

# Assessing the Multifaceted Influences on Current Coffee Prices\*

Coffee Pricing in Canadian Grocery Stores: Current Prices Strongly Shaped by Historical Trends

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This paper investigates the factors influencing coffee product prices in Canadian grocery stores, focusing on historical prices, vendor differences, and seasonal trends. Using a Bayesian multiple linear regression model, the study reveals that historical prices have the most significant positive impact on current prices, while vendor differences and seasonal variations also play measurable roles. These findings highlight how past prices serve as a benchmark for current pricing strategies, emphasizing the importance of historical data in retail decision-making. The results contribute to understanding the dynamics of coffee pricing and provide insights for optimizing retail pricing strategies and future research directions.

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\*Code and data are available at: [https://github.com/YiTang2/Canadian\\_Grocery\\_Analysis.git](https://github.com/YiTang2/Canadian_Grocery_Analysis.git)

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# 1 Introduction

Consuming goods is an integral part of everyone’s daily life, with pricing being a major factor that influences consumer behavior.(Arnot, Boxall, and Cash 2006) People are particularly interested in the price of goods, and whether there is a price premium or discount. What determines these prices? Is it the purchasing power of consumers, or perhaps the cost associated with each stage of production? This paper seeks to answer some of these questions by combining product data from Canadian grocery stores with additional raw data to identify key factors that influence product pricing. Specifically, we focus on coffee products and use the current price as the outcome variable, aiming to understand the influences behind it.

To explore this, I chose one of the most intuitive factors: the old price, since historical pricing often influences how vendors set current prices. Additionally, I included data from two vendors—Metro and SaveOnFoods—located in different parts of Canada to investigate any differences in pricing strategies between the eastern and western regions. The inclusion of month allows us to explore potential seasonal trends in coffee pricing, assessing whether specific times of the year see significant price variations.

In this study of coffee pricing strategies in Canadian grocery stores, the focus is on estimating how historical prices (old price), time of year (month), and vendor characteristics (vendor) affect current coffee prices. Using a Bayesian multiple linear regression model, I estimated these effects to better understand the pricing dynamics of coffee products and to determine how much each factor contributes to pricing decisions in the market.

The findings reveal that the old price has the most significant positive impact on current coffee prices among all the predictors considered. This suggests that vendors heavily rely on historical prices when determining current prices, possibly to maintain a level of consistency that consumers expect. Due to a lack of data for some months, it was challenging to establish a definitive analysis of seasonal trends, though this aspect remains an important factor for understanding pricing behavior comprehensively.

The paper is structured as following: Section 2 describes the data used for analysis, Section 3 describes how to set up, justify and validate the model, **Section 4** tells the finding of the data and model, Section 5 discusses the implication, potential problems, and future expectations.

## 2 Data

### 2.1 Overview

Price of each month’s coffee of different vendors data is provided by(Filipp 2024). This dataset records detailed sales about fast-moving consumer goods (FMCG) sold by various vendors, including volia, T&T, Loblaws, SaveOnFoods, Galleria, Metro, NoFrills and Walmart. It is

also includes product-level details, such as the product name, current price, historical price (old price), and the corresponding units and price per unit. The data also captures time-specific observations(2024-2-28 to 2024-6-22), with timestamps (nowtime) that can be used to analyze trends over days or months.

In order to simulate data, test simulated data, clean data, test cleaned data, exploratory data analysis and model data, we used R programming language (R Core Team 2023) to analyze the data and plot the graphs. The folder structure for this paper follows the startup folder created by (Wickham et al. 2019a). It is very helpful in keeping everything organized. I also referenced many of the examples and techniques provided by Telling Stories with Data (Alexander 2023), which helped me understand how to visualize the data and communicate the findings effectively. Specific libraries that assisted the analysis include `tidyverse` (Wickham et al. 2019b), `knitr` (Xie 2014), `arrow` (Richardson et al. 2024), `ggplot2` (Wickham 2016), `dplyr` (Wickham et al. 2023), `here` (Müller 2020), `kableExtra` (Zhu 2024), `gridExtra`(Auguie 2017), `modelsummary`(Arel-Bundock 2022), `rstanarm`(Goodrich et al. 2022).

The inspiration for my data processing came from my desire to study what factors would affect the current price of coffee products from two vendors in different regions of Canada, such as the current price of coffee products from two vendors, Metro and SaveOnFoods. Table 1 are the data I selected after cleaning the data, and new variable `month` extracted and transformed from raw data also.

Since the variable `nowtime` only records 4 months, it is considered a lack of Long-Term Trends, which means it's difficult to identify long-term pricing or demand patterns by using short data periods. So I only extracted a new variable—`month` from date of `nowtime`, which can simplify temporal analysis and identify trends, such as seasonal monthly pattern with price changes or demand patterns. It allows grouping data for monthly aggregation and supporting seasonality-focused insights or forecasting models.

Table 1: Variables and their Definitions for the Coffee Product Pricing.

Variable	Definition
<b>vendor</b>	The retailer selling the product in Canada.
<b>old price</b>	The historical price of the product, showing previous pricing or discounts.
<b>current price</b>	The price of the product at the time of observation..
<b>product name</b>	The specific product being sold, providing product-level insights
<b>month</b>	The month of data collection, extracted from 'nowtime'

To provide an preview of the coffee pricing with all potential factors that might affect it. Here,

Table 2 simply reveals the variation between current price and old price in June for Metro’s coffee products.

Table 2: Sample of Analysis Data Showing Products Sold by Both Vendors

vendor	product_name	current_price	old_price	month
Metro	Non-Dairy Vanilla Flavoured Latte Coffee Cream	7.49	8.99	6
Metro	Vanilla And Caramel Flavoured K-Cup® Coffee Capsules	9.99	12.99	6
Metro	Classic Black K-Cup® Coffee Capsules	9.99	12.99	6
Metro	Cold Brew Unsweetened Iced Coffee	7.49	7.99	6
Metro	Limited Edition Coffee Whitener, Coffee Mate	4.99	6.99	6
Metro	Italian Blend Dark Roast K-Cup Coffee Pods	6.49	6.99	6
Metro	Classic Roast Ground Coffee	8.99	12.49	6
Metro	Medium Roast Decafreinated K-Cup Coffee Pods, Pike P...	22.99	26.99	6
Metro	Medium Roast House Blend K-Cup Coffee Pods, Organic	6.49	6.99	6
Metro	Classic Decaf Ground Coffee	8.99	12.99	6

## 2.2 Measurement

The dataset from Hammer provides a comprehensive representation of real-world retail activities, capturing key elements such as product details, vendor listings, and price updates. When vendors make updates to product information, including pricing changes or availability adjustments, Hammer gathers and organizes this data into a structured dataset. This ensures that the dataset remains accurate and reflective of current retail conditions.

