

Sale Hat Analysis

Executive Summary

Purpose of Analysis:

1. How has company-wide sale hat section revenue responded to the August change from a “bogo” offer to flat priced sale sections?
2. If sale hat revenue was impacted, was the observed impact due to the offer being changed, seasonality, or other factors?
3. If there's been a decrease in hat sale section revenue, what opportunities exist to increase it?

Summary of Findings:

1. Weekly sale hat section revenue fell **40%** 8 weeks following the offer change.
2. Each of our top 5 full-price hat categories saw average weekly revenue grow by **9%** or more during the same time period that sale hats decreased.
3. Monthly revenue from transactions with 2 or more sale hats fell by **55%** following the offer change. Our findings suggest this was fueled by consumers making fewer multi-quantity purchases due to the removal of “Bogo” incentive pricing.
4. If the current flat-priced sale hat sections are kept, we can expect the segment to produce **~\$300k less annually**.

Recommendation:

- Given the large influence that multi-quantity purchases have on segment revenue, it is advised to reinstall a “Bogo” pricing model to the hat sale section in order to revive falling sales.
- Our proposed next steps are to first, brainstorm a new pricing model that incentivizes multi-quantity purchases, and second, track performance of this new model over a 90 day period to measure effectiveness.

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Additional Resources

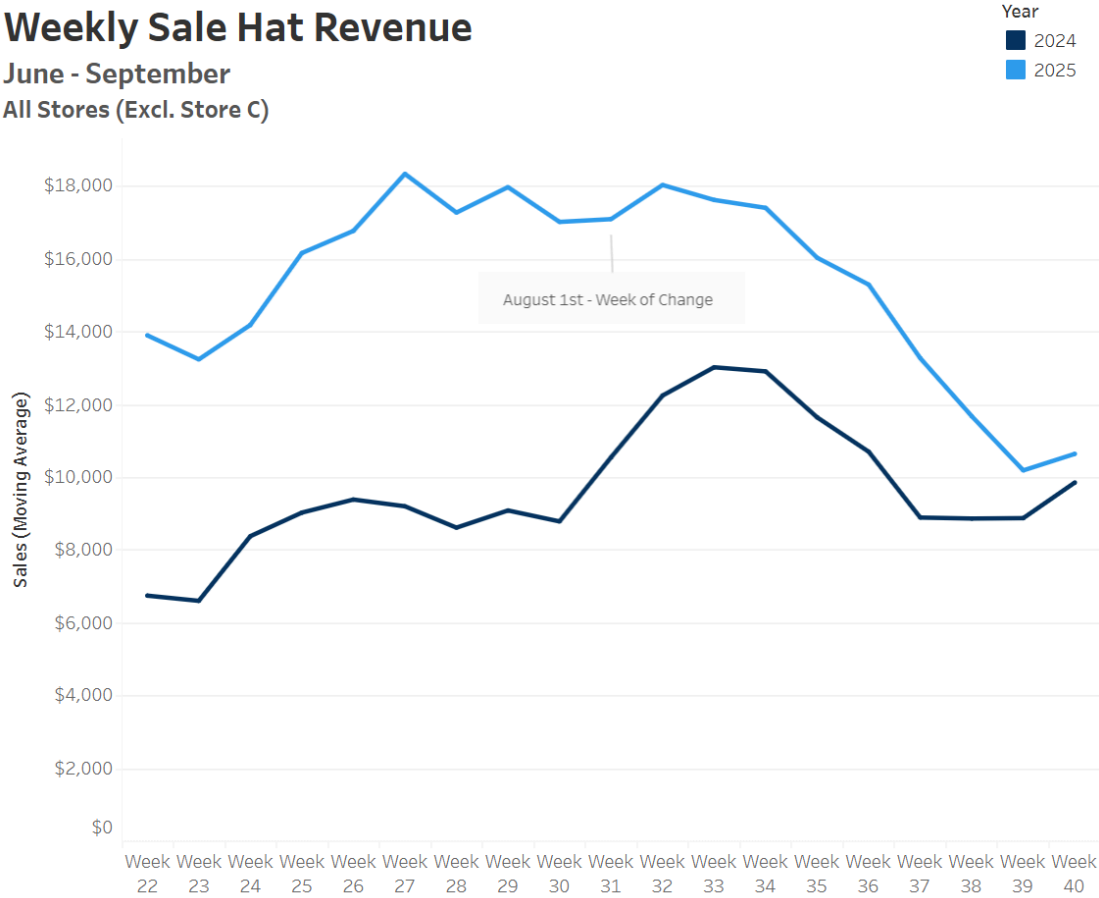
- Details on data gathering and methods used can be found in the [appendix](#)
- All SQL queries used to gather our data can be found [here](#)
- Charts used in this report and additional visualizations can be found [here](#)

Sale Hat Revenue Trend YoY

To reveal the short-term effects of the offer change, we plotted weekly revenue of the hat sale section in 2025 and 2024 eight weeks before and after August 1st (the week of the offer change). A two-week moving average was used to smooth volatility and identify the true direction of the trend.

Weekly Sale Hat Revenue

June - September
All Stores (Excl. Store C)



Insights:

- In 2024, after peaking in August, weekly sales returned to averages we were seeing previously. However, In 2025, we saw an alarming decrease in revenue beginning one week after the offer change that continued for seven straight weeks.
- In 2025 on the week of the change (August 1st), the average weekly sale hat revenue was **\$17k**. Eight weeks following the change, the average sale hat revenue fell to **\$10.2k (40% decrease)** in weekly revenue).
- Looking Month-over-Month, we saw this downward trend continue, with monthly sale hat revenue falling **39%** from August to September despite overall revenue increasing 4% during the same time period.

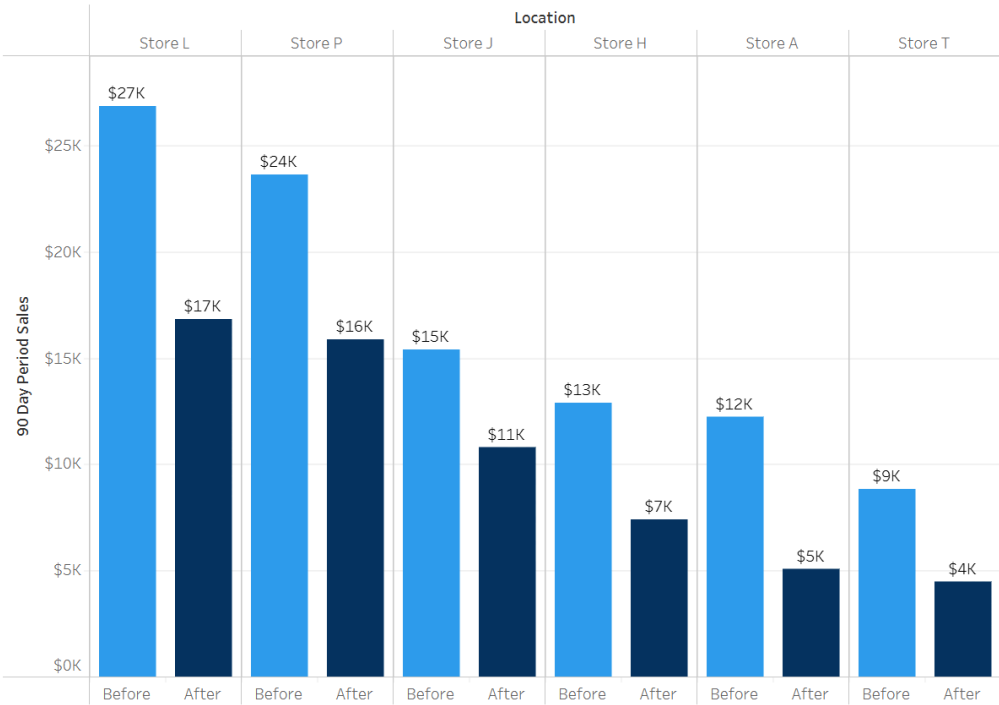
Sale Hat Revenue Per Store

Although a company-wide decrease in sale hat revenue was observed, we needed to evaluate revenue at the store level to see if this company-wide decrease in sale hat revenue was caused by a small segment of stores posting a decrease, or if we experienced a more widespread issue across locations.

The bar plot below shows sale hat revenue totals by store 90 days before and after the offer change. May through July (90 days before) and August through October (90 days after).

Lowest Performing Stores Post Change

Hat Sale Section Revenue Per Store
90 Days Before & After Change



Insights:

- 13 stores saw total sale hat revenue decrease by 10% or more in the 90 days post change compared to the 90 days pre-change, nine of which decreased by over **30%**.
- 5 stores had a significant positive response to the change. Stores F, C, Z, AB, and S each saw a **60%** increase in total sale hat revenue in the 90 day period post change
- We also compared the average weekly revenue of each store in the 90 days before and after the change. Similarly, we saw 9 stores average weekly revenue fall by **30%** or more post change. These findings indicate the observed decrease in overall sale hat revenue was not an isolated issue and was experienced across markets.

