

Task 2: Role: Part of a retail analytics team and is approached by the Category Manager for Chips. Asked to test the impact of new trial layouts to determine whether the layout should be rolled out to all stores. Timeline: Trial Period is February 2019 - April 2019

1. Select Control Stores: Explore the data and define metrics for control store
 - Think about what makes them a control store
 - Look at the drivers and visualize these graphs
 - Create a function
2. Assessments of the trial: Give insight for the store (Trial Stores are 77, 86, 88)
 - Check each store in comparison with control store to get overall performance
 - Define metrics to see if it is successful
3. Summarize findings
 - Summarize findings for each store and provide a recommendation that outlining the impact on sales during trial period
 - Visualization are very important and save tem.

Pearson Correlations

- Each case are independent from each other
- Must be a linear relationship between variables (straight line), can be verified using scatterplot (rectangle shape)

Degrees of Correlation (Relationship between 2 quant variables)

- Perfect: Value near ± 1 , meaning increasing one variable increase/decrease the other
- High Degree: Values between 0.5 to 1 suggests strong correlation
- Moderate Degree: Values between 0.3 and 0.49
- Low Degree: Values between 0.29
- No Correlation: Value = 0

```
In [462... import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```
In [463... df = pd.read_csv("Dataset/QVI_data.csv")
df
```

Out[463...

	LYLTY_CARD_NBR	DATE	STORE_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD
0	1000	2018-10-17	1	1	5	Natural Chip Compny SeaSalt175g	
1	1002	2018-09-16	1	2	58	Red Rock Deli Chikn&Garlic Aioli 150g	
2	1003	2019-03-07	1	3	52	Grain Waves Sour Cream&Chives 210G	
3	1003	2019-03-08	1	4	106	Natural ChipCo Hony Soy Chckn175g	
4	1004	2018-11-02	1	5	96	WW Original Stacked Chips 160g	
...
264829	2370701	2018-12-08	88	240378	24	Grain Waves Sweet Chilli 210g	
264830	2370751	2018-10-01	88	240394	60	Kettle Tortilla ChpsFeta&Garlic 150g	
264831	2370961	2018-10-24	88	240480	70	Tyrrells Crisps Lightly Salted 165g	
264832	2370961	2018-10-27	88	240481	65	Old El Paso Salsa Dip Chnky Tom Ht300g	
264833	2373711	2018-12-14	88	241815	16	Smiths Crinkle Chips Salt & Vinegar 330g	

264834 rows × 12 columns



In [464...

```
df["DATE"] = pd.to_datetime(df["DATE"])
df["YEAR_MONTH"] = df["DATE"].dt.strftime("%Y-%m")
df
```

Out [464...

	LYLTY_CARD_NBR	DATE	STORE_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROE
0	1000	2018-10-17	1	1	5	Natural Chip Compny SeaSalt175g	
1	1002	2018-09-16	1	2	58	Red Rock Deli Chikn&Garlic Aioli 150g	
2	1003	2019-03-07	1	3	52	Grain Waves Sour Cream&Chives 210G	
3	1003	2019-03-08	1	4	106	Natural ChipCo Hony Soy Chckn175g	
4	1004	2018-11-02	1	5	96	WW Original Stacked Chips 160g	
...
264829	2370701	2018-12-08	88	240378	24	Grain Waves Sweet Chilli 210g	
264830	2370751	2018-10-01	88	240394	60	Kettle Tortilla ChpsFeta&Garlic 150g	
264831	2370961	2018-10-24	88	240480	70	Tyrrells Crisps Lightly Salted 165g	
264832	2370961	2018-10-27	88	240481	65	Old El Paso Salsa Dip Chnky Tom Ht300g	
264833	2373711	2018-12-14	88	241815	16	Smiths Crinkle Chips Salt & Vinegar 330g	

264834 rows × 13 columns



In [465...

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 264834 entries, 0 to 264833
Data columns (total 13 columns):
#   Column                Non-Null Count  Dtype
---  -
0   LYLTY_CARD_NBR         264834 non-null int64
1   DATE                   264834 non-null datetime64[ns]
2   STORE_NBR              264834 non-null int64
3   TXN_ID                 264834 non-null int64
4   PROD_NBR               264834 non-null int64
5   PROD_NAME              264834 non-null object
6   PROD_QTY               264834 non-null int64
7   TOT_SALES              264834 non-null float64
8   PACK_SIZE              264834 non-null int64
9   BRAND                  264834 non-null object
10  LIFESTAGE              264834 non-null object
11  PREMIUM_CUSTOMER       264834 non-null object
12  YEAR_MONTH             264834 non-null object
dtypes: datetime64[ns](1), float64(1), int64(6), object(5)
memory usage: 26.3+ MB
```

Monthly Sales Experience: (Group by Store, then year-month)

- Only consider stores that have sales every month over July 2018 and June 2019. Select the best control store for each trial store during its pre-trial period.

- Total Sales Revenue
- Total Number of Customers
- Average number of transactions per customer

Total Sales Revenue