The dataset includes essential fields such as vendor, product name, current price, old price, and a timestamp referred to as nowtime. The data is collected through scraping and is systematically structured to support an in-depth analysis of retail trends, pricing strategies, and overall market dynamics across different periods. Each record captures a snapshot of a product’s market presence at a given time, enabling targeted analyses like monitoring price fluctuations for specific products, such as coffee. By offering such detailed and time-specific information, the dataset provides a valuable foundation for understanding the evolving dynamics of retail pricing and vendor strategies.

## 2.3 Data Visualization

Figure 1 shows a notable distribution with significant concentrations around 10 and 20 units. This suggests a pricing tier system where certain types of coffee products might be grouped by price points due to quality, brand, or other market factors. The dual peaks could indicate two main categories of coffee products, possibly differentiated by premium versus regular products.

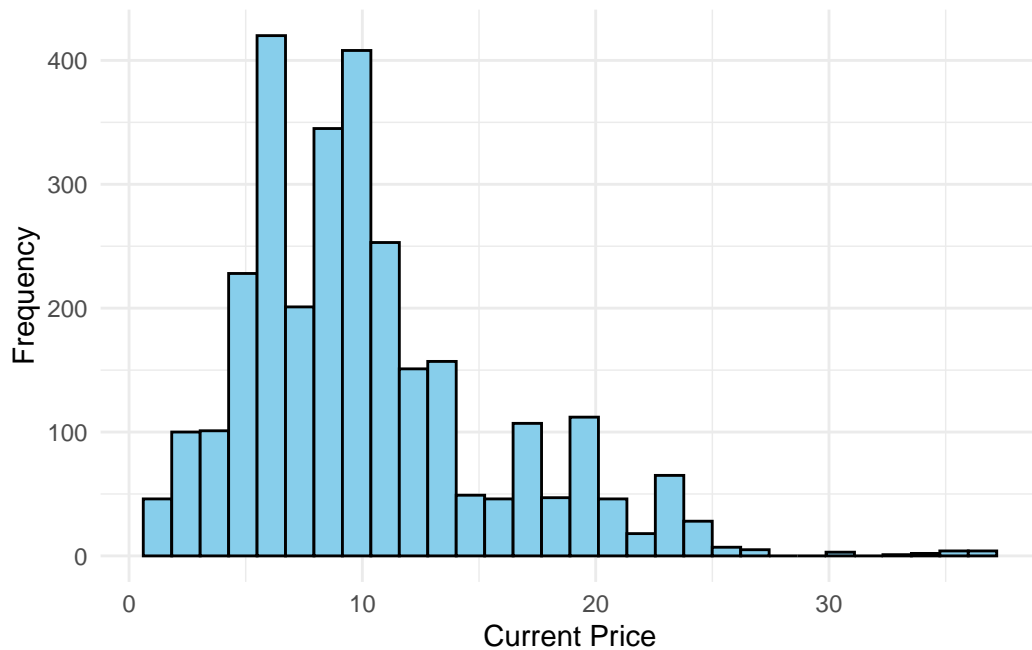


Figure 1: Frequency of Current Price

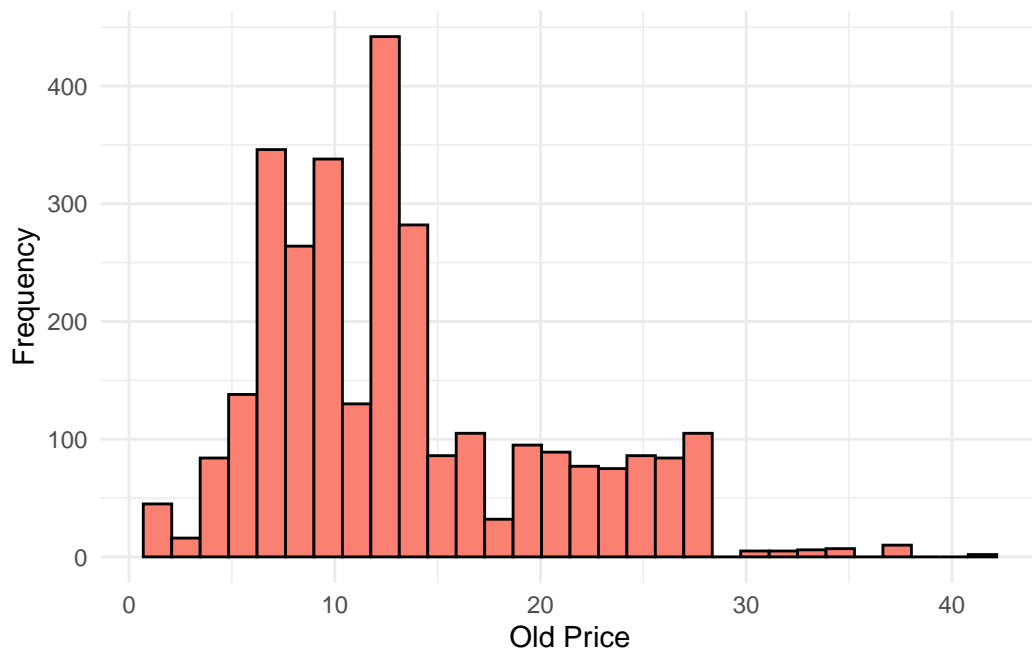


Figure 2: Frequency of Old Price

According to Figure 2, the distribution is mainly focused between 5 and 20 units, pointing to a past market strategy where products were clustered around these prices. The consistency in this price range might reflect a stable market before any recent pricing adjustments influenced by external factors like supplier changes or inflation.

