Quantium - Module 2

We will be examining the performance in trial vs control stores to provide a recommendation for each location based on our insight.

- **Select control stores – explore the data and define metrics for control store selection – "What would make them a control store?" Visualize the drivers to see suitability.**
- **Assessment of the trial – get insights of each of the stores. Compare each trial store with ontrol store to get its overall performance. We want to know if the trial stores were successful or not.**
- **Collate findings – summarise findings for each store and provide recommendations to share with client outlining the impact on sales during trial period.**

In [1]:

```
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import numpy as np
```

In [2]:

```
qvi = pd.read_csv("QVI_data.csv")
qvi.head()
```

Out[2]:

	LYLTY_CARD_NBR	DATE	STORE_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_SALES	PACK_SIZE	
0	1000	2018-10-17	1	1	5	Natural Chip Compny SeaSalt175g	2	6.0	175	I
1	1002	2018-09-16	1	2	58	Red Rock Deli Chikn&Garlic Aioli 150g	1	2.7	150	
2	1003	2019-03-07	1	3	52	Grain Waves Sour Cream&Chives 210G	1	3.6	210	G
3	1003	2019-03-08	1	4	106	Natural ChipCo Hony Soy Chckn175g	1	3.0	175	I
4	1004	2018-11-02	1	5	96	WW Original Stacked Chips 160g	1	1.9	160	WOOL

In [3]:

```
# Checking for nulls
qvi.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 264834 entries, 0 to 264833
Data columns (total 12 columns):
 #   Column          Non-Null Count   Dtype 
---  ------          --------------   ----- 
 0   LYLTY_CARD_NBR  264834 non-null  int64 
 1   DATE            264834 non-null  object
 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
```

```
 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
dtypes: float64(1), int64(6), object(5)
memory usage: 24.2+ MB
```

- **Client has selected store numbers 77, 86 and 88 as trial stores.**
- **Client wants control stores to be established stores that are operational for the entire observation period.**
- **Trial period = 1 Feb 2019 to 30 April 2019.**
- **Compare trial stores to control stores that are similar pre-trial. Similarity measurement:**
  - **Monthly overall sales revenue**
  - **Monthly number of customers**
  - **Monthly number of transactions per customer**

In [4]:

```
qvi["DATE"] = pd.to_datetime(qvi["DATE"])
qvi["YEARMONTH"] = qvi["DATE"].dt.strftime("%Y%m").astype("int")
```

Compile each store's monthly:

- **Total sales**
- **Number of customers,**
- **Average transactions per customer**
- **Average chips per customer**
- **Average price per unit**

In [5]:

```
def monthly_store_metrics():
    store_yrmo_group = qvi.groupby(["STORE_NBR", "YEARMONTH"])
    total = store_yrmo_group["TOT_SALES"].sum()
    num_cust = store_yrmo_group["LYLTY_CARD_NBR"].nunique()
    trans_per_cust = store_yrmo_group.size() / num_cust
    avg_chips_per_cust = store_yrmo_group["PROD_QTY"].sum() / num_cust
    avg_chips_price = total / store_yrmo_group["PROD_QTY"].sum()
    aggregates = [total, num_cust, trans_per_cust, avg_chips_per_cust, avg_chips_price]
    metrics = pd.concat(aggregates, axis=1)
    metrics.columns = ["TOT_SALES", "nCustomers", "nTxnPerCust", "nChipsPerTxn", "avgPri
cePerUnit"]
    return metrics
```

In [6]:

```
qvi_monthly_metrics = monthly_store_metrics().reset_index()
qvi_monthly_metrics.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3169 entries, 0 to 3168
Data columns (total 7 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   STORE_NBR       3169 non-null   int64
 1   YEARMONTH       3169 non-null   int64
 2   TOT_SALES       3169 non-null   float64
 3   nCustomers      3169 non-null   int64
 4   nTxnPerCust     3169 non-null   float64
 5   nChipsPerTxn    3169 non-null   float64
 6   avgPricePerUnit 3169 non-null   float64
dtypes: float64(4), int64(3)
memory usage: 173.4 KB
```

In [7]:

```
#pre trial observation
#filter only stores with full 12 months observation
observ_counts = qvi_monthly_metrics["STORE_NBR"].value_counts()
full_observ_index = observ_counts[observ_counts == 12].index
full_observ = qvi_monthly_metrics[qvi_monthly_metrics["STORE_NBR"].isin(full_observ_index
)]
pretrial_full_observ = full_observ[full_observ["YEARMONTH"] < 201902]

pretrial_full_observ.head(8)
```

Out[7]:

	STORE_NBR	YEARMONTH	TOT_SALES	nCustomers	nTxnPerCust	nChipsPerTxn	avgPricePerUnit
0	1	201807	206.9	49	1.061224	1.265306	3.337097
1	1	201808	176.1	42	1.023810	1.285714	3.261111
2	1	201809	278.8	59	1.050847	1.271186	3.717333
3	1	201810	188.1	44	1.022727	1.318182	3.243103
4	1	201811	192.6	46	1.021739	1.239130	3.378947
5	1	201812	189.6	42	1.119048	1.357143	3.326316
6	1	201901	154.8	35	1.028571	1.200000	3.685714
12	2	201807	150.8	39	1.051282	1.179487	3.278261

In [8]:

```
def calcCorrTable(metricCol, storeComparison, inputTable=pretrial_full_observ):
    """Calculate correlation for a measure, looping through each control store.
    Args:
        metricCol (str): Name of column containing store's metric to perform correlation
test on.
        storeComparison (int): Trial store's number.
        inputTable (dataframe):  Metric table with potential comparison stores.

    Returns:
        DataFrame: Monthly correlation table between Trial and each Control stores.
    """
    control_store_nbrs = inputTable[~inputTable["STORE_NBR"].isin([77, 86, 88])]["STORE_
NBR"].unique()
    corrs = pd.DataFrame(columns = ["YEARMONTH", "Trial_Str", "Ctrl_Str", "Corr_Score"])
    trial_store = inputTable[inputTable["STORE_NBR"] == storeComparison][metricCol].rese
t_index()
    for control in control_store_nbrs:
        concat_df = pd.DataFrame(columns = ["YEARMONTH", "Trial_Str", "Ctrl_Str", "Corr_
Score"])
        control_store = inputTable[inputTable["STORE_NBR"] == control][metricCol].reset_
index()
        concat_df["Corr_Score"] = trial_store.corrwith(control_store, axis=1)
        concat_df["Trial_Str"] = storeComparison
        concat_df["Ctrl_Str"] = control
        concat_df["YEARMONTH"] = list(inputTable[inputTable["STORE_NBR"] == storeCompari
son]["YEARMONTH"])
        corrs = pd.concat([corrs, concat_df])
    return corrs
```

In [9]:

```
corr_table = pd.DataFrame()
for trial_num in [77, 86, 88]:
    corr_table = pd.concat([corr_table, calcCorrTable(["TOT_SALES", "nCustomers", "nTxnP
erCust", "nChipsPerTxn", "avgPricePerUnit"], trial_num)])

corr_table.head(8)
```

Out[9]:

	YEARMONTH	Trial_Str	Ctrl_Str	Corr_Score

	YEARMONTH	Trial_Str	Ctrl_Str	Corr_Score
0	201807	77	1	0.070414
1	201808	77	1	0.027276
2	201809	77	1	0.002389
3	201810	77	1	-0.020045
4	201811	77	1	0.030024
5	201812	77	1	0.063946
6	201901	77	1	0.001470
0	201807	77	2	0.142957

