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Time-Series Methods for Forecasting and Modeling Uncertainty in the Food Price Outlook

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Abstract

This technical bulletin describes a time-series-based approach for forecasting food prices that includes prediction intervals to communicate uncertainty. The performance of forecasts created with this approach was compared to that of previously published USDA, Economic Research Service (ERS) Food Price Outlook (FPO) forecast ranges. The methods in this new approach are intended to be used in FPO data releases that provide monthly forecasts of annual food price changes and may also prove useful in other forecasting endeavors. The new approach used an autoregressive integrated moving average (ARIMA) model that was selected based on performance (information loss), generating a more accurate forecast than previously used methods as measured by root-mean-square errors. With the parameter estimates and estimated error distribution from the optimal ARIMA model, Monte Carlo simulations are used to develop prediction intervals, which reflect uncertainty about future food prices. These prediction intervals more often included the actual annual price changes than the archived forecast ranges. On average, the prediction intervals also included the actual annual price change earlier in the forecasting process. These properties generally held whether we used a higher (95 percent) or lower (90 percent) confidence level. The use of standardized econometric models and model selection also allowed for the inclusion of data not currently included in FPO. The methods easily tested whether including external variables improved forecast accuracy or could be used to create new forecasts. This report considered new price change forecasts of apples, seafood, and limited-service restaurants in 2020 and the potential forecast performance improvement from incorporating futures prices as case studies.

Keywords: Autoregressive integrated moving average (ARIMA), Consumer Price Index (CPI), food prices, Food Price Outlook (FPO), forecasting, model selection, Producer Price Index (PPI), time-series econometrics, uncertainty.

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A report summary from the Economic Research Service — *August 2022*

Time-Series Methods for Forecasting and Modeling Uncertainty in the Food Price Outlook

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What Is the Issue?

The USDA, Economic Research Service's (ERS) Food Price Outlook (FPO) provides monthly forecasts on a wide range of food prices along the food supply chain. Historically, these food price forecasts have been reported as 1-percent ranges of annual percent changes for the Consumer Price Index, which reflects retail food prices. Forecasts of percent annual changes for the Producer Price Index, which reflects farm- or wholesale-level food prices, have been reported in 3-percentage-point ranges. These ranges reflect the results of econometric models, expert opinion, and uncertainty about the future of food prices.

Between 2005 and 2020, annual increases in food prices above 3 percent and changes in the food supply chain (from events like natural disasters, the Great Recession, the Global Food Crisis of 2011, and the coronavirus COVID-19 pandemic) have suggested the potential value of evaluating the possibility of improving the models used to forecast food prices. These changes also exemplified the inherent uncertainty in forecasts and highlighted the necessity of a statistically rigorous means of addressing that uncertainty.

Public and private users of the FPO forecasts benefit from more accurate forecasts and more rigorous representations of uncertainty around forecasts. Additional forecasts provide more detailed information that can inform expectations about future food prices.

What Did the Study Find?

This study found substantial gains in forecasting accuracy from implementing time-series econometric techniques, as measured by root-mean-squared error values. Moreover, the new statistical methods (hereafter referred to as "time-series approach") led to several qualitative benefits and improvements to the efficiency of developing the FPO forecasts. In addition to enhancing standardization, transparency, and reproducibility, the study results indicate the time-series approach may advance the representation of uncertainty about forecasts in three ways:

- The forecasting approach used between 2011 and 2021 ("legacy approach") produced forecast ranges that included the actual percent changes in food prices relatively infrequently a year before the actual percent change was realized. Only 16.3 percent of forecast ranges (developed a year in advance) included the actual percent change in food prices across the food price categories. The time-series approach generated prediction intervals that contained the actual percent change in prices significantly more often at a 95 percent confidence level (85.5 percent of all forecasted categories) and a 90 percent confidence level (79.1 percent of all forecasted categories).

- Prediction intervals allow for uncertainty about food price changes to resolve, as more data become available. Prediction intervals are wider when forecasts are initially made, then continuously narrow as information becomes available throughout the year. These ranges also account for differences in the variation of each price index, explained by the forecasting model.

- Standardization of model selection allows additional data to be used in estimation or evaluated as a separate series. Apple prices and limited-service prices (a subcategory of food away from home) are evaluated as examples of how these methods may be applied to a new series as data availability and the food price environment change.

The prediction intervals more frequently contain the actual percent change in food prices and provide a more realistic representation of uncertainty about forecasts that adjust to changes in the food price environment.

How Was the Study Conducted?

This report primarily uses price indexes published by the U.S. Bureau of Labor Statistics (BLS) and food price forecast ranges generated by the USDA's Economic Research Service. Proprietary data from Urner Berry is used for a case study about seafood prices not currently covered by BLS. ERS economists use time-series econometrics which facilitate a model selection approach and allow for the generation of prediction intervals based on the data, parameter estimates, and fit of the model to the data.

The results of this forecasting approach are compared to previous Food Price Outlook forecasts. Root-mean-squared estimates are used to compare the accuracy across approaches. The approaches are then compared based on how frequently the forecast range/interval included the actual percentage change in food prices. Additionally, the average delays until a category's forecast range/interval includes the actual percentage change for the remainder of the year are calculated and compared.

Time-Series Methods for Forecasting and Modeling Uncertainty in the Food Price Outlook

Introduction

The USDA, Economic Research Service's Food Price Outlook (FPO) provides monthly forecasts of annual food price percent changes up to 18 months in advance. The forecasts add value to the U.S. Bureau of Labor Statistics' Consumer and Producer Price Indexes (CPI, PPI) by giving farmers, wholesalers, retailers, institutional buyers, consumers, and policymakers a uniform set of predictions about food prices. The more accurate the predictions, the more value FPO contributes. Events such as recent natural disasters, the Great Recession, the Food Crisis of 2011, and the COVID-19 pandemic have highlighted the importance of food price forecasting and the need for improvements to the forecasting methodology to enhance accuracy and treat uncertainty more rigorously. Rapid changes in prices or volatility warrant the use of simple and adaptable tools (Uddin et al., 2020 and Wright, 2011).

The previous Food Price Outlook Technical Bulletin detailed two estimation approaches (Kuhns et al., 2015). The first approach focuses on "pass-through modeling," a method widely used in agricultural economics. However, the declining fraction of total food costs represented by commodity costs has likely reduced the viability of pass-through models over time (Nakamura, 2008; ERS, 2022c). The second approach depends on a combination of expert opinion and model selection to identify a suitable autoregressive moving average model (ARMA).

Using several evaluation assessments reported in this technical bulletin, we present a new time-series approach (optimal autoregressive integrated moving average (ARIMA)) that typically outperforms the legacy pass-through and ARMA modeling approaches in prediction accuracy. Additional benefits of the new approach include incorporating current information and creating prediction intervals.

Recent work by Boussios et al. (2021) notes the improved accuracy and precision obtained from using time-series models and the need to regularly evaluate their performance. The methods we present in this technical bulletin build on the existing approaches in three ways. First, by consistently applying time-series methods and optimal model selection techniques across groups, we improve the fit of forecasting models to the underlying data. This improvement in fit improves forecasting accuracy, as measured by root-mean-squared estimates (RMSE). Second, we rigorously address uncertainty. Third, transparency and reproducibility are enhanced through the application of standardized methods.

This report provides an approach for defining a set of candidate ARIMA models, selecting a model based on information loss (Kullback and Leibler, 1951), and developing prediction intervals (McCullough, 1994). Models used in forecasting are selected and estimated each time a forecast is reported, ensuring the best available model is always used. This approach allows for rapid responses to changes in the underlying dynamics in food markets. Information loss is measured using a Bayesian Information Criteria (or Schwartz Criteria (BIC)), which judiciously balances model fit with parsimony, avoiding under- and overfitting the data. Prediction intervals reflect the historical uncertainty and dynamic trends of each series, and reflect the information that is available when the forecast is made.

The approach detailed in this report also supports including new data series as they become available or when specific series are of interest. As case studies, this report considers forecasts of apples (which saw a significant price decline in 2020), lobsters (which requires the use of proprietary data), and the subcategories of food-away-from-home (FAFH) prices. The FAFH series followed distinct paths, depending upon where food was obtained (e.g., at the workplace or in a restaurant). Additionally, we incorporate futures prices into the forecasts for fats and oils, and the wholesale and retail levels.

The report progresses as follows: The Food Price Outlook Overview describes the data and discusses publications relevant to the current study. The Time-Series Modeling for the Food Price Outlook section describes the new approach, which provides enhanced precision, removes potential biases from the specification process, and allows for a clearer characterization of uncertainty about future food prices. The Relative Performance of Food Price Forecasts section compares the statistical performances of the legacy and time-series approaches. Expanding the Set of Price Series section demonstrates how the approach can be used for price series not included in FPO forecasts, leaving the door open for future innovations. Finally, the report's key findings are presented in the conclusion.