Monthly Tickets Trend Comparison

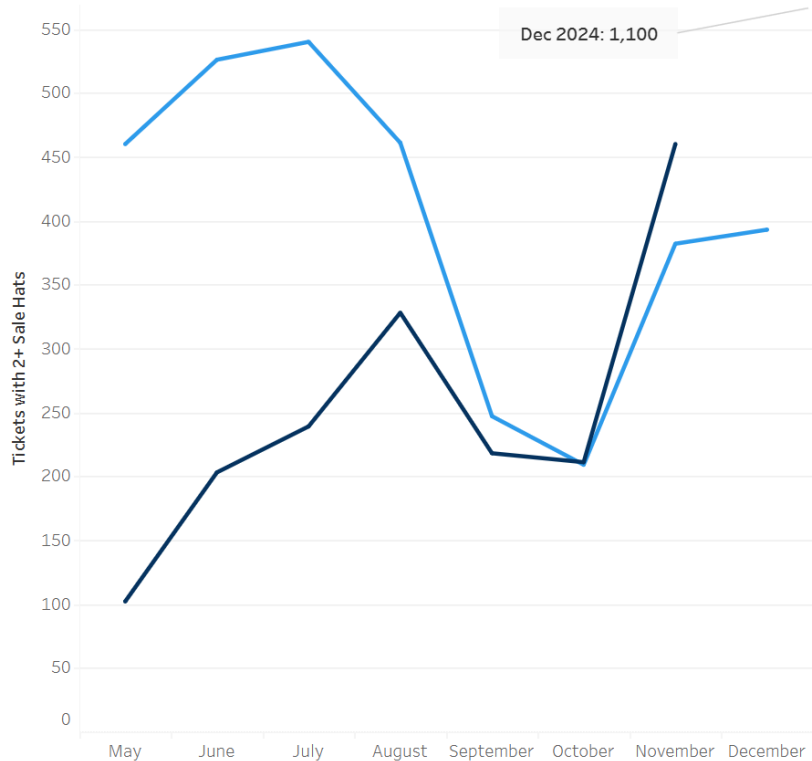
Considering the sale hat section pricing change from a “bogo” structure to flat priced sections, we analyzed the effect this change had on the number of transactions with two or more sale hats.

The chart below shows the number of transactions per month where a customer purchased two or more sale hats in 2025 and 2024.

Monthly Tickets with 2+ Sale Hats

May - December

All Stores (Excl. Store C)



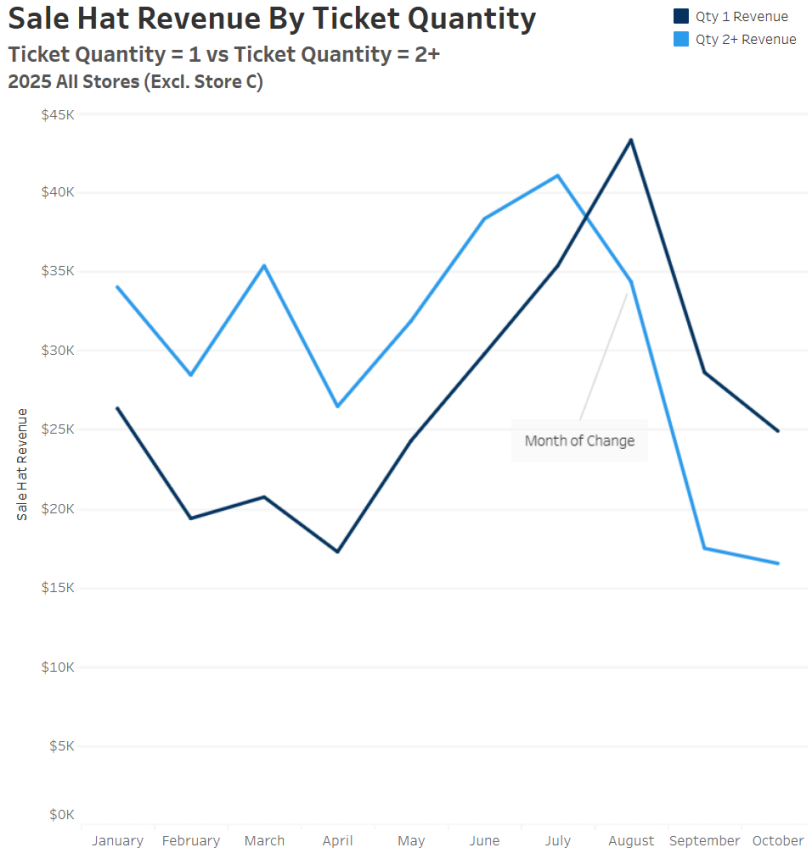
Insights:

- The number of sale hat transactions with 2 or more hats in 2025 saw a dramatic drop in the months following the offer change (**53% decrease from Jun. to Sep. 2025**). This shift in trend was not experienced in 2024.
- The observed decrease in the number of multi-quantity sale hat purchases can be behaviorally attributed to the pricing change, with customers no longer being incentivized or rewarded for purchasing more than one hat.

Impact of Multi-Quantity Purchases

After observing a 50% decrease in the number of monthly transactions with two or more sale hats, we needed to go deeper to understand the impact on revenue.

The chart below compares sale hat revenue per month from transactions containing exactly one sale hat to revenue from transactions containing two or more sale hats.



Insights:

- Prior to the pricing change, multi-quantity transactions consistently drove ~60% of total hat sale section revenue.
- After the August offer change to flat pricing occurred, revenue from multi-quantity transactions fell 55% (June vs September), and only accounted for ~40% of total revenue.
- This shift suggests that the removal of the “bogo” incentive reduced the number of customers purchasing multiple hats per transaction, leading to the decline in the number of higher value purchases and thus negatively affecting overall revenue.

Full Price Hats Trend Comparison

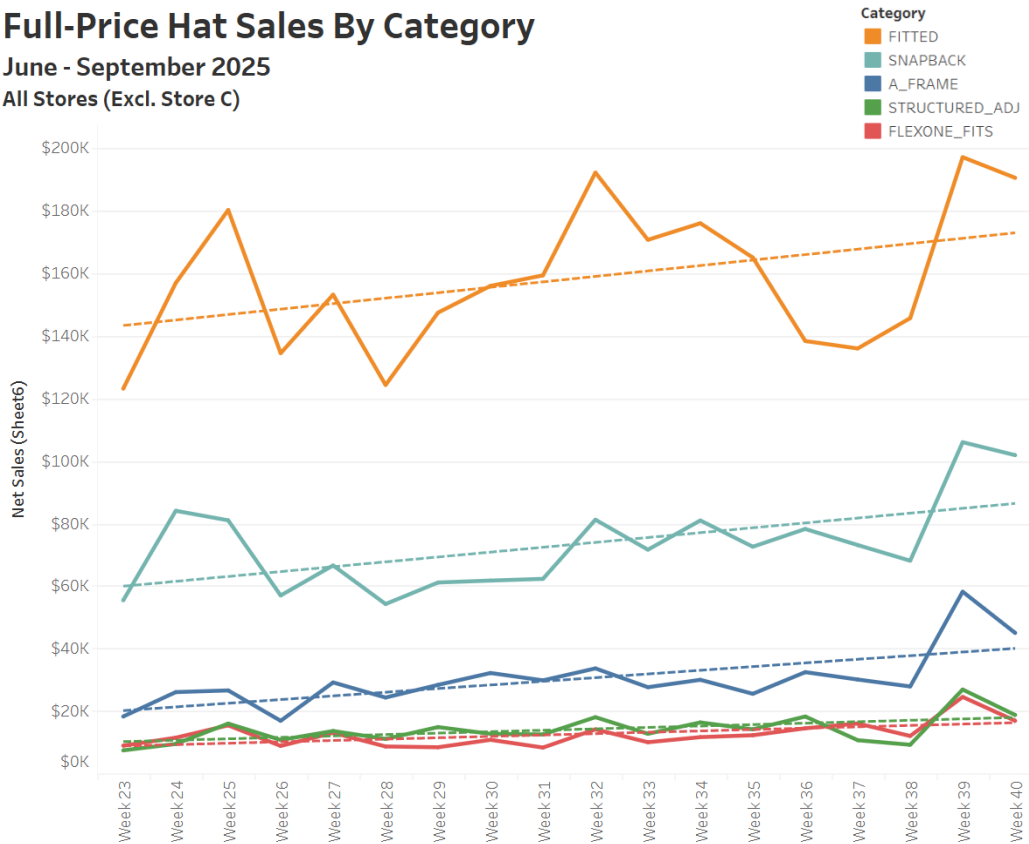
We found the decrease in sale hat revenue post offer change was being experienced at numerous locations rather than concentrated at a select few, but was this decrease specific to sale hats, or were other product segments experiencing a similar decline?