In [10]:

```
def calculateMagnitudeDistance(metricCol, storeComparison, inputTable=pretrial_full_observ):
    """Calculate standardised magnitude distance for a measure, looping through each control store.
    Args:
        metricCol (str): Name of column containing store's metric to perform distance calculation on.
        storeComparison (int): Trial store's number.
        inputTable (dataframe):  Metric table with potential comparison stores.

    Returns:
        DataFrame: Monthly magnitude-distance table between Trial and each Control stores.
    """
    control_store_nbrs = inputTable[~inputTable["STORE_NBR"].isin([77, 86, 88])]["STORE_NBR"].unique()
    dists = pd.DataFrame()
    trial_store = inputTable[inputTable["STORE_NBR"] == storeComparison][metricCol]
    for control in control_store_nbrs:
        concat_df  = abs(inputTable[inputTable["STORE_NBR"] == storeComparison].reset_index()[metricCol] - inputTable[inputTable["STORE_NBR"] == control].reset_index()[metricCol])
        concat_df["YEARMONTH"] = list(inputTable[inputTable["STORE_NBR"] == storeComparison]["YEARMONTH"])
        concat_df["Trial_Str"] = storeComparison
        concat_df["Ctrl_Str"] = control
        dists = pd.concat([dists, concat_df])
    for col in metricCol:
        dists[col] = 1 - ((dists[col] - dists[col].min()) / (dists[col].max() - dists[col].min()))
    dists["magnitude"] = dists[metricCol].mean(axis=1)
    return dists
```

In [11]:

```
dist_table = pd.DataFrame()
for trial_num in [77, 86, 88]:
    dist_table = pd.concat([dist_table, calculateMagnitudeDistance(["TOT_SALES", "nCustomers", "nTxnPerCust", "nChipsPerTxn", "avgPricePerUnit"], trial_num)])

dist_table.head(8)
dist_table
```

Out[11]:

	TOT_SALES	nCustomers	nTxnPerCust	nChipsPerTxn	avgPricePerUnit	YEARMONTH	Trial_Str	Ctrl_Str	magnitude
0	0.935431	0.980769	0.958035	0.739412	0.883569	201807	77	1	0.899443
1	0.942972	0.951923	0.993823	0.802894	0.886328	201808	77	1	0.915588
2	0.961503	0.836538	0.992126	0.730041	0.703027	201809	77	1	0.844647
3	0.988221	0.932692	0.989514	0.940460	0.590528	201810	77	1	0.888283
4	0.962149	0.951923	0.874566	0.730358	0.832481	201811	77	1	0.870296
...	...	...	...	...	...	...	...	...	...

	TOT_SALES	nCustomers	nTxnPerCust	nChipsPerTxn	avgPricePerUnit	YEARMONTH	Trial_Str	Ctrl_Str	magnitude
2	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	201809	88	272	[illegible]
3	0.346797	0.387597	0.571497	0.796875	0.971133	201810	88	272	0.614780
4	0.286706	0.310078	0.623883	0.813241	0.966999	201811	88	272	0.600181
5	0.347151	0.387597	0.376456	0.699748	0.962198	201812	88	272	0.554630
6	0.402353	0.449612	0.450378	0.739714	0.971335	201901	88	272	0.602678

5397 rows × 9 columns

We'll select control stores based on how similar monthly total sales in dollar amounts and monthly number of customers are to the trial stores by using correlation and magnitude distance.

In [12]:

```
def combine_corr_dist(metricCol, storeComparison, inputTable=pretrial_full_observ):
    corrs = calcCorrTable(metricCol, storeComparison, inputTable)
    dists = calculateMagnitudeDistance(metricCol, storeComparison, inputTable)
    dists = dists.drop(metricCol, axis=1)
    combine = pd.merge(corrs, dists, on=["YEARMONTH", "Trial_Str", "Ctrl_Str"])
    return combine
```

In [13]:

```
compare_metrics_table1 = pd.DataFrame()
for trial_num in [77, 86, 88]:
    compare_metrics_table1 = pd.concat([compare_metrics_table1, combine_corr_dist(["TOT_
SALES"], trial_num)])
```

In [14]:

```
corr_weight = 0.5
dist_weight = 1 - corr_weight
```

In [15]:

```
#Top 5 highest Composite Score for each Trial Store based on TOT_SALES
grouped_comparison_table1 = compare_metrics_table1.groupby(["Trial_Str", "Ctrl_Str"]).me
an().reset_index()
grouped_comparison_table1["CompScore"] = (corr_weight * grouped_comparison_table1["Corr_
Score"]) + (dist_weight * grouped_comparison_table1["magnitude"])
for trial_num in compare_metrics_table1["Trial_Str"].unique():
    print(grouped_comparison_table1[grouped_comparison_table1["Trial_Str"] == trial_num]
.sort_values(ascending=False, by="CompScore").head(), '\n')
```

```
     Trial_Str  Ctrl_Str  Corr_Score  magnitude  CompScore
218         77       233         1.0   0.986477   0.993238
239         77       255         1.0   0.979479   0.989739
177         77       188         1.0   0.977663   0.988831
49          77        53         1.0   0.976678   0.988339
120         77       131         1.0   0.976267   0.988134

     Trial_Str  Ctrl_Str  Corr_Score  magnitude  CompScore
356         86       109         1.0   0.966783   0.983391
401         86       155         1.0   0.965876   0.982938
464         86       222         1.0   0.962280   0.981140
467         86       225         1.0   0.960512   0.980256
471         86       229         1.0   0.951704   0.975852

     Trial_Str  Ctrl_Str  Corr_Score  magnitude  CompScore
551         88        40         1.0   0.941165   0.970582
538         88        26         1.0   0.904377   0.952189
582         88        72         1.0   0.903800   0.951900
517         88         4         1.0   0.903466   0.951733
568         88        58         1.0   0.891678   0.945839
```

In [16]:

```
compare_metrics_table2 = pd.DataFrame()
for trial_num in [77, 86, 88]:
    compare_metrics_table2 = pd.concat([compare_metrics_table2, combine_corr_dist(["nCus
tomers"], trial_num)])
```

In [17]:

```
#Top 5 highest Composite Score for each Trial Store based on nCustomers
grouped_comparison_table2 = compare_metrics_table2.groupby(["Trial_Str", "Ctrl_Str"]).me
an().reset_index()
grouped_comparison_table2["CompScore"] = (corr_weight * grouped_comparison_table2["Corr_
Score"]) + (dist_weight * grouped_comparison_table2["magnitude"])
for trial_num in compare_metrics_table2["Trial_Str"].unique():
    print(grouped_comparison_table2[grouped_comparison_table2["Trial_Str"] == trial_num]
.sort_values(ascending=False, by="CompScore").head(), '\n')
```

```
     Trial_Str  Ctrl_Str  Corr_Score  magnitude  CompScore
218         77       233         1.0   0.993132   0.996566
38          77        41         1.0   0.976648   0.988324
101         77       111         1.0   0.968407   0.984203
105         77       115         1.0   0.967033   0.983516
15          77        17         1.0   0.965659   0.982830

     Trial_Str  Ctrl_Str  Corr_Score  magnitude  CompScore
401         86       155         1.0   0.986772   0.993386
467         86       225         1.0   0.969577   0.984788
356         86       109         1.0   0.969577   0.984788
471         86       229         1.0   0.964286   0.982143
293         86        39         1.0   0.961640   0.980820

     Trial_Str  Ctrl_Str  Corr_Score  magnitude  CompScore
736         88       237         1.0   0.987818   0.993909
705         88       203         1.0   0.944629   0.972315
551         88        40         1.0   0.942414   0.971207
668         88       165         1.0   0.935770   0.967885
701         88       199         1.0   0.932447   0.966224
```

