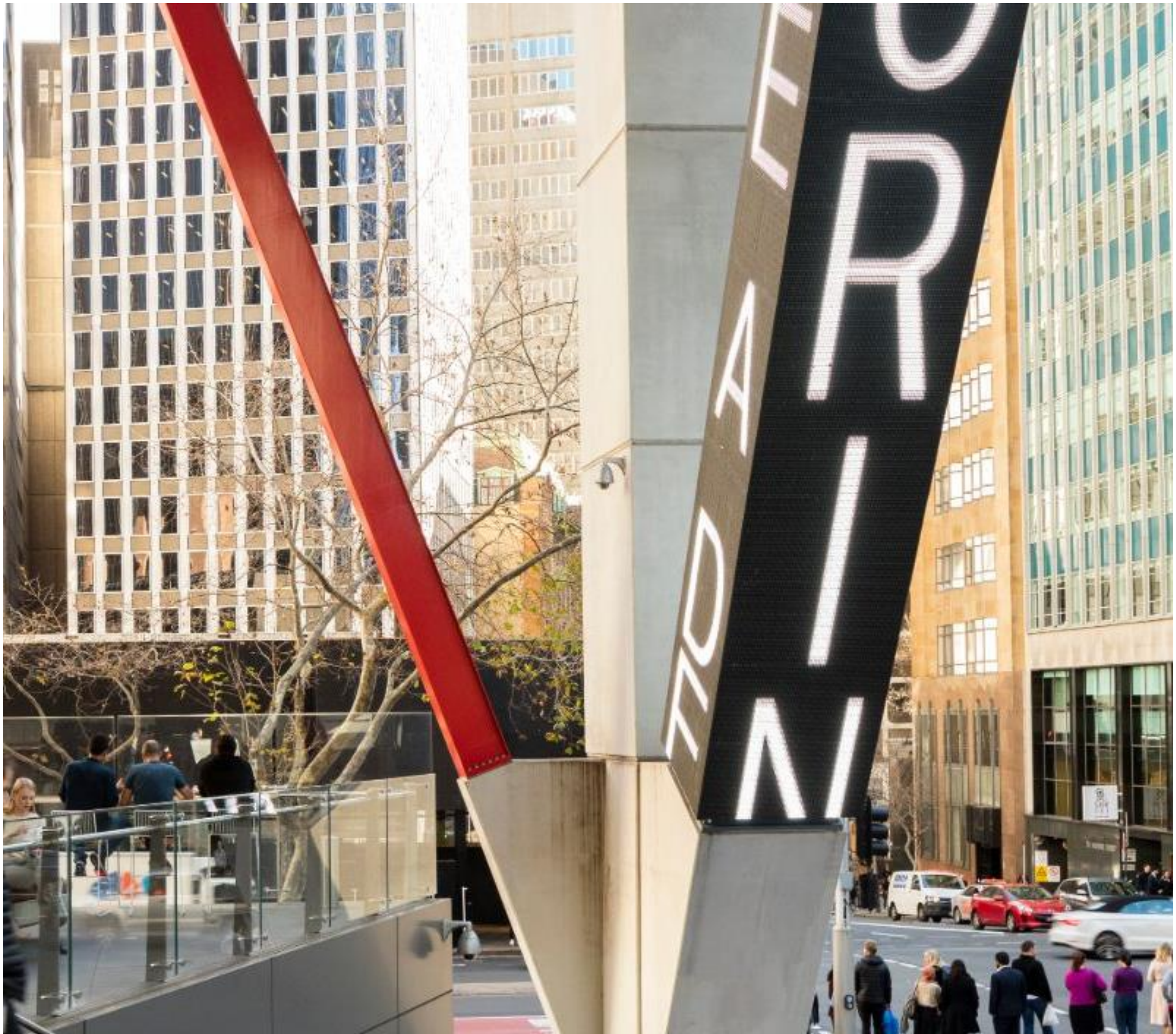


QUANTIUM VIRTUAL INTERNSHIP

TASK 2

JOEL DOMINGO

Joeldomingo117@gmail.com

NOTE: TO SKIP SUMMARY FOR RAW CODE AND OUTPUT PROCEEED TO PAGE 15
Libraries Used:

```
# Import Libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import datetime as dt
from scipy.ndimage.filters import gaussian_filter1d
import pandasql as ps
import warnings
warnings.filterwarnings('ignore')
from pylab import rcParams
from scipy.stats import f_oneway
from scipy.stats import ttest_ind
```

Establishing Control Stores

Our first task will be to establish control stores. Our trial stores are 77, 86 and 88 so we must find potential stores which have similar performance to the trial stores. We can do this by looking at specific metrics during the trial period beginning February 2019.

Metrics:

- Sales Revenue
- Number of Customers
- Number of Transactions

STORE_NBR	TOT_SALES	NBR_OF_CUST	AVG_QTY	AVG_UNIT_PRICE
86	5795.65	832	1.99	3.51
88	8832.80	1028	1.98	4.33
77	1595.50	298	1.52	3.56

Before writing a function to choose comparable control stores, we must first define what metric we will use. Our search criteria will be if all the features (total sales, number of customers and number of transactions) are within 5% of the trail store's feature value, all records being prior to the trial period.

For example, the number of customers, average quantity, and average unit price of the potential control store, must be within 5% of the same feature's value in the trial store.

- **If the trial store is Store 86:**
  - Total sales: 5795.65
  - Number of customers: 832
  - Average Quantity: 1.99
  - Average Unit Price: 3.51

- **Then the control store candidate must be within these parameters:**
  - Total sales: Within 5505.9 & 6084.75
  - Number of customers: Within 791.4 & 873
  - Average Quantity: Within 1.89 & 2.09
  - Average Unit Price: Within 3.33 & 3.68

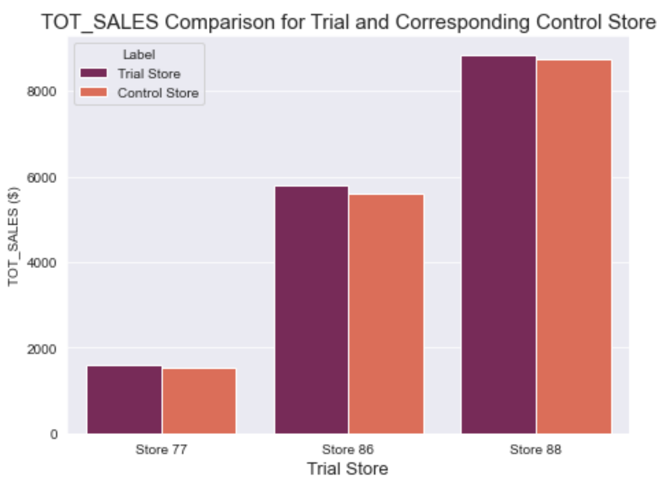
Control Store Candidates

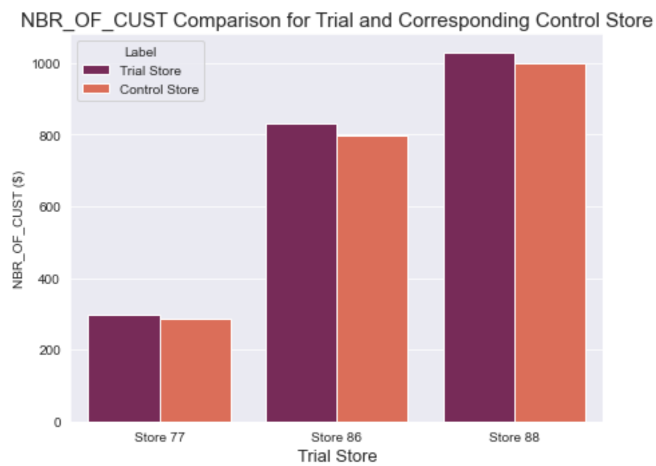
Our function has chosen the following control stores for the corresponding trial stores:

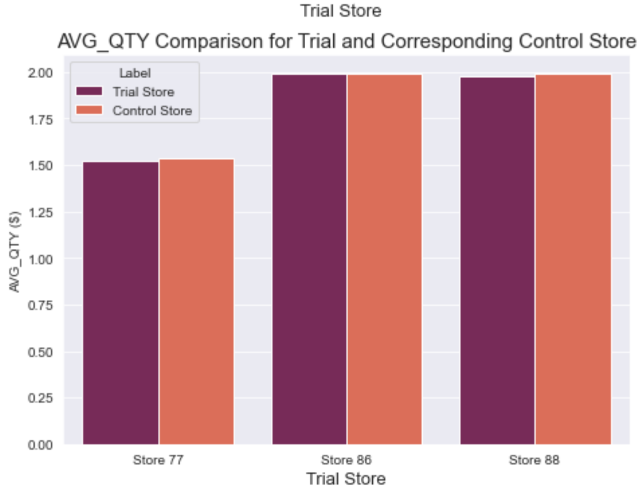
Trial Store	Control Store Candidate
77	233
86	67
88	165

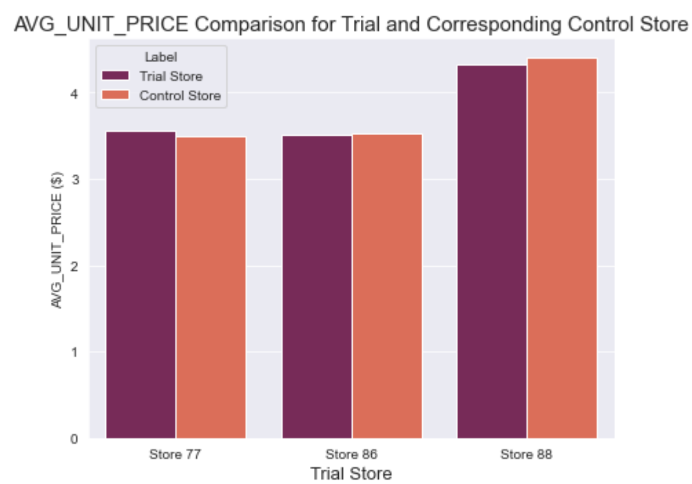
Below are the summary metric statistics for trial stores and their corresponding control stores prior to the trial period.

Metrics	Trial_store_77	Control_store_77	Trial_store_86	Control_store_86	Trial_store_88	Control_store_88
STORE_NBR	77.00	233.00	86.00	67.00	88.00	165.00
TOT_SALES	1595.50	1534.50	5795.65	5601.20	8832.80	8748.20
NBR_OF_CUST	298.00	285.00	832.00	798.00	1028.00	999.00
AVG_QTY	1.52	1.54	1.99	1.99	1.98	1.99
AVG_UNIT_PRICE	3.56	3.50	3.51	3.53	4.33	4.40









We can see from our visualizations that the control groups closely match the performance of the corresponding trial groups in all aspects, prior to the trial period.

Assessing Performance (Total Sales)

Now that we have our trial and control stores, we can now assess the performance of the trial period and the effect of the changes on the trial store and compare them to the control stores. To begin, we can gather the control and trial store data just prior to the trial period. Since the trial period if Feb to April, we need data from 2 months prior to the trial. However, we cannot use December as our comparison, due to the fact that sales in December contain outliers (Christmas period). Therefore, we will combine transaction data for the stores in November 2018 and January 2019.

STORE_NBR	TOT_SALES	NBR_OF_CUST	AVG_QTY	AVG_UNIT_PRICE	TYPE	Name
77	413.3	77	1.57	3.48	Trial Store	Store 77
233	328.6	65	1.42	3.58	Control Store	Store 77
86	1602.0	233	2.00	3.44	Trial Store	Store 86
67	1573.6	228	2.00	3.45	Control Store	Store 86
88	2449.8	282	2.00	4.34	Trial Store	Store 88
165	2479.2	285	1.99	4.37	Control Store	Store 88

Scaling Pre-Trial Figures (Sales)

Again, we can be reassured that the metric statistics for the trial stores and their corresponding control stores are very similar for the months prior to the trial. The above statistics are for the months of January 2019 and November the previous year.

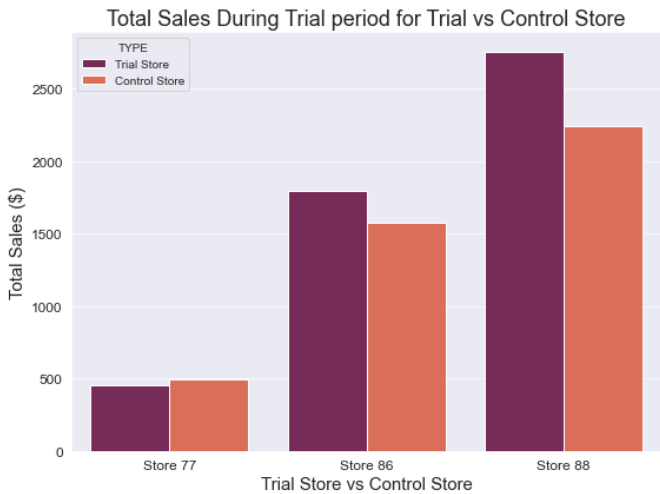
The trial period goes from the start of February 2019 to April 2019. We want to see if there has been an uplift in overall chip sales. We will start with scaling the control store's sales to a similar level to control for any differences between the two stores outside of the trial period.

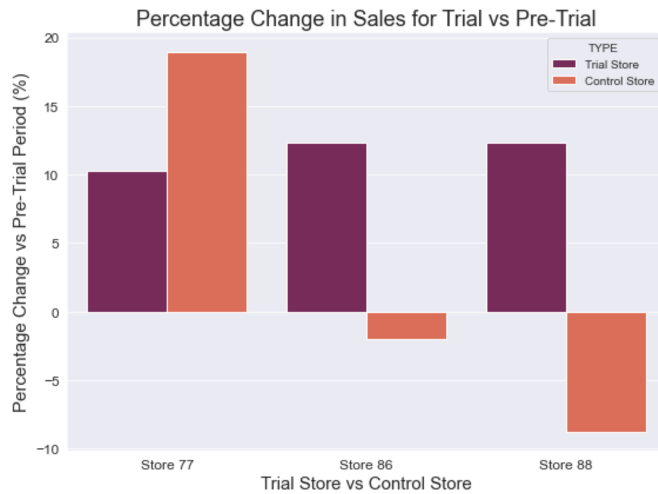
STORE_NBR	TOT_SALES	NBR_OF_CUST	AVG_QTY	AVG_UNIT_PRICE	TYPE	Name
77	413.3	77	1.57	3.48	Trial Store	Store 77
233	414.0	65	1.42	3.58	Control Store	Store 77
86	1602.0	233	2.00	3.44	Trial Store	Store 86
67	1605.1	228	2.00	3.45	Control Store	Store 86
88	2449.8	282	2.00	4.34	Trial Store	Store 88
165	2454.4	285	1.99	4.37	Control Store	Store 88

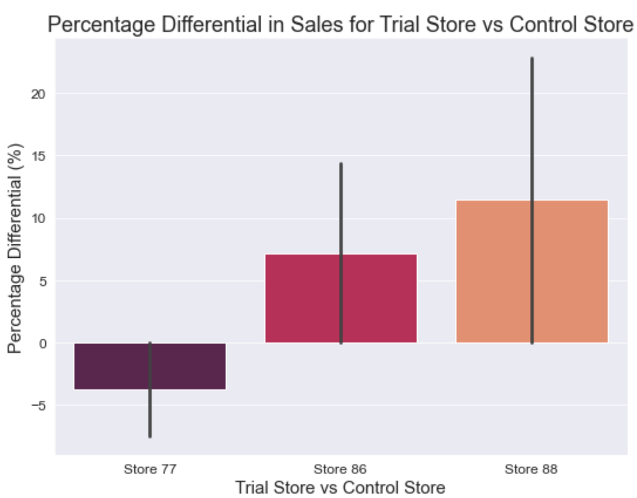
Now that we have our scaled figures for the baseline (pre-trial), we can scale the actual transactions for the trial period.

Trial Period Statistics:

STORE_NBR	TYPE	PRE_TRIAL_SALES	TRIAL_SALES	%_CHANGE	%_DIFFERENCE	TRIAL_STORE
77	Trial Store	413.3	455.70	10.26	-7.48	Store 77
233	Control Store	414.0	492.53	18.97	0.00	Store 77
86	Trial Store	1602.0	1799.60	12.33	14.36	Store 86
67	Control Store	1605.1	1573.66	-1.96	0.00	Store 86
88	Trial Store	2449.8	2752.60	12.36	22.89	Store 88
165	Control Store	2454.4	2239.88	-8.74	0.00	Store 88







Insights

Now that we have our results, we can see that 2/3 trial stores were able to have total sales increase over their corresponding control store. Similarly, those same stores were the only ones to have higher percentage change in sales from pre-trial to the end of the trial period, higher than their control store counterpart.

- Trial store 77 did not see a percentage increase higher than its control store.
- Trial stores 86 and 88 did see an increase in sales compared to their control stores.

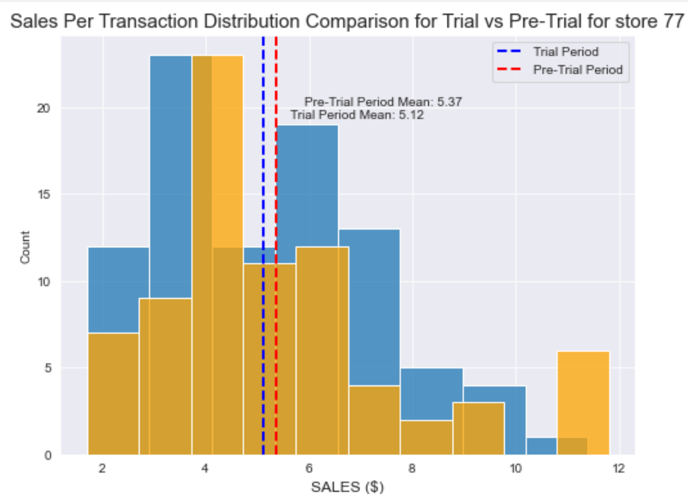
We see that stores 86 and 88 are the only stores during the trial to have a significant positive percentage differential over their control counterparts.

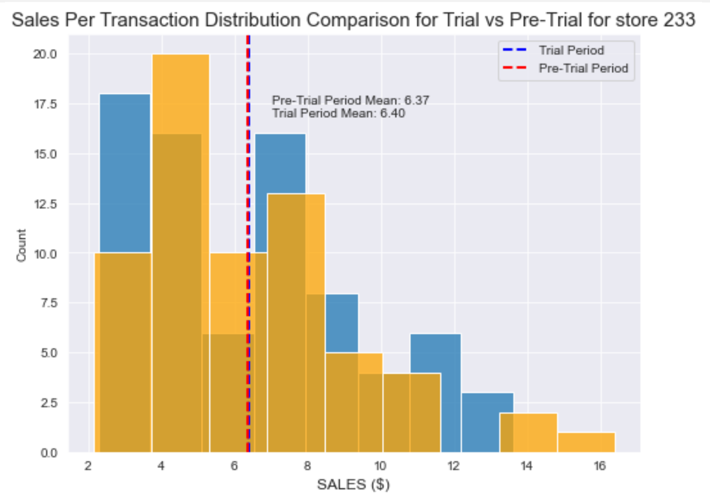
Significance Testing: T-Tests (Total Sales)

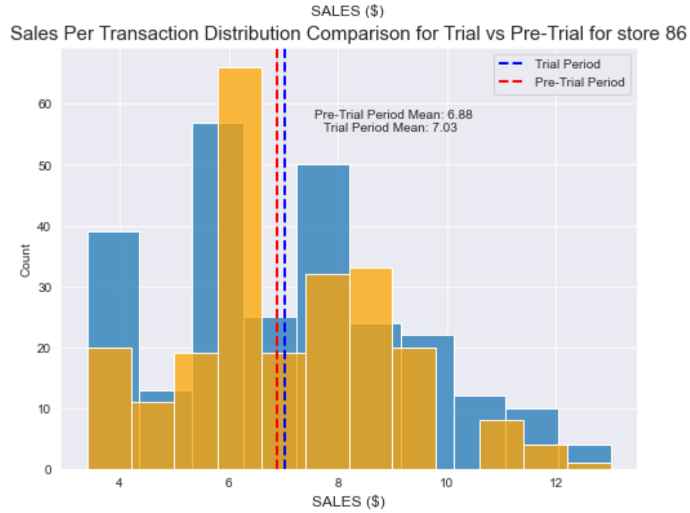
Now that we have our comparable statistics for total sales, we can check if the difference is significance by doing a T-Test. Our first test will have a null hypothesis being that the trial period is the same as the pre-trial period (total sales).

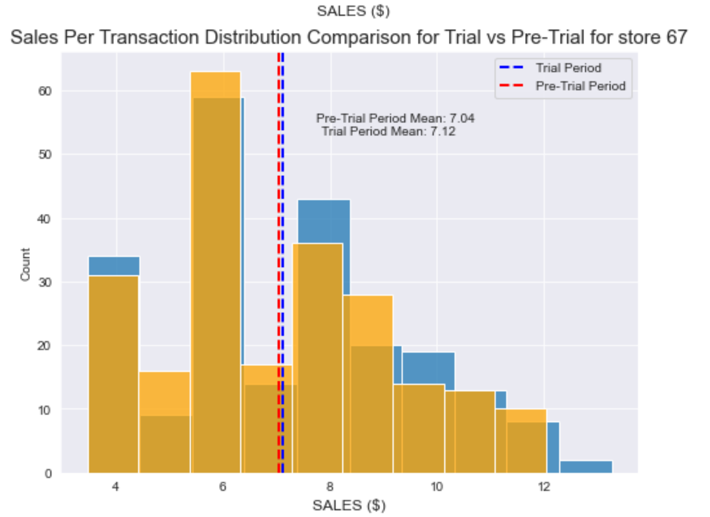
First, we can examine their distributions.