The graphic below shows the total sales per week of our top 5 full-price hat categories in 2025 during the same time period that sale hats experienced a significant decrease.

Full-Price Hat Sales By Category

June - September 2025

All Stores (Excl. Store C)



After plotting revenue per category, we evaluated each categories average weekly revenue for the six weeks before and after the sale hat offer change. This allowed for the most accurate analysis under normal conditions, as the eighth week following the change (start of October) saw a spike in revenue due to the MLB playoffs.

Insights:

- Each category saw their average weekly revenue increase between **9% and 17%** in the six week period following the change, indicating a seasonal shift may not be to blame for the decrease in sale hat revenue.

Annual Impact of The Offer Change

So far, we have discovered a steep decrease in sale hat revenue that occurred in the immediate weeks following the offer change, and found comparable segments didn't experience a decrease of the same magnitude.

To determine if the sale hat revenue decrease was statistically associated with the offer change, we used regression modeling to reveal the true difference in sale hat revenue after the offer change.

Our regression model used daily sale hat revenue totals from 2024 through 2025 and controlled for seasonality between months. It produced the following results:

	<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>
After Period	-1074.103516	420.546207	-2.554067776	0.010853784

Insights:

- Daily sales in the after-change period are approximately **\$1074 lower per day** on average while controlling for monthly seasonality.
- A p-value of < 0.05 indicates that this decrease is very unlikely to be due to chance, suggesting that the offer change to flat pricing sections coincided with a meaningful decline in sale hat revenue .
- These results confirm there is statistical evidence of a decline in hat sale section revenue beginning when the flat pricing sections were implemented.

To estimate the annual impact the change in sale hat offer has on revenue, we used sale section revenue data from January 2024 through July 2025 to create a seasonality index that expresses each month's sale hat revenue as a ratio to the yearly average, showing how strongly that month over or under-performed compared to the average month.

We used this index with our regression results to emulate what annual sales would be per month under an entire year of using flat priced sale hat sections.

Projected Monthly Sale Hat Revenue Using Flat Priced Sections:

MonthNum	AvgSales	Avg Month	Month Index	Monthly Impact	(Avg sales * index) + monthly impact
1	\$ 88,342.33	\$ 76,116.18	1.16062488	\$ (33,294.00)	\$ 55,048.33
2	\$ 84,832.29		1.11451063	\$ (30,072.00)	\$ 54,760.29
3	\$ 87,354.57		1.14764787	\$ (33,294.00)	\$ 54,060.57
4	\$ 59,522.90		0.78200064	\$ (32,220.00)	\$ 27,302.90
5	\$ 43,381.23		0.56993442	\$ (33,294.00)	\$ 10,087.23
6	\$ 61,468.07		0.80755591	\$ (32,220.00)	\$ 29,248.07
7	\$ 64,770.17		0.85093828	\$ (33,294.00)	\$ 31,476.17
8	\$ 82,573.40		1.08483376	\$ (33,294.00)	\$ 49,279.40
9	\$ 46,918.24		0.61640299	\$ (32,220.00)	\$ 14,698.24
10	\$ 42,176.86		0.55411163	\$ (33,294.00)	\$ 8,882.86
11	\$ 69,804.66		0.91708046	\$ (32,220.00)	\$ 37,584.66
12	\$182,249.42		2.39435852	\$ (33,294.00)	\$ 148,955.42

2024 Segment Revenue	\$ 938,416.22
2025 Segment Revenue	\$ 830,628.68
2026 Projection	\$ 521,384.14
2026 Projection - 2025	\$ (309,244.54)

Insights:

- Using the statistical models results and historical data to adjust for seasonality, we're able to estimate **annual sale hat revenue to be ~\$520k** using flat priced sections. **This would be a \$300k+ decrease from 2025, and a \$400k+ decrease from 2024.**

Summary of Conclusions & Recommendation

Summary of Findings:

1. Weekly sale hat section revenue fell **40%** 8 weeks following the offer change.
2. Each of our top 5 full-price hat categories saw average weekly revenue grow by **9%** or more during the same time period that sale hats decreased.
3. Monthly revenue from transactions with 2 or more sale hats fell by **55%** following the offer change. Our findings suggest this was fueled by consumers making fewer multi-quantity purchases due to the removal of “Bogo” incentive pricing.
4. If the current flat-priced sale hat sections are kept, we can expect the segment to produce **~\$300k less annually**.

Recommendation:

Five Stores Should Keep Flat Priced Sale Hat Sections

- Stores F, C, Z, AB, and S each saw average weekly revenue increase by 60% or more in the 90 days following the change. These stores should maintain the flat priced sections with performance monitoring in place in case these locations begin to see a decline.

Action For All Other Locations

- Given the large influence that multi-quantity purchases have on segment revenue, it is advised to reinstall a “Bogo” pricing model to the hat sale section in order to revive falling sales.
- Our proposed next steps are to first, brainstorm a new pricing model that incentivizes multi-quantity purchases, and second, track performance of this new model over a 90 day period to measure effectiveness.

Appendix

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Gathering Sale Hat Data

Our first step was to isolate the data on hat sale section revenue so we can analyze it specifically. To do this, we downloaded all line-by-line transaction data from the detailed sales by product report.

Example of data at this stage:

Date	Location	Product_Name	Category	Payment_Method	Ticket_Id	Selling_Price	Quantity	Discount	Tax	Net_Sales
1/1/2024	Store T	HELMETS	HELMETS	Credit/Debit Card	210702826	69.98	1	0	0	69.98
1/1/2024	Store V	Jersey	GAMEDAY	Credit/Debit Card	210715451	289.98	-1	0	-29.72	-289.98
1/1/2024	Store V	ADULT	ADULT	Credit/Debit Card	210688059	63.98	1	0	6.56	63.98
1/1/2024	Store Q	Fitted_Hat	FITTED	Cash	210715602	89.98	1	0	0	89.98
1/1/2024	Store L	DRINKWARE	DRINKWARE	Cash	210698274	29.98	1	0	2.72	29.98

The line-by-line transaction data was queried using SQL to extract data on sale section hats only. This query performed the following:

- Filtered for hats, then filtered out product names of hats whose list price is typically <\$40, but including instances where those products had a discount applied.
- Filtered for data only when net sales is < (quantity sold * \$40). As a result, our data now only shows hats that had a final sale price of \$40 or less, while still accounting for quantity, so if multiple hats were purchased those are still included.

Example of filtered data for sale hats only:

Date	Location	Product_Name	Category	Payment_Method	Ticket_Id	Selling_Price	Quantity	Discount	Tax	Net_Sales
1/1/2024	Store R	Flex_Fit_Hat	FLEXONE_FITS	Credit/Debit Card	210717257	75.98	1	56	0	19.98
1/1/2024	Store T	Structured_Hat	STRUCTURED_ADJ	Cash	210722929	49.98	1	30	0	19.98
1/1/2024	Store H	Snapback_Hat	SNAPBACK	Credit/Debit Card	210706128	69.98	1	49.98	0	20
1/1/2024	Store H	Fitted_Hat	FITTED	Credit/Debit Card	210706128	69.98	1	49.98	0	20
1/1/2024	Store C	Structured_Hat	STRUCTURED_ADJ	Credit/Debit Card	210696567	69.98	1	50	1.2	19.98

The exact query used can be found [here](#)

Now that our data is exclusively sale section hats, we ran a new SQL query that transformed the data into the total sales section hat revenue per store and per day.

Total Sale Hat Section Revenue Per Store & Day:

Date	Location	Net_sales
1/1/2024	Store A	589.78
1/1/2024	Store C	319.74
1/1/2024	Store D	239.96
1/1/2024	Store E	459.86
1/1/2024	Store G	19.98
1/1/2024	Store H	160
1/1/2024	Store J	159.98
1/1/2024	Store K	79.96
1/1/2024	Store L	149.94
1/1/2024	Store M	399.8
1/1/2024	Store N	179.94

The exact query used can be found [here](#)

Sale Hat Revenue Trend YoY

Objectives and Reasoning

To reveal the short-term effects of the offer change, we plotted weekly revenue of the hat sale section in 2025 and 2024 eight weeks before and after August 1st (the week of the offer change).

Methods and Steps Taken:

We took the following steps to create visualizations and arrive at our conclusions regarding the short-term change in trend after the sale hat offer change:

1. We uploaded our data set of daily sale hat revenue per store from 2024 to 2025 to Tableau.
2. Once the data was uploaded, we plotted net sales and filtered the date range to show the eight weeks before and after the week of the change.
3. Finally, we added a table calculation to view our data as a two week moving average.

Results of our plot showed sale hat revenue on the week of the change (week 31) to be \$17k and eight weeks following change (week 39) to be \$10.2k.

We then used the percent change formula below:

Percent Change Formula

$$\frac{(\text{New value} - \text{Old value})}{\text{Old value}} \times 100.0$$

\$17k = Old value

\$10.2k = New value

This was how we calculated the 40% decrease in average weekly revenue of the sale hat section.