```
In [466... df_have_sales = df.copy()
df_have_sales = df_have_sales[df_have_sales["DATE"].between("2018-07-01", "2019-06-30")]
print(f'Min: {df_have_sales["DATE"].min()}')
print(f'Max: {df_have_sales["DATE"].max()}')
```

```
Min: 2018-07-01 00:00:00
Max: 2019-06-30 00:00:00
```

```
In [467... valid_stores = []
df_have_sales_grouped = df_have_sales.groupby("STORE_NBR")
store_count = df_have_sales_grouped["YEAR_MONTH"].nunique()
for store_nbr, count in store_count.items():
    if count == 12:
        valid_stores.append(store_nbr)
print(len(valid_stores))
```

260

```
In [468... # Ready to use for all metric calculation
df_have_sales_filtered = df_have_sales[df_have_sales["STORE_NBR"].isin(valid_stores)]
df_have_sales_filtered["STORE_NBR"].nunique()
```

Out[468...] 260

```
In [469...] df_potential_trial = df_have_sales_filtered[df_have_sales_filtered["YEAR_MONTH"] <
print(f'Max: {df_potential_trial["YEAR_MONTH"].max()}')
```

Max: 2019-01

```
In [470...] tot_sales_per_store = df_potential_trial.groupby(["STORE_NBR", "YEAR_MONTH"])["TOT_
tot_sales_per_store
```

```
Out[470...] STORE_NBR  YEAR_MONTH
1          2018-07      206.9
          2018-08      176.1
          2018-09      278.8
          2018-10      188.1
          2018-11      192.6
          ...
272        2018-09      304.7
          2018-10      430.6
          2018-11      376.2
          2018-12      403.9
          2019-01      423.0
Name: TOT_SALES, Length: 1820, dtype: float64
```

```
In [471...] unique_customers_per_store = df_potential_trial.groupby(["STORE_NBR", "YEAR_MONTH"]
unique_customers_per_store
```

```
Out[471...] STORE_NBR  YEAR_MONTH
1          2018-07      49
          2018-08      42
          2018-09      59
          2018-10      44
          2018-11      46
          ..
272        2018-09      32
          2018-10      44
          2018-11      41
          2018-12      47
          2019-01      46
Name: LYLTY_CARD_NBR, Length: 1820, dtype: int64
```

```
In [472...] total_transactions_per_store = df_potential_trial.groupby(["STORE_NBR", "YEAR_MONTH"]
total_transactions_per_store
```

```
Out[472...] STORE_NBR  YEAR_MONTH
1          2018-07      52
          2018-08      43
          2018-09      62
          2018-10      45
          2018-11      47
          ..
272        2018-09      36
          2018-10      51
          2018-11      45
          2018-12      47
          2019-01      50
Name: TXN_ID, Length: 1820, dtype: int64
```

```
In [473...] average_trans_per_store = round(total_transactions_per_store/unique_customers_per_s
average_trans_per_store
```

```
Out[473...] STORE_NBR  YEAR_MONTH
1          2018-07      1.06
          2018-08      1.02
          2018-09      1.05
          2018-10      1.02
          2018-11      1.02
          ...
272        2018-09      1.12
          2018-10      1.16
          2018-11      1.10
          2018-12      1.00
          2019-01      1.09
Length: 1820, dtype: float64
```

```
In [474...] metrics_df = pd.DataFrame({
    'TOT_SALES': tot_sales_per_store,
    'UNIQUE_CUSTOMERS': unique_customers_per_store,
    'TOTAL_TXNS': total_transactions_per_store,
    'AVG_TXNS_PER_CUST': average_trans_per_store
})
metrics_df
```

Out[474...

		TOT_SALES	UNIQUE_CUSTOMERS	TOTAL_TXNS	AVG_TXNS_PER
STORE_NBR	YEAR_MONTH				
1	2018-07	206.9	49	52	
	2018-08	176.1	42	43	
	2018-09	278.8	59	62	
	2018-10	188.1	44	45	
	2018-11	192.6	46	47	
...
272	2018-09	304.7	32	36	
	2018-10	430.6	44	51	
	2018-11	376.2	41	45	
	2018-12	403.9	47	47	
	2019-01	423.0	46	50	

1820 rows × 4 columns



In [475...

```
store_list = metrics_df.index.get_level_values('STORE_NBR').unique()
store_list
```

Out[475...

```
Index([ 1,  2,  3,  4,  5,  6,  7,  8,  9, 10,
        ...
        263, 264, 265, 266, 267, 268, 269, 270, 271, 272],
      dtype='int64', name='STORE_NBR', length=260)
```

Pearson Filtering Rules

1. Find stores that have the same sale period
2. Then conduct actual similarity test

In [476...

