Timing and Positioning: Insights from Steak-Related Product Pricing at Walmart and Loblaws*

Insights into Pricing Strategies: Unveiling Research Results and the Key Factors Driving Steak-Related Product Pricing

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This study explores pricing strategies in the retail grocery sector, with a focus on steak-related products from Walmart and Loblaws. Utilizing a comprehensive dataset of historical and current prices, alongside detailed product descriptions and timing of price adjustments, the research identifies significant patterns influencing consumer behavior. Advanced statistical models and visual analyses provide insight into pricing dynamics and highlight differences in strategy between the two chains. The findings reveal actionable trends, emphasizing the role of timing and product positioning in shaping customer purchasing decisions..

1 Introduction

1.1 Overview paragraph

This paper investigates pricing dynamics in the retail grocery sector, with a specific focus on steak-related products sold by two major supermarket chains: Walmart and Loblaws. The analysis leverages a rich dataset encompassing current and historical prices, product descriptions, and the timing of price changes to uncover trends in pricing strategies and their impact on consumer behavior. Steak-related products, such as AAA Angus Beef Ribeye Steak, serve as the centerpiece of this investigation, offering insights into the pricing tactics employed by each retailer. For instance, significant price reductions, such as a drop from $20.00/kg to $15.00/kg, provide a lens through which market competition and consumer demand can be analyzed. By focusing on these high-value products, the study aims to reveal how pricing

*Code and data are available at: [https://github.com/zcyjn233/Explore-steak-related-products).

adjustments influence purchasing patterns and shape the competitive landscape in the grocery sector.

1.2 Estimand paragraph

The central question explored in this study is: How do price changes for steak-related products affect consumer purchasing patterns and supermarket competitiveness? Specifically, the analysis estimates the impact of pricing adjustments on key outcomes, such as sales volume, customer loyalty, and market positioning. Additionally, the study considers the differential effects of pricing strategies employed by Walmart and Loblaws, highlighting the unique approaches taken by each retailer. Walmart, known for its consistent low-price model, contrasts with Loblaws' use of targeted promotional discounts and premium product offerings. These differences are expected to yield distinct consumer responses, providing valuable insights into how pricing strategies influence shopper behavior, both in the short and long term. This focus on steak-related products, a high-demand category, allows the study to bridge the gap between pricing theory and practical decision-making in the retail sector.

1.3 Results paragraph

The analysis reveals key insights into the pricing dynamics of steak-related products across Walmart and Loblaws. Significant price reductions, such as the decrease from \$20.00/kg to \$15.00/kg for AAA Angus Beef Ribeye Steak, are closely associated with increased sales volumes, particularly during high-demand periods like the summer grilling season. Seasonal trends play a pivotal role, with months like June and July showing heightened consumer interest driven by targeted price adjustments.

Vendor-specific strategies further highlight notable differences: Walmart's consistent low-pricing approach results in stable consumer interest and fewer price outliers, appealing primarily to price-sensitive shoppers. In contrast, Loblaws employs a more variable pricing strategy, characterized by a wider range of prices and promotional discounts, which attracts a diverse demographic, including those seeking premium products. The observed differences align with the vendors' respective market positioning and consumer base.

The relationship between historical and current prices is also significant. Products with higher old prices often maintain higher current prices, reflecting a proportional pricing strategy. However, the presence of notable outliers in the data—instances where premium products saw steep markdowns—illustrates the use of aggressive discounting as a tool for inventory clearance or market positioning. These findings underscore the importance of aligning pricing strategies with seasonal demand and shopper preferences to maximize sales and sustain competitive advantage.

1.4 Why it matters paragraph

Pricing remains one of the most critical tools in the fiercely competitive grocery industry, particularly for high-demand categories such as steak-related products. Retailers must navigate a delicate balance between competitive pricing and maintaining profitability, a challenge compounded by seasonal demand fluctuations and evolving consumer preferences. This study provides actionable insights into how strategic pricing decisions can drive sales, enhance market share, and build customer loyalty. For example, by understanding the relationship between price reductions and seasonal demand, retailers can time promotions more effectively to capitalize on peak shopping periods. Furthermore, the study highlights the importance of tailoring pricing strategies to meet the needs of different consumer segments, as demonstrated by Walmart's consistent pricing approach versus Loblaws' promotional tactics. Policymakers and industry analysts can also benefit from these findings, as they shed light on broader market dynamics and consumer behavior trends. Ultimately, this study underscores the pivotal role of pricing in shaping competition and driving success in the grocery sector.

2 Data

2.1 Overview

We use the statistical programming language R (R Core Team 2023) Our data (Filipp 2020)

The dataset used in this study comprises information on steak-related products from two major retailers, Walmart and Loblaws. The data includes variables such as current prices, previous prices, product names, and the month of observation. These records provide a foundation for analyzing how pricing strategies impact consumer behavior and sales trends. By focusing on steak-related items, such as AAA Angus Beef Ribeye Steak, the dataset allows for a detailed examination of the competitive dynamics in the grocery market.

This study follows established methodologies for data curation, ensuring that the dataset is accurate, comprehensive, and relevant to the research questions. Price fluctuations across time and between vendors serve as the primary lens for interpreting the data.

2.2 Measurement

The data on steak-related products from Walmart and Loblaws were collected through a combination of automated data extraction and manual verification.Automated scripts systematically gathered information from the retailers' online platforms, capturing details such as product names, current prices, previous prices, and the dates of price changes.