Sale Hat Revenue Per Store

Objectives and Reasoning

After observing a company-wide decrease in sale hat revenue, we needed to evaluate revenue at the store level to see if this company-wide decline was caused by a small segment of stores posting a decrease, or if we experienced a more widespread issue across locations.

Methods and Steps Taken:

We took the following steps to create visualizations and arrive at our conclusions in the evaluation of individual stores performance in sale hat revenue before and after the offer change.

1. We began by uploading our data set of daily sale hat revenue per store for 2024 through 2025 to Tableau.
2. We then used the following calculated fields to isolate data on the 90 days before and after the change:

Calculated field for 90 day "Before Period":

```
IF [Date] >= DATE("2025-05-01")  
AND [Date] <= DATE("2025-7-31") THEN [Net sales]  
END
```

Calculated field for 90 day "After Period":

```
IF [Date] >= DATE("2025-08-01")  
AND [Date] <= DATE("2025-10-31") THEN [Net sales]  
END
```

3. We then plotted these before and after values per location in 2025 to create a bar chart showing the total revenue of each store in the 90 day period before and after the change.
4. The data was then exported in a spreadsheet view where we calculated the percent change to arrive at our conclusions of five locations seeing an increase in the post change period and seeing nine stores experience a decrease of 30% or more.

Percent Change Formula:

$$((\text{New value} - \text{Old value}) / \text{Old value}) \times 100.0$$

- To come to our conclusions regarding the average weekly revenue per store, we used a Tableau calculated field to get total hat sales section revenue per store in the 90 days before and after the change. This calculated field allowed labels to be placed on the before and after periods total sales.

Calculated field for both before and after change periods:

```

IF [Date] >= DATE("2025-05-05")
  AND [Date] <= DATE("2025-08-03")
THEN "Before"

ELSEIF [Date] >= DATE("2025-08-04")
  AND [Date] <= DATE("2025-11-02")
THEN "After"

END

```

- To gather the percentage gain/loss of each store in the 90 days post change, we exported a spreadsheet view of the average weekly sales per store in the 90 days before and after the change. We then calculated the percentage change between the 90 days before and after the change of each store using the percent change formula.

Percent Change Formula:

$$((\text{New value} - \text{Old value}) / \text{Old value}) \times 100.0$$

The table below shows each stores percentage change in average weekly hat sale section revenue of the 90 days after the offer change in comparison to the 90 days before.

Location	Period (Before/After)	Avg. Weekly Revenue	Percent Difference
Store L	After	\$1,238	-39.6%
Store L	Before	\$2,050	
Store P	After	\$1,122	-37.5%
Store P	Before	\$1,796	
Store J	After	\$790	-36.1%
Store J	Before	\$1,236	
Store H	After	\$517	-47.9%
Store H	Before	\$993	
Store A	After	\$379	-62.5%
Store A	Before	\$1,010	
Store G	After	\$713	-17.6%
Store G	Before	\$865	
Store W	After	\$452	-31.2%
Store W	Before	\$657	

Store T	After	\$336	-47.2%
Store T	Before	\$637	
Store AA	Before	\$49	
Store AB	After	\$491	93.9%
Store AB	Before	\$253	
Store C	After	\$3,186	63.4%
Store C	Before	\$1,950	
Store D	After	\$624	-0.8%
Store D	Before	\$629	
Store E	After	\$436	-4.9%
Store E	Before	\$458	
Store F	After	\$811	32.1%
Store F	Before	\$614	
Store I	After	\$489	-3.4%
Store I	Before	\$506	
Store K	After	\$337	7.7%
Store K	Before	\$313	
Store M	After	\$53	166.7%
Store M	Before	\$20	
Store N	After	\$1,068	-8.4%
Store N	Before	\$1,166	
Store O	After	\$40	-50.0%
Store O	Before	\$80	
Store Q	After	\$100	-48.1%
Store Q	Before	\$193	
Store R	After	\$449	-11.7%
Store R	Before	\$509	
Store S	After	\$552	84.7%
Store S	Before	\$299	
Store U	After	\$780	-17.2%
Store U	Before	\$942	
Store V	After	\$84	-74.9%
Store V	Before	\$334	
Store X	After	\$277	20.1%
Store X	Before	\$231	
Store Y	After	\$232	10.0%
Store Y	Before	\$211	
Store Z	After	\$107	-11.1%
Store Z	Before	\$120	

Monthly Tickets Trend Comparison

Objectives and Reasoning

The number of tickets per month with two or more sale hats purchased was studied in order to evaluate how much of an effect the changing of the “Bogo” offer had on the number of multi-quantity purchases.

Methods and Steps Taken:

1. To start, we used an SQL query which performed the following:
 - Gathered the total quantity of hats purchased in each ticket and specifically filtered only when the quantity purchased is two or more.
 - Then from that amount of tickets with two or more hats we aggregated the number of tickets per day and location.

The SQL query used can be viewed [here](#)

2. We then imported our data set of 2+ sale hat tickets per day and location into Tableau.
3. In Tableau, we plotted the number of tickets by month and put the date field aggregated to year in color in order to see 2024 and 2025 lines separately. This allowed us to produce the line chart used in our report.
4. After producing our graph, we calculated the percent change between June and September's total count of sale hat tickets with two or more hats purchased. The formula used for percent change is below.

Percent Change Formula:

$$((\text{New value} - \text{Old value}) / \text{Old value}) \times 100.0$$

Impact of Multi-quantity Purchases

Objectives and Reasoning

The revenue of single quantity and multi-quantity sale hat tickets were studied in order to evaluate how much of an effect the changing of the “Bogo” offer had on sale hat revenue when only 1 sale hat was purchased compared to multi-hat purchases.

Methods and Steps Taken:

1. To start, we used an SQL query which performed the following:
 - Querying the table of sale hats only, we gathered the total sales and quantity sold of each purchase.
 - Then created two columns per day and store. One which totaled revenue when quantity = 1, and the other totaled revenue when quantity = 2.

This allowed us to isolate sale hat revenue of single quantity purchases and multi-quantity purchases.

The SQL query used can be viewed [here](#)

2. Next, we uploaded our queries results to tableau and plotted our single quantity, and multi-quantity revenue columns on the X axis, and put date (as months) on the Y axis.
3. We then placed ‘measure names’ on the color mark to see the trend in sale hat revenue over time of single quantity purchases and multi-quantity purchases separately.
4. To determine the percentage of total sale hat revenue that purchases of 2 or more hats took up, we divided each months total sale hat revenue by each months total revenue of purchases of 2+ sale hats.
5. To calculate the 55% decline in revenue from transactions with 2+ hats from June to September, we used the percent change formula seen below using September's total sale hat revenue of transactions containing 2+ hats of \$17k as ‘new value’ and June's revenue of \$38k as ‘old value’.

Percent Change Formula:

$$((\text{New value} - \text{Old value}) / \text{Old value}) \times 100.0$$

Full-Price Hat Revenue By Category

Objectives and Reasoning

Although we found a company-wide decrease in sales that occurred at numerous locations, we still needed to confirm if other segments had been experiencing a simultaneous decline in revenue.

Full-price hats were chosen for comparison since they are in the same product family as sale hats. We broke the segment down further to the top five full-price hat categories to check for signs of decline among different styles and price points.

Methods and Steps Taken:

1. Our data began as item level transactions of all products from the detailed sales by product report from 2024 through 2025

Example of data at this stage:

Date	Location	Product_Name	Category	Payment_Method	Ticket_Id	Selling_Price	Quantity	Discount	Tax	Net_Sales
1/1/2024	Store T	HELMETS	HELMETS	Credit/Debit Card	210702826	69.98	1	0	0	69.98
1/1/2024	Store V	Jersey	GAMEDAY	Credit/Debit Card	210715451	289.98	-1	0	-29.72	-289.98
1/1/2024	Store V	ADULT	ADULT	Credit/Debit Card	210688059	63.98	1	0	6.56	63.98
1/1/2024	Store Q	Fitted_Hat	FITTED	Cash	210715602	89.98	1	0	0	89.98
1/1/2024	Store L	DRINKWARE	DRINKWARE	Cash	210698274	29.98	1	0	2.72	29.98

2. To gather data on full-price hats only we used an SQL [query](#) which performed the following:
 - Filtered to only display transaction data of hats where net sales is > (quantity sold * \$40), but Include instances of specific product names that have a normal price of < \$40 that did not have a discount applied.

This query allowed us to isolate data on full-price hats only.

