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Forecasting Meat Prices Using Consumer Expectations from the Food Demand Survey (FooDS)

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Abstract

We determine whether data from the Food Demand Survey are leading indicators of retail meat prices included in the Consumer Price Index. Accurate price forecasts allow retailers to formulate appropriate marketing strategies and justify strategic procurement decisions. Accurate price forecasts should also reduce asymmetric price information. This study relies on consumers' self-reported expectations about whether prices will increase or decrease in the coming weeks. Results from maximum likelihood stepwise autoregressions indicate that survey-based price expectations are leading indicators for chicken wing prices and contain the same information as BLS ground beef, pork chop, and deli ham prices. Future researchers can use this information in combination with theories from the demand, price analysis, and machine learning literatures to construct more accurate price forecasting models.

Keywords: beef, chicken, leading indicator, pork, price expectations

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Prices, as revealed by market transactions, are the mechanism that equates marginal rates of substitution and transformation. 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 affect which goods are produced and consumed as well as consumers' and firms' welfare. For this reason, among others, changes in the prices of goods and services are measured and reported by government agencies and predicted by academics, businesses, and private consultants. One of the most well-known reported prices is the Consumer Price Index (CPI) published by the Bureau of Labor Statistics. In this study, we focus on the prices of several meat items that make up the food component of the CPI.

Because of private and public interest in changing food prices, several entities attempt to forecast future food-related CPI values. For example, the U.S. Department of Agriculture (USDA) Economic Research Service (ERS) reports annual forecasts (updated monthly) for the food CPI. The ERS forecasts annual changes in food CPI using an autoregressive moving average (ARMA) framework (Kuhns et al., 2015). Other, similar approaches by academics, private industry consultants, and government agencies (ERS) have been used to forecast the food CPI (e.g., Joutz 1997). Our interests lie in predicting prices of disaggregate meat products, but we focus on monthly (rather than annual) values for disaggregate (rather than aggregate) food products. More importantly, we consider whether consumer price expectations are leading indicators of actual retail beef, pork, and chicken prices using data collected in a monthly Food Demand Survey (FooDS). In contrast to models like that used by the ERS, which use past prices to forecast future prices, our model incorporates consumers' forward-looking expectations to estimate future prices.

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 to improve producer and consumer welfare by providing more accurate price expectations (Irwin, 1997; Freebairn, 1976, 1978; Lusk, 2013b). Antonovitz and Roe (1986), Bradford and Kelejian (1978), and Arrow (1951) have attempted to estimate the financial and social welfare benefits associated with improved price expectations that accrue from firms being able to more optimally determine the quantity to produce.

While previous efforts at forecasting food prices have tended to rely on econometric models using auto-regressive frameworks, there is evidence that futures markets can help produce forecasts with lower prediction errors. 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, 2010). In layman's 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 numerous empirical studies have compared the accuracy of outlook forecasts and futures prices, including Just and Rausser (1981); Bessler and Brandt (1992); Irwin, Gerlow, and Liu (1994); Bowman and Husain (2004); and Sanders and Manfredo (2004, 2005). With a few exceptions, these studies all find that outlook forecasts are no more accurate (and are often *less* accurate) than comparable futures prices.

While there are futures markets for some farm-level products such as live cattle, there are no futures markets for retail cuts of beef (e.g., rib-eye). Although live cattle futures market prices may help in estimating future retail beef prices, it is unclear how accurate a forecast these can provide, especially considering that farmers' shares of the total beef and pork food dollar are 0.515 and 0.60, respectively (i.e., about 40%–49% of the cost of the retail product comprises goods beyond the agricultural commodity in 2015) (Hahn, 2015). In addition, many farm and retail products are not traded or sold in futures markets (such as chicken).

Aside from historical retail prices or farm-commodity futures prices, some other types of data might prove useful in predicting retail meat prices. Surowiecki (2005) popularized the idea that large groups may make more accurate predictions than any single expert. 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 in a variety of contexts.

Studies suggest that information collected from consumer surveys is beneficial when forecasting future prices (Anderson et al., 2011; Anderson, Kellogg, and Sallee, 2013). In these studies, consumer predictions of future gasoline prices yield increased forecast accuracy relative to forecasts based on historical monthly prices. Furthermore, Zakrzewicz, Brorsen, and Briggeman (2012, 2013) find that survey-based land value estimates elicited from agricultural bankers are leading indicators of land values and land value changes reported by the USDA.

Results from these studies and others like them suggest that there may be merit in using forward-looking information gathered from surveys of diverse individuals. This research determines whether survey-based data on consumers' expectations of meat price changes are leading indicators of changes in U.S. Bureau of Labor Statistics (BLS) retail meat prices. We rely on a unique dataset created by the Food Demand Survey (FooDS) that has been repeated monthly for 5 years (2013–2018).[1]

Data

Consumer Survey Data from FooDS

FooDS is a monthly online survey completed by at least 1,000 consumers nationwide each month. The FooDS survey has been issued every month since May 2013. FooDS is sent to respondents on the 10th of every month. If the 10th falls on a weekend, FooDS is sent the following Monday. The survey is sent to a sample of consumers in a panel maintained by Survey Sampling Incorporated (SSI). Survey responses are weighted to match the U.S. population in terms of age, gender, education, and region of residence. Our econometric models use aggregate FooDS results from June 2013 through May 2018, which yields 60 monthly observations.[2]

Among other questions, respondents are asked (separately) whether they expect the prices of beef, pork, and chicken to be higher in the next 2 weeks compared to the previous 2 weeks (see Figure 1). The wording of the question yields a measurement of expected price changes. Because the

[1] Additional information pertaining to FooDS can be found at http://www.agecon.okstate.edu/ agecon_research.asp.

[2] Due to the limited sample size, we did not consider any out-of-sample forecasts, focusing instead on which variables are leading indicators.

survey is administered in the middle of each month, beef, pork, and chicken price expectation measurements are interpreted as consumers' expected (monthly) price changes.

Figure 1. Example of Consumer Expectation Questions
Q. 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 (1)	**Disagree (2)**	**Neither Agree nor Disagree (3)**	**Agree (4)**	**Strongly Agree (5)**
I expect the price of beef to be higher (5)	○	○	○	○	○
I expect the price of pork to be higher (6)	○	○	○	○	○
I expect the price of chicken to be higher (7)	○	○	○	○	○

To derive an aggregate measure of price expectations in each month *t*, we subtracted the proportion of respondents who expected prices to increase from the proportion of respondents who expected prices to decrease. The proportion of respondents who neither agreed nor disagreed was subtracted from 1 and multiplied by the aforementioned measure. This procedure creates a measure of price expectation weighted by those who had an opinion regarding the future of meat prices. Formally, consumer price expectations (PE) for meat type *j* in month *t* are calculated as

$$(1) \qquad PE_{jt} = \left(1 - \frac{\sum_{i=1}^{nt} NAD_{ijt}}{n_t}\right)\left(\frac{\sum_{i=1}^{nt} AGREE_{ijt}}{n_t} - \frac{\sum_{i=1}^{nt} DISAGREE_{ijt}}{n_t}\right),$$

where PE_{jt} is the consumer PE for meat *j* = beef, pork, or chicken in each time period (month) *t*, where $t = 1, \ldots, 60$, and *n* is the total number of respondents at time *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. Likewise, NAD_{ijt} is a 0/1 dummy variable indicating that a respondent neither agreed nor disagreed that the price of meat type *j* would increase in the coming weeks.

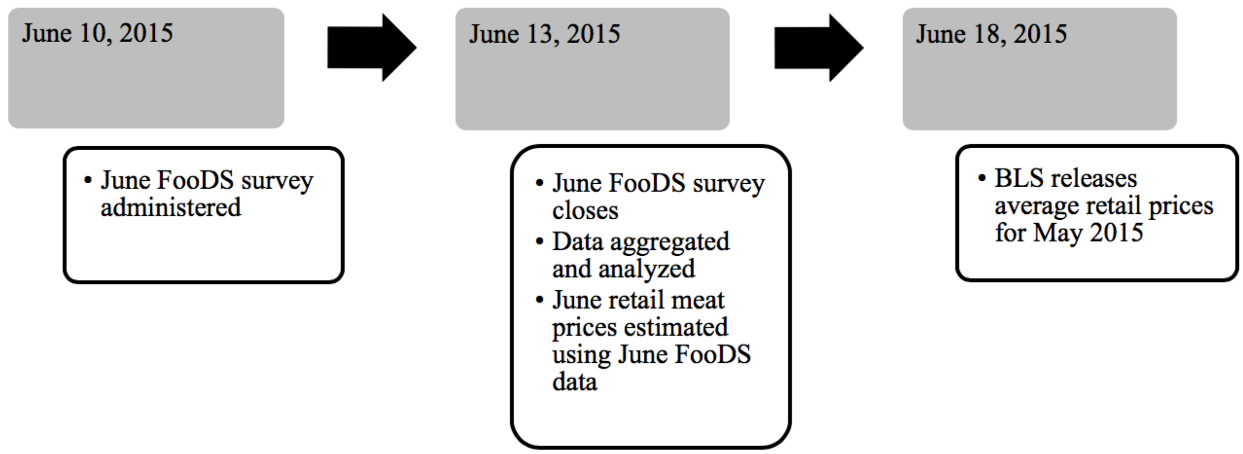
BLS Retail Prices

The Bureau of Labor Statistics publishes average prices of various consumer products in different U.S. cities on a monthly basis. Due to processing time, the monthly prices reported by the BLS are released 2–3 weeks following the month in question (BLS, 2014). For example, the average July prices are not released until mid to late August.[3] Figure 2 shows an example timeline. Average U.S. city prices for uncooked ground beef (APU0000FC1101), uncooked beef steak

[3] Because of this lag, we also investigate the use of retail meat prices reported by the Agricultural Marketing Service (AMS) as a proxy for lagged BLS prices. Results are provided in the Appendix.

(APU0000FC3101), boneless chicken breast (APU0000FF1101), and all pork chops (APU0000FD3101) for June 2013 to May 2018 were collected from the BLS website. The BLS does not report average U.S. city prices for deli ham or chicken wings. However, to provide a point of comparison with the FooDS data, we also collected BLS boneless ham excluding canned (APU0000704312) and bone-in chicken leg (APU0000706212) prices, respectively. Figures 3–8 show BLS prices and associated FooDS price expectations from June 2013–May 2018.