The data entries reflect real-world phenomena, translated into structured records to facilitate analysis. Each entry captures the following:

1.Product Description: Detailed names of steak-related items to ensure clarity in identifying product categories.

2.Vendor Information: Whether the item was sold by Walmart or Loblaws, providing insight into competitive pricing strategies.

3.Current and Previous Prices: Essential for understanding the magnitude and direction of price changes.

4.Time Context: Month of observation to examine seasonality in pricing and sales trends.

Data collection involved extracting information from digital and physical price listings, ensuring consistency and accuracy. Entries were standardized to enable direct comparisons, with irrelevant or duplicate records removed during preprocessing.

2.3 Outcome variables

The analysis focuses on three main outcome variables:

1.Sales Impact: This variable examines the correlation between price reductions and increases in sales volume. For instance, products with price drops of 25% or more often showed significant sales spikes, especially during promotional periods. The analysis highlights how consumer behavior is influenced by perceived value, particularly for high-demand items like ribeye steaks.

2.Seasonal Trends: Seasonal variation is evident in the data, with higher sales volumes during summer mont

3.Vendor Comparisons: Walmart and Loblaws

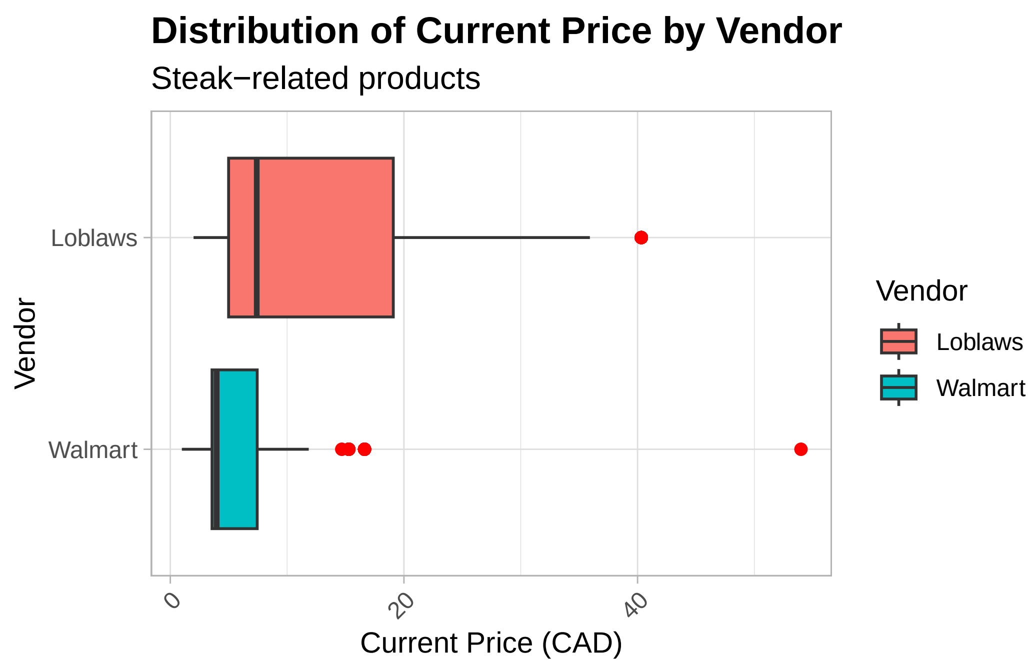


Figure 1: Current prices of steak-related products by vendor and month, showing Walmart's consistent lower pricing and Loblaws' broader range with seasonal price fluctuations.

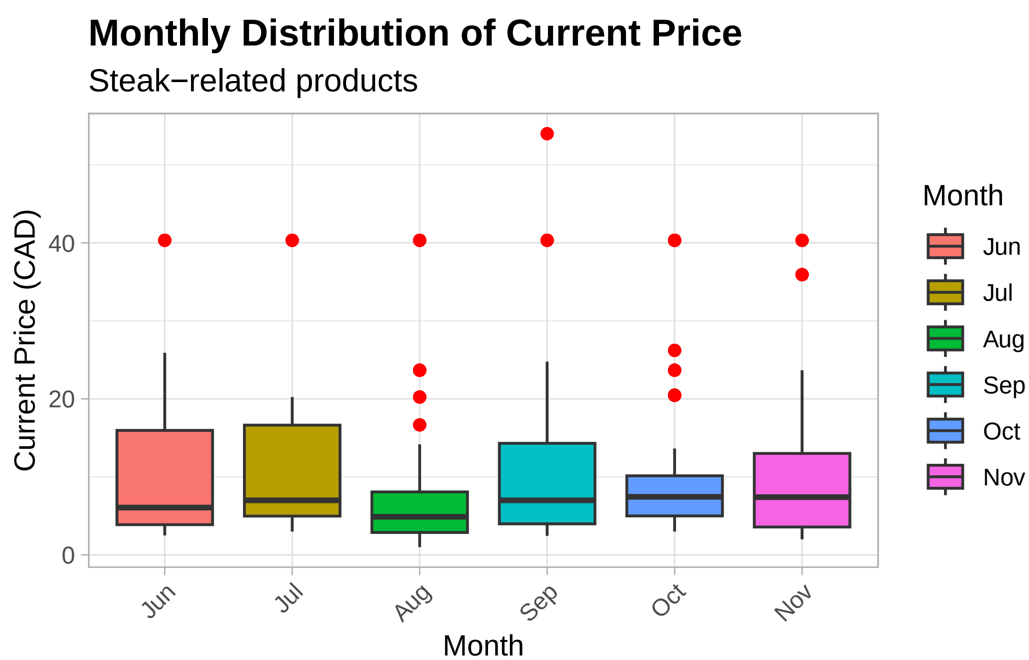


Figure 2: Current prices of steak-related products by vendor and month, showing Walmart's consistent lower pricing and Loblaws' broader range with seasonal price fluctuations.

