Forecasting U.S. Food Market Prices: A Bayesian Hierarchical Approach*

Developing a Robust Model for Predicting Temporal Variations in Food Price Dynamics

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This paper focuses on building an accurate and reliable model to explore the temporal dynamics of food-at-home prices in the United States at a national level. By incorporating key economic factors such as purchase volume, food categories, and the Consumer Price Index (CPI), our Bayesian Hierarchical Model (BHM) achieves high predictive accuracy (RMSE = 0.058) and effectively forecasts price trends. The study captures category-specific effects and temporal trends, leveraging historical data to predict future price trajectories. Our model will provide policymakers, businesses, and researchers with a robust predictive framework to anticipate market dynamics, mitigate risks, and make data-driven decisions that enhance economic resilience and consumer well-being.

Table of contents

*Code and data are available at: https://github.com/Tanmay-Shinde/Forcasting-US-Food-Prices.

1 Introduction

Food prices are a critical component of economic and social well-being, directly affecting food security, diet quality, and household expenditures. The Food-at-Home Monthly Area Prices (F-MAP) dataset, developed by the USDA Economic Research Service, offers detailed insights into food pricing trends across the United States. Covering the years 2012 to 2018, the dataset provides monthly price data for 90 food categories across 15 geographic areas, making it a valuable resource for understanding regional and temporal variations in food costs. This paper leverages the F-MAP data to analyze how regional disparities, and time-based trends influence food-at-home prices and explores the role of economic factors such as purchase volume, food categories, and the Consumer Price Index (CPI) in shaping these patterns.

The primary focus of this analysis is to estimate how food categories, various economic factors, and time affect overall national food prices in the U.S. The estimand is the expected food price for a given food category and time period, conditional on factors such as purchase volume and CPI. By modelling these variations, we aim to uncover the drivers of price changes and predict trends in food costs.

Using a Bayesian hierarchical model, this study analyzes monthly price data from the F-MAP dataset to uncover the drivers of food price variations. The model incorporates random effects to capture categorical disparities and fixed effects to analyze the impact of economic factors, such as CPI, purchase volume, and food categories, on price trends. Economic factors such as purchase volume, food categories, and CPI significantly influence these trends, with higher CPI values strongly correlating with increased prices. Furthermore, food categories with higher demand or limited supply exhibit more substantial price fluctuations, underscoring the importance of understanding market-specific dynamics.

Understanding food pricing trends is essential for addressing issues related to food affordability and access. These insights are particularly valuable for policymakers and stakeholders aiming to reduce regional disparities, promote equitable access to food, and mitigate the effects of inflation on low-income households. By analyzing the drivers of price variations, this study provides a framework for informed decision-making in food policy and economic planning.

The remainder of this paper is structured as follows: Section 2 discusses the data sources, the F-MAP dataset and its variables, and pre-processing methods. Section 3 explains the Bayesian hierarchical model and methodology used for analysis. Section 4 presents the results, followed by a discussion of the key findings and conclusion of the study, as well as the limitations of the data in Section 5. Finally, the appendix includes additional details and EDA about the data, details about model convergence and diagnostics, and an idealized sampling and measurement methodology for food price related data.

2 Data

2.1 Source and Overview

The Food-at-Home Monthly Area Prices (F-MAP) data product (U. S. Department of Agriculture 2024) is a comprehensive and detailed data product developed by the USDA Economic Research Service (ERS) that provides monthly U.S. food price data for 90 food-at-home (FAH) categories across 15 geographic areas of the United States. The dataset includes two primary price measures for each food group, geographic area, and month: (1) a mean unit value price (dollars per 100 grams) and (2) price indexes derived using advanced index formulas. These measures enable researchers to track food price trends at a granular level and compare them across geographic and temporal dimensions, while accounting for economic factors such as consumer purchasing volume, store characteristics, and inflation metrics like the Consumer Price Index (CPI). By utilizing Circana OmniMarket Core Outlets retail scanner data, the F-MAP captures detailed consumer purchasing data from over 50,000 retail stores annually, including grocery stores, supercentres, and convenience stores.

The F-MAP provides data across the following dimensions:

- Monthly, 2012–18
- 15 geographic areas
  - Nationally
  - 4 Census regions: Midwest, Northeast, South, West
  - 10 metropolitan areas: Atlanta, Boston, Chicago, Dallas, Detroit, Houston, Los Angeles, Miami, New York, and Philadelphia
- 90 ERS Food Purchase Groups (EFPGs)
  - 8 groups for grains
  - 23 groups for vegetables
  - 8 groups for fruit
  - 8 groups for dairy and plant-based milk products
  - 14 groups for meat and protein foods
  - 4 groups for prepared meals, sides, and salads
  - 25 groups for other foods

For each of these month, area, and food group combinations, the F-MAP includes the following value variables:

- Purchase_dollars_wtd: Total weighted sales in U.S. dollars (nominal, i.e., not adjusted for inflation)
- Purchase_dollars_unwtd: Total unweighted sales in U.S. dollars (nominal, i.e., not adjusted for inflation)

- Purchase_grams_wtd: Total weighted quantities in grams
- Purchase_grams_unwtd: Total unweighted quantities in grams
- Number_stores: Number of stores in geographic area
- Unit_value_mean_wtd: Weighted mean unit value per 100 grams
- Unit_value_se_wtd: Standard error of weighted mean unit value
- Unit_value_mean_unwtd: Unweighted mean unit value per 100 grams
- Price_index_GEKS: Weighted price index value, constructed using Gini-Eltetö-Köves-Szulc (GEKS) formula

The F-MAP dataset is designed to align closely with the USDA Dietary Guidelines for Americans, facilitating research into food affordability, diet quality, and food security. Unlike other datasets, F-MAP offers monthly frequency data, making it particularly valuable for tracking short-term and seasonal trends. The dataset's hierarchical structure—spanning individual food categories, metropolitan regions, and national aggregates—supports diverse research applications. For example, it can be used to model the effects of policy interventions such as soda taxes or subsidies on dietary behavior and public health outcomes.

While other datasets such as the Bureau of Labor Statistics (BLS) Consumer Price Index (CPI) and the USDA Purchase to Plate National Average Prices (PP-NAP) provide useful insights, they fall short in capturing the comprehensive geographic and categorical detail offered by F-MAP. For instance, the CPI lacks subnational comparability across regions and provides limited food category detail, while the PP-NAP is focused on prepared foods and lacks the temporal granularity needed for trend analysis. The F-MAP dataset bridges these gaps by offering a more detailed, frequent, and regionally comparable resource.

The data is available to download in .xlsx format on the USDA Economic Research Service website. Specifically, we use the "Food-at-Home Monthly Area Prices, 2012 to 2018" dataset for our analysis.

2.2 Data Processing and Cleaning

We use the statistical programming language R (R Core Team 2023) to clean the data using various helpful packages like, readxl (Wickham and Bryan 2023), dplyr (Wickham et al. 2023), tidyr (Wickham, Henry, and Friedland 2023), lubridate (Grolemund and Wickham 2023), and arrow (Richardson et al. 2023). Further, libraries like ggplot2 (Wickham 2016), knitr (Xie 2023) were used to analyze the data and create visualizations.

The initial step involved removing unnecessary variables, retaining only those essential for analysis. This included variables such as unit_value_mean_wtd (weighted unit value), purchase_grams_wtd (weighted purchase volume), price_index_GEKS (Consumer Price Index), EFPG (food category), metroregion_name (region), and time. Rows containing missing values in any of the key variables were removed to maintain data integrity. We also filter the data to only include the national-level data, since we want to capture price trends at a national level. The dependent variable, unitValue, was log-transformed to stabilize variance and linearize relationships, to ensure no assumptions are violations in modelling. The time variable, originally in year-month format, was converted into a continuous variable representing the number of months since January 2012. This allows temporal trends to be modelled effectively as a continuous variable. The category variable was standardized and converted into factor variables, enabling the model to treat them as categorical inputs. To improve the convergence of the Bayesian model, predictors such as cpi and purchaseVolume were normalized by centering them around zero and scaling them to have a standard deviation of one.

2.3 Measurement

The Food-at-Home Monthly Area Prices (F-MAP) dataset is built using high-frequency retail scanner data sourced from approximately 50,000–60,000 retail establishments annually. These include grocery stores, supercentres, club stores, drug stores, and convenience stores. The scanner data capture weekly sales in nominal dollars (not adjusted for inflation) and the quantities of food items sold. Weekly sales data are aggregated into monthly intervals to align with the dataset's temporal structure. If a sales week spans two months, the sales values and units are proportionately allocated based on the number of days in each month, ensuring temporal consistency.

To standardize the data, outliers in unit values are removed using the interquartile range (IQR) method, which identifies extreme values beyond 1.5 times the IQR from the 25th and 75th percentiles of the price distribution. This step eliminates inaccuracies that might arise from reporting errors or anomalous transactions. Package weights are converted into grams to ensure uniformity, using standard conversion factors (e.g., grams per ounce, fluid ounce, or pound). Prices are then expressed as unit values per 100 grams, providing a consistent measure of price across products of varying sizes.