Food Price Outlook Overview

Since its establishment in 1961, the Economic Research Service (ERS) has provided forecasts and evaluated trends in food prices and has become the primary source for retail-level U.S. food price inflation data (Koffsky, 1966; Joutz et al., 2000). The Food Price Outlook has a variety of users, with many people who follow and use the forecasts every month. Users include food retailers, food distributors, buyers for large institutions like schools and hospitals who use the forecasts for inventory and budgeting purposes, investment managers focused on the food and beverage industry who incorporate the ERS forecasts into their models, other USDA agencies that use the ERS forecasts as inputs into USDA food assistance program calculations, researchers who use the forecasts in studies on retail price formation and food choices, and the media that regularly use the forecasts to inform consumers about food price inflation.

The FPO estimates annual percentage changes in food prices, with monthly food price indexes. The U.S. Bureau of Labor Statistics (BLS) collects, develops, and reports these indexes regularly throughout the year (BLS, 2022a; BLS, 2022b). Price indexes (as opposed to actual prices) are commonly used to monitor inflation, since the indexes standardize comparisons across products. For example, consider a simplified example with a 10-cent price increase on two products: Steak and potatoes. If the price of steak increases 10 cents, from $10 per pound to $10.10 per pound, a price index will indicate that the steak experienced a 1-percent price increase. In contrast, a price index for the same 10-cent price increase for potatoes ($1 per pound to $1.10 per pound) will indicate a 10-percent price increase. In this example, price indexes help communicate that the same 10-cent price increase represents a much greater proportional price increase for potatoes than for steak.

ERS forecast ranges for annual percent changes in food prices run for the current year and go to the following year, beginning in July. In effect, the FPO forecasts the percent changes between the annual average prices in 2 consecutive years (last year to the current year, and the current year to next year). Since new price information is released each month—when the Bureau of Labor Statistics (BLS) publishes updates to the Consumer Price Index (CPI) and Producer Price Index (PPI)—forecasts include a combination of observed price changes (when available) and uncertain forecast prices. Forecast ranges reported by ERS reflect a combination of model results, expert opinion, and uncertainty about the future of food prices (Kuhns et al., 2015). ERS analysts compile expert opinions directly, and through forecasts generated by commodity and market specialists throughout USDA (e.g., Office of the Chief Economist, 2022). Forecast ranges have been reported as 1-percent point ranges for CPI and 3-percent point ranges for PPI series, to reflect greater uncertainty of the PPI estimates. Kuhns et al. (2015) note this approach "...accounts for some degree of inherent uncertainty in forecasting, as well as the specific factors that cannot be forecasted rigorously in our case, particularly the weather."

In addition to weather, other factors that introduce uncertainty into forecasts include international trade flows, consumer income and preferences, elevated levels of pests or pathogens that affect agriculture, and other unforeseen disruptions. Several recent events that induced large shifts into the forecasts include the Great Recession, the Global Food Crisis of 2011, and the COVID-19 pandemic that began in early 2020. The time-series approach to prediction intervals we present in this technical bulletin better addresses these observed forms of uncertainty and accommodates sources of risk not yet observed. This approach considers historical uncertainty about forecasts that vary by food type and level of aggregation. Additionally, the new prediction intervals narrow throughout the year, as uncertainty resolves substantially between February and January of the following year.

Estimating and forecasting annual percentage changes using monthly data

The food price percentage change (often referred to as an "inflation rate") for price series *j* in year *t*, $\Delta I_{j,t,}$ is the percent difference between the average CPI (or PPI) in years *t* and *t*–1. This formula can be expressed by summing over months *M={January,…,December}*. When all data are available, the percent change is calculated using the following equation:

$$\Delta I_{j,t} = 100 * \frac{\sum_{m \epsilon M} CPI_{j,t,m} - CPI_{j,t-1,m}}{\sum_{m \epsilon M} CPI_{j,t-1,m}} \tag{1}$$

Forecasts are made with partial information about prices. If, for example, a forecast was made using data through May 2020 about the index *k* for all of 2020, then equation 1 can be modified to combine known data with estimated forecasts as follows:

$$\Delta \hat{I}_{k,t} = 100 * \frac{\sum_{m=1}^{5} CPI_{k,t,m} + \sum_{m=6}^{12} \widehat{CPI}_{k,2020,m} - \sum_{m \epsilon M} CPI_{k,2019,m}}{\sum_{m \epsilon M} CPI_{k,2019,m}} \tag{1a}$$

where $\hat{I}$ and $\widehat{CPI}$ signify that the percent change in food prices and CPI values are (partially) forecast.

Equation 1a includes both certain observations and uncertain forecasts.[1] The fraction of months that are observed and the fraction that are forecasted influence the uncertainty about $\hat{I}$.

Recent methodological improvements

It is a best practice among economists to regularly evaluate and improve model performance. ERS periodically undertakes such efforts for methods used to develop its data products and forecasts to ensure the quality of its products. Among ERS's data products, documented improvements since 2010 have been made to: the ERS Loss-Adjusted Food Data (Muth et al., 2010), the Food Dollar (Canning, 2011), the U.S. Household Food Security Measures (Nord, 2012), the Quarterly Food-Away-From-Home Prices Data (Kumcu and Okrent, 2014), an International Food Security Assessment (Meade et al., 2015), the Healthy Eating Index (Mancino, Todd, and Scharadin, 2018), the Food Expenditure Series (Okrent et al., 2018), and the Purchase to Plate Price tool (Carlson et al., 2020). Several of ERS's forecasts have also been evaluated and improved: Dairy industry forecasts in the World Agricultural Supply and Demand Estimates (Moheim, 2012; OCE, 2022), the USDA 10-year Agricultural Projections (Baseline) (Good and Irwin, 2006; Boussios et al., 2021), and the Livestock Baseline (Maples et al., forthcoming).

The use of ARIMA models in FPO was first proposed by Denbaly et al. (1996). Since 2000, retail food price forecasts have been evaluated in three ERS studies that evaluated and improved the accuracy of ERS food price forecasts (Huang, 2000; Joutz et al., 2000; Kuhns et al., 2015). This technical bulletin aligns with this practice. We add to the published improvements to ERS's data products by providing practicable modifications to the existing approach.

Since the last update in 2015, the long-lasting COVID-19 pandemic—and the associated disruptions to agricultural and food markets—have renewed the interest in ensuring the use of the best available methods.

[1] Bureau of Labor Statistics Producer Price Index data are subject to revisions but are treated as certain in USDA forecasts.

Time-Series Modeling for the Food Price Outlook

The new unified and systematic time-series approach that is presented in this technical bulletin uses ARIMA modeling. ARIMA modeling provides an apt framework for modeling autocorrelation (high correlation among observations that occur near the same time) and accounting for non-stationarity (means, trends, or variances change over time). While the legacy approach partially accounted for these elements, the new approach evaluates alternative specifications to ensure we use the best available model for each monthly forecast (a model need not be optimal for longer than a single forecast). We develop prediction intervals using Monte Carlo methods, which better reflect historical uncertainty and the resolution of uncertainty throughout the year.

The new time-series approach contributes four key improvements compared to previous methods. Therefore, the approach is easily reproducible and may benefit from insights developed in other forecasting endeavors. The methods are standardized across each food price series and do not include subjective input from analysts, which improves the consistency of results and allows additional series to be included, as interest arises or data become available. The use of mainstream econometric approaches allows the methods used in the development of the Food Price Outlook to be used elsewhere in research, which requires high levels of transparency and reproducibility. Lastly, a rigorous treatment of uncertainty allows for a more predictable updating process for prediction intervals, as data become available and uncertainty resolves.

Autoregressive integrated moving average models for time-series analysis

This technical bulletin explores the use of ARIMA models. ARIMA models combine own lags (autoregressive), differencing (integrated), and moving averages to series, typically to develop forecasts (Box and Jenkins, 2015). An ARIMA model, $ARIMA(p,d,q)$, is generally defined for a forecasted variable (y) as the number of lags (p), the order of differencing (d), and the number of moving average terms (q). These functions can be expressed compactly and generally as follows:

$$\left(1-\sum_{i}^{p}\alpha_i L^i\right)(1-L^d)y_t=\left(1-\sum_{j=1}^{q}\theta_j L^j\right)\varepsilon_t \tag{2}$$

where α_i is the coefficient on the autoregressive term of lag-order L^i, θ_j is the coefficient of the moving-average term of lag order L^j, and ε_t is the error or innovation term at time t.

These models can also accommodate autoregressive terms and differencing that account for seasonality. Given the seasonality present in supply and demand, we also consider Seasonal ARIMA (SARIMA) models.

Including exogenous data, such as macroeconomic variables or energy prices, may also be desirable. All features can be jointly estimated in a SARIMAX model. Considering exogenous variables and specification certainty around how to include these variables was beyond the scope of this work, but we provide cursory evaluations in the subsections addressing pass-through models and the inclusion of futures data.