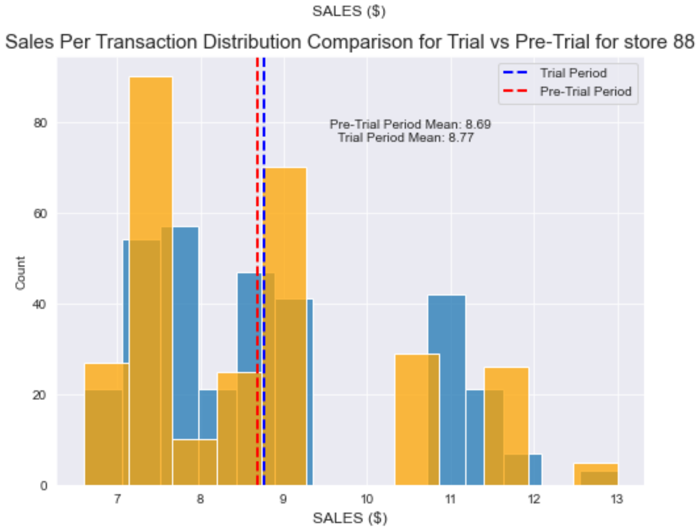
Trial Store	Control Store

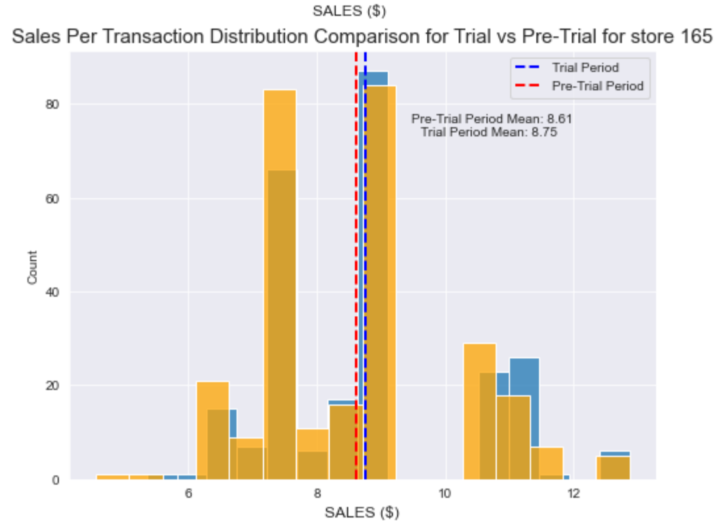












Significance Testing: T-Tests (cont.)

To refresh, our null hypothesis is that the trial period statistics are the same as the pre-trial transactions. The target we're aiming for is a p-value of 0.05, that the chance of H0 being true is below 5%. For our T-test, we went for a sample size of 50 to get an appropriate number of samples.

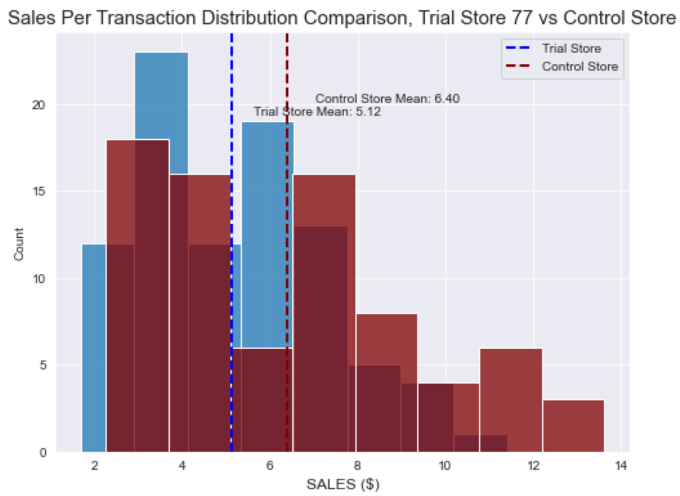
T-Test Results

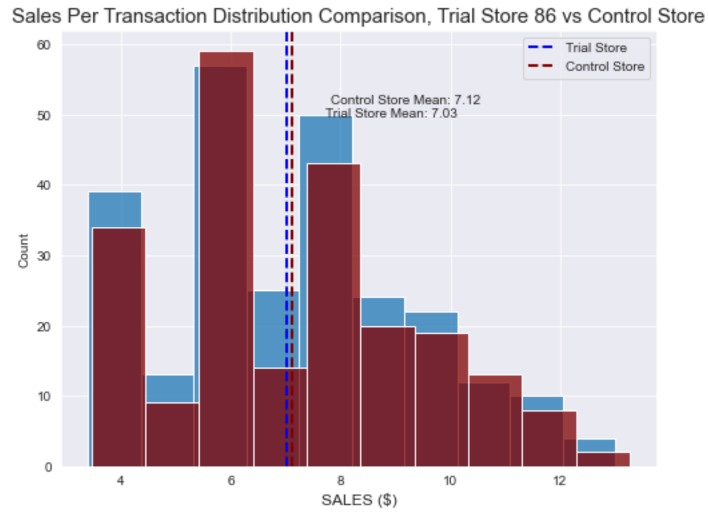
Trial Store	Statistics	P-Value	Outcome
77	2.316	0.023	Different distributions (Reject H0)
86	2.389	0.024	Different distributions (Reject H0)
88	-2.232	0.034	Different distributions (Reject H0)

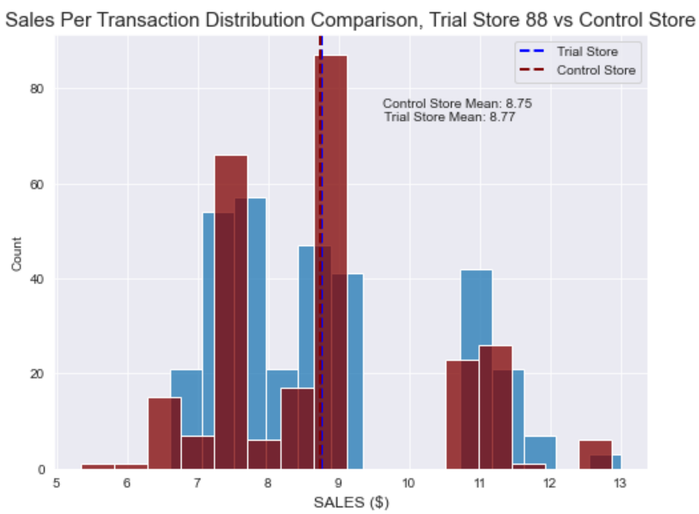
Insights

We see that there is a significant difference between the distributions of the trial stores during the trial period and outside the trial period. We will next run a test to see if the difference between the trial and control stores during the trial period are significantly different. First, we will look at the distributions of our groups as previous, then run a T-test on the 3 pairs of stores.

Distributions of Trial and Control Stores (Total Sales) During Trial Period







Significance Testing: T-Tests (cont.)

To run our T-test, we will need to set our null hypothesis. H0 in this case will be that the distribution of total sales in the trial stores are not significantly different to the control stores. Our p-value will again be set at 0.05, with a sample size of 50.

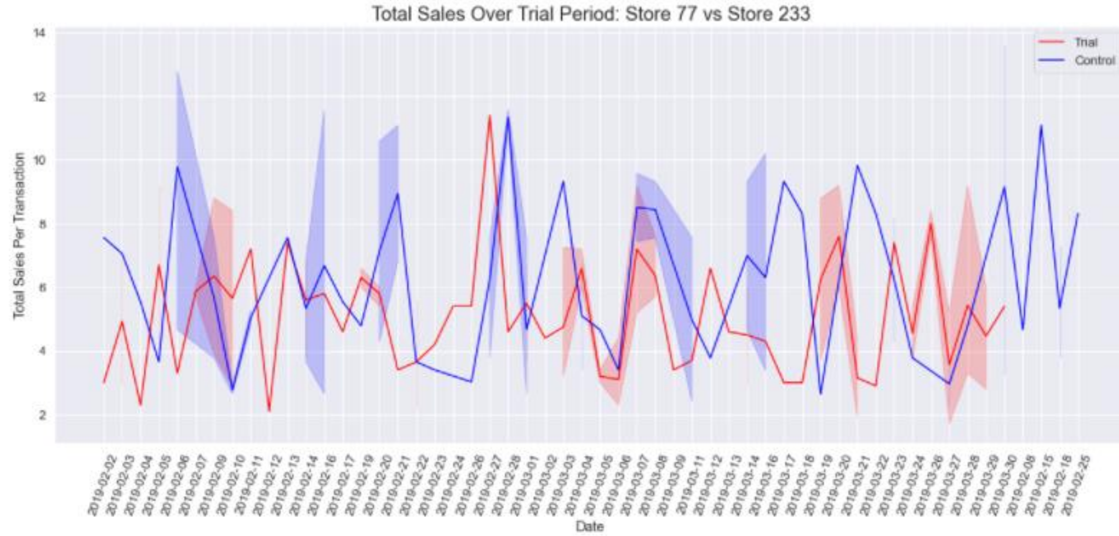
Trial Store	Control Store	Statistics	P-Value	Outcome
77	233	-2.092	0.039	Different distributions (Reject H0)
86	67	-1.002	0.319	Same distribution (Fail to reject H0)
88	165	2.762	0.007	Different distributions (Reject H0)

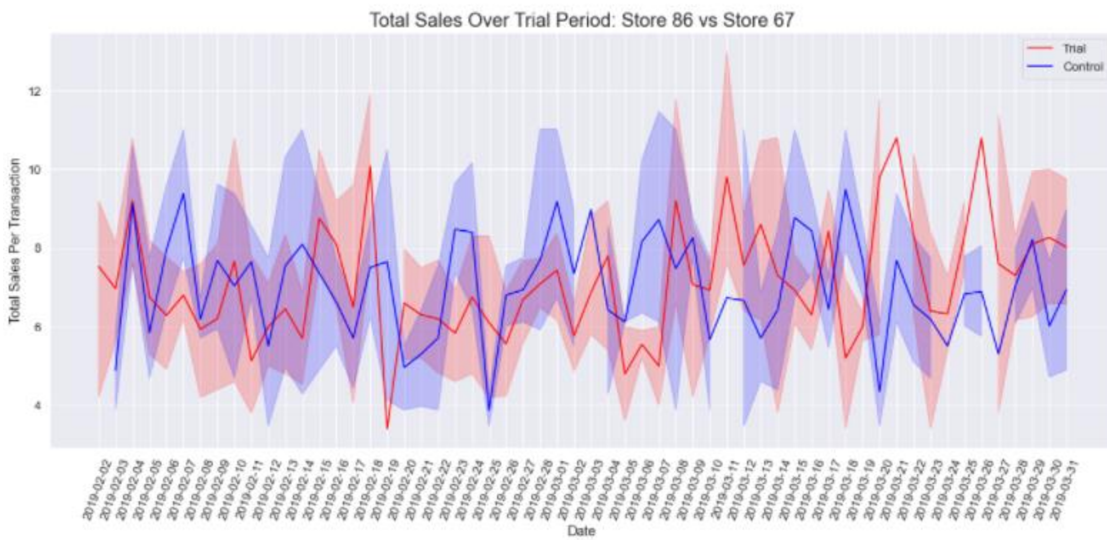
Insights

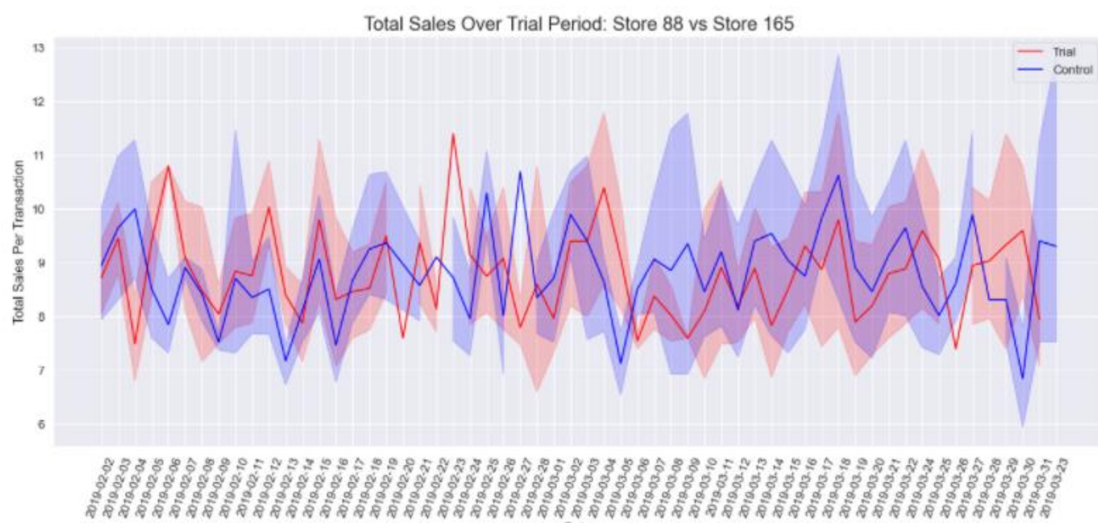
We see that the difference between the trial and control stores are significant in stores 77 & 233, and 88 & 165. However, the difference in stores 86 & 67 does for total sales does not seem to be significant.

Visualizations

Let’s visualize the sales over the trial period to see how different they are.







Assessing Performance (Number of Customers)

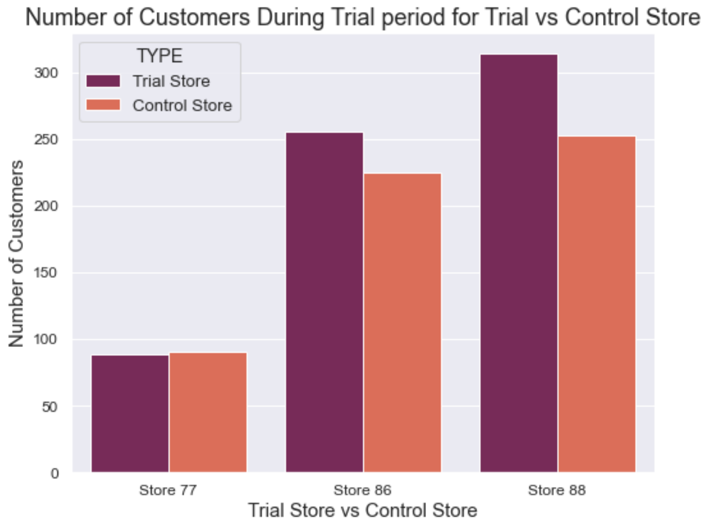
Now that we have our metrics for total sales, we can repeat the process and assess the performance of the trial period and its effect on the number of customers on the trial stores. We can assess them as we did before, by comparing them to the corresponding control stores.

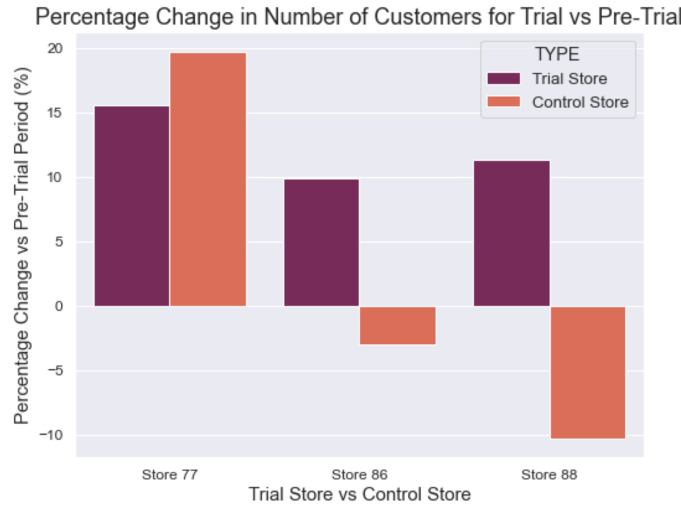
Post-Scaling Statistics

Store Number	Type	Pre-Trial Customers	Trial-Period Customers	Percentage Change (%)	Percentage Differential (%)
77	**Trial Store**	**77**	**89**	**15.58**	**-2.2**
233	Control Store	76	91	19.74	0
86	**Trial Store**	**233**	**256**	**9.87**	**13.78**
67	Control Store	232	225	-3.02	0
88	**Trial Store**	**282**	**314**	**11.35**	**24.11**
165	Control Store	282	253	-10.28	9

Column	Description
Store Number	The number of the store being assessed.
Type	Whether the store is the trial store or the control store.
Pre-Trial Customers	Number of customers for the period prior to the trial, scaled to the trial store numbers.
Trial-Period Customers	Number of customers during the trial period for each store, using the same scaling technique as previous.
Percentage Change (%)	Percentage value showing the percentage change of number of customers prior to the trial, to the end of the trial.
Percentage Differential (%)	The difference (percentage wise) of the trial store compared to the control store during the trial period. *(Number of Trial customers – Number of Pre-trial customers) / Number of Trial customers*

Statistics Visualizations





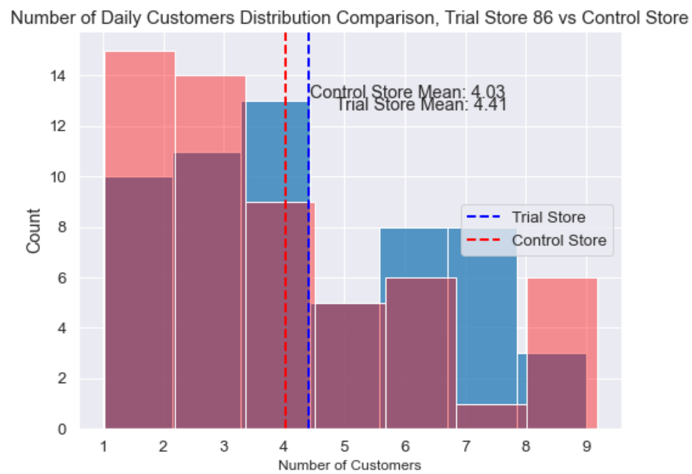
Insights

We see that 2/3 stores were able to increase their number of customers higher than that of their corresponding control store. Similarly, those same stores were the only ones capable of having higher percentage changes in number of customers compared to their control store counterpart.

- Trial store 77 did not see a percentage increase higher than its control store, and during the trial had 2.2% less customers.
- Trial stores 86 and 88 did see a significant increase higher than their control stores over the trial period, having percentage differentials of 13.78% and 24.11% respectively.

Next steps are to see if the differences are significant for each store, by comparing distributions and running T-Tests.

Distributions of Trial and Control Stores (Total Sales) During Trial Period



Significance Testing: T-Tests (Number of Customers)

Now that we've compared the distributions, and seen that they are indeed different, we will confirm whether the difference is significant via t-test. To run our T-test, we will need to set our null hypothesis. H0 in this case will be that the distribution of number of customers in the trial stores are not significantly different to the control stores. Our p-value will again be set at 0.05, but with a sample size of 10.