```
def pearson_correlation(trial, trial_nbr, potential_control, store_list): # we also
    trial_total_sales = trial["TOT_SALES"]
    trial_unique_customers = trial["UNIQUE_CUSTOMERS"]
    trial_average_trans = trial["AVG_TXNS_PER_CUST"]
    trial_mean_sales = trial["TOT_SALES"].mean()
    lower_bound = trial_mean_sales * 0.85
    upper_bound = trial_mean_sales * 1.15
    current_closest_store = 0 # we don't have a 0
    current_closest_coor = 0
    for cur_store_nbr in store_list:
        if cur_store_nbr != trial_nbr:
            potential_total_sales_mean = potential_control.loc[cur_store_nbr]["TOT_
            potential_total_sales = potential_control.loc[cur_store_nbr]["TOT_SALES
            potetial_unique_customers = potential_control.loc[cur_store_nbr]["UNIQUE
            potential_average_trans = potential_control.loc[cur_store_nbr]["AVG_TXN
```

```

        if (potential_total_sales_mean >= lower_bound) and (potential_total_sal
            cur_sales_coor = trial_total_sales.corr(potential_total_sales, meth
            cur_unique_customers_coor = trial_unique_customers.corr(potetial_un
            cur_average_trans_coor = trial_average_trans.corr(potential_average
            coor_average = round((cur_sales_coor + cur_unique_customers_coor +
            if coor_average >= current_closest_coor:
                current_closest_store = cur_store_nbr
                current_closest_coor = coor_average
    return current_closest_store, current_closest_coor

```

For each Trial

1. Compare Correlation for each of the three individually
 - Compare the months individually to see if they match
2. If the similarity is higher than a certain metric (0.65?) then we average it out
3. Save hte closest average similarity

```

In [477... trial_store_77 = metrics_df.loc[77]
control_store_77, control_store_77_coor = pearson_correlation(trial_store_77, 77, m
print(f"The control store for trial store 77 is: {control_store_77}, correlation is
trial_store_86 = metrics_df.loc[86]
control_store_86, control_store_86_coor = pearson_correlation(trial_store_86, 86, m
print(f"The control store for trial store 86 is: {control_store_86}, correlation is
trial_store_88 = metrics_df.loc[88]
control_store_88, control_store_88_coor = pearson_correlation(trial_store_88, 88, m
print(f"The control store for trial store 88 is: {control_store_88}, correlation is

```

The control store for trial store 77 is: 233, correlation is: 0.52
 The control store for trial store 86 is: 138, correlation is: 0.72
 The control store for trial store 88 is: 201, correlation is: 0.59

```

In [478... comparison_store_list = [77, 86, 88]
comparison_store_list.append(control_store_77)
comparison_store_list.append(control_store_86)
comparison_store_list.append(control_store_88)
comparison_store_list

```

Out[478... [77, 86, 88, 233, 138, 201]

Compare each Trial store with its Control store during the trial period (February 2019 - April 2019)

```

In [479... df_comparison = df_have_sales_filtered[df_have_sales_filtered["STORE_NBR"].isin(com
df_comparison = df_comparison[(df_comparison["YEAR_MONTH"] >= "2019-02") & (df_comp
print(f'Min: {df_comparison["YEAR_MONTH"].min()})')
print(f'Max: {df_comparison["YEAR_MONTH"].max()})')
df_comparison

```

Min: 2019-02
 Max: 2019-04

Out[479...

	LYLTY_CARD_NBR	DATE	STORE_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD
	73365	77000	2019-03-28	77	74911	18	Cheetos Chs & Bacon Balls 190g
	73366	77000	2019-04-13	77	74912	69	Smiths Chip Thinly S/Cream&Onion 175g
	73368	77001	2019-02-27	77	74913	7	Smiths Crinkle Original 330g
	73372	77003	2019-03-18	77	74917	80	Natural ChipCo Sea Salt & Vinegr 175g
	73377	77007	2019-03-20	77	74923	3	Kettle Sensations Camembert & Fig 150g

	232454	233470	2019-02-16	233	237252	17	Kettle Sensations BBQ&Maple 150g
	232457	233472	2019-04-10	233	237255	41	Doritos Salsa Mild 300g
	232468	233482	2019-02-16	233	237266	64	Red Rock Deli SR Salsa & Mzzrlla 150g
	232470	233486	2019-04-21	233	237268	35	Woolworths Mild Salsa 300g
	232475	233491	2019-03-22	233	237273	28	Thins Potato Chips Hot & Spicy 175g

1967 rows × 13 columns



In [480...

```
tot_sales_per_store_comp = df_comparison.groupby(["STORE_NBR", "YEAR_MONTH"])["TOT_
unique_customers_per_store_comp = df_comparison.groupby(["STORE_NBR", "YEAR_MONTH"]
total_transactions_per_store_comp = df_comparison.groupby(["STORE_NBR", "YEAR_MONTH
average_trans_per_store_comp = round(total_transactions_per_store_comp/unique_custo
comp_df = pd.DataFrame({
    'TOT_SALES': tot_sales_per_store_comp,
    'UNIQUE_CUSTOMERS': unique_customers_per_store_comp,
    'TOTAL_TXNS': total_transactions_per_store_comp,
    'AVG_TXNS_PER_CUST': average_trans_per_store_comp
```