The categorization of products into 90 detailed food categories is based on the USDA Economic Research Service (ERS) Food Purchase Groups (EFPG) system. This classification system organizes foods by their characteristics, such as ingredients, nutritional content, and convenience level. It aligns closely with the Dietary Guidelines for Americans and enables researchers to aggregate, disaggregate, or customize categories for specific research needs. These EFPG classifications are foundational to understanding price trends within and across food categories.

Retail sales data from certain retailers are reported at a broader Retailer Marketing Area (RMA) level rather than individual store locations. To ensure granularity, these RMA-level sales are disaggregated to individual stores using proportionate weighting methods, based on store-level weights developed specifically for the scanner data. These weights adjust the sales data to reflect the population of stores nationally and regionally, ensuring that the dataset is representative of real-world purchasing behaviors. Both weighted and unweighted unit value estimates are included, enabling diverse analytical approaches.

The dataset also includes price indexes, which measure the cost of a basket of goods over time and across locations. The GEKS multilateral price index, the primary index in the F-MAP, is constructed to compare prices dynamically while accounting for product substitution and turnover. This index is based on the geometric mean of bilateral indexes (Laspeyres, Paasche, Fisher Ideal) and employs a 1-year rolling window to maintain transitivity and minimize chain drift. By capturing the cost of goods relative to a base period (2016–2018 national averages), these price indexes provide a robust measure for temporal and spatial price comparisons, making the dataset suitable for inflation and affordability analyses.

Through this rigorous process, real-world phenomena such as regional price variations, inflationary trends, and food category-specific dynamics are translated into structured data entries. The combination of high-frequency retail data, standardized unit values, and multilateral price indexes ensures that the F-MAP dataset is both comprehensive and precise, supporting its use in economic research and policymaking.

2.4 Outcome variable

The response variable, unitValue, represents the weighted mean price per 100 grams of a food item within a specific food category, geographic region, and time period. In this analysis, the variable is log-transformed to create unitValue_lg, which helps stabilize variance, improve normality, and facilitate the interpretation of model coefficients in percentage terms. The log transformation allows us to understand the proportional changes in price rather than absolute changes, which is particularly useful for identifying relative price dynamics across categories and regions.

Table 1: Summary Statistics for log of Unit Value

mean	median	sd	min	max
-0.6922529	-0.7298112	0.6576483	-2.207275	1.086202

From Table 1, we can see that the transformed outcome variable, unitValue_lg, has a mean of -0.692 and a median of -0.713, indicating a near-symmetric distribution. The standard deviation of 0.687 reflects moderate variability in prices, while the range, spanning from a minimum of -2.813 to a maximum of 1.191, highlights significant disparities in food costs across categories, regions, and time periods. The log transformation normalizes the data, reducing skewness and ensuring that extreme values in the original price variable do not disproportionately influence the analysis.

Figure 1 illustrates a symmetric, unimodal distribution of unitValue_lg, centered near -0.7, with values ranging from approximately -2.8 to 1.2. This indicates that most food prices cluster around the median value, with fewer extreme high or low prices.

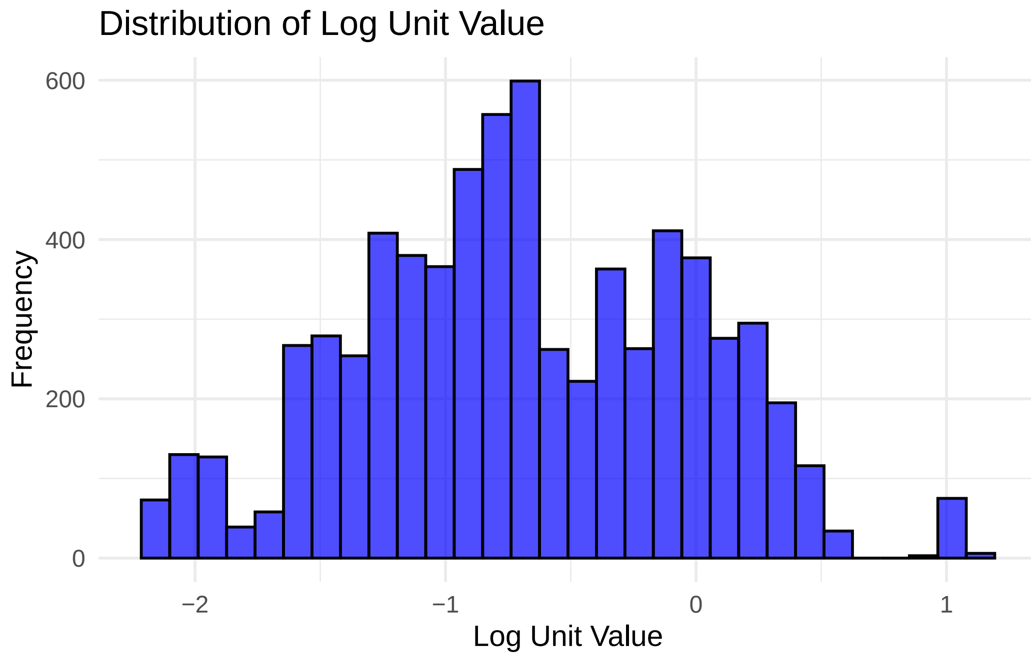


Figure 1: Distribution of Log-Transformed Food Prices (Unit Value)

More details and exploratory analysis about the outcome variable can be found in Appendix A

2.5 Predictor variables

2.5.1 Time

The time variable in the analysis dataset is a continuous variable, representing the number of months since January 2012 when the data was recorded. This variable is important to help us understand temporal trends in the data and fluctuations in the unit value over time. The first month Jan-2012 is represented as 0, Feb-2012 as 1, and so on until Dec-2018 represented as 83.

2.5.2 Category

It is a categorical variable representing the 90 ERS Food Purchase Groups (EFPGs). The categories include different types of grains, fruits and vegetables, dairy, meat and protein foods, prepared meals, salads, and other foods.

2.5.3 Region

The region variable represents 15 geographic regions (10 metropolitan areas and 4 Census regions and 1 National category). the region variable will help us analyze the regional and geographical trends and variations in food prices. We are only interested in the 'National' region data for this study.

2.5.4 Consumer Price Index (CPI)

The Consumer Price Index (CPI) variable in the dataset represents the weighted price index (GEKS index) that measures the cost of a basket of goods over time, standardized relative to a base period (2016–2018). The CPI is unitless, with values below 1 indicating prices lower than the base period average and values above 1 indicating higher prices. The cpi is normalized to improve accuracy in modelling. This variable is critical in understanding inflationary trends and regional price dynamics, as it allows comparisons of relative purchasing power and economic conditions over time and across regions.

Each value recorded under the CPI column represents the consumer price index of one particular food group out of the 90 EFPGs in a particular region for that month.

Table 2: Summary Statistics for CPI

mean	median	sd	min	max
0	-0.0558982	1	-5.500379	11.51913

Table 2 illustrates the normalization of the variable with mean as 0 and standard deviation as 1. The minimum and maximum values of -7.04 and 22.79, respectively, highlight the presence of extreme values or outliers. These statistics indicate notable regional or temporal differences in CPI values, reflecting the varying economic conditions or price trends across the observed time period and regions. Figure 2 also shows a spread of the data from -7 to 22, with most of the values clustered around 0 with a fairly normal distribution.

More details and exploratory analysis about the cpi variable can be found in Appendix A

2.5.5 Purchase Volume

The Purchase Volume variable represents the total quantity of food purchased, measured in grams, weighted by store-level survey weights to ensure representativeness across geographic areas and time. This variable is crucial in understanding consumer purchasing behavior, providing insights into the relationship between food quantity consumed and factors such as price, region, and time. It also helps in identifying demand patterns for various food categories and

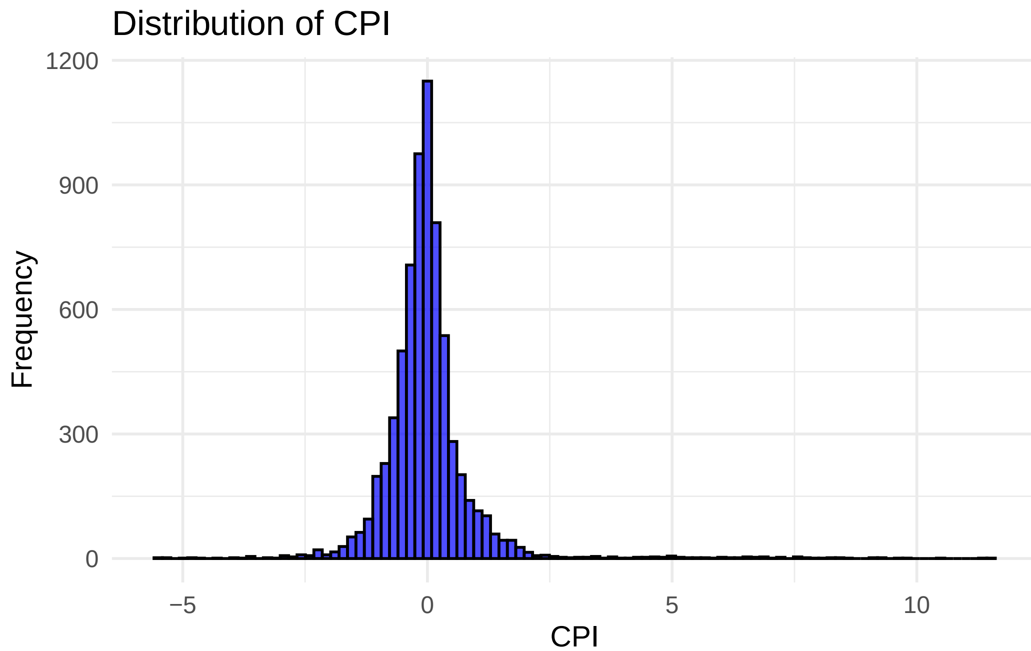


Figure 2: Distribution of GEKS Consumer Price Index (CPI)

regions, which can influence pricing and policy decisions. High purchase volumes could indicate greater demand or accessibility, whereas lower volumes might reflect supply constraints, lower demand, or higher relative prices. This variable is key for examining the impact of economic factors like Consumer Price Index (CPI) and regional trends on consumer behavior.

