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How USDA Forecasts Retail Food Price Inflation

Annemarie Kuhns, Richard Volpe, Ephraim Leibtag, and Ed Roeger

United States Department of Agriculture

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Abstract

Wholesale and retail food price forecasts are useful to farmers, processors, wholesalers, consumers, and policymakers alike, as the structure and environment of food and agricultural economies are continually evolving. USDA's Economic Research Service analyzes food prices and provides 12- to 18-month food price forecasts for 7 farm, 6 wholesale, and 19 retail food categories. In 2011, ERS's forecasting procedure was updated to employ a vertical price transmission method that incorporates input prices at each stage of production. Where this is not possible, an autoregressive moving average approach is used. This report provides a detailed description of the revised methodology as well as an analysis of the overall accuracy and performance of individual forecasts. The revised forecasting methods show modest increases in forecast accuracy compared with simple univariate approaches previously used by ERS.

Keywords: Food Price Outlook, food prices, Consumer Price Index (CPI), Producer Price Index (PPI), forecasts, vertical price transmission model, autoregressive moving average approach, error correction model, autoregressive distributed lag, univariate moving average approach

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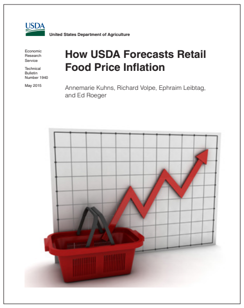
Contents

USDA

United States Department of Agriculture

A report summary from the Economic Research Service

May 2015



Find the full report at *www.ers.usda.gov/publications/tb-technical-bulletin/tb1940*

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What Is the Issue?

Each month, USDA's Economic Research Service (ERS) publishes wholesale and retail price forecasts for various food categories and subcategories, and policymakers, food suppliers, and researchers rely on these numbers. In recent years, as commodity and food prices have become more volatile and less easily predicted, users of the forecasts have expressed a greater need for more accurate forecasts.

ERS continually explores ways to improve its forecasts as new data and methods become available. In 2011, ERS revised its food price forecast methodology to use more rigorous statistical techniques and capture the impacts of the multistage U.S. food supply system on wholesale and retail food price formation. This updated approach incorporates far richer data available for farm, wholesale, and input prices, which could lead to more accurate forecasts.

What Did the Study Find?

- The precision of ERS food price forecasts has observably improved with the revised methodology. As a result, ERS food price forecasts are, on average, closer to the realized inflation figures.

- ERS forecasts using the new methodology required fewer and smaller revisions. For a given year, forecasts are subject to revision during a 17-month period. An average of 3.2 changes were made per food category using the new, current forecasting methods compared with 3.7 revisions using the previous method, and the average size of the adjustments dropped from 2.6 to 2.1 percentage points.

- Another measure of forecast accuracy was the extent to which initial forecasts differed from the actual Consumer Price Index (CPI) values. Using revised forecast methodology, the average difference from CPI values was 2 percentage points, compared with 2.6 percentage points for the previous methods.

- Although forecast accuracy and precision have improved relative to less rigorous approaches used by ERS before 2011, more years of data are needed to fully assess forecast performance.

ERS is a primary source of economic research and analysis from the U.S. Department of Agriculture, providing timely information on economic and policy issues related to agriculture, food, the environment, and rural America.

How Was the Study Conducted?

For those food categories with a sufficiently lengthy time series of historical retail and input prices, as well as reliable measures of forecast input prices, four separate vertical price transmission models are used to predict farm, wholesale, and retail-level food prices. The vertical price transmission approach relies on price forecasts at earlier stages of the production process, which are then "passed through" to forecast the CPI for food. For those categories subject to data limitations that preclude use of the vertical price transmission method, the autoregressive moving-average approach is used, which relies on lagged and current values of the CPI being forecast, as well as a time trend.

The accuracy of the current forecasting method is compared with the forecasting method used by ERS before 2011. Performance of the current forecasting methods is evaluated over the 2011-2013 period and compared with the performance of the previously used univariate moving average approach, which is evaluated over the 2003-2010 period. Various measures of forecast accuracy and adjustments are used to evaluate forecast performance.

Finally, the forecasting accuracies of the four vertical price transmission models are compared with each other using various performance statistics over the 2012-2013 period. Several accuracy tests were conducted, including a directional analysis to examine the extent to which the forecast models anticipate changes in the direction of price movements.

How USDA Forecasts Retail Food Price Inflation

Introduction

Food prices are fundamental to research related to the economics of food choices and the dynamics of food market competition. USDA, Economic Research Service (ERS) produces 12- to 18-month forecasts of the Consumer Price Index (CPI) and Producer Price Index (PPI) as indicators of where U.S. retail and wholesale food prices are headed.[1,2] The forecasting procedure has been significantly updated and extended in recent years. This report presents the food price forecasting methodology currently used at ERS, discussing its performance as well as the limitations and challenges facing forecasters.

Food price inflation forecasts are used in a number of ways. Researchers and policy analysts rely on them to anticipate changes that may be necessary in the structure, size, or regulations of various food assistance programs. Professionals working throughout the food industry use ERS's forecasts to project costs, expenditures, or demand for their products and services. Because we analyze individual food categories separately, revealing changes in prices relative to other food categories, with implications for consumer choice, the forecasts inform research and decision-making on dietary quality. Throughout academia and other outlets, the CPI forecasts have been used and cited in applied economic research on retail price transmission and formation. Finally, the media regularly and extensively uses ERS forecasts to inform U.S. consumers about expected changes in their expenditures and costs of living.

ERS has forecasted food prices for decades. Recently, the methodology has been updated substantially since the previous report on the forecasting approach (Joutz et al., 2000). The improvements to the forecasting procedure came about as the culmination of several factors. Forecasting in a multivariate framework that is supported by economic theory requires longitudinal data for the same variables. Over the past two decades, the data available for forecasting food prices have become far richer, with more information on farm, wholesale, and input prices. The fields of econometrics and statistics have advanced, and the forecasting toolkit has become more versatile, accessible, and effective. ERS stakeholders have also become more interested in retail food prices as they have grown more volatile and inflation has accelerated. Between 1990 and 2006, the food-at-home CPI (supermarket prices) increased by an average of 2.4 percent per year with a standard deviation of 0.85 percentage points. Since 2006, the average annual increase has been 3.1 percent with a standard deviation of 2.45 percentage points. Food price inflation has become far less predictable from year to year, and ERS has responded to this transition with greater scrutiny and analysis.

ERS's Food Price Outlook topic page features the CPI and PPI forecasts, available at: http://www.ers.usda.gov/data-products/food-price-outlook.aspx#.UqiO_dJDseE. Inflation forecasts for the current year are always available, and from July to December, ERS also forecasts inflation for the

[1]The CPI is a widely used measure of inflation of consumer goods and services, including food. The CPI is produced by the U.S. Bureau of Labor Statistics.

[2]The PPI is a measure of inflation for the selling prices received by domestic producers of goods and services. The PPI is produced by the U.S. Bureau of Labor Statistics.

upcoming year. The topic page is updated monthly with changes to the forecasts, as needed, and includes a discussion of food price trends during the prior month.[3] The documentation portion of the topic page provides a nontechnical overview of the ERS forecasting procedure, a discussion of the most important determinants of food prices, and highlights of relevant ERS research on retail food price formation and variation.

[3]The Food Price Outlook is updated monthly, as opposed to quarterly or yearly, to coincide with the release of PPI and CPI data, which are also published monthly.

What Are the Major Determinants of Food Prices?

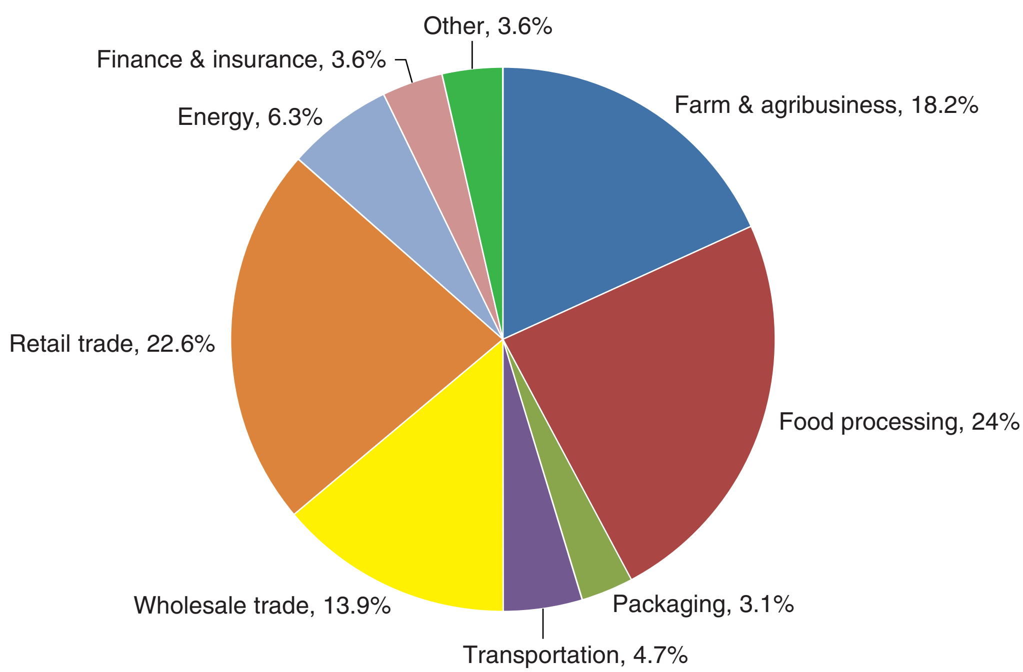
Commodity prices, transportation costs, manufacturing costs, and retailing costs are all factors to consider when modeling food price inflation. Measurements of these factors serve as the regressors in the econometric forecast models. Much research has been devoted to the determinants of food prices and food price volatility, but for the most part, these studies have focused on the agricultural commodity sector (Gilbert, 2010; Mitchell, 2008; Timmer, 2008). While there is little question that agriculture commodities are the most vital input to the food industry, the impact of commodity prices on retail food prices is a nuanced one in industrialized nations such as the United States.

Food in the United States travels from farms to supermarkets, restaurants, and other outlets through a supply system with multiple segments and industry sectors, each of which collects a share of every retail food dollar spent (fig. 1). The procedure varies across products and categories, but most foods undergo transportation, processing, and packaging to various degrees before reaching the retail sector. At one or more stages along this distribution chain, most foods also accrue additional costs, including advertising, finance, and labor wages, which factor into all industries involved in food supply systems.

When constructing a time series model of retail food prices based on input costs, researchers need to consider the extent to which input costs vary over time. There are a large number of potential input costs to consider, and since many are likely to be highly correlated over time, it is not feasible to include measurements for all of them. Factors that vary little over time will have no predictive power for food price variation. Similarly, inputs that are too closely interrelated will pose estimation

Figure 1

The industry groups' shares of the food dollar



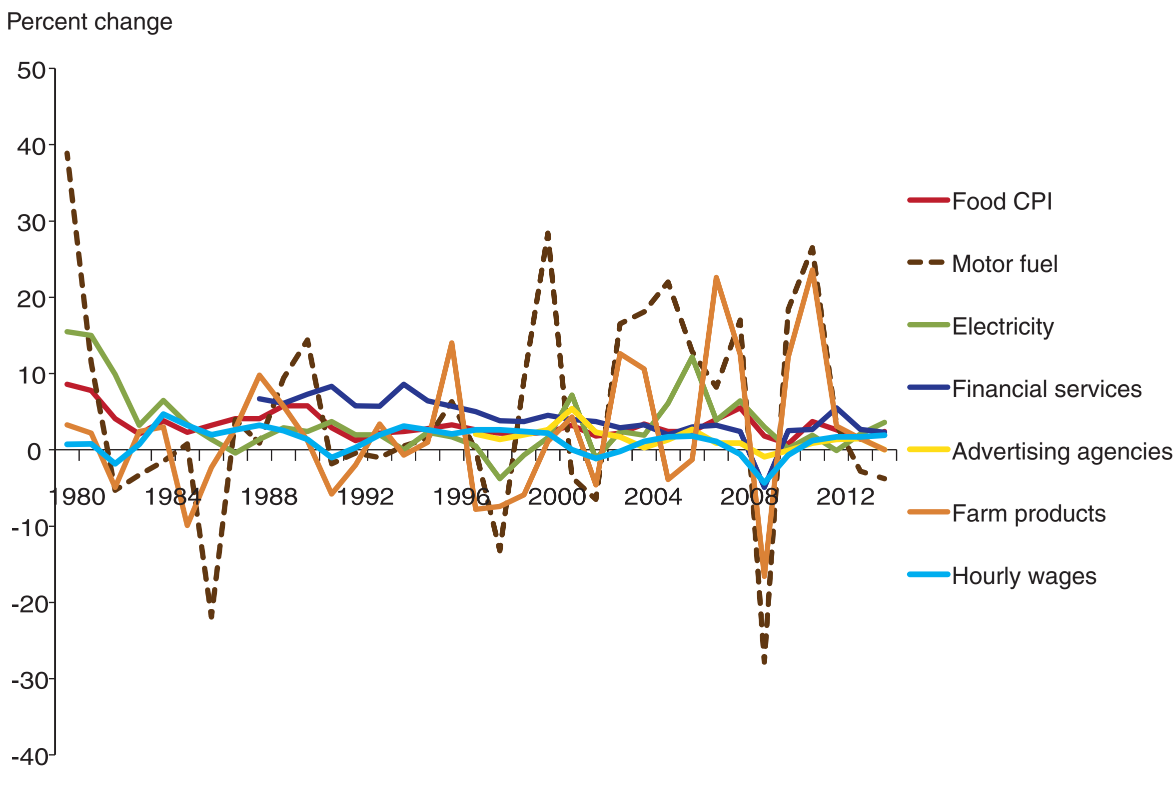
Source: Authors' calculations based on USDA, Economic Research Service's Food Dollar Series, Food-at-home dollar, 2012.

problems and complicate the interpretation of coefficients. For example, crude oil and motor fuel are both key inputs to the food processing and transportation process. The prices for these commodities correlate very closely, and if both are included in the same model, it may be impossible to identify the respective impacts of each.