```
})
comp_df
```

Out[480...

		TOT_SALES	UNIQUE_CUSTOMERS	TOTAL_TXNS	AVG_TXNS_PER_CUST
STORE_NBR	YEAR_MONTH				
77	2019-02	235.0	45	45	
	2019-03	278.5	50	55	
	2019-04	263.5	47	48	
86	2019-02	913.2	107	139	
	2019-03	1026.8	115	142	
	2019-04	848.2	105	127	
88	2019-02	1370.2	124	154	
	2019-03	1477.2	134	170	
	2019-04	1439.4	128	162	
138	2019-02	748.6	90	112	
	2019-03	940.6	106	138	
	2019-04	834.2	106	128	
201	2019-02	1139.2	111	128	
	2019-03	1364.2	130	152	
	2019-04	1246.6	122	146	
233	2019-02	244.0	45	47	
	2019-03	199.1	40	41	
	2019-04	158.6	30	33	

In [481...

```
def calculate_pre_post_growth(trial_store_nbr, control_store_nbr, metrics_df, trial_start, trial_end):
    trial_data = metrics_df.loc[trial_store_nbr].copy()
    control_data = metrics_df.loc[control_store_nbr].copy()
    pre_trial = trial_data[trial_data.index < trial_start]
    during_trial = trial_data[trial_data.index >= trial_start]
    pre_control = control_data[control_data.index < trial_start]
    during_control = control_data[control_data.index >= trial_start]
    metrics = ['TOT_SALES', 'UNIQUE_CUSTOMERS', 'TOTAL_TXNS', 'AVG_TXNS_PER_CUST']
    result = {}
    for metric in metrics:
        trial_growth = ((during_trial[metric].mean() - pre_trial[metric].mean()) /
                        (during_control[metric].mean() - pre_control[metric].mean()))
        control_growth = ((during_control[metric].mean() - pre_control[metric].mean()) /
                          (during_trial[metric].mean() - pre_trial[metric].mean()))
        did = trial_growth - control_growth
        result[metric] = {
            'trial_growth_pct': round(trial_growth, 2),
            'control_growth_pct': round(control_growth, 2),
            'did': did
        }
```

```

        'control_growth_pct': round(control_growth, 2),
        'difference_in_diff': round(did, 2)
    }

    return pd.DataFrame(result).T

```

```

In [482... full_df = pd.concat([metrics_df, comp_df])
trial_start_date = '2019-02'

```

Comparison for Trial Store 77, Control store is 119

```

In [483... store_77_stats = comp_df.loc[77].reset_index()
store_77_stats.insert(1, "STORE_NBR", [77,77,77])
store_233_stats = comp_df.loc[233].reset_index()
store_233_stats.insert(1, "STORE_NBR", [233, 233, 233])
store_77_233 = pd.concat([store_77_stats, store_233_stats])
store_77_233

```

	YEAR_MONTH	STORE_NBR	TOT_SALES	UNIQUE_CUSTOMERS	TOTAL_TXNS	AVG_TXNS_
0	2019-02	77	235.0	45	45	
1	2019-03	77	278.5	50	55	
2	2019-04	77	263.5	47	48	
0	2019-02	233	244.0	45	47	
1	2019-03	233	199.1	40	41	
2	2019-04	233	158.6	30	33	