In [18]:

```
for trial_num in compare_metrics_table2["Trial_Str"].unique():
    a = grouped_comparison_table1[grouped_comparison_table1["Trial_Str"] == trial_num].s
ort_values(ascending=False, by="CompScore").set_index(["Trial_Str", "Ctrl_Str"])["CompSc
ore"]
    b = grouped_comparison_table2[grouped_comparison_table2["Trial_Str"] == trial_num].s
ort_values(ascending=False, by="CompScore").set_index(["Trial_Str", "Ctrl_Str"])["CompSc
ore"]
    print((pd.concat([a,b], axis=1).sum(axis=1)/2).sort_values(ascending=False).head(3),
'\n')
```

```
Trial_Str  Ctrl_Str
77         233         0.994902
           41          0.986020
           46          0.984762
dtype: float64

Trial_Str  Ctrl_Str
86         155         0.988162
           109         0.984090
           225         0.982522
dtype: float64

Trial_Str  Ctrl_Str
88         40          0.970895
           26          0.958929
           72          0.954079
dtype: float64
```

Top 3 similarity based on TOT_SALES:

- **Trial store 77: Store 233, 255, 188**

- **Trial store 86: Store 109, 155, 222**
- **Trial store 88: Store 40, 26, 72**

Top 3 similartiy based on nCustomers:

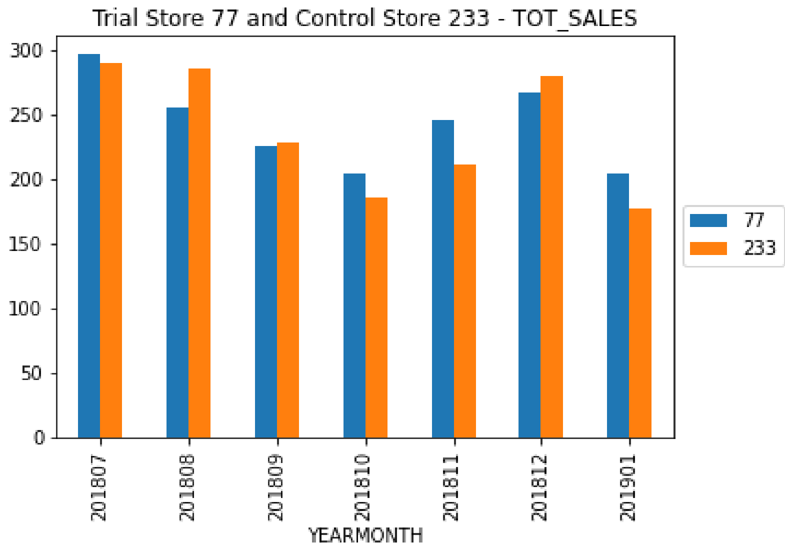
- **Trial store 77: Store 233, 41, 111**
- **Trial store 86: Store 155, 225, 109**
- **Trial store 88: Store 237, 203, 40**

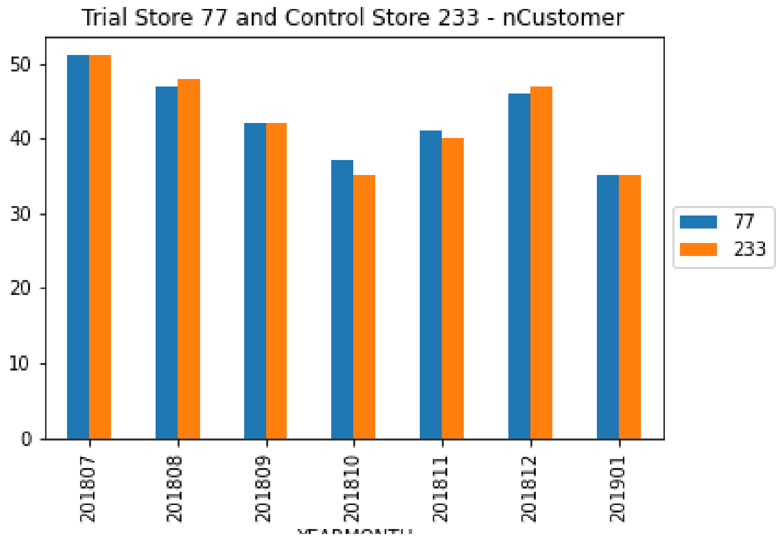
Based on highest average of both features combined:

- **Trial store 77: Store 233**
- **Trial store 86: Store 155**
- **Trial store 88: Store 40**

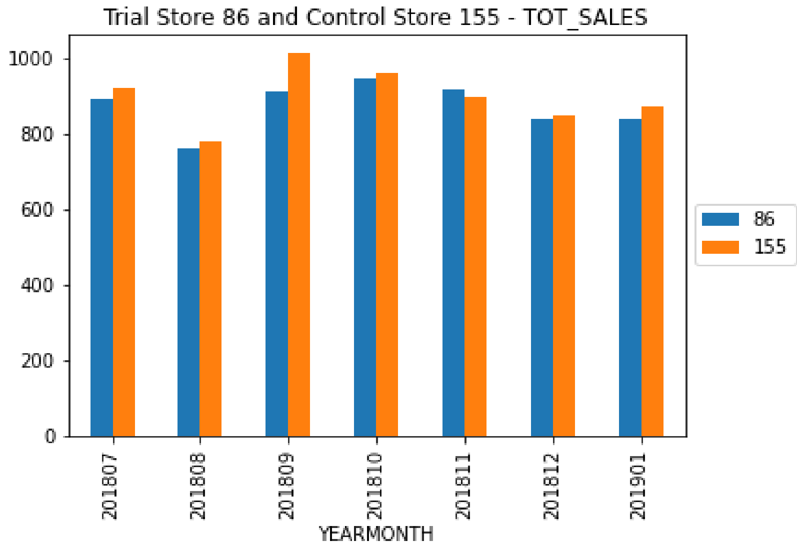
In [19]:

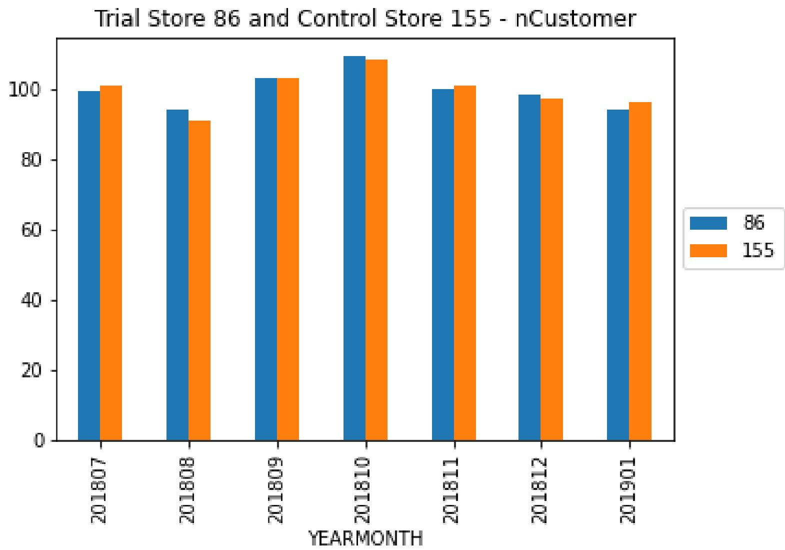
```
trial_control_dic = {77:233, 86:155, 88:40}
for key, val in trial_control_dic.items():
    pretrial_full_observ[pretrial_full_observ["STORE_NBR"].isin([key, val])].groupby(
        ["YEARMONTH", "STORE_NBR"]).sum()["TOT_SALES"].unstack().plot.bar()
    plt.legend(loc='center left', bbox_to_anchor=(1.0, 0.5))
    plt.title("Trial Store "+str(key)+" and Control Store "+str(val)+" - TOT_SALES")
    plt.show()
    pretrial_full_observ[pretrial_full_observ["STORE_NBR"].isin([key, val])].groupby(
    ["YEARMONTH", "STORE_NBR"]).sum()["nCustomers"].unstack().plot.bar()
    plt.legend(loc='center left', bbox_to_anchor=(1.0, 0.5))
    plt.title("Trial Store "+str(key)+" and Control Store "+str(val)+" - nCustomer")
    plt.show()
    print('\n')
```