Examining the changes in selected input costs over time (fig. 2) quickly illustrates which factors vary over time. Energy costs, including motor fuel and electricity rates, fluctuate greatly from year to year, regularly increasing or decreasing by more than 10 percent. The same is true for farm commodity prices. However, financial services and advertising costs (for which only a short time series is available) are far less volatile. Average hourly wages are also among the less volatile series, but wages do not seem to closely correlate with other input costs. Additionally, wages for industries specific to the food supply system may behave differently from those in other industries over time.

Taken in sum, previous research and data on prices in the industries contributing to the U.S. food supply suggest that our efforts in modeling and forecasting retail food prices are best focused on commodity and energy prices (Lamm and Westcott, 1981; Trostle, 2008). The estimated industry shares reported in figure 1 represent averages across all food and likely vary meaningfully across products and categories. Transportation and packaging costs may be important factors for certain foods that fluctuate considerably over time. Data on these industries, specific to their roles in food supply, are difficult to find. Fortunately, research has shown that fuel costs are the major drivers of transportation rates (Volpe et al., 2013). Additionally, packaging is an energy-intensive industry for which energy use has increased considerably in recent years (Canning et al., 2010). Therefore, accounting for energy prices may suffice to account for the roles played by these industries.

Figure 2
Annual percent changes in the food CPI and selected input costs, 1980-2012



Source: Consumer Price Index (CPI), U.S. Bureau of Labor Statistics.

Forecasting Methodology

In this chapter, the two types of forecasting methods are broadly defined and then each approach is discussed more in depth. Food CPI forecasts are of great interest to ERS data users and are some of the most cited and discussed estimates produced by ERS. However, it is not clear how to model effectively food CPI trends for such a disparate set of food categories in a forecasting framework. For example, what is the best way to select agricultural commodities most relevant to the food CPI? Or, if an aggregate commodity price index is preferable, how can we obtain reliable forecasts of such an index?

Owing to complications such as these, ERS forecasts individual CPI subcategories for which modeling is more tractable and for which data, including upstream forecasts, are more readily available. In 2011, ERS revised its forecasting procedure to improve precision. CPI subcategories are now forecasted using two distinct statistical methodologies: the vertical price transmission and the autoregressive moving-average approach. Which of the two methods is used depends entirely on data availability. In those categories for which we have a sufficiently long time series of data on historical retail and input prices, as well as a reliable measure of forecasted input prices, we use a vertical price transmission pass-through approach.[4,5] For those categories subject to data limitations, we apply the autoregressive moving-average approach, which relies on historical measures of economy-wide price movements, as well as a time trend.[6]

The forecasts for larger categories—including food-at-home and other aggregations such as meats or fruits and vegetables—are calculated as the weighted averages of the forecasted CPI subcategories. The weights for this process are drawn from the Bureau of Labor Statistics (BLS) relative importance shares, which are estimates of the shares of the average consumer's expenditures attributable to each spending category.[7] An example of an ERS CPI forecast table, as posted on the ERS website (table 1), helps illustrate how the various CPI categories relate to one another.

The food CPI constitutes 100 percent of consumer food spending, and all relative importance shares have been recalculated based on this denominator.[8] Food spending can be broadly organized into food at home (FAH) (60.1 percent) and food away from home (FAFH) (39.9 percent) spending.[9] Given the intrinsic differences in price formation between these two markets, one plausible approach to forecasting the food CPI is to forecast the FAH and FAFH CPIs individually and then weight the respective forecasts by their relative importance shares. However, the FAH CPI itself consists of an array of food categories and subcategories, each subject to unique modeling considerations and data demands. The boldfaced CPI categories in table 1 are those that ERS forecasts directly. The remaining categories are aggregates and consist of weighted averages of forecasts.

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[4]The historical CPI and PPI data we use date back to 1974.

[5]Pass-through approach refers to using first stage forecasts as inputs to the second stage forecast.

[6]An autoregressive model specifies that forecasts are estimated based on weighted sums of pervious values.

[7]Relative importance weights are updated in December of each year.

[8]For example, according to BLS, meats account for approximately 1.1 percent of all consumer spending, and since food represent 13.9 percent of spending, meats account for 7.9 percent of food spending.

[9]Food at home includes food purchased at food stores (grocery stores, supermarkets, etc.), other stores (commissary, military exchanges, etc.), home delivery and mail order, or purchases directly from farmers, manufacturers, and wholesalers. Food away from home includes purchases made at eating and drinking places, hotels and motels, retail stores, direct selling establishments, recreational places, schools, and colleges.

Table 1

A sample CPI forecast update from the ERS Food Price Outlook topic page

Item	Relative importance	Month-to-Month Sept 2013 to Oct 2013	Year-over-Year Oct 2012 to Oct 2013	Annual 2011	Annual 2012	Forecast 2013	Forecast 2014
	(Percent)	Consumer Price Indices *(Percent change)*					
All food	100.0	0.1	1.3	3.7	2.6	1.5 to 2.5	2.5 to 3.5
Food away from home	39.9	0.1	1.9	2.3	2.8	2.0 to 3.0	2.5 to 3.5
Food at home	60.1	0.2	0.8	4.8	2.5	1.0 to 2.0	2.5 to 3.5
Meats, poultry, and fish	12.9	0.6	3.1	7.4	3.6	1.5 to 2.5	2.5 to 3.5
Meats	8.3	0.4	2.0	8.8	3.4	1.0 to 2.0	2.5 to 3.5
Beef and Veal	3.9	0.3	1.4	10.2	6.4	2.0 to 3.0	2.5 to 3.5
Pork	2.5	0.6	3.7	8.5	0.3	0.5 to 1.5	2.0 to 3.0
Other meats	1.9	0.4	0.9	6.4	1.7	-0.5 to 0.5	2.0 to 3.0
Poultry	2.4	0.7	5.1	2.9	5.5	4.0 to 5.0	3.0 to 4.0
Fish and seafood	2.1	1.1	5.0	7.1	2.4	2.0 to 3.0	2.5 to 3.5
Eggs	0.8	1.1	0.9	9.2	3.2	2.0 to 3.0	2.0 to 3.0
Dairy products	6.3	-0.2	-0.2	6.8	2.1	0.0 to 1.0	2.5 to 3.5
Fats and oils	1.8	0.2	-1.8	9.3	6.1	-1.0 to 0.0	1.5 to 2.5
Fruits and vegetables	9.0	0.4	2.7	4.1	-0.6	2.0 to 3.0	2.5 to 3.5
Fresh fruits & vegetables	6.9	1.0	3.7	4.5	-2.0	2.5 to 3.5	2.5 to 3.5
Fresh fruits	3.7	1.5	1.2	3.3	1.0	2.0 to 3.0	2.5 to 3.5
Fresh vegetables	3.2	0.5	6.5	5.6	-5.1	4.0 to 5.0	2.0 to 3.0
Processed fruits & vegetables	2.1	-1.5	-0.5	2.9	3.8	0.0 to 1.0	2.5 to 3.5
Sugar and sweets	2.1	0.4	-2.1	3.3	3.3	-2.0 to -1.0	2.0 to 3.0
Cereals and bakery products	8.6	-0.2	0.9	3.9	2.8	1.0 to 2.0	2.0 to 3.0
Nonalcoholic beverages	6.6	0.4	-1.3	3.2	1.1	-1.0 to 0.0	2.5 to 3.5
Other foods	12.0	-0.3	-0.4	2.3	3.5	0.0 to 1.0	2.0 to 3.0

Notes: This table is reproduced from the November 27, 2013 update of the Food Price Outlook Topic Page. Some formatting has been changed slightly. The U.S. Bureau of Labor Statistics (BLS) published the relative importance shares in December 2012. BLS is the source for the month-to-month and year-to-year changes. Numbers in green indicate an upward revision in the annual forecast; numbers in red indicate a downward revision. Consumer Price Index (CPI) categories in bold are those which ERS forecasts directly using statistical methods.

Source: USDA, Economic Research Service Food Price Outlook topic page.

In the remainder of this chapter, we first introduce the concept of structural breaks, followed by a detailed discussion of the two broad types of forecasting methods used for forecasting the CPI subcategories. The type of forecasting method used for each food category is summarized in table 2.

Table 2
Forecasting method used for each CPI food category

CPI Category	Model
All Food	Weighted average
Food away from home	Autoregressive moving-average approach
Food at home	Weighted average
Meats, poultry, and fish	Weighted average
Meats	Weighted average
Beef and veal	Vertical price transmission ECM approach
Pork	Vertical price transmission ECM approach
Other meats	Autoregressive moving-average approach
Poultry	Vertical price transmission ECM approach
Fish and seafood	Autoregressive moving-average approach
Eggs	Vertical price transmission ARDL approach
Dairy products	Vertical price transmission ECM approach
Fats and oils	Vertical price transmission ECM approach
Fruits and vegetables	Weighted average
Fresh fruits and vegetables	Weighted average
Fresh fruits	Vertical price transmission ARDL approach
Fresh vegetables	Vertical price transmission ARDL approach
Processed fruits and vegetables	Autoregressive moving-average approach
Sugar and sweets	Autoregressive moving-average approach
Cereals and bakery products	Vertical price transmission ECM approach
Nonalcoholic beverages	Autoregressive moving-average approach

Notes: ECM = Error Correction Method, ARDL = Autoregressive Distributive Lag.
The indentation scheme illustrates how certain Consumer Price Index (CPI) categories comprise smaller subcategories. Food away from home, which is not disaggregated, contains no subcategories.

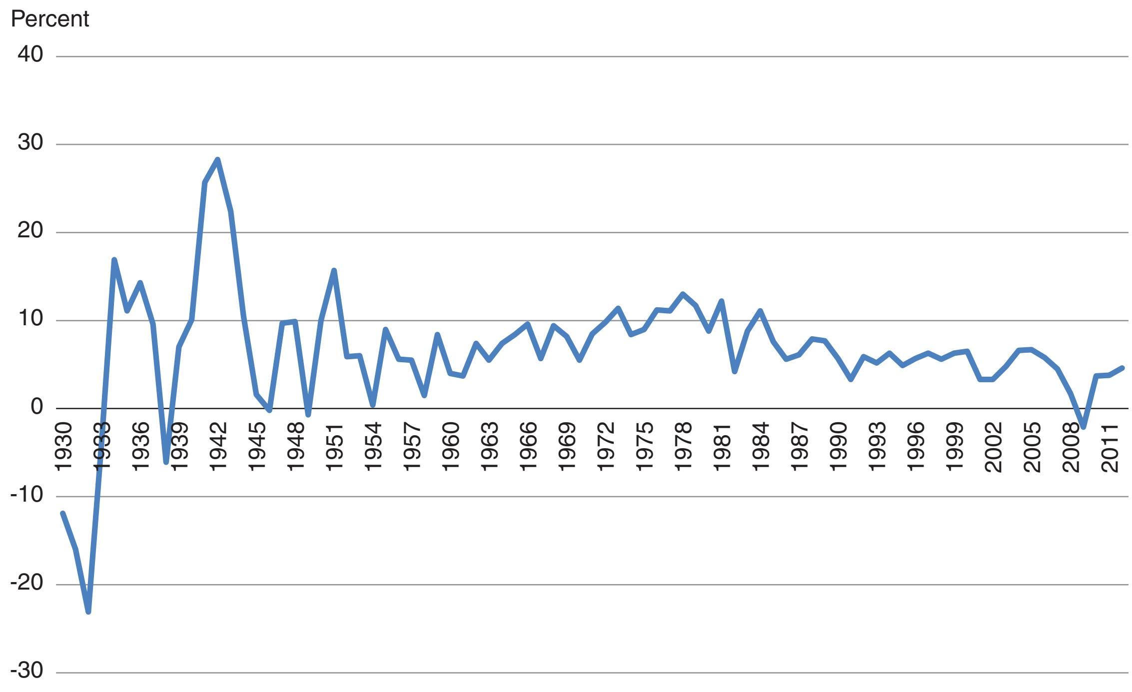
Source: USDA, Economic Research Service record of the methodology used with each category of CPI data.