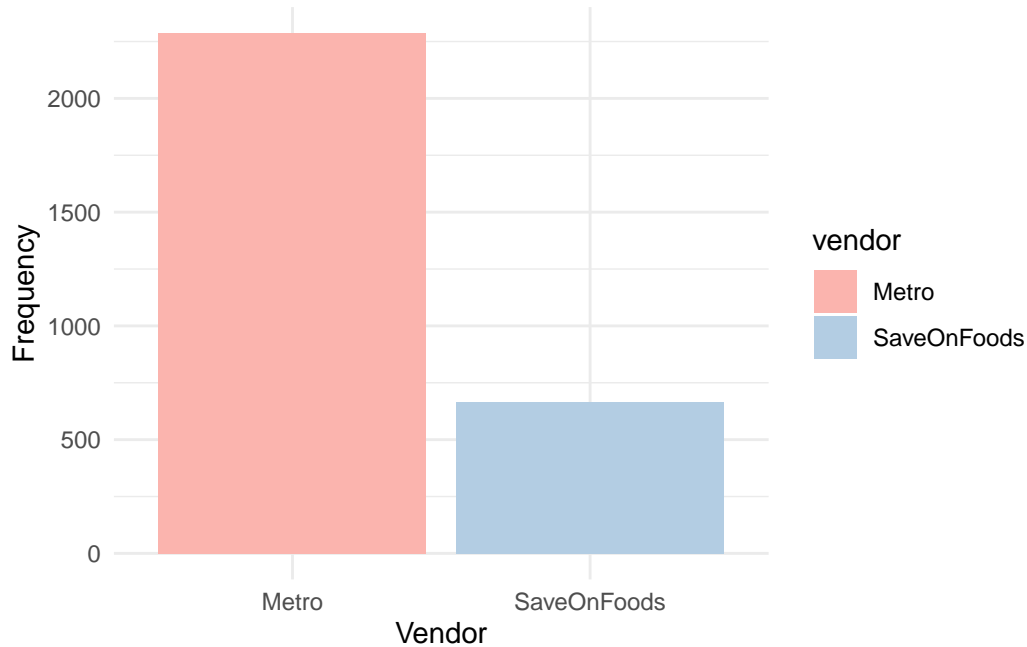


Figure 3: Frequency of Vendor

In **fig-Bar-plot-of-old-price**, the frequency of products available from Metro significantly surpasses that from SaveOnFoods, suggesting that Metro has a larger share of the market or a wider variety of coffee products. This dominance in product offerings could provide Metro with a competitive edge in attracting a broader customer base.

The positive relationship shown in Figure 4 here indicates that current prices are influenced by their historical prices, maintaining a proportional increase or decrease. This trend suggests a pricing policy that adjusts prices based on previous benchmarks while taking into account factors like cost adjustments or market demand.

**fig-Bar-plot-of-old-price** highlights how each vendor prices their products within the market. It shows that both vendors offer a wide range of prices, yet the spread and density of the data points may indicate Metro's pricing strategy targets both lower and upper market segments, whereas SaveOnFoods might be focusing on a specific niche.