Optimal model selection

Several approaches are available for selecting forecasting models that avoid over- or underfitting the data. Among the available criteria, Bayesian Information Criterion (BIC) is favored for selecting parsimonious (non-)linear models that perform well out of sample (Schwartz, 1978; Engle and Brown, 1986). BIC values improve (decrease) as model fit improves (as measured by a likelihood function), which helps avoid underfitting issues. Overfitting the data with overly complex models typically leads to poor out-of-sample performance (for a recent discussion, see Lever et al., 2016). The best model has the minimum BIC value, which balances model fit (likelihood function) against the number of included parameters, simultaneously avoiding under- or overfitting the data. The functional form can be represented as

$$BIC = k \ln(n) - 2 \ln(\hat{\mathcal{L}}) \tag{3}$$

where k is the number of parameters included in an ARIMA model, n is the number of observations used to fit the model (the starting values are not included in the fitting process due to the included lagged terms) and $\hat{\mathcal{L}}$ is the optimized value of the (quasi-) likelihood function (a measure of goodness of fit).

A BIC value is generated for each considered ARIMA model. The value includes different numbers of autoregressive terms, orders of differencing, and moving average terms. These values are then compared to identify the minimum BIC value, which indicates the optimality (minimum information loss or Kullbach-Leibler divergence). The model with the minimum BIC value is considered optimal and used to develop forecast median values and intervals.

In this technical bulletin, we consider models with seasonal ARIMA models with up to 12 lags, 12 moving average terms, 4 orders of differencing, 2 seasonal lags, 2 seasonal moving average terms, and 1 order of seasonal differencing. All elements may also be excluded during estimation. For each index in each month, 15,210 candidate models are considered.

Nau (2014) notes the importance of avoiding including redundant terms. Therefore, practitioners may want to consider a single moving-average term at most ($q<2$) or reduce the number of autoregressive terms or differencing. However, using BIC values in model selection reduces the risk of including unnecessary terms as these terms will not significantly improve fit but will increase the penalty for the number of included terms. A model selection approach also decreased the number of possible moving average terms to one; it did not materially affect the results.

Prediction intervals for modeling uncertainty

A prediction interval is developed using the parameter estimates from the optimal model for each series. These prediction intervals reflect the distinct degree of uncertainty about each forecast percent change across different food price categories.

The unobserved months in a forecasted year can be simulated using the current data, long-run trends, seasonality, and exogenous variables. In this report, the current and lagged CPI or PPI values and seasonal and long-term trends determine the expected path of each forecast. Therefore, to develop forecasts that include exogenous variables, separate forecasts of these exogenous variables must be generated first. This process is discussed in two subsections of this report.

Forecasts are simulated 10,000 times using the estimated forecast model and pseudo-random innovations (errors) to define distinct trajectories. The estimated model defines deterministic changes to a variable for each forecasted month based on past observations, and the error term is then added to this predicted value. The distribution from which the simulated innovations are drawn is estimated jointly with the optimal model. The distribution of these innovations will always be centered on zero (unbiased) and assumed to be normal. The variance of these innovations depends on the variation that a time-series model does not explain.

Because the innovations will lead to distinct trajectories, we can subsequently develop a distribution of possible annual price changes from these trajectories. After ordering the annual percent changes in the food price series of interest, the 95-percent prediction interval is defined by the average of the 250th and 251st (2.5th percentile) and the 9,750th and 9,751st observations (97.5th percentile). A similar approach is used to develop the 90-percent prediction interval described in the results.

As each year unfolds, fewer forecasted CPI terms are included, decreasing the prediction intervals' range in almost all cases. This resolution of uncertainty about the annual percent change in food price has been observed in other instances when additional information becomes available about prices (e.g., Adjemian et al., 2020) or whenever an economic agent learns about an unknown value (e.g., MacLachlan et al., 2017).

The span of the prediction intervals may also change, as only the previous 12 years of data are used to develop each prediction interval. When the time-series model explains less of the variation in food prices, these predictions will be wider.

Pass-through models

Given their historical use, pass-through models (which serve as the foundation for the legacy approach) bear consideration. Pass-through models assume that outputs at one point of the supply chain are inputs of downstream industries. Within agricultural economics, pass-through models have been used to reflect how changes in farm- and wholesale-level (upstream) food prices influence retail-level (downstream) food prices (e.g., Nakamura, 2008; Berck et al., 2009). It is typically assumed that farm and wholesale-level prices affect retail prices, not vice versa. However, the declining fraction of the "Food Dollar" received by producers brings the predictive ability of pass-through models into question (Nakamura, 2008; ERS, 2022c). We consider, as an example, whether wholesale pork prices improve the BIC values (and thus improve the goodness of fit) of models for retail-level pork price forecasts.

Finding the BIC value for the optimal model of retail pork prices (when wholesale pork prices are included and excluded as an exogenous variable) allows for the comparison of the statistical performance of a pass-through model. The inclusion of wholesale pork prices increases the BIC values, i.e., the pass-through model performs worse.[2] The change in BIC values between the two specifications is >10, which indicates a very strong preference for excluding the pass-through component of the model (Kass and Raftery, 1995). We cannot support an assumption that a contemporaneous pass-through model improves model fit (as measured by BIC values)—and we, therefore, do not consider pass-through as candidate models within this technical bulletin. However, this exclusion does not mean that upstream market prices are uninformative in all cases.

[2] Another measure of fit, the Akaike Information Criterion (AIC), also increases with the inclusion of wholesale pork prices. The AIC imposes a smaller penalty on the number of included parameters ($2k < k \ln(n) \; \forall \; n > 7$) and is consider consistent if the "true" data-generating model is not included in the considered set (Vrieze, 2012). While the suitability of a criterion is unknowable, the large number of considered models and the high model performance suggest that the assumptions behind the BIC are more tenable. Ultimately, the results do not differ based on the choice of information criterion.

Performance of Food Price Forecasts

We first compare the accuracy of the time-series approach with that of the legacy approach, finding that the time-series approach improves accuracy across forecasts. Subsequently, we demonstrate how the prediction intervals provide a better measure of uncertainty than the forecast ranges.

Measuring historical accuracy of the time-series and legacy approaches

We compare the root-mean-squared error (RMSE) values of the median of the prediction intervals with the center of each forecast range. While the latter represents an imperfect metric of the central moment or analysts' best prediction, it is also the most tenable available measure.

Averaging over all months, years, and categories, we find that the RMSE of the time-series approach (1.8) lies well below that calculated for the center of the forecast ranges of the legacy approach (2.2). This ex-post evaluation indicates an improvement in the representation of uncertainty and accuracy.

We compare the RMSE values by categories and years in table 1, which estimate how well each approach fits the actual data. However, the limited data within each category or year makes these estimates sensitive to outliers. Similarly, the very large RMSE estimates for eggs, as an example, may indicate a disproportionate impact on our aggregate RMSE estimates.

Table 1

Root-mean-squared error of the center of forecast ranges (legacy) and the median of the prediction intervals (time series) by food category and year, 2011–20

Category or year	RMSE of the legacy approach—center of the forecast range	RMSE of the time-series approach—prediction interval median	Best approach
All food*	0.8	0.6	Time series
Food away from home*	0.5	0.3	Time series
Food at home*	1.8	1.0	Time series
Meats, poultry, and fish*	4.4	1.3	Time series
Meats	6.8	1.8	Time series
Beef and veal	9.6	2.1	Time series
Pork	6.7	2.5	Time series
Other meats	4.2	1.2	Time series
Poultry	3.2	0.8	Time series
Fish and seafood	2.9	1.0	Time series
Eggs	36.3	5.6	Time series
Dairy products	4.2	1.6	Time series
Fats and oils	3.6	1.6	Time series
Fruits and vegetables*	1.1	1.4	Time series
Fresh fruits and vegetables*	1.3	1.9	Time series
Fresh fruits	2.8	1.7	Time series
Fresh vegetables	2.7	2.0	Time series
Processed fruits and vegetables	2.8	1.4	Time series
Sugar and sweets	3.1	0.9	Time series
Cereals and bakery products	1.8	1.0	Time series
Nonalcoholic beverages	3.4	0.8	Time series
Other foods	1.8	0.5	Time series
2011	3.6	2.7	Time series
2012	3.7	1.6	Time series
2013	2.8	1.9	Time series
2014	7.4	1.2	Time series
2015	8.8	0.8	Time series
2016	12.2	1.9	Time series
2017	1.6	2.2	Legacy
2018	1.6	2.9	Legacy
2019	2.3	1.1	Time series
2020	5.0	1.0	Time series
Total*	**2.2**	**1.8**	**Time series**

Notes: *Indicates an aggregate category composed of two or more reported categories. RMSE=Root-mean-squared error

Source: USDA, Economic Research Service calculations based on U.S. Bureau of Labor consumer price indexes.

When evaluating across months and years for each category, the time-series approach yielded a lower RMSE value. The time-series approach also yielded lower RMSE values when aggregating by year, except 2017 and 2018.