Structural Breaks

As discussed in the following sections, we test for the presence of structural breaks in our forecasting models. Whether food prices are forecasted using a vertical price transmission pass-through approach or an autoregressive model, the potential role of structural breaks must be considered in any time series analysis. Structural breaks occur when a time series variable undergoes a fundamental shift, which usually manifests as a change in the statistical distribution via the mean, variance, or both. If structural breaks are not accounted for, forecasting errors can result and a number of statistical tests can be rendered invalid.[10]

It is common practice to test for structural breaks in instances where they are suspected to occur. In a well-known example, economists modeling macroeconomic indicators over time typically find a structural break in time series when analyzing gross domestic product (GDP), a common measure of economic growth, for the years of World War II (Ben-David et al., 2003; Strazicich et al., 2004). Examining annual changes in U.S. GDP over many decades (fig. 3) illustrates this idea. Note that GDP growth is highly volatile for nearly 10 years before the war, which the United States entered in 1939, and during the war itself. Approximately at the end of the war, around 1945, the volatility significantly decreases, and economic growth follows a fairly steady pattern of mild ups and downs for several decades. Any attempt to model or forecast U.S. economic growth that did not account for the level of volatility toward the end of World War II would result in biased regression coefficients, as several researchers have found.

Figure 3
Annual percent changes in U.S. gross domestic product, 1930-2012



Source: U.S. Department of Commerce, Bureau of Economic Analysis.

[10]If a structural change has occurred, it would bias the Dickey-Fuller test toward the nonrejection of the null that a unit root exists (Perron, 1989).

An additional modeling complication arises when it is not obvious where structural breaks may occur. In these cases, structural breaks may be endogenous, and tests have been developed to identify multiple structural breaks in the absence of additional information. For our purposes, these tests are especially important because a number of factors may abruptly alter the course of food prices over time. For example, the imposition or elimination of Federal marketing orders can have discrete and significant impacts on prices in commodity markets, and researchers interested in commodity-specific supply and demand elasticities typically account for these (Russo et al., 2008).[11]

Other examples that may be pertinent to agriculture include the dynamics of international trade, food safety concerns, and severe weather events. We employ, whenever applicable, a technique derived by Kejriwal and Perron (2010) to identify endogenous structural breaks in the variables in the forecast models. The approach is rooted in deriving the limiting distribution of the Sup-Wald test on the error term of the model being estimated and then sequentially testing the null hypothesis of an autoregressive unit root with k breaks versus the alternative that there are k + 1 breaks.[12] Structural breaks are incorporated into regression models using dummy variables.

Vertical Price Transmission Approach

In this section, we discuss the approach of vertical price transmission forecasting used to make monthly forecasts for each CPI subcategory. Because of the multiple stages involved in the U.S. food supply system, we chose a vertical price transmission framework to capture the impacts of this process on food price formation. Before considering the statistical framework of the model in detail, it is important to understand the steps involved in the vertical price transmission pass-through approach, as well as the underlying data (fig. 4). Pass-through models are the incorporation of first-stage forecasts as explanatory variables of the final forecasted output of interest. Given data availability, the ERS forecast model uses farm price projections to forecast the relevant farm PPI. The predicted farm PPI is then used as the key input to predict the wholesale PPI, which in turn is "passed through" to forecast the CPI in the final stage.

Forecasts of the Farm PPI

In the first step of the vertical price transmission process, ERS farm forecasts are used as the primary independent variable to predict the farm PPI for most food subcategories. The availability of these forecasts is a primary limiting factor in applying the vertical price transmission approach across food categories. The livestock and crop prices used as input variables include steers, barrow and gilt, broilers, turkeys and hens, farm eggs, farm milk, farm wheat, and soybeans.[13]

The farm forecast data on average monthly prices are available for soybeans and wheat. The PPI and CPI data are also produced monthly, so these forecasts can be used directly in the forecast models. However, the farm forecasts for steers (cattle), barrow and gilt (hogs), broilers, turkeys and hens, eggs, and milk reflect average quarterly prices.[14] To adjust the quarterly forecasts to a monthly

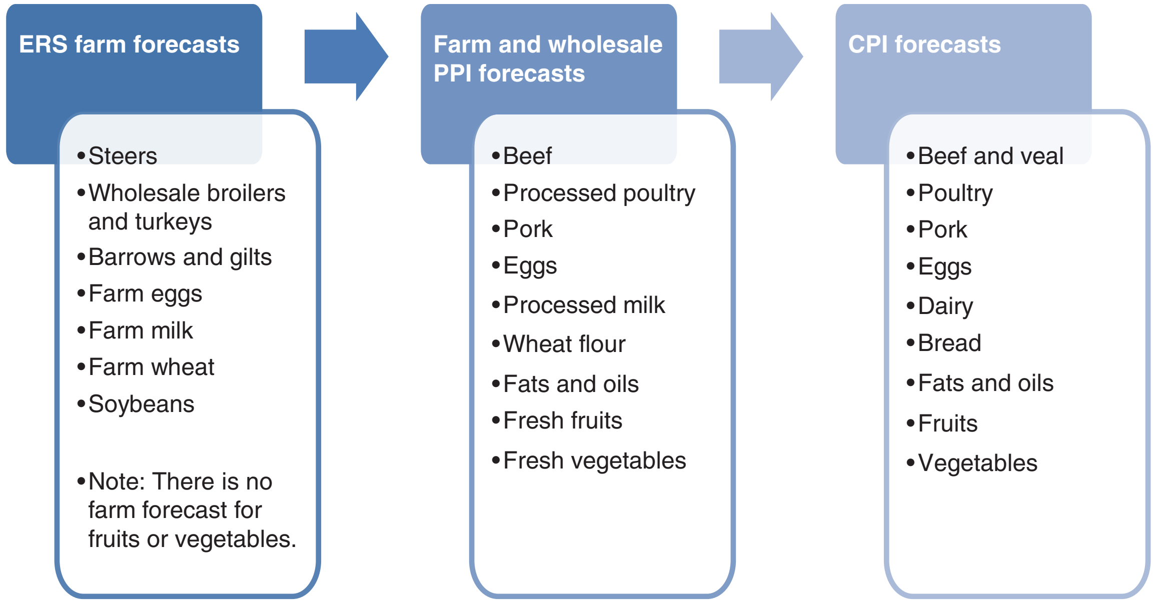
[11]Federal marketing orders are initiated by industry and may enforce quality, regulate product flow to the market, etc.

[12]Perron (1989) discusses the difference between a one-time change versus change in a trend. Both non-trending and trending instances are examined. The Sup-Wald test is used because it helps ease size distortions associated with the regular Wald test. For more information, see Kejriwal and Perron (2010).

[13]For poultry, wholesale prices are the farthest upstream point because the prevalence of contracting between farm and wholesale stages has made the farm price inconsistently related to wholesale price.

[14]ERS farm forecasts for these commodities reflect average quarterly pricing, but are updated monthly as new data becomes available.

Figure 4
Illustration of the vertical price transmission pass-through model



Notes: PPI = Producer Price Index. CPI = Consumer Price Index.
Source: USDA, Economic Research Service.

frequency, we employ the locally weighted scatter plot smoothing (Lowess) function. The Lowess function, developed by Cleveland (1979) and Cleveland and Devlin (1988), works to smooth the data by estimating the relationship between the historical quarterly commodity forecast and PPI series via regression. The estimated relationship from this regression is used to interpolate monthly average values for each of the quarterly commodity farm forecast series, which are then imported into the forecast models.

For fresh fruits and vegetables, the pass-through model goes directly from farm to retail. These retail foods are highly perishable and are thus defined by fixed proportions among inputs (Wohlgenant, 2001). Therefore, the wholesale stage adds little information, for the forecast model and price transmission may occur in these categories in under a month. For these categories, ERS farm forecasts are not available, so we use an augmented autoregressive distributed lag (ARDL) model to forecast future values of the respective PPI indices from historical data.

ARDL models use lagged (and potentially current) values of a variable of interest to forecast future values, in addition to current and lagged explanatory variables. In all applications of the ARDL approach, we take advantage of the lengthy time series of PPI and CPI data available to run in-sample forecasts to determine the optimal lag specification.[15] We allow for lags as long as 12 months.[16] By

[15]In this case, lagged values are used as predictors for the future value. The optimal lag must be determined so that the model can pick up the true error process. Not having enough lags takes away the residuals' ability to act as white noise. Whereas having too many lags reduces the ability of the Dickey-Fuller test to reject the null of a unit root.

[16]Lag length is determined using the Hannan-Quinn information criterion.

comparing actual future values with predicted values, we calculate prediction errors and select the model with the best performance.

Our model for fresh fruit and vegetable farm PPIs is estimated using 1972-2013 PPI data and takes the form

$$(1)\ \widehat{FarmPPI}_{i,t+1} = \alpha + \sum_j \beta_j \widehat{PPI}_{i,t-j} + \beta_d \widehat{diesel}_t + \beta'_s sbreaks_i + \beta'_q quarters_i + \varepsilon_{i,t}$$

where i is fruits or vegetables, t is month, and j is a lag length specification. The number of lags used and their lengths are decided individually for fresh fruits and vegetables using the criterion of lowest overall prediction error, as discussed above.[17] The model includes the diesel PPI to capture the role of transportation costs. The vector of structural breaks, which are incorporated into the model as dummy variables, are determined using the Kejriwal and Perron (2010) approach.[18] Finally, quarterly dummies account for seasonality.[19]

Some of the model inputs are also forecasted values. Given the monthly frequency of the BLS data and fact that ERS regularly forecasts inflation for the coming calendar year, equation (1) is used each month to forecast between 6 (in June) and 18 (in July) months of future values. Therefore, in many cases, both the lagged farm price values and the current diesel prices are themselves predicted values. For example, to forecast the fresh vegetable PPI 10 months ahead calls for the diesel PPI 9 months in the future, which necessarily must be a predicted value. Diesel prices are also forecasted using an ARDL approach.[20]

For the remaining categories for which we have proprietary farm forecasts, we forecast the farm PPI by estimating equation (1) but substituting the forecasted farm price from ERS for the autoregressive PPI forecasts. In these cases, equation (1) is no longer an ARDL model. For all other food categories forecasted using the error correction model (ECM), the farm forecast takes the following form:

$$(2)\ \widehat{FarmPPI}_{i,t+1} = \alpha + \sum_j \beta_j \widehat{ERS\_Farm}_{i,t-j} + \beta_d \widehat{diesel}_t + \beta'_s sbreaks_i + \beta'_q quarters_i + \varepsilon_{i,t}$$

where i represents the food category, t is month, and j is a lag length specification. The number of lags used and their lengths are decided individually. This model includes ERS farm forecasts in place of the farm PPI. The model also includes the diesel PPI to capture, again, the role of transportation costs.

[17]For fresh vegetables, the optimal distribution of lags is 1, 2, 6, 9, 10, and 11 months. For fresh fruit, it is 1, 6, 7, and 10 months. The remaining optimal lag distributions for food price indices are available from the authors upon request.

[18]The Kejriwal and Perron algorithm identified structural breaks for vegetable prices in April 1978, December 1986, and November 1996. For fruit prices, the most recent break was found in January 1997, and the fruit forecast models work with data starting at that date. The endogenously determined structural breaks for the remaining variables in the forecast models are available upon request.

[19]Seasonal dummies are necessary as seasonality plays a major role in agriculture, and we are using the non-adjusted CPI and PPI data.

[20]The diesel PPI was not found to have any endogenous structural breaks. The optimal lag distribution was determined to be 1, 2, 4, 5, 7, and 8 months. The remaining optimal lag distributions for input prices are available from the authors upon request.

With the farm PPI forecasts in hand, it is now possible to estimate a series of equations, for each food category, intended to measure the transmission of input prices throughout the food supply system and thereby enable forecasting. The farm forecast is used as an input to predict inflation at either the wholesale or retail level. There are two types of pass-through models to forecast the CPI—those that involve one stage of pass-through (farm to retail) and those that involve two (farm to wholesale and wholesale to retail). As shown in figure 4, some categories feature two stages of pass-through while some feature only one (table 3), depending on data availability and industry structure.

Table 3

The forecast models and U.S. Bureau of Labor Statistics (BLS) indices used

Food category	Industry sectors	Forecasted variable	Key explanatory variable
Beef and veal	Farm to wholesale	Beef and veal products, fresh or frozen PPI WPU022101	Slaughter cattle PPI WPUSOP0131
	Wholesale to retail	Beef and veal CPI CUUR0000SEFC	Beef and veal products, fresh or frozen PPI
Pork	Wholesale to retail	Pork CPI CUUR0000SEFD	Pork products, fresh, frozen, or processed PPI WPU022104
Eggs	Farm to retail	Eggs CPI CUUR0000SEFH	Chicken eggs PPI WPU017
Poultry	Wholesale to retail	Poultry CPI CUUR0000SEFF	Processed poultry PPI WPU0222
Dairy	Farm to wholesale	Dairy products PPI WPU023	Raw milk PPI WPU016
	Wholesale to retail	Dairy and related products CPI CUUR0000SEFJ	Dairy products PPI
Cereals and bakery	Farm to wholesale	Wheat flour PPI WPU021203	Wheat PPI WPU0121
	Wholesale to retail	Cereals and bakery products CPI CUUR0000SAF111	Wheat flour PPI
Fats and oils	Farm to wholesale	Fats and oils PPI WPU0113	Soybeans PPI WPU01830131
	Wholesale to retail	Fats and oils CPI CUUR0000SEFS	Fats and oils PPI
Fresh fruits	Farm to retail	Fresh fruits CPI CUUR0000SEFK	Fresh fruits and melons PPI WPU0111
Fresh vegetables	Farm to retail	Fresh vegetables CPI CUUR0000SEFL	Fresh and dry vegetables PPI WPU0121
Fish and seafood (preliminary)	Wholesale to retail	Fish and seafood CPI CUUR0000SEFG	UBC Wholesale seafood price index

Notes: The BLS series IDs are provided beneath the series descriptions. CPI = Consumer Price Index. PPI = Producer Price Index. UBC = Urner Barry Comtell.