Figure 2. Timeline of Foods Survey Administration, Price Estimations, and BLS Price Release Dates



Methods

We seek to determine whether consumer expectations are leading indicators of retail meat prices. FooDS data for a given month are known at least 2 months prior to the release of corresponding BLS prices. Thus, we can predict price changes in the current period, say July, before the BLS release of the July data occurs (August).

After considering some simple correlations between consumer price expectations and BLS prices (see Table 1), we move to econometric models that seek to determine whether FooDS data are a leading indicator of BLS prices even after controlling for past BLS prices. Our main analysis focuses on an ordinary least squares (OLS) model,

$$BLSPrice_{j,t} = \beta_{0,j} + \beta_{1,j}BLS_{t-2} + \beta_{2,j}PE_{j,t} + \sum_{i=1}^{11} \varphi_{i,j}M_i + \varepsilon_{j,t}, \tag{2}$$

where $BLSPrice_{j,t}$ represents the BLS price of food product j at time t, $PE_{j,t}$ represents expected

Figure 3. Uncooked Beef Steak BLS Prices and FooDS Price Expectations: June 2013–May 2018

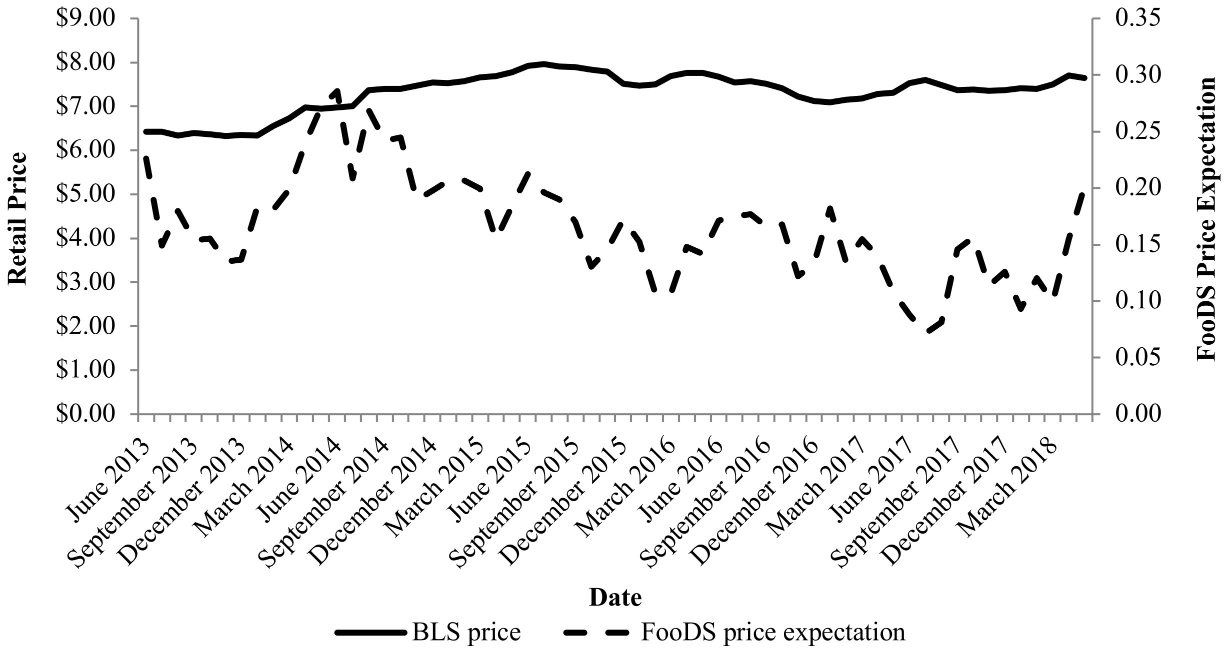


Figure 4. Uncooked Ground Beef BLS Prices and FooDS Price Expectations: June 2013–May 2018