These results indicate that the time-series approach provides more accurate forecasts than the legacy approach. The time-series approach could be further enhanced by including other, exogenous series, so long as those series reduce information loss as measured by BIC values. In the subsequent subsections, we also characterize how Monte Carlo simulations can be used to provide more reliable measures of uncertainty to consumers of FPO reports.

Comparison of the legacy and new time-series approaches

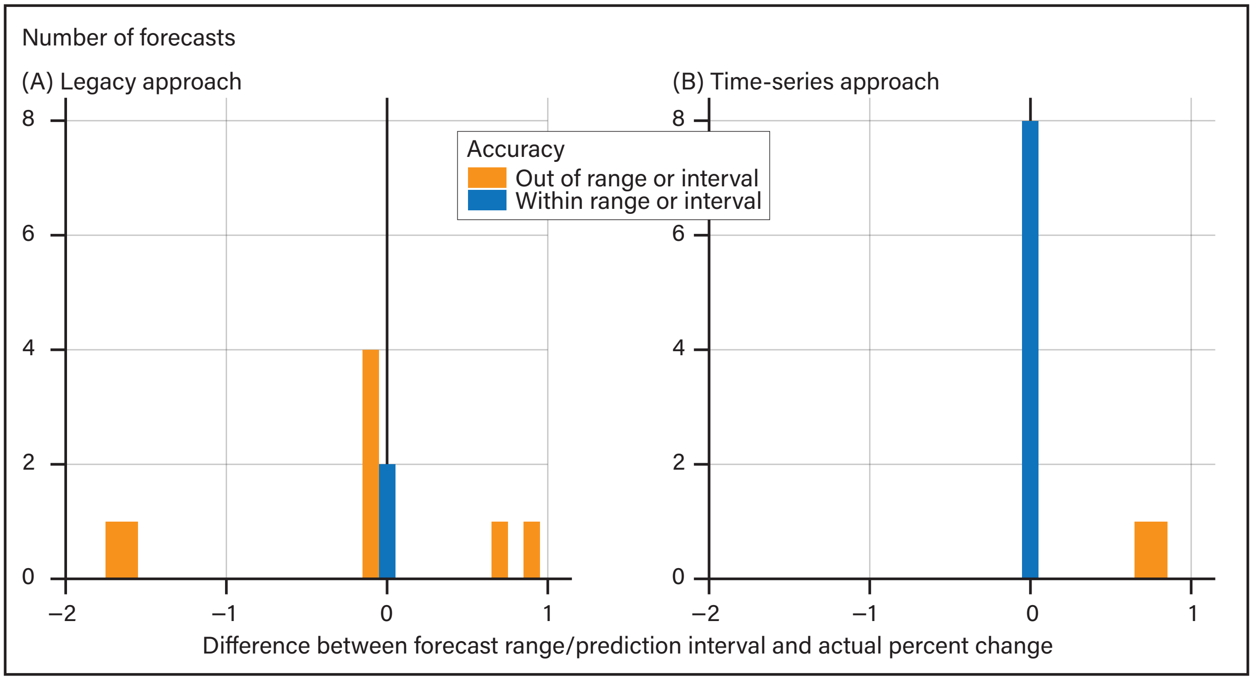
Any new model should outperform the legacy approach to justify a methodological change. To evaluate the representation of uncertainty used in the legacy approach, we examine how frequently the forecast range for the percent change in all food prices contained the actual percent change from 2011 to 2020. While we include additional years later in this report, in this subsection, we assess this performance of the legacy approach between these years to best capture performance following the previous model updates.

The all-food price series is relatively stable and covers the other 21 reported food categories. Because forecasts made throughout the year are informed by increasing amounts of information, only the forecasts made using data through December of the previous year were included. Figure 1 shows the observations that fall within the forecast range or interval (blue) and those that fall outside the range (red). The distance between the closest edge of the range/interval and the actual percent change is also reported. For example, in January 2018, the legacy model predicted all food prices would increase 1.5 to 2.5 percent over 2018. However, the actual percent change of the food prices was 1.4 percent, and the actual percent change was 0.1 percent outside the predicted range. These estimates and data are depicted in figure 1 (A) in red, at 0.1 on the x-axis. This distance represents the magnitude of the errors.[3]

[3] "Forecast errors" typically refer to the distance between a forecasted point and the actual value. Because Food Price Outlook forecasts are only reported as ranges that are rounded to the nearest 0.5 percent, we instead choose this alternative measure of forecast error.

Figure 1

Counts of all food forecast ranges from the legacy approach (A) and prediction intervals from the time-series approach (B) that either include the actual percent and the distance between the closest edge of the range/interval for those observations that did not fall within the range/interval, 2011–20



Source: USDA, Economic Research Service calculations based on U.S. Bureau of Labor consumer price indexes.

Figure 1 (A) indicates that only twice did the forecast range for the percent change in food prices include the actual percent change (count of two for the blue bar in panel (A). While the distances between the forecast ranges and actual percent change were typically small (six out of the eight inaccurate predictions were less than 1-percentage point from the forecast range), these ranges show that improved accuracy or an acknowledgment of greater uncertainty about future food prices—as represented by a wider range or interval around the point estimate or best projection—could improve the quality of these forecasts.

As evaluated in the previous subsection, implementing the time-series approach improves the accuracy of the forecasts. Each year, this approach allows the model to adjust rapidly to new price information, both in terms of median values and representations of uncertainty (prediction intervals). These benefits hold across food categories but are most pronounced for those with the largest volatility.

Following the comparison in figure 1 (A), figure 1 (B) shows the count and magnitude of differences between the actual annual percent change in food price and the forecast range predicted using data through December of the previous year. The majority of actual percent changes (8 out of 10) were within the prediction intervals estimated, using data through December of the previous year.

Table 2 applies the same accuracy/counting evaluation method used to generate the blue bars in figure 1 to each CPI category individually. Table 2 compares the number of times each range (legacy approach) and prediction interval (time-series approach) included the actual percent change in food price.

Table 2

Count of times each Consumer Price Index for different food categories falls within the forecast range (legacy approach) and prediction interval (time-series approach), 2011–20

Food category	Count within forecast range (out of 10 possible)	Count within 95-percent prediction interval (10 possible)	Count within 90-percent prediction interval (10 possible)
All food*	2	8	7
Food away from home*	6	9	8
Food at home*	1	8	6
Meats, poultry, and fish*	1	7	7
Meats	0	7	7
Beef and veal	1	7	7
Pork	1	8	7
Other meats	0	9	7
Poultry	1	9	9
Fish and seafood	2	9	7
Eggs	1	9	9
Dairy products	0	10	9
Fats and oils	3	9	9
Fruits and vegetables*	2	10	10
Fresh fruits and vegetables*	3	10	10
Fresh fruits	1	10	10
Fresh vegetables	2	8	8
Processed fruits and vegetables	2	9	8
Sugar and sweets	1	8	7
Cereals and bakery products	1	8	8
Nonalcoholic beverages	2	8	8
Other foods	3	8	8
Total	**36 (16.4 percent)**	**188 (85.5 percent)**	**176 (80 percent)**

*Indicates an aggregate category composed of two or more reported categories.

Source: USDA, Economic Research Service calculations based on U.S. Bureau of Labor consumer price indexes.

The legacy approach's forecast range included the actual percent change of food price infrequently (<17 percent of year-category pairs), and accuracy tended to be worse for disaggregated/individual categories (<13 percent of year-category pairs). This success rate would suit a low confidence level (e.g., below a standard deviation). However, the rate does not reflect the higher confidence levels typically used in prediction intervals (e.g., 90 percent, 95 percent, or even 1 standard deviation).

As a particularly problematic example, the highly volatile category of dairy products never included the actual percent change in its forecast range during the period of interest.