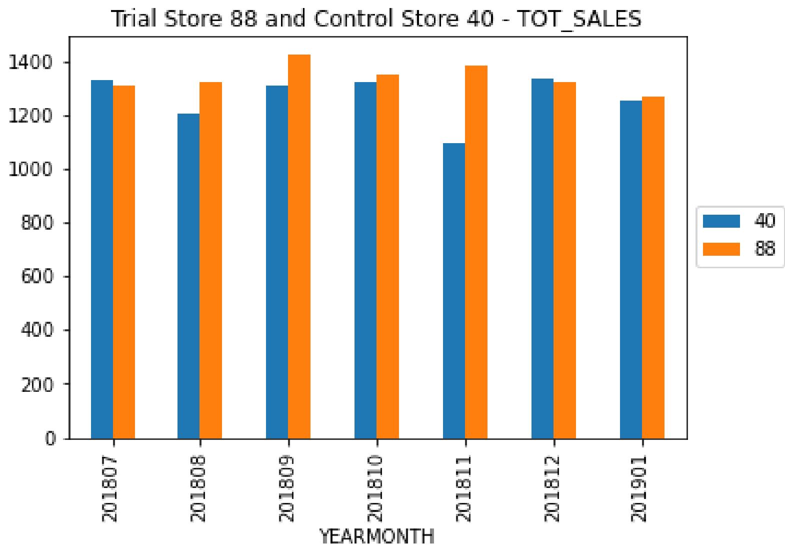


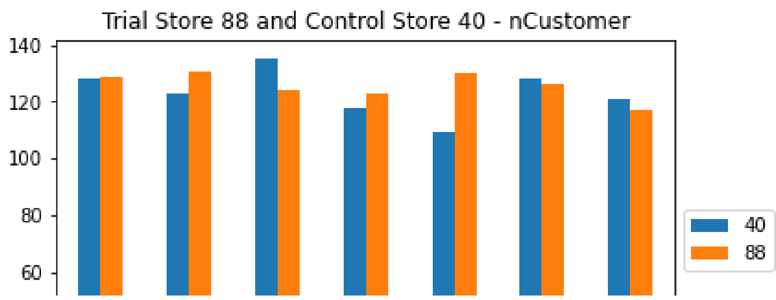


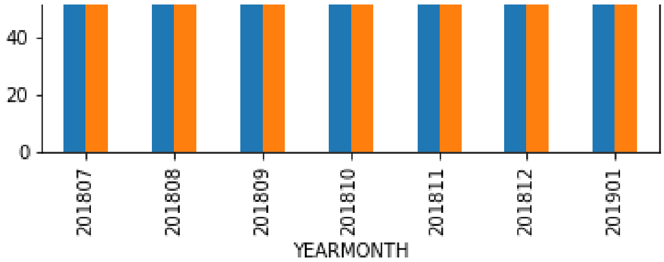
YEARMONTH


Trial Store 86 and Control Store 155 - TOT_SALES
0
200
400
600
800
1000
201807
201808
201809
201810
201811
201812
201901
YEARMONTH
86
155


Trial Store 86 and Control Store 155 - nCustomer
0
20
40
60
80
100
201807
201808
201809
201810
201811
201812
201901
YEARMONTH
86
155


Trial Store 88 and Control Store 40 - TOT_SALES
0
200
400
600
800
1000
1200
1400
201807
201808
201809
201810
201811
201812
201901
YEARMONTH
40
88


Trial Store 88 and Control Store 40 - nCustomer
60
80
100
120
140
40
88



Next we'll compare the performance of Trial stores to Control stores during the trial period. To ensure their performance is comparable during Trial period, we need to scale (multiply to ratio of trial / control) all of Control stores' performance to Trial store's performance during pre-trial. Starting with TOT_SALES.

In [20]:

```
#Ratio of Store 77 and its Control store.
sales_ratio_77 = pretrial_full_observ[pretrial_full_observ["STORE_NBR"] == 77]["TOT_SALE
S"].sum() / pretrial_full_observ[pretrial_full_observ["STORE_NBR"] == 233]["TOT_SALES"].
sum()

#Ratio of Store 86 and its Control store.
sales_ratio_86 = pretrial_full_observ[pretrial_full_observ["STORE_NBR"] == 86]["TOT_SALE
S"].sum() / pretrial_full_observ[pretrial_full_observ["STORE_NBR"] == 155]["TOT_SALES"].
sum()

#Ratio of Store 77 and its Control store.
sales_ratio_88 = pretrial_full_observ[pretrial_full_observ["STORE_NBR"] == 88]["TOT_SALE
S"].sum() / pretrial_full_observ[pretrial_full_observ["STORE_NBR"] == 40]["TOT_SALES"].s
um()
```

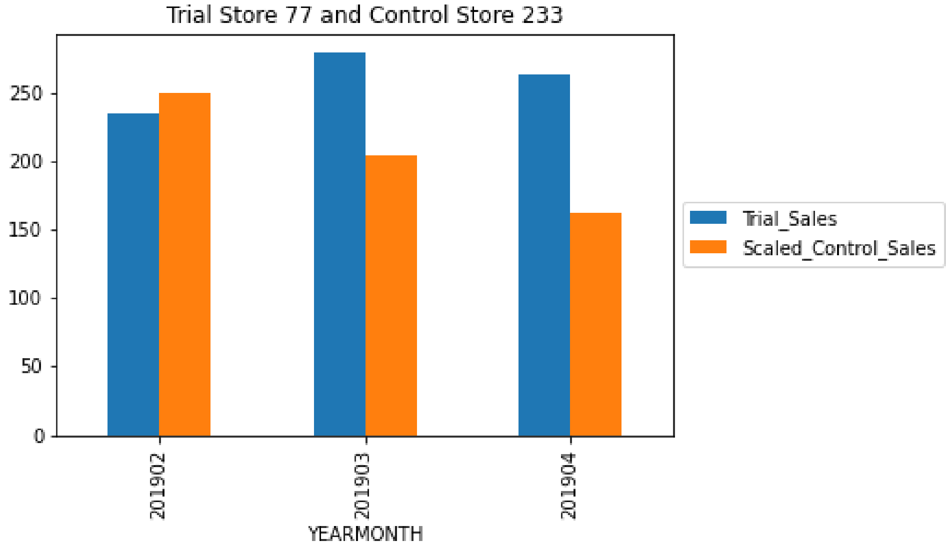
In [21]:

