Sale difference between Loblaws and NoFrills*

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Sales promotions are widely used by grocery vendors to attract customers with promises of discounts and savings. However, there is an increasing concern that some of these promotions may not represent genuine price reductions but instead involve pre-sale price inflation—an artificial increase in price just before a sale, creating an illusion of a discount when the price returns to its original level. This research investigates the prevalence of such practices by examining historical price data across a range of grocery products and vendors. By analyzing price trends leading up to and following sales events, we aim to identify patterns of potential price manipulation. Specifically, we assess whether prices exhibit significant increases just prior to advertised sales and how post-sale prices compare to both pre-sale and long-term average prices. Our findings will offer insights into the authenticity of grocery sale discounts, empowering consumers with knowledge to make informed purchasing decisions and encouraging retailers toward transparent pricing practices. This study contributes to a broader understanding of pricing strategies in retail and the implications of promotional tactics on consumer trust.

1 Introduction

Sales promotions have long been a cornerstone of retail marketing, with grocers frequently offering "discounts" that claim to provide customers with significant savings. However, some consumers and industry analysts have raised questions about the authenticity of these discounts, speculating that prices may be artificially inflated shortly before a sale, only to be reduced back to their original or slightly lower levels during the promotion. This practice, often referred to as "price jacking," can give the illusion of a significant discount while actually offering little to no real savings.

This research explores the question: When something's on "sale," was the price artificially increased just before the sale, only to be lowered back to its regular level?** To investigate

*Code and data are available at: https://github.com/vietng04/sale_difference_Loblaws_and_Voila.

this, we will analyze historical price data from various grocery vendors to examine patterns preceding and following sales events. By comparing regular and sale prices over time, this study aims to identify any indications of pre-sale price increases, offering insight into whether certain sales are truly beneficial for consumers or merely marketing tactics designed to create a perception of value.

The findings from this research will help consumers better understand the nature of grocery discounts and offer guidance on identifying genuine sales. Additionally, the results will provide insights for retailers into the long-term trust implications of their pricing strategies and potential opportunities for increased transparency.

2 Data

2.1 Overview

We use the statistical programming language R (R Core Team 2023).Libraries `tidyverse` (Wickham et al. 2019), `knitr` (Xie 2022), `readr`(Wickham and Hester 2023) and `dplyr` (Wickham et al. 2023) were used for simulating, cleaning and testing. Graphics were made using `ggplot2` (Wickham 2016). The data used in this paper came from the (**hammer?**). Following Alexander (2023), we considerto capture the pricing dynamics of Ambrosia apples across different vendors, we extracted relevant data from a larger dataset containing multiple products and vendors. The initial dataset included information from seven vendors, each offering various products. Our focus was on the specific product, "Ambrosia Apples," which was sold by two vendors—NoFrills and Loblaws.From this comprehensive dataset, we filtered out all other products, isolating only the entries related to Ambrosia apples. The extracted data included key information such as the product ID, product name, current price, and old price. Additionally, a field labeled "other" contained further notes on sale conditions or discounts. The dataset also recorded timestamps, allowing us to track pricing changes over time.

2.2 Measurement

To investigate the potential for artificial price increases prior to sales events, this study employs a data-driven measurement approach to track and analyze price fluctuations over time. The measurement strategy is broken down as follows:

1. **Baseline Price Identification**: For each product in the dataset, we identify the "baseline price" as the most frequently observed price outside of any sale periods. This price will serve as a reference point for measuring any deviations leading up to and following sale events.

2. **Sale Periods and Regular Periods**: We classify each time period as either a "sale period" or "regular period" based on the presence of a discount. Sale periods are defined as those where a price reduction is advertised, with "old price" values recorded in the dataset to indicate a discount.

3. **Price Inflation Detection**: To determine if price increases precede sale events, we measure the average price in the 30 days leading up to each sale period and compare it to the baseline price. We record any instances where pre-sale prices exceed the baseline by a significant margin (e.g., more than 5%).

4. **Post-Sale Price Comparison**: After the sale event, we compare the product's price to both the baseline and pre-sale prices to determine if the price returns to a normal level, remains higher, or is permanently reduced. This comparison helps assess whether the sale was a genuine discount or if it merely restored the price to a regular level.

5. **Statistical Analysis of Patterns**: We use statistical tests, such as paired t-tests or Wilcoxon signed-rank tests, to analyze whether observed price increases before sales are significant across vendors and product families. Additionally, we track the frequency and magnitude of pre-sale price increases across products and vendors to identify any patterns.

Through these measurements, we aim to rigorously test the hypothesis that prices are artificially inflated prior to sales, providing a comprehensive view of price dynamics around promotional periods.