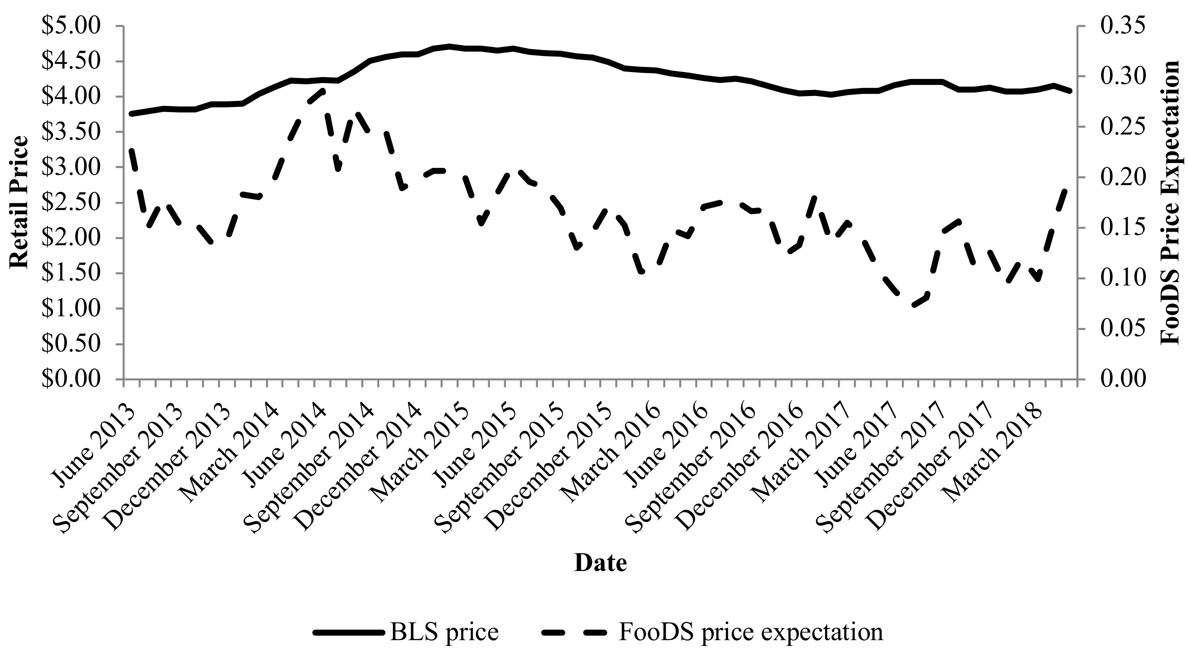


Figure 5. Pork Chop BLS Prices and FooDS Price Expectations: June 2013–May 2018

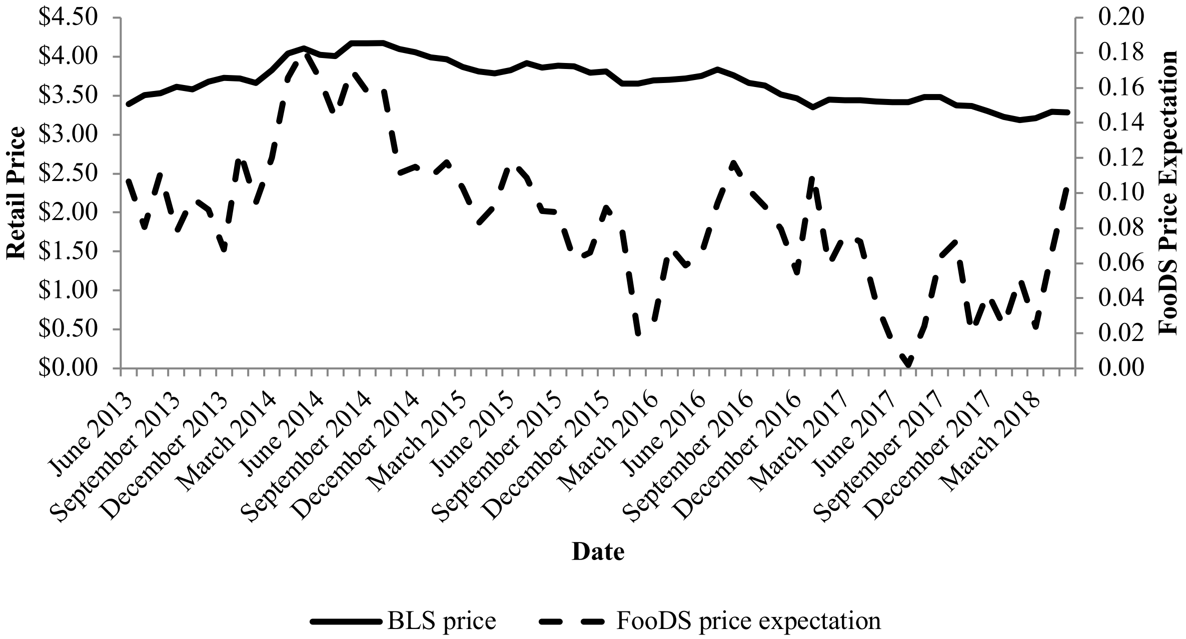


Figure 6. Deli Ham BLS Prices and FooDS Price Expectations: June 2013–May 2018

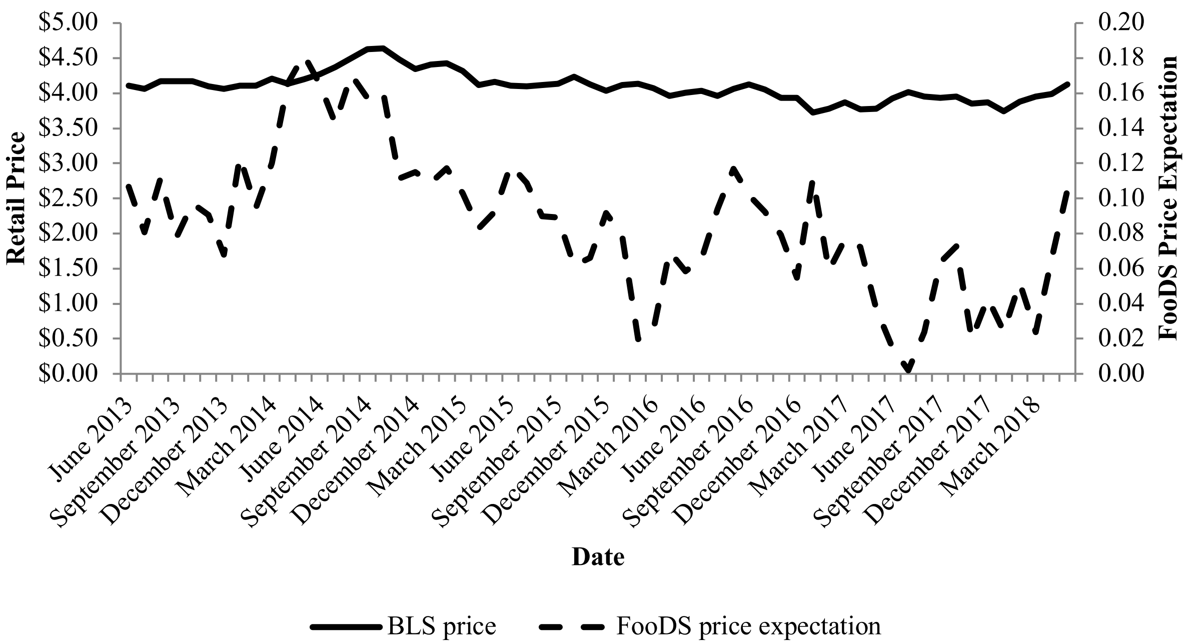


Figure 7. Chicken Breast BLS Prices and FooDS Price Expectations: June 2013–May 2018

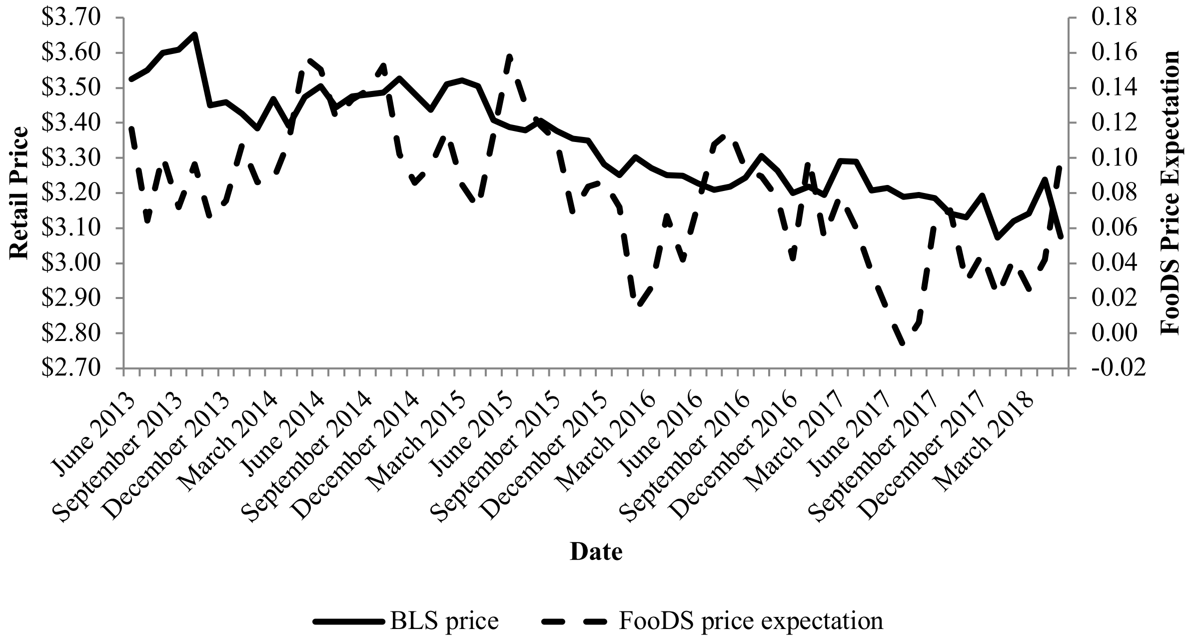
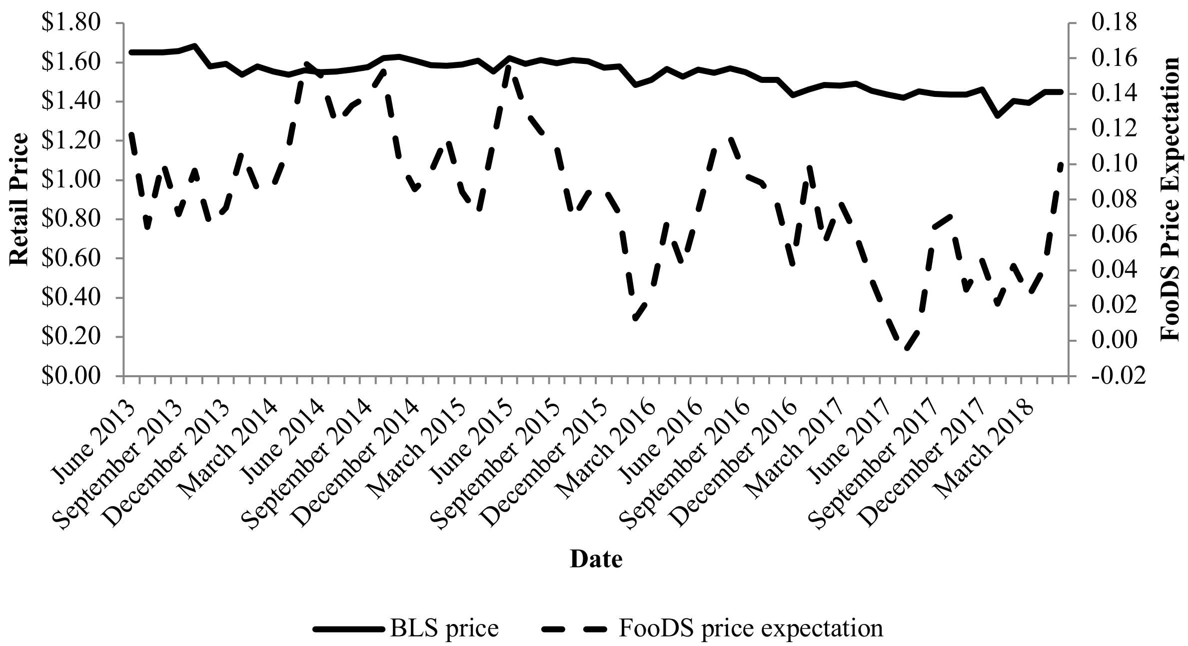


Figure 8. Chicken Wing BLS Prices and FooDS Price Expectations: June 2013–May 2018



price change(s) measured in FooDS for food product j at time t, M_i is a 0/1 monthly dummy variable (the month of December is dropped), and $\varepsilon_{j,t} \sim N(\mu_j, \sigma_{j,t}^2)$. BLS prices are specified at time t as a function of BLS prices two periods prior to the release date. This specification is adopted because the BLS does not release price data timely enough to use a one-period lag in real-world forecasting. While it would be possible to estimate a model with a one-period lag for BLS price changes, actual applied forecasts with this type of model would require forecasting 1 month ahead, and using this forecast to then forecast 2 months ahead to arrive at an actual forecast of the current period. Rather than adopting this approach, we chose the more practical method of estimating a model that has the data on hand needed to make the forecast of interest. The model in equation (2) uses current FooDS responses (e.g., June) to estimate current BLS prices (also June).

Table 1. Correlations between Same-Period BLS Prices and Survey-Based Expected Prices

Item	**Correlation**
Ground beef	0.277**
Beef steak	−0.116
Pork chop	0.718***
Deli ham	0.661***
Chicken breast	0.572***
Chicken wing	0.624***

Notes: Double and triple asterisks (**,***) represent significance at the 0.05 and 0.01 levels, respectively.

Before conducting any hypothesis tests regarding model specification, we first check to determine whether the linear relationship specified in equation (2) is mean-reverting. Engle and Granger (1987) discuss the decreased power of traditional Dickey–Fuller tests when multiple regressors are used in OLS regressions. For this reason, we use the Engle–Granger cointegration test, in which a Monte Carlo simulation is conducted to determine the critical value of test statistics. If data are not cointegrated, we take the first difference of BLS prices (i.e., price changes) and achieve cointegration.

After data in all models are cointegrated, we conduct diagnostic tests for autocorrelation and heteroskedasticity. By redefining the error terms and variances as $\varepsilon_{j,t} = \rho_j \varepsilon_{j,t-1} + v_{j,t}$ and $\sigma_{j,t}^2 = \delta_0 + \delta_{1,j} Z_{j,t}$, we test for the presence of autocorrelation and heteroskedasticity with the following hypotheses:

$$H_{01}: \rho_j = 0 \; vs. H_{a1}: \rho_j \neq 0, \text{ and}$$

$$H_{02}: \delta_{1,j} = 0 \; vs. H_{a2}: \delta_{1,j} \neq 0.$$

We use Durbin–Watson tests to test for the presence of autocorrelation and White's test for the presence of heteroskedasticity. If autocorrelation is present, we estimate autoregressive parameters; if heteroskedasticity is present, homoskedasticity is achieved through maximum likelihood estimation. Additionally, we conduct a joint hypothesis test to determine whether seasonal effects are present for all meats. Once appropriate corrections have been made, we test the key hypothesis that price expectations are a leading indicator of BLS prices by exploring whether $\beta_{2,j} = 0$.