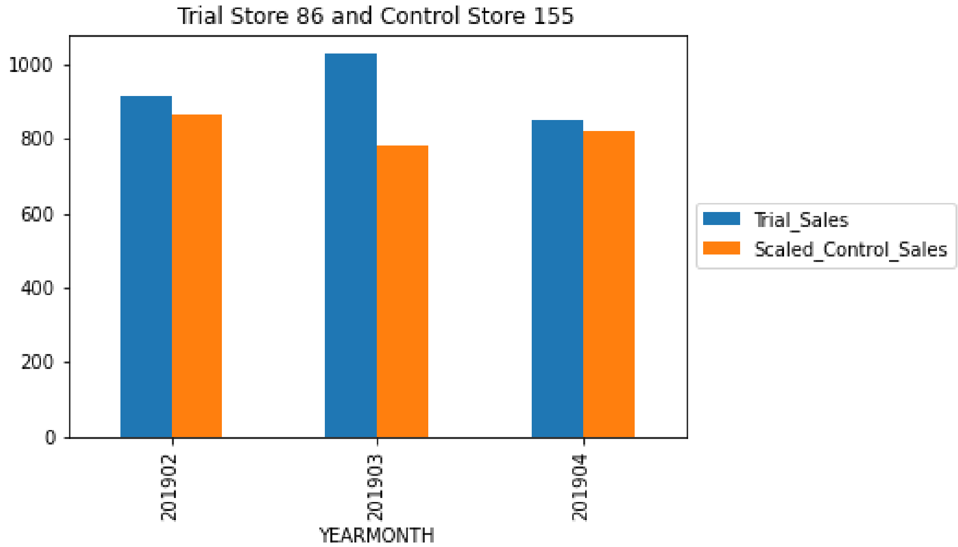
```
trial_full_observ = full_observ[(full_observ["YEARMONTH"] >= 201902) & (full_observ["YEA
RMONTH"] <= 201904)]
scaled_sales_control_stores = full_observ[full_observ["STORE_NBR"].isin([233, 155, 40])]
[["STORE_NBR", "YEARMONTH", "TOT_SALES"]]

def scaler(row):
    if row["STORE_NBR"] == 233:
        return row["TOT_SALES"] * sales_ratio_77
    elif row["STORE_NBR"] == 155:
        return row["TOT_SALES"] * sales_ratio_86
    elif row["STORE_NBR"] == 40:
        return row["TOT_SALES"] * sales_ratio_88

scaled_sales_control_stores["ScaledSales"] = scaled_sales_control_stores.apply(lambda row
: scaler(row), axis=1)

trial_scaled_sales_control_stores = scaled_sales_control_stores[(scaled_sales_control_sto
res["YEARMONTH"] >= 201902) & (scaled_sales_control_stores["YEARMONTH"] <= 201904)]
pretrial_scaled_sales_control_stores = scaled_sales_control_stores[scaled_sales_control_s
tores["YEARMONTH"] < 201902]
```

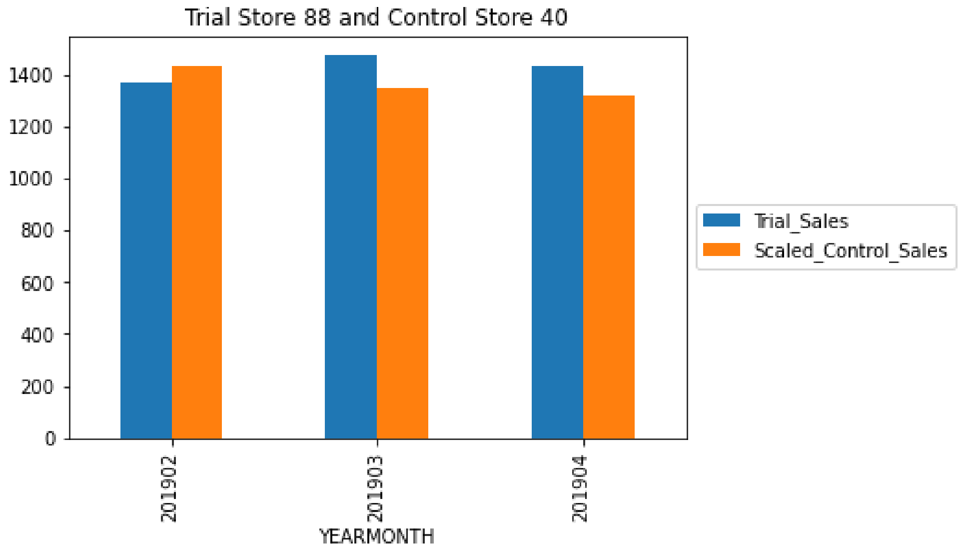
In [22]:

```
percentage_diff = {}

for trial, control in trial_control_dic.items():
    a = trial_scaled_sales_control_stores[trial_scaled_sales_control_stores["STORE_NBR"]
== control]
    b = trial_full_observ[trial_full_observ["STORE_NBR"] == trial][["STORE_NBR", "YEARMO
NTH", "TOT_SALES"]]
    percentage_diff[trial] = b["TOT_SALES"].sum() / a["ScaledSales"].sum()
    b[["YEARMONTH", "TOT_SALES"]].merge(a[["YEARMONTH", "ScaledSales"]],on="YEARMONTH").
set_index("YEARMONTH").rename(columns={"ScaledSales":"Scaled_Control_Sales", "TOT_SALES"
:"Trial_Sales"}).plot.bar()
    plt.legend(loc='center left', bbox_to_anchor=(1.0, 0.5))
```

```
    plt.title("Trial Store "+str(trial)+" and Control Store "+str(control))
```







In [23]:

```
percentage_diff
```

Out[23]:

```
{77: 1.2615468650086274, 86: 1.13150143573637, 88: 1.0434583458542188}
```

In [24]:

```
#Creating a compiled percentage_difference table
temp1 = scaled_sales_control_stores.sort_values(by=["STORE_NBR", "YEARMONTH"], ascending
```

```
=[False, True]).reset_index().drop(["TOT_SALES", "index"], axis=1)
temp2 = full_observ[full_observ["STORE_NBR"].isin([77,86,88])][["STORE_NBR", "YEARMONTH"
, "TOT_SALES"]].reset_index().drop(["index", "YEARMONTH"], axis=1)
scaledsales_vs_trial = pd.concat([temp1, temp2], axis=1)
scaledsales_vs_trial.columns = ["c_STORE_NBR", "YEARMONTH", "c_ScaledSales", "t_STORE_NB
R", "t_TOT_SALES"]
scaledsales_vs_trial["Sales_Percentage_Diff"] = (scaledsales_vs_trial["t_TOT_SALES"] - sc
aledsales_vs_trial["c_ScaledSales"]) / (((scaledsales_vs_trial["t_TOT_SALES"] + scaledsal
es_vs_trial["c_ScaledSales"])/2))
def label_period(cell):
    if cell < 201902:
        return "pre"
    elif cell > 201904:
        return "post"
    else:
        return "trial"
scaledsales_vs_trial["trial_period"] = scaledsales_vs_trial["YEARMONTH"].apply(lambda cel
l: label_period(cell))
scaledsales_vs_trial[scaledsales_vs_trial["trial_period"] == "trial"]
```

Out[24]:

	c_STORE_NBR	YEARMONTH	c_ScaledSales	t_STORE_NBR	t_TOT_SALES	Sales_Percentage_Diff	trial_period
7	233	201902	249.762622	77	235.0	-0.060907	trial
8	233	201903	203.802205	77	278.5	0.309755	trial
9	233	201904	162.345704	77	263.5	0.475075	trial
19	155	201902	864.522060	86	913.2	0.054764	trial
20	155	201903	780.320405	86	1026.8	0.272787	trial
21	155	201904	819.317024	86	848.2	0.034642	trial
31	40	201902	1434.399269	88	1370.2	-0.045781	trial
32	40	201903	1352.064709	88	1477.2	0.088458	trial
33	40	201904	1321.797762	88	1439.4	0.085182	trial

Check significance of Trial minus Control stores TOT_SALES Percentage Difference Pre-Trial vs Trial.