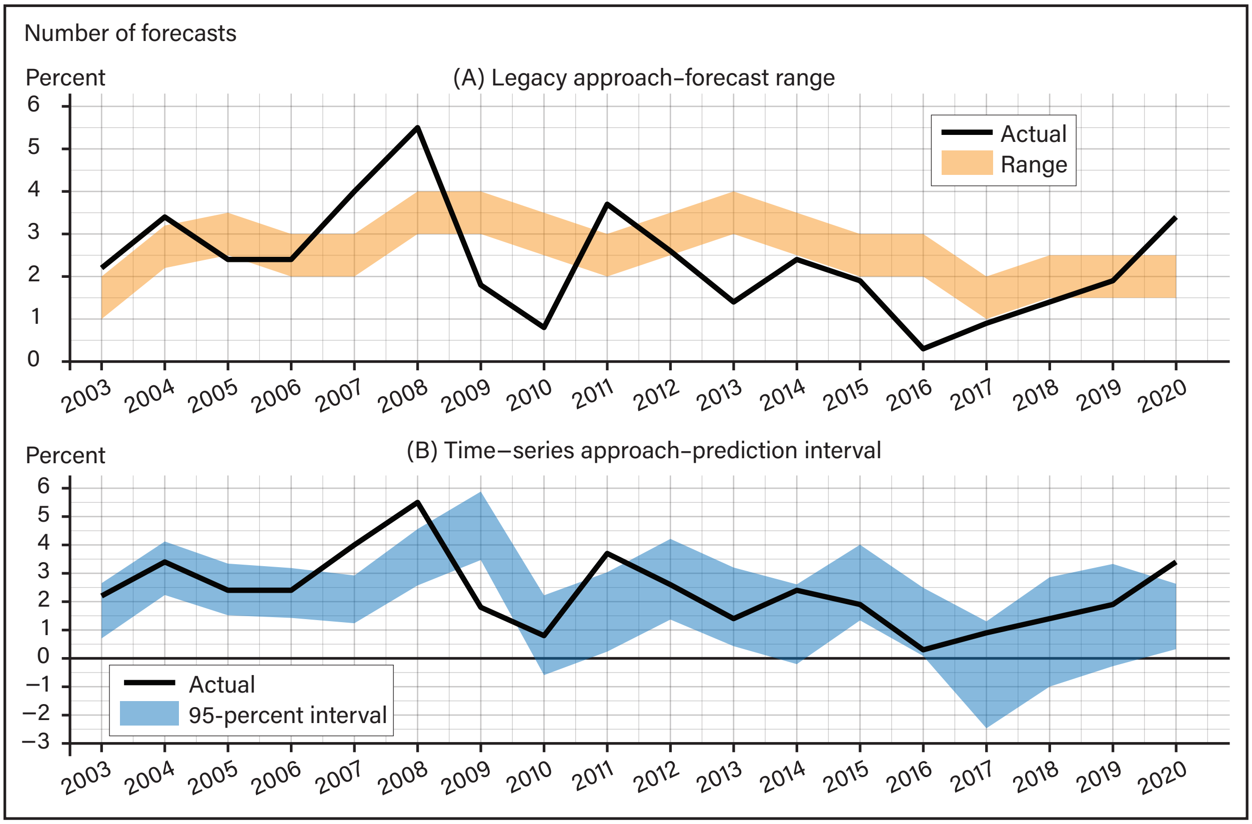
In contrast, more than 85 percent of the actual changes in food prices lay within their prediction interval, and this percentage still falls below the 95 percent suggested by the interval range. However, the forecasting approach presented in this report is informed by past observations and several impactful events during the study period.

The appendix presents a similar analysis for PPI. The results in the appendix do not qualitatively differ from those presented here. The forecast ranges for PPI include the actual percent change for only 5.5 percent of year-category pairs, compared to 68.1 percent for the prediction intervals.

Performance of uncertainty measures across years

Evaluating a longer period, 2003–20, allows for a more comprehensive evaluation of when actual percent changes lay outside the prediction intervals developed at the beginning of the year. For comparison, we represent the forecast ranges (developed using data through the previous year) in figure 2 (A). These forecast ranges were not developed using a single method and only represent a point of comparison. The observations that did not lie within the prediction interval indicate the time-series approach misses some years. As shown in figure 2B, the years when the prediction interval does not include the actual percent changes occurred exclusively during major disruptions to food prices—the Great Recession, the Food Crisis of 2011, and the 2020 COVID-19 pandemic.

Figure 2
Actual annual percent change in all food prices, forecast range, and the 95-percent prediction interval, 2003–20



Note: The forecast ranges presented in figure 2 (A) reflect several different forecasting approaches.

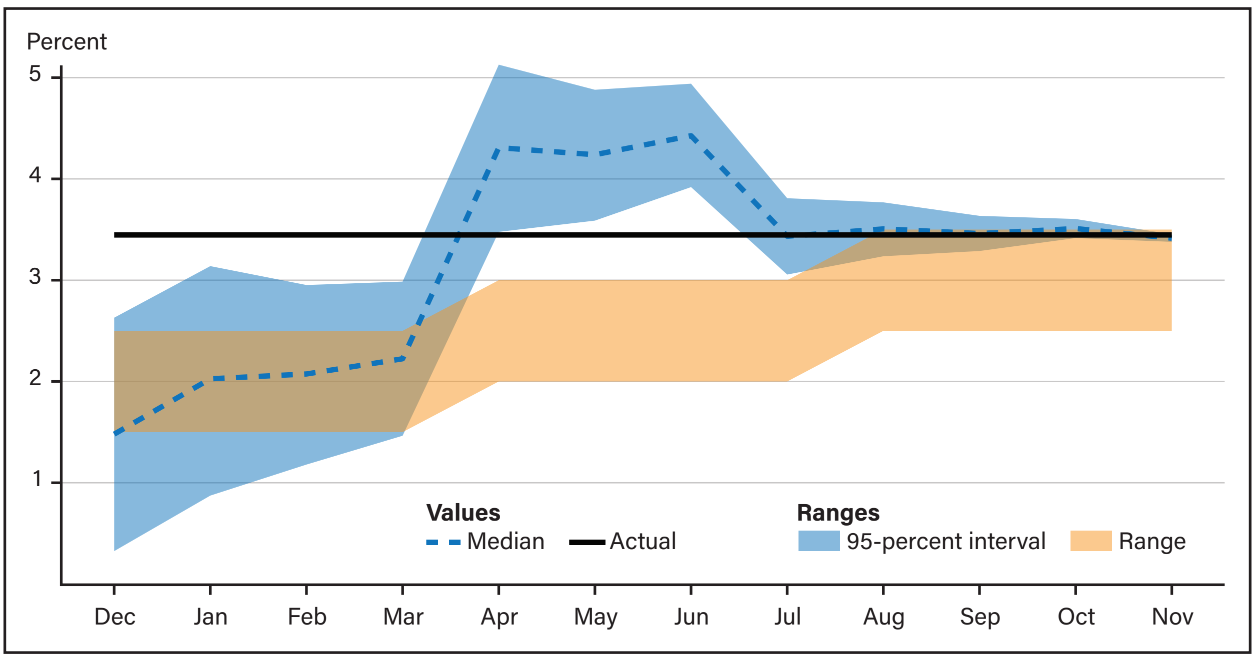
Source: USDA, Economic Research Service calculations based on U.S. Bureau of Labor consumer price indexes.

The time-series approach also allows the span of the prediction interval to change as price uncertainty changes from year to year. For example, between 2007 and 2011, food prices experienced high volatility. The new time-series approach accounts for this period by widening the confidence interval following 2011. The prediction interval in 2006 was 2.1–3.3, while the prediction interval in 2013 was 1.7–3.9. The prediction interval in 2013 was approximately 83 percent larger than in 2006.

Performance of uncertainty measures within years

The time-series approach also adjusts to a changing food-price environment within a volatile year. As a recent example, food-at-home prices increased dramatically in 2020, due to the COVID-19 pandemic. Many food prices (particularly meat prices) increased at the pandemic's onset, then slowly decreased toward pre-COVID levels in 2020. The time-series approach quickly responded to the new information (e.g., higher meat prices). After over-correcting in May (using April data), the time-series approach provided an "all food" prediction interval that ultimately included the actual percent change for all months following July 2020 using June (and later) data. In contrast, the legacy model forecasts did not include the actual percent change in the all-food price within range until August data were included (the forecast was made in September 2020). The within-year convergence for the "all food" forecast during 2020 can be observed in figure 3 for both the legacy approach (gold) and the new time-series approach (blue).

Figure 3
Convergence of estimated prediction intervals for the percent change in the all-food price, December 2019–November 2020

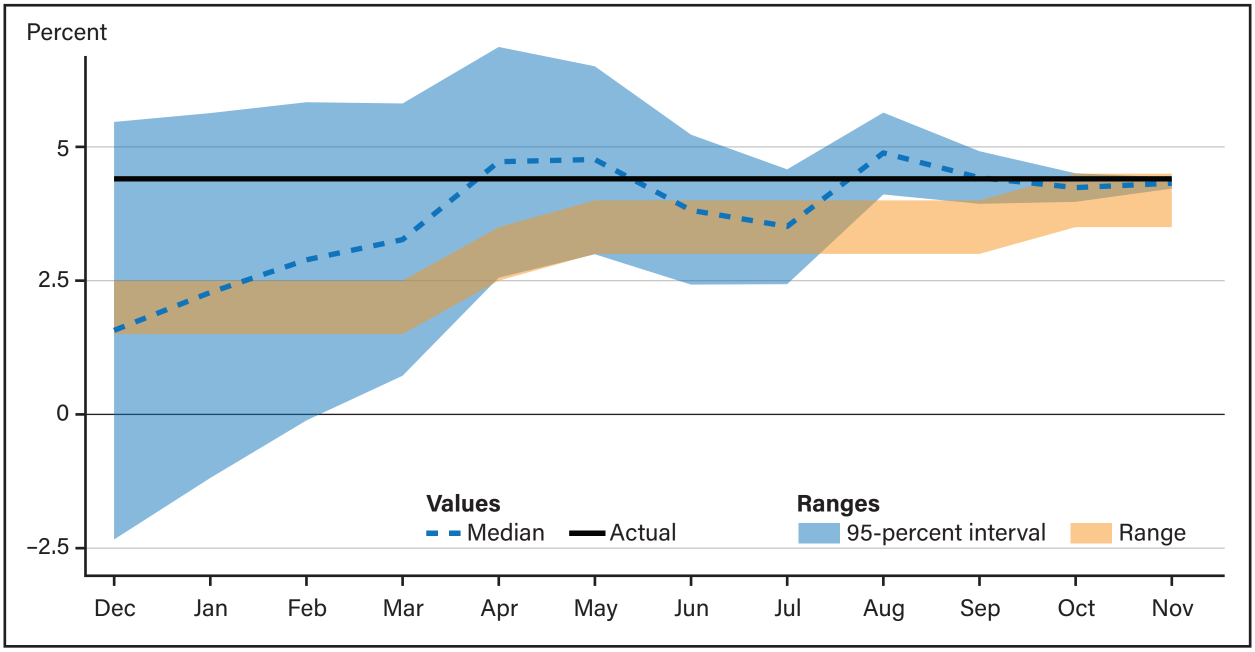


Source: USDA, Economic Research Service calculations based on U.S. Bureau of Labor consumer price indexes.