We are also interested in the predictive power of equation (2), which can easily be defined as a general model nesting two separate autoregressive models. These autoregressive models are

$$BLSPrice_{j,t} = \alpha_{0,j} + \alpha_{1,j}BLSPrice_{j,t-2} + \sum_{i=1}^{11} \varphi_{i,j}M_i + \varepsilon_{j,t} \quad (3)$$

$$BLSPrice_{j,t} = \gamma_{0,j} + \gamma_{1,j}PE_{j,t} + \sum_{i=1}^{11} \varphi_{i,j}M_i + \varepsilon_{j,t}. \quad (4)$$

Because these models are not special cases of one another, an orthodox test can be conducted with equation (2) to determine which of equations (2) through (4) is the most appropriate, and accurate, forecast model. Specifically, the following hypotheses are tested independently:

$$H_{03}: \beta_{1,j} = 0 \; vs. H_{a3}: \beta_{1,j} \neq 0, \text{ and}$$

$$H_{04}: \beta_{2,j} = 0 \; vs. H_{a4}: \beta_{2,j} \neq 0.$$

If H_{03} is rejected but we fail to reject H_{04}, then equation (3) will yield the most accurate forecast. Similarly, if results indicate failure to reject H_{03} but reject H_{04}, then equation (4) is the most appropriate forecast model. If both H_{03} and H_{04} are rejected, then lagged BLS prices (or price changes) and price expectations from FooDS contain unique information and equation (2) will yield the most accurate forecast. Lastly, if we fail to reject both H_{03} and H_{04}, BLS prices and price expectations from FooDS contain the same information. In this case, equations (3) and (4) should yield similar forecast results.

Results

We calculated the correlation between BLS prices and FooDS variables to explore the same-period linear relationships between the variables. As shown in Table 1, a statistically significant positive correlation exists for all meat price measures, excluding beef steak. The correlation between beef steak BLS price change and FooDS price expectations is negative but not statistically significant.

Cointegration, Model Specification, and Orthodox Tests

Table 2 contains estimates from equation (2) as well as test statistics and associated statistical significance measures used to determine whether variables are cointegrated. It is important to note we failed to reject the hypothesis of no cointegration when estimating ground beef prices. As a result, we take the first difference of ground beef BLS prices and estimate respective price changes using the first difference of BLS prices lagged two periods and FooDS price expectations. All other meat prices are estimated in levels.

Table 2. Relationship between BLS Prices and FooDS Price Expectations: Equation (2)

Date	Beef Steak[a]	Ground Beef[b]	Chicken Breast[a]	Chicken Wing[a]	Pork Chop[a]	Ham[a]
β_0, constant	1.453***	−0.068	0.284	0.358***	3.286***	2.179
	(0.461)	(0.044)	(0.168)	(0.109)	(0.579)	(1.123)
β_1, BLS price lagged two periods	0.784***	-	0.889***	0.724***	0.053	0.441
	(0.060)	-	(0.053)	(0.071)	(0.156)	(0.266)
β_1, first difference of BLS price	-	−0.146	-	-	-	-
lagged two periods	-	(0.173)	-	-	-	-
β_2, FooDS price expectation	0.080	0.317	0.400	0.545***	0.592	0.260
	(0.386)	(0.229)	(0.230)	(0.139)	(0.391)	(0.412)
φ_1, January	0.032	0.005	−0.112	−0.028	−0.087***	0.017
	(0.038)	(0.025)	(0.022)	(0.022)	(0.032)	(0.052)
φ_2, February	0.141**	0.044	0.048**	0.003	−0.077	0.089
	(0.053)	(0.030)	(0.022)	(0.022)	(0.043)	(0.070)
φ_3, March	0.259***	0.043	0.113***	0.029	−0.047	0.115
	(0.050)	(0.033)	(0.022)	(0.022)	(0.053)	(0.073)
φ_4, April	0.324***	0.042	0.083***	0.044	−0.004	−0.003
	(0.045)	(0.035)	(0.022)	(0.022)	(0.058)	(0.064)
φ_5, May	0.250***	−0.015	−0.007	0.011	−0.001	0.049
	(0.049)	(0.036)	(0.022)	(0.022)	(0.059)	(0.066)
φ_6, June	0.230***	0.026	0.012	0.007	−0.002	0.136
	(0.056)	(0.038)	(0.025)	(0.023)	(0.059)	(0.088)
φ_7, July	0.188***	0.001	0.016	0.018	0.042	0.136
	(0.051)	(0.037)	(0.024)	(0.023)	(0.058)	(0.075)
φ_8, August	0.163	0.042	0.052**	0.028	0.064	0.166**
	(0.046)	(0.037)	(0.023)	(0.022)	(0.055)	(0.064)
φ_9, September	0.148***	0.031	0.072***	0.029	0.066	0.199***
	(0.050)	(0.033)	(0.023)	(0.022)	(0.050)	(0.064)
φ_{10}, October	0.086	−0.010	0.062***	0.024	0.035	0.178***
	(0.053)	(0.032)	(0.023)	(0.022)	(0.043)	(0.059)
φ_{11}, November	0.038	0.027	0.037	0.023	0.016	0.052
	(0.038)	(0.026)	(0.022)	(0.021)	(0.031)	(0.041)
Autocorrelation coefficients						
$\rho_{j,t-1}$	−0.890***	−0.533***	-	-	−0.968***	−0.857***
	(0.131)	(0.146)	-	-	(0.038)	(0.154)
$\rho_{j,t-2}$	0.647***	-	-	-	-	0.413
	(0.155)	-	-	-	-	(0.231)
$\rho_{j,t-3}$	−0.411***	-	-	-	-	−0.418**
	(0.125)	-	-	-	-	(0.172)
$\rho_{j,t-12}$	0.372***	-	-	-	-	-
	(0.083)	-	-	-	-	-
Diagnostic statistics						
Engle–Granger cointegration test	−4.373***	−5.140***	−5.791***	−5.668***	−5.178	−4.221***
Durbin–Watson test[c]	0.923***	1.253***	1.648	1.569	1.043***	1.062***
White's test[c]	50.740***	38.590***	44.100***	46.420**	39.050***	31.390**
$\varphi_1 = \varphi_2 = \cdots = \varphi_{10} = \varphi_{11} = 0$	6.160***	1.500	6.390***	1.470	1.210	2.520**
R^2	0.872	0.299	0.942	0.847	0.276	0.482

Notes: Double and triple asterisks (**,***) represent significance at the 0.05 and 0.01 levels, respectively. Numbers in parentheses are standard errors. *F*-value test statistics are shown for the joint hypothesis autocorrelation tests.

[a] Models are estimated in levels ($N = 58$).

[b] Model estimating price changes. In other words, the dependent variable(s) are in first-difference form ($N = 57$).

[c] Test conducted prior to maximum likelihood stepwise autoregression estimation.

Durbin–Watson tests indicate that positive autocorrelation is present in models estimating beef- and pork-related prices but absent when estimating chicken breast and wing prices. Failing to correct for positive autocorrelation would result in smaller error variance estimates; as a result, confidence intervals would be too small and true null hypotheses would be rejected with a higher probability than the stated significance. In addition, we reject the null hypothesis of no heteroskedasticity for all meat price estimation models. As a result, $\delta_{1,j}$ is statistically different from 0 in all models. We correct for autocorrelation and heteroskedasticity using maximum likelihood stepwise autoregression estimation, resulting in the recovery of all efficiency properties.

Results in Table 2 indicate that β_1 and β_2 are statistically different from 0 when estimating chicken wing prices. That is, we reject H_{03} and H_{04} for chicken wing and BLS prices and FooDS chicken price expectations are both considered leading indicators. H_{03} is rejected when estimating beef steak and chicken breast, whereas we fail to reject H_{04}. This means that previous beef steak and chicken breast BLS prices are leading indicators of current (and future) beef steak and chicken breast prices but associated FooDS price expectations are not. Additionally, we fail to reject H_{03} and H_{04} for ground beef, pork chop, and ham price estimates. That is, ground beef, pork chop, and ham FooDS price expectation(s) and lagged BLS prices (differences) contain the same information, and forecasts from equations (3) and (4) will yield similar estimates. In short, equation (2) is the most appropriate for estimating chicken wing prices, equation (3) is most appropriate for estimating beef steak and chicken breast prices, and either equation (3) or equation (4) can be used to estimate ground beef, pork chop, and ham prices.

Table 3 contains results associated with beef steak, ground beef, chicken breast, pork chop, and ham price estimates using equation (3), and Table 4 contains results associated with ground beef, pork chop, and ham price estimates using equation (4). Both equations indicate that seasonal variation is present in ham prices, and equation (3) indicates that beef steak and chicken breast prices are seasonal. Although orthodox tests indicate lagged BLS price changes and FooDS beef price expectations contain the same information, different effects are captured by respective parameters. For example, for every \$1 increase in ground beef prices (e.g., $BLS_{ground\ beef,July}$), retail ground beef prices ($BLSPrice_{beef\ steak,September}$) are expected to decrease by an average of \$0.11. The opposite relationship is observed between retail ground beef price changes and FooDS beef price expectations through equation (4); for every one unit increase in consumers' beef price expectations (e.g., $PE_{beef,July}$), retail ground beef prices ($BLSPrice_{ground\ beef,July}$) are expected to increase by an average of \$0.27. Interestingly, FooDS pork price expectations and lagged pork chop and deli ham prices are both found to have positive relationships with respective prices.