Step 1: Check null hypothesis of 0 difference between control store's Pre-Trial and Trial period performance.

Step 2: Proof control and trial stores are similar statistically

Check p-value of control store's Pre-Trial vs Trial store's Pre-Trial. If <5%, it is significantly different. If >5%, it is not significantly different (similar). Step 3: After checking Null Hypothesis of first 2 step to be true, we can check Null Hypothesis of Percentage Difference between Trial and Control stores during pre-trial is the same as during trial.

Check T-Value of Percentage Difference of each Trial month (Feb, March, April 2019). Mean is mean of Percentage Difference during pre-trial. Standard deviation is stdev of Percentage Difference during pre-trial. Formula is Trial month's Percentage Difference minus Mean, divided by Standard deviation. Compare each T-Value with 95% percentage significance critical t-value of 6 degrees of freedom (7 months of sample - 1)

In [25]:

```
from scipy.stats import ttest_ind, t

# Step 1
for num in [40, 155, 233]:
    print("Store", num)
    print(ttest_ind(pretrial_scaled_sales_control_stores[pretrial_scaled_sales_control_st
ores["STORE_NBR"] == num]["ScaledSales"],
                   trial_scaled_sales_control_stores[trial_scaled_sales_control_stores["
STORE_NBR"] == num]["ScaledSales"],
                   equal_var=False), '\n')
    #print(len(pretrial_scaled_sales_control_stores[pretrial_scaled_sales_control_stores[
"STORE_NBR"] == num]["ScaledSales"]), len(trial_scaled_sales_control_stores[trial_scaled_
```

```
sales_control_stores["STORE_NBR"] == num]["ScaledSales"]))

alpha = 0.05
print("Critical t-value for 95% confidence interval:")
print(t.ppf((alpha/2, 1-alpha/2), df=min([len(pretrial_scaled_sales_control_stores[pretr
ial_scaled_sales_control_stores["STORE_NBR"] == num]),
                       len(trial_scaled_sales_control_stores[trial_scaled_sales_control_
stores["STORE_NBR"] == num])])-1))
```

```
Store 40
Ttest_indResult(statistic=-0.5958372343168585, pvalue=0.5722861621434009)

Store 155
Ttest_indResult(statistic=1.429195687929098, pvalue=0.19727058651603258)

Store 233
Ttest_indResult(statistic=1.1911026010974504, pvalue=0.29445006064862156)

Critical t-value for 95% confidence interval:
[-4.30265273  4.30265273]
```

In [26]:

```
a = pretrial_scaled_sales_control_stores[pretrial_scaled_sales_control_stores["STORE_NBR"
] == 40]["ScaledSales"]
b = trial_scaled_sales_control_stores[trial_scaled_sales_control_stores["STORE_NBR"] == 4
0]["ScaledSales"]
```

Null hypothesis is true. There isn't any statistically significant difference between control store's scaled Pre-Trial and Trial period sales.

In [27]:

```
# Step 2
for trial, cont in trial_control_dic.items():
    print("Trial store:", trial, ", Control store:", cont)
    print(ttest_ind(pretrial_full_observ[pretrial_full_observ["STORE_NBR"] == trial]["TO
T_SALES"],
                   pretrial_scaled_sales_control_stores[pretrial_scaled_sales_control_st
ores["STORE_NBR"] == cont]["ScaledSales"],
                   equal_var=True), '\n')
    #print(len(pretrial_full_observ[pretrial_full_observ["STORE_NBR"] == trial]["TOT_SALE
S"]),len(pretrial_scaled_sales_control_stores[pretrial_scaled_sales_control_stores["STORE
_NBR"] == cont]["ScaledSales"]))

alpha = 0.05
print("Critical t-value for 95% confidence interval:")
print(t.ppf((alpha/2, 1-alpha/2), df=len(pretrial_full_observ[pretrial_full_observ["STOR
E_NBR"] == trial])-1))
```

```
Trial store: 77 , Control store: 233
Ttest_indResult(statistic=-1.2533353315065926e-15, pvalue=0.999999999999999)

Trial store: 86 , Control store: 155
Ttest_indResult(statistic=0.0, pvalue=1.0)

Trial store: 88 , Control store: 40
Ttest_indResult(statistic=0.0, pvalue=1.0)

Critical t-value for 95% confidence interval:
[-2.44691185  2.44691185]
```

Null hypothesis is true. There isn't any statistically significant difference between Trial store's sales and Control store's scaled-sales performance during pre-trial.

In [28]:

```
# Step 3
for trial, cont in trial_control_dic.items():
    print("Trial store:", trial, ", Control store:", cont)
```

```python
    temp_pre = scaledsales_vs_trial[(scaledsales_vs_trial["c_STORE_NBR"] == cont) & (scaledsales_vs_trial["trial_period"]=="pre")]
    std = temp_pre["Sales_Percentage_Diff"].std()
    mean = temp_pre["Sales_Percentage_Diff"].mean()
    #print(std, mean)
    for t_month in scaledsales_vs_trial[scaledsales_vs_trial["trial_period"] == "trial"]["YEARMONTH"].unique():
        pdif = scaledsales_vs_trial[(scaledsales_vs_trial["YEARMONTH"] == t_month) & (scaledsales_vs_trial["t_STORE_NBR"] == trial)]["Sales_Percentage_Diff"]
        print(t_month,":",(float(pdif)-mean)/std)
    print('\n')

print("Critical t-value for 95% confidence interval:")
conf_intv_95 = t.ppf(0.95, df=len(temp_pre)-1)
print(conf_intv_95)
```

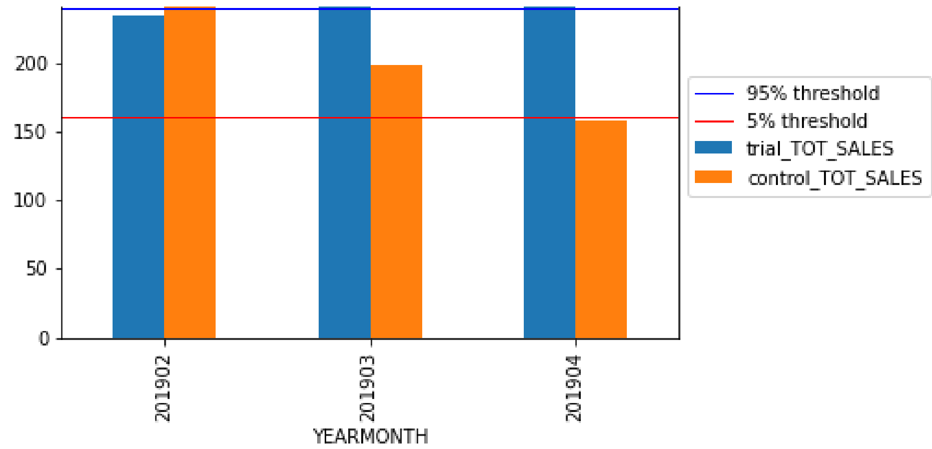
```
Trial store: 77 , Control store: 233
201902 : -0.7171038288055888
201903 : 3.035317928855662
201904 : 4.708944418758203


Trial store: 86 , Control store: 155
201902 : 1.4133618775921797
201903 : 7.123063846042149
201904 : 0.8863824572944162


Trial store: 88 , Control store: 40
201902 : -0.5481633746817604
201903 : 1.0089992743637755
201904 : 0.9710006270463645


Critical t-value for 95% confidence interval:
1.9431802803927816
```