Table 3: Summary Statistics for Purchase Volume

mean	median	sd	min	max
0	-0.4829133	1	-0.8398009	3.185714

Table 3 illustrates the normalization of the variable with mean as 0 and standard deviation as 1. The minimum and maximum values of -0.736 and 4.266, respectively, highlight the presence of extreme values or outliers on the right side. The median of -0.444 indicates that there might be a slight right skew in the data. Figure 3 also shows a high spread in the data and a heavily right-skewed histogram that accurately represent the expected purchasing trends, with most purchasing volumes being at the lower end and then becoming lesser and lesser as one goes right.

More details and exploratory analysis about the purchaseVolume variable can be found in Appendix A

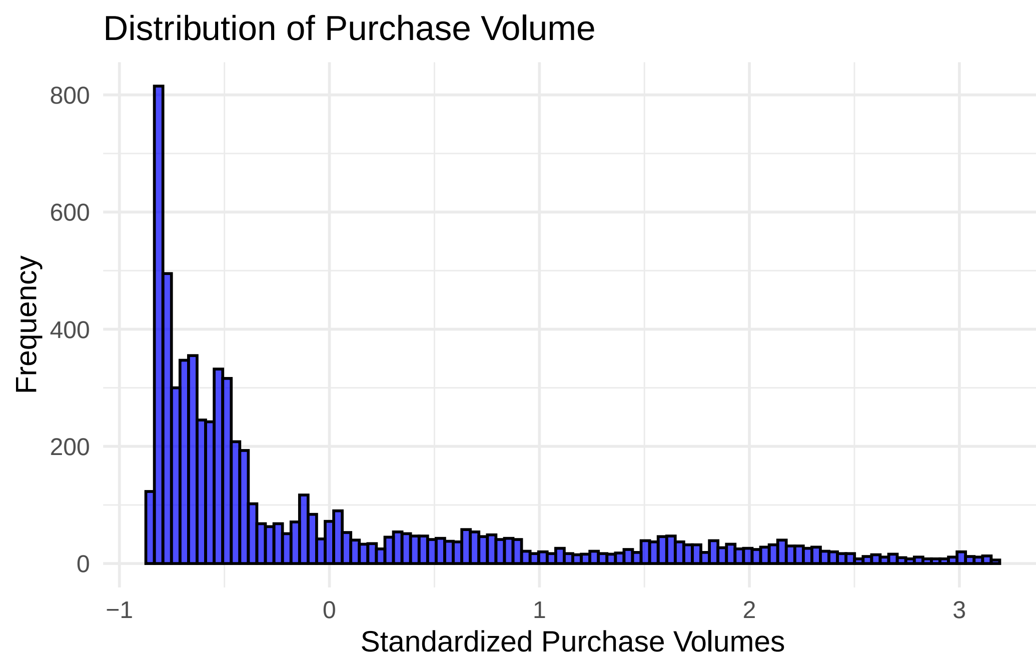


Figure 3: Distribution of Purchase Volume of Groceries

3 Model

We employ a Bayesian Hierarchical Model (BHM) in this study to capture the complex relationships between food-at-home prices and their predictors, such as purchase volume, food categories, the Consumer Price Index (CPI), and time. The hierarchical structure allows the model to account for variability across different food categories while leveraging the overall data trends at the national level. By including time as a predictor, the model effectively captures temporal trends, while predictors like CPI and purchase volume elucidate economic and consumer-driven influences on prices.

3.1 Overview

The outcome variable is **unitValue_lg**, which represents the log of weighted mean price per 100 grams of a food item within a specific food category and time period. he log-transformation stabilizes variance and helps handle skewness in the price distribution, ensuring that the Gaussian family used in the model is appropriate.

cpi, **purchaseVolume**, and **time** are treated as fixed effects predictors. CPI models the overall inflationary trends and their influence on food prices. It is a continuous variable that captures macroeconomic factors affecting food price levels. Purchase Volume represents the total weighted quantity of food purchased. It acts as a demand-side predictor, reflecting consumer purchasing behavior's effect on price trends. Time is continuous variable representing the time elapsed since January 2012. It models the temporal trend in food prices, allowing the capture of long-term changes over time.

category captures variability in price trends across different food categories. By converting this variable to a factor, we allow each food category to have its own baseline price level while maintaining the overall hierarchical structure of the model.

To train the model, we use data from the year 2012 to 2017, and use the 2018 data as a benchmark to test the predictive accuracy of the model.

3.2 Model Specifications

Let y_{it} denote the log-transformed unit value (unitValue_lg) for category i and time t. Then, the model can be written as:

$$y_{it} = \beta_0 + \beta_i^{category} + \beta_1.CPI_{it} + \beta_2.purchaseVolume_{it} + \beta_3.time + \epsilon_{it}$$

Where:

- β_0: Global intercept (average log unit value across all regions and categories).
- $\beta_j^{category}$: Random effect for category i, capturing category-specific deviations.
- β_1: Coefficient for the CPI predictor.
- β_2: Coefficient for the purchaseVolume predictor.
- β_3: Coefficient for the time variable.
- $\epsilon_{ijt} \sim N(0, \sigma^2)$: Residual Error

We use the following heirarchical priors for our model:

- $\beta_0 \sim N(0, 10^2)$: Weakly informative prior for the global intercept.
- $\beta_j^{category} \sim N(0, \sigma^2_{category})$: Category-level random effects.
- $\beta_1, \beta_2, \beta_3 \sim N(0, 10^2)$: Weakly informative priors for the predictors
- $\sigma^2_{category} \sim HalfCauchy(0, 5)$: Priors for variance components.

We run the model in R (R Core Team 2023) using the `brms` package of Bürkner (2023).

3.3 Model Justification

The prediction of long-term trends in the outcome variable, log-transformed unit value (unitValue_lg), requires a model that can effectively handle complex data structures and temporal dynamics. We use a Bayesian Hierarchical Model (BHM) since the dataset has a natural hierarchical structure with food categories as grouping factors. BHM can model the variability within categories while borrowing strength across these groups through partial pooling. This approach improves predictive accuracy, by allowing group members to have some influence over one another. The data spans multiple years and involves time-dependent variations influenced by economic factors, purchase volumes, and Consumer Price Index (CPI).

We facilitate out-of-sample testing by dividing the dataset into two distinct, non-overlapping temporal segments: a training set (2012–2017) and a testing set (2018). The training set is used to build and calibrate the Bayesian Hierarchical Model (BHM), leveraging historical patterns in food prices, consumer purchasing volume, and other predictors like the Consumer Price Index (CPI). The testing set, comprising data exclusively from 2018, remains untouched during the model training phase, serving as unseen data for evaluating the model's performance.

Underlying Assumptions:

1. **Hierarchical Structure Validity**: The assumption that categories introduce random effects is reasonable given the heterogeneity in geographic and product-specific dynamics. The assumption is based on the nested nature of the data, where observations are grouped by region and food categories. This reflects real-world dynamics, as food prices are influenced by category-specific factors (e.g., perishability, demand patterns). By introducing random effects for regions and categories, the model captures these unobserved heterogeneities effectively. For example, the average price trend in one region may systematically differ from others, and this variation is modelled through the random intercepts. Without this hierarchical framework, the model would risk oversimplifying the underlying relationships, potentially leading to biased estimates and less reliable predictions.

2. **Normality of Residuals**: The BHM assumes that the residuals (differences between observed and predicted values) are normally distributed. This assumption underpins the use of Gaussian likelihoods in Bayesian modelling and ensures that the posterior distributions are well-defined and interpretable. Normality of residuals implies that the model captures all systematic patterns in the data, leaving random noise as the primary unexplained variation. Posterior predictive checks are used to validate this assumption, comparing the observed data distribution with the model-predicted posterior distributions. If deviations from normality are detected (e.g., skewness or heavy tails), adjustments such as alternative likelihoods (e.g., Student-t distributions) can be incorporated. The normality assumption is reasonable here because the dataset represents aggregated measures (e.g., regional or category-specific prices), which tend to exhibit normal-like properties due to the Central Limit Theorem.