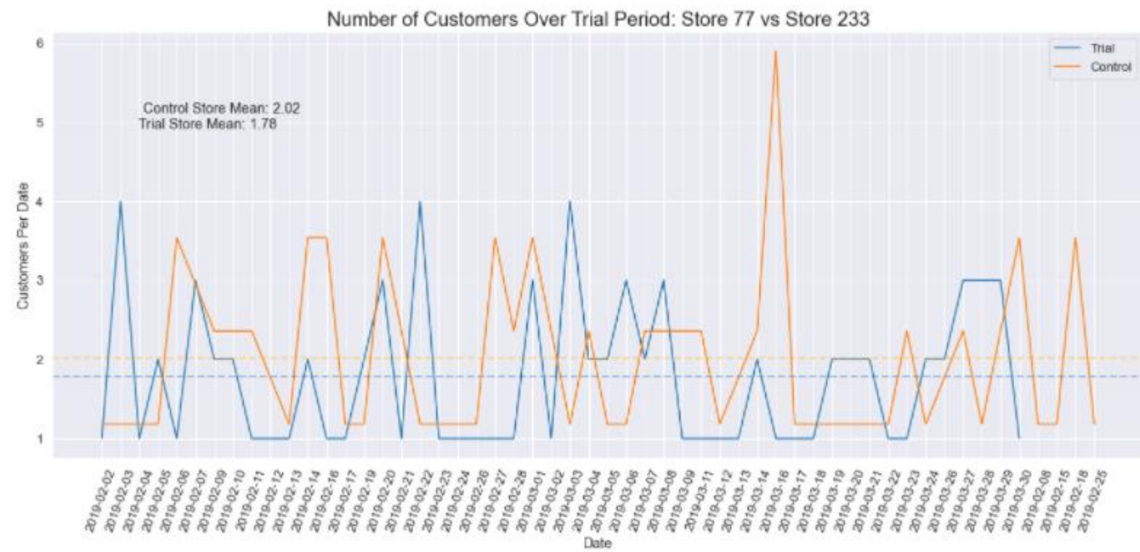
Trial Store	Control Store	Statistics	P-Value	Outcome
77	233	-6.071	0.000	Different distributions (Reject H0)
86	67	-2.135	0.037	Different distributions (Reject H0)
88	165	-2.783	0.007	Different distributions (Reject H0)

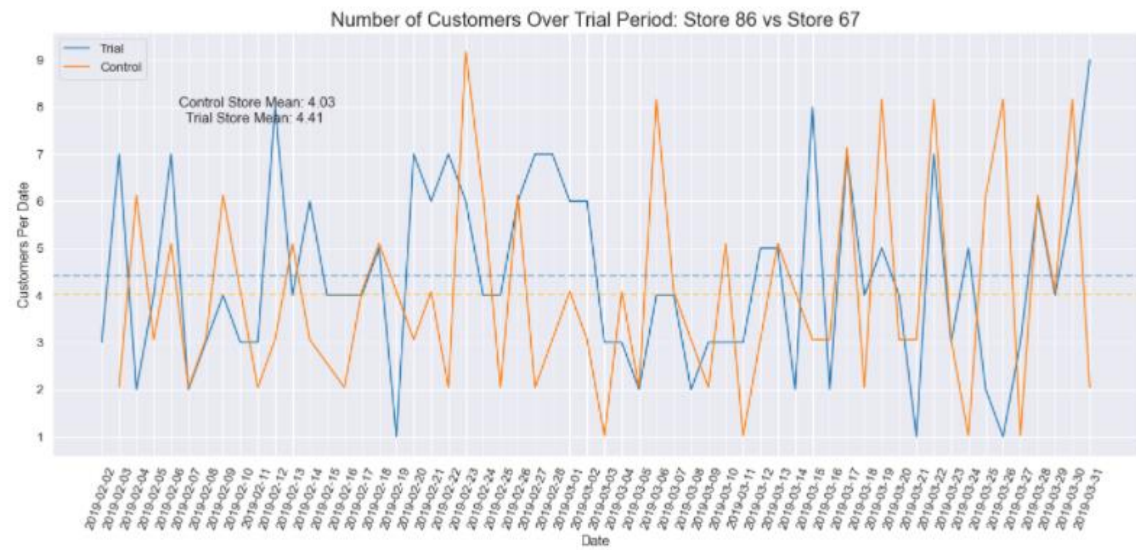
Insights

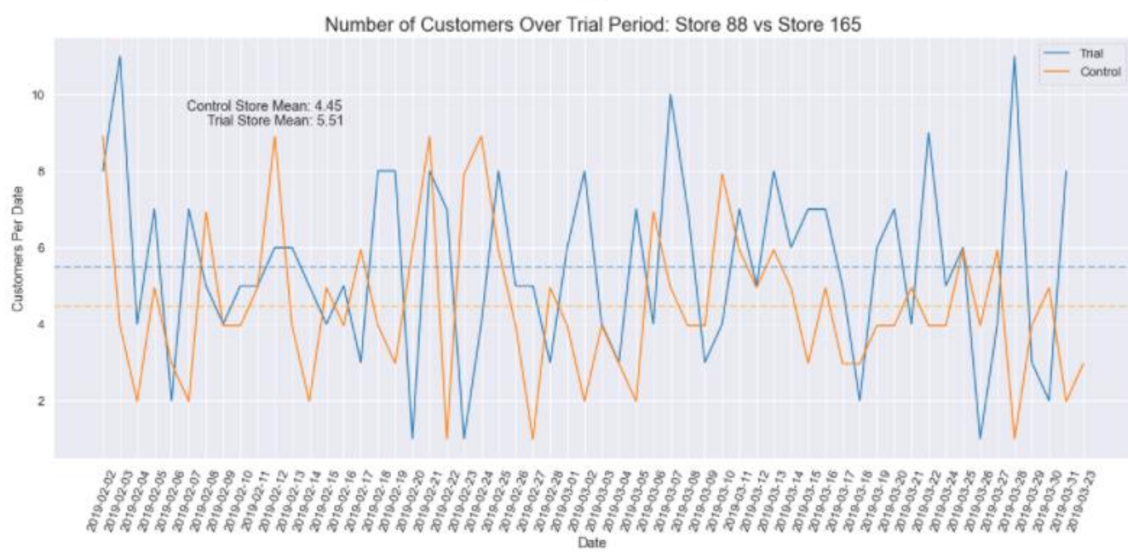
We see that the difference between the trial and control stores in all 3 trials are significantly different.

Visualizations

Let’s visualize the sales over the trial period to see how different they are.







Trial Summaries Per Store

Store NBR	Type	Pre-Trial Sales ($)	Trial Sales ($)	Sales % Change	Sales % Differential	Pre-Trial Customers	Trial Customers	Customer % Change	Customer % Differential
77	**Trial**	**413.3**	**455.7**	**10.26**	**-7.48**	**77**	**89**	**15.58**	**-2.20**
233	Control	414.0	492.5	18.97	0	76	91	19.74	0
86	**Trial**	**1602.0**	**1799.6**	**12.33**	**14.36**	**233**	**256**	**8.87**	**13.78**
67	Control	1605.1	1573.7	-1.96	0	232	225	-3.02	0
88	**Trial**	**2449.8**	**2752.6**	**12.36**	**22.89**	**282**	**314**	**11.35**	**24.11**
165	Control	2454.4	2238.9	-8.74	0	282	253	-10.28	0

Store 77

In terms of total sales, the results from our t-test showed that the trial in store 77 is significantly different to its control store in the trial period, as the trial store performance lies outside the 5% to 95% confidence interval of the control store. This means that the trial did have an effect, however, the results show a negative return. Compared to its control store, which had a percentage increase in sales of 18.97% from the pre-trial period, the trial negatively impacted store 77's performance over the trial period. We saw a sales increase of 10.26% compared to its pre-trial performance, however, we also see a negative sales differential of -7.48%. this means that trial store 77 did 7.48% worse in terms of sales over the trial period in comparison to control store 233. For customers, we also see that our t-test for store 77 showed its distribution of customers significantly different to its control store in the trial period, having a p-value lower than 0.05, meaning there was less than a 5% chance that the number of customers were from the same distribution as the control store. Similarly, to total sales, we saw that store 77 had a positive percentage increase in number of customers over the trial period compared to the pre-trial period, being an increase of 15.58%. However, again we saw that in comparison to the control store, the trial had a negative effect, resulting in 2.2% less customers than the control store 233. Overall, the trial was unsuccessful in store 77.

Store 86

For total sales in store 86, our t-test highlighted that the stores performance during the trial lay within the 5% to 95% confidence interval. Despite this, store 86 had a significant sales increase of 12.33% over the trial compared to the pre-trial period, with a percentage differential of 14.36% higher sales than its control store 67. With the t-test in mind, this large difference in sales can be attributed to the higher number of customers over the trial. Our T-test for number of customers saw that the performance lay outside the 5% to 95% confidence interval of the control store. This means that the trial did have a significant effect on the number of customers. Trial store 86 saw a 9.86% increase compared to its pre-trial metrics and saw 13.78% more customers over the trial period compared to control store 67. Overall, the trial was successful in increase the number of customers significantly over the trial period, however sales were not able to significantly increase per transaction. A recommendation is to check with the Category manager whether there were any special offers in the trial store that may have resulted in lower prices, impacting the overall sales statistics.

Store 88

Trial store 88 saw a distinguishable increase in sales compared to its pre-trial period. Over the course of the trial, store 88 was able to increase sales by 12.36%, contrasting the control store, which made 8.74% less sales than its pre-trial performance. Additionally, the trial appeared to have a dramatic effect on the stores total sales compared to the control store during the same period. The trial resulted in a percentage differential of 22.89%, meaning that over the course of the trial, store 88 made 22.89% more sales with the changes, compared to store 165 which didn't involve the trial strategy. Checking for significance using the T-test, the sampled distributions of both the trial store and control store resulted in a p-value of 0.007, meaning that the chance that there was no difference between the distributions of store 88 and 165 is close to zero. In terms of number of customers, our T-test saw that the performance lay outside the 5% to 95% confidence interval of the control store. This means the trial had a significance effect on the number of customers. Compared to the pre-trial period, the trial saw an increase of 11.35% in number of customers for store 88. Similarly, to sales, the trial had a profound effect on number of customers for the period of the trial, compared to its control store, which saw a significant dip in customer volume. Control store 165 saw a decrease of 10.28% compared to its pre-trial period, and when comparing both stores in the trial period, we see trial store 88 having 24.11% more customers than store 165. Overall, the trial was successful in store 88, having had significant increases in sales and number of customers.

PROJECT CODE (JUPYTER NOTEBOOK)

Language Used: Python & SQL

In [57]:

```
# Import Libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import datetime as dt
from scipy.ndimage.filters import gaussian_filter1d
import pandasql as ps
import warnings
warnings.filterwarnings('ignore')
from pylab import rcParams
from scipy.stats import f_oneway
from scipy.stats import ttest_ind
```

In [3]:

```
# Import dataset
file = r'C:\Users\Joel\Dropbox\Vitrual Internships\Quantium\Task 2\Data\QVI_clean_data.
csv'
data = pd.read_csv(file, index_col= 0)
data
```

Out[3]:

	real_date	STORE_NBR	TXN_ID	PROD_NAME	BRAND_NAME	PACKET_SIZE	PR
0	2018-07-01	9	8808	Smiths Thinly Cut Roast Chicken 175g	Smiths	175	
1	2018-07-01	86	84237	Red Rock Deli Sp Salt & Truffle 150G	RRD	150	
2	2018-07-01	129	132474	Smith Crinkle Cut Mac N Cheese 150g	Smiths	150	
3	2018-07-01	58	53145	Pringles Sthrn FriedChicken 134g	Pringles	134	
4	2018-07-01	97	97311	WW Crinkle Cut Chicken 175g	Woolworths	175	
...	...	...	...	...	...	...	
246735	2019-06-30	91	89519	Thins Chips Seasonedchicken 175g	Thins	175	
246736	2019-06-30	84	83704	Doritos Corn Chips Nacho Cheese 170g	Doritos	170	
246737	2019-06-30	24	20917	Smiths Crinkle Cut Chips Chs&Onion170g	Smiths	170	
246738	2019-06-30	199	198068	Doritos Corn Chips Nacho Cheese 170g	Doritos	170	
246739	2019-06-30	220	219497	Dorito Corn Chp Supreme 380g	Doritos	380	

246738 rows × 12 columns

- First Task will be to establish a control store. The trial stores are 77, 86, and 88, so we must find potential stores which have similar performance to the trial stores.
- We can do this by looking at specifics metrics during the trail period of Feb 2019.

Metrics:

- Monthly sales revenue
- Monthly number of customers
- Monthly number of transactions per customer

In [4]:

```
# Isolate stores which have been active throughout trial
data_active_feb = data[(data['real_date'] > '2019-02-01') & (data['real_date'] < '2019-
04-01')]
data_active_feb['STORE_NBR'].value_counts()

active_stores = data_active_feb['STORE_NBR'].unique()
active_store_records = data[data.STORE_NBR.isin(active_stores)]

# Select all stores outside of trial stores BEFORE FEB
data_prior_feb = active_store_records[active_store_records['real_date'] < '2019-02-01']

query = """
        SELECT *
        FROM data_prior_feb
        WHERE STORE_NBR NOT IN (77, 86, 88)
        """
control_rec = ps.sqldf(query, locals())

# Create df of all stores outside of trial stores
# Create df of all stores active in febuary
stores = control_rec.STORE_NBR.unique()
control_stores = pd.DataFrame(stores, columns = ['STORE_NBR'])

# Add metrics to active stores

# Monthly Sales Rev
rev = []
for store in control_stores['STORE_NBR']:
    df = control_rec[control_rec['STORE_NBR'] == store]
    rev.append(round(np.sum(df['TOT_SALES']), 2))

control_stores['TOT_SALES'] = rev

# Monthly Number of Customers
cust = []
for store in control_stores['STORE_NBR']:
    df = control_rec[control_rec['STORE_NBR'] == store]
    cust.append(len(df.index))

control_stores['NBR_OF_CUST'] = cust

# Monthly number of transactions per customer
avg_qty = []
for store in control_stores['STORE_NBR']:
    df = control_rec[control_rec['STORE_NBR'] == store]
    avg_qty.append(round(np.mean(df['PROD_QTY']), 2))

control_stores['AVG_QTY'] = avg_qty

# Average Unit price
avg_unit = []
for store in control_stores['STORE_NBR']:
    df = control_rec[control_rec['STORE_NBR'] == store]
    avg_unit.append(round(np.mean(df['AVG_CHIP_PRICE']), 2))

control_stores['AVG_UNIT_PRICE' ] = avg_unit

control_stores
```

Out[4]:

	STORE_NBR	TOT_SALES	NBR_OF_CUST	AVG_QTY	AVG_UNIT_PRICE
0	9	2297.40	373	1.76	3.51
1	129	5227.60	748	1.99	3.52
2	58	8576.95	994	1.99	4.35
3	97	5793.35	836	1.98	3.50
4	199	8200.50	943	1.98	4.39
...	...	...	...	...	...
257	244	176.60	31	1.58	3.58
258	258	156.20	23	1.96	3.50
259	117	91.80	27	1.04	3.29
260	252	3.70	1	1.00	3.70
261	193	1.80	1	1.00	1.80

262 rows × 5 columns

In [5]:

```
# Create df for only trial stores BEFORE FEB

# Get only trial stores 77, 86, 88
query = """
        SELECT *
        FROM data_prior_feb
        WHERE STORE_NBR IN (77, 86, 88)
        """
trial_rec = ps.sqldf(query, locals())

# Create df of all trial stores
stores = trial_rec.STORE_NBR.unique()
trial_stores = pd.DataFrame(stores, columns = ['STORE_NBR'])

# Add metrics to trial stores

# Monthly Sales Rev
rev = []
for store in trial_stores['STORE_NBR']:
    df = trial_rec[trial_rec['STORE_NBR'] == store]
    rev.append(round(np.sum(df['TOT_SALES']), 2))

trial_stores['TOT_SALES'] = rev

# Monthly Number of Customers
cust = []
for store in trial_stores['STORE_NBR']:
    df = trial_rec[trial_rec['STORE_NBR'] == store]
    cust.append(len(df.index))

trial_stores['NBR_OF_CUST'] = cust

# Monthly number of transactions per customer
avg_qty = []
for store in trial_stores['STORE_NBR']:
    df = trial_rec[trial_rec['STORE_NBR'] == store]
    avg_qty.append(round(np.mean(df['PROD_QTY']), 2))

trial_stores['AVG_QTY'] = avg_qty

# Average Unit price
avg_unit = []
for store in trial_stores['STORE_NBR']:
    df = trial_rec[trial_rec['STORE_NBR'] == store]
    avg_unit.append(round(np.mean(df['AVG_CHIP_PRICE']), 2))

trial_stores['AVG_UNIT_PRICE' ] = avg_unit

trial_stores
```

Out[5]:

	STORE_NBR	TOT_SALES	NBR_OF_CUST	AVG_QTY	AVG_UNIT_PRICE
0	86	5795.65	832	1.99	3.51
1	88	8832.80	1028	1.98	4.33
2	77	1595.50	298	1.52	3.56

Before writing the function to choose comparable control stores, we must first define what metric we will use. Our test metric will be if all the features (total sales, number of customers etc.) are within 5% of the trial store's feature value.

For example:

- Total sales, number of customers, average quantity, and average unit price of the potential control store, must be within 5% of the same feature's value in the trial store.
- If the trial store is Store 86:
  - Total sales: 5795.65
  - Number of customers: 832
  - Average Quantity: 1.99
  - Average Unit Price: 3.51
- Then the control store candidate must be within these parameters:
  - Total sales: Within 5505.9 & 6084.75
  - Number of customers: Within 791.4 & 873
  - Average Quantity: Within 1.89 & 2.09
  - Average Unit Price: Within 3.33 & 3.68

In [7]:

```
# Writing Function to choose store
def compare_stores(trial_df, control_df):
    columns = ['TOT_SALES', 'NBR_OF_CUST', 'AVG_QTY', 'AVG_UNIT_PRICE']
    similar_stores = []
    trial_store_compared = []
    for store in trial_df.index:
        for x in control_df.index:
            score = 0
            for feature in columns:
                if (control_df.loc[x][feature] >= (0.95 * trial_df.loc[store][feature
])) & (control_df.loc[x][feature] <= (1.05 * trial_df.loc[store][feature])):
                    score += 1

            if score == 4:
                similar_stores.append(control_df.loc[x]['STORE_NBR'])
                trial_store_compared.append(store)

    comparison = pd.DataFrame(trial_store_compared, columns = ['trial_store'])
    comparison['Control_store_candidate'] = similar_stores
    comparison['trial_store'].replace({0:86, 1:88, 2:77}, inplace = True)

    store_86_df = comparison[comparison['trial_store'] == 86]
    store_88_df = comparison[comparison['trial_store'] == 88]
    store_77_df = comparison[comparison['trial_store'] == 77]

    # Select at random, control store for each trial store
    store_86_control = store_86_df.sample(1, random_state = 7)
    store_88_control = store_88_df.sample(1, random_state = 23)
    store_77_control = store_77_df.sample(1, random_state = 117)

    control_stores = pd.concat([store_77_control, store_86_control, store_88_control])
    return control_stores
```

In [8]:

```
compare_stores(trial_stores, control_stores)
```

Out[8]:

	trial_store	Control_store_candidate
41	77	233.0
32	86	67.0
37	88	165.0

Our sample has chosen the following control stores for corresponding trial stores:

- The Store 77 Control store = Store 233
- The Store 86 Control store = Store 67
- The Store 88 Control store = Store 165

In [9]:

```
# Create comparison DF
trial_store_77 = trial_stores[trial_stores['STORE_NBR'] == 77]
control_store_77 = control_stores[control_stores['STORE_NBR'] == 233]
trial_store_86 = trial_stores[trial_stores['STORE_NBR'] == 86]
control_store_86 = control_stores[control_stores['STORE_NBR'] == 67]
trial_store_88 = trial_stores[trial_stores['STORE_NBR'] == 88]
control_store_88 = control_stores[control_stores['STORE_NBR'] == 165]

comparison_df = pd.concat([trial_store_77,control_store_77,trial_store_86,control_store
_86,trial_store_88,control_store_88])

# Transpose DF
comparison_df = comparison_df

# Rename Columns

comparison_df['Metrics'] = [
    'Trial_store_77',
    'Control_store_77',
    'Trial_store_86',
    'Control_store_86',
    'Trial_store_88',
    'Control_store_88']

comparison_df.set_index('Metrics', inplace = True)

comparison_df.T
```

Out[9]:

Metrics	Trial_store_77	Control_store_77	Trial_store_86	Control_store_86	Trial_sto
STORE_NBR	77.00	233.00	86.00	67.00	
TOT_SALES	1595.50	1534.50	5795.65	5601.20	88
NBR_OF_CUST	298.00	285.00	832.00	798.00	10
AVG_QTY	1.52	1.54	1.99	1.99	
AVG_UNIT_PRICE	3.56	3.50	3.51	3.53	

In [10]:

```
trial_stores.sort_values(by = 'STORE_NBR', inplace = True)
trial_stores
```

Out[10]:

	STORE_NBR	TOT_SALES	NBR_OF_CUST	AVG_QTY	AVG_UNIT_PRICE
2	77	1595.50	298	1.52	3.56
0	86	5795.65	832	1.99	3.51
1	88	8832.80	1028	1.98	4.33

In [11]:

```
control_stores_df = pd.concat([control_store_77, control_store_86, control_store_88])
control_stores_df
```

Out[11]:

	STORE_NBR	TOT_SALES	NBR_OF_CUST	AVG_QTY	AVG_UNIT_PRICE
203	233	1534.5	285	1.54	3.50
192	67	5601.2	798	1.99	3.53
20	165	8748.2	999	1.99	4.40

In [12]:

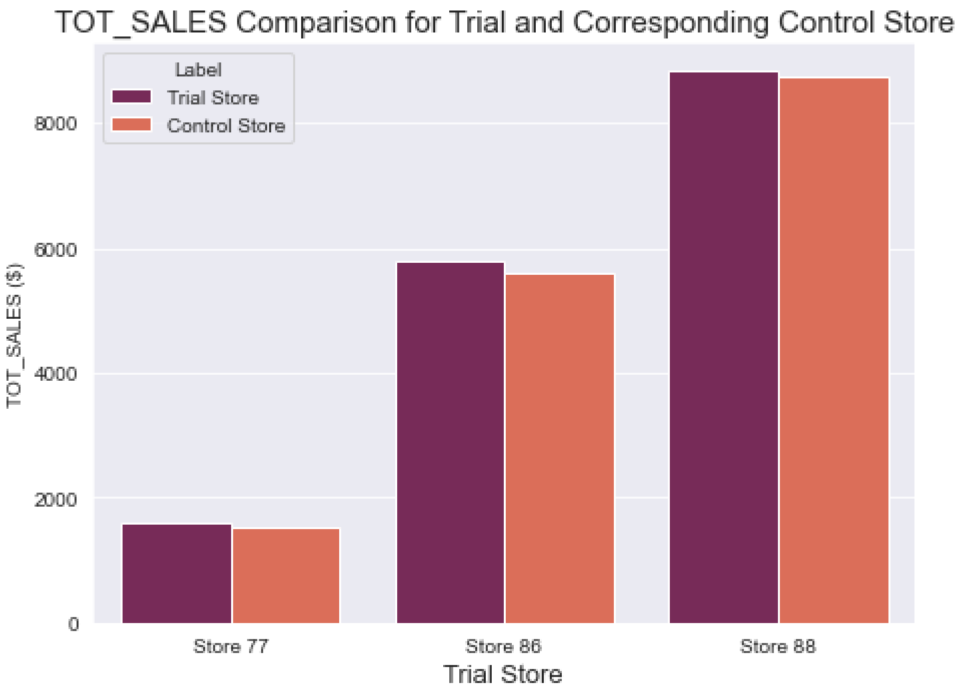
```
plot_comparison_df = trial_stores
plot_comparison_df = pd.concat([trial_stores, control_store_77, control_store_86, contr
ol_store_88], axis = 0)
plot_comparison_df['Label'] = ['Trial Store', 'Trial Store', 'Trial Store', 'Control St
ore', 'Control Store', 'Control Store']
plot_comparison_df.reset_index(drop = True, inplace = True)
plot_comparison_df = plot_comparison_df.reindex([0,3,1,4,2,5])
plot_comparison_df['Name'] = ['Store 77','Store 77','Store 86','Store 86','Store 88','S
tore 88',]
plot_comparison_df
```