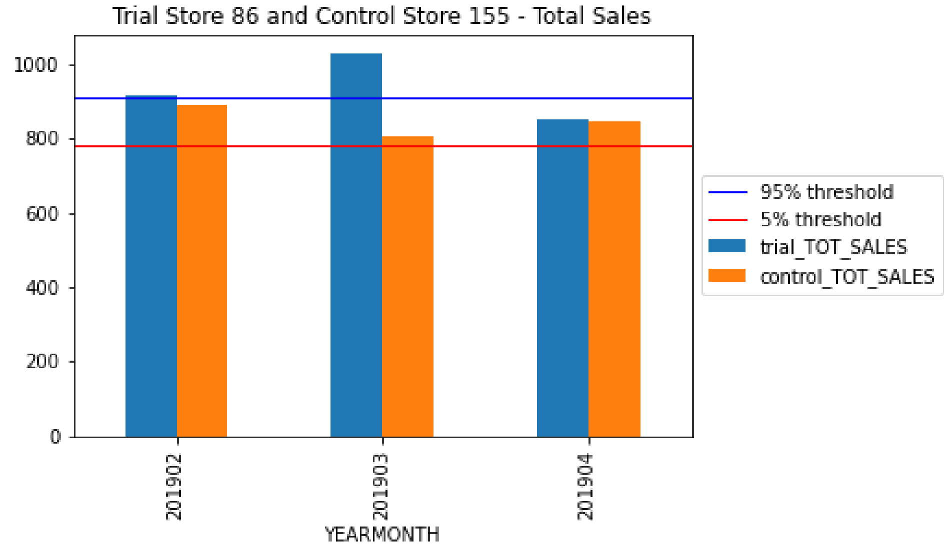
There are 3 months' increase in performance that are statistically significant (Above the 95% confidence interval t-score):

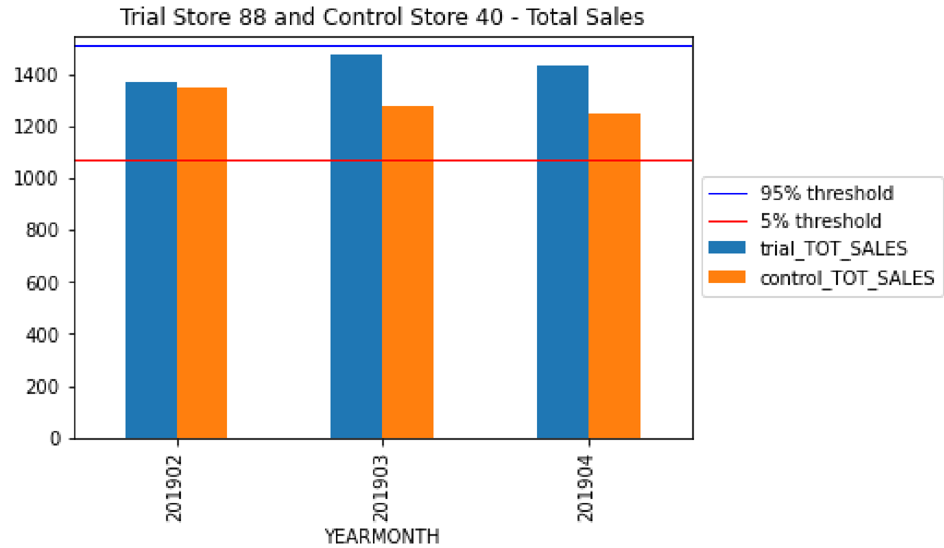
- **March and April trial months for trial store 77**
- **March trial months for trial store 86**

In [29]:

```python
for trial, control in trial_control_dic.items():
    a = trial_scaled_sales_control_stores[trial_scaled_sales_control_stores["STORE_NBR"] == control].rename(columns={"TOT_SALES": "control_TOT_SALES"})
    b = trial_full_observ[trial_full_observ["STORE_NBR"] == trial][["STORE_NBR", "YEARMONTH", "TOT_SALES"]].rename(columns={"TOT_SALES": "trial_TOT_SALES"})
    comb = b[["YEARMONTH", "trial_TOT_SALES"]].merge(a[["YEARMONTH", "control_TOT_SALES"]],on="YEARMONTH").set_index("YEARMONTH")
    comb.plot.bar()
    cont_sc_sales = trial_scaled_sales_control_stores[trial_scaled_sales_control_stores["STORE_NBR"] == control]["TOT_SALES"]
    std = scaledsales_vs_trial[(scaledsales_vs_trial["c_STORE_NBR"] == control) & (scaledsales_vs_trial["trial_period"]=="pre")]["Sales_Percentage_Diff"].std()
    thresh95 = cont_sc_sales.mean() + (cont_sc_sales.mean() * std * 2)
    thresh5 = cont_sc_sales.mean() - (cont_sc_sales.mean() * std * 2)
    plt.axhline(y=thresh95,linewidth=1, color='b', label="95% threshold")
    plt.axhline(y=thresh5,linewidth=1, color='r', label="5% threshold")
    plt.legend(loc='center left', bbox_to_anchor=(1.0, 0.5))
    plt.title("Trial Store "+str(trial)+" and Control Store "+str(control)+" - Total Sales")
    plt.savefig("TS {} and CS {} - TOT_SALES.png".format(trial,control), bbox_inches="tight")
```







We can see that Trial store 77 sales for March and April exceeds 95% threshold of control store. Same goes to store 86 sales for March.

Next, we'll look into nCustomers.

In [30]:

```
#Ratio of Store 77 and its Control store.
ncust_ratio_77 = pretrial_full_observ[pretrial_full_observ["STORE_NBR"] == 77]["nCustome
rs"].sum() / pretrial_full_observ[pretrial_full_observ["STORE_NBR"] == 233]["nCustomers"
].sum()

#Ratio of Store 86 and its Control store.
ncust_ratio_86 = pretrial_full_observ[pretrial_full_observ["STORE_NBR"] == 86]["nCustome
rs"].sum() / pretrial_full_observ[pretrial_full_observ["STORE_NBR"] == 155]["nCustomers"
].sum()
```