```

In [484... results_77 = calculate_pre_post_growth(77, 233, full_df, '2019-02')
results_77

```

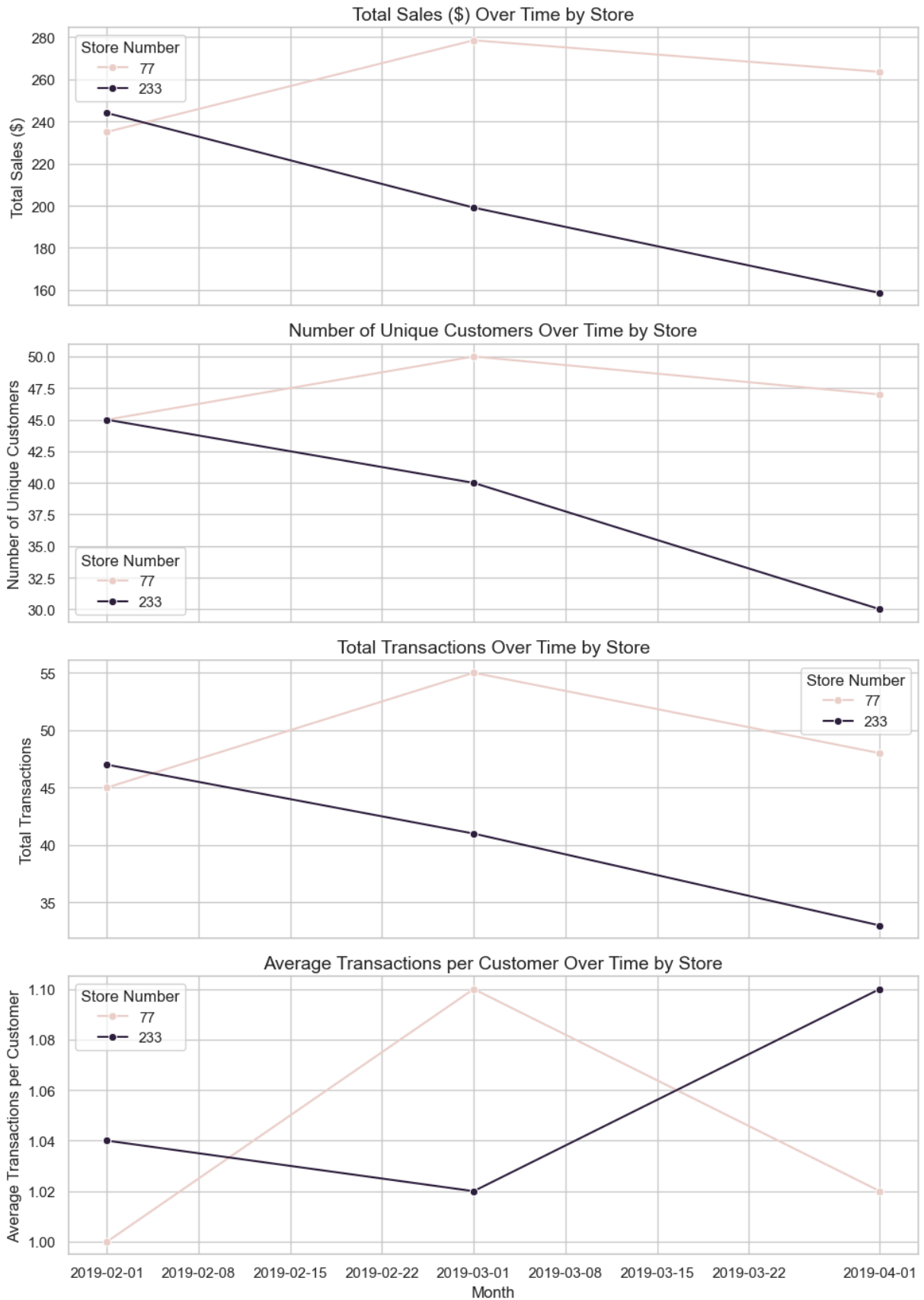
	trial_growth_pct	control_growth_pct	difference_in_diff
TOT_SALES	6.71	-15.41	22.12
UNIQUE_CUSTOMERS	10.81	-9.96	20.77
TOTAL_TXNS	8.94	-9.22	18.16
AVG_TXNS_PER_CUST	-2.02	1.28	-3.30

```

In [485... store_77_233['YEAR_MONTH'] = pd.to_datetime(store_77_233['YEAR_MONTH'])
sns.set_style("whitegrid")
metrics_info = {
    'TOT_SALES': 'Total Sales ($)',
    'UNIQUE_CUSTOMERS': 'Number of Unique Customers',
    'TOTAL_TXNS': 'Total Transactions',
    'AVG_TXNS_PER_CUST': 'Average Transactions per Customer'
}
fig, axes = plt.subplots(len(metrics_info), 1, figsize=(10, 14), sharex=True)

```

```
for i, (metric, ylabel) in enumerate(metrics_info.items()):
    sns.lineplot(
        data=store_77_233,
        x='YEAR_MONTH',
        y=metric,
        hue='STORE_NBR',
        marker='o',
        ax=axes[i]
    )
    axes[i].set_title(f'{ylabel} Over Time by Store', fontsize=14)
    axes[i].set_ylabel(ylabel, fontsize=12)
    axes[i].legend(title='Store Number')
axes[-1].set_xlabel('Month', fontsize=12)
plt.tight_layout()
plt.show()
```



Trial 77 and Control 233 Analysis Total Sales:

- Trial store 77 experienced a 6.71% increase in total sales during the trial period, while control store 233 saw a significant decline. This suggests that the trial layout may have

had a positive impact on revenue. However, the result should be interpreted with caution, as the drop in the control store's sales could be due to external factors unrelated to the trial. To further enhance sales, a possible recommendation is to position high demand or seasonal items near the entrance to drive early conversion.

Unique Customers:

- Store 77 showed a 10.8% increase in unique customers, while store 233 experienced a 9.96% decline. This indicates that the trial layout may have been effective in attracting new customers or attracting returning customers. To build on this momentum, the store could implement a monthly rotation of featured products near high visibility areas to maintain novelty and broaden appeal across customer segments.

Average Transactions per Customer

- While average transactions per customer decreased at the trial store, total sales and unique customers increased. This suggests that although individual customers are making fewer trips, they may be spending more per visit, or new customers are compensating with higher value. This shift should be monitored further, and the store might consider bundling or upselling strategies to encourage more frequent transactions.

Trial Store 86, 138

```
In [486... store_86_stats = comp_df.loc[86].reset_index()
store_86_stats.insert(1, "STORE_NBR", [86, 86, 86])
store_138_stats = comp_df.loc[138].reset_index()
store_138_stats.insert(1, "STORE_NBR", [138, 138, 138])
store_86_138 = pd.concat([store_86_stats, store_138_stats])
store_86_138
```