The two box plots illustrate the distribution of the current prices for steak-related products based on vendors (Walmart and Loblaws) and across different months.

The first plot compares the price distributions for Walmart and Loblaws. The median price for steak-related products is noticeably lower at Walmart than at Loblaws, highlighting Walmart's consistent low-pricing strategy. Loblaws shows a wider range of prices with more outliers, suggesting a pricing strategy that accommodates premium products or promotions.

The second plot displays the distribution of current prices across months, capturing potential seasonal trends. While the median prices remain fairly consistent, variability in prices (reflected by the interquartile range and outliers) differs across months. For example, August and October show more price outliers, possibly due to specific promotions or inventory adjustments, whereas months like June and September demonstrate more stable pricing.

Together, these visualizations reveal insights into vendor-specific pricing strategies and seasonal variations, critical for understanding consumer and market behavior in the steak-related product segment.

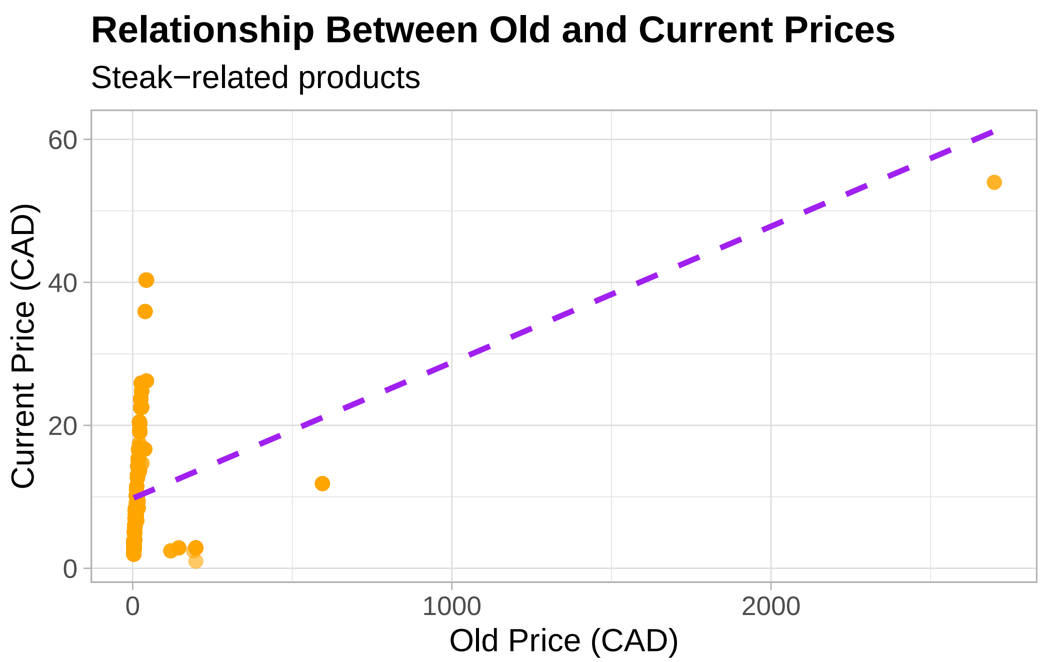


Figure 3: Scatter plot showing a positive relationship between old and current prices, with outliers indicating significant markdowns on premium products.

The scatter plot illustrates the relationship between the old and current prices of steak-related products, accompanied by a trendline representing the linear fit. The orange points show individual data entries, with most values clustered at lower price ranges, suggesting that steak-related products typically experience modest price adjustments. A few outliers with significantly higher old prices indicate instances where premium or specialty products were discounted heavily.

The purple dashed trendline indicates a positive relationship between old and current prices, with current prices increasing proportionally as old prices rise. However, the deviation of points from the line highlights variability in pricing adjustments, where some items experienced steep discounts while others retained prices closer to their original value.

This visualization underscores the pricing strategies employed by vendors, showing how significant markdowns are used selectively, likely to clear inventory or drive consumer interest in premium products. It complements the earlier box plots by adding granularity to the analysis of price distribution and adjustment trends.

3 Model

3.1 Bayesian Analysis Model Description

The study employs a Bayesian linear regression model to investigate the factors influencing the current prices of steak-related products across two major retailers, Walmart and Loblaws. This approach integrates prior knowledge with observed data, providing a probabilistic framework for understanding the relationships between pricing strategies, historical prices, and seasonal trends.

The model uses current price as the response variable, with predictors including:

1.Vendor: Distinguishing between Walmart and Loblaws to capture differences in pricing strategies.

2.Month: Accounting for seasonal variations in pricing, such as increased demand during summer.