Example of filtered data for full-price hats sales per category, store and day only:

Date	Location	Category	Net_sales
1/1/2024	Store A	FITTED	2069.56
1/1/2024	Store A	SNAPBACK	371.9
1/1/2024	Store C	FITTED	689.82
1/1/2024	Store C	FLEXONE_FITS	143.96
1/1/2024	Store C	SNAPBACK	877.76
1/1/2024	Store D	FITTED	391.92
1/1/2024	Store D	FLEXONE_FITS	68
1/1/2024	Store D	SNAPBACK	229.98
1/1/2024	Store E	FITTED	1387.7
1/1/2024	Store E	FLEXONE_FITS	75.98
1/1/2024	Store E	SNAPBACK	279.92

- Next we uploaded this data to Tableau and plotted a line chart of net sales per week from June through September to show how revenue trended during the eight weeks before and after the sale hat offer change.
- Our final step in Tableau was to place the category field in the color mark which assigned a color to each hat category.
- After plotting revenue per category, we evaluated the average weekly revenue of each category for the six weeks before and after the sale hat offer change. Studying the six weeks on either end of the offer change allowed for the most accurate analysis under normal conditions, as the eighth week following the change (start of October) saw a spike in revenue due to the MLB playoffs.
- To determine the average weekly revenue of each full-price hat category in the six weeks prior to and after the change, we exported a spreadsheet view of the data per category similar to the example below:

Weekly Revenue Per Full-Price Hat Category:

Week of Date	Category	Net Sales
Week 32	SNAPBACK	81188.02
Week 33	SNAPBACK	71601.6
Week 34	SNAPBACK	80948.48
Week 35	SNAPBACK	72549.32
Week 36	SNAPBACK	78225.76
Week 37	SNAPBACK	73079.06
Week 38	SNAPBACK	68071.44
Week 39	SNAPBACK	105976.58
Week 40	SNAPBACK	101843
Week 23	FITTED	123108.5
Week 24	FITTED	156894.12
Week 25	FITTED	180250.82

7. We then used the formula below on each category for the six weeks leading up to August 1st and the six weeks after August 1st including the first week of the change to determine the average weekly revenue of each category in both periods.

Formula used to calculate the average weekly revenue of each full-price hat category in the 90 days before the change:

$$=\text{average}(\text{week 25: week 30})$$

Formula used to calculate the average weekly revenue of each full-price hat category in the 90 days after the change:

$$=\text{average}(\text{week 31: week 36})$$

8. After calculating the average weekly revenue of each category in the six weeks prior to and following the change, we then used the percent change formula below to calculate the percent difference in each category's average weekly revenue in the six weeks following the offer change compared to the six weeks before the change.

Percent Change Formula:

$$((\text{After period} - \text{Before period}) / \text{Before period}) \times 100.0$$

STRUCTURED_ADJ	Avg. Weekly Revenue	Percent Difference
6 Weeks Before Change	\$13,157	16.5%
6 Weeks After Change	\$15,329	
Flexfit		
6 Weeks Before Change	\$10,857	8.7%
6 Weeks After Change	\$11,806	
Fitted		
6 Weeks Before Change	\$149,257	11.8%
6 Weeks After Change	\$166,938	
Snapback		
6 Weeks Before Change	\$63,593	17.1%
6 Weeks After Change	\$74,463	
A-Frame		
6 Weeks Before Change	\$26,238	13.7%
6 Weeks After Change	\$29,828	

These were the steps taken to arrive at our conclusion of each full-price hat category seeing their average weekly revenue increase between 9% and 17% in the 6 week period following the sale hat offer change.

Regression Statistical Modeling

Objectives and Reasoning

Our main goal was to determine if there was a statistically significant decrease of sale hat revenue in the period following the offer change. Regression is a statistical technique used to find out how much an outcome variable changes as a result of changes in multiple input variables. In our case, we wanted to find out how the post change period affected sale hat revenue while controlling for seasonality and time trends to determine if there truly was a statistical decrease in revenue after the offer change occurred.

Methods and Steps Taken:

1. Our data began as item level transactions of all products from the detailed sales by product report from 2024 through 2025.

Example of data at this stage:

Date	Location	Product_Name	Category	Payment_Method	Ticket_Id	Selling_Price	Quantity	Discount	Tax	Net_Sales
1/1/2024	Store T	HELMETS	HELMETS	Credit/Debit Card	210702826	69.98	1	0	0	69.98
1/1/2024	Store V	Jersey	GAMEDAY	Credit/Debit Card	210715451	289.98	-1	0	-29.72	-289.98
1/1/2024	Store V	ADULT	ADULT	Credit/Debit Card	210688059	63.98	1	0	6.56	63.98
1/1/2024	Store Q	Fitted_Hat	FITTED	Cash	210715602	89.98	1	0	0	89.98
1/1/2024	Store L	DRINKWARE	DRINKWARE	Cash	210698274	29.98	1	0	2.72	29.98

2. We then created an SQL [query](#) to gather the variables used in the regression model. Fields made and their purposes are outlined below:
 - a. **Date:** Each day from January 2024 through 2025.
 - b. **Net sales:** Hat sale section revenue on each day.
 - c. **Time index:** Counted the number of passing days starting from 1 on January 1st 2024 and counted through 2025. This variable was used in our regression in order to control for how much sales naturally increase or decrease per day over time independent of monthly seasonality and the offer change.
 - d. **After period:** This column is used to identify sales that occurred in the days following the sale hat offer change. Days prior to the change are represented with a 0 and days post change are represented with a 1. This allows our regression model to understand which days came after the change, and correctly attribute a difference in daily sales to the offer change itself rather than seasonality and trends over time.
 - e. **Month names (Jan - Dec):** Using a similar principle as the after period column, we made columns for each month of the year and assigned a 1 to sales values that occurred on days in that month in both 2024 and 2025 and a 0 to days that didn't occur in that month. These columns were created so our model could control for recurring monthly seasonality in sales. This means our afterperiod variable was not impacted by the usual increase in sales seen in November / December. The month of March was omitted from our month columns to serve as a baseline month under normal conditions.

Example Data Used for Regression Model:

Date	Net_Sales	Time_index	After_Period	Jan	Feb
1/1/2024	3610.88	1	0	1	0
1/2/2024	2643.1	2	0	1	0
1/3/2024	2629.08	3	0	1	0
1/4/2024	2649.18	4	0	1	0
1/5/2024	3804.72	5	0	1	0
1/6/2024	6875.62	6	0	1	0
1/7/2024	5377.92	7	0	1	0
1/8/2024	1759.56	8	0	1	0
1/9/2024	1319.56	9	0	1	0
1/10/2024	2349.24	10	0	1	0
1/11/2024	1709.56	11	0	1	0
1/12/2024	3016.94	12	0	1	0
1/13/2024	4024.64	13	0	1	0
1/14/2024	3816.9	14	0	1	0
1/15/2024	2445.1	15	0	1	0

- Next, we imported our new data set into Excel.
- We then ran our regression using the Excel add in “data analysis tool pak”. Net sales was used as our Y variable, and all other columns were used as X variables. Running regression produced the following initial result:

SUMMARY OUTPUT									
Regression Statistics									
Multiple R	0.433636006								
R Square	0.188040186								
Adjusted R Square	0.173256603								
Standard Error	1533.139251								
Observations	728								
ANOVA									
	df	SS	MS	F	Significance F				
Regression	13	388666896.1	29897453.55	12.71952797	2.20651E-25				
Residual	714	1678268398	2350515.963						
Total	727	2066935294							
	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%	
Intercept	2654.625579	221.2897852	11.99615055	2.46406E-30	2220.169105	3089.082052	2220.169	3089.082	
Time_index	-0.611569509	0.40757839	-1.500495426	0.13392817	-1.411764916	0.188625898	-1.41176	0.188626	
After_Period	-147.5051636	230.2307497	-0.640684026	0.52193356	-599.5153611	304.505034	-599.515	304.505	
Jan	-25.99741806	276.425763	-0.094048463	0.925097045	-568.7019172	516.7070811	-568.702	516.7071	
Feb	138.5872928	281.6540399	0.492047949	0.622836693	-414.3818409	691.5564265	-414.382	691.5564	
Apr	-689.4597751	277.9232756	-2.48075579	0.013339703	-1235.104329	-143.815221	-1235.1	-143.815	
May	-1229.866518	276.4800692	-4.448300819	1.00362E-05	-1772.677636	-687.0554	-1772.68	-687.055	
Jun	-662.4287017	280.1385607	-2.364646623	0.018313843	-1212.422507	-112.434896	-1212.42	-112.435	
July	-526.2117457	279.813559	-1.880579867	0.060435891	-1075.567478	23.14398651	-1075.57	23.14399	
Aug	-176.2372833	289.3428688	-0.609094961	0.542655246	-744.3018335	391.8272669	-744.302	391.8273	
Sep	-862.8273918	291.2819549	-2.962172484	0.003156216	-1434.698934	-290.955849	-1434.7	-290.956	
Oct	-1017.380253	289.400568	-3.515474278	0.000466693	-1585.558084	-449.202422	-1585.56	-449.202	
Nov	-208.1289114	293.0781163	-0.71014825	0.477844077	-783.5268434	367.2690205	-783.527	367.269	
Dec	1696.761649	293.6925005	5.777340741	1.13317E-08	1120.157501	2273.365796	1120.158	2273.366	

When running a regression with time series data, it is good practice to test for autocorrelation which, if present, can produce results that are less precise. We tested for autocorrelation using the Durbin-Watson test which tests whether the errors in one period predict errors in the next.