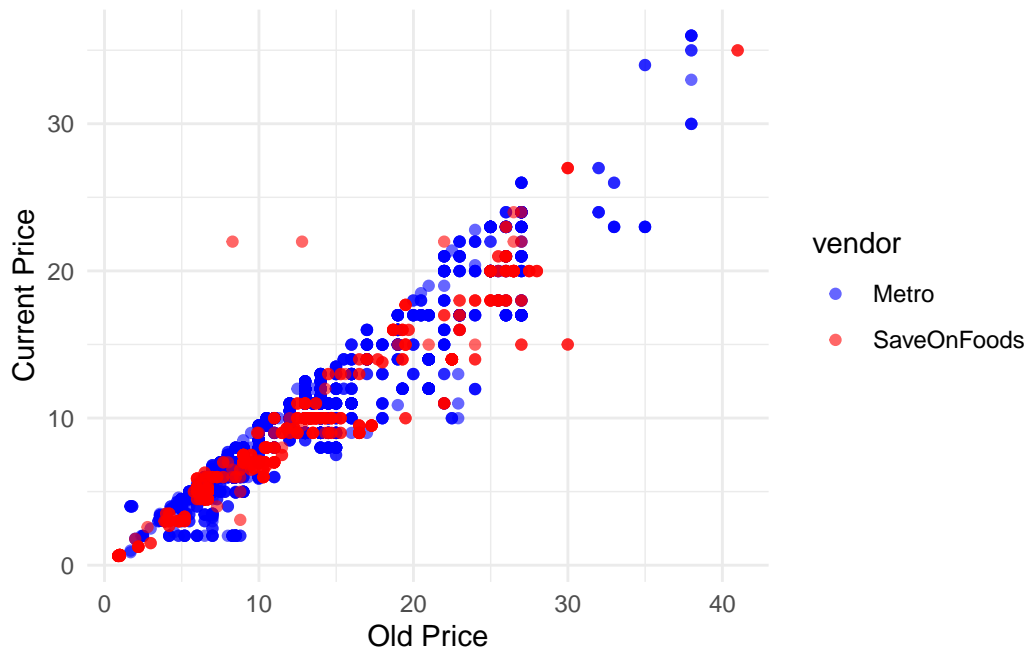


Figure 4: Current Price vs Old Price

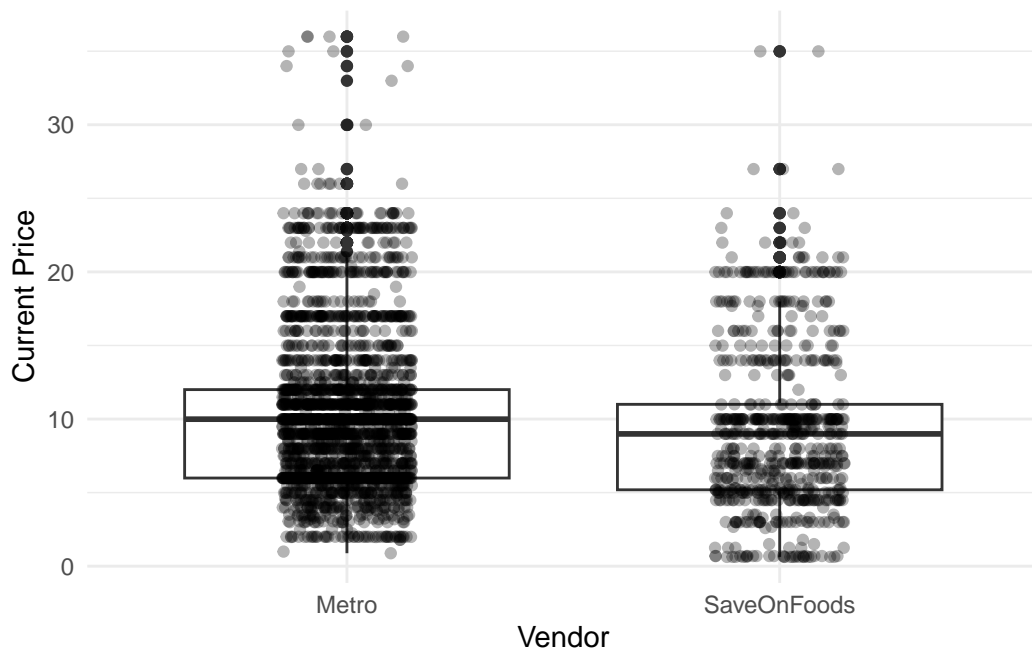


Figure 5: Current Price by Vendor



## 2.4 Outcome variables

The outcome variable for this analysis is the current price of coffee products. This variable is crucial for understanding the dynamics of pricing in the retail market, as it reflects the final cost faced by consumers. Analyzing the current price helps uncover patterns in how vendors adjust prices over time, respond to market conditions, and compete in a fluctuating retail environment. By focusing on the current price, we can measure the impact of historical trends, vendor-specific strategies, and seasonal changes on pricing decisions.

## 2.5 Predictor variables

The predictor variables selected from the raw dataset are old price, month, and vendor. The old price serves as a predictor because it provides valuable insight into how past pricing decisions influence current prices. Vendors often make incremental adjustments based on historical pricing data, consumer behavior, and market reactions, which makes it a key factor in understanding pricing strategies. Month is included to account for possible seasonal trends in pricing, as consumer demand and promotional activities often vary throughout the year, potentially impacting coffee prices. Lastly, vendor is used to examine pricing variations between Metro and SaveOnFoods. Each vendor may have distinct pricing approaches based on factors like target market, cost structures, or regional positioning, and including this variable enables a comparative analysis of vendor-specific pricing dynamics.

# 3 Model

The goal of our Bayesian multiple linear regression is to investigate the factors that influence the current price of coffee in our dataset. Specifically, we try to understand how historical pricing, vendor differences, and seasonal monthly pattern affect current coffee prices.

## 3.1 Model set-up

Define  $y_i$  as the current price of coffee for the  $i$ -th observation in the dataset. The predictors include:

- $X_{\text{Old Price},i}$ , the old price of the coffee,
- $X_{\text{Vendor},i}$ , dummy variable for the vendor, where:  
 $X_{\text{Vendor},i} = 1$ : Vendor is “SaveOnFoods”;  $X_{\text{Vendor},i} = 0$ : Vendor is “Metro”,
- $X_{\text{Month},i}$ , the numeric month variable.

The model is formulated as follows:

$$y_i | \mu_i, \sigma \sim \text{Normal}(\mu_i, \sigma), \quad (1)$$

$$\mu_i = \alpha + \beta_1 \cdot X_{\text{Old Price},i} + \beta_2 \cdot X_{\text{Vendor},i} + \beta_3 \cdot X_{\text{Month},i}, \quad (2)$$

$$\alpha \sim \text{Normal}(0, 2.5), \quad (3)$$

$$\beta_1 \sim \text{Normal}(0, 2.5), \quad (4)$$

$$\beta_2 \sim \text{Normal}(0, 2.5), \quad (5)$$

$$\beta_3 \sim \text{Normal}(0, 2.5), \quad (6)$$

$$\sigma \sim \text{Exponential}(1). \quad (7)$$

This model describes the relationship between the current price of coffee  $y_i$  and three predictors: the old price of coffee  $X_{\text{Old Price},i}$ , a categorical vendor variable  $X_{\text{Vendor},i}$  indicating whether the vendor is “Metro” or “SaveOnFoods,” and a numeric variable for the month  $X_{\text{Month},i}$ . The response variable  $y_i$  is modeled as normally distributed with mean  $\mu_i$  and standard deviation  $\sigma$ . The mean  $\mu_i$  is defined as a linear combination of these predictors, with coefficients  $\beta_1, \beta_2$ , and  $\beta_3$ , and an intercept  $\alpha$ . Prior distributions for the parameters are specified, including normal priors for  $\alpha$  and the coefficients, and an exponential prior for  $\sigma$ . Intercept  $\alpha$  represents the baseline mean current price for Metro if  $X_{\text{Vendor},i} = 1$ ; otherwise when  $X_{\text{Vendor},i} = 0$ , it represents the mean current price for SaveOnFoods. Also, when old price and month is equal to 0, the intercept is not meaningful. Coefficient  $\beta_1$  captures how changes in the old price affect the current price. Coefficient  $\beta_2$  measures the difference in the mean coffee price between SaveOnFoods ( $X_{\text{Vendor},i} = 1$ ) and Metro ( $X_{\text{Vendor},i} = 0$ ). Coefficient  $\beta_3$  reflects how the month influences current pricing, potentially capturing seasonal effects.

To implement this Bayesian model, we use the `rstanarm` package (Goodrich et al. 2022) in R (R Core Team 2023).

### 3.2 Model justification

The Bayesian Multiple Linear Regression (MLR) model is a suitable choice for analyzing the relationship between **current price** (the dependent variable) and the predictors in the dataset. The dependent variable is continuous, and the Bayesian framework assumes a normal distribution for the response, which aligns well with the nature of coffee prices. This model captures the linear relationships between **old price** (continuous), **vendor** (categorical, represented as a dummy variable), and **month** (numeric). These predictors are assumed to have additive effects on the response, which fits the linear regression framework. Logistic regression is used when the outcome variable is binary (e.g. 0 or 1). However, in our dataset, the dependent variable, **current price**, is continuous. Since logistic regression cannot model continuous outcomes, it is unsuitable for this analysis. Also, poisson or negative binomial regression is typically applied when the response variable represents count data (e.g., the number of events occurring in a

fixed period). `current_price` does not represent counts but rather continuous pricing data. Thus, these models do not align with the nature of the dependent variable.