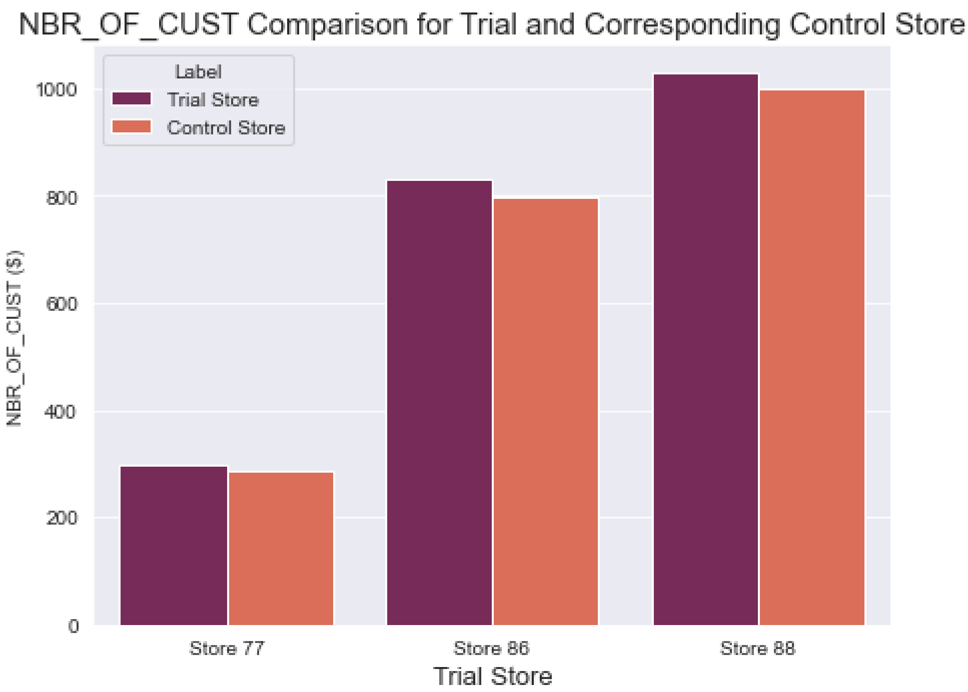
Out[12]:

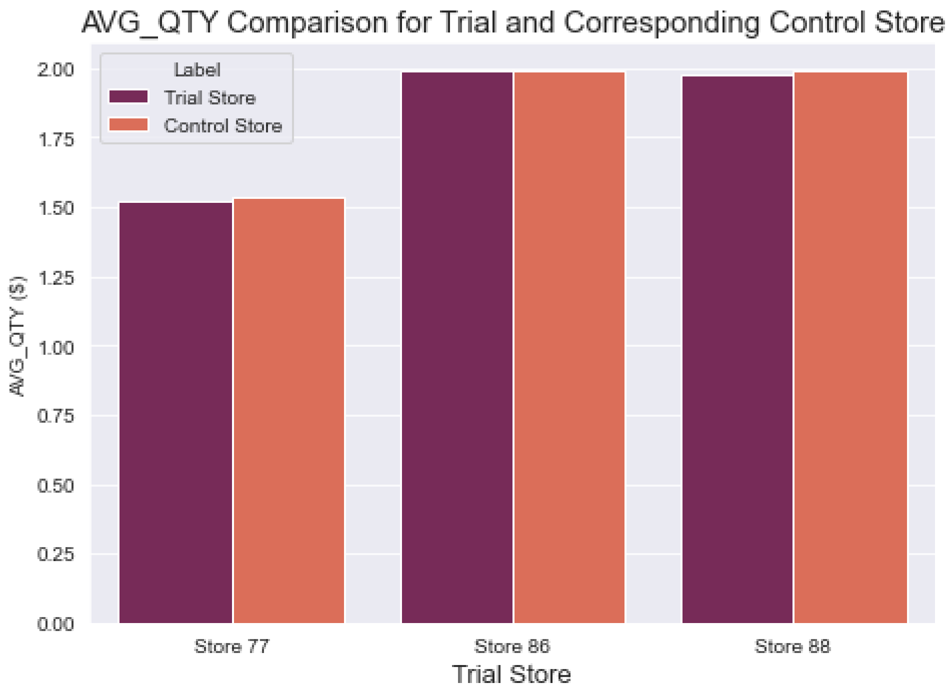
	STORE_NBR	TOT_SALES	NBR_OF_CUST	AVG_QTY	AVG_UNIT_PRICE	Label	Name
0	77	1595.50	298	1.52	3.56	Trial Store	Store 77
3	233	1534.50	285	1.54	3.50	Control Store	Store 77
1	86	5795.65	832	1.99	3.51	Trial Store	Store 86
4	67	5601.20	798	1.99	3.53	Control Store	Store 86
2	88	8832.80	1028	1.98	4.33	Trial Store	Store 88
5	165	8748.20	999	1.99	4.40	Control Store	Store 88

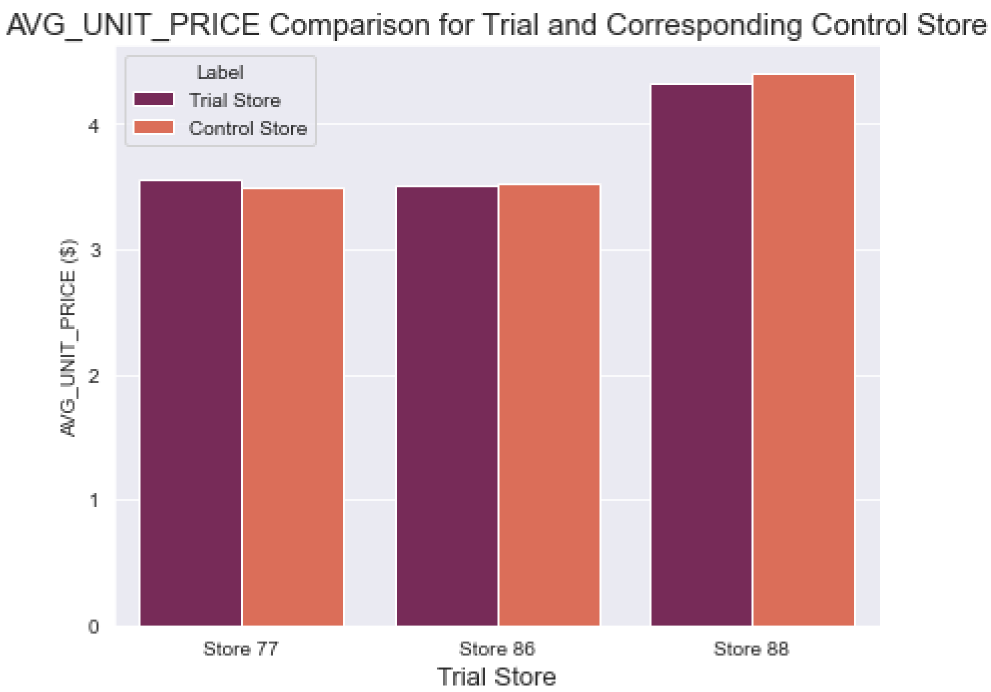
In [13]:

```
# Visualize trial vs control store metrics to see if theyre similar

columns = ['TOT_SALES', 'NBR_OF_CUST', 'AVG_QTY', 'AVG_UNIT_PRICE']

for metric in columns:
    if metric == 'TOT_SALES' or 'AVG_UNIT_PRICE':
        plt.figure(figsize=(7,5))
        ax = sns.set_style('darkgrid')
        ax = sns.barplot(x = 'Name', y = metric, data = plot_comparison_df,hue='Label',
palette = 'rocket')
        ax.set_xlabel('Trial Store', fontsize = 13)
        ax.set_ylabel( f'{metric} ($)')
        ax.axes.set_title(f'{metric} Comparison for Trial and Corresponding Control Sto
re', fontsize = 15)
        plt.xticks()
        plt.yticks()
        plt.tight_layout()

    else:
        plt.figure(figsize=(7,5))
        ax = sns.set_style('darkgrid')
        ax = sns.barplot(x = 'Name', y = metric, data = plot_comparison_df,hue='Label',
palette = 'rocket')
        ax.set_xlabel('Trial Store')
        ax.set_ylabel(metric)
        ax.axes.set_title(f'{metric} Comparison for Trial and Corresponding Control Sto
re', fontsize = 15)
        plt.xticks()
        plt.yticks()
        plt.tight_layout()
```


TOT_SALES Comparison for Trial and Corresponding Control Store
Label
Trial Store
Control Store
TOT_SALES ($)
0
2000
4000
6000
8000
Store 77
Store 86
Store 88
Trial Store


NBR_OF_CUST Comparison for Trial and Corresponding Control Store
Label
Trial Store
Control Store
NBR_OF_CUST ($)
0
200
400
600
800
1000
Store 77
Store 86
Store 88
Trial Store


AVG_QTY Comparison for Trial and Corresponding Control Store
Label
Trial Store
Control Store
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
AVG_QTY ($)
Store 77
Store 86
Store 88
Trial Store


AVG_UNIT_PRICE Comparison for Trial and Corresponding Control Store
Label
Trial Store
Control Store
4
3
2
1
0
AVG_UNIT_PRICE ($)
Store 77
Store 86
Store 88
Trial Store

We can see from our visualizations that the control group closely matches the performance of the corresponding trial group in all aspects, prior to the trial period.

To refresh:

- The Store 77 Control store = Store 233
- The Store 86 Control store = Store 67
- The Store 88 Control store = Store 165

Now that we have our trial and control stores, we can now assess the performance of the trial period and the effect of the changes on the trial stores, and compare them to the control stores.

To begin, lets gather the control and trial store data just prior to the trial period.

Since the trial period is 2 months long (feb to apr), we will need data from 2 months prior to the trial. However, we cannot use december as our comparison, due to the fact that sales in December contain outliers, therefore, we will combine transaction data for the stores in November 2018 and January 2019.

In [33]:

```
pre_trial_jan = active_store_records[(active_store_records['real_date'] < '2019-02-01')
& (active_store_records['real_date'] > '2019-01-01')]

# Gather trial and control stores jan and nov
query = """
        SELECT *
        FROM pre_trial_jan
        WHERE STORE_NBR IN (77, 86, 88, 233, 67, 165)
        """
pre_trial_rec_jan = ps.sqldf(query, locals())

pre_trial_nov = active_store_records[(active_store_records['real_date'] < '2018-12-01')
& (active_store_records['real_date'] > '2018-11-01')]

query = """
        SELECT *
        FROM pre_trial_nov
        WHERE STORE_NBR IN (77, 86, 88, 233, 67, 165)
        """

pre_trial_rec_nov = ps.sqldf(query,locals())

# combine jan and nov into one df
pre_trial_rec = pd.concat([pre_trial_rec_jan, pre_trial_rec_nov])


# Create df of all stores pre_trial
stores = pre_trial_rec.STORE_NBR.unique()
pre_trial_data = pd.DataFrame(stores, columns = ['STORE_NBR'])

# Add metrics to active stores

# Sales Rev Jan
rev = []

# Number of Customers
cust = []

# Avg Qty
avg_qty = []

# Avg Unit Price
avg_unit = []

for store in pre_trial_data['STORE_NBR']:
    df = pre_trial_rec[pre_trial_rec['STORE_NBR'] == store]
    rev.append(round(np.sum(df['TOT_SALES']), 2))
    cust.append(len(df.index))
    avg_qty.append(round(np.mean(df['PROD_QTY']), 2))
    avg_unit.append(round(np.mean(df['AVG_CHIP_PRICE']), 2))

pre_trial_data['TOT_SALES'] = rev
pre_trial_data['NBR_OF_CUST'] = cust
pre_trial_data['AVG_QTY'] = avg_qty
pre_trial_data['AVG_UNIT_PRICE'] = avg_unit

pre_trial_data = pre_trial_data.reindex([5,2,4,3,1,0])
pre_trial_data['TYPE'] = ['Trial Store', 'Control Store', 'Trial Store', 'Control Stor
e', 'Trial Store', 'Control Store']
```

```
pre_trial_data['Name'] = ['Store 77','Store 77','Store 86','Store 86','Store 88','Store 88']
pre_trial_data = pre_trial_data.set_index('STORE_NBR')
pre_trial_data
```

Out[33]:

STORE_NBR	TOT_SALES	NBR_OF_CUST	AVG_QTY	AVG_UNIT_PRICE	TYPE	Name
77	413.3	77	1.57	3.48	Trial Store	Store 77
233	328.6	65	1.42	3.58	Control Store	Store 77
86	1602.0	233	2.00	3.44	Trial Store	Store 86
67	1573.6	228	2.00	3.45	Control Store	Store 86
88	2449.8	282	2.00	4.34	Trial Store	Store 88
165	2479.2	285	1.99	4.37	Control Store	Store 88

- Again, we can be reassured that the metric statistics for the trial stores and their corresponding control stores are very similar for the month of January.
- The above statistics are for the months of January and November the previous year.

The trial period goes from the start of Feb 2019 to Apr 2019. We want to see if there has been an uplift in overall chip sales. We will start with scaling the control store's sales to a similar level to control for any differences between the two stores outside of the trial period.

In [40]:

```
pre_trial_scaled = pre_trial_data
pre_trial_scaled
```

Out[40]:

STORE_NBR	TOT_SALES	NBR_OF_CUST	AVG_QTY	AVG_UNIT_PRICE	TYPE	Name
77	413.3	77	1.57	3.48	Trial Store	Store 77
233	328.6	65	1.42	3.58	Control Store	Store 77
86	1602.0	233	2.00	3.44	Trial Store	Store 86
67	1573.6	228	2.00	3.45	Control Store	Store 86
88	2449.8	282	2.00	4.34	Trial Store	Store 88
165	2479.2	285	1.99	4.37	Control Store	Store 88

In [42]:

```
trial_stores = [77, 86, 88]
control_stores = [233, 67, 165]

scaling_factors = []

# Get scaling factors for tot_sales
for trial_store, control_store in zip(trial_stores, control_stores):
    df = pre_trial_rec[pre_trial_rec['STORE_NBR'] == trial_store]
    df2 = pre_trial_rec[pre_trial_rec['STORE_NBR'] == control_store]
    tot_sales_trial = np.sum(df['TOT_SALES'])
    tot_sales_control = np.sum(df2['TOT_SALES'])
    scaler = tot_sales_trial / tot_sales_control
    scaling_factors.append(round(scaler,2))

for control_store, scaler in zip(control_stores, scaling_factors):
    new_value = round((pre_trial_data[pre_trial_data.index == control_store]['TOT_SALE
S']) * scaler, 1)
    pre_trial_scaled.at[control_store, 'TOT_SALES'] = new_value

pre_trial_scaled
```

Out[42]:

	TOT_SALES	NBR_OF_CUST	AVG_QTY	AVG_UNIT_PRICE	TYPE	Name
STORE_NBR						
77	413.3	77	1.57	3.48	Trial Store	Store 77
233	414.0	65	1.42	3.58	Control Store	Store 77
86	1602.0	233	2.00	3.44	Trial Store	Store 86
67	1605.1	228	2.00	3.45	Control Store	Store 86
88	2449.8	282	2.00	4.34	Trial Store	Store 88
165	2454.4	285	1.99	4.37	Control Store	Store 88

Now that we have scaled figures for the baseline (pre_trial), we can scale the actual transactions for the trial period.

In [51]:

```
scaled_trial_data = pre_trial_scaled[['TYPE','TOT_SALES']]
scaled_trial_data['SCALING_FACTOR'] = [0, 1.26, 0, 1.02, 0, 0.99]
scaled_trial_data
```

```
<ipython-input-51-0c761027fcf2>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-doc
s/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  scaled_trial_data['SCALING_FACTOR'] = [0, 1.26, 0, 1.02, 0, 0.99]
```

Out[51]:

	TYPE	TOT_SALES	SCALING_FACTOR
STORE_NBR			
77	Trial Store	413.3	0.00
233	Control Store	414.0	1.26
86	Trial Store	1602.0	0.00
67	Control Store	1605.1	1.02
88	Trial Store	2449.8	0.00
165	Control Store	2454.4	0.99

In [73]:

```
# Gather data for period of the trial
trial_period_data = data[(data['real_date'] > '2019-02-01') & (data['real_date'] < '201
9-04-01')]
trial_period_data

# select only control stores
query = """
        SELECT *
        FROM trial_period_data
        WHERE STORE_NBR IN (233, 67, 165)
        """
control_store_trial_data = ps.sqldf(query,locals())

trial_stores = [77, 86, 88]
control_stores = [233, 67, 165]


scaled_tot_sales = []

for trial_store, control_store, scaler in zip(trial_stores, control_stores, scaling_fac
tors):

    # Trial store sales
    trial_df = trial_period_data[trial_period_data['STORE_NBR'] == trial_store]
    trial_tot_sales = round(np.sum(trial_df['TOT_SALES']), 2)
    scaled_tot_sales.append(trial_tot_sales)

    # Scaling the control store sales
    control_df = trial_period_data[trial_period_data['STORE_NBR'] == control_store]
    control_df['TOT_SALES'] = control_df['TOT_SALES'] * scaler
    control_tot_sales = round(np.sum(control_df['TOT_SALES']), 2)
    scaled_tot_sales.append(control_tot_sales)

scaled_trial_data['TOT_SALES'] = scaled_tot_sales

# Create Comparison DF
comparison = pre_trial_scaled[['TYPE', 'TOT_SALES']]
comparison.rename(columns = {'TOT_SALES': 'PRE_TRIAL_SALES'}, inplace = True)
comparison['TRIAL_SALES'] = scaled_trial_data['TOT_SALES']

# Get Percentage Change
comparison['%_CHANGE'] = round(((comparison['TRIAL_SALES'] - comparison['PRE_TRIAL_SALE
S']) / comparison['PRE_TRIAL_SALES']) * 100, 2)

# Percentage differential
comparison['%_DIFFERENCE'] = 0
differential = []
for i,x in zip(trial_stores,control_stores):
    diff_trial = round(((comparison.at[i, 'TRIAL_SALES'] - comparison.at[x, 'TRIAL_SALE
S']) / comparison.at[x, 'TRIAL_SALES'])*100,2)
    diff_control = round(((comparison.at[x, 'TRIAL_SALES'] - comparison.at[i, 'TRIAL_SA
LES']) / comparison.at[x, 'TRIAL_SALES'])*100,2)
    differential.append(diff_trial)
    differential.append(diff_control)
comparison['%_DIFFERENCE'] = differential

for i in control_stores:
    comparison.at[i, '%_DIFFERENCE'] = 0
```

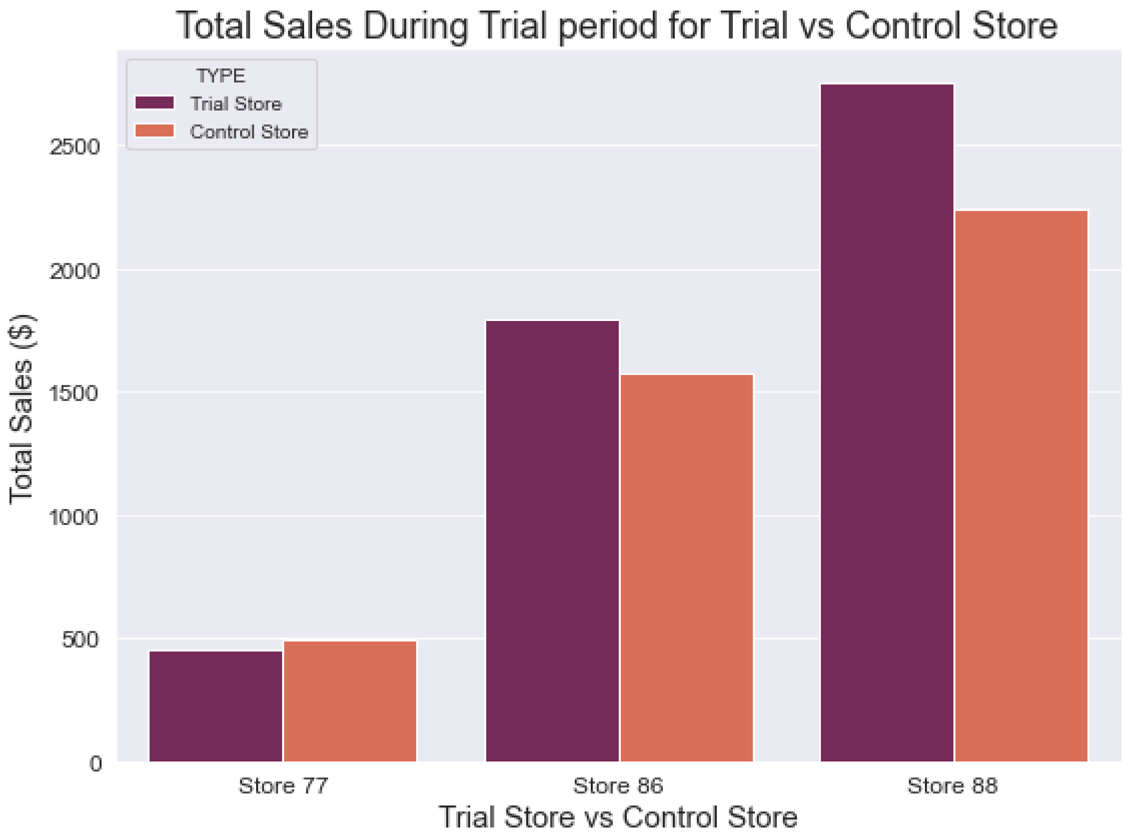
```
comparison['TRIAL_STORE'] = ['Store 77', 'Store 77', 'Store 86', 'Store 86', 'Store 88'
, 'Store 88']
comparison
```