To perform the Durbin-Watson test we took the following steps:

- a. We started by using our residuals to produce a column of lagged residuals.
- b. Then created a column of differences between residuals and lagged residuals.
- c. We then squared the differences column and the residuals column.
- d. Took the sum of squared differences as the numerator and the sum of squared residuals as the denominator and divided to calculate a Durbin--Watson statistic.

Example Data Used To Conduct Durbin Watson Test:

<i>Observation</i>	<i>Predicted net_sales</i>	<i>Residuals</i>	<i>Lag Residuals</i>	<i>Residual - Lag</i>	<i>SQ Differences</i>	<i>SQ Residuals</i>
1	2628.016591	982.863409		982.863409	966020.4808	966020.4808
2	2627.405021	15.69497854	982.863409	-967.1684305	935414.7729	246.3323513
3	2626.793452	2.286548048	15.69497854	-13.40843049	179.7860082	5.228301974
4	2626.181882	22.99811756	2.286548048	20.71156951	428.9691115	528.9134112
5	2625.570313	1179.149687	22.99811756	1156.15157	1336686.452	1390393.985
6	2624.958743	4250.661257	1179.149687	3071.51157	9434183.322	18068121.12

SUM SQ Differences	SUM SQ Residuals
1445654388	1678268398
SUM SQ Differences / SUM SQ Residuals	
0.861396419	

The results of our test indicated positive autocorrelation (0.86) which means the result of our initial regression was invalid. To produce a more accurate regression result we used the Cochrane–Orcutt Procedure, which corrects for autocorrelation.

5. To perform the Cochrane–Orcutt procedure we took the following steps:
 - a. First, we ran a new Excel “data analysis tool pak” regression using our original outputs residuals as our y variable and our lagged residuals as our X variable. This produced a slope coefficient (ρ) of **0.569** in our case.
 - b. Now for each individual column in our original input (Y = Net Sales, X = Variables) we used a formula to transform each columns values so the regression model now runs on variables that are uncorrelated.

Formula Used To Transform Y variable:

$$=SUM(Y2-(\rho * Y1))$$

Y2 = the second value in net sales

Y1 = the first value in net sales

Formula Used To Transform X variable:

$$=SUM(X2-(\rho * X1))$$

X2 = the second value in net sales

X1 = the first value in net sales

6. After transforming each variable we then ran a new Excel “data analysis tool pak” regression using the transformed variable for net sales as Y and the transformed X variables as X. When setting up the dialogue box for regression, we also checked the box “constant is zero” for the intercept.

Running a regression on these transformed variables produced the following result:

SUMMARY OUTPUT									
<i>Regression Statistics</i>									
Multiple R	0.569363931								
R Square	0.324175285								
Adjusted R Square	0.311416327								
Standard Error	1299.831919								
Observations	727								
<i>ANOVA</i>									
	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Significance F</i>				
Regression	13	578653306.6	44511792.81	26.34515098	1.54822E-52				
Residual	714	1206347995	1689563.019						
Total	727	1785001302							
	<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>	<i>Lower 95%</i>	<i>Upper 95%</i>	<i>ower 95.0%</i>	<i>pper 95.0%</i>	
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
Transformed Time_Index	2.042761455	0.686983379	2.973523838	0.003043176	0.694012457	3.39151045	0.694012	3.39151	
Transformed After Period	-1074.103516	420.546207	-2.554067776	0.010853784	-1899.758535	-248.4485	-1899.76	-248.448	
Jan	1970.311785	392.99786	5.013543293	6.74707E-07	1198.742216	2741.88135	1198.742	2741.881	
Feb	1938.372748	389.6708064	4.974385343	8.20799E-07	1173.335157	2703.41034	1173.335	2703.41	
Apr	1046.900447	400.1500246	2.616269855	0.009077569	261.2890901	1832.5118	261.2891	1832.512	
May	636.1108542	414.1677935	1.535877159	0.125011504	-177.0214767	1449.24318	-177.021	1449.243	
Jun	1138.841929	430.2281031	2.647065408	0.008298393	294.1785203	1983.50534	294.1785	1983.505	
July	1069.527894	438.4027711	2.439601126	0.014945857	208.8152245	1930.24056	208.8152	1930.241	
Aug	1800.260255	422.2125774	4.263871688	2.27925E-05	971.3336643	2629.18685	971.3337	2629.187	
Sep	1153.737861	434.5357889	2.655104344	0.008105123	300.6172065	2006.85851	300.6172	2006.859	
Oct	902.830146	439.6391682	2.053570772	0.04038096	39.69006799	1765.97022	39.69007	1765.97	
Nov	1759.09744	454.1702717	3.873211324	0.000117278	867.4285618	2650.76632	867.4286	2650.766	
Dec	3062.218945	462.017751	6.627924875	6.71151E-11	2155.143173	3969.29472	2155.143	3969.295	

We then repeated the Durbin-Watson test on our new regression results to determine if autocorrelation still exists. This time, our resulting Durbin-Watson statistic was **1.63** which is within the threshold for no autocorrelation, meaning we can use our results.

These were the steps that were taken to arrive at our conclusion of daily sales in the hat sale section being on average \$1074 lower after the sale hat pricing change was implemented.

Estimation of Annual Impact

Objectives and Reasoning:

After gathering the average decrease in hat sale section revenue per day, we needed to estimate what the loss would be on an annual basis to get a sense of the bigger picture effects of the offer change.

Methods and Steps Taken:

1. **Average Sales Month:** To estimate the annual impact the change in sale hat offer has on revenue, we first calculated the average sale section revenue of each month that was under normal “bogo” conditions from January 2024 through July 2025. We used sale section revenue totals for August 2024 - December 2024 as the average for those months as they are the only values in our data set for those months under normal conditions. The query used to gather the average hat sales section revenue per month can be found [here](#).
2. After calculating the average hat sale section revenue for each month, we calculated the hat sale section revenue overall average month using:

$$=AVERAGE(B2:B13)$$

3. **Month index creation:** Now that we know what the average hat sale section revenue for a given month is, we can create a month index, which is a ratio that represents how much higher or lower a month's average sales are compared to the average month. This is done by dividing the average month by each month's average. For example:

$$= \text{January average sales} / \text{overall average month}$$

4. **Monthly Impact:** We then used our regressions coefficient for the difference in daily sale hat revenue and multiplied it by the number of days in each month to represent a monthly decrease in sales that can be expected. Example for January:

$$= -1074 * 31$$

5. **Projected sales:** the final step is to calculate the projected sales for that month under the flat priced sections. This is done by using the overall average month multiplied by that index of the month you're projecting for, and lastly, adding that product to the monthly impact.

$$=(\text{overall average month} * \text{month index}) + \text{monthly impact for that month}$$

performing the series of steps mentioned above allowed us to create the table seen below:

Projected Monthly Sale Hat Revenue Using Flat Priced Sections.

MonthNum	AvgSales	Avg Month	Month Index	Monthly Impact	(Avg sales * index) + monthly impact
1	\$ 88,342.33	\$ 76,116.18	1.16062488	\$ (33,294.00)	\$ 55,048.33
2	\$ 84,832.29		1.11451063	\$ (30,072.00)	\$ 54,760.29
3	\$ 87,354.57		1.14764787	\$ (33,294.00)	\$ 54,060.57
4	\$ 59,522.90		0.78200064	\$ (32,220.00)	\$ 27,302.90
5	\$ 43,381.23		0.56993442	\$ (33,294.00)	\$ 10,087.23
6	\$ 61,468.07		0.80755591	\$ (32,220.00)	\$ 29,248.07
7	\$ 64,770.17		0.85093828	\$ (33,294.00)	\$ 31,476.17
8	\$ 82,573.40		1.08483376	\$ (33,294.00)	\$ 49,279.40
9	\$ 46,918.24		0.61640299	\$ (32,220.00)	\$ 14,698.24
10	\$ 42,176.86		0.55411163	\$ (33,294.00)	\$ 8,882.86
11	\$ 69,804.66		0.91708046	\$ (32,220.00)	\$ 37,584.66
12	\$182,249.42		2.39435852	\$ (33,294.00)	\$ 148,955.42