### 3.3 Model validation

Figure 6 shows that our model accurately captures the central tendency of the data, though there are some deviations in the tail ends suggesting that the fit could be improved for extreme values. Additionally, the parameter estimation comparison chart highlights that most parameter estimates closely align with their priors, indicating a strong influence of prior settings on the estimates, especially under limited data. This is particularly evident with the `vendorSaveOnFoods` parameter, where its posterior distribution significantly diverges from others, hinting at potential anomalies in data sources or unique behaviors that warrant further investigation.

?@fig-trace-plot illustrate that our Bayesian model parameters are converging and demonstrating stability, essential for robust statistical inference. The slight oscillation of the intercept around -0.5 indicates minor variability. Meanwhile, the old price coefficient shows remarkable consistency at approximately 0.77, underlining dependable estimates. The month parameter's minor fluctuations suggest a subtle yet consistent temporal effect. The `vendorSaveOnFoods` coefficient consistently remains near -0.6, indicating a persistently negative price influence compared to Metro. Finally, sigma's stability around 1.75 ensures the model's error variability is well-accounted for. These observations collectively affirm that the model's parameters are effectively calibrated, offering a reliable foundation for understanding the influences on coffee prices.

In Figure 8 analysis of coffee product pricing in Canada, the use of the  $\hat{R}$  values to assess model convergence reveals that all parameters have  $\hat{R}$  values below 1.05, indicating excellent convergence of the model. This result validates the reliability of our model in estimating coffee prices and ensures the robustness of the analysis outcomes. It allows us to trust the model outputs, providing a solid foundation for further strategic decision-making and market analysis.

## 4 Results

Table 3 indicates a strong fit with a high  $R^2$  of 0.900, suggesting a strong explanatory power of the model regarding the variance in coffee product prices. The model's parameters show that the old price of coffee (coefficient = 0.77) has a significant positive influence on the current price, suggesting that past pricing trends are good predictors of current pricing strategies. Vendor impact, specifically `SaveOnFoods`, shows a negative association with current price (coefficient = -0.61), indicating that coffee products from `SaveOnFoods` tend to be cheaper compared to Metro. Additionally, the month coefficient (0.06) implies a slight monthly variation in coffee pricing. The model's predictive performance is validated by low WAIC and LOOIC scores, and a small RMSE of 1.75, enhancing confidence in the reliability of its predictions.

Figure 7 illustrates the posterior distributions for the parameters in your Bayesian regression model, analyzing factors influencing coffee prices. The intercept shows a slight positive baseline effect. The old price of coffee strongly and positively affects the current price, indicating a direct relationship. The month variable shows a minimal and variable impact. SaveOnFoods, as a vendor, is associated with lower prices compared to Metro. The sigma parameter, indicating the model's error variance, shows a sharp and precise estimation, suggesting consistent variability in the data explained by the model.

## 5 Discussion

### 5.1 Overall findings and Implication

This research conducted a detailed examination of coffee product pricing across major Canadian grocery store chains, specifically Metro and SaveOnFoods. By utilizing a regression model, the study uncover how historical price data (by month) can predict current coffee prices. This approach not only helped identify pricing trends but also provided a systematic framework to analyze the economic factors influencing those trends.

The findings highlight a dynamic interaction between past and present pricing strategies, underscoring the influence of historical prices on current market behaviors. This analysis reveals that historical prices are strong predictors of current prices, suggesting that vendors likely use past data as a benchmark for future pricing decisions. This could imply a strategy focused on maintaining market stability and optimizing profit margins, which is crucial in a competitive retail environment.

### 5.2 Additional understanding from the Data Analysis

The coffee products prices are influenced by more than just historical trends; they also respond to a range of external economic factors. The study highlights how variations in coffee prices align with broader economic indicators like inflation rates and consumer demand. This insight is crucial for understanding the dynamic nature of the coffee market, suggesting that vendors adjust their pricing strategies not only based on past price behavior but also in reaction to economic conditions. This deeper understanding of price adjustments helps illustrate the broader economic landscape within which these businesses operate, emphasizing the strategic decisions vendors make in response to economic pressures. This analysis significantly enriches our understanding of market behaviors and the economic strategies that drive vendor actions in the competitive grocery sector.

## 5.3 Shortcomes and Future outlook

### 5.3.1 Limitation

This study integrates two distinct raw datasets to construct the analysis dataset, which presents unique challenges due to varying variable names and formats. The process involved carefully aligning these variables to ensure consistency and accuracy in the dataset used for modeling. This integration underscores the importance of meticulous data preparation in ensuring the reliability of the results obtained from statistical analyses.

A significant limitation of this study is the absence of geographic data for the vendors. Although our analysis provides insights into the pricing strategies of Metro and SaveOnFoods, we lack the data to explore how geographical location influences pricing strategies across Canada. Metro and SaveOnFoods operate in different regions of Canada, potentially the Eastern and Western parts, and it is plausible that regional economic conditions, competition, and consumer demographics could affect pricing strategies. The absence of this data restricts our ability to analyze and understand regional pricing dynamics comprehensively. lack of month: only have data of coffee prouduct pricing in June to November.

### 5.3.2 Weaknesses and next steps

While the model provides valuable insights, there are limitations due to the dataset only covering a short period (June to November). This limits the ability to analyze long-term trends or seasonal impacts beyond this timeframe. Additionally, the model assumes linear relationships among variables, which may not fully capture more complex dynamics in price fluctuations.

Future research could expand the timeframe of data collection to include multiple years to better understand long-term trends and seasonal variations. Incorporating additional variables such as promotional activities, competitor prices, and economic indicators could also enrich the analysis. Further, exploring non-linear models or machine learning approaches may provide deeper insights into the pricing strategies of different vendors. To address these limitations, future research should focus on acquiring and integrating geographic data into the analysis. This would allow for a more detailed examination of how location-specific factors influence pricing, enhancing our understanding of regional market behaviors. Exploring geographical influences on pricing can reveal targeted strategies that vendors might use to cater to local consumer preferences or to respond to regional competition. Incorporating such data would significantly enrich the analytical framework and potentially yield insights that could inform more localized or region-specific business strategies for these vendors.