Source: USDA, Economic Research Service record of the sources of data used in the forecast models.

Farm-to-Wholesale, Farm-to-Retail, and Wholesale-to-Retail Models

The farm-to-wholesale model, when applicable, is as follows:

$$(3)\ \widehat{WholesalePPI}_{i,t+1} = \alpha + \sum_j \beta_j \widehat{FarmPPI}_{i,t-j} + \beta_e \widehat{electricity}_t + \beta_d \widehat{diesel}_t + \beta_s^{'} sbreaks_i + \sum_k \beta_k \hat{\varepsilon}_{i,t-k} + \varepsilon_{i,t}$$

In this setting, the wholesale PPI is modeled as a function of a lag distribution for the predicted farm PPI. We also include the electricity PPI as a key measure of operating and processing costs at this stage, which similarly is forecasted using the ARDL process outlined above. When we estimate the wholesale beef PPI only, the electricity PPI is replaced by the slaughtering wage PPI.[21] Diesel is included here to represent transportation costs from the farm to wholesaler.

Importantly, equation (3) explicitly includes information from lagged residuals, or error terms, when applicable. This information forms the foundation of the ECM forecasting approach. There are many varieties of ECMs, and they are commonly used for forecasting (Ghosh, 1993; Granger and Lee, 1989) because they account for both short- and longrun impacts of a key independent variable (X) on the dependent variable of interest (Y). The underlying premise of the ECM approach is that X and Y share a longrun equilibrium relationship that largely defines the trajectory of Y and can be estimated. To parameterize this longrun relationship requires a lengthy time series of data, and this step is the primary reason that the existing data are insufficient to apply the vertical price transmission approach to selected CPIs.

Changes in X or in other variables in the model can cause deviations from the equilibrium in the short run. The magnitude of these deviations can also be estimated and incorporated into the model, which for forecasting purposes increases precision (Greene, 2008). In our model, equation (3), these deviations manifest as a distribution of lagged residuals, which is established on a case-by-case basis using an algorithm developed by Nielsen (2001). The process essentially repeats the search pattern used to find the optimal lag distribution for X or the input price series, in our case, given the basic longrun relationship between X and Y.

Establishing the equilibrium relationship between X and Y is a process that depends on the statistical properties of the variables being studied. Every price index used in the forecast models is initially subjected to the augmented Dickey-Fuller test to test for the presence of an autoregressive unit root (Dickey and Fuller, 1981).[22] Time series variables with unit roots are said to be nonstationary and are problematic in regression analysis and particularly forecasting. Regressions conducted on nonstationary variables are often spurious, because the relationship described between key variables of interest is an artifact of the data and does not reflect reality. In the cases where the Dickey-Fuller test indicates the presence of a single unit root, which is very common in time series data, variables are integrated to the order 1 (I(1)), which means that they are stationary if

[21]The slaughtering wage is used specifically for beef, as it well represents the main processing cost to produce beef, whereas electricity better represents processing costs for other food categories.

[22]A process that has a unit root means that the mean is not stationary; it changes over time. Therefore, the null hypothesis of the Dickey-Fuller test is that the data needs to be differenced to make it stationary, and the alternative hypothesis is that the data is already stationary and does not need to be differenced.

first differenced.[23] Further action may be necessary in these cases, and Hamilton (1994) provides a thorough discussion of stationarity, unit roots, and the solutions to relevant problems.

Having tested for unit roots, we next test for cointegration for all pairs of stationary I(1) indices to be modeled.[24] Cointegration occurs when a linear combination of nonstationary variables is stationary. In other words, the variables share a stable relationship over time that can be described, in our case, as $a*X + b*Y$ where a and b are constants. Engle and Granger (1987) developed a well-known test for cointegration and established the importance of cointegration for ECM estimation. In essence, the stationary, linear relationship that defines cointegration also provides the longrun equilibrium between X and Y. We apply the Engle Granger test and find that most of our key pairs of price indices are cointegrated.[25] For all estimations involving pairs of cointegrated indices, we apply a series of ECMs to conduct our forecasts. In the remaining cases, we use ARDL models, which have been shown to be comparable under a wide range of circumstances (Keele and De Boef, 2004). For these estimations, equation (3) does not include lagged residuals.

We next test for endogenous structural breaks. We apply the Kejriwal and Perron (2010) procedure for identifying multiple structural breaks at unknown intervals in the data to the joint probability distribution of X and Y. That is, we test for shifts in the statistical properties of both key indices simultaneously. This procedure is applied whether or not the two series were found to be cointegrated. Doing so can greatly improve precision and accuracy in forecasts, relative to running the algorithm individually for X and Y. This explains why, in some cases, we do not use the full time series available from BLS when estimating our models. For example, a structural break in fruit prices leads us to use only CPI and PPI data for fruit from 1997 on.

The final step in crafting the ECMs is to determine the appropriate lag length of X, or the farm PPI series. Unlike estimating ARDL models, ECMs are constrained in that the lags of X must be consecutive. We, therefore, follow a standard procedure of beginning with the default option of a single lag of 1 month and extending the model from there. The optimal lag distribution is chosen as the one that minimizes the Hannan-Quinn information criterion (HQIC), a common model selection statistic that is rooted in the sum of squared errors (Hannan and Quinn, 1979).[26] The selected lag distribution must also be logically appropriate for the industry sectors to which it is being applied. For example, the HQIC may be minimized for a lag distribution that is implausible for a given food, either too long or too short to facilitate pass-through. For this reason, ERS subject specialists for the relevant commodities and markets have been consulted for their input and guidance on model selection.

[23]Multiple unit roots are possible though less common in time series analysis. Stationary (d) indicates a variable that must be differenced d times in order to be stationary.

[24]Results from the unit root tests are available from the authors upon request.

[25]We also apply other established tests for cointegration, including that devised by Phillips and Perron (1988), to find the same effect throughout.

[26]The HQIC is one of three very common model selection criteria; the others are the Akaike Information Criterion and the Schwartz Information Criterion. For very large sample sizes, there is no meaningful difference among the three, but for small to moderate sample sizes, as is the case in our forecast models, the three differ in the extent to which they penalize the differences between predicted and actual values of the dependent variable. The HQIC, in these cases, is neither the most nor the least penalizing criterion.

Each of the steps outlined for the estimation of equation (3) also apply to the farm-to-retail and wholesale-to-retail models. Price transmission to the retail sector is modeled in the same way, regardless of the nearest downstream sector. The regression equation is:

$$(4)\ \widehat{CPI}_{i,t+1} = \alpha + \sum_j \beta_j \widehat{PPI}_{i,t-j} + \beta_e \widehat{gsw} + \beta_d \widehat{diesel}_t + \beta'_s sbreaks_i + \sum_k \beta_k \hat{\varepsilon}_{i,t-k} + \varepsilon_{i,t}\,.$$

where the only substantive change from equation (3) is the use of the grocery store wage, another PPI, as a key input price.[27] It is used to capture labor costs. In this equation, diesel is used to represent the cost of transport from wholesale to retail.

Estimation of Forecasting Models

For those pairs of series found to be cointegrated, there are a number of estimation options within the ECM family, including the threshold, symmetric, and asymmetric. When exploiting a longrun equilibrium between X and Y using an ECM, the default choice is to estimate a symmetric ECM. This model treats deviations from the equilibrium in the same manner, regardless of direction. Two other options that may be suitable for our purposes are the asymmetric ECM and the threshold ECM and they are worth discussing briefly.

The asymmetric ECM, developed by Granger and Lee (1989), posits that the dependent variable may respond differently to deviations from the longrun equilibrium, depending on the direction. Practically, this effect requires estimating separate coefficients for lagged residuals for deviations upward and downward. For our specific purposes, the effect implies that agents in the food supply chain may respond differently to price increases and decreases. A lengthy literature of theoretical and applied research examines asymmetric price transmission and input price pass-through. (See Meyer and von Cramon-Taubadel, 2004 for a review of the work specific to food prices.) Kinnucan and Forker (1987) found evidence that input price increases are passed along faster and more completely than are decreases.[28]

The threshold ECM treats deviations from the longrun equilibrium differently depending on their magnitude. Balke and Fomby (1997) argued that market forces may not always be strong enough to drive a relationship back to equilibrium in the short run. If adjustment costs, as an example, are higher than the deviation, then agents have no incentive to return to equilibrium. We are motivated to apply this model to food prices based on the empirical evidence that food prices are rigid—that they do not change as frequently as theory would suggest they ought to (Bils and Klenow, 2004). Menu printing costs are commonly cited as a cause of retail food price rigidity. Even small supermarkets have thousands of products with prices posted on the shelves. The labor and printing costs associated with frequently changing these prices have been estimated to be high (Levy et al., 1997), potentially contributing to a threshold approach in price adjustment.

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[27] The PPI variable here can be interchanged with the farm and wholesale PPI, depending on the food category being forecasted. Farm-to-retail models use the Farm PPI, and the wholesale-to-retail models use the wholesale PPI.

[28] The complete theoretical underpinnings of such a finding, as well as the consensus or lack thereof with respect to this phenomenon, are beyond the scope of this bulletin. However, industrial organization theory suggests that, in certain conditions, retailer incentives favor passing cost increases on to consumers to protect profits, while absorbing cost decreases to widen margins.

We provide a summary of the results of cointegration testing, the estimated importance of error correction, and the lag length specifications (table 4). For egg, fruit, and vegetable prices, we are unable to apply ECMs due to the lack of cointegration, but the BLS data are rich enough to enable the estimation of ARDL models. Also notable is that for all three of these foods, prices are estimated to pass-through (at least partially) from farm to retail in under a month. These are foods characterized by minimal processing and high perishability.

Autoregressive Moving Average Approach

For the remaining CPIs that ERS forecasts directly—other meats, fish and seafood, processed fruits and vegetables, sugar and sweets, nonalcoholic beverages, other foods, and food away from home—the data currently available do not enable use of any of the vertical price transmission models discussed above. Therefore, since it is not necessary to examine the statistical properties of more

Table 4
Diagnostics used to determine the ideal forecasting approach, by model

Category	Model	Cointegration[1]	Error correction[2]	Timing[3]
Beef	Farm to wholesale	Yes	Symm. ECM	1
	Wholesale to retail	Yes	Threshold ECM	1 to 2
			Asymm. ECM	1 to 5
Pork	Wholesale to retail	Yes	Symm. ECM	1 to 3
			Threshold ECM	1 to 3
Eggs	Farm to retail	No	None (ARDL)	0 to 5
Poultry	Wholesale to retail	Yes	Threshold ECM	1 to 4
			Symm. ECM	1 to 4
Dairy	Farm to wholesale	Yes	Symm. ECM	1 to 2
	Wholesale to retail	Yes	Threshold ECM	1
			Asymm. ECM	1 to 2
Bread	Farm to wholesale	Yes	Symm. ECM	1
	Wholesale to retail	Yes	Threshold ECM	1 to 4
			Asymm. ECM	1 to 4
Fats & Oils	Farm to wholesale	Yes	Symm. ECM	0 to 2
	Wholesale to retail	Yes	Asymm. ECM	1 to 3
			Threshold ECM	1 to 5
Fresh Fruit	Farm to retail	No	None (ARDL)	0, 11, 12
Fresh Vegetables	Farm to retail	No	None (ARDL)	0 to 3, 6 to 8

[1]Each pair of indices was tested for cointegration using the approach developed by Engle and Granger (1987).
[2]These are the ECM models that were found to be statistically significant for each category. For the cases in which cointegration was rejected, the ARDL model was used.
[3]These give the lag distribution of the key independent variable that minimized prediction error.
Notes: ECM = Error Correction Method, ARDL = Autoregressive Distributive Lag.

Source: USDA, Economic Research Service record of the methodology used for each forecasted category.

than one index for these CPI subcategories, tests for cointegration or joint probability distribution are not applicable.