Figure 3 includes the relatively stable category of all food prices. Prediction intervals generated from the ARIMA model include the actual percent change for all months, beginning in July 2020. However, the legacy model only includes the actual percent change for 4 months, from August to December 2020. Considering this moderate improvement, what is the relative performance of these approaches across years and categories?

The ARIMA approach is particularly well-suited to addressing the relatively high volatility of many disaggregate food price categories. For example, dairy prices typically have large percent changes between months. Figure 4 shows the same comparison as figure 3, but for retail dairy prices instead of food.

Figure 4
Convergence of prediction intervals for the annual percent change in the retail dairy price, December 2019–November 2020



Source: USDA, Economic Research Service calculations based on U.S. Bureau of Labor consumer price indexes.

The annual percent change of dairy prices was difficult to predict between 2011 and 2020, with no initial forecast ranges, including the actual value (table 1). The volatile nature of this category was particularly salient in May 2020, at the start of the COVID-19 pandemic (figure 4). Dairy prices were on an upward trajectory, increasing by 0.5 percent in March and 1.4 percent in April. It was unclear if this price change would be a short-lived impulse or persist. The legacy approach—which involves making as few adjustments as possible throughout the year (Kuhns et al., 2015)—resulted in a forecast range of 2.5 to 3.5 percent in May (using data through April). The forecast range was gradually adjusted upward over eight months until it included the actual percent change (4.4 percent). The legacy model included the actual percent change by November of 2020 (using October data), reporting a range of 3.5 to 4.5 percent.

In contrast, the time-series model incorporated the uncertainty generated by the March and April price spikes when the increases happened and the model forecast an interval of 1.8 to 7.6, using data through April. This interval contained the actual percent change and continued for the rest of the year. The interval narrowed each month as additional data resolved the remaining forecast uncertainty.

The example of 2020 dairy prices highlights the problem of modeling uncertainty about food price changes using a single percentage point range. New data do not reduce forecast uncertainty in the legacy approach. Furthermore, the previous technical bulletin did not guide when and how to make changes within the legacy approach. The ARIMA model incorporates uncertainty by design. Prediction intervals change with real-time data and accurately reflect the remaining uncertainty in each month.

This pattern is similar across multiple food categories. On average, the ARIMA model includes the actual percent change in prices in the prediction interval within 4.3 months, whereas the legacy model includes the actual percent change (on average) within 7.4 months (table 3). However, neither the legacy nor the time-series model performs better each month across all food categories. In general, the number of months needed for the measure of uncertainty (forecast ranges or intervals) to include the actual percent change partially captures how well data are used to predict and reflect uncertainty. Table 3 presents the average of this delay between 2011 and 2020, across all Consumer Price Index groups.

The time-series approach provides a representation of uncertainty that includes the actual level much earlier in the year, after 4.3 months on average. For some categories, the inclusion of the actual percent change occurs within less than 2 months (fats and oils, fresh vegetables, and nonalcoholic beverages). In contrast, the legacy approach takes an average of at least 4.9 and up to 9.9 months.

Table 3

Average number of months needed for the forecast range or interval, to include the actual percent change for the duration of the year

Food category	Average delay of the legacy model	Average delay of 95-percent prediction interval (time-series approach)	Average delay of 90-percent prediction interval (time-series approach)
All food*	6.2	7.2	7.2
Food away from home*	4.9	4.7	6.1
Food at home*	6.7	7.2	7.2
Meats, poultry, and fish*	7.4	8.4	8.6
Meats	7.3	7.6	7.6
Beef and veal	8.7	7.2	7.2
Pork	7.9	7.2	7.2
Other meats	9.3	7.6	8.8
Poultry	7.6	7.8	8.1
Fish and seafood	7.0	6.5	7.2
Eggs	9.9	2.4	6.0
Dairy products	6.6	7.2	7.2
Fats and oils	8.9	4.8	4.8
Fruits and vegetables*	6.3	4.8	5.1
Fresh fruits and vegetables*	6.3	4.8	5.3
Fresh fruits	6.6	4.8	5.7
Fresh vegetables	9.1	4.8	5.1
Processed fruits and vegetables	8.0	8.4	9.6
Sugar and sweets	6.6	6.0	6.0
Cereals and bakery products	7.7	6.0	6.0
Nonalcoholic beverages	7.4	6.0	6.0
Other foods	5.6	8.4	8.4
Total	**7.4**	**6.4**	**6.8**

Source: USDA, Economic Research Service calculations based on U.S. Bureau of Labor consumer price indexes.

Expanding the Set of Price Series

Changes in data availability and the U.S. food price environment often necessitate the examination of an additional series. Food Price Outlook (FPO) analysts are frequently asked to provide forecasts or expert opinions on some series that are not currently included in the legacy model. There is no existing framework to develop a forecast for a new series, using methodologies that are consistent with the legacy model.

However, the time-series approach could easily be used to model additional types of series. The resulting forecasts could improve the accuracy of current forecasts or be reported graphically, qualitatively, or quantitatively as a separate series with the FPO.

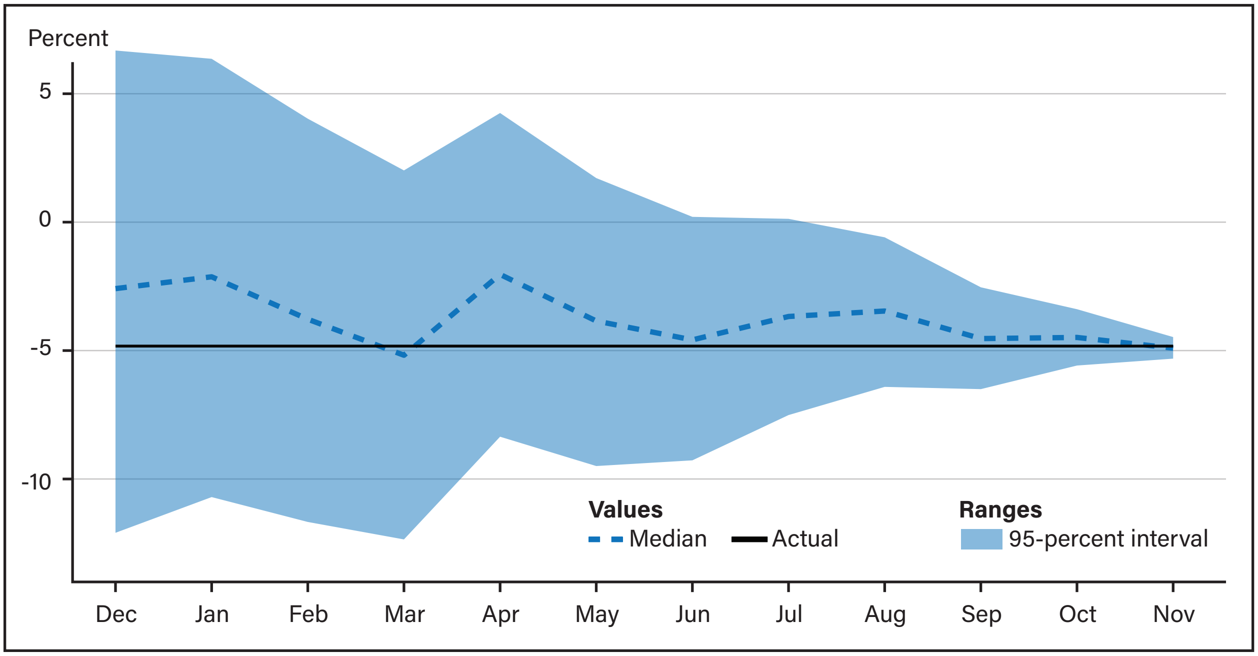
Additional sources of information may improve the accuracy of forecasts and will typically do so if their inclusion reduces BIC values.