```
Out[486...  YEAR_MONTH  STORE_NBR  TOT_SALES  UNIQUE_CUSTOMERS  TOTAL_TXNS  AVG_TXNS_
0      2019-02         86      913.2             107         139
1      2019-03         86     1026.8             115         142
2      2019-04         86      848.2             105         127
0      2019-02        138      748.6              90         112
1      2019-03        138      940.6             106         138
2      2019-04        138      834.2             106         128
```



```
In [487... results_86 = calculate_pre_post_growth(86, 138, full_df, '2019-02')
results_86
```

Out[487...

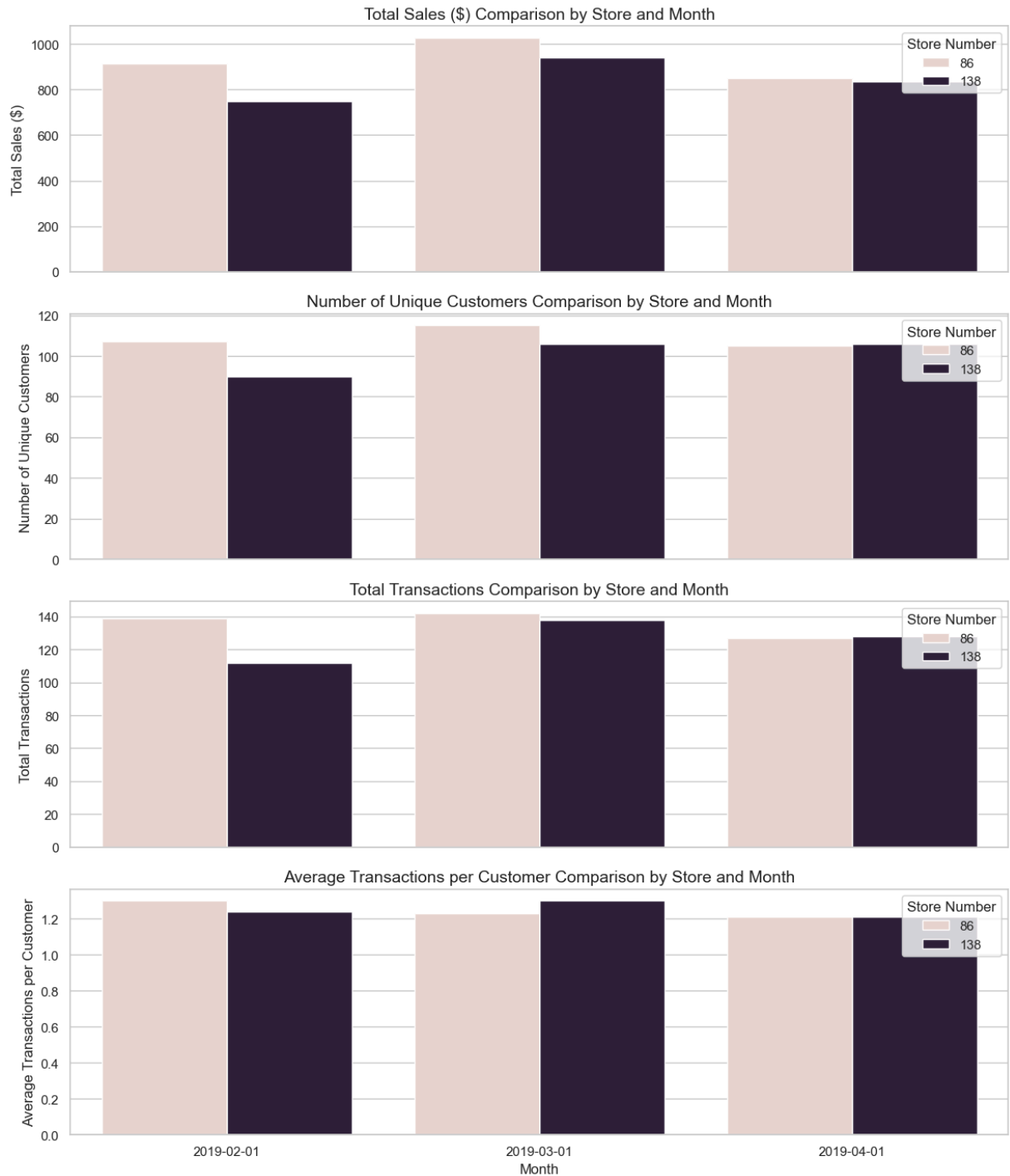
	trial_growth_pct	control_growth_pct	difference_in_diff
TOT_SALES	6.31	-6.88	13.19
UNIQUE_CUSTOMERS	9.47	-1.86	11.33
TOTAL_TXNS	7.94	-3.61	11.54
AVG_TXNS_PER_CUST	-1.39	-1.80	0.40

In [488...