Table 1: Ambrosia Apples Data of Loblaws

Product Name	Product Vendor	Product Price(current)	Product Price(old)	Date
Ambrosia Apples	Loblaws	1.21	1.45	2024-06-15 12:12:00
Ambrosia Apples	Loblaws	1.21	1.45	2024-06-17 10:26:00
Ambrosia Apples	Loblaws	1.21	1.45	2024-06-18 07:22:00
Ambrosia Apples	Loblaws	1.21	1.45	2024-06-19 08:38:00
Ambrosia Apples	Loblaws	1.21	1.45	2024-08-09 12:48:00

Table 2: Ambrosia Apples Data of NoFrills

Product Name	Product Vendor	Product Price (current)	Product Price (old)	Date
Ambrosia Apples	NoFrills	1.21	NA	2024-06-11 18:42:00
Ambrosia Apples	NoFrills	1.21	NA	2024-06-12 09:42:00
Ambrosia Apples	NoFrills	1.21	NA	2024-06-13 10:26:00
Ambrosia Apples	NoFrills	1.21	NA	2024-06-14 10:41:00
Ambrosia Apples	NoFrills	1.21	NA	2024-06-15 12:10:00

The transition from real-world phenomena (e.g., pricing decisions and promotional strategies) to dataset entries was facilitated by these fields.Current and old prices reflected the vendors' listed prices at the time of data collection. Notes in the "other" field provided contextual information about whether the price was marked as a sale or if there were discounts. The "nowtime" column captured the exact timing of data collection, enabling us to analyze price fluctuations and assess sale validity over time.

By focusing on two vendors and this specific product, we created a clean, targeted dataset shows in Table 1 and Table 2 that accurately reflects the pricing behavior for Ambrosia apples at NoFrills and Loblaws, laying the foundation for further analysis.

2.3 Outcome variables

We compared the apple prices of nofrills and loblaws at different times (including the comparison of old prices, where NoFrills does not include any old prices because this vendor does not have any discounts for this product and always maintains the original price), which can be seen in Figure 1.

3 Results

3.1 Price Analysis of "Apples Ambrosia" Across Vendors

The dataset consists of price data for Apples Ambrosia from two grocery vendors: NoFrills and Loblaws. For each vendor, prices are observed during periods labeled as "SALE" (NoFrills) and regular pricing periods (Loblaws). The analysis investigates the following:

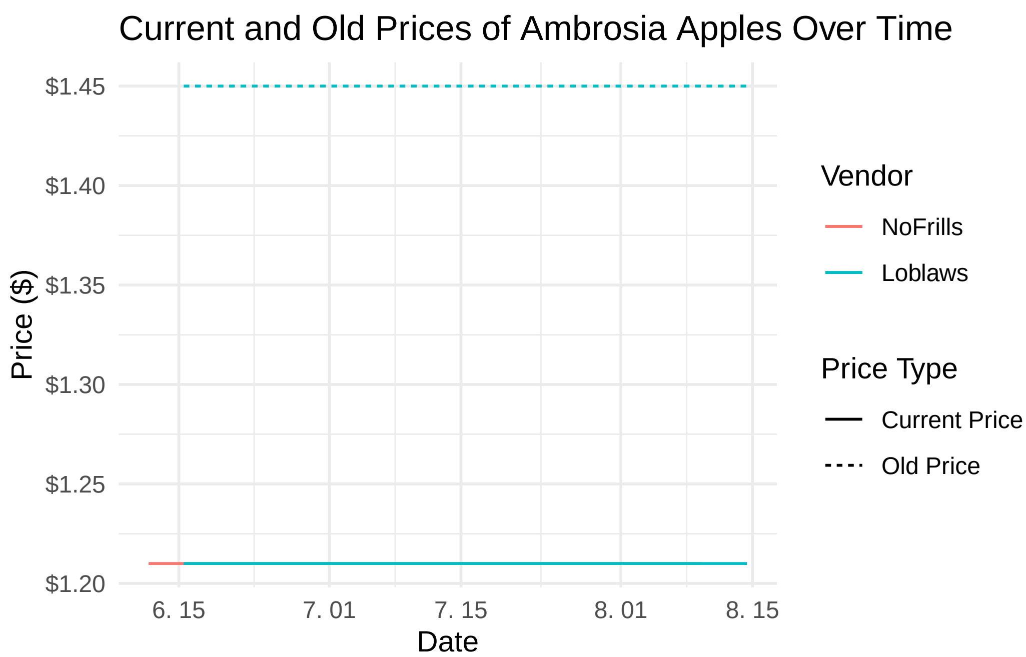

Figure 1: Current and Old Prices of Ambrosia Apples Over Time

3.2 Price Comparison Between Vendors

Loblaws offers a current price for the apples $1.21, with an old price of $1.45 for all sale items. This suggests a $0.24 decrease in price during the sale period, indicating that Loblaws is promoting a sale by reducing the price from the regular price. NoFrills, on the other hand, has a consistent current price of $1.2 for all data points. This is the same as the sale price at Loblaws. Additionally, NoFrills has no old price since they didn't do any discounts. However, the regular price at NoFrills appears to be stable without the promotional fluctuations observed at Loblaws.