## Appendix

### A Idealized Survey and Methodology

To address the collection of data regarding coffee prices through an idealized survey and methodology, we have meticulously designed a survey that aligns with best practices in research and data collection (Filipp 2024). The survey begins with an introductory section, welcoming participants to the “Coffee Price Insights Survey.” This introduction serves to inform respondents of the purpose of the survey, which is to gather data on coffee prices across different regions to analyze market trends and pricing strategies. The introduction reassures participants of the value and importance of their input and provides an estimated completion time of 5 minutes.

Contact information for the survey overseer is clearly listed, with Dr. Jane Brewer as the point of contact, providing her email and a contact number to ensure respondents can reach out with questions or require further assistance. This transparency builds trust and aids in increasing response rates.

The survey itself comprises a series of well-constructed questions designed to gather comprehensive data while being easy to understand and respond to. It starts with basic multiple-choice questions regarding where respondents buy their coffee and how frequently. This is followed by checkbox options for the type of coffee they purchase, allowing for multiple selections to capture all preferences. The survey progresses to more detailed questions, such as ranking their preferred coffee brands and disclosing their monthly coffee expenditure through an open-ended question. Additionally, a simple yes/no question about noticing seasonal price variations is included to gather data on temporal pricing trends.

Each question is strategically ordered from the most straightforward to the more detailed to prevent respondent fatigue and ensure logical flow, maintaining engagement throughout the survey. The varied types of questions (multiple-choice, checkboxes, ranking, open-ended, and binary) cater to different data needs and enhance the richness of the data collected, making the analysis more robust.

The survey concludes with a thank-you section, expressing gratitude to the respondents for their time and insights, which reinforces the value of their contribution and ends the survey on a positive note.

For the methodology, a stratified sampling strategy is employed to ensure a diverse and representative sample by dividing the population into subgroups based on geographical regions. This approach not only improves the generalizability of the results but also allows for detailed analysis of regional variations in coffee prices. Data collection is conducted via an online survey platform, chosen for its wide reach and efficiency, as well as its built-in data validation features to ensure accuracy in the responses gathered.

Data analysis involves quantitative techniques to assess pricing trends and consumer behavior, utilizing statistical software for precision. Qualitative responses from open-ended questions undergo thematic analysis to uncover deeper insights. This comprehensive analysis approach ensures that both numerical data and rich textual data are effectively utilized.

The overall survey design and methodology are grounded in the literature on survey research, drawing from established frameworks and studies that underscore the effectiveness of such approaches. Additionally, preliminary simulations using historical data are conducted to test and refine the survey and sampling strategy, ensuring that the actual data collection is as effective and efficient as possible.

This idealized survey and methodology framework is not only methodically sound and strategically designed but also extensively planned to achieve detailed insights into coffee pricing, thereby fulfilling the objectives set out for this research initiative.

## B Model details

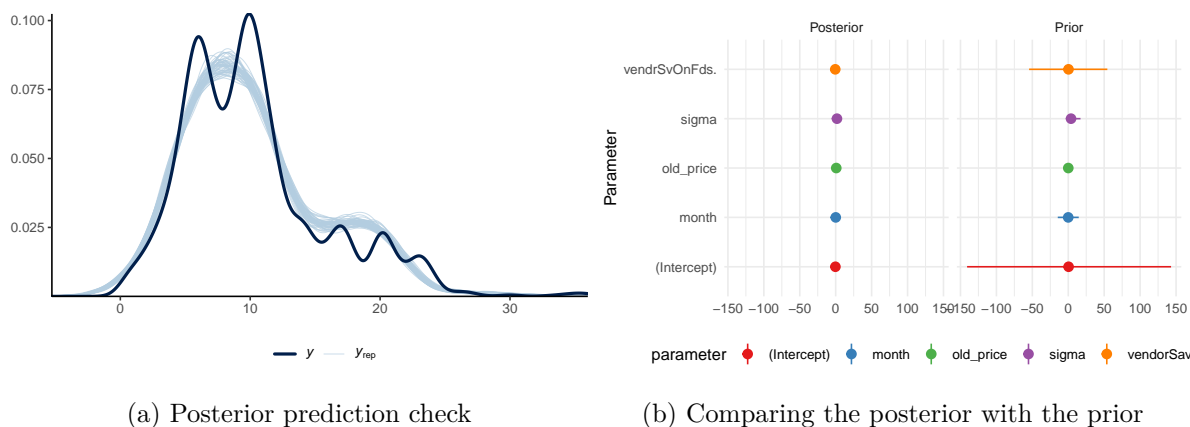


Figure 6: PPcheck & Posterior vs Prior

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#| fig-subcap: ["Trace plot of Intercept", "Trace plot of old_price", "Trace plot of month",
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```

Table 3: Model summary of Coffee product pricing

Coffee product pricing	
(Intercept)	−0.41
old_price	0.77
month	0.06
vendorSaveOnFoods	−0.61
Num.Obs.	2954
R2	0.900
R2 Adj.	0.900
Log.Lik.	−5837.981
ELPD	−5843.3
ELPD s.e.	71.3
LOOIC	11 686.6
LOOIC s.e.	142.6
WAIC	11 686.6
RMSE	1.75