We estimate three series currently not part of the Food Price Outlook using the approach described in this report: apples, limited-service FAFH, and lobster prices. Each series experienced significant changes during the COVID-19 pandemic that warranted additional examination. Additionally, futures prices for fats and oils are incorporated into the forecasts for their wholesale- and retail-level counterparts.

Case Study A: Consideration of fresh fruit prices as a separate series

Most food-at-home price categories increased in 2020, while fresh fruit prices declined. This decline was largely driven by declining prices of apples, a significant portion of fresh fruit prices (Kramer, Simnitt, and Calvin, 2020). The time-series model outlined above allows us to easily forecast apple prices using the standardized approach—an exercise that would have been useful in 2020. Figure 5 shows prediction intervals and median values for the percent change in CPI of fresh apples.

Figure 5
Convergence of estimated prediction intervals for the percent change of retail fresh apple prices, December 2019–November 2020



Source: USDA, Economic Research Service calculations based on U.S. Bureau of Labor consumer price indexes.

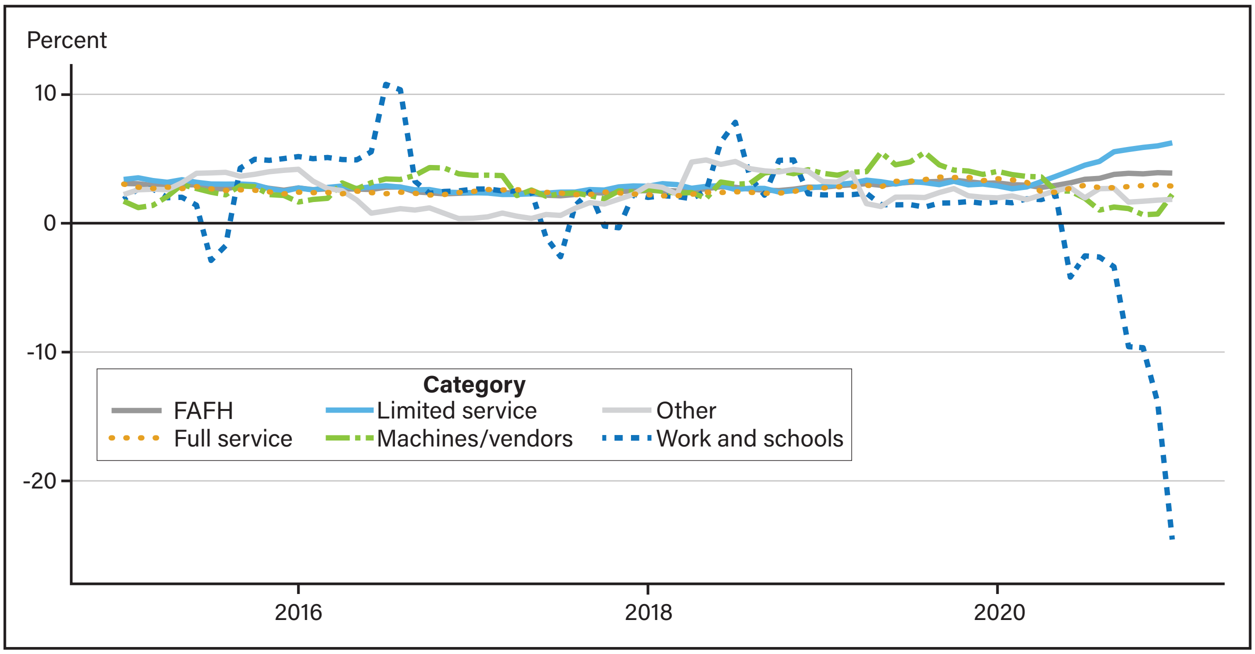
"Apples" is a small, volatile food price category. The prediction interval includes the actual percent change (-5 percent) throughout the time series, while narrowing in on this change. The median value for the forecast closely tracks the actual percent change, even under unprecedented circumstances, such as the COVID-19 pandemic. A graph like figure 5 could have been provided to USDA policymakers or the general public that would have shed light on the trajectory of fruit prices during the pandemic.

Case Study B: Considering limited-service food-away-from-home prices as a separate category

As FAFH consumption declined during the COVID-19 pandemic, the interest in the FAFH subseries increased (ERS, 2022a). There are five food price subcategories within FAFH: Full service, limited service, food purchased at worksites and schools, food from vending machines and other vendors, and other food away from home. While the percent change in food prices in most FAFH series was low during the pandemic, limited-service food prices increased at a rate well above the historical average. The increases in limited-service food prices led to aggregate FAFH price increases. These increases offset enormous price decreases for food consumed at worksites and schools and, to a lesser extent, each of the other FAFH subcategories.

Figure 6 shows the monthly percent price change relative to a year before, between January 2015 and January 2021. Each point represents the percent changes for the previous 12 months, over the average prices observed between 13 and 24 months prior.

Figure 6
Rolling average of food price changes by month, 2014–20



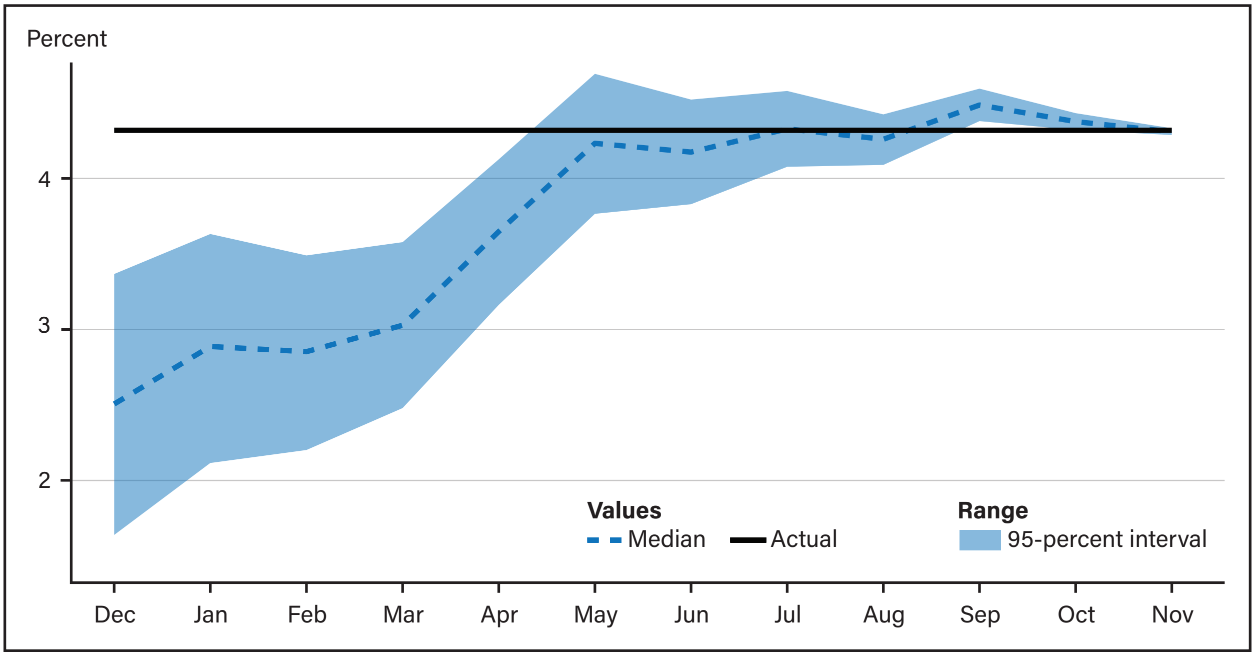
FAFH= Food-away-from-home

Note: Each month is compared to the same time a year ago for five categories of food-away-from-home prices and all food-away from home.

Source: USDA, Economic Research Service calculations based on U.S. Bureau of Labor consumer price indexes.

The limited-service price increases were surprising, given the reduced aggregate expenditures (ERS, 2022c). Monthly forecasts of percent changes in prices for limited-service restaurants during 2020 provide another example of how the set of Food Price Outlook price series could be expanded. These forecasts are shown in figure 7.

Figure 7
Convergence of estimated prediction intervals for limited-service price changes, December 2019–November 2020



Source: USDA, Economic Research Service calculations based on U.S. Bureau of Labor consumer price indexes.

Such forecasts can be developed and visualized quickly, even without a previously used approach. These visualizations could be released as part of regular FPO reporting, charts for public consumption, or internal documents developed for stakeholders.

Case Study C: Using proprietary data to include lobster prices

Data need not be gathered from public sources, but public data have the advantage of meeting rigorous standards to be either nationally or regionally representative. Private data, in contrast, may provide information that is not (yet) covered by public sources. This case study uses proprietary data from Urner Barry (2021) to forecast average retail lobster prices.

