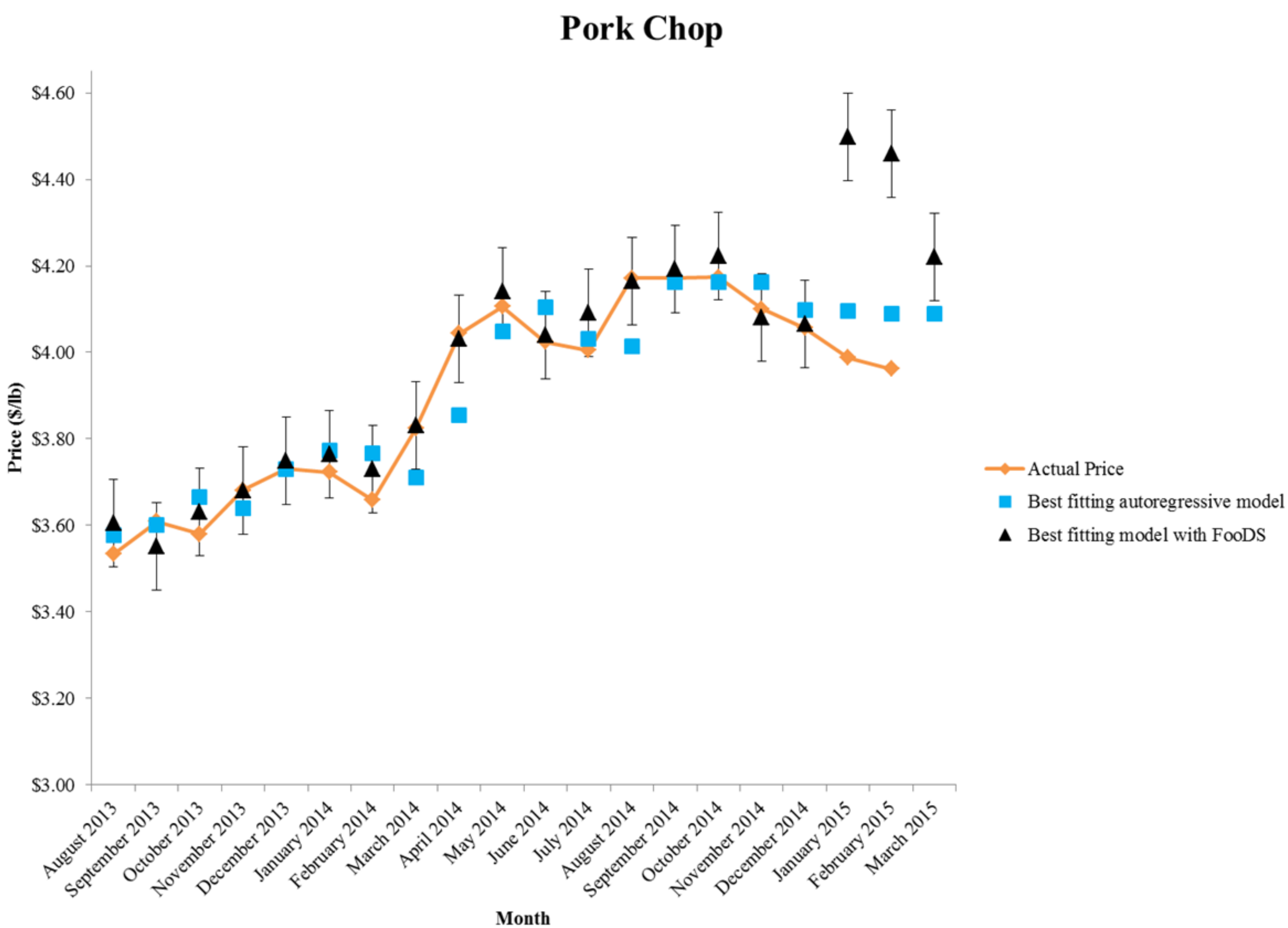

Figure 11. Pork Chop Price Estimates

February 2015 by Model 12 in Table 4. This model also estimates March 2015 prices to be $3.76 per pound. Comparatively, Model 99 (Table 8) estimates deli ham prices to be $4.25 in January 2015, $4.23 in February 2015, and $4.29 in March 2015. This information is graphically displayed in Figure 12.