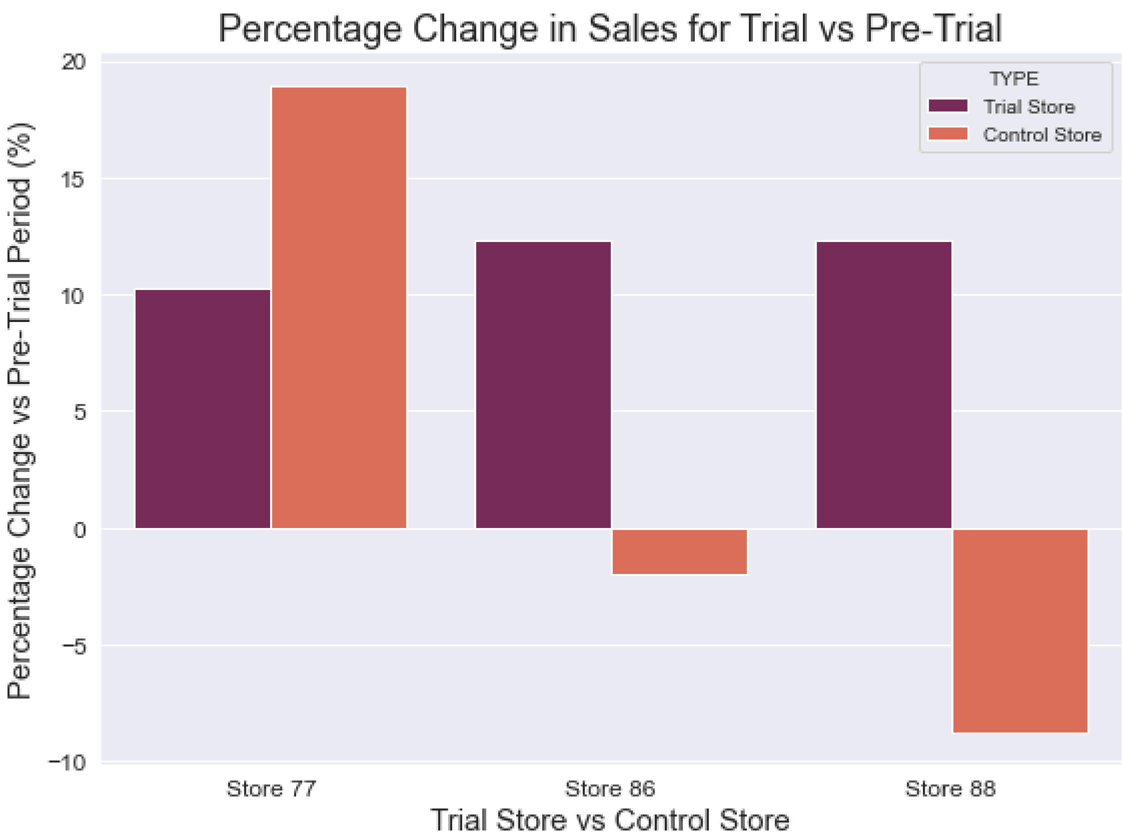
Out[73]:

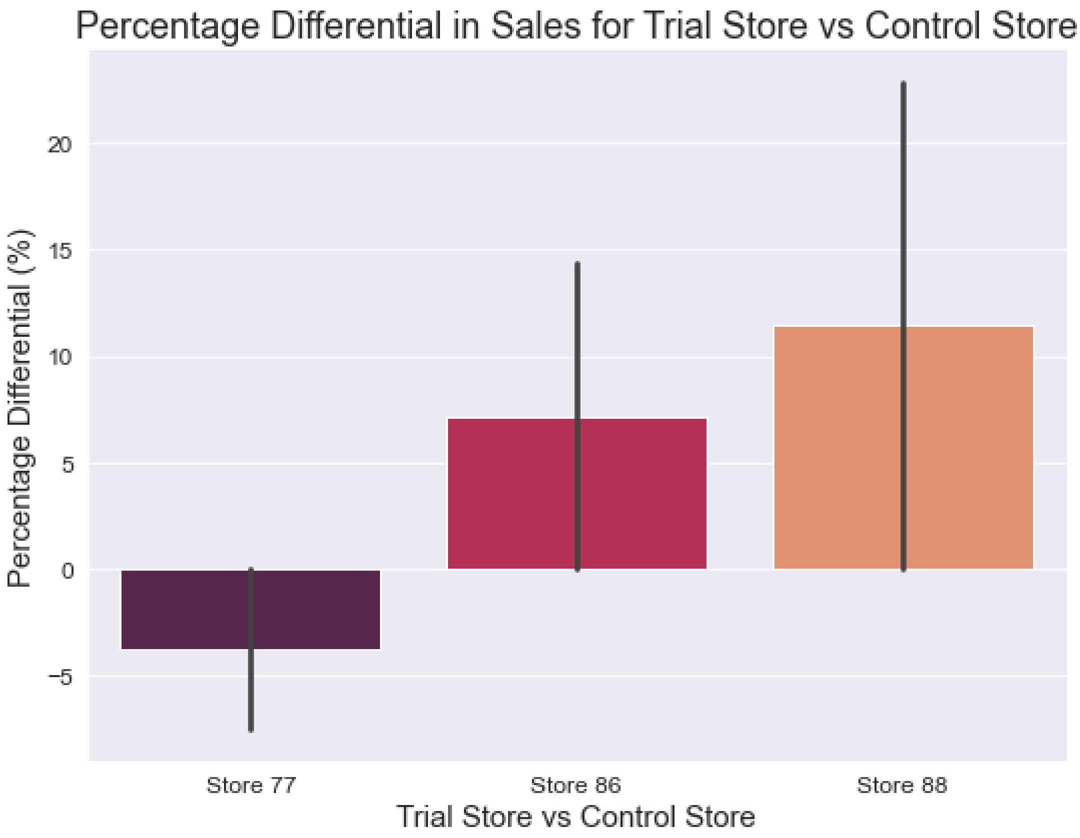
STORE_NBR	TYPE	PRE_TRIAL_SALES	TRIAL_SALES	%_CHANGE	%_DIFFERENCE	TRIA
77	Trial Store	413.3	455.70	10.26	-7.48	
233	Control Store	414.0	492.53	18.97	0.00	
86	Trial Store	1602.0	1799.60	12.33	14.36	
67	Control Store	1605.1	1573.66	-1.96	0.00	
88	Trial Store	2449.8	2752.60	12.36	22.89	
165	Control Store	2454.4	2239.88	-8.74	0.00	

In [80]:

```
# Plotting results

# Total Sales
plt.figure(figsize = (8,6))
ax = sns.set_style('darkgrid')
ax = sns.barplot(x = 'TRIAL_STORE', y = 'TRIAL_SALES', data = comparison, hue = 'TYPE',
palette = 'rocket')
ax.set_xlabel('Trial Store vs Control Store', fontsize = 15)
ax.set_ylabel('Total Sales ($)', fontsize = 15)
ax.axes.set_title('Total Sales During Trial period for Trial vs Control Store', fontsiz
e = 18)
plt.xticks(fontsize = 12)
plt.yticks(fontsize = 12)
plt.tight_layout()

# % Change compared to pre-trial period
plt.figure(figsize = (8,6))
ax = sns.set_style('darkgrid')
ax = sns.barplot(x = 'TRIAL_STORE', y = '%_CHANGE', data = comparison, hue = 'TYPE', pa
lette = 'rocket')
ax.set_xlabel('Trial Store vs Control Store', fontsize = 15)
ax.set_ylabel('Percentage Change vs Pre-Trial Period (%)', fontsize = 15)
ax.axes.set_title('Percentage Change in Sales for Trial vs Pre-Trial', fontsize = 18)
plt.xticks(fontsize = 12)
plt.yticks(fontsize = 12)
plt.tight_layout()

# % Differential of sales for Trial Store vs Control Store
plt.figure(figsize = (8,6))
ax = sns.set_style('darkgrid')
ax = sns.barplot(x = 'TRIAL_STORE', y = '%_DIFFERENCE', data = comparison, palette = 'r
ocket')
ax.set_xlabel('Trial Store vs Control Store', fontsize = 15)
ax.set_ylabel('Percentage Differential (%)', fontsize = 15)
ax.axes.set_title('Percentage Differential in Sales for Trial Store vs Control Store',
fontsize = 18)
plt.xticks(fontsize = 12)
plt.yticks(fontsize = 12)
plt.tight_layout()
```


Total Sales During Trial period for Trial vs Control Store
TYPE
Trial Store
Control Store
Total Sales ($)
0
500
1000
1500
2000
2500
Store 77
Store 86
Store 88
Trial Store vs Control Store


Percentage Change in Sales for Trial vs Pre-Trial
TYPE
Trial Store
Control Store
Percentage Change vs Pre-Trial Period (%)
20
15
10
5
0
−5
−10
Store 77
Store 86
Store 88
Trial Store vs Control Store



Now that we have our results, we can see that 2/3 trial stores were able to have total sales increase over their corresponding control store. Similarly, those same stores were the only ones to have a higher percentage change in sales from pre-trial, over to the trial, higher than their control counterpart.

- Trial store 77 did not see a percentage increase higher than it's control store.
- Trial stores 86 and 88 did see an increase in sales compared to their control stores.

We see that stores 86 and 88 are the only stores during the trial to have a significant positive percentage differential over their control counterparts.

Let's check if the difference is significant by doing a T test. Our first test will have a null hypothesis being that the trial period is the same as the pre-trial period.

First we will look at their distributions.

In [98]:

```
scaled_trial_data
```

Out[98]:

STORE_NBR	TYPE	TOT_SALES	SCALING_FACTOR
77	Trial Store	455.70	0.00
233	Control Store	492.53	1.26
86	Trial Store	1799.60	0.00
67	Control Store	1573.66	1.02
88	Trial Store	2752.60	0.00
165	Control Store	2239.88	0.99

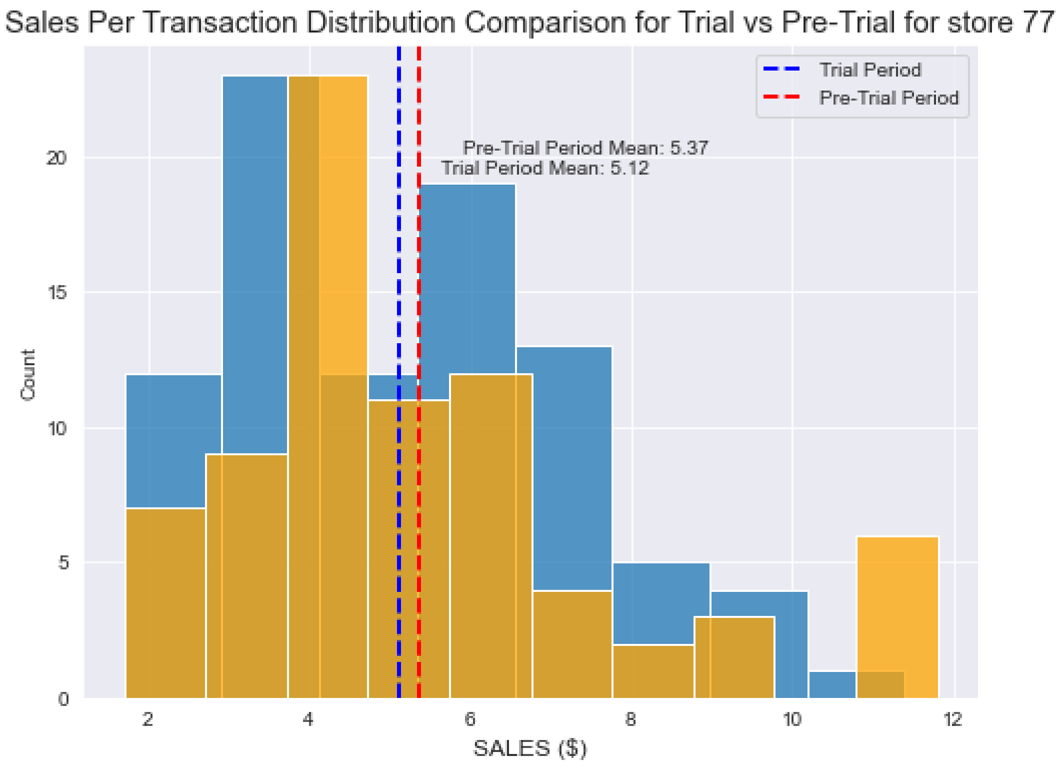
In [107]:

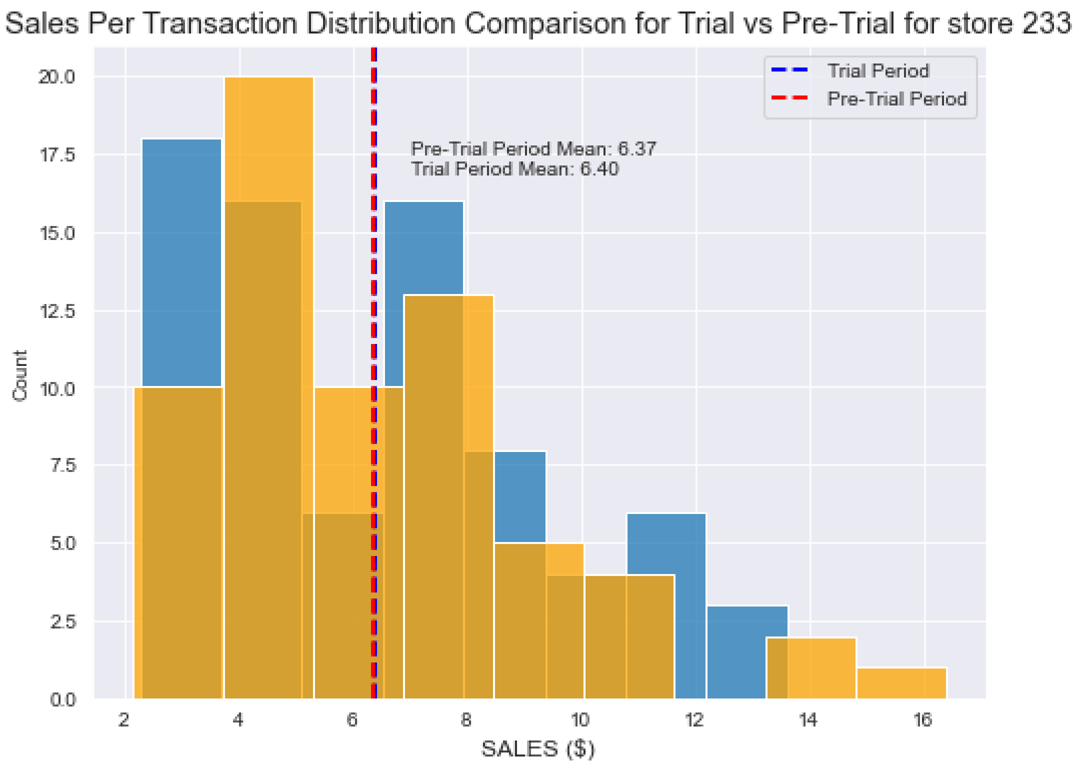
```
def create_scaled_sales_pre_trial_isolated_df(store, scaler):
    sub_df = pre_trial_rec
    query = f"SELECT * FROM sub_df WHERE STORE_NBR = {store}"
    df = ps.sqldf(query, locals())
    df['TOT_SALES'] = df['TOT_SALES'] * scaler
    return df

def create_trial_sales_pre_trial_isolated_df(store):
    sub_df = pre_trial_rec
    query = f"SELECT * FROM sub_df WHERE STORE_NBR = {store}"
    df = ps.sqldf(query, locals())
    return df

def create_trial_isolation_df(store):
    sub_df = trial_period_data
    query = f"SELECT * FROM sub_df WHERE STORE_NBR = {store}"
    df = ps.sqldf(query, locals())
    return df

def create_trial_control_isolation_df(store, scaler):
    sub_df = trial_period_data
    query = f"SELECT * FROM sub_df WHERE STORE_NBR = {store}"
    df = ps.sqldf(query, locals())
    df['TOT_SALES'] = df['TOT_SALES'] * scaler
    return df

# Display Distributions

def compare_distributions(trial, pre_trial, store):
    plt.figure(figsize = (8,6))
    ax1 = sns.histplot(trial['TOT_SALES'])
    ax2 = sns.histplot(pre_trial['TOT_SALES'], color = 'orange')
    plt.axvline(np.mean(trial['TOT_SALES']), color = 'b', linestyle = 'dashed', linewid
th = 2)
    plt.axvline(np.mean(pre_trial['TOT_SALES']), color = 'red', linestyle = 'dashed', l
inewidth = 2)
    _, max_ = plt.ylim()
    plt.text(
        trial['TOT_SALES'].mean() + trial['TOT_SALES'].mean() / 10,
        max_ - max_ / 5,
        "Trial Period Mean: {:.2f}".format(trial['TOT_SALES'].mean())
    )

    _, max_ = plt.ylim()
    plt.text(
        pre_trial['TOT_SALES'].mean() + pre_trial['TOT_SALES'].mean() / 10,
        max_ - max_ / 6,
        "Pre-Trial Period Mean: {:.2f}".format(pre_trial['TOT_SALES'].mean())
    )
    plt.xlabel('SALES ($)', fontsize = 12)
    plt.title(f'Sales Per Transaction Distribution Comparison for Trial vs Pre-Trial fo
r store {store}', fontsize = 15)
    plt.legend(['Trial Period', 'Pre-Trial Period'], loc = 'best')


def compare_trial_period_distributions(trial, pre_trial, store):
    plt.figure(figsize = (8,6))
    ax1 = sns.histplot(trial['TOT_SALES'])
    ax2 = sns.histplot(pre_trial['TOT_SALES'], color = 'maroon')
```

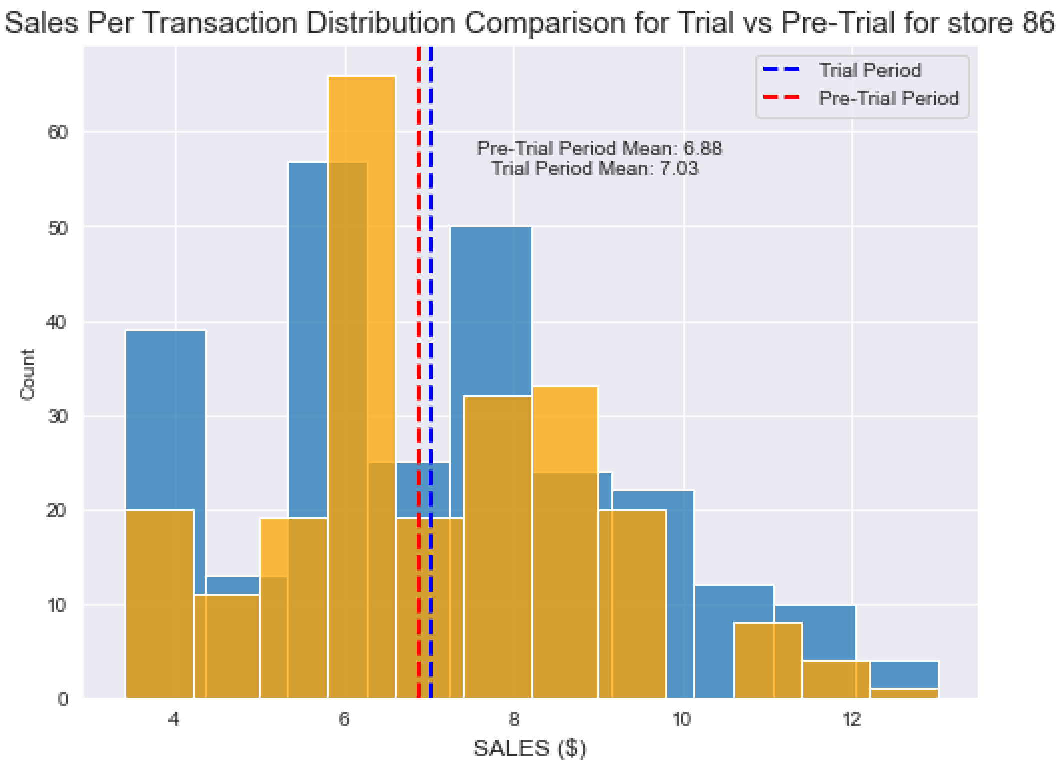
```
    plt.axvline(np.mean(trial['TOT_SALES']), color = 'b', linestyle = 'dashed', linewid
th = 2)
    plt.axvline(np.mean(pre_trial['TOT_SALES']), color = 'maroon', linestyle = 'dashed'
, linewidth = 2)
    _, max_ = plt.ylim()
    plt.text(
        trial['TOT_SALES'].mean() + trial['TOT_SALES'].mean() / 10,
        max_ - max_ / 5,
        "Trial Store Mean: {:.2f}".format(trial['TOT_SALES'].mean())
    )

    _, max_ = plt.ylim()
    plt.text(
        pre_trial['TOT_SALES'].mean() + pre_trial['TOT_SALES'].mean() / 10,
        max_ - max_ / 6,
        "Control Store Mean: {:.2f}".format(pre_trial['TOT_SALES'].mean())
    )
    plt.xlabel('SALES ($)', fontsize = 12)
    plt.title(f'Sales Per Transaction Distribution Comparison, Trial Store {store} vs C
ontrol Store', fontsize = 15)
    plt.legend(['Trial Store', 'Control Store'], loc = 'best')

# Pre Trial df's

pre_trial_77 = create_trial_sales_pre_trial_isolated_df(77)
pre_trial_233 = create_scaled_sales_pre_trial_isolated_df(233, 1.26)

pre_trial_86 = create_trial_sales_pre_trial_isolated_df(86)
pre_trial_67 = create_scaled_sales_pre_trial_isolated_df(67, 1.02)

pre_trial_88 = create_trial_sales_pre_trial_isolated_df(88)
pre_trial_165 = create_scaled_sales_pre_trial_isolated_df(165, 0.99)

# Trial period df's
trial_77 = create_trial_isolation_df(77)
trial_233 = create_trial_control_isolation_df(233, 1.26)

trial_86 = create_trial_isolation_df(86)
trial_67 = create_trial_control_isolation_df(67, 1.02)

trial_88 = create_trial_isolation_df(88)
trial_165 = create_trial_control_isolation_df(165, 0.99)
```