Limitations:

1. **Limited Explanatory Variables**: The model incorporates CPI and purchase volume as key predictors, which are useful but may not fully capture the multifaceted nature of food price dynamics. External factors such as supply chain disruptions, climatic events, or geopolitical influences on agriculture could significantly impact prices yet remain unaccounted for in the model. The exclusion of such variables may lead to omitted variable bias, where the model attributes unexplained variability to random effects rather than systematic external factors. Expanding the set of predictors to include weather patterns, fuel prices, or global trade indices could enhance the model's comprehensiveness and accuracy, albeit at the cost of increased complexity.

2. **Computational Complexity**: Bayesian hierarchical models, especially when paired with ARIMA components, require substantial computational resources due to their iterative sampling-based inference methods, such as Markov Chain Monte Carlo (MCMC). While modern software like brms in R or PyStan in Python facilitates these computations, running the model on large datasets with multiple hierarchical levels can still be time-intensive and hardware-dependent. This limitation might restrict the ability to conduct extensive sensitivity analyses or real-time updates. Additionally, ensuring model convergence requires careful tuning and monitoring, which demands expertise and can prolong the modeling process. Despite these challenges, the benefits of Bayesian methods—such as flexibility and probabilistic interpretation—often justify the computational overhead.

4 Results

4.1 Model Metrics

The Bayesian model, presented in Table 4, explores the relationships between the unit value of a food item within a specific food category and predictors such as cpi, consumer purchase volumes, and time.

The intercept estimate of -0.745 represents the baseline log-transformed unit value (unitValue_lg) when all predictors—Consumer Price Index (CPI), purchase volume, and time—are at their reference or mean levels. A negative intercept suggests that the baseline food-at-home prices, in log scale, are below zero, implying prices below 1 on the original scale.

The CPI predictor has an estimate of 0.044, indicating that a one-unit increase in CPI leads to a 0.044 increase in the log-unit value, holding all other variables constant. This positive relationship aligns with expectations, as rising inflation levels typically correlate with increasing food prices.

The purchase volume variable exhibits a negative relationship with the response, with an estimate of -0.170. This means that for every one-unit increase in normalized purchase volume, the log-unit value decreases by 0.170, holding other variables constant. This result is consistent with economic principles, reflecting economies of scale where bulk purchases reduce per-unit costs.

The time variable shows a small positive effect on log-unit value, with an estimate of 0.001. This result suggests a gradual increase in food prices over time.

Table 4: Coefficients of Predictor Variables

	Estimate	Est.Error	l-95% CI	u-95% CI	Rhat
Intercept	-0.745	0.073	-0.890	-0.583	1.234
cpi	0.044	0.001	0.043	0.046	1.002
purchaseVolume	-0.170	0.005	-0.179	-0.161	1.010
time	0.001	0.000	0.001	0.001	1.000

Across all predictors—CPI, purchase volume, and time—the standard errors are small, indicating high precision in the parameter estimates. This precision is particularly evident in the case of CPI and time, where the standard errors are close to zero, signifying that the data provides strong evidence for the relationship between these variables and the log-unit value.

Table 5 provides a clear assessment of the model's performance. With 5944 observations, the model uses a substantial dataset, enhancing the reliability of its estimates. The R^2 value of 0.744 shows that 74.4% of the variability in the log-transformed unit value is explained by the predictors, indicating a strong fit and relevance of variables like CPI, purchase volume, and time. An AIC of -16810.9 reflects the model's effectiveness in balancing fit and complexity. The high log-likelihood (Log.Lik.) value of 8405.5 further supports the model's ability to explain the data well. The Root Mean Square Error (RMSE) of 0.058 indicates high predictive accuracy, showing minimal difference between observed and predicted values. These metrics confirm that the model is robust and reliable for capturing trends and making future predictions.

Table 5: Model Metrics

Metric	Value
Num.Obs.	5944.000
R^2	0.744
AIC	-16810.900
Log.Lik.	8405.500
RMSE	0.058

4.2 Predictions

In this section, we use the model to make some predictions, to visualize and assess the accuracy of the model. As mentioned before, we the data from Jan 2018 to Dec 2018 serves as our test dataset. We will look at the model's predictions for the unit values of 5 food categories and compare them against the actual recorded values.

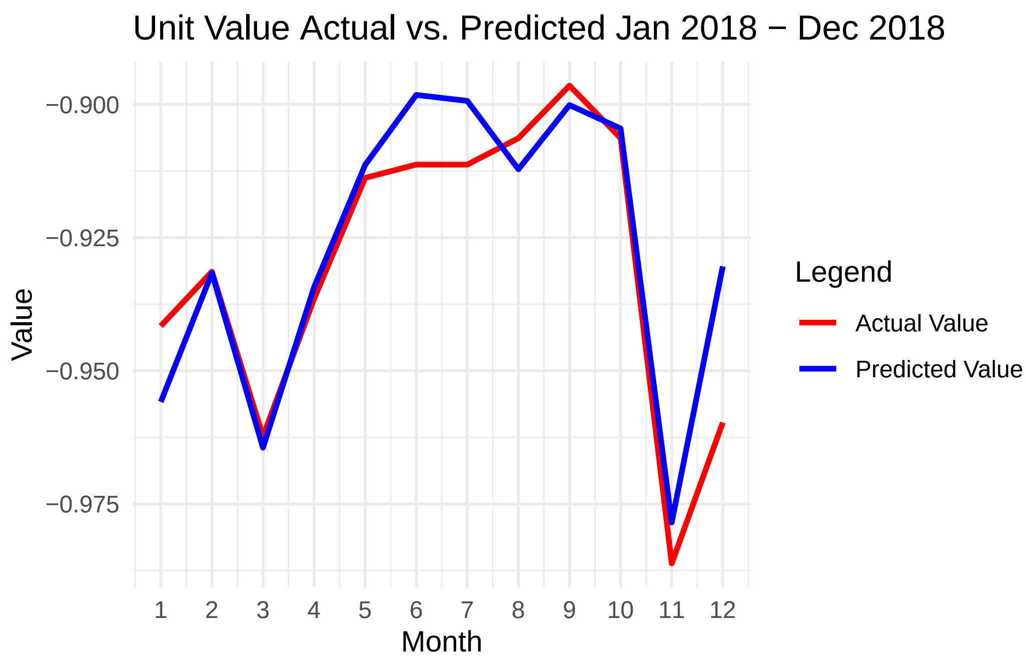


Figure 4: Prediction for Whole Fruit Prices

Figure 4 visualizes the comparison between the actual and predicted log-transformed unit values (unitValue_lg) for whole fruit prices during the test period (January to December 2018).

Figure 5 visualizes the comparison between the actual and predicted log-transformed unit values (unitValue_lg) for tomatoes (canned) prices during the test period (January to December 2018).

Figure 6 visualizes the comparison between the actual and predicted log-transformed unit values (unitValue_lg) for eggs and egg substitutes prices during the test period (January to December 2018).

Figure 7 visualizes the comparison between the actual and predicted log-transformed unit values (unitValue_lg) for canned starchy vegetable prices during the test period (January to December 2018).