Chicken Breast

Model 13 from Table 4 estimates average U.S. city chicken breast prices to be $3.49 per pound in January and February 2015 and $3.48 per pound in March 2015. Conversely, Model 111 from Table 9 estimates January, February, and March 2015 prices to be $3.55. Figure 13 depicts forecast accuracy of each model graphically.

Chicken Wing

Model 16 (Table 4) estimates January 2015 average U.S. city chicken wing prices to be $1.61 per pound and $1.60 per pound in February and March of 2015. Likewise, using information gathered from FooDS, Model 140 (Table 10) estimates chicken wing prices to be $1.65 per pound in January 2015, $1.72 per pound in February 2015, and $1.74 in March 2015. These estimates can be compared to realized, historical chicken wing prices in Figure 14.

Beans and Rice

From Table 11, Model 148 estimates average U.S. city beans and rice prices to be $2.20 per pound in January, February, and March 2015. Similarly, the autoregressive forecast model, Model 20 (Table 4), estimates the price of beans and rice to be $2.18 in January 2015 and $2.17 per pound in the months of February and March 2015. Realized beans and rice prices are graphed with the estimated prices in Figure 15.

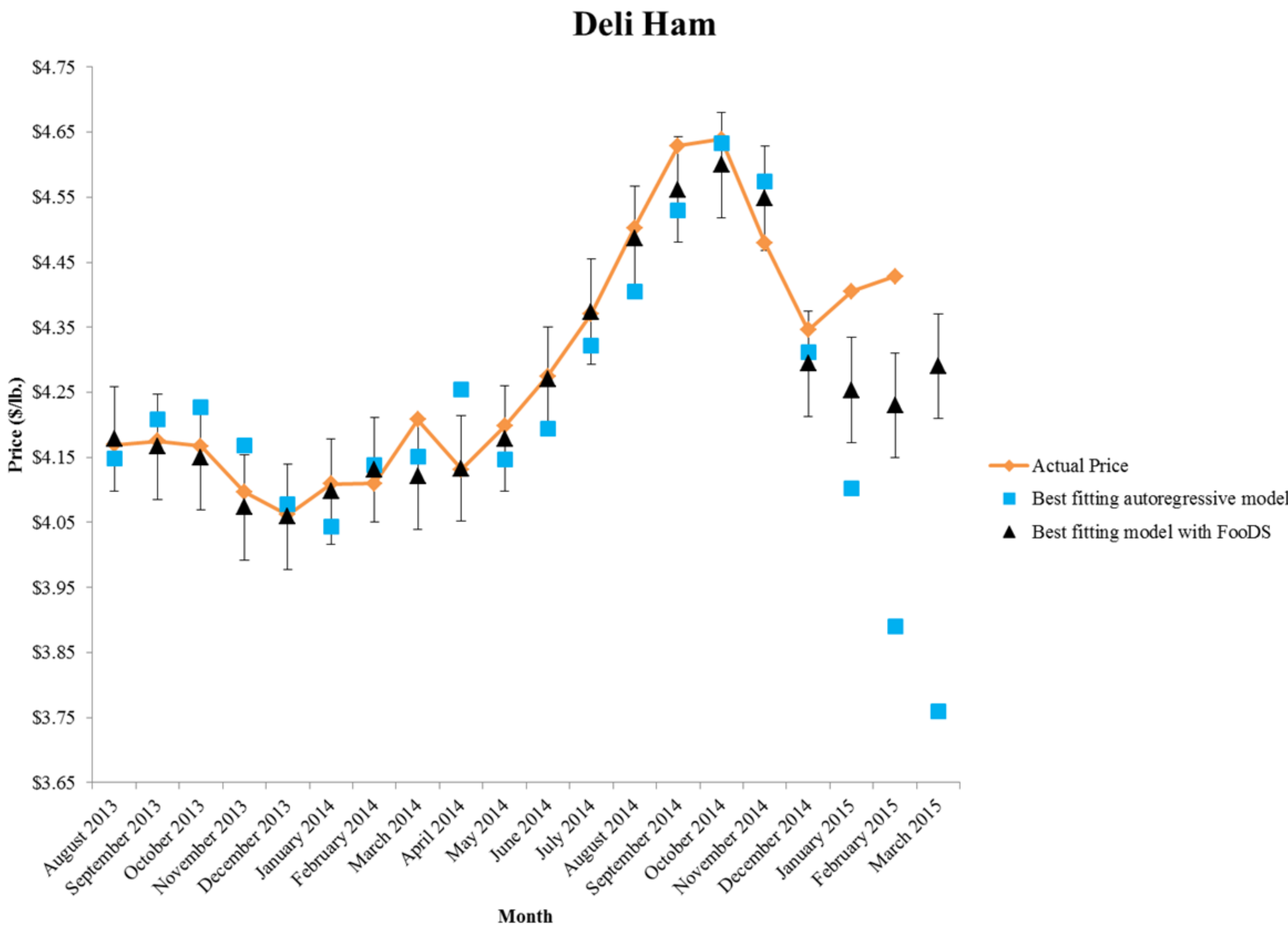

Figure 12. Deli Ham Price Estimates

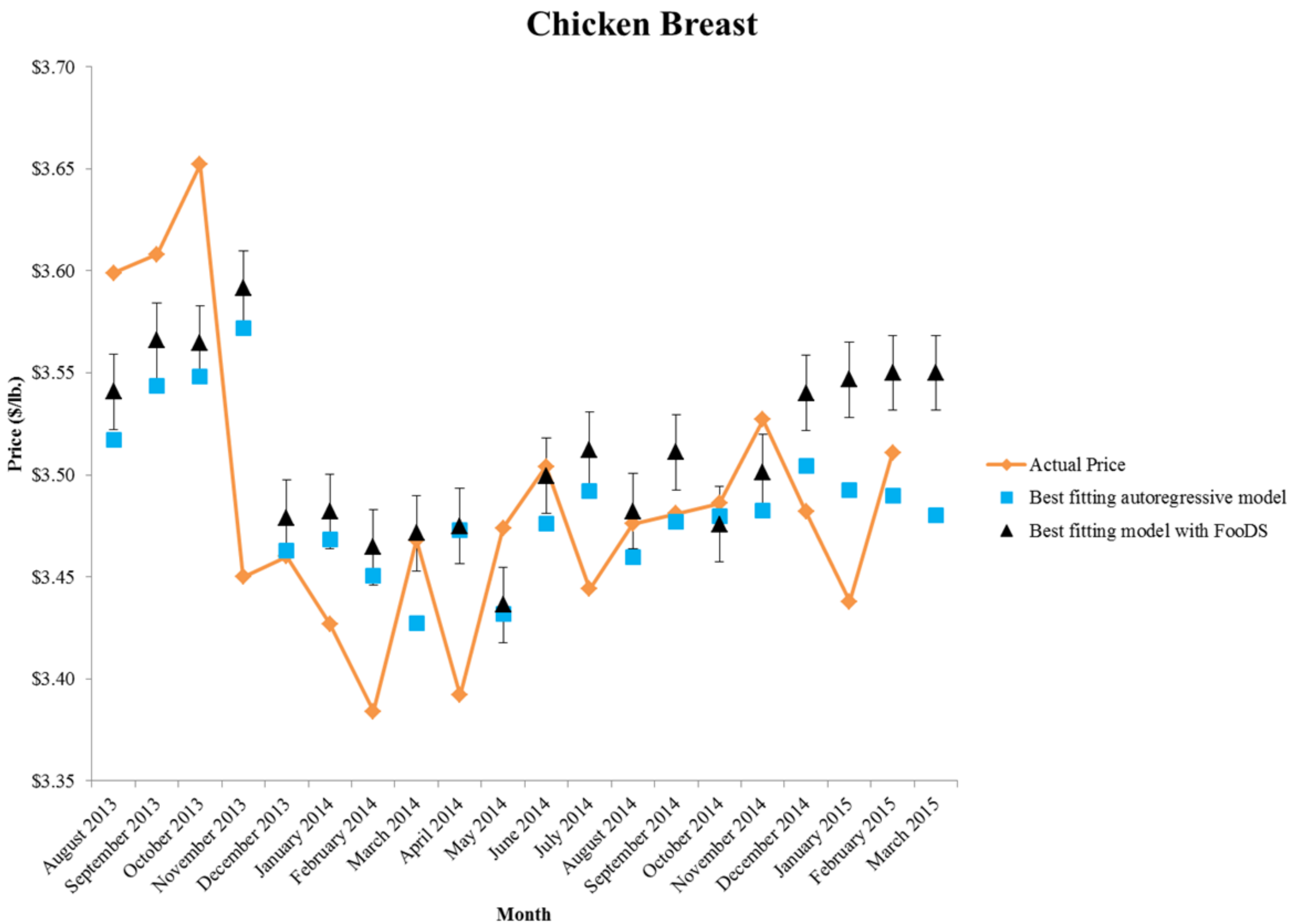

Figure 13. Chicken Breast Price Estimates

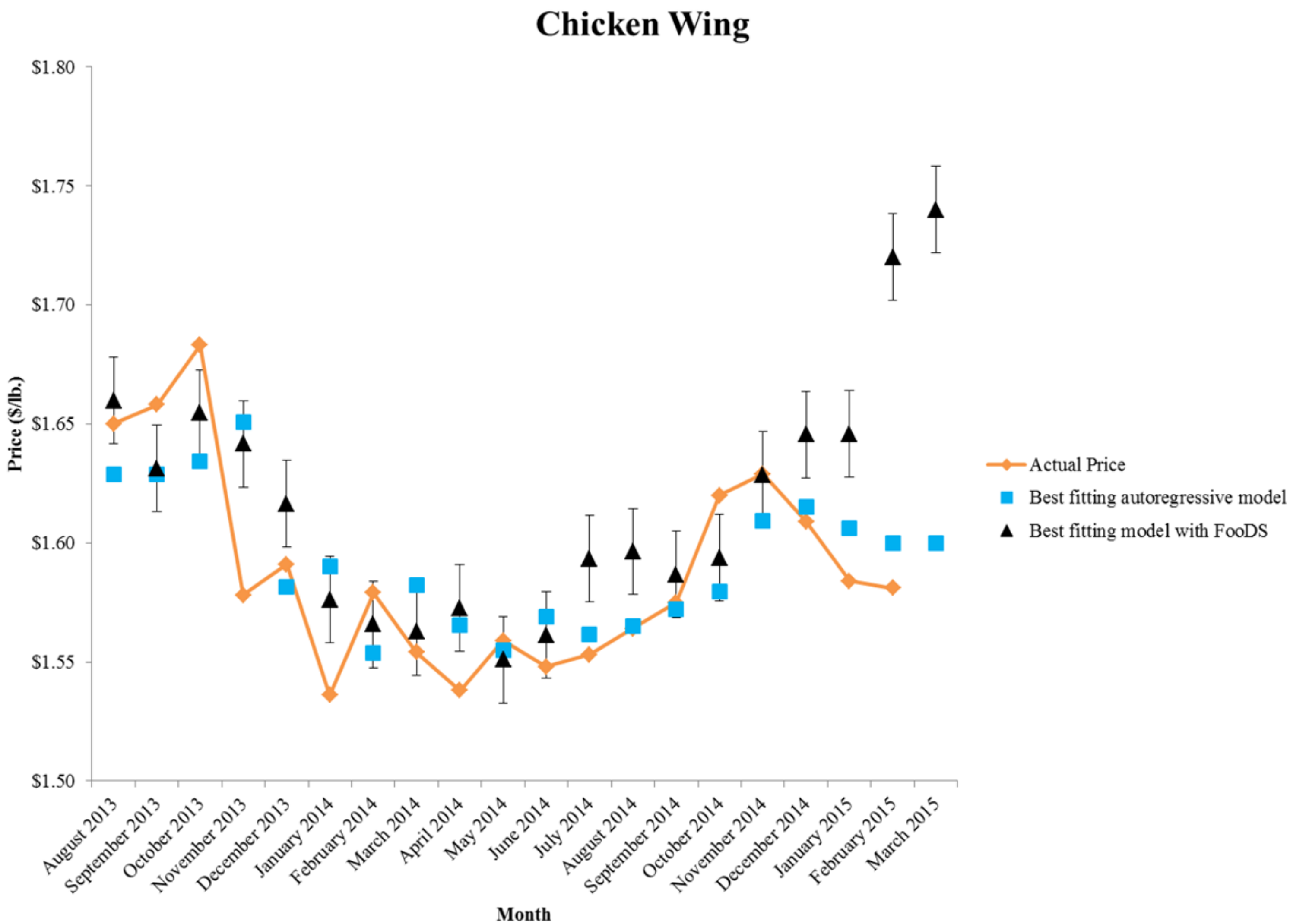

Figure 14. Chicken Wing Price Estimates

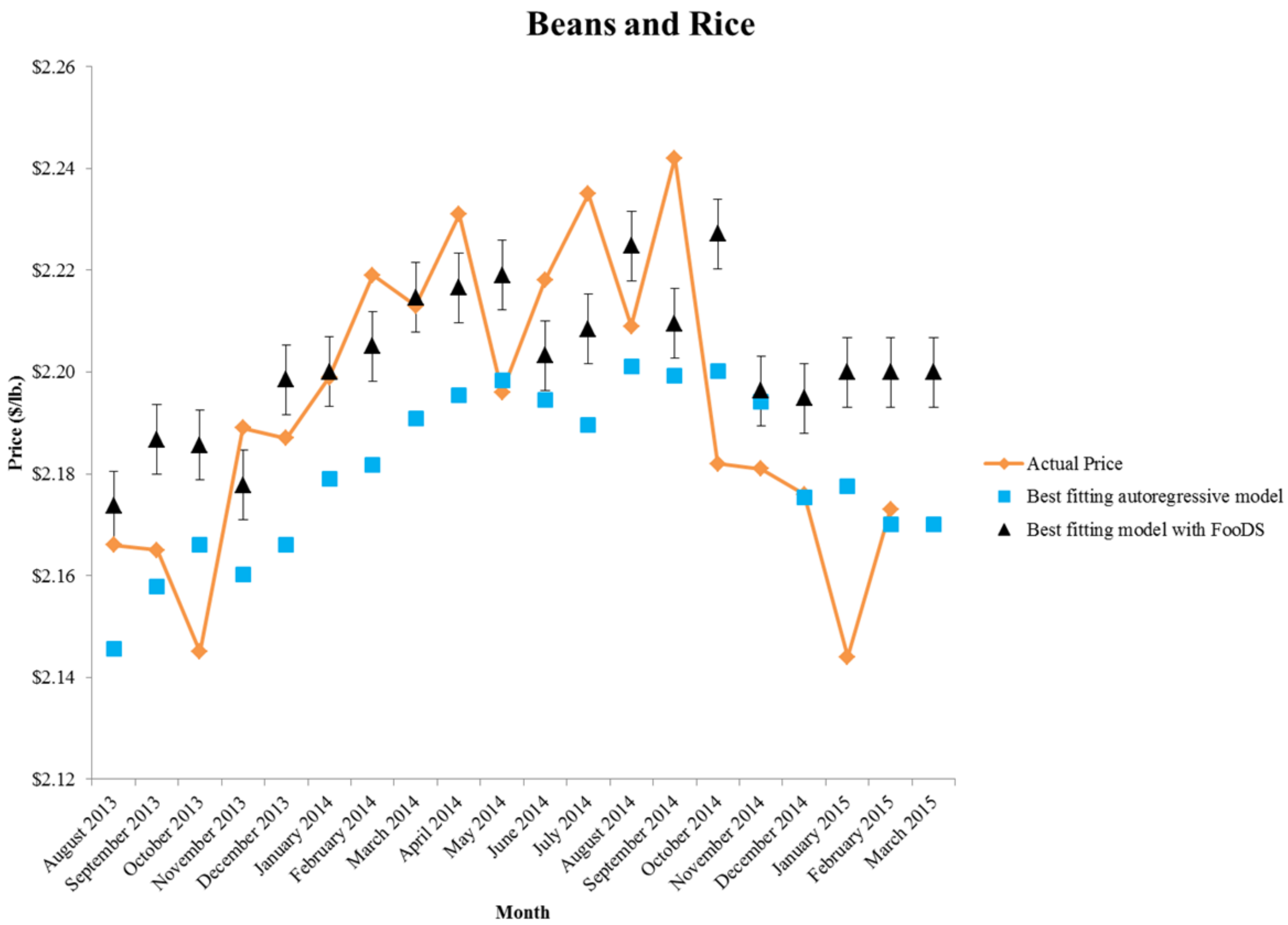

Figure 15. Beans and Rice Price Estimates

CHAPTER VI

SUMMARY AND CONCLUSIONS

Overall, this study was conducted to determine if information gathered from consumer surveys increases forecast accuracy of autoregressive price forecast models. Ultimately, Granger Causality was (indirectly) used to determine if information gathered from FooDS is a leading indicator of future beef, pork, and chicken prices through the use of F-tests.

As reported in the previous section, lower AIC values are associated with forecast models estimating future hamburger, beef steak, pork chop, and deli ham prices that consider both historical prices and information gathered from FooDS; thus, satisfying criteria for