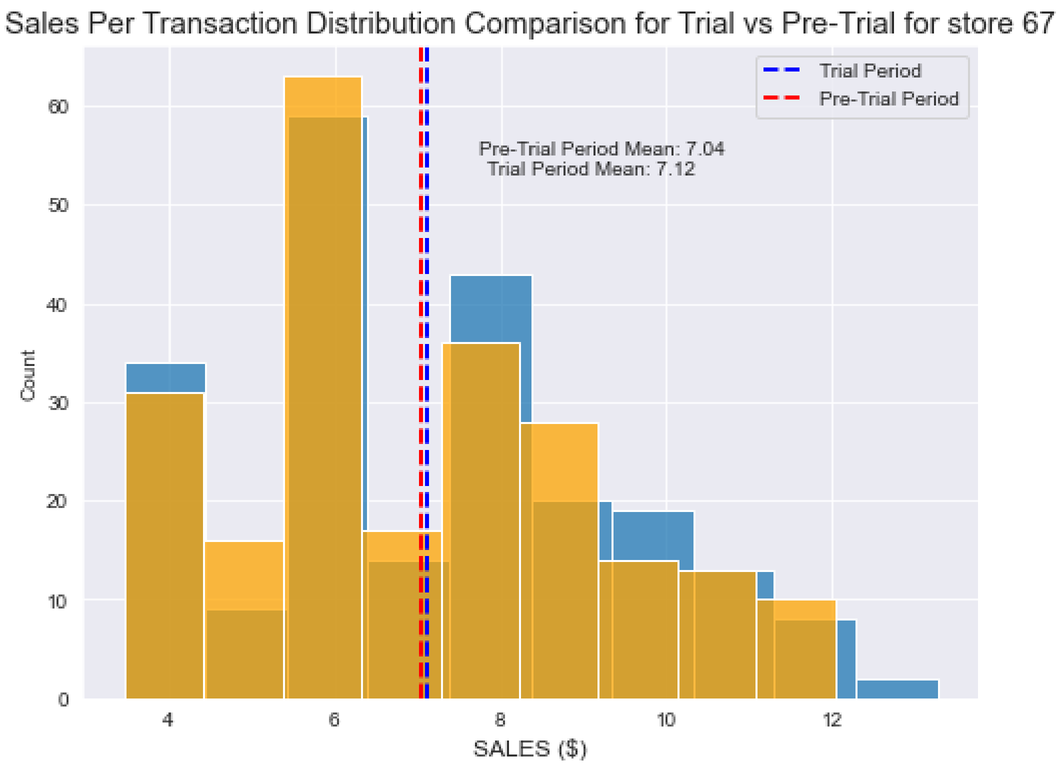
In [108]:

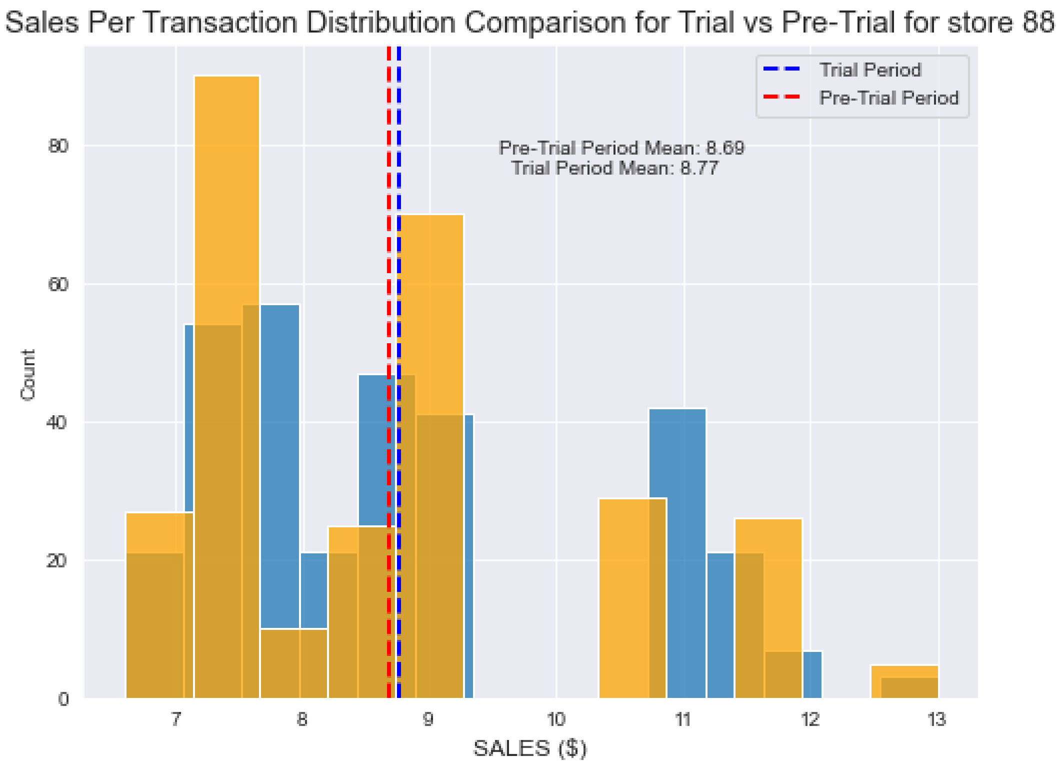
```
# Display Distributions for trial vs pre_trial

trial_dfs = [trial_77, trial_233, trial_86, trial_67, trial_88, trial_165]
pre_trial_dfs = [pre_trial_77, pre_trial_233, pre_trial_86, pre_trial_67, pre_trial_88,
pre_trial_165]
stores = [77,233,86,67,88,165]

for trial, pre_trial, store in zip(trial_dfs, pre_trial_dfs, stores):
    compare_distributions(trial, pre_trial, store)
```

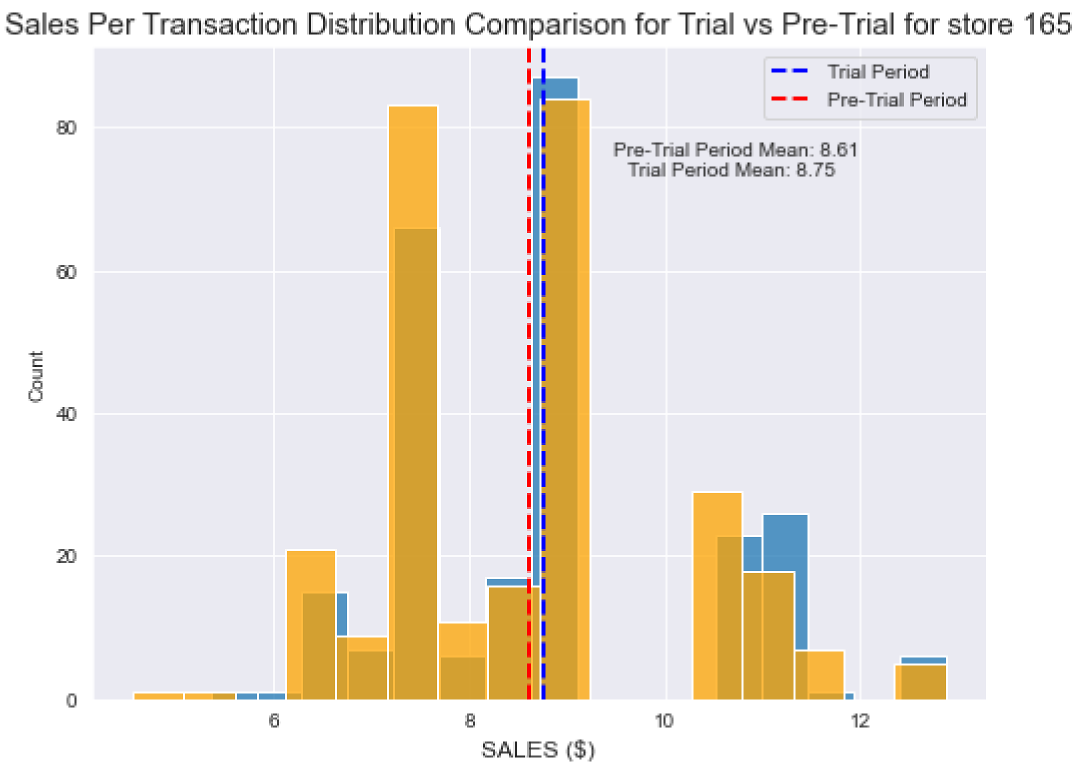

Sales Per Transaction Distribution Comparison for Trial vs Pre-Trial for store 77
Trial Period
Pre-Trial Period
Pre-Trial Period Mean: 5.37
Trial Period Mean: 5.12
Count
SALES ($)


Sales Per Transaction Distribution Comparison for Trial vs Pre-Trial for store 233
Trial Period
Pre-Trial Period
Pre-Trial Period Mean: 6.37
Trial Period Mean: 6.40
Count
SALES ($)


Sales Per Transaction Distribution Comparison for Trial vs Pre-Trial for store 86
Trial Period
Pre-Trial Period
Pre-Trial Period Mean: 6.88
Trial Period Mean: 7.03
Count
SALES ($)
0
10
20
30
40
50
60
4
6
8
10
12


Sales Per Transaction Distribution Comparison for Trial vs Pre-Trial for store 67
Trial Period
Pre-Trial Period
Pre-Trial Period Mean: 7.04
Trial Period Mean: 7.12
Count
SALES ($)
0
10
20
30
40
50
60
4
6
8
10
12





In [109]:

```
# compare 2 groups func
def compare_2_groups(arr_1, arr_2, alpha, sample_size):
    stat, p = ttest_ind(arr_1, arr_2)
    print('Statistics = %.3f, p=%.3f' % (stat, p))
    if p > alpha:
        print('Same distribution (fail to reject H0)')
    else:
        print('Different distributions (reject H0)')
```

In [171]:

```
# Perform T-Test
sample_size = 50

# Store 77
store_77_pre_trial_sampled = np.random.choice(pre_trial_77['TOT_SALES'], sample_size)
store_77_trial_sampled = np.random.choice(trial_77['TOT_SALES'], sample_size)

# Store 77 trial vs pre_trial
compare_2_groups(store_77_pre_trial_sampled, store_77_trial_sampled, 0.05, sample_size)
```

```
Statistics = 2.316, p=0.023
Different distributions (reject H0)
```

In [134]:

```
# Store 86
store_86_pre_trial_sampled = np.random.choice(pre_trial_86['TOT_SALES'], sample_size)
store_86_trial_sampled = np.random.choice(trial_86['TOT_SALES'], sample_size)

# Store 86 trial vs pre_trial
compare_2_groups(store_86_pre_trial_sampled, store_86_trial_sampled, 0.05, sample_size)
```

```
Statistics = 2.389, p=0.024
Different distributions (reject H0)
```

In [136]:

```
# Store 88
store_88_pre_trial_sampled = np.random.choice(pre_trial_88['TOT_SALES'], sample_size)
store_88_trial_sampled = np.random.choice(trial_88['TOT_SALES'], sample_size)

# Store 88 trial vs pre_trial
compare_2_groups(store_88_pre_trial_sampled, store_88_trial_sampled, 0.05, sample_size)
```

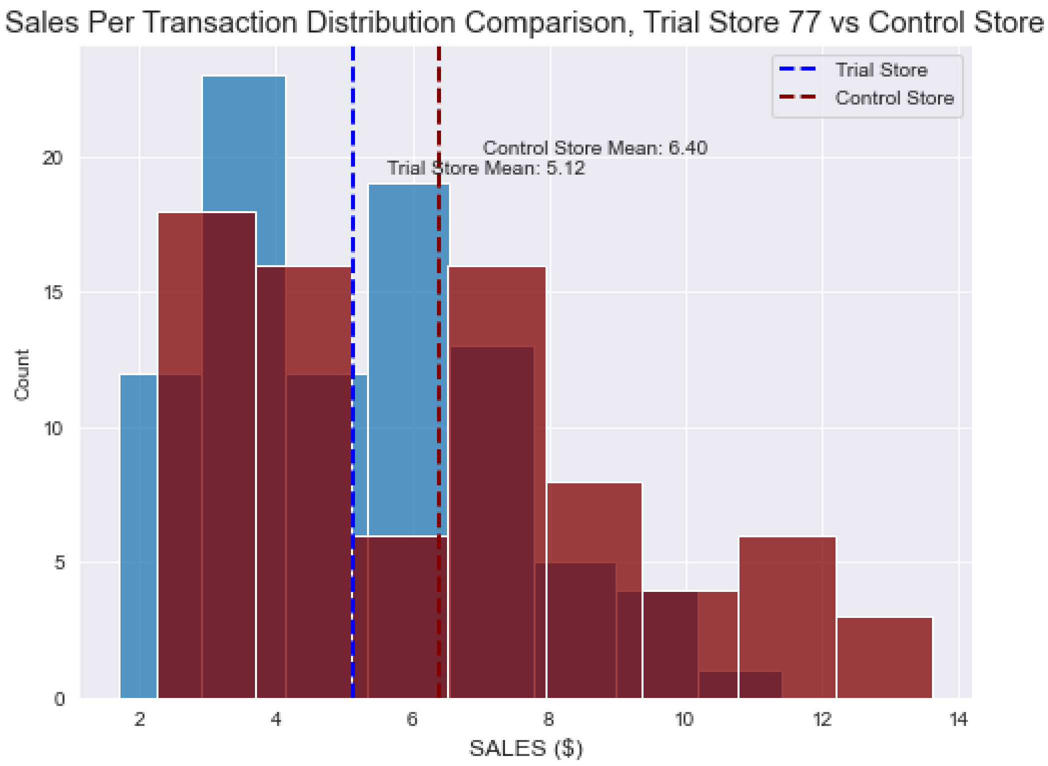
```
Statistics = -2.232, p=0.034
Different distributions (reject H0)
```

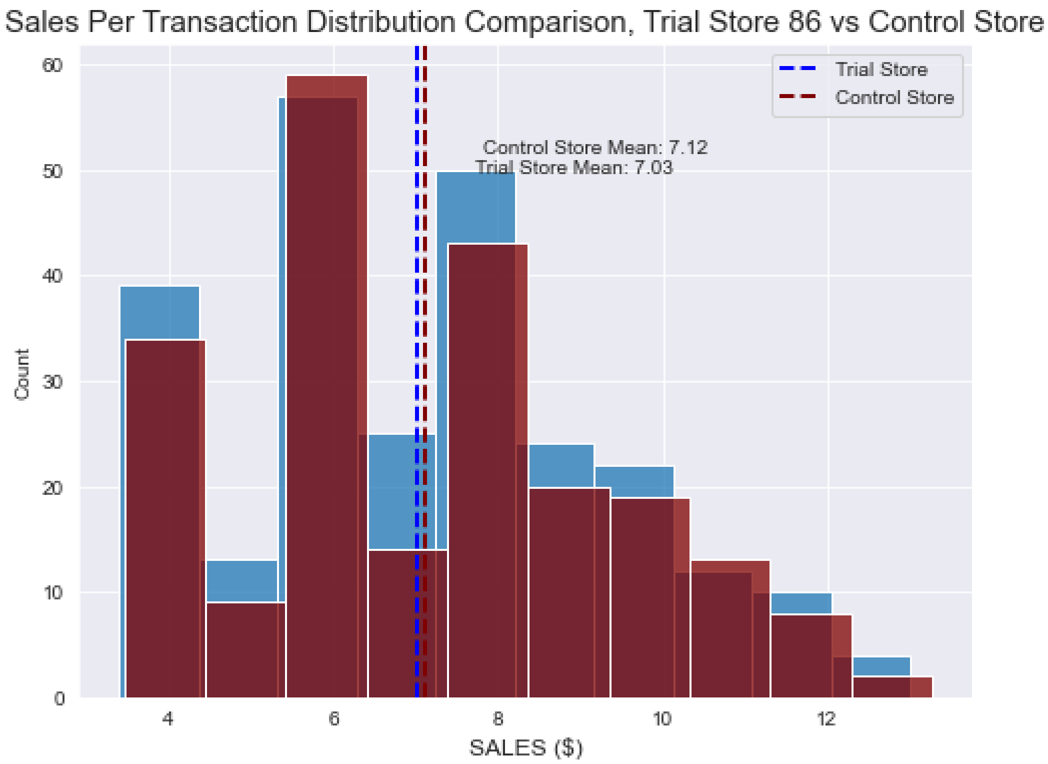
Great! We see that there is a significant difference between the distributions of the trial stores during the trial period and outside the trial period.

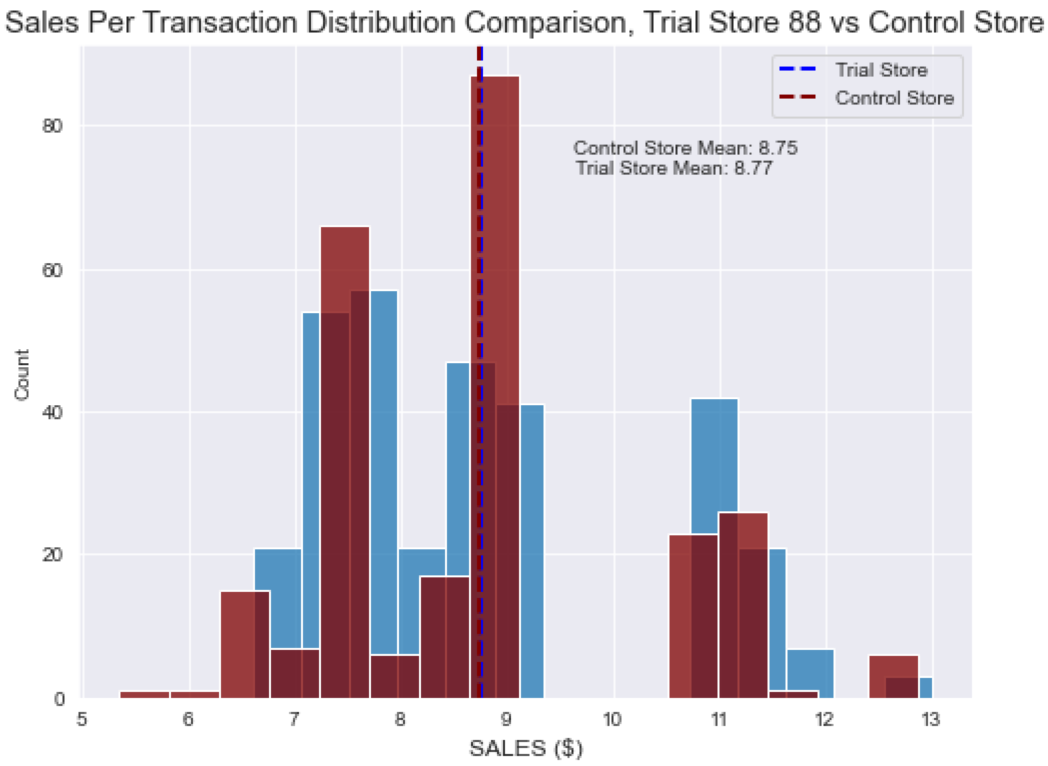
We will next run a test to see if the difference between the trial and control stores during the trial period are significantly different. We will first look at the distributions as previous, then run a t test on the 3 pairs of stores.

In [137]:

```
# Display distributions of trial and control stores during trial period.

trial_store_dfs = [trial_77, trial_86, trial_88]
trial_control_dfs = [trial_233, trial_67, trial_165]
stores = [77, 86, 88]

for trial, control, store in zip(trial_store_dfs, trial_control_dfs, stores):
    compare_trial_period_distributions(trial, control, store)
```


Sales Per Transaction Distribution Comparison, Trial Store 77 vs Control Store
Trial Store
Control Store
Control Store Mean: 6.40
Trial Store Mean: 5.12
Count
0
5
10
15
20
2
4
6
8
10
12
14
SALES ($)


Sales Per Transaction Distribution Comparison, Trial Store 86 vs Control Store
Trial Store
Control Store
Control Store Mean: 7.12
Trial Store Mean: 7.03
Count
0
10
20
30
40
50
60
4
6
8
10
12
SALES ($)



Now we can run a T-test with a null hypothesis being that the sales in the trial store is not significantly different from it's control store.