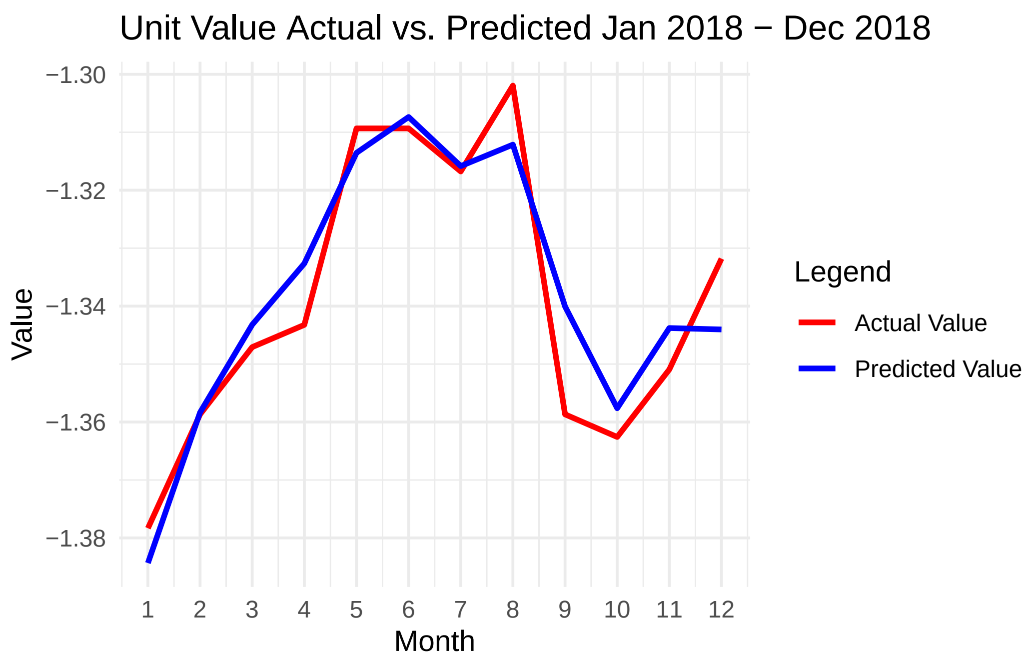


Figure 5: Prediction for Canned Tomatoes Prices

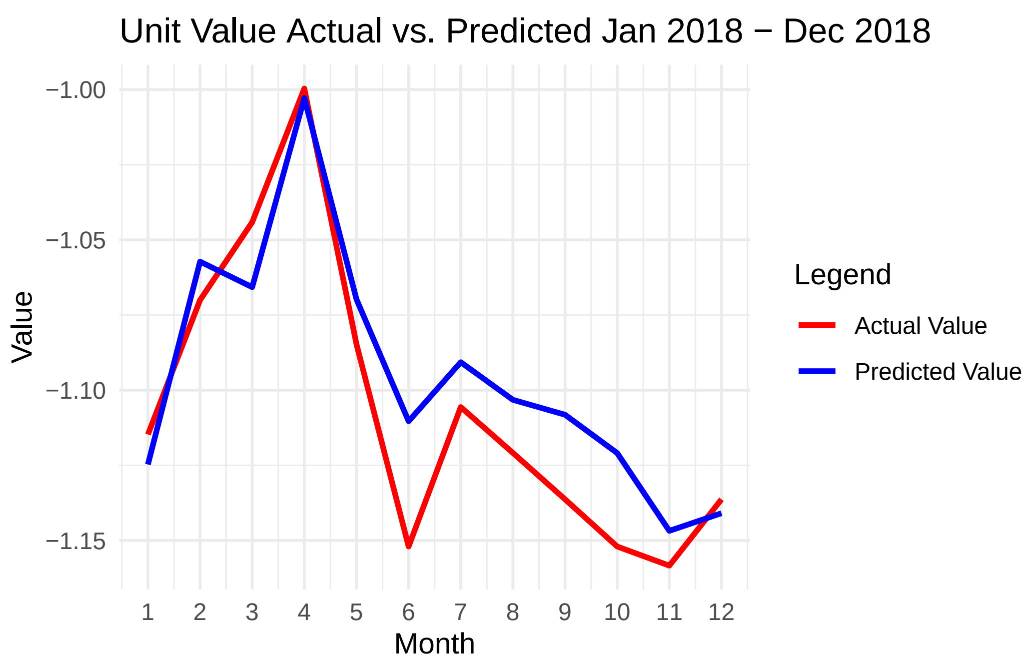


Figure 6: Prediction for Eggs and Egg Substitutes Prices

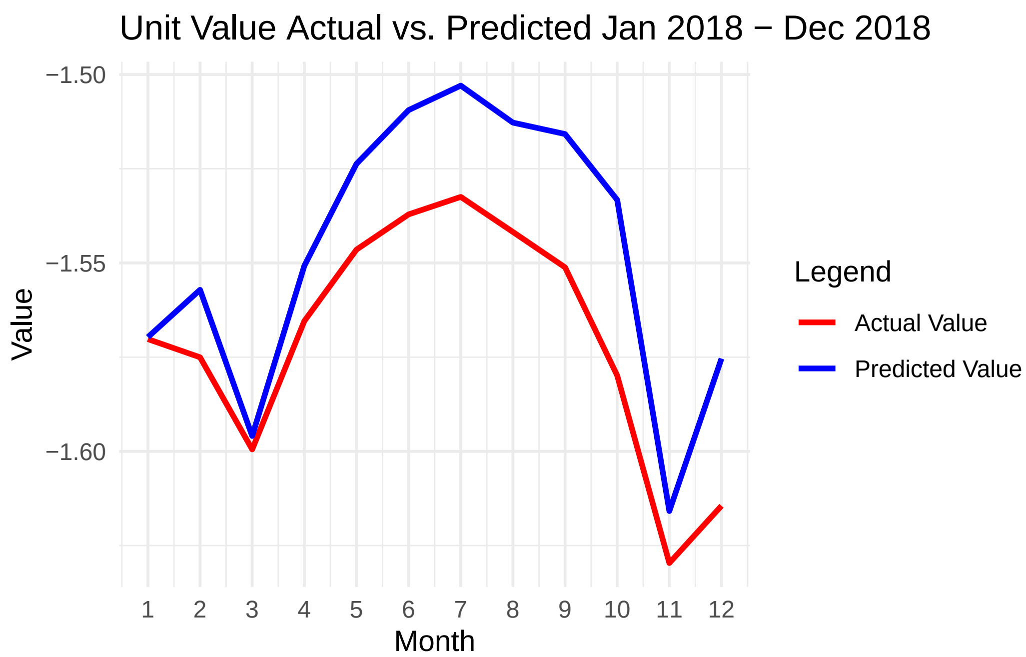


Figure 7: Prediction for Canned Starchy Vegetables Prices

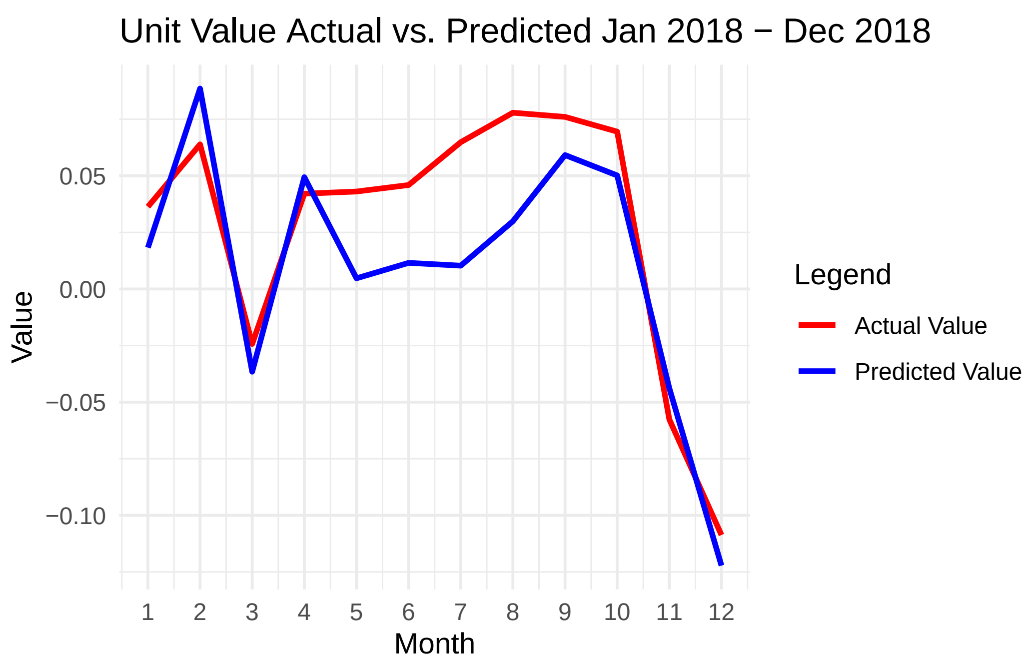


Figure 8: Prediction for Bacon, Sausage, and Lunch Meat Prices

Figure 8 visualizes the comparison between the actual and predicted log-transformed unit values (unitValue_lg) for bacon, sausage, and other lunch meat prices during the test period (January to December 2018).

The predicted values for all categories closely follow the actual trend, demonstrating the model's ability to capture temporal and category-specific variations effectively. While minor deviations are visible at certain points, the overall alignment underscores the predictive accuracy of the Bayesian hierarchical model. These results validate the model's reliability in forecasting price trends, providing valuable insights for economic analysis and policy-making.

Plots for all 90 categories are available in the "other/plots/" directory. The code to generate all plots is available in "scripts/05_model_data.R"

5 Discussion

5.1 Model Performance and Predictive Insights

The Bayesian Hierarchical Model (BHM) developed in this study demonstrates strong predictive performance, as evidenced by an RMSE of 0.058. This low RMSE underscores the model's precision in estimating food-at-home prices at the national level, providing a reliable tool for forecasting future trends. The model's ability to integrate temporal, category-level, and economic predictors ensures its robustness and applicability to real-world scenarios.

A key strength of the model lies in its ability to capture temporal price trends while accommodating variations across food categories. For example, categories like dairy, fresh produce, and meats, known for their price volatility, are effectively modelled within this framework. The hierarchical structure allows for simultaneous analysis of overarching trends and granular category-level dynamics. This dual focus ensures that the model not only reflects overall price increases over time but also provides insights into category-specific patterns. For instance, periods of seasonal demand or supply shocks in specific categories are well-represented in the model's predictions, making it a valuable tool for understanding nuanced market dynamics.

To ensure the reliability and validity of the Bayesian Hierarchical Model (BHM), a series of robustness checks and diagnostics were conducted. Key metrics like R-hat values were examined to evaluate the convergence of the Markov Chain Monte Carlo (MCMC) sampling process. Ideally, R-hat values should be close to 1.0, indicating that the chains have mixed well and the posterior distribution has been accurately sampled. For this model, R-hat values across most parameters were within acceptable thresholds, confirming convergence, though a few parameters required adjustments in sampling settings (e.g., increasing iterations or adapt-delta values) to achieve stability. Posterior predictive checks further validated the model by comparing observed data to simulated data generated from the posterior distributions. The checks showed that the model could adequately replicate the observed trends, reinforcing its capacity to capture key dynamics in the dataset.