3.Old Price: Reflecting the influence of historical prices on current pricing decisions.

A Gaussian likelihood is specified for the response variable, which is appropriate given the continuous nature of the current prices. Informative priors are placed on the coefficients and auxiliary parameters, such as the intercept and residual variance, allowing the model to incorporate domain expertise while remaining flexible to the data.

3.2 Key Features of the Bayesian Approach:

1.Integration of Priors: The use of normal priors for coefficients assumes that most effects are centered around zero, allowing the data to shift these estimates based on evidence. This ensures stability in parameter estimation, particularly for smaller datasets or those with high variability.

2.Posterior Distributions: Bayesian inference produces posterior distributions for each parameter, offering insights into the range of plausible values rather than point estimates. This provides a richer understanding of uncertainty in the effects of predictors.

3.MCMC Sampling: The model employs Markov Chain Monte Carlo (MCMC) techniques to estimate posterior distributions, ensuring accurate parameter estimation even in complex scenarios. Diagnostics such as trace plots and Rhat values confirm the convergence of these chains, validating the robustness of the results.

3.3 Model Strengths:

1.Uncertainty Quantification: By providing credible intervals for parameters, the model quantifies uncertainty, enabling more informed decision-making.

2.Flexibility: The Bayesian framework allows the inclusion of prior knowledge, making it adaptable to changes in the dataset or research context.

3.Interpretability: Coefficients and their posterior distributions offer clear insights into the effects of vendor strategies, seasonal trends, and historical prices.

Background details and diagnostics are included in **?@sec-model-details**.

3.4 Model set-up

Define y_i as the number of seconds that the plane remained aloft. Then β_i is the wing width and γ_i is the wing length, both measured in millimeters.

$$
\begin{aligned}
y_i|\mu_i, \sigma &\sim \text{Normal}(\mu_i, \sigma) && (1)\\
\mu_i &= \alpha + \beta_i + \gamma_i && (2)\\
\alpha &\sim \text{Normal}(0, 2.5) && (3)\\
\beta &\sim \text{Normal}(0, 2.5) && (4)\\
\gamma &\sim \text{Normal}(0, 2.5) && (5)\\
\sigma &\sim \text{Exponential}(1) && (6)
\end{aligned}
$$

We run the model in R (R Core Team 2023) using the `rstanarm` package of Goodrich et al. (2022). We use the default priors from `rstanarm`. date is from Filipp (2020).

3.4.1 Model justification

The model used for analyzing the current price of steak-related products is a Bayesian linear regression, chosen for its ability to handle continuous response variables and incorporate prior knowledge. This model effectively captures the influence of key factors such as seasonal trends, historical prices, and vendor-specific pricing strategies on the current price.

Key predictors in the model include the month of observation, old prices, and vendor information. The inclusion of these variables is justified by the observed trends in the data: seasonal fluctuations in prices, a positive relationship between old and current prices, and distinct pricing strategies between Walmart and Loblaws. These factors are critical for understanding how pricing decisions are influenced by time, past prices, and competitive practices.

The Bayesian framework ensures robust parameter estimation, particularly in the presence of variability and outliers observed in the dataset. Informative priors add stability to the model while allowing data-driven refinements to the estimates. Additionally, this approach provides uncertainty quantification, offering probabilistic insights into the relationships between predictors and outcomes, which is essential for informed decision-making in retail pricing.

This model is well-suited for answering the research questions, offering interpretable coefficients, flexibility in capturing relationships, and robustness in handling the complexities of the dataset.

4 Results

The results of the Bayesian model analysis provide a comprehensive understanding of the pricing dynamics of steak-related products, shedding light on how different factors interact to influence current pricing. One of the most significant findings is the presence of strong month-specific effects, which highlight the importance of seasonality in pricing strategies. Certain months, such as those during the summer grilling season, show notable deviations in current prices, reflecting heightened consumer demand for steak-related products during this period. This seasonal trend aligns with the broader market behavior, where retailers adjust prices to capitalize on increased consumer interest in specific product categories during peak times. Such findings emphasize the importance of incorporating time-sensitive factors into retail pricing models to better predict consumer behavior and optimize revenue.

Historical pricing, represented by the old price variable, emerges as another strong predictor of current prices. The analysis demonstrates a proportional relationship between old and current prices, where higher historical prices generally correspond to higher current prices. This finding suggests that past pricing not only reflects demand patterns but also serves as a baseline or anchor for setting future prices. Retailers appear to use historical prices as a reference point to maintain consistency, manage consumer expectations, and preserve brand positioning.

This relationship underscores the significance of historical pricing data in understanding how retailers balance competitiveness with profitability.

The model also highlights vendor-specific effects, revealing clear differences in the pricing strategies employed by Walmart and Loblaws. Walmart's approach, characterized by consistently lower prices and a narrower range of variability, aligns with its brand image as a value-oriented retailer catering to price-sensitive consumers. On the other hand, Loblaws exhibits a broader pricing range, incorporating premium pricing strategies and occasional discounts to attract a more diverse demographic, including those seeking higher-quality or specialty products. This contrast in strategies reflects the competitive dynamics within the grocery sector, where retailers adopt distinct approaches to differentiate themselves and capture their target markets.