```

store_86_138['YEAR_MONTH'] = pd.to_datetime(store_86_138['YEAR_MONTH'])
metrics_info = {
    'TOT_SALES': 'Total Sales ($)',
    'UNIQUE_CUSTOMERS': 'Number of Unique Customers',
    'TOTAL_TXNS': 'Total Transactions',
    'AVG_TXNS_PER_CUST': 'Average Transactions per Customer'
}
fig, axes = plt.subplots(len(metrics_info), 1, figsize=(12, 14), sharex=True)
for i, (metric, ylabel) in enumerate(metrics_info.items()):
    sns.barplot(
        data=store_86_138,
        x='YEAR_MONTH',
        y=metric,
        hue='STORE_NBR',
        ax=axes[i]
    )
    axes[i].set_title(f'{ylabel} Comparison by Store and Month', fontsize=14)
    axes[i].set_ylabel(ylabel, fontsize=12)
    axes[i].legend(title='Store Number')
axes[-1].set_xlabel('Month', fontsize=12)
plt.tight_layout()
plt.show()

```



Trial 86 and Control 138 Analysis

Total Sales:

- Trial store 86 experienced a 6.31% increase in total sales during the trial period, while control store 138 experienced a 6.88 decrease. The growth rate is fairly similar to trial store 77, which further supports that the trial layout had a positive impact on revenue. Interestingly, control store 233 saw a similar decline in total sales, indicating that most trial stores may have experienced a decline in sales during the trial period.

Unique Customers:

- Store 86 saw a 9.47% increase in unique customers, while store 138 experienced a slight decrease in 1.86 percent. This further supports the positive effect of the trial layout in attracting more customers.

Average Transactions per Customer

- For both stores, average transactions per customers decreased slightly. Despite this, the two stores saw different returns in terms of total sales and total transactions. Trial store 86 saw an increase in transactions, whereas store 138 saw a small decrease. This indicates that for store 86, despite a decrease in average transactions per customer, the increase in unique customersa ultimately led to higher sales.

Trial Store 88, Control 178

In [489...

```
store_88_stats = comp_df.loc[88].reset_index()
store_88_stats.insert(1, "STORE_NBR", [88, 88, 88])
store_201_stats = comp_df.loc[201].reset_index()
store_201_stats.insert(1, "STORE_NBR", [201, 201, 201])
store_88_201 = pd.concat([store_88_stats, store_201_stats])
store_88_201
```

Out[489...

	YEAR_MONTH	STORE_NBR	TOT_SALES	UNIQUE_CUSTOMERS	TOTAL_TXNS	AVG_TXNS
0	2019-02	88	1370.2	124	154	
1	2019-03	88	1477.2	134	170	
2	2019-04	88	1439.4	128	162	
0	2019-02	201	1139.2	111	128	
1	2019-03	201	1364.2	130	152	
2	2019-04	201	1246.6	122	146	

In [490...

```
results_88 = calculate_pre_post_growth(88 , 201, full_df, '2019-02')
results_88
```

Out[490...

	trial_growth_pct	control_growth_pct	difference_in_diff
TOT_SALES	6.60	6.77	-0.17
UNIQUE_CUSTOMERS	2.35	4.44	-2.09
TOTAL_TXNS	4.81	5.30	-0.49
AVG_TXNS_PER_CUST	2.44	0.65	1.79

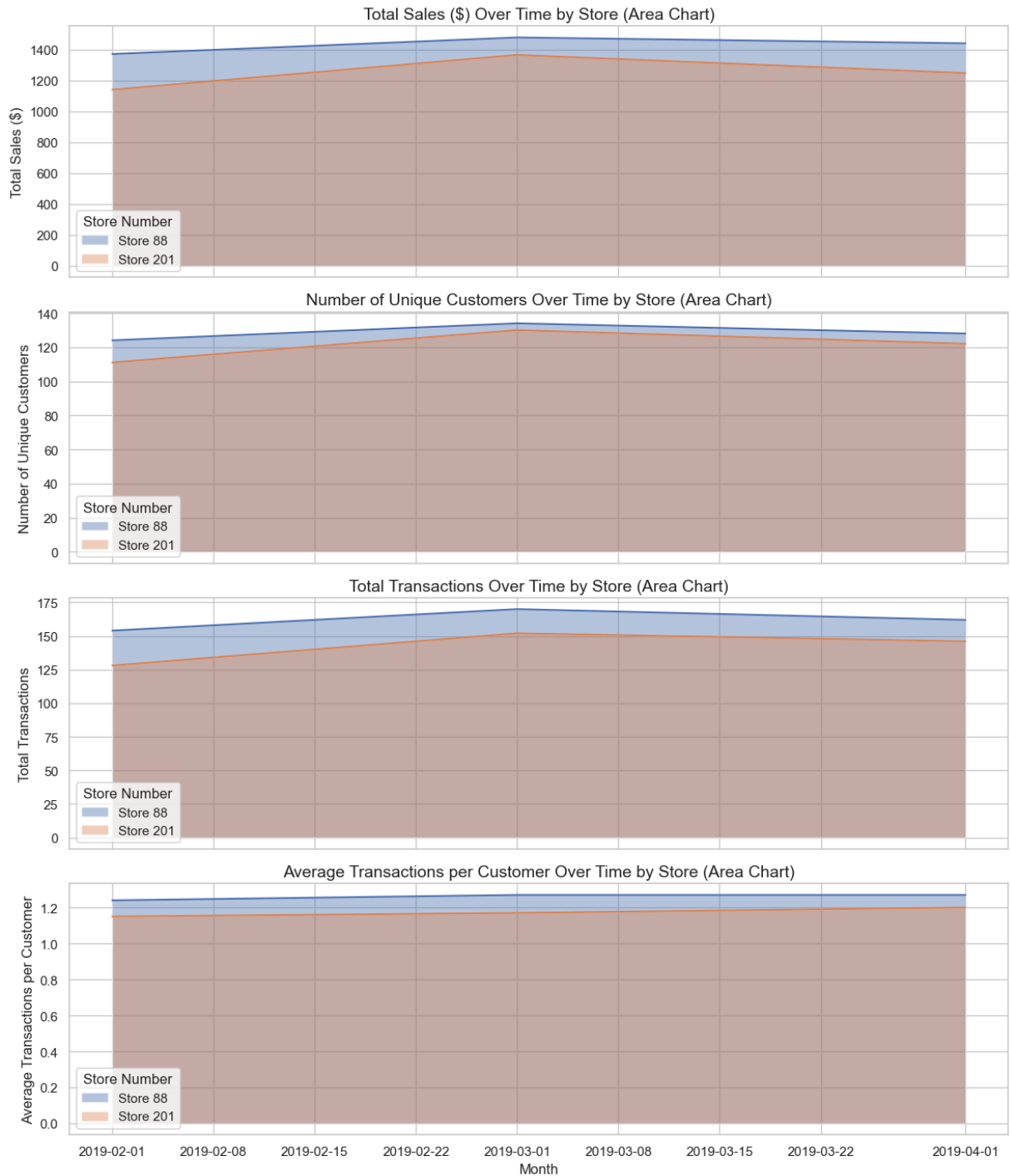
In [491...