In [159]:

```
# Perform T-test
sample_size = 50

# Store 77
store_77_trial_sampled = np.random.choice(trial_77['TOT_SALES'], sample_size)
store_233_trial_sampled = np.random.choice(trial_233['TOT_SALES'], sample_size)

compare_2_groups(store_77_trial_sampled, store_233_trial_sampled, 0.05, sample_size)
```

```
Statistics = -2.092, p=0.039
Different distributions (reject H0)
```

In [314]:

```
# Store 86
sample_size = 50
store_86_trial_sampled = np.random.choice(trial_86['TOT_SALES'], sample_size)
store_67_trial_sampled = np.random.choice(trial_67['TOT_SALES'], sample_size)

compare_2_groups(store_86_trial_sampled, store_67_trial_sampled, 0.05, sample_size)
```

```
Statistics = -1.002, p=0.319
Same distribution (fail to reject H0)
```

In [168]:

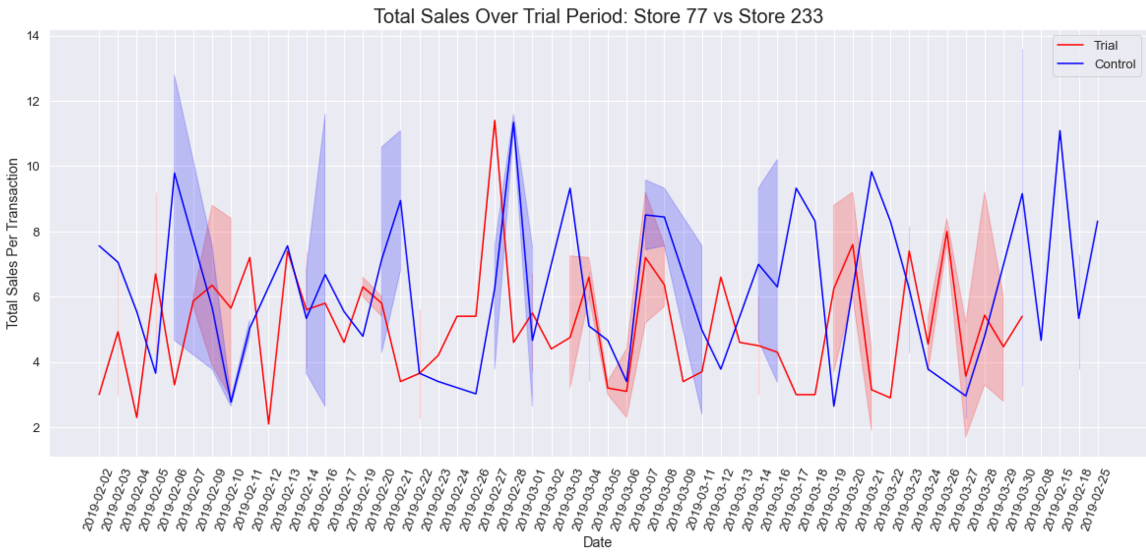
```
# Store 88
store_88_trial_sampled = np.random.choice(trial_88['TOT_SALES'], sample_size)
store_165_trial_sampled = np.random.choice(trial_165['TOT_SALES'], sample_size)

compare_2_groups(store_88_trial_sampled, store_165_trial_sampled, 0.05, sample_size)
```

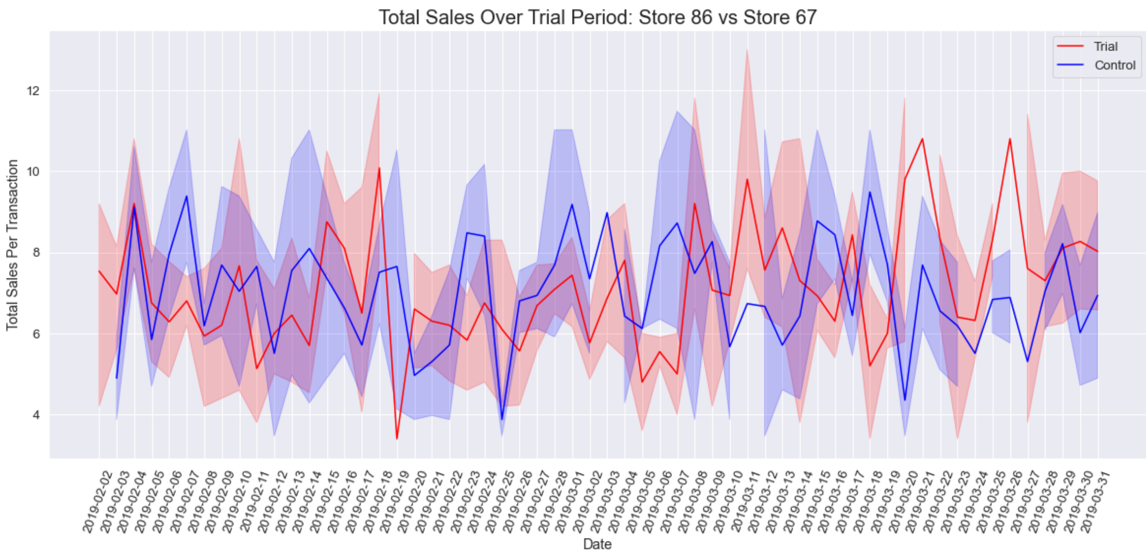
```
Statistics = 2.762, p=0.007
Different distributions (reject H0)
```

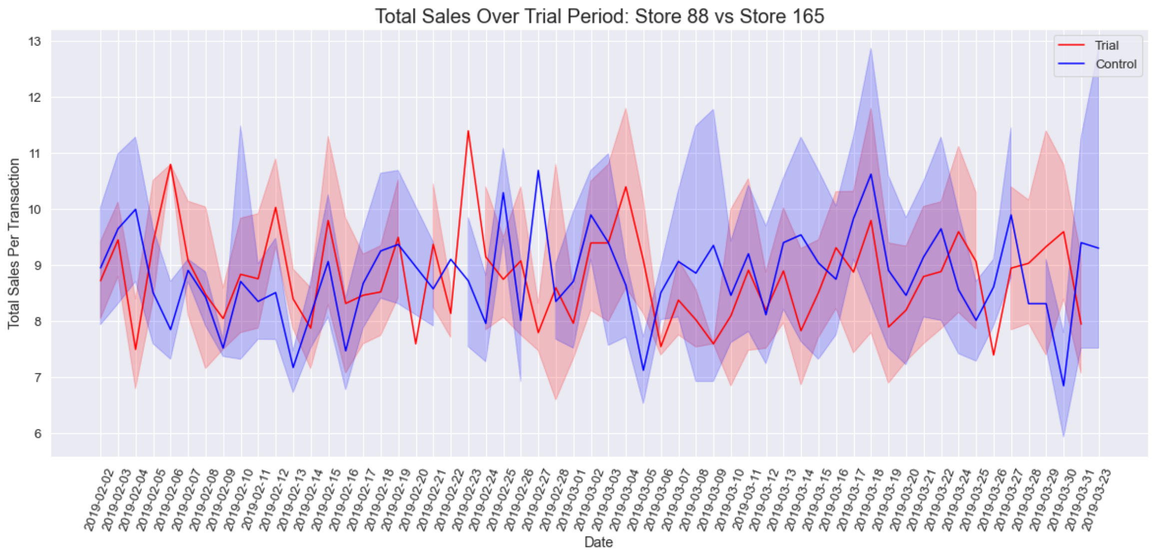
Let's visualize the sales of the trial and the control stores to see how different they are.

In [188]:

```
def plot_difference(trial, control, trial_store, control_store):
    plt.figure(figsize = (20,8))
    sns.set_style('darkgrid')
    sns.set_context('notebook', font_scale = 1.2)
    sns.lineplot(data = trial, x = 'real_date', y = 'TOT_SALES', palette = 'rocket', co
lor = 'r')
    sns.lineplot(data = control, x = 'real_date', y = 'TOT_SALES', palette = 'rocket',
color = 'b')
    plt.xlabel('Date')
    plt.ylabel('Total Sales Per Transaction')
    plt.title(f'Total Sales Over Trial Period: {trial_store} vs {control_store}', fonts
ize = 20)
    plt.legend(['Trial', 'Control'])
    plt.xticks(rotation = 70)

plot_difference(trial_77, trial_233, 'Store 77', 'Store 233')
plot_difference(trial_86, trial_67, 'Store 86', 'Store 67')
plot_difference(trial_88, trial_165, 'Store 88', 'Store 165')
```


Total Sales Over Trial Period: Store 77 vs Store 233
Trial
Control
Total Sales Per Transaction
Date


Total Sales Over Trial Period: Store 86 vs Store 67
Trial
Control
Total Sales Per Transaction
Date



Now that we have our data and assessment of the trial on total sales, we can do the same for number of customers.

In [199]:

```
# Scaling the pre_trial number of customers for the control stores

pre_trial_customers_scaled = pre_trial_data[['NBR_OF_CUST', 'TYPE']]

trial_stores = [77, 86, 88]
control_stores = [233, 67, 165]

scaling_factors = []

for trial_store, control_store in zip(trial_stores, control_stores):
    df = pre_trial_rec[pre_trial_rec['STORE_NBR'] == trial_store]
    df2 = pre_trial_rec[pre_trial_rec['STORE_NBR'] == control_store]
    cust_trial = len(df)
    cust_control = len(df2)
    scaler = cust_trial / cust_control
    scaling_factors.append(round(scaler,2))

for control_store, scaler in zip(control_stores, scaling_factors):
    new_value = round((pre_trial_data[pre_trial_data.index == control_store]['NBR_OF_CU
ST']) * scaler, 1)
    pre_trial_customers_scaled.at[control_store, 'NBR_OF_CUST'] = new_value

pre_trial_customers_scaled
```

Out[199]:

	NBR_OF_CUST	TYPE
STORE_NBR		
77	77	Trial Store
233	76	Control Store
86	233	Trial Store
67	232	Control Store
88	282	Trial Store
165	282	Control Store

In [201]:

```
print(scaling_factors)
```

```
[1.18, 1.02, 0.99]
```

Now that we have scaled figures for the baseline (pre_trial) we can scale the actual transactions for the trial period.

In [203]:

```
scaled_trial_customers = pre_trial_customers_scaled[['TYPE', 'NBR_OF_CUST']]
scaled_trial_customers['SCALING_FACTOR'] = [0, scaling_factors[0], 0, scaling_factors[1
], 0, scaling_factors[2]]
scaled_trial_customers
```

Out[203]:

STORE_NBR	TYPE	NBR_OF_CUST	SCALING_FACTOR
77	Trial Store	77	0.00
233	Control Store	76	1.18
86	Trial Store	233	0.00
67	Control Store	232	1.02
88	Trial Store	282	0.00
165	Control Store	282	0.99

In [214]:

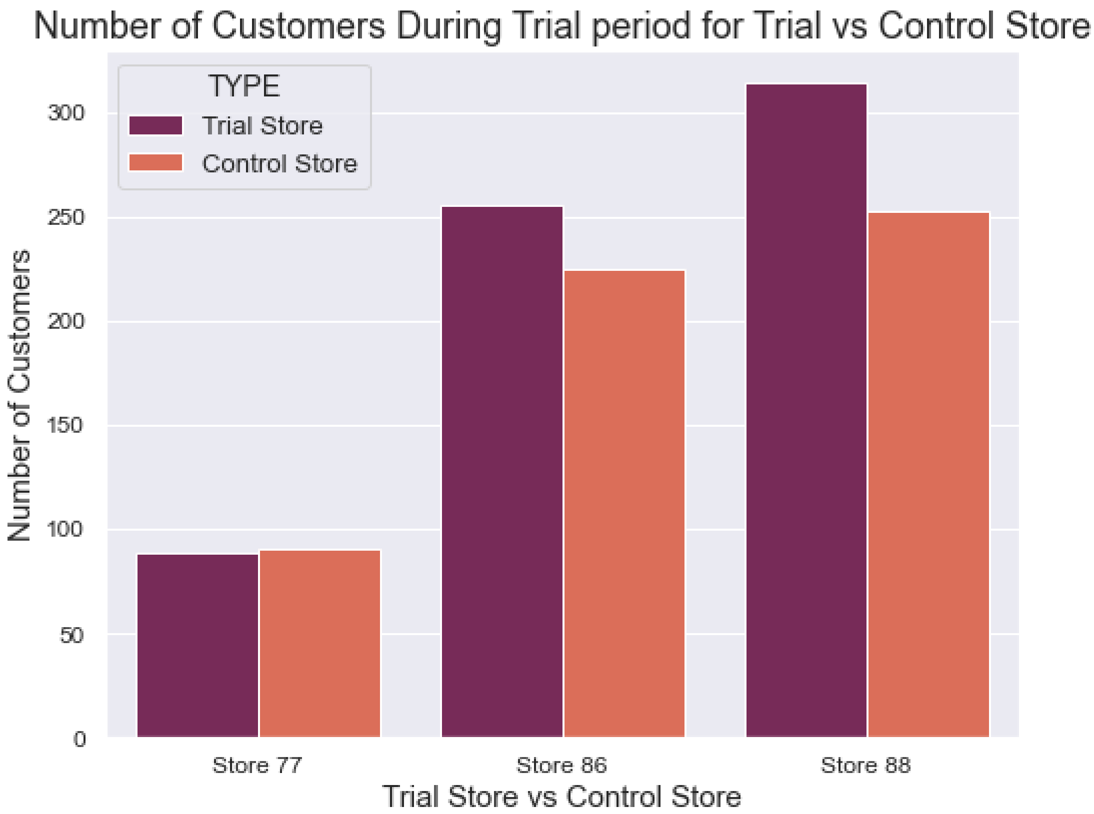
```
# Gather data for period of trail

#control_store_trial_data

#trial_period_data

trial_stores = [77, 86, 88]
control_stores = [233, 67, 165]

scaled_cust = []
for trial_store, control_store, scaler in zip(trial_stores, control_stores, scaling_fac
tors):

    # Trial store customers
    trial_df = trial_period_data[trial_period_data['STORE_NBR'] == trial_store]
    trial_cust = len(trial_df)
    scaled_cust.append(trial_cust)

    # Scaling the control store customers
    control_df = control_store_trial_data[control_store_trial_data['STORE_NBR'] == cont
rol_store]
    control_cust = int(round(len(control_df) * scaler, 0))
    scaled_cust.append(control_cust)

scaled_trial_customers['TRIAL_NBR_CUST'] = scaled_cust

# Create comparison df
comparison_cust = scaled_trial_customers[['TYPE', 'NBR_OF_CUST']]
comparison_cust.rename(columns = {'NBR_OF_CUST': 'PRE_TRIAL_CUST'}, inplace = True)
comparison_cust['TRIAL_CUST'] = scaled_cust

# Get % change
comparison_cust['%_CHANGE'] = round(((comparison_cust['TRIAL_CUST'] - comparison_cust[
'PRE_TRIAL_CUST']) / comparison_cust['PRE_TRIAL_CUST']) * 100, 2)

# Percentage Differential
differential = []

for i,x in zip(trial_stores, control_stores):
    diff_trial = round(((comparison_cust.at[i, 'TRIAL_CUST'] - comparison_cust.at[x, 'T
RIAL_CUST'])/ comparison_cust.at[x, 'TRIAL_CUST'])*100, 2)
    diff_control = round(((comparison_cust.at[x, 'TRIAL_CUST'] - comparison_cust.at[i,
'TRIAL_CUST']) / comparison_cust.at[x, 'TRIAL_CUST'])* 100, 2)
    differential.append(diff_trial)
    differential.append(diff_control)
comparison_cust['%_DIFFERENCE'] = differential

for i in control_stores:
    comparison_cust.at[i, '%_DIFFERENCE'] = 0

comparison_cust['TRIAL_STORE'] = ['Store 77', 'Store 77', 'Store 86', 'Store 86', 'Stor
e 88', 'Store 88']
comparison_cust
```

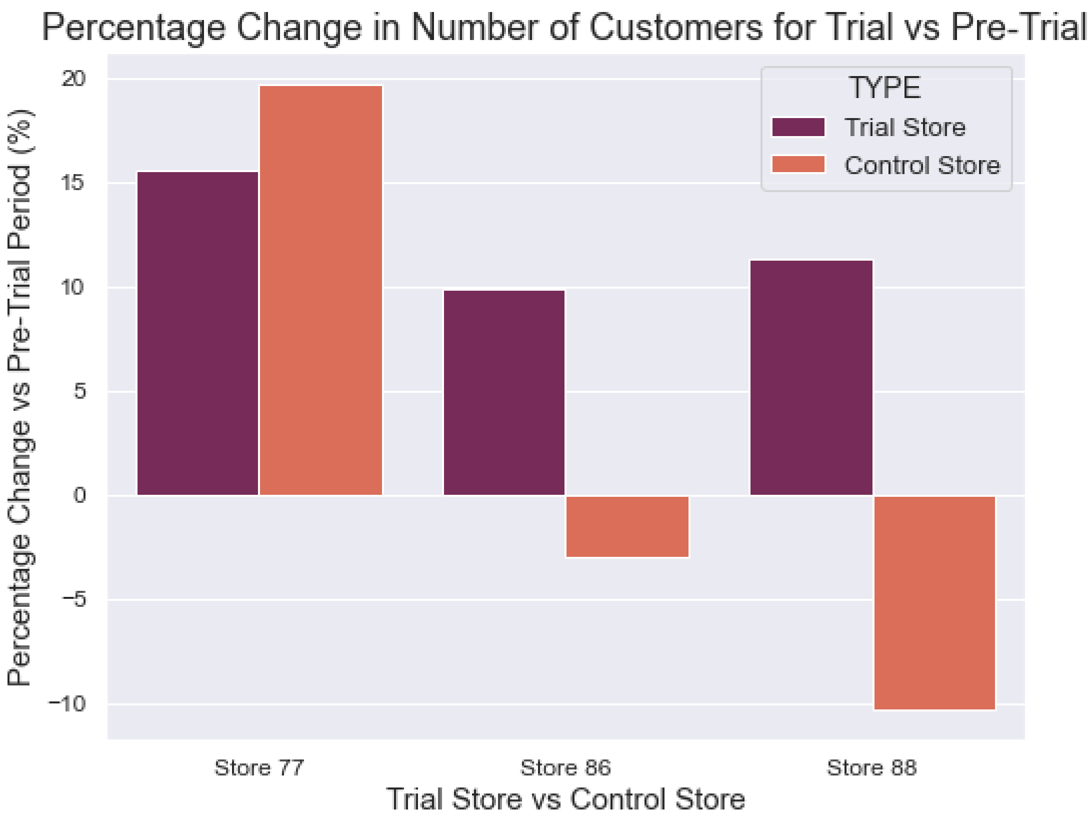
Out[214]:

STORE_NBR	TYPE	PRE_TRIAL_CUST	TRIAL_CUST	%_CHANGE	%_DIFFERENCE	TRIAL_
77	Trial Store	77	89	15.58	-2.20	S
233	Control Store	76	91	19.74	0.00	S
86	Trial Store	233	256	9.87	13.78	S
67	Control Store	232	225	-3.02	0.00	S
88	Trial Store	282	314	11.35	24.11	S
165	Control Store	282	253	-10.28	0.00	S

In [215]:

```
# plotting the results

# Number of Customers during Trial Period
plt.figure(figsize = (8,6))
ax = sns.set_style('darkgrid')
ax = sns.barplot(x = 'TRIAL_STORE', y = 'TRIAL_CUST', data = comparison_cust, hue = 'TY
PE', palette = 'rocket')
ax.set_xlabel('Trial Store vs Control Store', fontsize = 15)
ax.set_ylabel('Number of Customers', fontsize = 15)
ax.axes.set_title('Number of Customers During Trial period for Trial vs Control Store',
fontsize = 18)
plt.xticks(fontsize = 12)
plt.yticks(fontsize = 12)
plt.tight_layout()

# % Change compared to pre-trial period
plt.figure(figsize = (8,6))
ax = sns.set_style('darkgrid')
ax = sns.barplot(x = 'TRIAL_STORE', y = '%_CHANGE', data = comparison_cust, hue = 'TYP
E', palette = 'rocket')
ax.set_xlabel('Trial Store vs Control Store', fontsize = 15)
ax.set_ylabel('Percentage Change vs Pre-Trial Period (%)', fontsize = 15)
ax.axes.set_title('Percentage Change in Number of Customers for Trial vs Pre-Trial', fo
ntsize = 18)
plt.xticks(fontsize = 12)
plt.yticks(fontsize = 12)
plt.tight_layout()

# % Differential of sales for Trial Store vs Control Store
plt.figure(figsize = (8,6))
ax = sns.set_style('darkgrid')
ax = sns.barplot(x = 'TRIAL_STORE', y = '%_DIFFERENCE', data = comparison_cust, palette
= 'rocket')
ax.set_xlabel('Trial Store vs Control Store', fontsize = 15)
ax.set_ylabel('Percentage Differential (%)', fontsize = 15)
ax.axes.set_title('Percentage Differential in Number of Customers for Trial Store vs Co
ntrol Store', fontsize = 18)
plt.xticks(fontsize = 12)
plt.yticks(fontsize = 12)
plt.tight_layout()
```


Number of Customers During Trial period for Trial vs Control Store
TYPE
Trial Store
Control Store
Number of Customers
0
50
100
150
200
250
300
Store 77
Store 86
Store 88
Trial Store vs Control Store


Percentage Change in Number of Customers for Trial vs Pre-Trial
TYPE
Trial Store
Control Store
Percentage Change vs Pre-Trial Period (%)
20
15
10
5
0
−5
−10
Store 77
Store 86
Store 88
Trial Store vs Control Store

We see that 2/3 stores were able to increase their number of customers higher than that of their corresponding control store. Similarly, those same stores were the only ones capable of having a higher percentage change in number of customers compared to it's control store coutnerpart.

- Trial store 77 did not see a percentage increase higher than its control store, and during the trail had 2.2% less customers.
- Trial stores 86 and 88 did see significant increases in customers over the trial period compared to their control stores, having percentage differentials of 13.78% and 24.11% respectively.

Let's see if the differences are significant for each store, by comparing distributions and running T-Tests. The null hypothesis for our t_test will be that there is no significant difference between the control store and the trial store for the length of the trial.