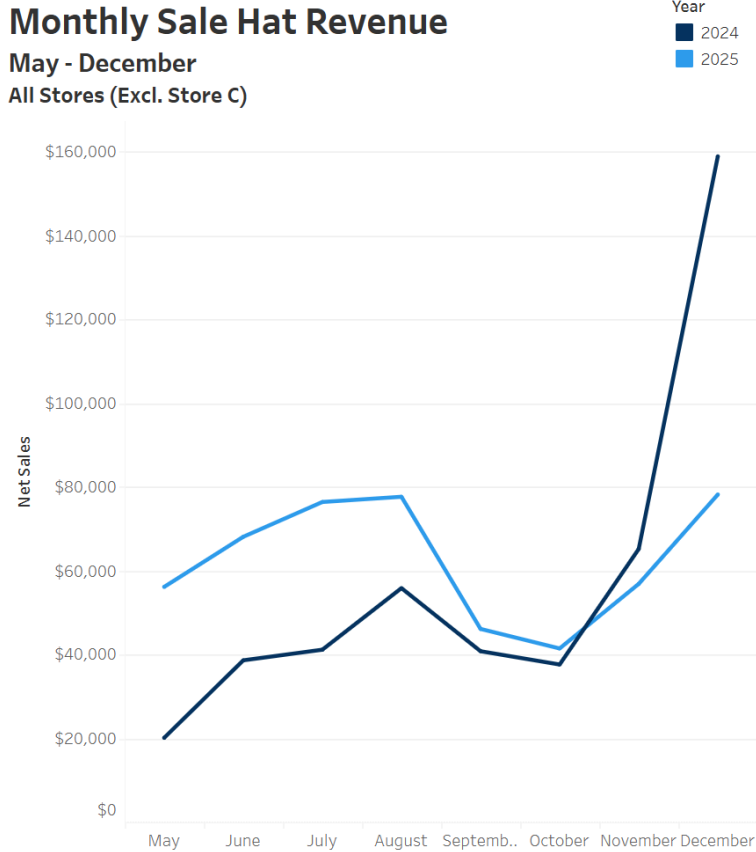
2024 Segment Revenue	\$ 938,416.22
2025 Segment Revenue	\$ 830,628.68
2026 Projection	\$ 521,384.14
2026 Projection - 2025	\$ (309,244.54)

Following that series of steps is what allowed us to reach our conclusion of expecting annual sales to be approximately \$300k lower under flat priced sections.

Q4 YoY Comparison of Sale and Full-Price Hat Revenue

In addition to our primary findings, we also plotted the overall monthly trend of sale, and full-price hat revenue from May to December of 2024 and 2025.

First, let's take a look at monthly sale hat revenue:



Insights:

- Total sale hat revenue in December 2024 was \$158k
- Total sale hat revenue in December 2025 was \$78k
- We experienced a 50% decrease YoY (-\$80k)

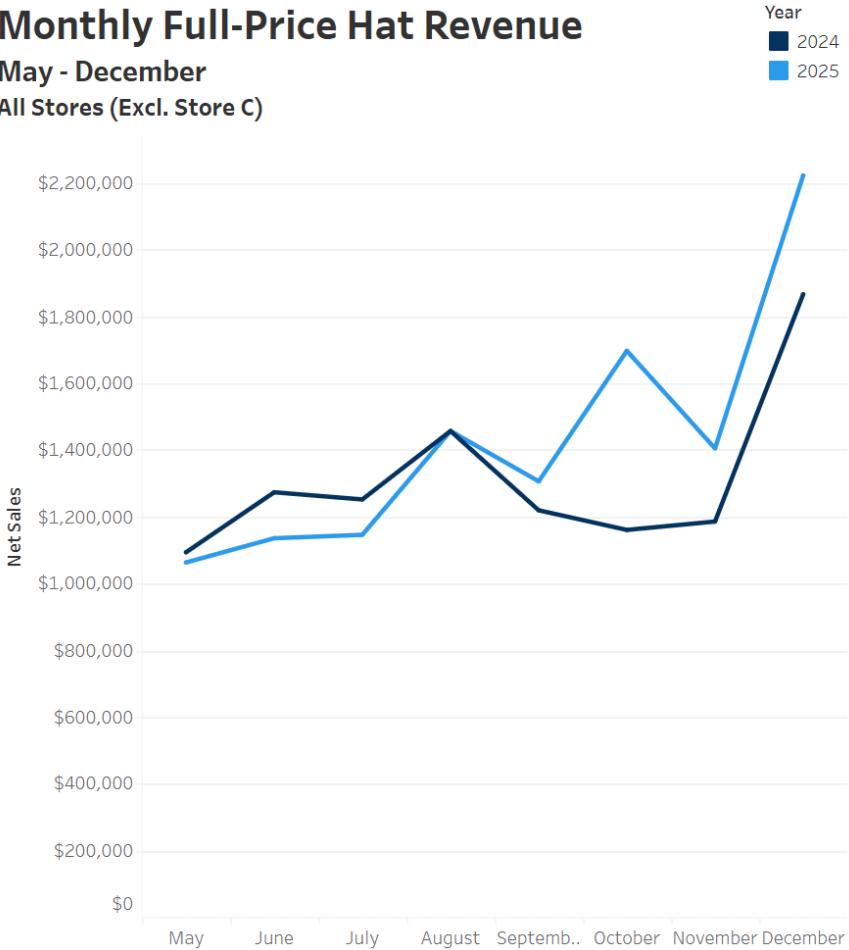
Methods and Steps Taken:

1. To come to our conclusions about December sale hat performance, we used the same data gathered from the first section of the appendix and uploaded it to Tableau.
2. Net sales was plotted per month with a year filter on color in order to plot a line for 2024 and 2025
3. Lastly, we used the percent change formula to calculate the percentage decrease.

Next, we observed how full-price hats trended in total sales per month during the same time period, with a focus on December performance to compare to sale hats.

Monthly Full-Price Hat Revenue

May - December
All Stores (Excl. Store C)



Insights:

- December 2024 full-price hat revenue \$1.86M
- December 2025 full-price hat revenue \$2.2M
- We experienced an increase of \$340k (18%)
- December 2025 sale hat revenue was **50%** lower than December 2024, despite full-price hats in December 2025 out performing December 2024 by **17%**.

Methods and Steps Taken:

1. Using the same data on full-price hats and uploading to tableau, we plotted net sales per month with a year filter on color in order to plot a line for 2024 and 2025.
2. Lastly, we used the percent change formula to calculate the percentage decrease.

Percent Change Formula:

$$\frac{((\text{New value} - \text{Old value}) / \text{Old value}) \times 100.0}{}$$

SQL Queries Used

All SQL queries used to gather data for this analysis can be found in [GitHub](#), and are also included below for ease of use.

Gathering Data On Sale Hats Only

```
-- This query isolated data on sale hats only and was also used to create the  
'ClearanceSales' Table.
```

```
-- First, we cleaned the field names to proper names that SQL can read.
```

```
WITH Cleaned_Data AS (  
    SELECT  
        Date,  
        Ticket_Id,  
        Location,  
        Payment_Methods,  
        REPLACE(Product_Name, ' ', '_') AS Product_Name,  
        TRIM((REPLACE(REPLACE(Category, ' ', '_'), '/', ''))) AS Category,  
        Selling_Price,  
        Quantity,  
        Discount,  
        Tax,  
        Net_Sales  
    FROM  
        `Portfolio_Data.Sales`  
    WHERE  
        Date BETWEEN '2024-01-01' AND '2025-12-31'  
)
```

```
-- This block filters for hat categories only and filters out special product names  
that have a typical price that is the same as our sale section while keeping  
instances where those products were discounted.
```

```
Categories AS (  
    SELECT  
        *  
    FROM
```

```

Cleaned_Data
WHERE
  Category IN (
    'SNAPBACK', 'ROPER', 'A_FRAME', 'BUCKET', 'HATS',
    'UNSTRUCTURED_ADJ', 'FITTED', 'FLEXONE_FITS', 'STRUCTURED_ADJ', 'VISOR')
AND
  (Product_Name NOT IN (
    'Special_Product1', 'Special_Product2', 'Special_Product3')
   OR Discount > 0
  )
AND Net_Sales > 17
)

-- Our dataset's 'discount' field often shows $0 for items that are real sale hat
-- transactions, so we had to find another way to isolate sale hat data. The solution
-- was to filter our results to only show data where the total sales at each quantity
-- sold could only be at or lower than the sale section price point ( "Net_Sales <
-- (Quantity * 42)" ).
SELECT
  Date,
  Location,
  Product_Name,
  Category,
  Payment_Methods,
  Ticket_Id,
  Selling_Price,
  Quantity,
  Discount,
  Tax,
  Net_Sales,
FROM
  Categories
WHERE
  Net_Sales < (Quantity * 42)

ORDER BY
  Date;

```

Hat Sale Section Revenue Per Store & Day

```
SELECT
    Date,
    Location,
    ROUND(SUM(Net_Sales),2) AS Net_sales
FROM
    Portfolio_Data.ClearanceSales
GROUP BY
    Date,
    Location
ORDER BY
    Date,
    Location;
```

Gathering Data on Full-Price Hats Only

-- This query isolated data on full-price hats only and was also used to create the 'FullPriceSales' Table.