```
store_88_201['YEAR_MONTH'] = pd.to_datetime(store_88_201['YEAR_MONTH'])

metrics_info = {
    'TOT_SALES': 'Total Sales ($)',
```

```
'UNIQUE_CUSTOMERS': 'Number of Unique Customers',
'TOTAL_TXNS': 'Total Transactions',
'AVG_TXNS_PER_CUST': 'Average Transactions per Customer'
}

fig, axes = plt.subplots(len(metrics_info), 1, figsize=(12, 14), sharex=True)
for i, (metric, ylabel) in enumerate(metrics_info.items()):
    for store in store_88_201['STORE_NBR'].unique():
        data = store_88_201[store_88_201['STORE_NBR'] == store]
        axes[i].fill_between(data['YEAR_MONTH'],
                             data[metric],
                             alpha=0.4,
                             label=f'Store {store}')
        axes[i].plot(data['YEAR_MONTH'], data[metric]) # plot line on top for clar
    axes[i].set_title(f'{ylabel} Over Time by Store (Area Chart)', fontsize=14)
    axes[i].set_ylabel(ylabel, fontsize=12)
    axes[i].legend(title='Store Number')
axes[-1].set_xlabel('Month', fontsize=12)
plt.tight_layout()
plt.show()
```



Trial Store 88 and Control Store 201 Analysis

Total Sales:

- Trial store 88 saw a 6.6% increase in total sales during the trial period, while control store 201 saw a similar 6.77% increase in total sales. This is the first instance during the experiment where both stores saw an increase in total sales. Despite the increase in total sales for store 201, trial store 88 remained fairly consistent in terms of growth comparing to other trial store, indicating that there is a positive impact with the trial layout and total sales.

Unique Customers:

- Store 88 saw a modest 2.35% increase in unique customers, compared to a 4.44% increase at the control store. This raises concerns about the trial layout's effectiveness in attracting new or returning customers, as the control store outperformed in this area. One explanation may be that Store 201 has stronger baseline performance or more effective local marketing. The result suggests that layout changes alone may not be enough to drive customer growth without supporting promotions.

Average Transactions Per Customer:

- Here, Store 88 outperformed, with a 2.44% increase in average transactions per customer, compared to 0.65% at the control store a difference in difference of +1.79%. This suggests that while Store 88 didn't attract significantly more customers, those who did shop there were more engaged, possibly purchasing more frequently or spending more per visit. This could be a result of improved product placement, easier navigation, or a more appealing in store experience.

Conclusion:

- The trial layout seems effective in increasing total sales, as all three stores experienced a boost in around 6.5%. However, as control store 201 experienced a similar increase in total sales during that period at around 6.77%, the solution may not be as simple as changing the layout. Better marketing and bundle deals should also be considered alongside the new layout to maximize sales.
- The driver of change seems to be more unique customers purchasing from the store. All 3 trial stores saw an increase in unique customers, with trial store 77 and 86 seeing a massive growth. The new layout seems to be attracting more customers to enter and view items they may not have noticed prior. A potential suggestion could be implementing a monthly "hot" items display, attracting new customers and retaining returning customers' interest.