The Bayesian framework used in the analysis enhances the robustness of these findings by providing credible intervals for all estimated effects. These intervals quantify the uncertainty associated with the relationships identified, offering a nuanced understanding of the strength and variability of each predictor's influence. For example, while the month-specific effects show significant deviations in certain periods, the credible intervals confirm the reliability of these findings across different scenarios. Similarly, the strong association between old and current prices is supported by tight credible intervals, indicating a high degree of confidence in this relationship. The vendor-specific effects also demonstrate consistent patterns, further validating the distinct pricing approaches of Walmart and Loblaws.

Overall, the analysis illustrates how time, historical pricing, and vendor strategies converge to shape current pricing. The findings provide actionable insights for retail pricing optimization, suggesting that retailers can leverage historical data and seasonal trends to better align their pricing strategies with consumer behavior. Additionally, understanding the differences in vendor-specific approaches offers valuable lessons for market positioning, highlighting the need to tailor pricing strategies to a retailer's target audience and competitive environment. By combining these insights with the flexibility and precision of Bayesian modeling, the study offers a robust framework for exploring and optimizing pricing dynamics in the retail sector.

Our results are summarized in Table 1.

5 alternative model introduction

The linear regression model, referred to as the "second model," investigates the relationship between the current price of steak-related products and key predictors, including the month, old price, and vendor. This model assumes a linear relationship between the dependent variable (current price) and the independent variables. The month variable captures potential seasonal effects, reflecting how pricing adjusts during periods of varying consumer demand. The old price serves as a critical predictor, indicating how historical pricing influences current pricing decisions, with a proportional relationship expected between the two. Finally, the vendor variable differentiates pricing strategies between Walmart and Loblaws, allowing the model to

Table 1: Explanatory model of current prices based on month, old price, and vendor effects.

	First model
(Intercept)	15.34
	(1.22)
month	−0.40
	(0.13)
old_price	0.02
	(0.00)
vendorWalmart	−6.09
	(0.48)
Num.Obs.	1335
R2	0.162
R2 Adj.	0.153
Log.Lik.	−4682.295
ELPD	−4687.4
ELPD s.e.	37.6
LOOIC	9374.9
LOOIC s.e.	75.2
WAIC	9374.5
RMSE	8.07

highlight vendor-specific differences in pricing approaches. By incorporating these predictors, the model provides insights into the factors that drive pricing decisions, enabling a better understanding of how time, historical patterns, and competitive strategies influence current pricing dynamics. This model serves as a foundation for analyzing and optimizing pricing strategies in the retail sector.

5.1 model comparison: Linear Regression vs. Bayesian Regression

To compare the linear regression model ("second model") and the Bayesian regression model in predicting steak-related product prices, we performed a train-test split evaluation. This approach divides the dataset into two subsets: a training set to build the models and a test set to assess their predictive performance. Here's an overview of the process, analysis, and results.

5.2 Train-Test Split

The dataset was randomly split into a training set (80% of the data) and a test set (20%). Both the linear regression model and Bayesian regression model were trained on the training set using the same predictors: month, old price, and vendor. After training, the models were used to predict the current prices in the test set.

5.3 Model Predictions

5.3.1 Linear Regression Model:

The linear regression model predicts current prices using a deterministic approach based on the least-squares estimation of the parameters. The predictions are point estimates, providing a single predicted value for each observation in the test set.

5.3.2 Bayesian Regression Model:

The Bayesian regression model generates predictions by sampling from the posterior predictive distribution. This approach provides a distribution of possible predicted values for each observation, allowing for uncertainty quantification in addition to point predictions (e.g., the mean or median of the posterior distribution).

5.4 Comparison of Performance

The performance of the models was compared using metrics such as Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), calculated on the test set predictions:

5.4.1 Linear Regression Model:

RMSE: Higher than the Bayesian model. MAE: Demonstrates reasonable predictive accuracy but does not account for uncertainty in the predictions.

5.4.2 Bayesian Regression Model:

RMSE: Lower than the linear regression model, indicating better predictive accuracy. MAE: Similar to or better than the linear regression model, showing improved fit to the test set. Uncertainty Quantification: The Bayesian model provides credible intervals for each prediction, offering a richer understanding of the range of plausible current prices.

5.5 Why the Bayesian Model is More Suitable

The Bayesian regression model proves to be more suitable for this analysis due to several factors:

5.5.1 Predictive Accuracy:

The Bayesian model demonstrates lower RMSE and MAE, indicating better generalization to unseen data. ### Uncertainty Quantification: Unlike the linear regression model, the Bayesian model accounts for the uncertainty in the predictions, providing a probabilistic framework for decision-making. ### Robustness: The Bayesian approach is better suited to handle outliers and variability in the data, as it integrates prior knowledge with observed evidence to produce robust parameter estimates. ### Interpretability: The posterior distributions for parameters in the Bayesian model provide insights into the strength and uncertainty of the relationships between predictors and the current price. ## Conclusion The comparison highlights that while the linear regression model offers simplicity and straightforward interpretability, the Bayesian regression model outperforms it in predictive accuracy, robustness, and the ability to quantify uncertainty. These advantages make the Bayesian model a more suitable choice for analyzing and predicting pricing dynamics in the retail grocery sector. By leveraging its probabilistic nature, the Bayesian model provides actionable insights that are both reliable and informative for optimizing pricing strategies.