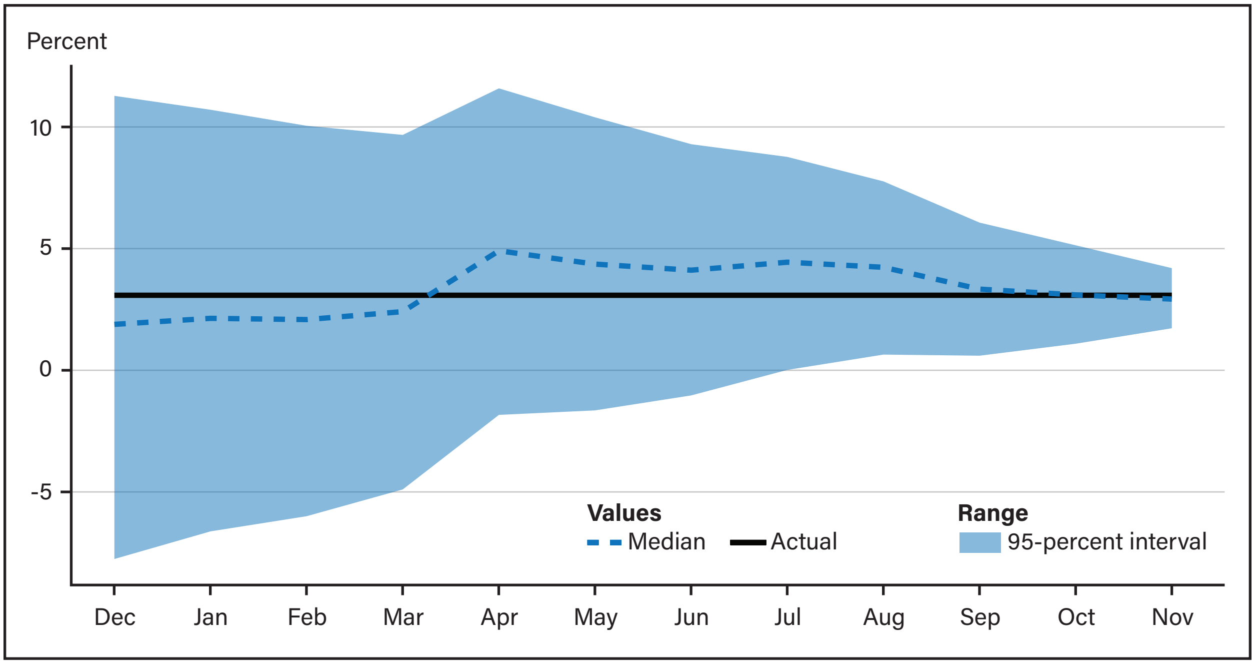
Lobster represents a significant retail product of the seafood industry. It is the second most valuable seafood species (annual revenues of $668 million in 2019, representing 12.1 percent of the total U.S. seafood market) and the 10th most harvested species (130 million pounds in 2019, representing 1.4 percent of the total seafood harvest) (NOAA, 2021). The lobster fishing industry is concentrated in Maine (approximately 72 percent, by volume) and primarily comprises individual operations on dayboats. Many news outlets described expectations of decreased retail lobster prices in the summer of 2020 (Associated Press, 2020; Gibbons-Neff, 2020; Losneck, 2020; Southard, 2020). A combination of supply-and-demand changes indicated that prices would decrease: FAFH establishments (such as restaurants, hotels, and cruise ships) closed due to the COVID-19 pandemic, eliminating a significant source of lobster consumption in the United States. The suspension of commercial air travel prevented lobster from reaching consumers overseas. Tourism decreased in Maine, hindering out-of-state visitors from consuming local lobster. The catch of lobster increased in 2020 due to warm weather.

Counterintuitively, lobster prices increased during 2020. Lobster price forecasts would have provided significant value for those seeking to understand these significant economic changes' impacts on the lobster markets. Using the time-series approach, ERS analysts could have met this demand.

Figure 8 shows forecast prices for lobster, generated using proprietary retail price data (dollars per pound, 2012–21). We develop a retail-level price index for lobster, then plot percent changes in price alongside the actual percent change, representing the observed percent price increase for lobster in 2020.

Figure 8

Convergence of estimated prediction intervals for percent changes in average retail lobster prices, December 2019–November 2020



Source: USDA, Economic Research Service calculations based on U.S. Bureau of Labor consumer price indexes.

Figure 8 shows a range of potential percent changes, with an interpretable median value. The range in June (-1.0 to 9.3) reflects the uncertainty in lobster prices, given lobster is an individual category within seafood, with notable price fluctuations. The median forecast percent change in lobster prices in 2020 (4.1 percent) suggests prices would increase, not decrease, as others had predicted. The actual percent change, 3.1 percent, was relatively close to the median prediction. A figure similar to figure 8 would have provided a more statistically rigorous prediction of the percent change in lobster prices.

Case Study D: Incorporating futures prices in food price forecasts

Futures prices often capture expectations about the trajectory of prices within a market, and this price information may be particularly valuable when prices change significantly from long-term trends. Given that several large changes occurred during the short study period covered in this technical bulletin, consideration of futures prices in food systems is warranted.

We consider futures prices for fats and oils derived from soybeans at the wholesale level (Urner Barry, 2021). Previous research indicates that futures prices may provide marginal improvements to the forecasts of commodity prices in some cases (e.g., Reev and Vigfusson, 2011). Prices of fats and oils are included at the wholesale and retail levels within the FPO forecasts. We used BIC values to evaluate the ability of these futures prices to improve model fit for both of these series.

Using data from 2009 to 2020, we find that the inclusion of the (Chicago Board of Trade's) futures data on soybean oil prices, projected for 1 month out as exogenous variables, significantly improves the model in-sample model fit (as measured by BIC value) for wholesale-level fats and oil prices. The BIC value decreases (improves) by approximately 14.5 when including futures prices in this model. This improvement indicates that modelers should strongly prefer to include futures prices in models of wholesale prices of fats and oils.

In contrast, the BIC value increases by approximately 3.5 percent when including futures prices in the model of retail prices—indicating these particular futures prices should not be included, as we have in these models. The lack of improvement in model performance reinforces the need to examine wholesale-level prices as an exogenous variable in a pass-through model of retail prices but indicates that futures prices may be useful in forecasting wholesale-level prices.

Conclusion

The approach presented in this report improves the accuracy of forecasts and allows for systematic adaptation to rapidly changing food prices. As shown in table 1, the number of times the forecast range/interval includes the actual percent change from 2011–20 markedly improves (from 16 to 86 percent across Consumer Price Index categories).

The methods presented here provide a more rigorous treatment of uncertainty than previous approaches and acknowledge group-specific differences. Similarly, our model selection approach is standardized and used to select all specification choices within the time-series (ARIMA) models. The ability of time-series models that can be used to explain variation can differ across different types of series and that precision is reflected in the representation of uncertainty. The range of prediction intervals typically becomes smaller within a year, which better characterizes how uncertainty resolves, as more information about food prices becomes available each month.

A limitation of this approach is that it no longer accommodates the incorporation of expert opinion. However, removing expert opinion allays concerns of consistency when staff turns over. The RMSE estimates also indicate that accuracy improves.

The approach presented in this report benefits from its efficiency, consistency, transparency, and reproducibility. ERS analysts can adjust these approaches as research on forecasting methodologies and food price analyses improve. Other types of series—such as apples, limited-service, or lobster prices—can be incorporated quickly to meet information needs in a rapidly changing food price environment, such as the COVID-19 pandemic. Furthermore, the methods can be directly extended to consider additional specifications and data sources, such as futures. While our ability to use standard accuracy and precision measures in this report was limited by the unorthodox nature of rounded forecast ranges, future research could delve deeper into such comparisons.

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Appendix

Accuracy of forecasts for the producer price indicies

We replicated table 1 to show the forecasted Producer Price Index (PPI) categories in table A1. These indexes tend to be more volatile and subject to rapid changes, with shocks to production systems or changes in trade flows. The development of forecast ranges partially acknowledges this by providing 3-percent point ranges instead of the 1-point ranges used for Consumer Price Index (CPI). Historical data are available for fewer years (2014–20) among the PPI categories than for CPI categories (ERS, 2022b).

Table A1

The count of times each Producer Price Index category falls within the forecast range and the prediction interval, using data through the previous year, 2014–20

Food category	Count within forecast range (out of 7 possible)	Count within 95 percent prediction interval (out of 7 possible)
Farm-level cattle	1	5
Wholesale beef	0	5
Wholesale pork	0	5
Wholesale poultry	0	5
Farm-level eggs	0	4
Farm-level milk	0	5
Wholesale dairy	1	5
Farm-level soybeans	1	3
Wholesale fats and oils	0	3
Farm-level fruits	0	7
Farm-level vegetables	1	6
Farm-level wheat	2	4
Wholesale wheat flour	0	5
Total	**6 (6.6 percent)**	**62 (68.1 percent)**

Source: USDA, Economic Research Service calculations based on U.S. Bureau of Labor, producer price indexes.

The prediction intervals include the actual percent change in PPI 68 percent of the category-year pairs, compared to 6.6 percent for forecast ranges. Like the CPI categories presented in table 2, the prediction intervals for the PPI categories provide a better representation of uncertainty than the forecast ranges.