Out-of-sample testing using 2018 data provided an additional layer of validation. By training the model on data from 2012–2017 and testing its predictions on unseen 2018 data, the analysis assessed the model's generalizability and predictive accuracy. The results demonstrated strong alignment between predicted and actual values, with a low root mean squared error (RMSE) indicating minimal deviations. This robust performance not only validates the model's reliability but also highlights its utility in forecasting future food price trends. Such diagnostic and validation efforts are essential in confirming that the model is both theoretically sound and practically applicable for policy and decision-making contexts.

5.2 Key Predictors and Their Role

The Consumer Price Index (CPI) emerges as a significant positive predictor in the model, reflecting its central role in shaping food price dynamics. As CPI increases, it indicates broader inflationary pressures within the economy, which are directly associated with higher food prices. This positive correlation underscores the sensitivity of food markets to macroeconomic factors, reinforcing the importance of CPI as a key driver in understanding and forecasting food price trends.

Purchase volume also plays a critical role, demonstrating a negative association with unit value. This inverse relationship is indicative of economies of scale, where higher purchase volumes often lead to lower per-unit costs. Bulk purchasing patterns by consumers or retailers may contribute to this trend, particularly in categories like packaged foods or staples. By capturing this dynamic, the model provides valuable insights into the mechanisms of pricing efficiency and the economic behaviors influencing food markets.

The inclusion of time as a variable further enhances the model's capability to capture long-term trends in food pricing. Time allows the model to account for underlying patterns, such as seasonal fluctuations, gradual price increases, and structural changes in the food market over the study period. By incorporating time, the model not only delivers accurate predictions but also enriches the understanding of long-term market dynamics, which is crucial for strategic planning and forecasting.

5.3 Insights for Policymakers and Stakeholders

The findings from this Bayesian Hierarchical Model (BHM) offer valuable insights for policymakers and stakeholders in addressing food price stability and affordability. The model's ability to identify temporal trends and category-specific price variations can inform targeted interventions. For instance, policymakers could design subsidies for volatile food categories, such as fresh produce or dairy, to stabilize prices and mitigate their impact on low-income households. By pre-emptively addressing these fluctuations, governments can help ensure food security and affordability across diverse consumer demographics.

For food retailers and manufacturers, the model provides an empirical foundation to understand demand-supply dynamics and optimize pricing strategies. The negative correlation between purchase volume and unit prices underscores the benefits of bulk purchasing and economies of scale. Retailers could leverage these insights to offer strategic discounts or promotions in response to shifting CPI levels or seasonal demand changes. Manufacturers, in turn, could better align production schedules and inventory management to anticipated price trends, minimizing disruptions in supply chains.

Additionally, the predictive capabilities of the model can play a crucial role in forecasting affordability crises. By identifying periods of likely price spikes due to economic shifts or seasonal factors, stakeholders can take proactive measures, such as stockpiling essential goods or implementing price caps. This foresight empowers both public and private sectors to collaborate in maintaining food accessibility, particularly during crises like pandemics or economic downturns. The model, thus, serves as a powerful tool for long-term planning and immediate action in the evolving landscape of food economics.

5.4 Weaknesses and Limitations

One limitation of this analysis stems from the non-probability nature of the data used. The dataset, while extensive, does not represent a true random sample of all retail food sales in the United States. This introduces potential biases, as the dataset may over-represent certain retailer types or geographic regions, leading to conclusions that may not fully generalize to the entire market. For example, the exclusion of smaller retailers or niche market participants might skew price estimates or trends observed in the analysis.

From a computational perspective, Bayesian Hierarchical Modelling (BHM) presents challenges, particularly the time required for convergence when dealing with large datasets and complex model specifications. The high-dimensional nature of hierarchical structures, can lead to long processing times and potential difficulties in achieving reliable convergence. For instance, diagnostics like high R-hat values in earlier model iterations highlight the need for adjustments, such as increasing the number of iterations, tuning parameters like adapt_delta, or simplifying priors.

Despite the model's strong overall performance, certain discrepancies between predicted and observed values were noted in specific categories and timeframes. For instance, predictions for fresh produce during periods of extreme weather events showed slight deviations, likely due to unmodeled external shocks affecting supply chains. Similarly, the model occasionally struggled with categories that exhibit irregular demand patterns, such as niche processed foods. These divergences highlight the potential for incorporating additional predictors, such as climatic variables or consumer sentiment indices, to enhance the model's adaptability. This limitation underscores the challenge of modeling unprecedented events and highlights the importance of complementing predictive models with real-time market analysis during periods of significant uncertainty. These findings emphasize the need for adaptive models capable of integrating new data to improve resilience against unforeseen disruptions.

5.5 Broader Implications and Future Work

This study contributes to the broader landscape of food price modeling by offering a sophisticated Bayesian Hierarchical Model (BHM) tailored to capture temporal and category-level variations in food prices at a national level. Previous research often focused on narrower scopes, such as specific food categories, regions, or linear trends, without accounting for the layered complexities inherent in hierarchical structures and non-linear temporal dynamics. By integrating predictors such as the Consumer Price Index (CPI), purchase volume, and time, the study addresses critical gaps in understanding how economic indicators and consumer behavior shape food prices. The incorporation of both fixed and random effects allows for nuanced insights into category-specific trends while ensuring robust generalization across broader contexts.

The findings offer actionable insights for stakeholders, particularly in predicting price volatility and understanding long-term trends. For instance, the model's ability to identify categories with greater susceptibility to price fluctuations, such as fresh produce and dairy, provides a foundation for targeted interventions. Furthermore, the strong predictive accuracy demonstrated by the model underscores its potential as a tool for pre-empting affordability crises, stabilizing food prices, and informing policy decisions.

Future work could build on this foundation by incorporating more granular household-level consumption data to bridge the gap between retail pricing trends and consumer affordability. Household-level data would allow for a deeper understanding of the interplay between income, purchasing power, and dietary choices, offering more targeted insights into consumer welfare. Additionally, expanding the scope to include non-retail settings, such as farmers' markets or direct-to-consumer channels, could capture alternative price trends that are increasingly relevant in the context of sustainable food systems and localized supply chains.

Another promising direction would involve applying the methodology to different geographic regions or international contexts. Comparing trends across countries or regions with varying economic structures, cultural practices, and policy frameworks could reveal universal patterns and context-specific dynamics. Temporal extensions beyond the current dataset, especially during periods of economic instability, such as the COVID-19 pandemic or global financial crises, could further validate the model's robustness and adaptability to real-world shocks.

Finally, incorporating additional predictors such as weather patterns, trade policies, or transportation costs could enhance the model's explanatory power and predictive accuracy. These factors, often overlooked in aggregate-level studies, play a crucial role in shaping food supply chains and price formation. By addressing these avenues, future research can extend the scope and utility of the current work, contributing to a more comprehensive understanding of food price dynamics and their implications for economic resilience and consumer welfare.

Appendix

A Additional data details

A.1 EDA for Outcome Variable

A.1.1 Temporal Trends

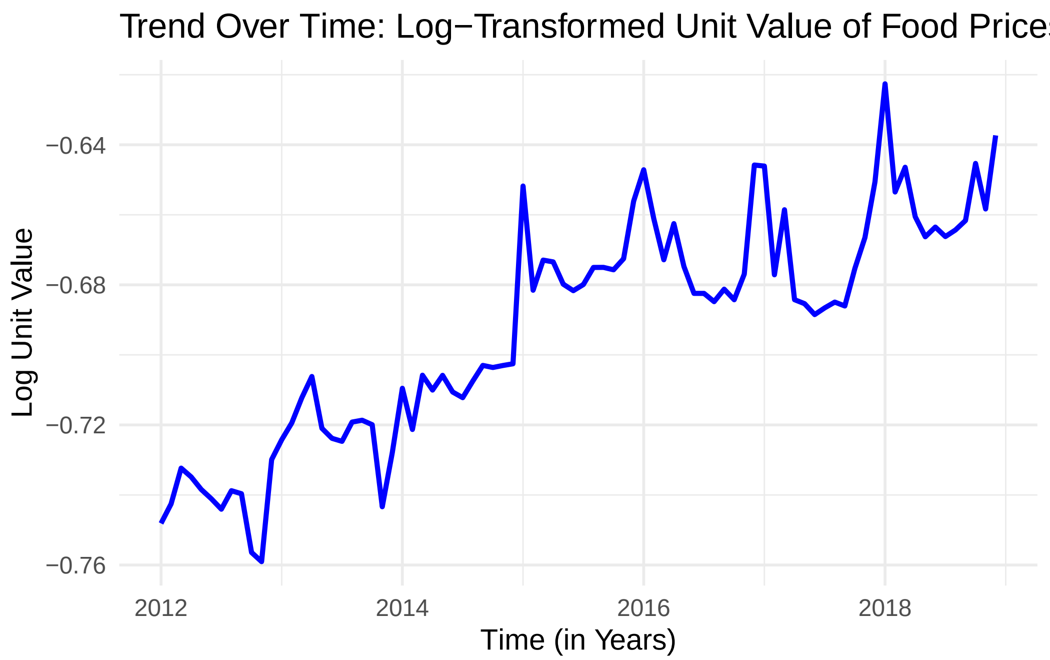


Figure 9: Temporal Variations in Log-Transformed Food Prices

Figure 9 illustrates the log-transformed unit value of food prices from 2012 to 2018, revealing a general upward trend over time. Initially, from 2012 to 2014, there is only a modest increase in the log-transformed values. However, in 2014, prices increase sharply followed by a period of 3 years characterized by heightened volatility, with pronounced peaks and troughs, and another increase in the prices in 2018. Thus, the overall trajectory for the log-transformed unit value of food prices from 2012 to 2018 remains upwards.