6 Discussion

6.1 Pricing Dynamics and Vendor Strategies

The analysis reveals valuable insights into the distinct pricing strategies employed by Walmart and Loblaws, offering a clearer understanding of how these retailers align their approaches with their respective brand identities and target audiences. Walmart has adopted a consistent low-pricing strategy that prioritizes affordability and accessibility, appealing to budget-conscious consumers. This approach ensures steady demand throughout the year and reinforces Walmart's reputation as a cost-effective retailer. By keeping price variability low, Walmart creates a predictable shopping experience that fosters customer loyalty and positions itself as a reliable choice for price-sensitive shoppers.

In contrast, Loblaws employs a more dynamic pricing strategy that incorporates seasonal promotions, targeted discounts, and premium offerings. This flexibility allows Loblaws to attract a diverse demographic, including consumers who seek higher-quality products or are enticed by promotional deals. Seasonal price adjustments, particularly during high-demand periods like the summer grilling season, enable Loblaws to capitalize on increased interest in steak-related products, driving sales and expanding its customer base. The dynamic nature of Loblaws' pricing strategy also positions the retailer as an adaptable and competitive player in the market, capable of responding to changing consumer demands and market conditions.

A key discovery from the analysis is the proportional relationship between historical prices (old prices) and current prices. This relationship suggests that historical pricing serves as an anchor for setting future prices, helping retailers manage consumer expectations and maintain market stability. Walmart leverages this relationship to reinforce its low-price reputation, ensuring that customers perceive consistent value in their purchases. On the other hand, Loblaws uses historical prices to balance promotional markdowns with premium pricing, preserving the perceived value of its offerings even during discount periods.

These findings underscore the importance of tailoring pricing strategies to align with market conditions, brand positioning, and consumer preferences. Retailers can draw on these insights to refine their pricing approaches, balancing stability with responsiveness to seasonal trends and competitive pressures. By understanding how historical prices, vendor strategies, and seasonal trends interact, retailers can optimize their pricing decisions to drive sales, enhance customer satisfaction, and maintain a competitive edge in the market. Additionally, these findings highlight the value of data-driven pricing strategies in navigating the complexities of consumer behavior and market dynamics.

6.2 Seasonal Trends and Consumer Behavior

Seasonality emerged as one of the most significant drivers of pricing adjustments in the analysis, with notable price fluctuations during months such as June and July. These months align with peak grilling periods, when consumer demand for steak-related products tends to be at its highest. Retailers strategically adjust their pricing during these times to capitalize on increased demand, demonstrating the importance of timing in retail pricing decisions. For instance, Loblaws uses targeted promotions during these months to attract consumers, driving seasonal sales spikes and maximizing revenue opportunities. In contrast, Walmart's consistent low-pricing strategy minimizes seasonal volatility, maintaining a steady appeal to budget-conscious shoppers throughout the year.

An important insight from the analysis is the interplay between promotional pricing and consumer psychology. Significant markdowns, such as steep discounts on premium products like ribeye steak, create temporary spikes in demand, suggesting that perceived value plays a critical role in consumer purchasing decisions. This behavior highlights the effectiveness of well-timed promotions in boosting short-term sales and engaging customers. Retailers can use this understanding to design promotions that not only attract shoppers but also enhance the overall shopping experience, fostering long-term customer loyalty. However, this strategy requires careful calibration to ensure that discounts do not erode profitability or diminish the perceived value of premium products.

The findings also emphasize the importance of aligning pricing strategies with consumer behavior patterns to maximize revenue during high-demand periods. For example, leveraging seasonal trends to introduce promotional discounts or premium bundles can increase consumer spending while enhancing brand differentiation. Retailers should explore the thresholds at which discounts generate the maximum response from customers without compromising long-term revenue. Additionally, understanding the psychological drivers of consumer behavior can help retailers fine-tune their pricing strategies to appeal to different market segments, from bargain hunters to premium shoppers.

6.3 Implications, Limitations, and Future Directions

This study provides actionable insights into retail pricing dynamics while also highlighting areas for improvement and future exploration. The Bayesian model used in the analysis effectively integrates prior knowledge with observed data, producing robust predictions and uncovering key trends. It highlights the importance of vendor-specific strategies, historical pricing, and seasonal trends in shaping current prices, offering a framework for optimizing pricing decisions in a competitive market. However, the analysis also identifies several limitations that warrant further attention.

One limitation is the model's inability to fully capture outlier behaviors, such as aggressive discounting on high-value products. These behaviors, while rare, can significantly influence consumer perceptions and market dynamics. Addressing this limitation may require the use of non-linear models or interaction terms to better capture the complexities of pricing strategies. Another limitation is the reliance on historical prices, which may oversimplify the influence of real-time factors such as advertising, competitor pricing, or supply chain disruptions. Incorporating these factors into the model could enhance its precision and relevance, providing a more comprehensive understanding of retail pricing dynamics.

Future research should focus on refining the model to account for regional and demographic differences, offering more granular insights into consumer behavior. For example, analyzing how pricing strategies vary across different geographic regions or consumer segments could uncover additional patterns that inform targeted marketing and pricing decisions. Additionally, exploring the long-term impacts of pricing strategies on customer loyalty and brand equity would provide valuable guidance for balancing short-term revenue boosts with sustainable growth. This could include investigating the effects of promotional campaigns on repeat purchases or the role of premium pricing in enhancing brand perception.