-- First, we cleaned field names to proper names that SQL can read.

```
WITH Cleaned_Data AS (
    SELECT
        Date,
        Ticket_Id,
        Location,
        Payment_Methods,
        REPLACE(Product_Name, ' ', '_') AS Product_Name,
        TRIM((REPLACE(REPLACE(Category, ' ', '_'), '/', ''))) AS Category,
        Selling_Price,
        Quantity,
        Discount,
        Tax,
        Net_Sales
    FROM
        Portfolio_Data.Sales
    WHERE
```

```

        Date BETWEEN '2024-01-01' AND '2025-12-31'
    ),
-- filters for hat categories only
Categories AS (
    SELECT
        *
    FROM
        Cleaned_Data
    WHERE
        Category IN (
            'SNAPBACK', 'ROPER', 'A_FRAME', 'BUCKET', 'HATS',
            'UNSTRUCTURED_ADJ', 'FITTED', 'FLEXONE_FITS', 'STRUCTURED_ADJ', 'VISOR')
)
-- Due to our discount column frequently showing $0 even for sale items we couldn't
use it to isolate full price hats. The solution was to filter our data to only show
items that had a sale price that was above the sale section threshold or were a
special product name whose typical price was less than the sale section threshold
but had no discount applied.

SELECT
    Date,
    Location,
    Product_Name,
    Category,
    Payment_Methods,
    Ticket_Id,
    Selling_Price,
    Quantity,
    Discount,
    Tax,
    Net_Sales
FROM
    Categories
WHERE
    Net_Sales > (Quantity * 42)
    OR (
        Product_Name IN (
            'Special_Product1', 'Special_Product2', 'Special_Product3')
        AND Discount = 0
    )
ORDER BY
    Date;

```

Total Full-Price Hat Sales Per Day

```
SELECT
  Date,
  Location,
  Category,
  ROUND(SUM(Net_Sales),2) as Net_sales
FROM
  Portfolio_Data.FullPriceSales
GROUP BY
  Date,
  Location,
  Category
ORDER BY
  Date,
  Location,
  Category;
```

Setting Up Regression Model

-- The purpose of this query was to gather the variables needed for our regression model to determine whether sale hat section revenue meaningfully declined after the pricing model change in August while keeping seasonality constant.

```
SELECT
Date,
ROUND(SUM(Net_Sales),2) AS Net_Sales, -- Total sales per day
ROW_NUMBER() OVER(order by date) AS Time_index, -- Running count of days from 2024 -
2025
CASE WHEN Date >= '2025-08-01' THEN 1 ELSE 0 END AS After_Period, -- Assigns
post-sale-section-pricing-change days with a 1 and pre-change with a 0.

-- The following columns assign a 1 to days in the corresponding month and a 0
otherwise so the regression can account for seasonality between months.
CASE WHEN CAST(DATE_TRUNC(Date, MONTH) AS STRING) LIKE '%01-01%' THEN 1 ELSE 0 END
AS Jan,

CASE WHEN CAST(DATE_TRUNC(Date, MONTH) AS STRING) LIKE '%02-01%' THEN 1 ELSE 0 END
AS Feb,

CASE WHEN CAST(DATE_TRUNC(Date, MONTH) AS STRING) LIKE '%03-01%' THEN 1 ELSE 0 END
AS Mar,

CASE WHEN CAST(DATE_TRUNC(Date, MONTH) AS STRING) LIKE '%04-01%' THEN 1 ELSE 0 END
AS Apr,

CASE WHEN CAST(DATE_TRUNC(Date, MONTH) AS STRING) LIKE '%05-01%' THEN 1 ELSE 0 END
AS May,

CASE WHEN CAST(DATE_TRUNC(Date, MONTH) AS STRING) LIKE '%06-01%' THEN 1 ELSE 0 END
AS Jun,

CASE WHEN CAST(DATE_TRUNC(Date, MONTH) AS STRING) LIKE '%07-01%' THEN 1 ELSE 0 END
AS July,

CASE WHEN CAST(DATE_TRUNC(Date, MONTH) AS STRING) LIKE '%08-01%' THEN 1 ELSE 0 END
AS Aug,

CASE WHEN CAST(DATE_TRUNC(Date, MONTH) AS STRING) LIKE '%09-01%' THEN 1 ELSE 0 END
```

```

AS Sep,

CASE WHEN CAST(DATE_TRUNC(Date, MONTH) AS STRING) LIKE '%10-01%' THEN 1 ELSE 0 END
AS Oct,

CASE WHEN CAST(DATE_TRUNC(Date, MONTH) AS STRING) LIKE '%11-01%' THEN 1 ELSE 0 END
AS Nov,

CASE WHEN CAST(DATE_TRUNC(Date, MONTH) AS STRING) LIKE '%12-01%' THEN 1 ELSE 0 END
AS Dec

FROM
    `Portfolio_Data.ClearanceSales`
WHERE
    LOWER(Location) NOT LIKE '%store c%' -- Omits outlier store
GROUP BY
    Date
ORDER BY Date;

```

Average Monthly Hat Sale Section Revenue

--This query was used to gather the average sales per month pre-pricing-change (Before 8/25) to later use in our annual sales projection.

```

WITH Base AS (
    SELECT
        DATE_TRUNC(Date, MONTH) AS Date,
        SUM(Net_Sales) AS Net_Sales
    FROM
        `Portfolio_Data.ClearanceSales`
    WHERE
        Date < '2025-08-01'
        AND LOWER(Location) NOT LIKE '%store c%' -- Omits outlier store
    GROUP BY
        DATE_TRUNC(Date, MONTH)
)

SELECT
    EXTRACT(MONTH FROM Date) AS MonthNum,
    ROUND(AVG(Net_Sales), 2) AS AvgSales
FROM

```

```
Base
GROUP BY
    EXTRACT(MONTH FROM Date)
ORDER BY
    MonthNum;
```

Monthly ATV

--Typical ATV calculation of total sales / total tickets was not used because the total number of tickets post-pricing-change also saw a decrease along with sales which normalized the resulting calculation.

```
WITH Base AS (
    SELECT
        Date,
        Ticket_Id,
        SUM(Net_Sales) AS SalesPerTicket
    FROM
        Portfolio_Data.ClearanceSales
    GROUP BY
        Ticket_Id,
        Date
)

SELECT
    DATE_TRUNC(Date, MONTH) AS Date,
    ROUND(AVG(SalesPerTicket), 2) AS ATV
FROM
    Base
GROUP BY
    DATE_TRUNC(Date, MONTH)
ORDER BY
    Date;
```

Tickets With 2+ Sale Hats

-- We first isolate transactions containing 2 or more sale hats by filtering our sale hat sales dataset to only show rows of sales that occurred when the quantity of the ticket is two or more.

```
WITH TwoPlusHatTickets AS (  
    SELECT  
        Ticket_Id,  
        Location,  
        Date,  
        SUM(Quantity) AS TicketWithTwoPlusHats  
    FROM  
        Portfolio_Data.ClearanceSales  
    GROUP BY  
        Ticket_Id,  
        Location,  
        Date  
    HAVING  
        (SUM(Quantity) >= 2)  
),
```

-- We then gather the total number of tickets containing 2+ sale hats per store and day.

```
Total2PlusTickets AS (  
    SELECT  
        Location,  
        Date,  
        COUNT(DISTINCT Ticket_Id) AS Days2PlusHatTickets  
    FROM  
        TwoPlusHatTickets  
    GROUP BY  
        Location,  
        Date  
)
```

-- Our final output shows the total number of tickets with 2+ sale hats per store and day.

```
SELECT  
    Date,  
    Location,  
    Days2PlusHatTickets,  
FROM  
    Total2PlusTickets
```

```
ORDER BY
    Date,
    Location;
```

Multi-Quantity Vs Single-Quantity Sale Item Revenue Per Store & Day

-- Querying our dataset of just sale hat revenue, we first totaled sales and quantity sold of each ticket, location, and day.

```
WITH TicketsCombined AS (
    SELECT
        Location,
        Date,
        SUM(Net_Sales) AS Net_Sales,
        SUM(Quantity) AS Quantity
    FROM
        Portfolio_Data.ClearanceSales
    GROUP BY
        Ticket_Id,
        Location,
        Date
),
```

-- Case statements were used to gather total sales of sale hats when only 1 hat was sold as well as when 2 or more hats were sold.

```
QtyCase AS (
    SELECT
        Date,
        Location,
        COALESCE(ROUND(SUM(CASE WHEN Quantity = 1 THEN Net_Sales ELSE 0 END), 2), 0)
AS Qty1Revenue,
        COALESCE(ROUND(SUM(CASE WHEN Quantity > 1 THEN Net_Sales ELSE 0 END), 2), 0)
AS Qty2PlusRevenue
    FROM
        TicketsCombined
    GROUP BY
        Date,
        Location
)
```

-- Our final output shows separate columns for sales of the hat sale section when quantity = 1 and when quantity is 2+ per date and location

SELECT

 Date,
 Location,
 Qty1Revenue,
 Qty2PlusRevenue

FROM

 QtyCase

ORDER BY

 Date,
 Location;