A.2 EDA for Predictor Variables

A.2.1 CPI

Figure 10 illustrates the general upward trend in the CPI values from 2012 to 2018.

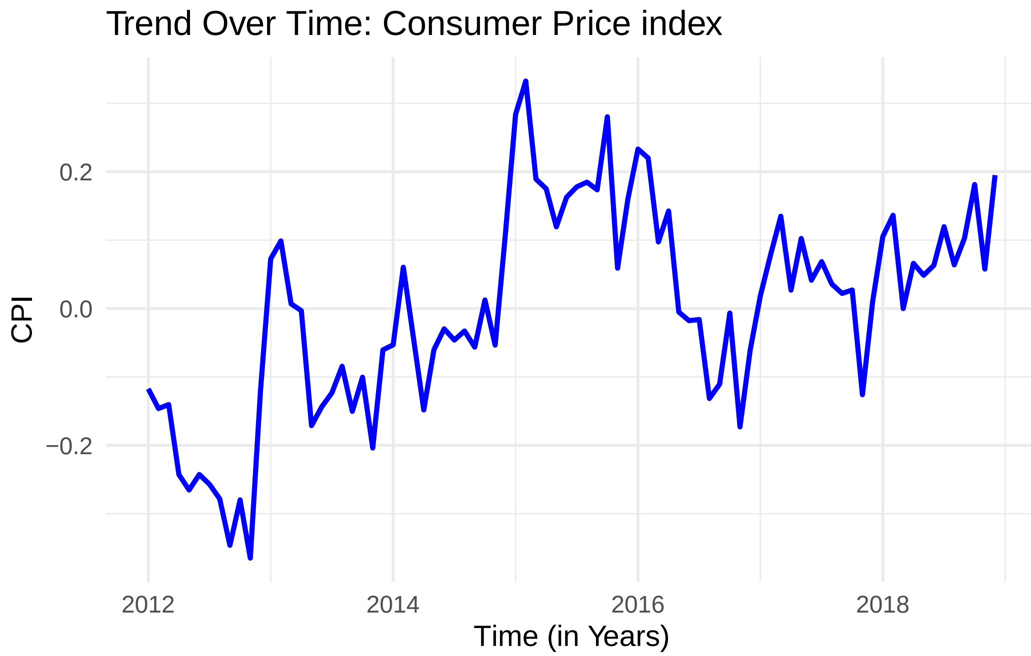


Figure 10: Temporal Variations in the Consumer price Index (CPI)

A.2.2 Purchase Volume

Figure 11 shows notable fluctuations from 2012 to 2018, suggesting periodic variability in consumer purchasing behavior. Peaks are observed around specific intervals, likely reflecting seasonal trends (peaks usually occur during the year-end i.e. the holiday season) or external economic factors influencing consumer demand. Over time, the periodic nature of these fluctuations appears consistent, with no clear upward or downward trend, indicating that the purchase volume stabilizes around recurring patterns.

B Idealized Methodology for Data Collection

This section describes an idealized methodology that could be used for acquiring and processing the food price data for the Food-at-Home Monthly Area Prices (F-MAP) dataset. The approach ensures rigorous data collection, transformation, and integration to create a reliable dataset for modeling temporal price trends at a national level.

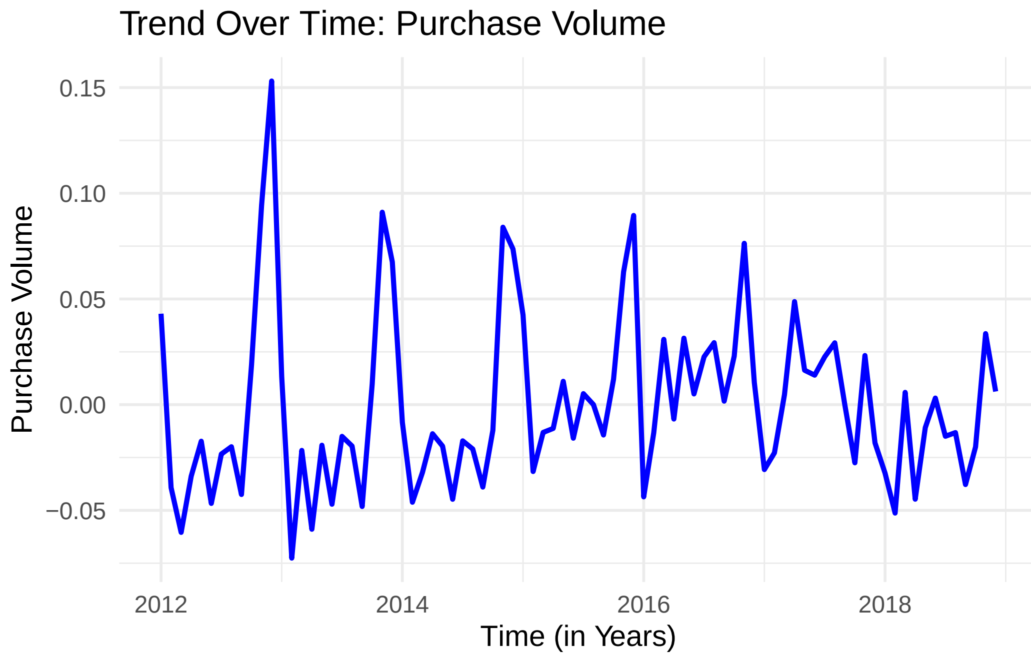


Figure 11: Temporal Variations in the Purchase Volume of Groceries

B.1 Sampling and Data Acquisition

The data for this study will be obtained from Circana OmniMarket Core Outlets, which report weekly retail scanner data on sales and prices across the United States. These datasets are augmented with macroeconomic indicators like the Consumer Price Index (CPI) to capture inflation trends and their effects on food prices. The USDA and ERS currently use this proprietary data to support their economic and market research.

We employ a nonprobability sampling technique to collect retail food-at-home (FAH) sales data from approximately 55,000–65,000 stores annually, including grocery stores, mass merchandisers, supercenters, club stores, convenience stores, dollar stores, and drugstores. Given the logistical and financial challenges of obtaining data from every retail store in the United States, nonprobability sampling is a practical and feasible choice, enabling us to work with a diverse subset of stores that provide meaningful insights into consumer purchasing behaviors. Although the sample is not strictly random, its breadth across different retailer types and regions ensures significant coverage of the FAH sector. To address potential biases, we apply store-level weights to align the sample with national and regional retail sales distributions, enhancing the dataset's representativeness. Retail outlets without scanning capabilities (e.g., small retailers, farmer's markets, and other direct-to-consumer sales) are not represented in the data. Direct-to-consumer food sales were about $2.9 billion in 2020 USDA, National Agricultural Statistics Service (NASS) (2022), compared with approximately $717 billion in sales from food stores (food and nonfood products) in 2019 USDA, Economic Research Service (ERS) (2022).

B.2 Data Preparation

The data contain weekly UPC-level (or item-level) revenue and quantity of food items sold at FAH retail establishments. The retail scanner data report sales on a weekly basis. Since we need monthly data, weekly sales are grouped into the respective months that the sales occurred. In cases where the week straddles 2 months, sales units and values are allocated proportionately based on the number of days in each month. Unit value outliers will be eliminated using the interquartile range (IQR) method. The IQR is the difference between the 25th and 75th percentiles of the price distribution, in this case across all unit values by store and week for each item. A unit value is considered an outlier if the value is below the 25th percentile minus 1.5 multiplied by the IQR or above the 75th percentile plus 1.5 multiplied by the IQR.

The weights of each package will be converted into grams to calculate unit values on a per 100-gram basis: a. Convert from ounces: gram weight = 28.35 x ounces per package b. Convert from pounds: gram weight = 28.35 x 16 x pounds per package c. Convert from fluid ounces: gram weight = 29.57 x fluid ounces per package

Individual food items sold in the scanner data (about 600,000 per year) will be identified and categorized into 90 food groups, based on the EFPG classification system. The USDA Economic Research Service (ERS) Food Purchase Groups (EFPGs) system is a comprehensive categorization framework designed to facilitate the analysis of food purchase data. Aligned with USDA's 2015–20 and 2020–25 Dietary Guidelines for Americans, EFPGs categorize foods based on attributes like ingredients, nutritional content, convenience, and store aisle placement. The framework includes three tiers, with tier 1 covering broad dietary categories (e.g., grains, dairy, and meat), and tiers 2 and 3 delving into subcategories and individual EFPG codes.