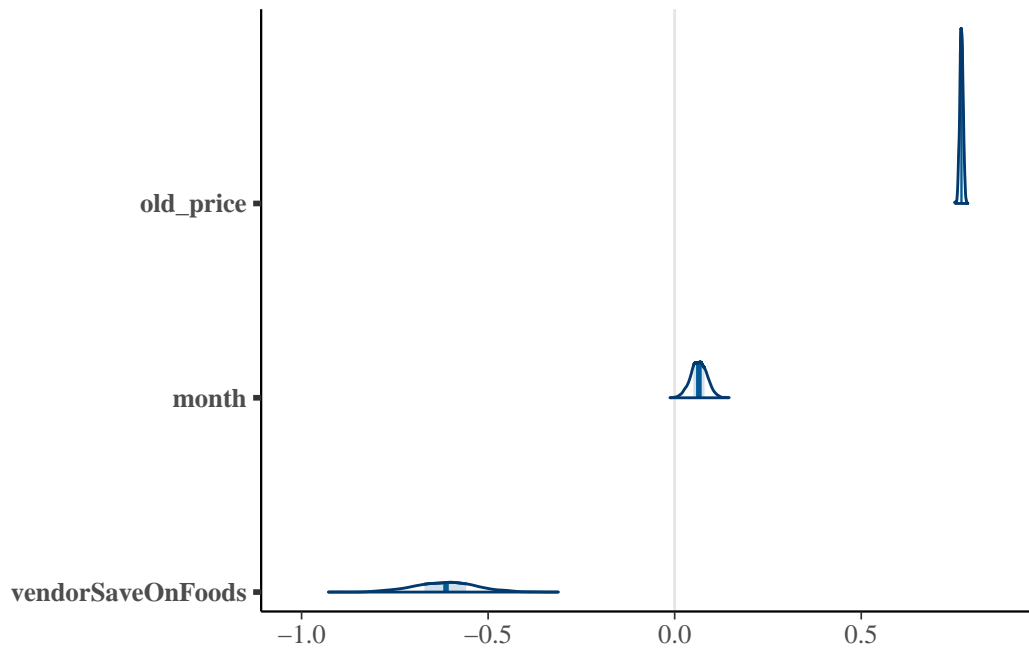
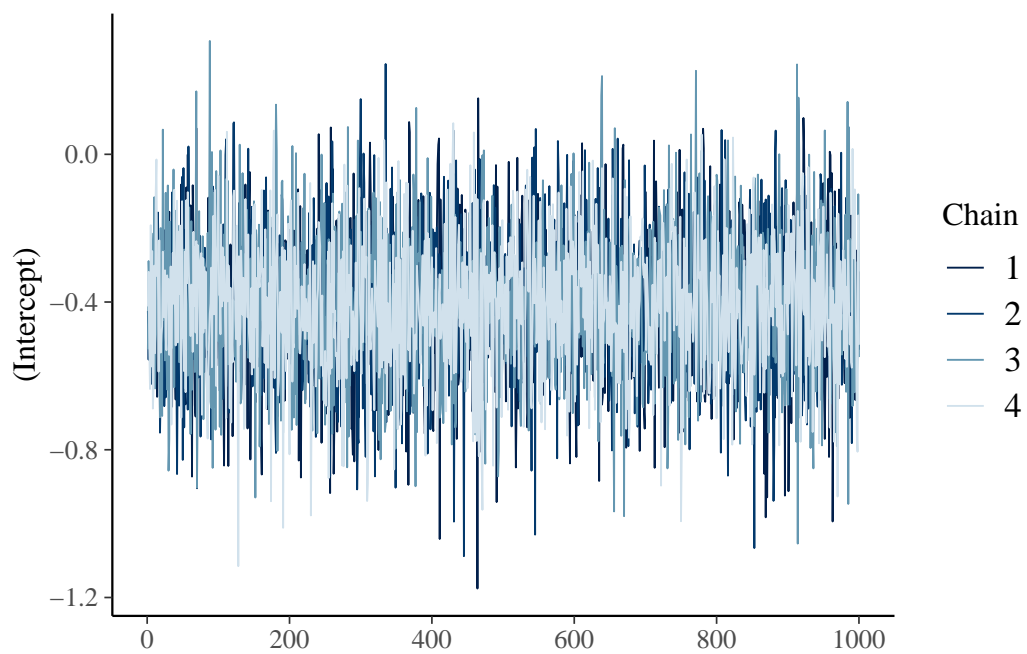