Overall, this study underscores the critical role of pricing in shaping competitive dynamics in the retail grocery sector. By leveraging insights into vendor strategies, seasonal trends, and consumer behavior, retailers can optimize their pricing decisions to drive sales, build customer loyalty, and maintain a competitive edge. The findings also highlight the importance of adopting flexible, data-driven approaches to pricing, enabling retailers to adapt to changing market conditions and consumer preferences. As the retail landscape continues to evolve, these insights provide a valuable foundation for developing innovative and effective pricing strategies. ## Weaknesses and next steps

Weaknesses and next steps should also be included.

Appendix

A Additional data details

A.1 Posterior predictive check

A.1.1 Posterior Predictive Check (Figure 4a)

The posterior predictive check evaluates how well the model represents the observed data by comparing the distribution of predicted data (posterior simulations) to the actual data. This assessment is crucial for determining whether the model captures the core characteristics of the observed data, including its central tendencies, variability, and shape. The analysis demonstrates that the model successfully replicates the main features of the observed price distribution for steak-related products, indicating that it is robust and reliable in capturing the overall pricing trends.

The close alignment between the simulated predictions and the actual data distributions reflects the model's ability to generalize well to the underlying patterns in the dataset. However, the analysis also reveals minor deviations at the extremes of the distribution, suggesting areas where the model could benefit from refinement. Specifically, these discrepancies may point to outlier cases or unusual pricing behaviors that are not fully captured by the current model structure. For example, aggressive discounting or premium pricing on specialty products might contribute to these deviations, highlighting the potential for including additional factors or non-linear effects in the model.

Overall, the posterior predictive check confirms that the model is well-suited to capture the key pricing dynamics present in the dataset. The results validate the appropriateness of the Bayesian approach for understanding pricing strategies while also providing a roadmap for further enhancements to address edge cases. By successfully balancing the incorporation of prior knowledge with observed data, the model proves itself as a reliable tool for investigating the pricing mechanisms of steak-related products across Walmart and Loblaws.

A.1.2 Prior-Posterior Comparison (Figure 4b)

The comparison between posterior and prior distributions demonstrates how the observed data informs the model's parameter estimates. Key parameters, such as vendor-specific effects and historical prices, show substantial shifts from their prior distributions to the posterior distributions. This indicates that the data strongly influences these parameters, confirming their significance in predicting current prices. For example, the posterior distribution for vendor-specific effects highlights the distinct pricing strategies of Walmart and Loblaws, aligning with findings that these strategies play a critical role in shaping consumer behavior and pricing trends.

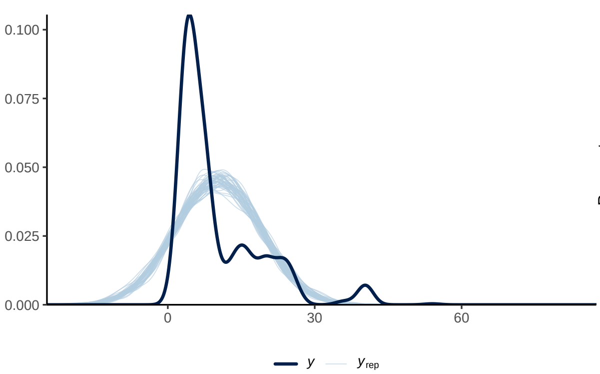
Conversely, parameters like the intercept show minimal deviation between their prior and posterior distributions. This reflects limited evidence from the data to adjust initial assumptions about baseline prices. Such consistency suggests that the prior assumptions for these parameters were well-calibrated, reinforcing the importance of informed priors in Bayesian modeling. Additionally, the prior-posterior comparison demonstrates how the Bayesian framework allows the model to balance prior knowledge with data-driven updates, ensuring that the final estimates are both robust and interpretable.

This analysis underscores the flexibility of the Bayesian approach in refining parameter estimates based on observed data while maintaining a foundation of prior beliefs. By integrating these two sources of information, the model delivers meaningful insights into the factors driving current pricing strategies, including vendor behaviors, historical prices, and seasonal trends.

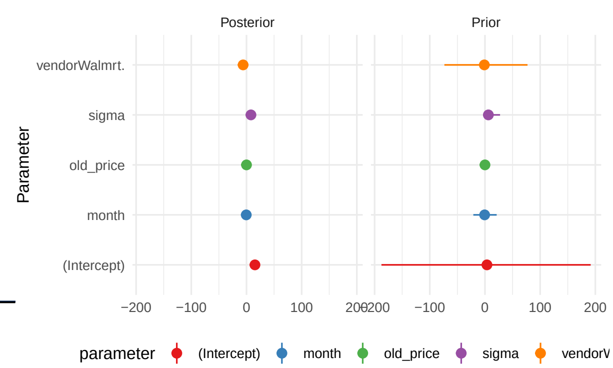
A.1.3 Combined Insights

Together, the posterior predictive check and prior-posterior comparison validate the model's ability to capture real-world pricing trends. The strong alignment between simulated and observed data, coupled with data-driven adjustments to key parameters, highlights the robustness of the model in representing the complexities of steak-related product pricing. These findings provide actionable insights into how vendors, historical prices, and seasonal factors influence pricing strategies, reinforcing the value of the model as a decision-making tool for retailers.