Lastly, store-level survey weights will be applied to adjust for biases in the scanner data, as the dataset is not a probability sample and does not represent all U.S. stores equally. These weights help align the sample data with the broader population of U.S. stores, ensuring representativeness across national and geographic areas. By applying these weights, the dataset will provide both weighted and unweighted estimates, enabling the calculation of price indexes and unit values that reflect real-world purchasing patterns.

B.3 Unit Values

Sales (in U.S. dollars) and quantity (in grams) are summed over each month and EFPG. Mean unit values will be calculated by dividing the food group sales by the food group quantity and standardized to the price per 100 grams. This process will comprise of: 1. Calculating the total purchase values in dollars and in grams for each EFPG in a given month, weighted by the store weight for that year of data (note: weight will be 1 for unweighted estimates); and 2. Dividing the total (weighted or unweighted) purchase dollars by the total (weighted or unweighted) grams to get the unit price.

The methodology also involves calculating the standard errors for the weighted unit values. This is done by re-estimating the weighted unit values 200 times using replicate weights. The standard errors measure the precision of the estimates and are used to construct confidence intervals, providing a range of values that likely contain the true population mean.

B.4 Price Indices

Price indexes are a unitless measure of the cost of a basket of goods and are used to measure price changes over time. A price index converts many item-level price comparisons into a single value that quantifies the overall price of the basket at a time and location relative to a base period. The base period for the F-MAP is the national average for each EFPG from 2016 through 2018. Index values lower than 1 indicate prices lower than the national average from 2016 through 2018, while index values higher than 1 indicate prices higher than the national average from 2016 through 2018.

The primary price index for our dataset will be constructed using a weighted GEKS index formula (named for contributors Gini, Eltetö, Köves, and Szulc). GEKS is a multilateral price index specifically designed to compare prices over time and space. A GEKS index can also be extended for future years without revising the index numbers that have already been published. A GEKS price index is available for all years of the F-MAP (2012–18). A set of supplemental indexes is also available for 2016–18 as a research series, which includes the bilateral Laspeyres, Paasche, Törnqvist, Fisher Ideal indexes and the multilateral Caves-Christensen-Diewert (CCD) index.

Multilateral price indexes are transitive, which means that any month-area pairing (or entity) can be compared directly with another pairing or through a third pairing, and the ratio between any two pairings is independent of the choice of base period. Transitive indexes are advantageous if the mix of goods being measured is dynamic; that is, if the basket of goods changes due to product turnover. Indexes based on scanner data are dynamic because the indexes include all goods sold in stores, which may change in each time period, rather than a sample of goods selected through a survey. Indexes that are transitive also allow spatial comparisons, regardless of the choice of area used for the base.

As additional years of price data become available beyond the base period, the GEKS index can be updated using a rolling window, or the time period over which the index is calculated. In standard multilateral indexes, as new data become available beyond the initial base period, the index numbers for existing entities must be recalculated because the multilateral index compares product prices in an entity with prices in all other entities. A rolling-window GEKS index compares product prices in a new entity with prices of entities within a rolling window.

The F-MAP GEKS uses a 1-year rolling window, which allows maintaining published indexes without revising historical numbers.

Bilateral indexes with a fixed base period can become less representative of the cost of food as the indexes move further away from the base, due to the effects of product turnover, as products are discontinued, and new products are introduced. Although bilateral price indexes can be updated using chained indexes, which capture product substitution, chained indexes are subject to drifting. Chain drift is a phenomenon in which the price index drifts lower even as item-level prices return to their base levels. Multilateral indexes are fully transitive and free of chain drift. While chain drift is possible in rolling-window multilateral indexes, if a wide window length is chosen, the rolling-window index will be largely free of drift despite not being fully transitive. The 1-year rolling window used in the F-MAP GEKS has been found to be sufficient to remove chain drift caused by high-frequency data and seasonal variation in variety.

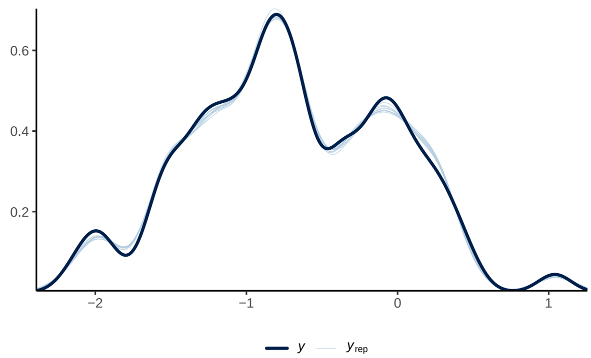
The GEKS index builds upon bilateral indexes as elements. The multilateral GEKS index is the geometric mean of all possible Fisher Ideal index month-area pairings. The Fisher Ideal index is, in turn, based on the geometric mean of the Laspeyres and Paasche indexes. Therefore, constructing a GEKS index requires first calculating Laspeyres, Paasche, and Fisher Ideal indexes. We avoid going into deeper details of the above indices as the math gets extremely complicated. For more information about the construction of the F-MAP GEKS, the rolling-window GEKS, and the five supplemental indexes (i.e., Laspeyres, Paasche, Törnqvist, Fisher Ideal, and Caves-Christensen-Diewert (CCD)), you can refer to ERS's report on the F-MAP methods. (Sweitzer et al. 2024)

C Model details

C.1 Posterior predictive check

The posterior predictive check (PPC) graph in Figure 12 shows a strong alignment between the observed data (y) and the replicated data (y_rep), indicating that the model effectively captures the underlying data distribution. The overlapping peaks and troughs suggest that the model accurately reflects the central tendencies and variability of the data, while the uncertainty bands demonstrate that it accounts for variability in a calibrated manner.

This alignment implies that the model is well-suited for generalization and reliable prediction, as it avoids significant overestimation or underestimation. While the PPC supports the model's adequacy, additional diagnostics such as R-hat values and effective sample size (ESS) are essential to confirm parameter convergence and overall robustness. These combined assessments ensure the model's reliability for forecasting future trends.

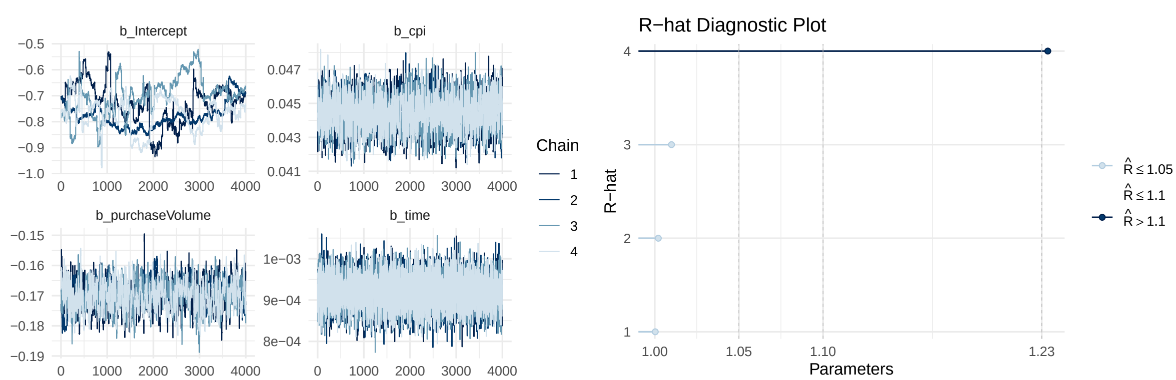


(a) Posterior prediction check

Figure 12: Examining how the model fits, and is affected by, the data

C.2 Diagnostics

The trace plot in Figure 13a for the Bayesian Hierarchical Model (BHM) illustrates the convergence and mixing of the four Markov Chain Monte Carlo (MCMC) chains for each parameter: b_Intercept, b_cpi, b_purchaseVolume, and b_time. Each chain oscillates consistently within the same parameter space, indicating good mixing and convergence for most parameters. For example, the parameter b_cpi demonstrates tightly packed, overlapping chains, suggesting stable posterior estimates. However, the b_Intercept shows some variability, which could indicate slower convergence. Overall, the trace plots confirm the reliability of the posterior samples, but further diagnostics like R-hat values and effective sample sizes should be inspected to ensure full convergence.



(a) Trace plot

(b) Rhat plot

Figure 13: Checking the convergence of the MCMC algorithm

The R-hat diagnostic plot in Figure 13b assesses the convergence of the Markov Chain Monte Carlo (MCMC) chains in the Bayesian model. Ideal convergence is indicated by R-hat values close to 1, which ensures that all chains are sampling from the same posterior distribution. In this plot, R-hat values exceed 1.1 for some parameters, signaling poor convergence and potential issues with chain mixing. This suggests that additional iterations, fine-tuning of priors, or adjusting MCMC settings (e.g., increasing adapt_delta or max_treedepth) may be required to improve model reliability and ensure accurate posterior estimates.

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