At this time, ERS forecasts these CPIs using an autoregressive moving average (ARMA) approach that is designed to capture the general trajectory of the prices in question.[29] The model used to forecast these CPIs is as follows:

$$(5)\ \widehat{CPI}_i = \alpha + \sum_k \beta_k CPI_{i,t-k} + \beta_1 CPI_{i,Lag1Year} + \beta_2 CPI_{i,Lag2Years} + \beta_3 \frac{\sum_{j=5}^{t-3} CPI_{i,LagjYears}}{3} +$$

$$\beta_4 AllCPI_{i,Lag1Year} + \beta_5 AllCPI_{i,Lag2Years} + \beta_6 \frac{\sum_{j=5}^{t-3} AllCPI_{i,LagjYears}}{3} + \beta'_s sbreaks_i + \beta'_t trend_t +$$

$$\varepsilon_{i,t}.$$

Model (5) contains two lag structures, one monthly and one yearly. Indexed by *k*, the monthly lag structure includes lagged and current values of the CPI being forecasted and captures seasonality without adding unnecessary structure. For example, it is not clear that the standard four-quarter approach serves as a meaningful control for fish prices, even though its usefulness for products such as fresh produce is well established. The number of lags used depends on the month in which the forecasts are made. For current-year forecasts, the distribution begins with December of the previous year for the January forecast and is extended with each available month of data, through the June forecast, which includes data through May. Forecasts for the upcoming year begin each July, and the monthly lags include all data available for the current year. This lagging scheme is intended to capture and account for deviations from expected price movements in recent history.

The yearly lag structure includes the realized CPI values for the previous 2 years as well as the average for the 3 years prior, incorporating data from 5 historical years in total. This data-generating process cannot forecast or correct for extreme shocks, such as severe weather events, but captures longrun trajectory of average prices, which is seen by a plot of annual changes in the food CPI over the years (fig. 5). From 1991 to 2013, food prices have increased by an average of about 2.6 percent. Deviations from this average value are followed by changes in the opposite direction, effectively returning the course of inflation back to normal.[30] We apply these annual lags to both the forecasted CPI and the all-items CPI, which is the index used by BLS to measure economywide inflation across all consumer spending. In this way, we attempt to capture the cyclicality of the economy as a whole.

Structural breaks are once again determined, on a univariate basis, following the Kejriwal and Perron (2010) approach. They are then incorporated into equation (5) using dummy variables. Selected estimations of equation (5) include a linear time trend. Trends are commonly used in time series analysis to capture intangibles such as technological change. In our case, a time trend is used in those cases for which a joint test of significance rejects the importance of the yearly lag structure for the forecasted CPI. The rejection of this hypothesis indicates that recent changes in the CPI do not effectively explain the direction of prices and the time trend is used to capture a potentially more nuanced pattern than that shown in figure 4.

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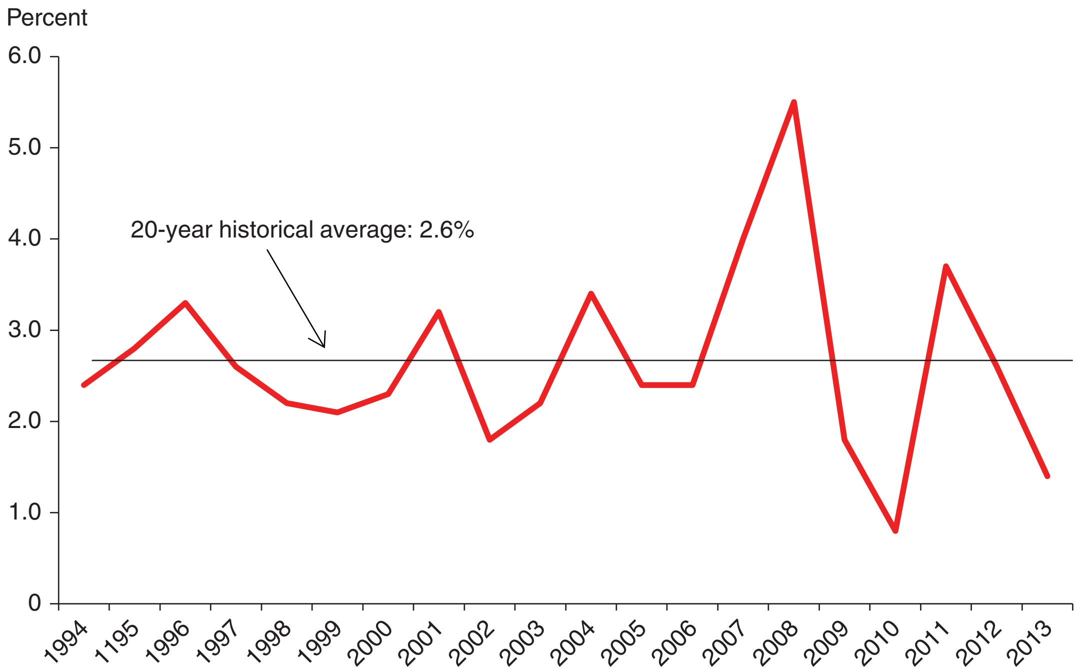
[29]An ARMA model applies both autoregressive and moving average analysis to the time series data. The model assumes the time series data is stationary around a time-invariant mean.

[30]Though not explicitly tested (as it is not forecasted directly), the food CPI almost surely exhibits structural breaks that very nearly follow calendar decades. Over time, food price inflation has fallen considerably in both average levels and volatility. During the 1970s, the average annual increase in the food CPI was over 8 percent. In the 1980s, it was over 5 percent.

Figure 5
Annual changes in the food Consumer Price Index, 1991-2013



Note: CPI = Consumer Price Index.
Source: U.S. Bureau of Labor Statistics and USDA, Economic Research Service calculations.

Post-Estimation Evaluation and Forecast Intervals

Whether CPI forecasts are made using the vertical price transmission approach or the autoregressive methodology, the forecasted estimates are evaluated in light of the breadth of current knowledge on the relevant commodity markets and price trends. As an example, when ERS conducted the CPI forecasts in June 2012, a drought of potentially historic proportions was settling on the Midwest United States. Although the relevant crop forecasts lacked the information to incorporate the drought's impact, the drought's size suggested that the forecast models for certain affected foods underestimated inflation and, therefore, needed a post-estimation adjustment.

Each month, ERS forecasters consult a variety of sources for information on food price trends. These sources include the respective ERS *Outlook* publications for the various commodities used in the forecast models, updates from USDA's World Agricultural Supply and Demand Estimates (WASDE) and USDA's Foreign Agricultural Service (FAS), as well as publications of the International Monetary Fund (IMF) and selected private forecasters. In most instances when information drawn from outside the forecast models motivates a change in the forecast, ERS forecasters discuss the potential change with the appropriate ERS commodity or crop subject specialist to confirm that the adjustment is reasonable in both magnitude and direction.

For the vertical price transmission estimations with established cointegration, the forecast models uniformly produce four forecast estimations—symmetric ECM, asymmetric ECM, threshold ECM, and ARDL. In nearly all cases to date, the four estimates suggest the same direction for food price inflation (upward or downward), but the magnitude can vary. The ARDL result is typically apportioned the least weight of the four in determining the published forecast, though it is useful as a measure of the robustness of the forecast. Among the ECM results, the symmetric ECM result is given the greatest weight for all estimates of price transmission to the wholesale sector. For transmission to the retail sector, those estimations for which error correction was found to be significant are given greater weight (see table 4). In the following paragraphs, we discuss more in-depth the model diagnostics and the relative performance of these four estimation methods.

The monthly frequency of the BLS data, which contrasts with the annual frequency of the ERS forecasts, provides an additional measure for the post-estimation calibration of forecasts. Each month, ERS calculates the average value for each forecasted CPI to date in the current year. Typically, ERS forecasters then impute CPI values for the months remaining in the current year according to a selection of hypothetical scenarios, including no changes to food prices or heavy inflation—e.g. 0.5 percent, each month. Then the actual and imputed monthly values for the current year are averaged and compared to the realized annual CPI of the previous year to obtain point estimates of inflation. This approach is of very limited value early in the calendar year, and it is not used to generate forecasts. However, as the year progresses, the approach is very helpful in judging how well the forecast estimates from our models compare to the behavior of prices. For the year's final few months, enormous price shocks would be required for forecasts to deviate from the inflation estimates calculated using this approach.

With a forecast point estimate in hand, after running the models and calibrating as needed using additional information, we construct an interval of 1 percentage point in order to report the forecasts (see table 1).[31] Doing so accounts for some degree of inherent uncertainty in forecasting, as well as

[31] Rounded 1-percentage-point intervals are used for ease of communicating with the general audience.

the specific factors that cannot be forecasted rigorously in our case, particularly the weather. Each month, a new set of point estimates is calculated across the food categories and compared to the published intervals. When a forecast's point estimate lies outside of the current interval, the forecast is updated accordingly to capture the revised point estimate.

Comparing Forecast Performance of Previous and Revised Forecasting Methods

Prior to 2011, ERS food price forecasts were conducted using primarily a univariate moving average approach, the details of which are available in Joutz et al. (2000). Given that we have electronic records of monthly forecast releases dating back to January 2003, it is appropriate to apply the vertical price transmission pass-through and augmented ARMA approaches to conduct out-of-sample forecasts for the period 2003-2010 and compare accuracy and precision between the previous and current methodologies.[32,33] However, the 2003-2010 forecasts, in the same manner as those made today, also incorporated institutional knowledge drawn from commodity market experts, farm price forecasts, and financial markets to adjust the point estimates drawn from the forecast models.

Given that it is not possible to access the same portfolio of institutional information available to ERS forecasters at the time older forecasts were made and subsequently adjusted, directly comparing the previous and revised approaches over the 2003-2010 period is not appropriate. As an alternative, we present statistics on aggregate forecast performance of both the revised methods over the 2011-2013 period and the previous method over the 2003-2010 period (table 5) for readers to compare. We also provide statistics on the overall volatility of food prices and input costs during these two time periods.

All of the statistics presented indicate an increase in forecast accuracy and precision using the revised forecasting methods. Changes in the quality of forecast performance can reflect perceived shocks to food prices that could not be predicted (e.g. severe weather events), but if all else is equal, fewer forecast revisions indicate greater forecast accuracy. Recall that ERS forecasts for any given year are published and subject to revision for 17 months. On average, per category, 3.7 changes were made between 2003-2010 and 3.2 changes from 2011-2013.

We also measured, in absolute terms, the extent to which initial forecasts differed from the realized CPI values. From 2003-2010, initial forecast midpoints were 2.6 percentage points removed from actual values, while the average difference was 2 percentage points for 2011-2013.[34] There is also a notable difference in the maximum divergence between the initially forecasted and actual CPI outcomes over the two time periods. From 2003-2010, the maximum difference between initially forecasted and realized values averaged 12.5 percentage points. From 2011-2013, this value was only 6 percentage points. This disparity indicates that under the revised forecast methodology, initial predictions were closer to the ultimately realized CPI value. The statistics for forecast adjustments, by year and category, are available in table A.1 of the appendix.

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[32]An out-of-sample forecast uses historical and current data to make forecasts into the future. We then wait until that future date to compare the predicted with the actual amounts.

[33]The published forecasts for any period of time from 2003 onward are available from ERS upon request.

[34]Given that ERS forecast intervals are 1 percentage point, an alternative measure of forecast precision is to measure the difference between the forecast bounds and the realized CPI values. In this setting, the average differences were 2.1 percentage points for 2003-2010 and 1.5 percentage points for 2011-2013.

Table 5

Aggregate statistics on forecast adjustments, performance, and price volatility, 2003-2010 and 2011-2013

	2003-2010	2011-2013
Average forecast changes, across categories, per year	81.37	71.33
Average forecast changes, per category, per year	3.69	3.24
Average forecast change (% points), across categories	2.61	2.07
Average minimum adjustment per year (% points), across categories	0.13	0.08
Average maximum adjustment per year (% points), across categories	12.56	6.08
Average annual CV[a]		
Food CPI	0.008	0.006
Food-at-home CPI	0.010	0.006
Crude foods and feeds PPI	0.052	0.034
Intermediate foods and feeds PPI	0.028	0.024
Finished consumer foods PPI	0.014	0.011
Diesel PPI	0.216	0.097
Electricity PPI	0.036	0.053
Average monthly change (%)[b]		
Food CPI	0.556	0.525
Food-at-home CPI	0.758	0.691
Crude foods and feeds PPI	3.427	3.586
Intermediate foods and feeds PPI	1.958	1.975
Finished consumer foods PPI	1.239	1.114
Diesel PPI	7.070	7.567
Electricity PPI	1.735	1.736

Notes: Average forecast changes, per year: total number of times the forecast was changed, either across all 19 categories or by individual category. Average forecast change (percentage points): change in the forecast in percentage point terms across categories. Average minimum adjustment per year: the average minimum percentage point change per year. Average maximum adjustment per year: the average maximum percentage point change per year.

[a]CV is the coefficient of variation, calculated as the sample standard deviation divided by the sample mean. It is a unitless measure of dispersion. We calculated the CV for each year to measure volatility across the months, then calculated average annual CVs for the two time periods of our analysis.

[b]U.S. Bureau of Labor Statistics (BLS) calculates monthly percentage changes for all Consumer Price Indices (CPIs) and Producer Price Indices (PPIs). These are averages of the absolute values of the changes, taken across all monthly observations within each time period.

Source: USDA, Economic Research Service (ERS) calculations using ERS Food Price Outlook forecast data and BLS's CPI and PPI.