Conclusions

Analysis of study results indicates that U.S. consumers' chicken price expectations obtained through a consumer survey (FooDS) are leading indicators of chicken wing prices in the United States. Increased accuracy of future price estimates not only affords retailers the ability to formulate appropriate marketing strategies at an earlier date, but also empowers them with confidence regarding procurement decisions. That is, accurate price forecasts allow retailers to determine the market equilibrium more confidently in terms of quantity demanded of each

Table 3. Relationship between BLS Prices and Lagged BLS Prices: Equation (3)

Date	Beef Steak[a]	Ground Beef[b]	Chicken Breast[a]	Pork Chop[a]	Ham[a]
β_0, constant	1.502***	−0.018	0.094	1.321**	2.241
	(0.436)	(0.027)	(0.130)	(0.612)	(1.123)
β_1, BLS price lagged two periods	0.779***	-	0.953***	0.623***	0.431
	(0.059)	-	(0.038)	(0.172)	(0.266)
β_1, first difference of BLS price lagged	-	−0.112	-	-	-
two periods	-	(0.170)	-	-	-
φ_1, January	0.032	0.007	−0.004	−0.057	0.019
	(0.038)	(0.025)	(0.022)	(0.039)	(0.050)
φ_2, February	0.140**	0.043	0.049**	−0.051	0.085
	(0.053)	(0.031)	(0.022)	(0.057)	(0.069)
φ_3, March	0.257***	0.042	0.117***	0.025	0.112
	(0.050)	(0.034)	(0.022)	(0.058)	(0.072)
φ_4, April	0.324***	0.045	0.087***	0.084	0.0001
	(0.045)	(0.036)	(0.022)	(0.053)	(0.063)
φ_5, May	0.251***	−0.009	0.002	0.078	0.053
	(0.048)	(0.037)	(0.022)	(0.056)	(0.065)
φ_6, June	0.233***	0.036	0.027	0.041	0.138
	(0.055)	(0.038)	(0.023)	(0.060)	(0.086)
φ_7, July	0.189***	0.004	0.030	0.074	0.138
	(0.051)	(0.038)	(0.023)	(0.055)	(0.074)
φ_8, August	0.166***	0.047	0.066***	0.112**	0.171***
	(0.044)	(0.038)	(0.022)	(0.049)	(0.062)
φ_9, September	0.150***	0.037	0.087***	0.079	0.204***
	(0.049)	(0.034)	(0.022)	(0.054)	(0.062)
φ_{10}, October	0.087	−0.007	0.074***	0.029	0.183***
	(0.053)	(0.032)	(0.022)	(0.056)	(0.057)
φ_{11}, November	0.037	0.021	0.041	−0.005	0.052
	(0.038)	(0.026)	(0.022)	(0.039)	(0.040)
Autocorrelation coefficients					
$\rho_{j,t-1}$	−0.897***	−0.576***	-	−1.094***	−0.870***
	(0.128)	(0.137)	-	(0.132)	(0.152)
$\rho_{j,t-2}$	0.651***	-	-	0.747***	0.398
	(0.154)	-	-	(0.187)	(0.236)
$\rho_{j,t-3}$	−0.423***	-	-	−0.564***	−0.405**
	(0.121)	-	-	(0.131)	(0.181)
$\rho_{j,t-12}$	0.364***	-	-	-	-
	(0.080)	-	-	-	-
Diagnostic statistics					
$\varphi_1 = \varphi_2 = \cdots = \varphi_{10} = \varphi_{11} = 0$	6.280***	1.460	6.450***	1.520	2.640**
R^2	0.865	0.277	0.940	0.527	0.467

Notes: Double and triple asterisks (**,***) represent significance at the 0.05 and 0.01 levels, respectively. Numbers in parentheses are standard errors.
[a] Models are estimated in levels ($N = 58$).
[b] Model is estimating price changes. In other words, the dependent variable is in first difference form ($N = 57$).

Table 4. Relationship between BLS Prices and FooDS Price Expectations: Equation (4)

Date	**Ground Beef**[a]	**Pork Chop**[b]	**Ham**[b]
β_0, constant	−0.057	3.450***	4.048***
	(0.040)	(0.238)	(0.119)
β_2, FooDS price expectation	0.273	0.526	0.147
	(0.207)	(0.378)	(0.423)
φ_1, January	0.001	−0.089***	−0.031
	(0.025)	(0.031)	(0.035)
φ_2, February	0.042	−0.082	0.019
	(0.030)	(0.041)	(0.046)
φ_3, March	0.041	−0.058	0.034
	(0.032)	(0.048)	(0.053)
φ_4, April	0.036	−0.015	−0.061
	(0.033)	(0.052)	(0.058)
φ_5, May	−0.020	−0.012	−0.001
	(0.034)	(0.055)	(0.061)
φ_6, June	0.027	−0.013	0.046
	(0.035)	(0.056)	(0.062)
φ_7, July	0.012	0.048	0.058
	(0.033)	(0.055)	(0.061)
φ_8, August	0.040	0.068	0.114
	(0.033)	(0.053)	(0.059)
φ_9, September	0.028	0.072	0.151***
	(0.032)	(0.048)	(0.054)
φ_{10}, October	−0.018	0.041	0.159***
	(0.030)	(0.042)	(0.047)
φ_{11}, November	0.020	0.019	0.049
	(0.025)	(0.030)	(0.034)
Autocorrelation coefficient			
$\rho_{j,t-1}$	−0.465**	−0.973***	−0.921***
	(0.136)	(0.030)	(0.053)
Diagnostic statistics			
$\varphi_1 = \varphi_2 = \cdots = \varphi_{10} = \varphi_{11} = 0$	1.450	1.480	2.680***
R^2	0.277	0.288	0.392

Notes: Double and triple asterisks (**,***) represent significance at the 0.05 and 0.01 levels, respectively. Numbers in parentheses are standard errors.
[a] Model is estimating price changes. In other words, the dependent variable is in first difference form ($N = 59$).
[b] Models are estimated in levels ($N = 60$).

product at the retail level. This prevents retailers from procuring more of a product than will be demanded by consumers, ultimately resulting in the loss of potential profit from procurement costs not covered by overestimated sales. Accurate forecasts of future retail prices should also reduce asymmetric price information.

Although results suggest there is some explanatory power in the aggregation of (FooDS) survey responses, there are some (difficult to handle) issues that might restrict forecast performance. Changes in the survey itself might be beneficial. The main problem with the survey pertains to the timing of administration. That is, the administration of FooDS occurs at a different time than when BLS price data are *released*. Due to the longevity of the survey, imposing drastic changes to FooDS would pose larger problems than any associated with this study. As a result, we sought out alternative solutions. Disaggregated, weekly prices were obtained from the Agricultural Marketing Service (AMS) and used as a proxy for lagged BLS prices; results are similar to those discussed above.[4]

In addition, the distinction between measurements reported by FooDS and the BLS should be considered. For instance, the wording of the questions asked in FooDS used to construct price expectations can be interpreted as consumers' expectations regarding beef, pork, and chicken prices in the next 2 weeks relative to the previous 2 weeks. Therefore, because the survey is administered in the middle of each month, price expectation measurements are interpreted as consumers' expected (monthly) price changes. Although asked differently in FooDS, respondents are asked comparable questions to those in the highly regarded and closely followed Conference Board's Consumer Confidence Index Survey and the Michigan Survey of Consumers administered by the University of Michigan. On the other hand, the BLS reports average retail prices rather than price changes.

While economic theory is typically void of anomalies, there are instances in which deviations from commonly accepted principles arise. Specific to the study at hand, Baucells and Hwang (2017) note five prominent anomalies in which decision making deviates from classical economic rationality: i) sunk-cost effects (Thaler, 1980; Arkes and Blumer, 1985), ii) payment depreciation (Gourville and Soman, 1998), iii) reluctance to trade (Thaler, 1985; Novemsky and Kahneman, 2005), iv) preference for up-front payment (Prelec and Loewenstein, 1998), and v) flat-rate bias (Della Vigna and Malmendier, 2006; Lambrecht and Skiera, 2006). Anomalies such as these are not compatible with traditional discounted utility model(s) and have resulted in modifications of the rational model. Namely, Thaler (1985) recognizes the central role of reference-price comparisons and proposes a model in which consumers obtain transaction utility by comparing reference prices with actual prices to explain anomalies i) and iii). Koszegi and Rabin (2006) propose a model in which reference prices form and adapt by a process of anticipation. This model explains anomalies i), iii), and v). Because purchase decisions are made by consumers with reference prices in mind, quantity of products demanded sets the retail market equilibrium prices. Moreover, deviations from classical economic rationale, now supported by updated theories, provide insight into why consumer expectations about future prices (derived from reference prices) provide more accurate price forecasts than lagged (realized) prices alone.

[4] Results associated with models incorporating AMS retail price data are in the appendix.

Perhaps knowledge gained from this study, as well as various demand studies, will enable researchers to develop more accurate price estimation models. For instance, Piggott and Marsh (2010) discuss the possibility of demand models specifying prices as a function of quantities. This is motivated by the perishable nature of many foods now consumed and, consequently, limited storage, and the biological lag inherent in the production of most food products and byproducts sold in the retail setting. Because of the biological lag, many food products are essentially fixed in quantity in the short run (Christensen and Manser, 1977; Huang, 1988). This model specification, grounded in economic theory, suggests food quantities are exogenous (supply is inelastic), and prices must adjust to establish a market equilibrium. This specification of demand model(s) and others similar to it are often estimated as a complete system of demand in which not only the quantity of good i affects equilibrium prices for good i, but the quantity of $n - 1$ complements and substitutes does as well. In turn, this allows for the estimation of elasticity measurements to determine the effect of complements and substitutes on the prices of each food. In other words, the literature has built on the economic theory of cross-price and cross-quantity relationships. Future research should not limit econometric models seeking to estimate (future) prices to exogenous variables directly related to endogenous variables. Instead, exogenous variables shown to have indirect effects on endogenous variables in question should also be considered.

Often, the topic of external validity arises when researchers implement primary data in their analyses. While researchers exercise extreme caution in the methods used to collect and analyze primary data, this study supports the notion that external validity is associated with information collected through experiments and surveys. In the same vein, external validity is not always associated with primary data collection, as observed through results associated with ground beef, pork chop, and deli ham price estimations.

Results presented in this study verify findings by Thaler (1985) and Koszegi and Rabin (2006) that consumers use reference prices to dictate purchasing decisions. However, we show that there is merit in using aggregate price expectations to forecast future meat prices through econometric modeling. As alluded to earlier, it seems that piecing together knowledge provided by the study at hand and studies in the demand (e.g., Deaton and Muellbauer, 1980; Eales and Unnevehr; 1994), machine learning (e.g., Bryant, Bessler, and Haigh, 2009; Pearl, 2014), and price analysis (e.g., Thaler 1985; Koszegi and Rabin, 2006) literatures will help future researchers as they attempt to accurately forecast prices. Moreover, although advances in technology and increased access to information have yielded instrumental variables not previously available, inadequate data or inappropriate alternatives often forces researchers to settle for less appropriate data generating process specifications or abandon research projects when unavoidable econometric problems arise and no viable solution is available. Because prices are often used to evaluate market structures and competition, estimate demand, determine project feasibility, or determine the most profitable production practices, future research might benefit from the use of aggregate price expectations as instrumental variables in lieu of realized prices.