a more accurate forecast. However, out-of-sample price estimates are not as accurate as they could have been due to the BLS release schedule of food CPI values. Realized, past prices of food options were unknown at the time of each forecast (e.g., January BLS prices are not released until the end of February). Due to the lag in reported prices, the predicted price for each food option in period $t-1$ was used as a proxy for past prices lagged one period. Therefore, because regressions were fitted to consider realized meat prices lagged one, two, and three periods and not predicted prices, out-of-sample price estimates were less accurate than in-sample estimates. Furthermore, models forecasting food CPI two periods in the future, as opposed to one period, should be considered. This would prohibit the use of predicted prices as proxies for realized, past prices in period $t-1$.

In this scenario, a Granger Causality framework should be considered in order to determine if measures from FooDS is a leading indicator of future food CPI values. Additionally, the mean and variance of past prices should be evaluated in order to determine if prices are random, or if stationarity exists.

It is important to note that although information gathered from FooDS may not have been statistically significant, this information did help improve price forecast accuracy. Therefore, there is not sufficient evidence to indicate whether WTP, EP, or EQ is the better predictor of future prices. Additionally, mean absolute error measurements will prove to be more beneficial forecast accuracy indicators as additional out-of-sample forecasts are generated.

Due to the small sample size, these results should be considered preliminary. With more data points, or months, it will be easier to decipher which method is more accurate when predicting future retail prices of meat. Moreover, additional information from the FooDS survey will be available for use due to an increase in degrees of freedom within the models. Questioning the frequency that consumers purchase beef, pork, and chicken in FooDS might provide additional, useful information; thus, better explaining future retail meat prices. Moreover, predictions of directional changes in meat prices could prove to be just as useful as predictions of actual retail price levels. Survey bias should also be considered when using results to forecast future prices. It would be interesting to see if results change when considering only the middle 80% of respondents' answers based off of time to survey completion. Also, these estimates are based on a macro-level. Food prices vary depending on the region of the country. Estimating regional prices based off of respondent's permanent residency should also be considered and may lead to increased accuracy.

The information acquired in this study should be considered by food retailers as they make marketing and pricing decisions. Consumer expectations and willingness-to-pay should be considered to estimate and set a competitive, revenue maximizing price for products sold in retail stores. Additionally, literature suggests that increased price forecast accuracy leads to increased consumption forecast accuracy. This idea should be explored in future research while considering results gathered from this study.