The challenges associated with forecasting are directly related to the volatility of the variables of interest. An economic indicator that varies little over time and follows a clear trajectory is relatively easy to forecast with precision. Therefore, we compare the volatility of food prices and key measures of upstream costs across the two time periods. We measure volatility in two ways. One common measure of dispersion is the coefficient of variation (CV), which is calculated as the sample standard deviation divided by the sample mean. The other is the average absolute value of the monthly change in indices, which is reported in percentage points. Under certain circumstances, the two measures can give conflicting results.[35] But the overall pattern that emerges is that wholesale and retail food

[35]For example, the average annual CVs suggest that diesel prices were more volatile from 2003-2010, while the average monthly changes showed slightly greater volatility during 2011-2013. The CV increases as variables trend away from their measure of central tendency. The diesel PPI exhibits large swings over time, which typically feature increases followed by decreases of comparable size. In the first time period, the magnitudes of the swings were larger on average. But in the second time period, the increases were relatively larger than the decreases, resulting in a clear upward trend.

prices, as well as energy prices, were slightly more volatile during the 2003-2010 period. The difference is not economically significant; for example, the average monthly change in the food CPI across the time periods is 0.03 percentage points.

Taken together, the findings support the notion that overall forecast accuracy is improved since the methodology was revised. However, it is important to note that more years of data are needed to properly assess forecast performance. Moreover, there is substantial room for improvement among the forecasts conducted from 2011-2013. In the Conclusion, we discuss options under exploration for improving and refining the ERS forecast methodology.

Comparing Forecast Accuracy Across Vertical Price Transmission Approaches

As outlined in the description of the forecast methodology, the vertical price transmission pass-through models are estimated in four distinct, but related, ways. In this section, we analyze a series of quarterly forecasts conducted using symmetric ECM, asymmetric ECM, threshold ECM, and ARDL for all of the categories featuring sufficient data. As previously noted, the significance or lack thereof of error components suggests the models that are most likely to fit the data and perform well for forecasting purposes (see table 4). For this exercise, the forecasts produced by the models have not been adjusted using additional information. We conduct out-of-sample, one-quarter ahead forecasts for all of the price transmission models estimated in our vertical price transmission approach (fig. 6). We compare the forecasts to actual CPI and PPI values for the years 2012-2013.

Forecasting favors techniques that produce the smallest errors, or alternatively achieve the greatest precision, over time. To assess precision, we employ a series of diagnostics. The first measure of precision that we calculate is the mean squared error (MSE), which is a measure of forecast error dispersion. The MSE has been used as a forecasting diagnostic tool for decades and is appropriate in a wide range of circumstances and model specifications (Gneiting, 2014). Choosing the method with the smallest MSE is equivalent to selecting the model with the smallest sum of squared residuals in typical regression analysis—the model of best fit.[36] The equation used to calculate the MSE is:

$$(6)\ MSE = (\sum_{t=1}^{n} e_t^2) / n$$

where $e_t = y_t - \hat{y}_t$, the forecast error, and n represents the number of observations. Granger and Newbold (1986) developed a methodology for testing the null hypothesis of equality in MSE across forecast models.[37] We apply this method here to test if there are significant differences in performance across the pass-through models by food category.

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[36] R^2 is not an appropriate measure of fit in terms of forecasting models (Diebold, 2006), and hence it is not included in this analysis.

[37] The test for equality in MSE across models consists of testing that the variances in the errors across models are equal, or Var(e1) – Var(e2) = 0, for models 1 and 2. Simple arithmetic boils this testing if (e1 + e2) and (e1 - e2) are correlated. One of the assumptions underlying this test is that models 1 and 2 are unbiased over time, and in the pages that follow, we demonstrate evidence that this may not be true in some cases. Therefore, particularly in those cases where bias cannot be ruled out, the tests of equality in MSE must be considered with that caveat in mind. The complete details of this test are available from Granger and Newbold (1986).

Figure 6

One-quarter ahead in-sample forecasts, by vertical price transmission approach, compared with realized CPI values

Note: m = month (as in "2012m1"). ECM = error correction model. ARDL = autoregressive distributed lag. CPI = Consumer Price Index.
Source: USDA, Economic Research Service.

The MSE does not measure the relative scale of the error across the food categories. Therefore, we also calculate the mean squared percentage error (MSPE), which measures the dispersion of forecast error as a percentage of the estimated value (Diebold, 2006). This is useful for our purposes in that BLS indices can vary substantially in magnitude. Here the MSPE is calculated using the following equation:

$$(7)\ MSPE = \frac{\sum_{t=1}^{n}[(y_{t+h} - \hat{y}_{t+h}) / y_{t+h}]^2}{n} * (100).$$

One of the most basic forecasting diagnostic is the mean error (ME), which is simply the average forecast error across the time series. The ME is calculated as follows:

$$(8)\ ME = (\sum_{t=1}^{n} e_t) / n.$$

The key distinguishing characteristic among ME and MSE, MSPE, and other commonly used metrics such as the mean absolute error is that it maintains the sign of residuals. In doing so, information can be lost when calculating the mean because overestimations are canceled out by underestimations. Therefore, the ME is of limited use in determining the precision of forecast models, but it is helpful in establishing whether or not models are biased. Statistically, a forecast model is biased if it is significantly more likely to over- or underestimate the variable of interest over time. The Congressional Budget Office identifies bias as a major priority in assessing the performance of agency forecasts and relies chiefly on the ME to test for bias (Burns, 2013).

A series of statistical tests have been devised to establish biasedness based on ME and related metrics. Most, however, rely on large samples of data, and we are limited in that regard. Croushore (2012) developed a test for the null hypothesis that the forecast error has a mean of zero (ME = 0), which is valid in small samples. The test consists of regressing the forecast error, as defined above, against an intercept only and testing if the estimated intercept term is equal to zero.

Next, we calculate Theil's U statistic, another measure of relative forecasting error. Theil's U compares forecasted values using our vertical price transmission approaches with a naïve forecast that draws on only information from the preceding time period. In essence, this technique compares forecast results to a random walk of value for the variable of interest. Following Diebold (2006), Theil's U statistic is calculated as follows:

$$(9)\ Theil's U = \frac{\sum_{t-1}^{n}(y_{t+1} - y_{t+1,t})^2}{\sum_{t-1}^{n}(y_{t+1} - y_t)^2}$$

where $y_{t+1,t}$ is referred to as the naïve forecast. The resulting value is a ratio, where a value of one indicates that the forecast values are as likely to be as correct as those drawn from a random walk, or by guessing. Values less than one indicate forecasting performance greater than a random walk, and values greater than one indicate forecasting performance that is no superior to guessing. Diebold (2006) notes that, in select circumstances, it is not appropriate to equate these naïve forecasts with a random walk. Therefore, for our purposes, we compare Theil's U statistics across models and ascertain that, according to this metric, the model yielding the lowest value has thus far produced the most precise forecast estimates.

The different model performance statistics (table 6) do not always yield a consensus as to which approach performs the best over time. It is worth stressing that these forecast models have only been in use by ERS for a short time and, given more data, it will likely become clearer which is the preferred approach. The MSE and MSPE mostly yield qualitatively similar rankings across the models. For fruits, vegetables, and eggs—the categories for which cointegration could not be established and error correction components were insignificant—the ARDL model performs best or nearly best. However, the ARDL also is more accurate for fats and oils and dairy retail prices, raising questions about the stability of the longrun equilibria governing the two price series.

Comparing forecast accuracy across the different vertical price transmission models is useful in attributing weight to the forecasted point estimates each month when studying the updated BLS data and considering forecast revisions. For some categories, the model with the lowest MSE performed significantly better than at least one alternative. This was true for the following CPIs: Beef, Eggs, Pork, Dairy, Vegetables, and Fats and Oils—and for the Fats and Oils PPI. In other cases, one model performed significantly better than all of the other choices. For example, the threshold ECM is clearly favored when forecasting the Beef CPI, and therefore, this point estimate is given the greatest consideration in the analysis. It is also notable that the threshold error component was found to be highly significant in the beef CPI models (see table 4). Alternatively, for the case of the Eggs CPI, the ARDL model has the lowest mean squared error, but this difference is only significant when compared to the threshold ECM. Therefore, when evaluating point estimates for this category, the threshold ECM result is of interest only for checking robustness while the three remaining estimates are given approximately equal weight.

The diagnostics indicate that some of the forecast models may be biased. As with any regression model, the forecast errors should be random over time, indicating that the estimated coefficients are correct on average. Evidence to the contrary suggests that the forecast model requires changes to the specification or more information. In some cases, only some of the pass-through models exhibit evidence of bias. For example, the asymmetric ECM and ARDL models do not reject the null hypothesis of zero average mean error despite potential problems with the symmetric and threshold ECMs. However, ERS consistently overestimates inflation for the Dairy and Vegetable CPIs while underestimating in the case of retail egg prices. As with all of our forecast point estimates, the output of these models is consistently considered in tandem with additional information from the underlying commodity markets and other sources, which serves to mitigate the issue of bias. Moreover, the time series for these ECM and ARDL models is too short to facilitate traditional tests of model bias, which have more power. In practice, ERS forecasters treat evidence of bias similar to significant differences in MSE across models. Those specifications exhibiting the greatest likelihood of bias, within product categories, are afforded the least weight in the forecast adjustment procedure.

By and large, Theil's U statistic supports the notion that all four models yield highly comparable forecast estimates. However, the metric also reveals some interesting comparisons across models that warrant further observation given a longer time series of data. For example, the asymmetric ECM clearly outperforms all other models in forecasting the beef CPI. This result is consistent with the notion that retailers pass on upstream beef price increases quickly and more completely to consumers than they do decreases. Alternatively, the asymmetric ECM performs rather poorly for the poultry CPI while the threshold ECM performs the best. This result suggests that retail poultry prices require greater input price shocks before adjusting than do, for example, pork or beef prices. The threshold ECM is also the best performing model for breads and cereal products.

Table 6

Performance statistics for the four vertical price transmission, out-of-sample forecasting approaches, by category and stage of processing

	Mean Squared Error[a]				Mean Squared % Error			
Price Transmission	Thresh-old ECM	Asymm. ECM	Symm. ECM	ARDL	Thresh-old ECM	Asymm. ECM	Symm. ECM	ARDL
Cattle PPI – beef PPI	*5.46*	5.57	5.70	6.38	2.72	2.78	2.84	3.20
Beef PPI – beef CPI	*1.96*	**2.77**	**2.55**	**2.36**	0.74	1.05	0.97	0.89
Eggs PPI – eggs CPI	**10.77**	9.39	9.18	*8.62*	4.92	4.29	4.20	3.94
Poultry PPI – processed poultry CPI	3.04	*1.71*	2.63	*1.71*	1.34	0.76	1.16	0.75
Pork PPI – pork CPI	*3.58*	**4.07**	**4.24**	**4.18**	0.38	0.43	0.45	0.44
Milk PPI – dairy PPI	*7.92*	8.10	8.09	8.08	3.60	3.68	3.69	3.69
Dairy PPI – dairy CPI	**3.01**	**3.18**	**3.27**	*2.79*	1.39	1.47	1.51	1.29
Wheat PPI – wheat flour PPI	14.09	13.00	12.87	*10.21*	6.10	5.63	5.57	4.45
Wheat flour PPI – bread CPI	3.44	3.16	3.13	*3.11*	1.08	1.00	0.98	0.98
Fruit PPI – fruit CPI	7.39	9.43	7.55	*6.76*	2.16	2.80	2.24	2.00
Vegetables PPI – vegetables CPI	**18.18**	18.80	*17.74*	**18.18**	5.87	6.07	5.72	5.86
Soybeans PPI – fats and oils PPI	*9.16*	10.57	**9.34**	8.01	3.12	3.60	3.20	2.78
Fats and oils PPI – fats and oils CPI	**3.90**	**4.57**	3.55	*3.05*	1.68	1.97	1.53	1.31

	Mean Error[b]				Theil's U Statistic			
Price Transmission	Thresh-old ECM	Asymm. ECM	Symm. ECM	ARDL	Thresh-old ECM	Asymm. ECM	Symm. ECM	ARDL
Cattle PPI – beef PPI	3.40*	3.26*	3.45*	1.36	1.15	1.14	1.13	1.03
Beef PPI – beef CPI	1.13*	1.89	0.21	-0.62	1.13	0.81	1.08	1.17
Eggs PPI – eggs CPI	7.33***	5.83***	5.46**	5.26**	1.25	1.29	1.30	1.27
Poultry PPI – processed poultry CPI	2.84***	0.29	2.41***	0.70	0.57	0.96	0.66	1.09
Pork PPI – pork CPI	-0.07	-1.49	-0.89	-1.54	0.62	0.71	0.68	0.70
Milk PPI – dairy PPI	1.04	0.60	-0.58	-2.54	0.85	0.86	0.87	0.89
Dairy PPI – dairy CPI	-1.65**	-2.77***	-3.01***	-2.25***	0.76	0.78	0.77	0.73
Wheat PPI – wheat flour PPI	11.74***	10.98***	10.73***	2.98	0.85	0.84	0.84	0.82
Wheat flour PPI – bread CPI	0.95	-1.25	-0.13	-1.47	0.67	0.74	0.72	0.83
Fruit PPI – fruit CPI	4.02**	-8.31***	-4.88***	-3.97**	1.16	1.12	1.14	1.13
Vegetables PPI – vegetables CPI	-14.36***	-14.42***	-12.62***	-11.78***	0.86	0.87	0.85	0.83
Soybeans PPI – fats and oils PPI	1.83	0.40	0.58	-5.75**	0.85	0.82	0.82	0.75
Fats and oils PPI – fats and oils CPI	3.84***	4.57***	3.39***	0.21	1.17	1.15	1.18	1.15

[a]Differences were tested in MSE across models following Granger and Newbold (Granger, C.W., and P. Newbold. 1986. *Forecasting Economic Time Series, 2nd Edition*. Orlando, FL: Academic Press). Following Park (Park, T.A. 1990. "Forecast Evaluation for Multivariate Time-Series Models: The U.S. Cattle Market," *Western Journal of Agricultural Economics* 15(1):133-143), the lowest MSE per category is italicized, and those MSEs that are statistically higher than the minimum are boldfaced.