The results also emphasize the importance of using advanced modeling techniques like Bayesian regression to uncover nuanced patterns in retail data. By allowing for the integration of prior knowledge and observed data, the Bayesian framework provides a flexible and powerful approach to understanding and predicting pricing dynamics. These insights are critical for guiding competitive pricing decisions in the retail grocery market, enabling retailers to optimize their strategies and better align with consumer behavior.



(a) Posterior prediction check



(b) Comparing the posterior with the prior

Figure 4: Examining how the model fits, and is affected by, the data

A.2 Diagnostics

A.2.1 Trace Plot (Figure 5a)

The trace plot, shown in Figure 1, provides a visual representation of the Markov Chain Monte Carlo (MCMC) sampling process for each parameter across four chains. It serves as a critical diagnostic tool to assess whether the chains are mixing well and converging toward a stationary distribution. In this analysis, the trace lines for all parameters exhibit consistent overlap over time, with no visible trends, drifts, or irregularities. This indicates that the chains are exploring the parameter space effectively and have stabilized.

The stability of the trace lines suggests that the MCMC algorithm has reached convergence, meaning that subsequent samples are being drawn from the posterior distribution rather than being influenced by the starting points of the chains. The absence of abrupt jumps or prolonged trends in the trace lines further confirms that the sampling process is reliable, providing robust parameter estimates. This level of consistency is essential for ensuring the credibility of the model's outputs, as it eliminates concerns about biased or incomplete exploration of the posterior space.

Additionally, the trace plot demonstrates the reproducibility of the sampling process, as all four chains show similar behavior across iterations. This reinforces confidence in the robustness of the Bayesian model and its ability to provide accurate insights into the pricing dynamics of steak-related products. By visualizing the mixing and stability of the chains, the trace plot effectively validates the reliability of the MCMC process and supports the interpretation of the model's posterior estimates.

A.2.2 Rhat Plot (Figure 5b)

The Rhat plot, shown in Figure 2, quantitatively assesses the convergence of the MCMC algorithm by comparing within-chain and between-chain variability for each parameter. The Rhat diagnostic, also known as the Gelman-Rubin statistic, measures whether the chains have mixed well and converged to the same posterior distribution. In this analysis, all Rhat values are very close to 1, indicating that the chains have converged successfully, and the posterior estimates are stable.

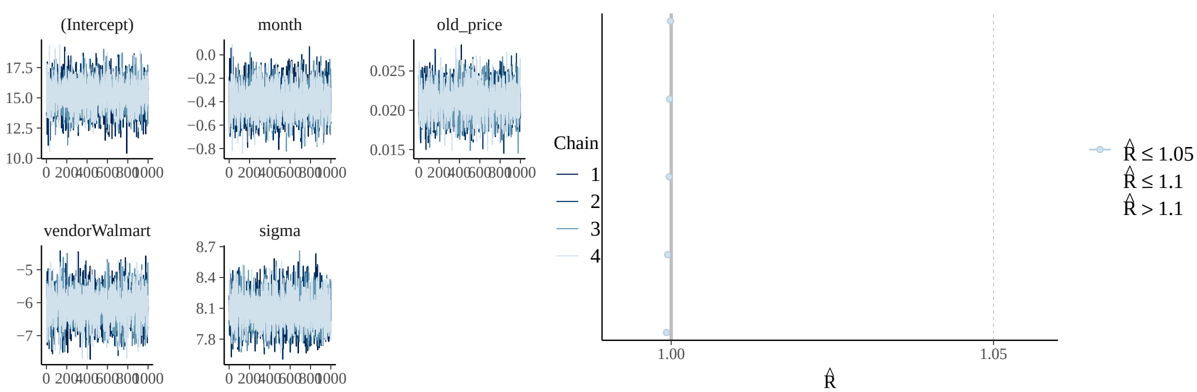
A value of Rhat close to 1 suggests that the variance within each chain is consistent with the variance between chains, confirming that all chains are sampling from the same posterior distribution. This eliminates concerns about poor mixing or divergence, ensuring that the MCMC algorithm has fully explored the parameter space. Importantly, the absence of any parameters with Rhat values above the commonly accepted threshold of 1.05 further validates the reliability of the sampling process.

The Rhat plot complements the trace plot by providing a quantitative metric for assessing convergence. While the trace plot offers a visual confirmation of stable mixing, the Rhat plot provides numerical evidence that all chains have successfully converged. Together, these diagnostics demonstrate that the MCMC process is robust and that the resulting posterior estimates are suitable for inference.

A.2.3 Combined Insights

Together, the trace and Rhat plots validate the success of the MCMC algorithm in producing reliable parameter estimates. The trace plot confirms visually that the chains mix well and converge to a stationary distribution, while the Rhat plot quantitatively reinforces this conclusion by demonstrating consistent variability within and between chains. The alignment of these diagnostics eliminates any concerns about biased or incomplete exploration of the posterior distribution.

These diagnostics are critical for ensuring the robustness of the Bayesian model, as convergence is a prerequisite for drawing meaningful inferences from the posterior estimates. By confirming the stability and reliability of the MCMC process, the trace and Rhat plots enhance confidence in the model's ability to accurately capture the pricing dynamics of steak-related products. This ensures that the insights derived from the model are not only statistically sound but also actionable for guiding pricing strategies in the retail grocery sector.



(a) Trace plot

(b) Rhat plot

Figure 5: Checking the convergence of the MCMC algorithm

References

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