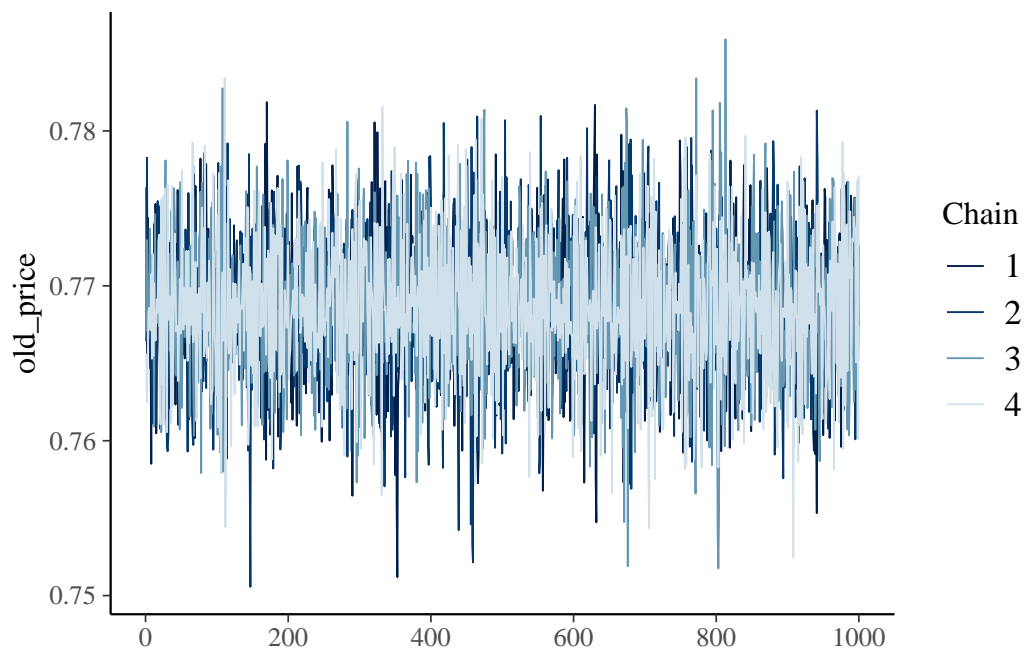
Figure 7: credibility interval



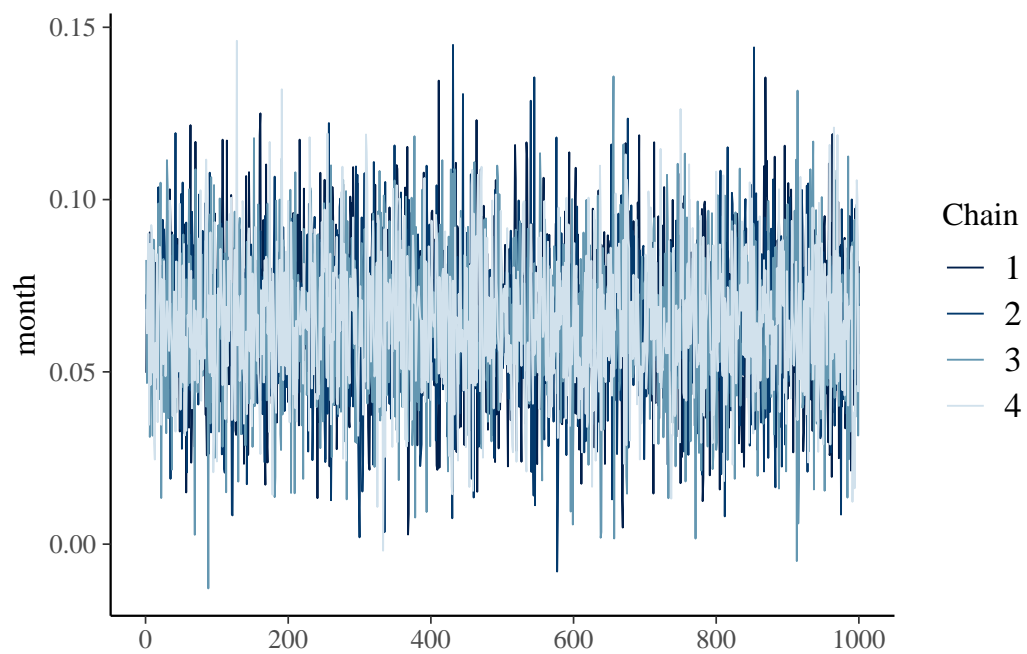
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```
plot(Coffee_product_pricing, "trace", "old_price")
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```
plot(Coffee_product_pricing, "trace", "month")
```



```
plot(Coffee_product_pricing, "trace", "vendorSaveOnFoods")
```

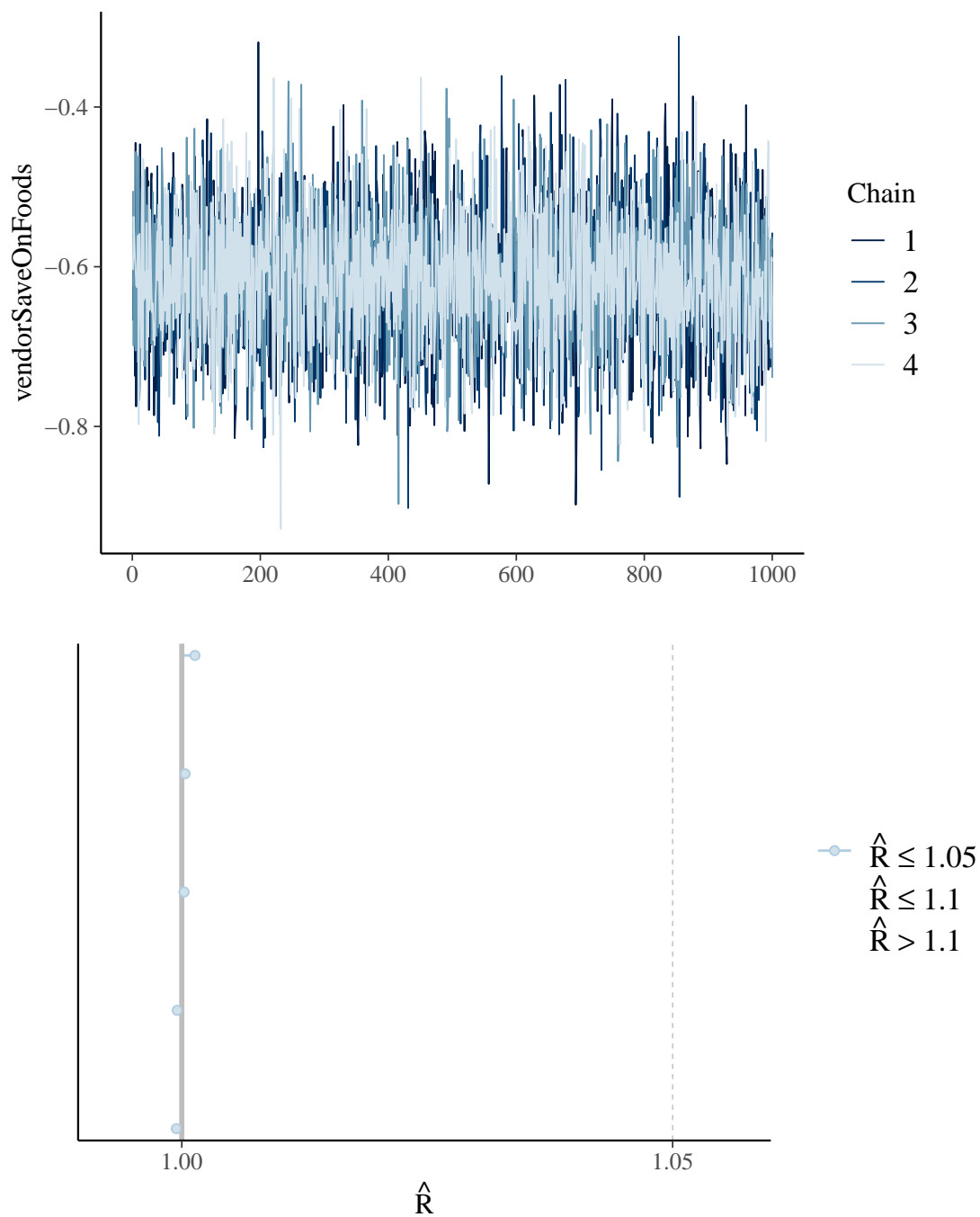


Figure 8: R-hat plot of Coffee products pricing

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