[b]Forecast bias was tested for, following Croushore (Croushore, D. 2012. "Forecast Bias in Two Dimensions," Working paper 12-9, Federal Reserve Bank of Philadelphia. Available at:http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2040747), modifying the classic test of biasedness for small samples. If the average mean error is statistically different from zero, then the forecast model is said to yield biased results that are statistically more likely to over- or underestimate the actual value.

*indicates that the mean error is statistically different from zero at the 0.10 level; **at the 0.05 level; and ***at the 0.01 level.

CPI = Consumer Price Index. PPI = Producer Price Index.

Source: USDA, Economic Research Service (ERS) calculations using ERS Food Price Outlook forecast data.

Lastly, we perform a directional analysis to examine the extent to which the forecast models anticipate changes in the direction of price movements. We calculate the number of times the forecast predicts a movement in the same direction as the index throughout the time series—that is, how effective the models are at predicting directional changes in the variables of interest.[38] The optimal forecast for our purposes minimizes expected loss, where loss is defined as incorrectly forecasting the sign of monthly price changes. The loss function is written as follows:

$$(10)\quad Loss\,Function: L\left(y,\hat{y}\right)=\begin{cases} 0, & if\ sign\left(\Delta y\right)=sign\ (\Delta \hat{y}) \\ 1, & if\ sign\left(\Delta y\right)\neq sign\ (\Delta \hat{y}) \end{cases}$$

In our setting, this function is useful for identifying two key types of forecasting errors. Using standard statistical terminology, forecasts can result in two potential errors with respect to directional changes: type I and type II. Type I errors occur when a directional change is forecasted but no such event takes place in the data. Type II errors occur when a directional change in the data is not correctly forecasted. Both occurred regularly throughout the 2012-2013 time period (table 7).

Contrary to the discussion of MSE, there are no clear differences in performance across the models. The threshold ECM and ARDL committed the fewest type II errors while the asymmetric ECM produced the fewest type I errors. In many cases, a substantial share, or even the majority, of directional changes were not accurately predicted. Additionally, for a number of models, more of the predicted directional changes proved to be false than occurred as predicted in the data. Many of the errors portrayed in table 7 are the result of very small or brief directional changes in the data. As discussed in the Conclusion, further statistical analysis is called for to understand the extent to which directional changes with significant economic implications are accurately predicted in our forecasting framework.

[38]Mathematically, directional changes are extrema in the price indices. Both local and global maxima and minima represent points at which the trend changes from positive to negative or vice versa. Directional changes are distinct from turning points, in which the series of interest changes direction and maintains the new course for a period of time (Wecker, 1979). Most food prices increase steadily over time, meaning that turning points are uncommon. For this reason, we restrict our analysis to directional changes.

Table 7

Results of the directional analysis, by category and out-of-sample forecasting method, 2012-2013

		Threshold ECM		Asymmetric ECM		Symmetric ECM		ARDL	
Price Transmission	Directional Changes[a]	Type I Errors[b]	Type II Errors[c]	Type I Errors	Type II Errors	Type I Errors	Type II Errors	Type I Errors	Type II Errors
Cattle PPI – beef PPI	11	6	3	6	3	6	3	6	3
Beef PPI – beef CPI	8	6	3	8	4	7	3	9	3
Eggs PPI – eggs CPI	15	4	7	4	8	4	8	4	8
Poultry PPI – proc. poultry CPI	12	5	5	3	5	4	5	4	5
Pork PPI – pork CPI	9	6	6	6	5	6	6	6	6
Milk PPI – dairy PPI	7	8	4	5	4	5	4	5	4
Dairy PPI – dairy CPI	6	7	4	6	5	8	5	5	4
Wheat PPI – wheat flour PPI	10	5	5	6	4	6	4	5	5
Wheat flour PPI – bread CPI	15	4	8	4	9	3	8	3	8
Fruit PPI – fruit CPI	7	7	2	9	3	9	3	9	2
Vegetables PPI – vegetables CPI	7	7	5	5	4	5	5	6	4
Soybeans PPI – fats and oils PPI	8	6	4	3	5	3	5	3	4
Fats and oils PPI – fats and oils CPI	13	4	3	3	4	4	3	4	3
Total	128	73	59	68	63	70	62	69	59

[a]Directional changes occur when the index being forecasted changes direction over the time period.
[b]Type I errors occur when the forecast model predicts a directional change that does not take place in the data when predicted. Type II errors occur when the forecast model fails to predict a directional change.
[c]Type I errors occur when the forecast model predicts a directional change that does not take place in the data when predicted.
CPI = Consumer Price Index. PPI = Producer Price Index.

Source: USDA, Economic Research Service (ERS) calculations using ERS Food Price Outlook forecast data.

Conclusion: Ongoing and Future Work

Model performance statistics and diagnostics indicate that the precision of ERS's food price forecasts has somewhat improved with the new technique. While the model has improved, potential forecast bias is still a concern regarding forecast accuracy. Additionally, some aspects of the forecasting methodology remain *ad hoc* due to data limitations or modeling complications. A number of efforts, either in the planning stage or already underway at ERS, aim to expand and enhance the food price forecasting methodology.

Weather stands as the greatest source of uncertainty in forecasting food prices. ERS cannot accurately predict severe weather events, such as droughts. However, it may be possible to incorporate seasonal and climatic forecast data from sources such as the National Oceanic and Atmospheric Administration to better account for expected weather patterns. With a better understanding of expected deviations from seasonal temperature and precipitation norms in agricultural regions, ERS may be better able to anticipate commodity price fluctuations.

Moreover, given that the most important mechanism by which weather affects food prices is through commodity price changes, ERS has a strong incentive to fill the gaps in the economic understanding of commodity price transmission. The review by Meyer and von Cramon-Taubadel (2004) concludes that much of the empirical research on this topic fails to reach consensus and often conflicts with theory. To help foster consensus, ERS has ongoing collaborations with academic researchers to study commodity price transmission using proprietary datasets of retail food prices.

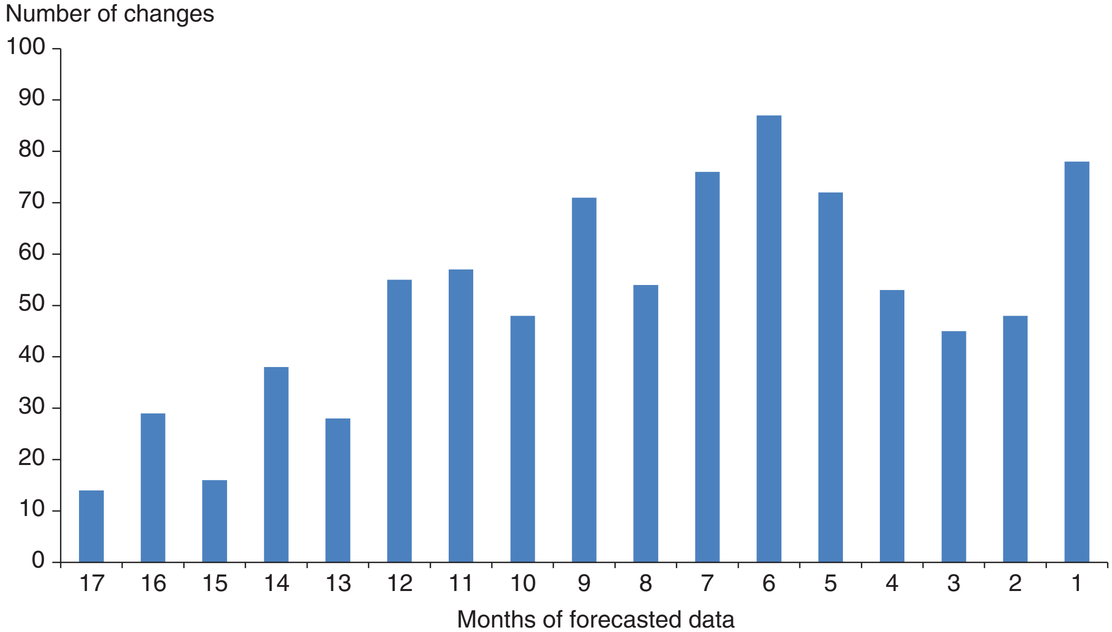
The directional analysis, based on equation (9), indicates that the forecasts are prone to errors with respect to directional changes in the CPIs and PPIs. However, it is clear that many of the directional changes that the models fail to anticipate (type II errors) are either very small in magnitude, very short lived, or both. Additionally many of the false directional changes suggested by the models (type I errors) simply take place 1 to 2 months following the prediction. Therefore, a number of actual directional changes in the data simultaneously generate errors of both kinds. To identify precisely where the models have the greatest shortcomings in predicting price changes that impact inflation estimates, more work is called for in delineating between large and small directional changes, as well as developing time intervals to place around the points at which the models predict directional changes.

Given the impact that changes in the food price forecasts can have on policy, the decisions made by agents in the food supply chain, and the outlook of U.S. consumers, ERS strives to minimize the number of forecast revisions while maximizing precision. The annual forecast for each CPI is subject to revision for 17 months. Examining the frequency of forecast revisions by month, the distribution peaks at about the midpoint of the year being forecasted (fig. 7).[39] That is, in May or June, with about half of the year's CPI monthly values realized, ERS researchers obtain a clearer picture of food prices on the year and adjust forecasts accordingly. However, a disproportionate share of revisions takes place early, and many of these early forecast changes are ultimately reversed, either partially or completely.[40] This finding likely indicates that a number of forecast revisions are made too early and with too little information. ERS is conducting a statistical analysis of revisions that

[39]The complete set of forecast revisions, by month and by CPI, is available in the appendix in table A.2.

[40]For example, ERS adjusted the 2012 forecast for the eggs CPI five times over the 18-month period. But the final forecast, made in December 2012, matched the initial forecast made in July 2011.

Figure 7
Total number of forecast changes, by month



Note: Each year's forecasts are initially released in July of the previous year, and at this point, 18 months of data are forecasted. The inaugural forecasts are not counted as changes or revisions.
Source: USDA Economic Research Service calculations based on changes made to ERS Food Price Outlook forecasts.

were reversed, drawing in part on the information from the loss function analysis, to reduce the incidence of these occurrences.

Work is underway in applying the vertical price transmission pass-through methodology to additional food categories. The stage-of-processing PPIs for carbonated beverages, juices, and other drinks may provide enough information to establish a longrun equilibrium relationship with the nonalcoholic beverages CPI and, therefore, apply ECM approaches. Similarly, a weighted combination of PPIs for canned, frozen, and juiced fruits and vegetables offers promise for the processed fruits and vegetables CPI. ERS has acquired a subscription to the Urner Barry Comtell seafood price data. Researchers are working on constructing a price index for wholesale fish and seafood that is intended to serve as the foundation for an ECM framework applied to the fish and seafood CPI. Kumcu and Okrent (2014) illustrate the construction of price indices for FAFH prices. Applying the ECM methodology to these indices may allow for subcategories of FAFH, such as fast food or full-service restaurants to be forecasted.

Finally, an avenue by which ERS food price forecasts have the potential to inform policy decisions is through the expected impacts of food price changes on food price expenditures. BLS's Consumer Expenditure Survey (CE) measures and reports information on household food expenditures by category and across a range of demographics. A simple comparison of annual food price inflation and changes in spending according to the CE in recent years reveals that spending does not increase proportionally with prices. Households economize, shift their expenditures among supermarkets and restaurants, and impacts vary substantially by income and geographic region, among other factors. ERS is currently exploring how food price forecasts may be used to produce food expenditure forecasts, drawing on information from both the CE and proprietary data sources.