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APPENDICES

Oklahoma State University Institutional Review Board

Date: Monday, March 17, 2014 — Protocol Expires: 3/16/2017

IRB Application No: AG1326

Proposal Title: Food Consumer Tracking Survey

Reviewed and Processed as: Exempt **Continuation**

Status Recommended by Reviewer(s) **Approved**

Principal Investigator(s)

Jayson Lusk
411 Ag Hall
Stillwater, OK 74078

Susan E. Murray
526 Ag Hall
Stillwater, OK 74078

Approvals are valid until the expiration date, after which time a request for continuation must be submitted. Any modifications to the research project approved by the IRB must be submitted for approval with the advisor's signature. The IRB office MUST be notified in writing when a project is complete. Approved projects are subject to monitoring by the IRB. Expedited and exempt projects may be reviewed by the full Institutional Review Board.

☒ The final versions of any printed recruitment, consent and assent documents bearing the IRB approval stamp are attached to this letter. These are the versions that must be used during the study.

The reviewer(s) had these comments:

New subject enrollment still in progress Approximately 12,000 per year will participate. New change – future surveys will have 3 to 5 ad hoc questions that will relate to consumer knowledge about food and agricultural issues and/or preferences for food/agricultural attributes and policies. No reportable events, withdraws, increased risk, complaints, or new/additional funding.

Signature:

Shelia K

Shelia Kennison, Chair, Institutional Review Board

Monday, March 17, 2014
Date

Food Consumption_IRBApplication

Q1 Thank you for participating in this study. The following contains information about your study and your rights as a research participant. Project Title: Food Consumption Investigator: Jayson Lusk, Ph.D., Oklahoma State University Purpose: This is a web-based survey research study designed to tracking consumer preferences and sentiments on the safety, quality, and price of food consumed at home and away from home. Procedures: Proceeding with the web-based survey will imply your consent to participate in this study. There are about 40 questions asking about your preferences for food in addition to questions asking about your food expenditures. We also ask some basic demographic questions. The survey will take about 15 minutes to complete. Risks of Participation: The risks associated with this study are minimal. The risks are not greater than those ordinarily encountered in daily life. Moreover, you may stop the survey at any time. Benefits: This research will assist researchers anticipate the demand for various meat products, awareness of food-related issues or events that could affect demand. Confidentiality: The researchers will not have access to your name. At no point will a data file be constructed in which your name is linked with your responses. The data will be stored by the principal investigators in his office with no intention to destroy the data. The data will only be released in summaries in which no individual's answers can be identified. Contacts: If you have any questions or concerns about this project, please contact Dr. Jayson Lusk, (405) 744-7465, jayson.lusk@okstate.edu. If you have questions about your rights as a research volunteer, you may contact Dr. Shelia Kennison, IRB Chair, 219 Cordell North, Stillwater, OK 74078, 405-744-3377 or irb@okstate.edu. Participant Rights: Your participation in this research in voluntary. You can discontinue the survey at any time without reprisal or penalty. Consent: I have read and fully understand the consent form. I understand that my participation is voluntary. By clicking below, I am indicating that I freely and voluntarily and agree to participate in this study and I also acknowledge that I am at least 18 years of age. It is recommended that you print a copy of this consent page for your records before you begin.

VITA

Aaron Michael Ates

Candidate for the Degree of

Master of Science

Thesis: FORECASTING MEAT PRICES USING THE FOOD DEMAND SURVEY (FooDS)

Major Field: Agricultural Economics

Biographical:

Education:

Completed the requirements for the Master of Science in Agricultural Economics at Oklahoma State University, Stillwater, Oklahoma in May, 2015.

Completed the requirements for the Bachelor of Science in Agricultural Economics at Texas A&M University, College Station, Texas in 2013.

Experience:

Research Assistant at Oklahoma State University, Stillwater, OK
August 2013 – May 2015

Intern at Berkeley Research Group, College Station, TX
July 2012 – August 2013

Research Assistant at the Agribusiness, Food, and Consumer Economic Research Center, College Station, Texas
August 2011 – July 2012

Professional Memberships:

Agricultural and Applied Economics Association: 2014 – Present