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Appendix

AMS Retail Prices

The USDA Agriculture Marketing Service (AMS) publishes average U.S. retail meat prices on a weekly basis. Table A1 shows AMS retail items averaged each week to determine weekly AMS beef steak, ground beef, pork chop, deli ham, chicken breast, and chicken wing retail prices. Because FooDS is administered on the 10th of each month (unless the 10th falls on a weekend), we use AMS retail prices reported on or before the 10th of each month (from June 2013–May 2018). Figures A1–A6 show BLS and AMS prices and associated FooDS price expectations.

Table A1. AMS Retail Item Definitions

Food Product	**AMS–Defined Retail Item(S)**
Beef steak	Ground beef 70%–79%, Ground beef 80%–89%, Ground beef 90% or more
Ground beef	Bone-in ribeye steak, boneless ribeye steak, T-bone steak, porterhouse steak, filet mignon, bone-in strip steak, boneless New York strip steak, sirloin steak, boneless sirloin steak, sirloin tip steak, boneless top sirloin steak, top round steak, bottom round steak, eye of round steak, rump steak, chuck/shoulder/arm steak, flat iron steak, flank steak, minute/cube steaks, tri-tip, skirt steak
Pork chop	Rib end chops bone-in, sirloin chops bone-in, center cut chops bone-in, assorted chops bone-in, rib chops boneless, sirloin chops boneless, center cut chops boneless, smoked chops
Deli ham	Deli ham
Chicken breast	Boneless/skinless marinated breast, boneless/skinless thin-sliced breast, boneless/skinless IQF breast, boneless/skinless regular pack breast, boneless/skinless organic breast, boneless/skinless specialty breast, boneless/skinless value pack breast
Chicken wing	Fried/baked bone-in wings, fried/baked boneless wings, party wings IQF, specialty whole wings, conventional whole wings, conventional whole wings IQF

Figure A1. Uncooked Beef Steak BLS, AMS, and FooDS Price Expectations: June 2013–May 2018

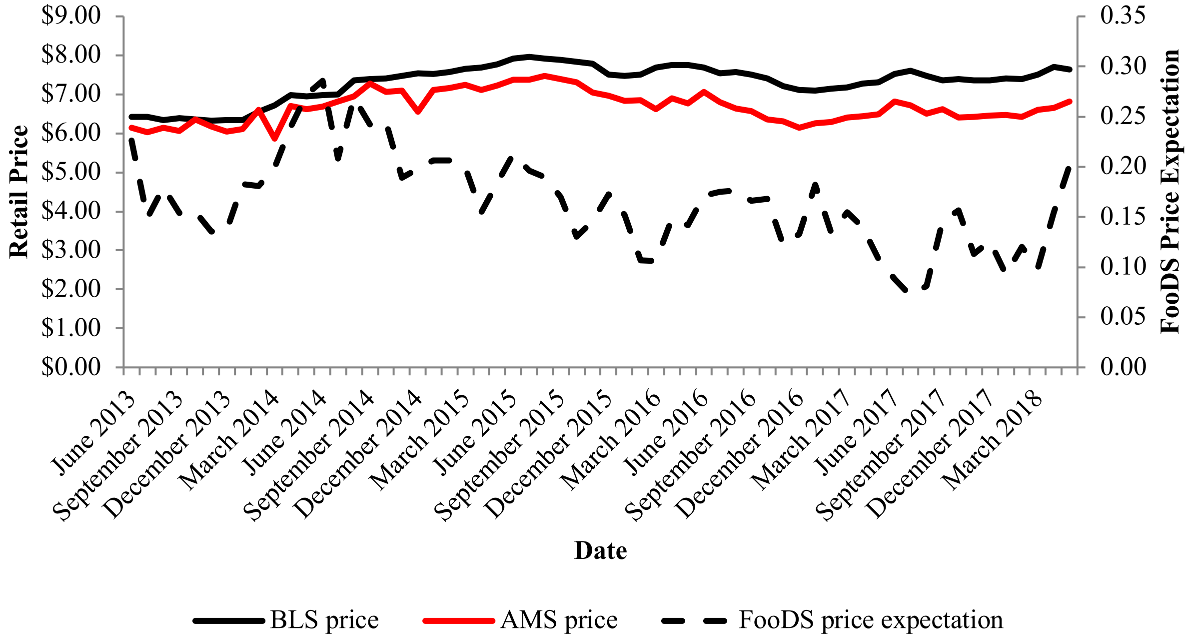


Figure A2. Uncooked Ground Beef BLS, AMS, and FooDS Price Expectations: June 2013–May 2018