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Table A.1
Total number of forecast revisions, magnitudes of forecast changes, and volatility, by year and CPI category, 2003 to 2013

CPI category		2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
All food	Revisions	1	3	2	0	4	5	5	3	2	1	3
	Change	0.5	1.0	1.0	N/A	1.0	2.5	2.5	2.5	1.5	0.0	1.5
	Avg. CPI Δ	0.59	0.43	0.45	0.46	0.81	1.01	0.37	0.33	0.90	0.37	0.30
Food away from home	Revisions	0	1	0	0	1	2	2	3	2	1	1
	Change	N/A	0.5	N/A	N/A	0.5	1.0	1.0	2.5	0.25	0.75	0.25
	Avg. CPI Δ	0.40	0.47	0.51	0.52	0.67	0.87	0.34	0.27	0.56	0.49	0.41
Food at home	Revisions	3	4	2	1	5	5	6	2	4	2	4
	Change	1.0	2.0	1.0	0.5	1.5	3.0	3.5	2.0	2.5	0.5	2.0
	Avg. CPI Δ	0.75	0.58	0.62	0.67	0.91	1.31	0.77	0.46	1.22	0.44	0.41
Meats, poultry, and fish	Revisions	4	7	2	2	4	2	5	1	5	4	3
	Change	1.5	5.0	0.5	1.0	2.5	1.0	5.0	0.5	4.75	0.0	1.0
	Avg. CPI Δ	1.68	0.84	0.50	0.56	1.01	1.39	0.79	1.32	1.45	0.80	0.86
Meats	Revisions	7	9	2	3	4	2	6	2	5	2	3
	Change	4.0	6.0	0.5	0.5	2.5	1.0	6.6	1.5	6.0	0.25	1.75
	Avg. CPI Δ	2.13	1.03	0.62	0.55	1.03	1.48	1.04	1.61	1.74	0.79	0.77
Beef and veal	Revisions	6	8	2	2	5	3	6	2	5	5	3
	Change	5.5	8.0	0.0	0.0	3.5	1.5	7.5	1.5	7.25	0.25	2.0
	Avg. CPI Δ	3.56	1.77	1.50	1.23	1.50	2.07	1.98	2.00	2.49	1.29	0.87
	Avg. wholesale PPI Δ	6.62	6.16	3.55	2.38	4.68	4.66	4.77	6.37	6.05	5.23	2.98
	Avg. farm PPI Δ	6.75	4.49	4.32	3.21	3.13	4.61	3.09	4.82	5.26	4.52	2.70
Pork	Revisions	2	5	2	4	6	1	6	6	5	4	5
	Change	1.0	3.5	0.5	1.5	1.0	0.5	7.5	4.5	5.25	3.75	1.5
	Avg. CPI Δ	1.59	1.98	1.20	0.97	2.03	2.22	1.49	2.93	2.22	1.56	1.81
	Avg. wholesale PPI Δ	3.11	3.74	2.96	4.13	3.60	5.50	2.08	4.38	3.83	5.25	4.67
Other meats	Revisions	5	5	1	2	3	2	2	4	3	1	4
	Change	3.5	3.0	0.5	0.5	1.0	2.0	1.5	3.0	4.75	0.75	3.0
	Avg. CPI Δ	2.12	1.23	1.08	1.43	2.18	1.78	1.68	1.70	1.65	1.28	1.51
Poultry	Revisions	2	8	2	6	6	4	4	1	1	2	3
	Change	0.5	6.0	0.5	4.0	3.5	2.5	3.5	1.0	0.75	2.25	1.75
	Avg. CPI Δ	1.24	1.48	1.59	1.23	1.58	1.29	1.33	1.40	1.10	1.83	1.65
	Avg. wholesale PPI Δ	1.29	2.61	1.88	2.85	2.20	1.46	2.38	2.48	1.58	1.87	1.32
Fish and seafood	Revisions	3	3	1	3	5	4	5	4	4	3	2
	Change	0.5	1.5	1.0	2.0	0.5	2.0	1.0	3.0	4.25	1.5	0.0
	Avg. CPI Δ	1.45	1.28	1.29	1.38	1.43	1.98	1.57	2.22	1.81	1.48	2.42
Eggs	Revisions	6	8	10	4	8	5	7	7	4	5	2
	Change	11.0	3.5	15.0	2.5	23.0	16.5	18.5	0.0	6.0	0.0	0.0
	Avg. CPI Δ	5.30	6.53	5.29	6.68	8.64	4.77	6.64	9.02	3.56	5.15	3.57
	Avg. farm PPI Δ	10.80	15.53	13.88	18.25	20.42	20.53	16.37	22.32	17.86	18.60	19.29

continued—

Table A.1
Total number of forecast revisions, magnitudes of forecast changes, and volatility, by year and CPI category, 2003 to 2013—continued

CPI category		2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Dairy products	Revisions	2	8	3	3	6	4	5	1	4	3	3
	Change	0.0	7.0	2.0	2.0	7.5	6.0	11.0	1.0	3.5	0.75	3.25
	Avg. CPI Δ	1.31	2.31	1.19	0.88	2.13	1.51	1.98	0.93	1.54	1.09	0.72
	Avg. wholesale PPI Δ	1.77	4.66	1.33	1.59	3.43	2.78	3.71	2.33	3.93	3.18	1.77
	Avg. farm PPI Δ	4.13	7.91	2.52	3.35	5.60	5.43	6.34	4.78	6.30	6.55	3.68
Fats and oils	Revisions	3	9	3	4	2	11	1	4	7	5	4
	Change	0.5	4.5	3.0	0.5	0.5	11.0	0.5	3.0	7.25	1.5	3.25
	Avg. CPI Δ	1.34	1.68	1.90	1.71	1.23	3.31	1.07	1.33	2.57	1.37	1.14
	Avg. wholesale PPI Δ	4.39	3.27	1.48	2.20	5.18	13.98	5.30	3.68	5.80	2.90	2.47
	Avg. farm PPI Δ	6.08	12.38	7.53	4.32	10.27	16.77	18.81	7.60	8.49	13.75	12.08
Fruits and vegetables	Revisions	3	1	2	2	7	6	5	5	3	6	3
	Change	1.0	1.0	1.0	1.5	0.0	3.0	6.0	2.5	1.75	2.75	0.5
	Avg. CPI Δ	2.12	3.57	4.64	3.19	4.35	3.25	1.84	3.48	2.84	2.06	2.07
Fresh fruits and vegetables	Revisions	3	5	4	4	7	4	5	5	3	6	3
	Change	1.0	0.5	0.5	2.0	1.5	2.0	9.5	2.5	2.0	4.0	1.25
	Avg. CPI Δ	3.13	5.62	6.85	4.59	6.50	4.12	2.95	5.39	3.95	3.00	2.79
Fresh fruits	Revisions	3	2	4	5	5	5	5	3	3	5	3
	Change	0.5	2.0	0.0	2.5	0.5	1.5	10.5	3.0	0.75	0.75	0.5
	Avg. CPI Δ	3.45	7.04	5.91	3.53	6.64	7.23	3.39	7.75	5.24	4.78	3.42
	Avg. farm PPI Δ	5.62	8.37	6.17	9.71	10.54	5.95	5.23	9.41	6.70	3.68	5.03
Fresh vegetables	Revisions	4	3	7	9	7	5	4	5	4	5	4
	Change	3.5	0.0	1.0	1.5	2.0	2.0	7.5	1.5	3.25	7.5	1.75
	Avg. CPI Δ	3.55	6.04	8.28	7.28	7.37	4.95	4.63	4.95	7.09	3.63	4.95
	Avg. farm PPI Δ	12.81	19.17	15.54	19.93	20.76	16.14	14.98	26.11	31.81	11.49	24.88
Processed fruits and vegetables	Revisions	4	4	2	4	3	5	2	4	3	1	2
	Change	1.5	1.0	1.5	1.5	0.5	6.5	3.0	3.5	0.25	0.75	1.75
	Avg. CPI Δ	0.96	1.05	1.29	0.70	1.02	1.86	1.15	1.36	1.39	1.01	1.24
Sugar and sweets	Revisions	4	1	2	5	1	4	1	2	3	1	4
	Change	0.5	1.0	0.0	3.0	0.5	2.5	2.0	1.5	1.75	1.25	3.5
	Avg. CPI Δ	0.59	0.96	1.48	1.00	0.91	1.22	1.08	1.64	1.66	1.16	1.10
Cereals and bakery products	Revisions	2	1	1	1	2	6	1	4	3	3	4
	Change	0.5	0.5	1.0	0.5	1.5	6.5	0.5	2.5	1.75	0.25	2.0
	Avg. CPI Δ	0.68	0.52	0.68	0.77	1.17	2.28	0.62	0.46	1.28	0.81	0.57
	Avg. wholesale PPI Δ	2.10	2.38	1.35	3.78	7.90	15.22	5.19	5.31	7.73	4.56	4.42
	Avg. farm PPI Δ	6.08	3.99	3.81	5.35	14.03	23.83	8.63	7.85	14.46	6.41	5.37

continued—

Table A.1
Total number of forecast revisions, magnitudes of forecast changes, and volatility, by year and CPI category, 2003 to 2013—continued

CPI category		2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Nonalcoholic beverages	Revisions	2	2	3	1	6	5	2	2	2	1	2
	Change	0.0	1.5	2.0	0.5	3.5	1.5	1.0	2.5	2.25	0.25	3.25
	Avg. CPI Δ	0.92	0.61	0.64	0.65	1.09	1.17	0.87	0.83	0.97	0.59	0.73
Other foods	Revisions	3	3	1	1	4	5	1	3	2	2	4
	Change	0.5	1.5	0.5	0.5	1.0	3.0	1.0	2.5	0.25	1.5	2.0
	Avg. CPI Δ	0.78	0.79	0.98	0.68	0.78	1.30	0.76	0.46	1.03	0.71	0.68
Sum	Revisions	72	100	58	66	101	95	86	73	77	68	69
Mean	Revisions	3.27	4.54	2.63	3.0	4.59	4.31	3.90	3.31	3.5	3.09	3.14
	Change	1.81	2.75	1.5	1.29	2.71	3.59	5.03	2.18	3.09	1.42	1.71
Min	Revisions	0	1	0	0	1	1	1	1	1	1	1
Max	Revisions	7	9	10	9	8	11	7	7	7	6	5

Notes: Δ = change. The Wholesale Producer Price Index (PPI) and/or Farm PPI is not included in this analysis for some food categories as they use a farm to retail or wholesale to retail model. Change is the percent difference between the initial forecast made in July of the previous year and the final forecast made in December of the listed year. This is calculated as the absolute value of the difference between the midpoints of the two forecasts. For 2003, forecasts were not made in the previous year, meaning comparisons with the remaining years are not entirely applicable. The change in the forecast is based on the comparison between the January and December forecasts.
CPI = Consumer Price Index.

Source: USDA, Economic Research Service calculations using ERS Food Price Outlook forecast data.

Table A.2

Forecast revisions, by month and Consumer Price Index (CPI) category

	Months of forecasted data																
CPI category	17	16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1
All food	-	1	-	1	-	5	1	3	2	3	2	2	3	1	1	1	3
Food away from home	-	-	-	1	-	1	2	-	1	1	1	1	2	-	-	1	2
Food at home	-	1	-	2	1	4	2	4	2	3	3	4	2	2	2	2	4
Meats, poultry, and fish	1	1	-	1	1	3	2	2	4	2	2	3	4	4	2	3	4
Meats	1	1	1	1	1	3	3	2	3	4	2	6	2	4	4	4	3
Beef and veal	1	1	-	2	2	4	2	2	4	3	3	5	4	3	3	4	5
Pork	2	1	-	2	2	5	1	2	2	2	4	6	3	4	3	2	5
Other meats	-	1	-	-	1	4	3	2	4	3	2	2	1	1	1	3	4
Poultry	-	1	-	1	2	1	5	2	4	1	4	3	3	3	2	5	2
Fish and seafood	-	2	1	1	1	5	2	2	2	2	4	3	3	2	2	2	3
Eggs	1	3	2	2	3	4	5	6	7	3	6	5	4	4	4	2	6
Dairy products	-	2	2	2	3	2	2	3	3	4	5	4	3	4	1	1	1
Fats and oils	2	3	3	2	-	3	5	4	5	3	5	5	3	5	1	-	4
Fruits and vegetables	1	1	-	3	-	1	3	1	3	4	3	5	5	2	4	2	5
Fresh fruits and vegetables	1	3	1	3	1	2	3	1	4	2	3	4	6	3	4	3	5
Fresh fruits	1	1	1	1	1	1	4	2	3	2	5	5	6	2	2	2	4
Fresh vegetables	2	2	-	3	3	2	3	3	3	5	3	3	7	5	4	5	4
Processed fruits and vegetables	-	1	2	2	1	1	4	1	2	1	6	4	3	-	3	1	2
Sugar and sweets	-	-	-	2	-	2	1	3	5	3	4	3	1	1	-	-	3
Cereals and bakery products	1	1	-	3	2	1	1	2	4	-	3	6	1	-	-	2	3
Nonalcoholic beverages	-	1	2	2	2	-	2	-	2	1	3	3	3	2	2	1	2
Other foods	-	1	1	1	1	1	1	1	2	2	3	5	3	1	-	2	4
Total Changes	14	29	16	38	28	55	57	48	71	54	76	87	72	53	45	48	78

Notes: A dash signifies no change was made in that month for the specified food category.
Each year's forecast is initially published in July of the previous year. At this point, there are 18 months of data to be forecasted, but the initial forecast is not counted as a revision. The final forecast for each year is made in December when CPI data for November are released, meaning there is 1 month of data to be forecast.

Source: USDA, Economic Research Service calculations using ERS Food Price Outlook forecast data.