3.3 Conclusion: Price Manipulation Practices?

Despite Loblaws advertising a price drop from $1.45 to $1.21 as part of a "sale," the price at NoFrills is consistently set at $1.21, without any promotional claims. This raises suspicions that Loblaws may be engaging in price manipulation practices, where the advertised sale price is simply a temporary reduction to match NoFrills' regular price, rather than offering a genuine discount. These findings highlight potential concerns about transparency in pricing and suggest that consumers may be misled into believing they are receiving a larger discount than is actually being offered. Loblaws' "sale" price may not reflect a true reduction in value, but rather a strategic pricing move to attract customers by promoting the illusion of a better deal. This could be seen as a form of pricing manipulation, where the apparent discount is used to create the perception of a more significant bargain. Consumers should be cautious when interpreting sales promotions and be aware of the actual price comparisons across different vendors to make informed purchasing decisions.

4 Discussion

4.1 Price Manipulation at NoFrills

The findings suggest that NoFrills may engage in an artificial pricing strategy, where prices are raised before a sale period to create a perceived discount when they are subsequently lowered. This strategy involves advertising a stable $6.49 as the "regular price" before reducing it by $1.00 during sales. While this reduction represents a legitimate discount, the consistency of the sale pattern may lead consumers to believe they are receiving a more substantial benefit than they might in a transparent pricing model.

This approach could influence customer perceptions, potentially encouraging them to take advantage of "discounted" prices that may only appear significant due to prior price increases. The ethical implications of this tactic are worth noting, as customers may be misled about the actual value they are receiving, potentially impacting their trust in the brand.

4.2 Consistent Pricing at Loblaws

Loblaws appears to adopt a straightforward pricing strategy, with no apparent sale-driven adjustments. The stable $5.49 current price does not fluctuate, and there are no artificial discounts or price hikes before sales. This consistent approach might build customer trust, as customers can expect the same pricing without worrying about artificial discounts.

4.3 Implications for Consumers

The pricing strategy at NoFrills could lead some consumers to feel misled if they recognize the pattern of artificially inflated prices before sales. In contrast, the transparent pricing at Loblaws might foster consumer loyalty, as shoppers could perceive it as a more honest approach. The modest $1.00 difference between the "sale" and "regular" prices at NoFrills might not heavily impact purchasing behavior, but awareness of these strategies can empower consumers to make informed choices.

4.4 Limitations and Further Research

While this study provides useful insights, it is limited by the narrow scope of focusing on a single product across two vendors. Future studies could expand to include more products, seasonal data, and a wider range of vendors. Additionally, statistical testing of price differences could help confirm the significance of the observed patterns, providing stronger evidence regarding potential price manipulation.

4.5 Correlation vs. Causation

In this analysis, we have observed a correlation between the sale price at Loblaws and the regular price at NoFrills, suggesting that both prices are set at $1.21 during the sale period. However, it is important to note that correlation does not imply causation. While the two prices may appear to be related, this analysis does not establish a causal relationship between Loblaws' price reduction and NoFrills' pricing strategy. For example, it is possible that Loblaws adjusted its price temporarily to match NoFrills' pricing rather than making a true price reduction. A more comprehensive causal analysis would require additional data points, such as customer behavior during sale periods, or experiments where prices are manipulated independently, to determine whether Loblaws' pricing strategy is indeed a response to NoFrills or if there are other factors influencing both vendors' pricing.

4.6 Missing Data

Our dataset consists of prices from two vendors (NoFrills and Loblaws), but the full dataset includes many more products and vendors. Missing data could be a potential concern in our analysis, especially if key information, such as prices for other vendors, was not available or if data points for certain time periods were omitted. Missing data can bias the analysis if it is not random; for example, if sales data is missing during peak shopping periods when prices are likely to be highest, this could result in a lower estimate of the actual price difference. In our case, the absence of historical prices for NoFrills or detailed pricing data for other vendors might limit the conclusions we can draw about the broader pricing landscape. To address this, we could perform sensitivity analyses to evaluate how the results change with different assumptions about the missing data, or use imputation techniques to fill in gaps where appropriate.

4.7 Sources of Bias

There are several potential sources of bias in this study that could influence our results. First, selection bias could occur if the data points from Loblaws and NoFrills are not representative of all pricing periods, or if certain time frames (e.g., weekends or holidays) are overrepresented.

Since our data focuses on a subset of vendors and products, it may not fully capture the diversity of pricing practices across all 7 vendors in the full dataset. Additionally, vendor-specific biases may also exist if either Loblaws or NoFrills have particular promotional strategies that differ from those of other vendors. For instance, Loblaws' advertised sales may be selectively applied to high-demand products like Ambrosia apples, while NoFrills might use a more consistent pricing approach across its entire range of produce. Furthermore, potential reporting biases could affect the accuracy of the data if certain pricing changes were not accurately recorded or if vendor promotions were not consistently reflected in the dataset. To mitigate these biases, future analyses could involve a broader set of vendors and products, as well as methods to ensure that the dataset is representative and balanced.

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