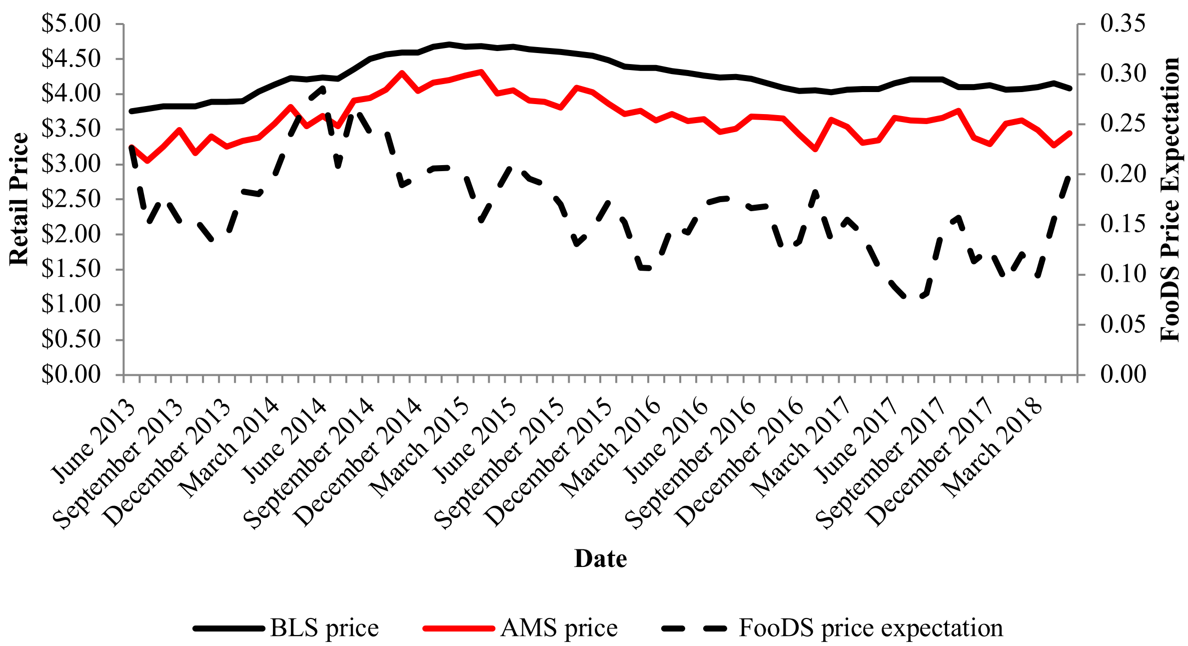


Figure A3. Pork Chop BLS, AMS, and FooDS Price Expectations: June 2013–May 2018

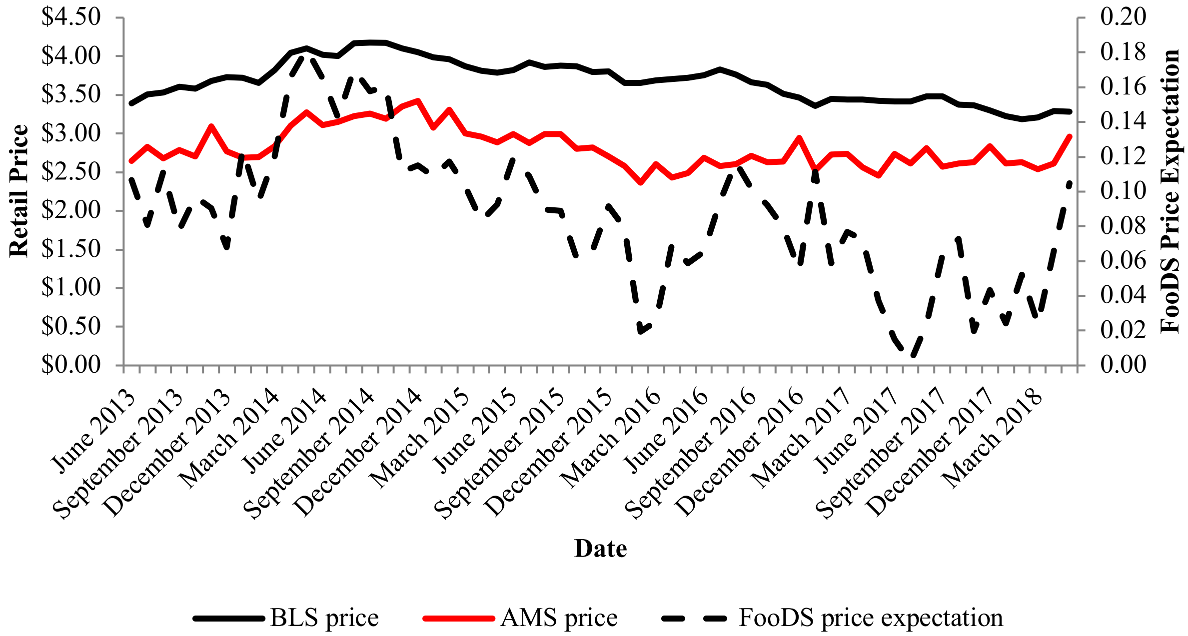


Figure A4. Deli Ham BLS, AMS, and FooDS Price Expectations: June 2013–May 2018

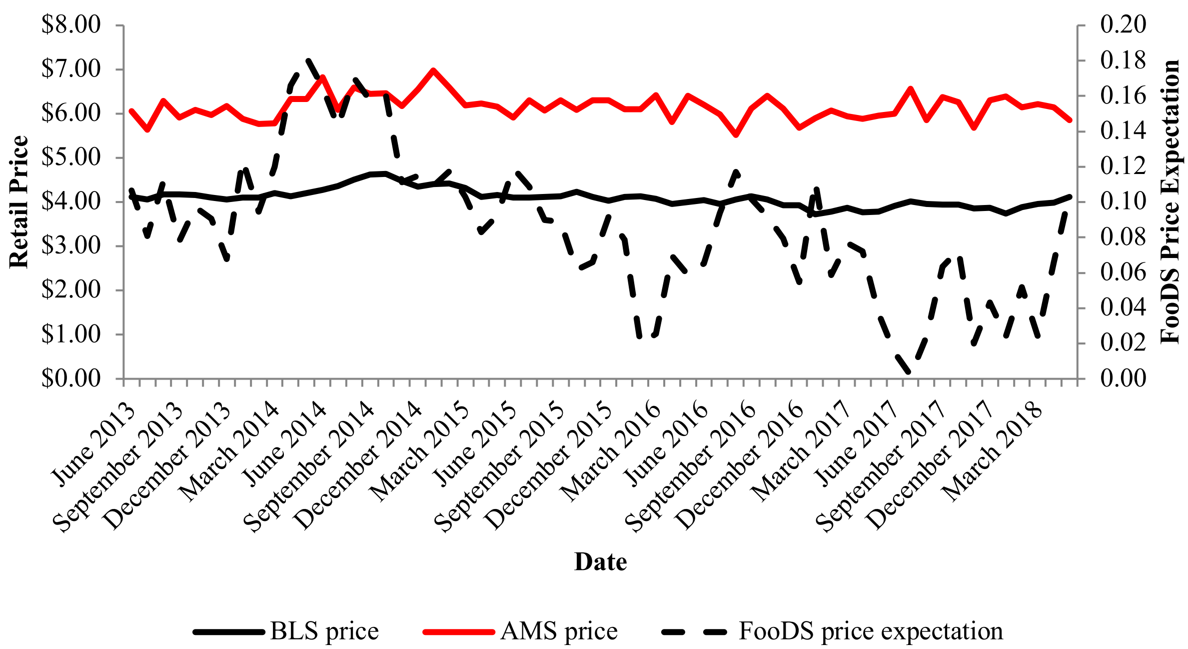


Figure A5. Chicken Breast BLS, AMS, and FooDS Price Expectations: June 2013–May 2018

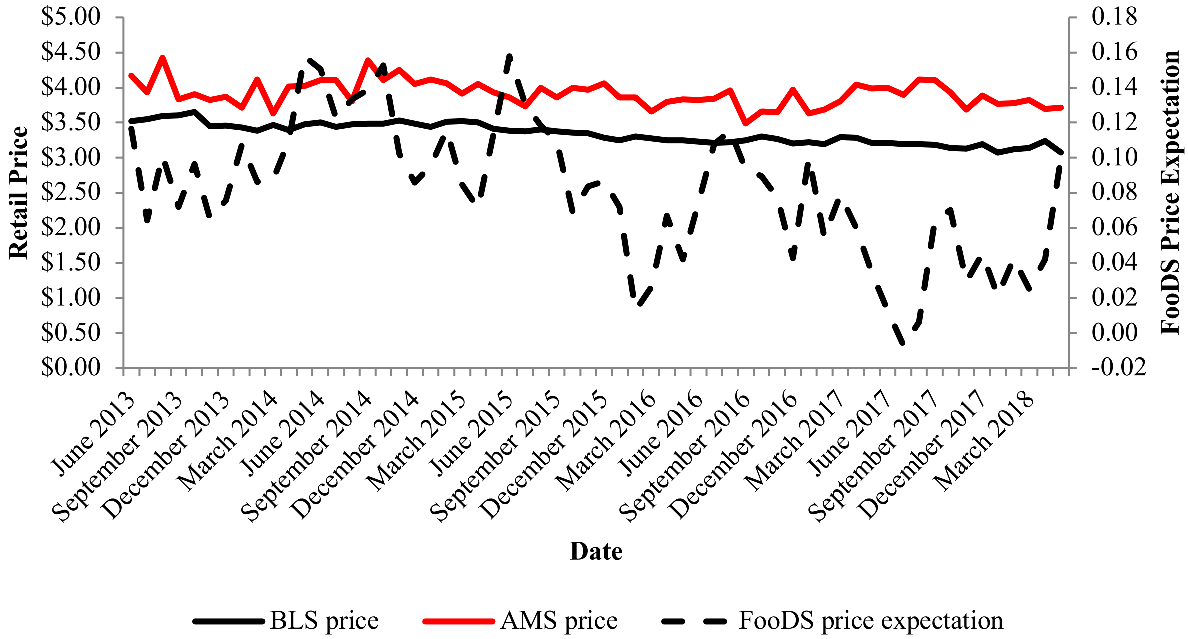
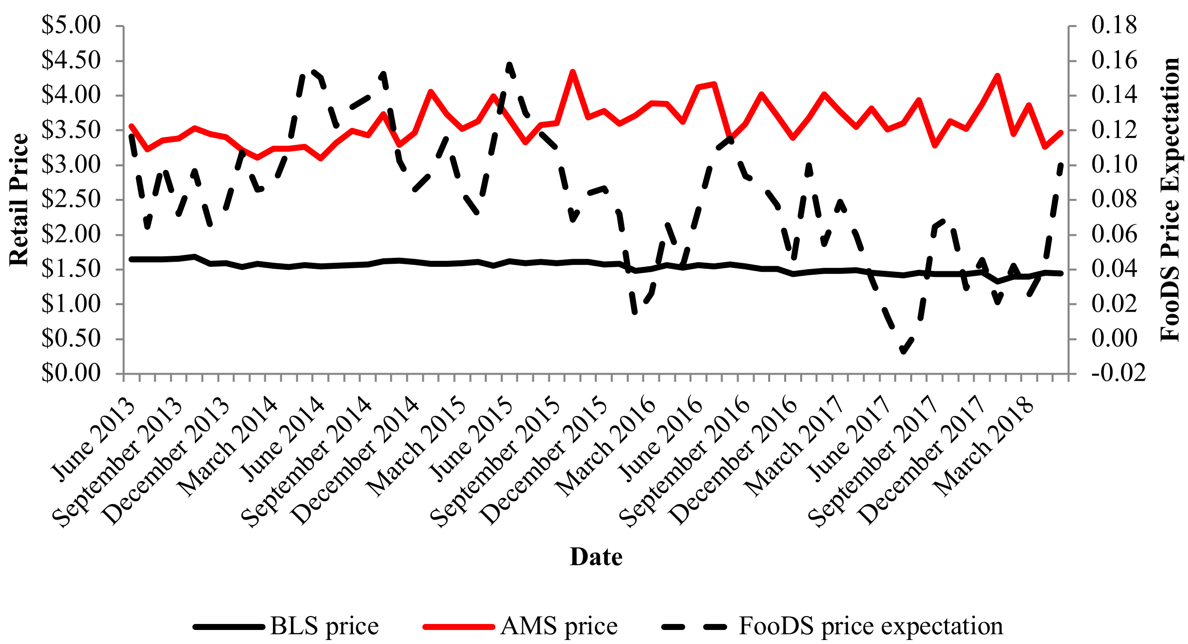


Figure A6. Chicken Wing BLS, AMS, and FooDS Price Expectations: June 2013–May 2018



To determine whether AMS prices are more appropriate leading indicators than FooDS price expectations, we conduct an orthodox test using the following model specification:

$$\text{(A1)} \qquad BLSPrice_{j,t} = \beta_{0,j} + \beta_{1,j}AMSPrice_{j,t} + \beta_{2,j}PE_{j,t} + \sum_{i=1}^{11} \varphi_{i,j}M_i + \varepsilon_{j,t}$$

because, like equation (2), we can define equation (A1) as a general model nesting two separate autoregressive models. These autoregressive models are

$$\text{(A2)} \qquad BLSPrice_{j,t} = \gamma_{0,j} + \gamma_{1,j}AMSPrice_{j,t} + \sum_{i=1}^{11} \varphi_{i,j}M_i + \epsilon_{j,t}$$

$$\text{(A3)} \qquad BLSPrice_{j,t} = \alpha_{0,j} + \alpha_{2,j}PE_{j,t} + \sum_{i=1}^{11} \varphi_{i,j}M_i + v_{j,t}$$

where all variables are as previously defined and $AMSPrice_{j,t}$ represents the AMS retail price of good j at time t. After ensuring stationarity, accounting for and correcting autocorrelation and heteroskedasticity, and checking for seasonality, we conduct an orthodox test in which the following hypotheses are tested independently:

$$H_{05}: \beta_{1,j} = 0 \; vs. H_{a5}: \beta_{1,j} \neq 0, \text{ and}$$

$$H_{06}: \beta_{2,j} = 0 \; vs. H_{a6}: \beta_{2,j} \neq 0.$$

Results are presented in the same manner as those regarding the relationship between BLS prices and FooDS price expectations. Table A2 indicates that all variables in all models estimating prices in levels are cointegrated, excluding pork chop. Thus, we take the first difference of BLS and AMS pork chop prices to ensure estimates associated with data are mean-reverting. Results indicate that positive autocorrelation is present in all meat price estimation models, except for pork chop, and heteroskedasticity is an issue for all equations. In turn, we estimate these models with maximum likelihood stepwise autoregression. Results in Table A2 indicate rejection of H_{06} when estimating chicken wing prices but failure to reject H_{05}. This suggests that FooDS chicken price expectations are leading indicators of chicken wing prices, while AMS chicken wing prices are not leading indicators. Furthermore, when estimating beef steak, ground beef, chicken breast, and ham prices along with pork chop price changes, we fail to reject both H_{05} and H_{06}. In other words, AMS prices and FooDS price expectations contain similar information. Table A3 shows estimates associated with equation (A2) and Table A4 shows estimates associated with equation (A3), when necessary.