In [232]:

```
# Get proper distributions of customers by value_counting date then scaling by scalers

def create_trial_customer_distribution_df(trial_store):
    dictionary = dict(trial_store['real_date'].value_counts().sort_index())
    df = pd.DataFrame.from_dict(dictionary, orient = 'index', columns = ['customers'])
    return df

def create_scaled_control_distribution_df(control_store, scaler):
    dictionary = dict(control_store['real_date'].value_counts().sort_index())
    df = pd.DataFrame.from_dict(dictionary, orient = 'index', columns = ['customers'])
    df['customers'] = df['customers'] * scaler
    return df

# trial stores
trial_77_cust_dist = create_trial_customer_distribution_df(trial_77)
trial_86_cust_dist = create_trial_customer_distribution_df(trial_86)
trial_88_cust_dist = create_trial_customer_distribution_df(trial_88)

# control stores
trial_233_cust_dist = create_scaled_control_distribution_df(trial_233, scaling_factors[
0])
trial_67_cust_dist = create_scaled_control_distribution_df(trial_67, scaling_factors[1
])
trial_165_cust_dist = create_scaled_control_distribution_df(trial_165, scaling_factors[
2])
```

In [244]:

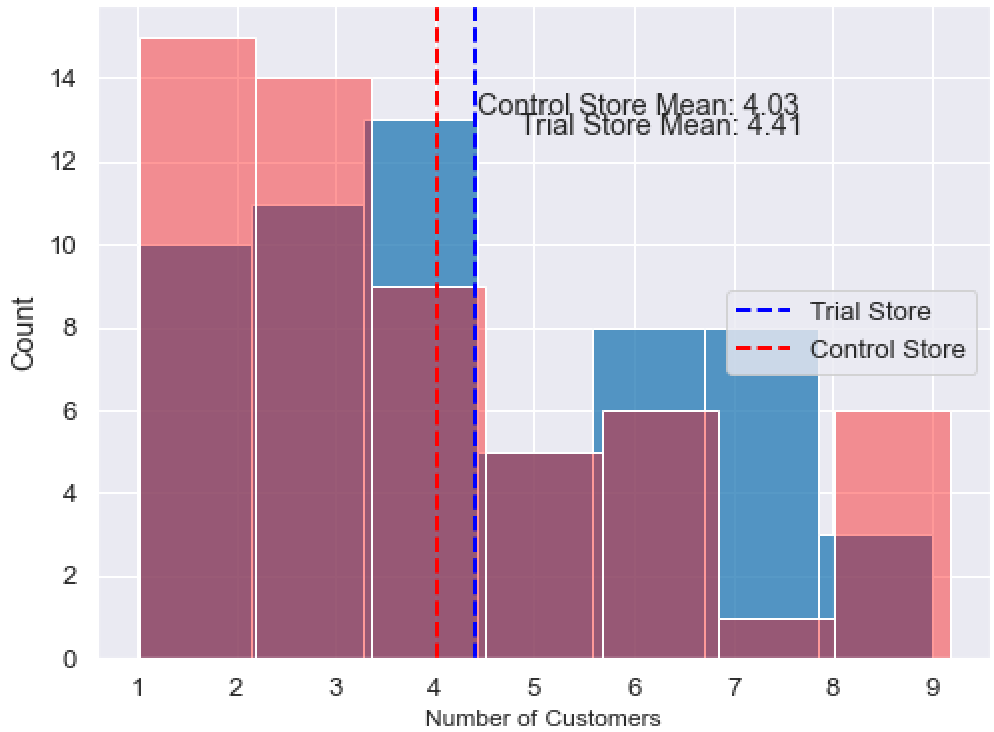
```
def compare_trial_period_distributions(trial, control, store):
    plt.figure(figsize = (8,6))
    ax1 = sns.histplot(trial['customers'])
    ax2 = sns.histplot(control['customers'], color = 'red', alpha = 0.4)
    plt.axvline(np.mean(trial['customers']), color = 'b', linestyle = 'dashed', linewid
th = 2)
    plt.axvline(np.mean(control['customers']), color = 'red', linestyle = 'dashed', lin
ewidth = 2)
    _, max_ = plt.ylim()
    plt.text(
        trial['customers'].mean() + trial['customers'].mean() / 10,
        max_ - max_ / 5,
        "Trial Store Mean: {:.2f}".format(trial['customers'].mean())
    )

    _, max_ = plt.ylim()
    plt.text(
        control['customers'].mean() + control['customers'].mean() / 10,
        max_ - max_ / 6,
        "Control Store Mean: {:.2f}".format(control['customers'].mean())
    )
    plt.xlabel('Number of Customers', fontsize = 12)
    plt.title(f'Number of Daily Customers Distribution Comparison, Trial Store {store}
 vs Control Store', fontsize = 15)
    plt.legend(['Trial Store', 'Control Store'], loc = 'right')
```

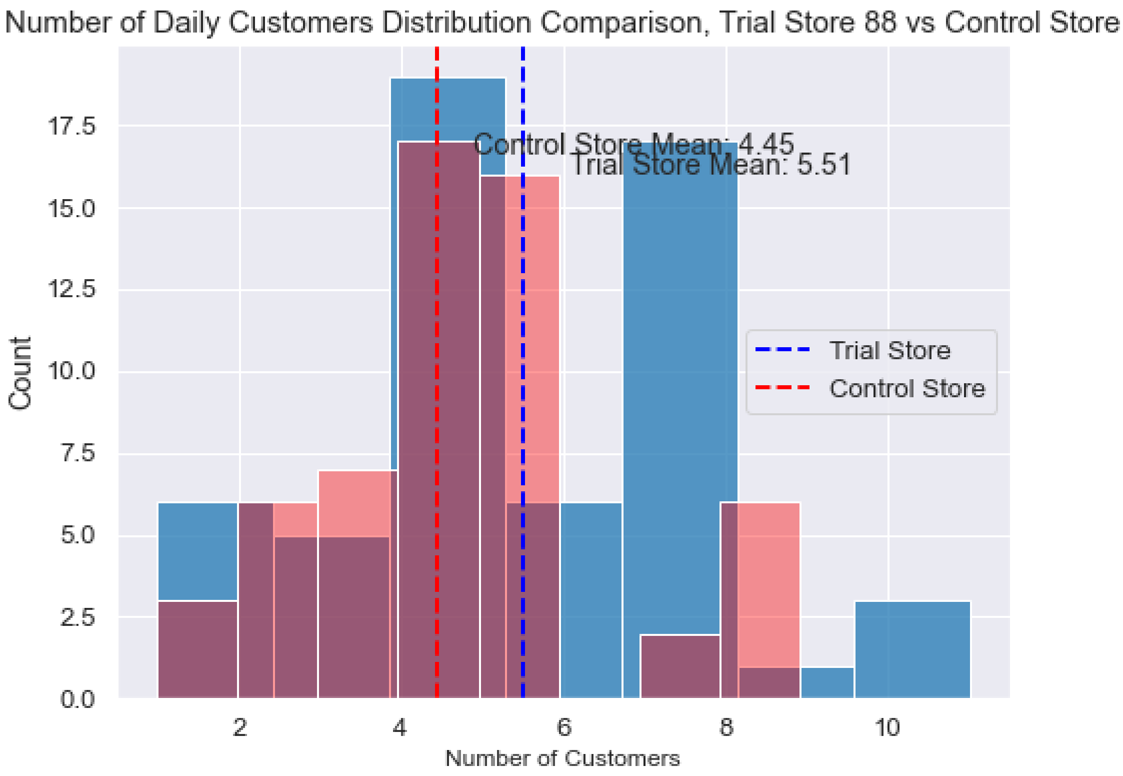
In [245]:

```
trial_store_dfs = [trial_77_cust_dist, trial_86_cust_dist, trial_88_cust_dist]
control_store_dfs = [trial_233_cust_dist, trial_67_cust_dist, trial_165_cust_dist]
stores = [77, 86, 88]

for trial, control, store in zip(trial_store_dfs, control_store_dfs, stores):
    compare_trial_period_distributions(trial, control, store)
```

Number of Daily Customers Distribution Comparison, Trial Store 77 vs Control Store

Number of Daily Customers Distribution Comparison, Trial Store 86 vs Control Store





Now that we've compared the distributions, and seen that they are different, we will confirm the significance of the difference using the t-test with a null hypothesis being that there is no difference.

In [262]:

```
# Performing the T-Test
sample_size = 10

# Store 77
store_77_cust_sampled = np.random.choice(trial_77_cust_dist['customers'], sample_size)
store_233_cust_sampled = np.random.choice(trial_233_cust_dist['customers'], sample_size
)

compare_2_groups(store_77_cust_sampled, store_233_trial_sampled, 0.05, sample_size)
```

```
Statistics = -6.071, p=0.000
Different distributions (reject H0)
```

In [270]:

```
# Store 86
store_86_cust_sampled = np.random.choice(trial_86_cust_dist['customers'], sample_size)
store_67_cust_sampled = np.random.choice(trial_67_cust_dist['customers'], sample_size)

compare_2_groups(store_86_cust_sampled, store_67_trial_sampled, 0.05, sample_size)
```

```
Statistics = -2.135, p=0.037
Different distributions (reject H0)
```

In [273]:

```
# Store 88
store_88_cust_sampled = np.random.choice(trial_88_cust_dist['customers'], sample_size)
store_165_cust_sampled = np.random.choice(trial_165_cust_dist['customers'], sample_size
)

compare_2_groups(store_88_cust_sampled, store_165_trial_sampled, 0.05, sample_size)
```

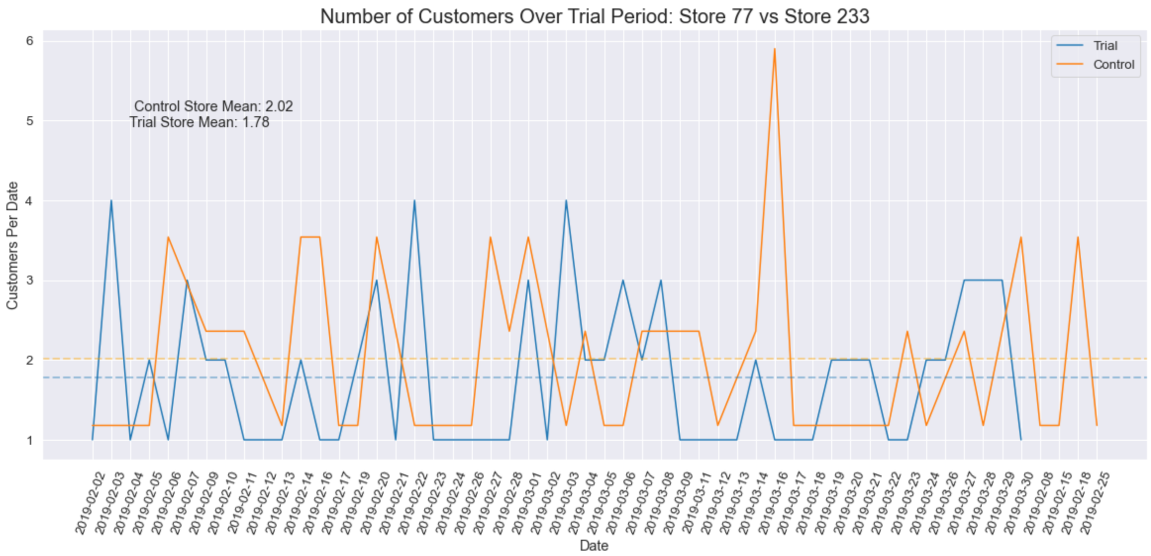
```
Statistics = -2.783, p=0.007
Different distributions (reject H0)
```

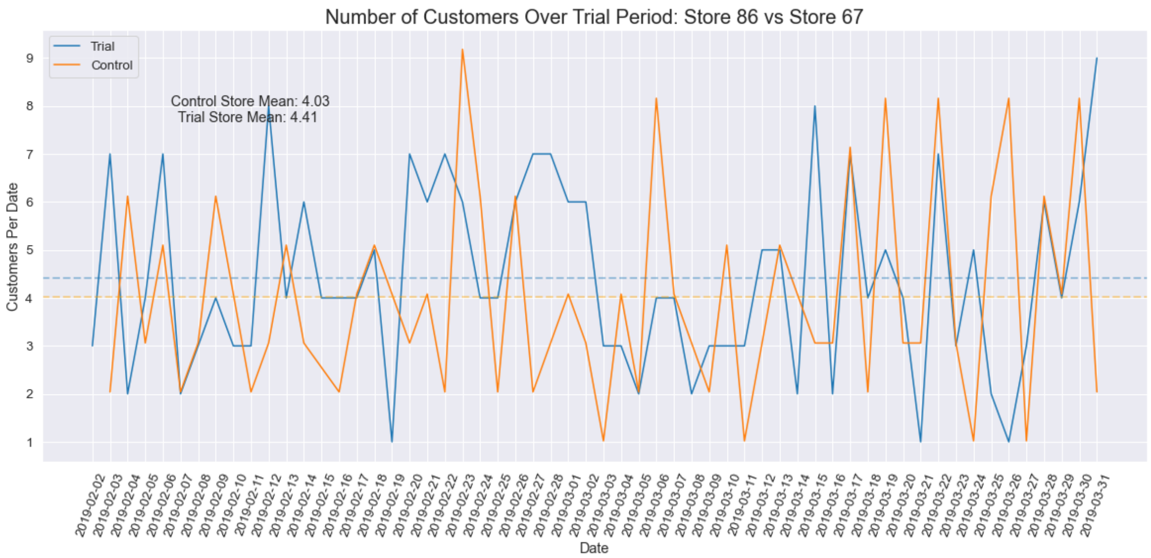
Our t-tests resulted in all trial stores being significantly different from their control store's distributions.

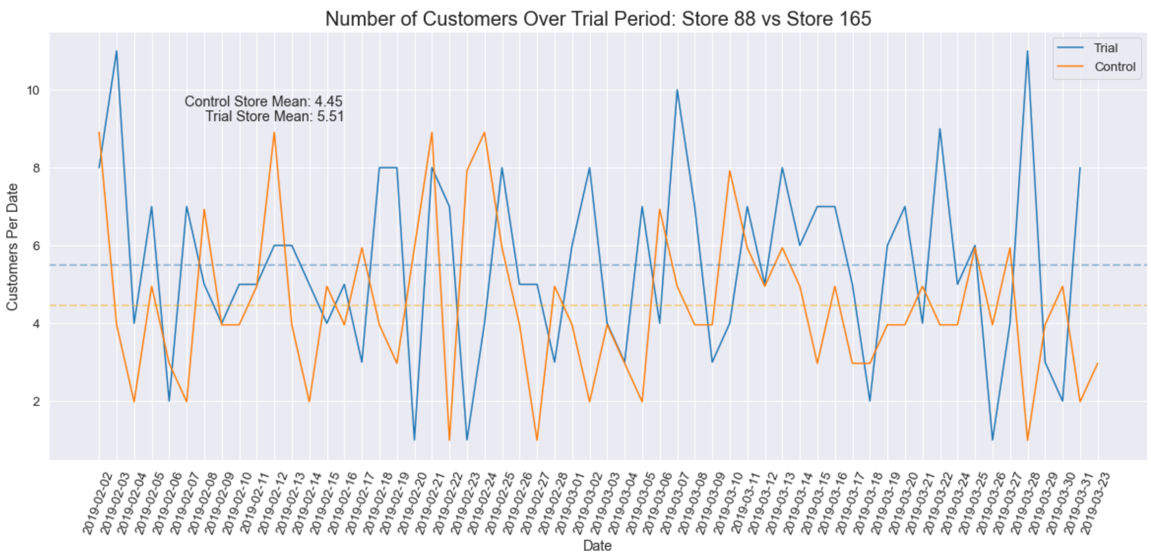
Let's visualize the customers of the trial and control stores over the trial period to see how different they are.

In [288]:

```
def plot_difference_cust(trial, control, trial_store, control_store):
    plt.figure(figsize = (20,8))
    sns.set_style('darkgrid')
    sns.set_context('notebook', font_scale = 1.2)
    sns.lineplot( x = trial.index, y = trial['customers'], palette = 'rocket')
    sns.lineplot( x = control.index, y = control['customers'], palette = 'rocket')
    plt.axhline(np.mean(trial['customers']), linestyle = 'dashed', linewidth = 2, alpha
= 0.4)
    plt.axhline(np.mean(control['customers']), linestyle = 'dashed', color = 'orange',
linewidth = 2, alpha = 0.4)
    _, max_ = plt.ylim()
    plt.text(
        trial['customers'].mean() + trial['customers'].mean() / 10,
        max_ - max_ / 5,
        "Trial Store Mean: {:.2f}".format(trial['customers'].mean())
    )

    _, max_ = plt.ylim()
    plt.text(
        control['customers'].mean() + control['customers'].mean() / 10,
        max_ - max_ / 6,
        "Control Store Mean: {:.2f}".format(control['customers'].mean())
    )
    plt.xlabel('Date')
    plt.ylabel('Customers Per Date')
    plt.title(f'Number of Customers Over Trial Period: {trial_store} vs {control_store}
', fontsize = 20)
    plt.legend(['Trial', 'Control'])
    plt.xticks(rotation = 70)

plot_difference_cust(trial_77_cust_dist, trial_233_cust_dist, 'Store 77', 'Store 233')
plot_difference_cust(trial_86_cust_dist, trial_67_cust_dist, 'Store 86', 'Store 67')
plot_difference_cust(trial_88_cust_dist, trial_165_cust_dist, 'Store 88', 'Store 165')
```







Summary DataFrame

In [317]:

```
summary_df = comparison[['TYPE', 'PRE_TRIAL_SALES', 'TRIAL_SALES', '%_CHANGE','%_DIFFER
ENCE']]
summary_df.rename(columns = {'%_CHANGE': 'SALES_%_CHANGE',
                            '%_DIFFERENCE': 'SALES_%_DIFFERENTIAL'}, inplace = True)
summary_df['PRE_TRIAL_CUST'] = comparison_cust['PRE_TRIAL_CUST']
summary_df['TRIAL_CUST'] = comparison_cust['TRIAL_CUST']
summary_df['CUST_%_CHANGE'] = comparison_cust['%_CHANGE']
summary_df['CUST_%_DIFFERENTIAL'] = comparison_cust['%_DIFFERENCE']
summary_df
```

Out[317]:

	TYPE	PRE_TRIAL_SALES	TRIAL_SALES	SALES_%_CHANGE	SALES_%_DIFF
STORE_NBR					
77	Trial Store	413.3	455.70	10.26	
233	Control Store	414.0	492.53	18.97	
86	Trial Store	1602.0	1799.60	12.33	
67	Control Store	1605.1	1573.66	-1.96	
88	Trial Store	2449.8	2752.60	12.36	
165	Control Store	2454.4	2239.88	-8.74	

Store 77

In terms of total sales, the results from our t-test showed that the trial in store 77 is significantly different to its control store in the trial period, as the trial store performance lies outside the 5% to 95% confidence interval of the control store. This means that the trial did have an effect, however, the results show a negative return. Compared to its control store, which had a percentage increase in sales of 18.97% from the pre-trial period, the trial negatively impacted store 77's performance over the trial period. We saw a sales increase of 10.26% compared to its pre-trial performance, however, we also see a negative sales differential of -7.48%. this means that trial store 77 did 7.48% worse in terms of sales over the trial period in comparison to control store 233. For customers, we also see that our t-test for store 77 showed its distribution of customers significantly different to its control store in the trial period, having a p-value lower than 0.05, meaning there was less than a 5% chance that the number of customers were from the same distribution as the control store. Similarly, to total sales, we saw that store 77 had a positive percentage increase in number of customers over the trial period compared to the pre-trial period, being an increase of 15.58%. However, again we saw that in comparison to the control store, the trial had a negative effect, resulting in 2.2% less customers than the control store 233. Overall, the trial was unsuccessful in store 77.

Store 86

For total sales in store 86, our t-test highlighted that the stores performance during the trial lay within the 5% to 95% confidence interval. Despite this, store 86 had a significant sales increase of 12.33% over the trial compared to the pre-trial period, with a percentage differential of 14.36% higher sales than its control store 67. With the t-test in mind, this large difference in sales can be attributed to the higher number of customers over the trial. Our T-test for number of customers saw that the performance lay outside the 5% to 95% confidence interval of the control store. This means that the trial did have a significant effect on the number of customers. Trial store 86 saw a 9.86% increase compared to its pre-trial metrics and saw 13.78% more customers over the trial period compared to control store 67. Overall, the trial was successful in increase the number of customers significantly over the trial period, however sales were not able to significantly increase per transaction. A recommendation is to check with the Category manager whether there were any special offers in the trial store that may have resulted in lower prices, impacting the overall sales statistics.

Store 88

Trial store 88 saw a distinguishable increase in sales compared to its pre-trial period. Over the course of the trial, store 88 was able to increase sales by 12.36%, contrasting the control store, which made 8.74% less sales than its pre-trial performance. Additionally, the trial appeared to have a dramatic effect on the stores total sales compared to the control store during the same period. The trial resulted in a percentage differential of 22.89%, meaning that over the course of the trial, store 88 made 22.89% more sales with the changes, compared to store 165 which didn't involve the trial strategy. Checking for significance using the T-test, the sampled distributions of both the trial store and control store resulted in a p-value of 0.007, meaning that the chance that there was no difference between the distributions of store 88 and 165 is close to zero. In terms of number of customers, our T-test saw that the performance lay outside the 5% to 95% confidence interval of the control store. This means the trial had a significance effect on the number of customers. Compared to the pre-trial period, the trial saw an increase of 11.35% in number of customers for store 88. Similarly, to sales, the trial had a profound effect on number of customers for the period of the trial, compared to its control store, which saw a significant dip in customer volume. Control store 165 saw a decrease of 10.28% compared to its pre-trial period, and when comparing both stores in the trial period, we see trial store 88 having 24.11% more customers than store 165. Overall, the trial was successful in store 88, having had significant increases in sales and number of customers.

In [ ]:

```
```