Table A2. Relationship between BLS Prices, FooDS Price Expectations, and AMS Prices: Equation (A1)

Date	Beef Steak[a]	Ground Beef[a]	Chicken Breast[a]	Chicken Wing[a]	Pork Chop[b]	Ham[a]
β_0, constant	6.114***	4.011***	3.212***	1.498***	−0.034	4.047***
	(0.767)	(0.183)	(0.184)	(0.092)	(0.038)	(0.223)
β_1, AMS price	0.130	0.042	0.022	0.0004	-	0.0003
	(0.073)	(0.038)	(0.033)	(0.022)	-	(0.029)
β_1, first difference of AMS price	-	-	-	-	0.058	-
	-	-	-	-	(0.047)	-
β_2, FooDS price expectation	−0.241	0.074	0.208	0.537***	0.147	0.147
	(0.501)	(0.208)	(0.287)	(0.187)	(0.265)	(0.432)
φ_1, January	0.0001	−0.014	−0.032	−0.040**	−0.054	−0.031
	(0.047)	(0.019)	(0.026)	(0.016)	(0.047)	(0.035)
φ_2, February	0.038	0.009	−0.001	−0.019	0.017	0.019
	(0.061)	(0.025)	(0.034)	(0.022)	(0.046)	(0.048)
φ_3, March	0.098	0.019	0.040	−0.017	0.051	0.034
	(0.070)	(0.029)	(0.040)	(0.025)	(0.046)	(0.054)
φ_4, April	0.205**	0.040	0.042	0.007	0.075**	−0.061
	(0.077)	(0.031)	(0.043)	(0.027)	(0.037)	(0.059)
φ_5, May	0.165	0.003	−0.007	−0.023	0.028	−0.001
	(0.084)	(0.034)	(0.046)	(0.029)	(0.046)	(0.062)
φ_6, June	0.217**	0.020	−0.001	−0.004	0.009	0.050
	(0.087)	(0.035)	(0.047)	(0.029)	(0.048)	(0.063)
φ_7, July	0.204**	0.024	−0.008	−0.003	0.081	0.058
	(0.082)	(0.033)	(0.045)	(0.029)	(0.046)	(0.062)
φ_8, August	0.203**	0.044	0.022	0.012	0.042	0.114
	(0.080)	(0.031)	(0.043)	(0.028)	(0.037)	(0.060)
φ_9, September	0.177**	0.061**	0.033	0.007	0.013	0.151***
	(0.072)	(0.029)	(0.041)	(0.026)	(0.046)	(0.055)
φ_{10}, October	0.124	0.022	0.048	0.018	−0.015	0.159***
	(0.062)	(0.025)	(0.035)	(0.022)	(0.046)	(0.035)
φ_{11}, November	0.046	0.016	0.012	0.014	−0.011	0.049
	(0.048)	(0.019)	(0.025)	(0.016)	(0.046)	(0.035)
Autocorrelation coefficients						
$\rho_{j,t-1}$	−0.987***	−1.113***	−0.953***	−0.883***	-	−0.921***
	(0.021)	(0.035)	(0.052)	(0.071)	-	(0.054)
$\rho_{j,t-6}$	-	0.162***	-	-	-	-
	-	(0.034)	-	-	-	-
Diagnostic statistics						
Engle–Granger cointegration test	−5.472***	−5.054***	−4.655***	−4.566***	−6.648	−4.476**
Durbin–Watson test[c]	0.876***	1.207***	0.438***	0.481***	1.648	0.917***
White's test[c]	40.960***	31.120***	38.910***	39.350***	44.730***	39.920***
$\varphi_1 = \varphi_2 = \cdots = \varphi_{10} = \varphi_{11} = 0$	1.280	1.340	1.190	1.340	1.890	2.620**
R^2	0.332	0.280	0.240	0.343	0.354	0.392

Notes: Double and triple asterisks (**,***) represent significance at the 0.05 and 0.01 levels, respectively. Numbers in parentheses are standard errors. F-value test statistics are shown for the joint hypothesis autocorrelation tests.
[a] Model(s) are estimated in levels (N=60).
[b] Model estimating price changes. In other words, the dependent variable(s) are in first difference form ($N = 59$).
[c] Test conducted prior to maximum likelihood stepwise autoregression estimation.

Table A3. Relationship between BLS Prices and AMS Prices: Equation (A2)

Date	**Beef Steak**[a]	**Ground Beef**[a]	**Chicken Breast**[a]	**Pork Chop**[b]	**Ham**[a]
β_0, constant	6.128***	4.022***	3.195***	−0.023	4.075***
	(0.772)	(0.178)	(0.224)	(0.032)	(0.216)
β_1, AMS price	0.124	0.044	0.032	-	−0.002
	(0.071)	(0.037)	(0.038)	-	(0.029)
β_1, first difference of AMS price	-	-	-	0.062	-
	-	-	-	(0.046)	-
φ_1, January	−0.004	−0.013	−0.028	−0.051	−0.029
	(0.046)	(0.019)	(0.027)	(0.047)	(0.035)
φ_2, February	0.038	0.009	−0.001	0.016	0.017
	(0.061)	(0.025)	(0.028)	(0.046)	(0.048)
φ_3, March	0.099	0.018	0.038	0.050	0.032
	(0.069)	(0.028)	(0.031)	(0.047)	(0.055)
φ_4, April	0.202**	0.040	0.043	0.078**	−0.059
	(0.076)	(0.031)	(0.033)	(0.036)	(0.060)
φ_5, May	0.161	0.004	−0.002	0.031	0.001
	(0.083)	(0.033)	(0.035)	(0.046)	(0.062)
φ_6, June	0.209**	0.022	0.012	0.011	0.049
	(0.084)	(0.034)	(0.035)	(0.048)	(0.063)
φ_7, July	0.204**	0.024	−0.003	0.083	0.060
	(0.081)	(0.033)	(0.034)	(0.046)	(0.063)
φ_8, August	0.199**	0.045	0.030	0.045	0.118
	(0.079)	(0.030)	(0.033)	(0.036)	(0.060)
φ_9, September	0.173**	0.063**	0.041	0.017	0.155***
	(0.071)	(0.028)	(0.032)	(0.046)	(0.055)
φ_{10}, October	0.121	0.024	0.056**	−0.011	0.162***
	(0.061)	(0.024)	(0.027)	(0.046)	(0.047)
φ_{11}, November	0.051	0.015	0.012	−0.011	0.048
	(0.046)	(0.019)	(0.026)	(0.046)	(0.035)
Autocorrelation coefficients					
$\rho_{j,t-1}$	−0.988***	−1.113***	−0.581***	-	−0.936***
	(0.021)	(0.034)	(0.150)	-	(0.111)
$\rho_{j,t-2}$	-	-	−0.393**	-	-
	-	-	(0.152)	-	-
$\rho_{j,t-3}$	-	-	-	-	0.014
	-	-	-	-	(0.112)
$\rho_{j,t-6}$	-	0.163***	-	-	-
	-	(0.033)	-	-	-
Diagnostic statistics				-	
$\varphi_1 = \varphi_2 = \cdots = \varphi_{10} = \varphi_{11} = 0$	1.280	1.380	1.630	1.970	2.620**
R^2	0.328	0.279	0.295	0.351	0.391

Notes: Double and triple asterisks (**,***) represent significance at the 0.05 and 0.01 levels, respectively. Numbers in parentheses are standard errors.

[a] Models are estimated in levels ($N = 60$).

[b] Model estimating price changes. In other words, the dependent variable(s) are in first difference form ($N = 59$).

Table A4. Relationship between BLS Prices and FooDS Price Expectations: Equation (A3)

Date	Beef Steak[a]	Ground Beef[a]	Chicken Breast[a]	Chicken Wing[a]	Pork Chop[b]	Ham[a]
β_0, constant	6.908***	3.974***	3.300***	1.499***	−0.049	4.048***
	(0.675)	(0.272)	(0.137)	(0.042)	(0.028)	(0.119)
β_2, FooDS price	−0.067	0.198	0.220	0.536***	0.322	0.147
expectation	(0.503)	(0.266)	(0.285)	(0.181)	(0.236)	(0.423)
φ_1, January	−0.027	−0.019	−0.037	−0.040**	−0.069**	−0.031
	(0.046)	(0.024)	(0.025)	(0.016)	(0.030)	(0.035)
φ_2, February	0.017	0.004	−0.006	−0.019	0.030	0.019
	(0.061)	(0.032)	(0.034)	(0.021)	(0.030)	(0.046)
φ_3, March	0.112	0.023	0.038	−0.017	0.042	0.034
	(0.071)	(0.038)	(0.039)	(0.025)	(0.030)	(0.053)
φ_4, April	0.220***	0.038	0.039	0.007	0.060**	−0.061
	(0.078)	(0.041)	(0.043)	(0.027)	(0.026)	(0.058)
φ_5, May	0.206**	−0.0001	−0.010	−0.023	0.024	−0.001
	(0.083)	(0.044)	(0.045)	(0.028)	(0.030)	(0.061)
φ_6, June	0.256***	0.013	−0.002	−0.004	0.022	0.046
	(0.086)	(0.045)	(0.046)	(0.029)	(0.032)	(0.062)
φ_7, July	0.237***	0.016	−0.008	−0.003	0.071**	0.058
	(0.081)	(0.043)	(0.045)	(0.028)	(0.030)	(0.061)
φ_8, August	0.242	0.039	0.021	0.012	0.038	0.114
	(0.079)	(0.042)	(0.043)	(0.027)	(0.027)	(0.059)
φ_9, September	0.200***	0.054	0.028	0.007	0.008	0.151***
	(0.072)	(0.038)	(0.040)	(0.025)	(0.031)	(0.054)
φ_{10}, October	0.148**	0.022	0.045	0.018	−0.010	0.159***
	(0.062)	(0.033)	(0.034)	(0.022)	(0.031)	(0.047)
φ_{11}, November	0.076	0.023	0.013	0.014	−0.024	0.049
	(0.046)	(0.024)	(0.025)	(0.016)	(0.030)	(0.034)
Autocorrelation coefficients						
$\rho_{j,t-1}$	−0.988***	−0.985***	−0.952***	−0.884***	-	−0.921***
	(0.020)	(0.018)	(0.051)	(0.070)	-	(0.053)
Diagnostic statistics						
$\varphi_1 = \varphi_2 = \cdots = \varphi_{10} = \varphi_{11} = 0$	0.163	0.790	1.230	1.410	3.900***	2.680***
R^2	0.284	0.166	0.233	0.343	0.509	0.392

Notes: Double and triple asterisks (**,***) represent significance at the 0.05 and 0.01 levels, respectively. Numbers in parentheses are standard errors.
[a] Models are estimated in levels ($N = 60$).
[b] Model estimating price changes. In other words, the dependent variable(s) are in first difference form ($N = 59$).