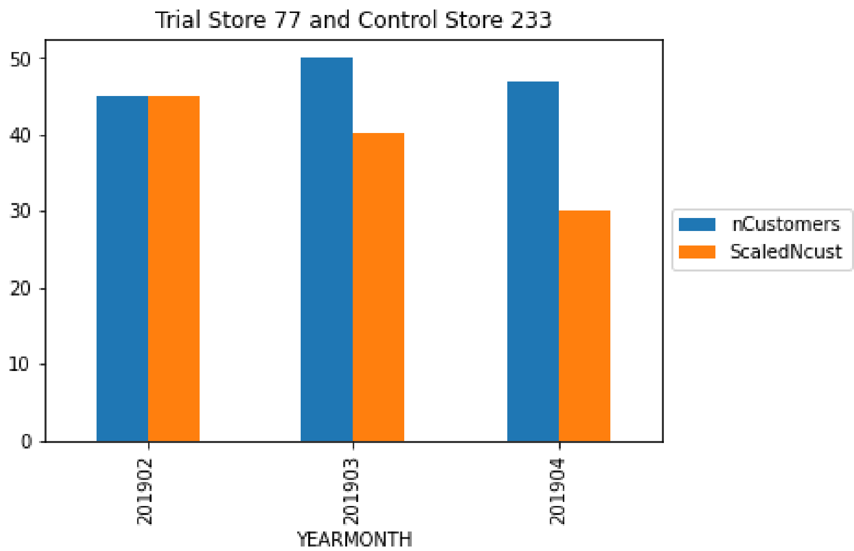
```
#Ratio of Store 77 and its Control store.
ncust_ratio_88 = pretrial_full_observ[pretrial_full_observ["STORE_NBR"] == 88]["nCustome
rs"].sum() / pretrial_full_observ[pretrial_full_observ["STORE_NBR"] == 40]["nCustomers"]
.sum()
```

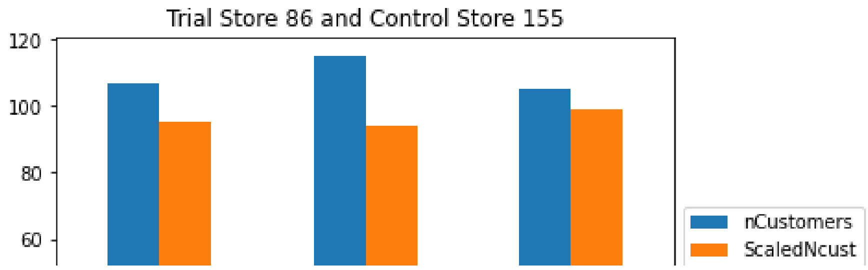
In [31]:

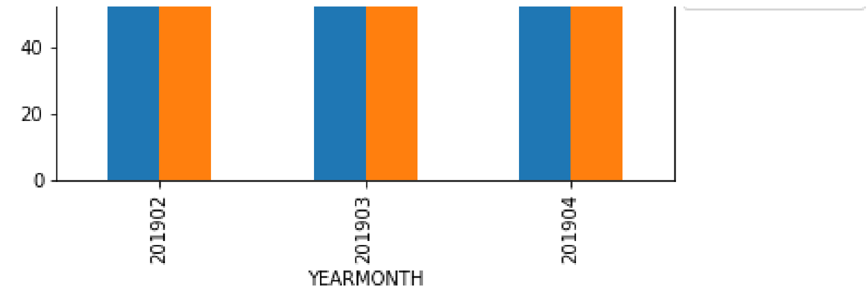
```
#trial_full_observ = full_observ[(full_observ["YEARMONTH"] >= 201902) & (full_observ["YEA
RMONTH"] <= 201904)]
scaled_ncust_control_stores = full_observ[full_observ["STORE_NBR"].isin([233, 155, 40])]
[["STORE_NBR", "YEARMONTH", "nCustomers"]]

def scaler_c(row):
    if row["STORE_NBR"] == 233:
        return row["nCustomers"] * ncust_ratio_77
    elif row["STORE_NBR"] == 155:
        return row["nCustomers"] * ncust_ratio_86
    elif row["STORE_NBR"] == 40:
        return row["nCustomers"] * ncust_ratio_88

scaled_ncust_control_stores["ScaledNcust"] = scaled_ncust_control_stores.apply(lambda row
: scaler_c(row), axis=1)

trial_scaled_ncust_control_stores = scaled_ncust_control_stores[(scaled_ncust_control_sto
res["YEARMONTH"] >= 201902) & (scaled_ncust_control_stores["YEARMONTH"] <= 201904)]
pretrial_scaled_ncust_control_stores = scaled_ncust_control_stores[scaled_ncust_control_s
tores["YEARMONTH"] < 201902]
```

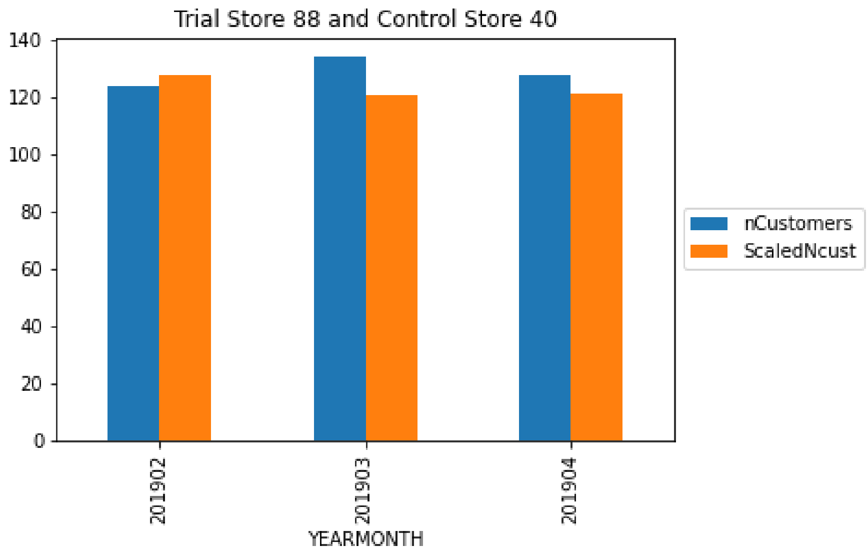
In [32]:

```
ncust_percentage_diff = {}

for trial, control in trial_control_dic.items():
    a = trial_scaled_ncust_control_stores[trial_scaled_ncust_control_stores["STORE_NBR"]
== control]
    b = trial_full_observ[trial_full_observ["STORE_NBR"] == trial][["STORE_NBR", "YEARMO
NTH", "nCustomers"]]
    ncust_percentage_diff[trial] = b["nCustomers"].sum() / a["ScaledNcust"].sum()
    b[["YEARMONTH", "nCustomers"]].merge(a[["YEARMONTH", "ScaledNcust"]],on="YEARMONTH")
.set_index("YEARMONTH").rename(columns={"ScaledSales":"Scaled_Control_nCust", "TOT_SALES
":"Trial_nCust"}).plot.bar()
    plt.legend(loc='center left', bbox_to_anchor=(1.0, 0.5))
    plt.title("Trial Store "+str(trial)+" and Control Store "+str(control))
```









In [33]:

```
ncust_percentage_diff
```

Out[33]:

```
{77: 1.2306529009742622, 86: 1.1354166666666667, 88: 1.0444876946258161}
```

In [34]:

```
#Creating a compiled ncust_percentage_difference table
temp1 = scaled_ncust_control_stores.sort_values(by=["STORE_NBR", "YEARMONTH"], ascending
=[False, True]).reset_index().drop(["nCustomers", "index"], axis=1)
temp2 = full_observ[full_observ["STORE_NBR"].isin([77,86,88])][["STORE_NBR", "YEARMONTH"
, "nCustomers"]].reset_index().drop(["index", "YEARMONTH"], axis=1)
scaledncust_vs_trial = pd.concat([temp1, temp2], axis=1)
scaledncust_vs_trial.columns = ["c_STORE_NBR", "YEARMONTH", "c_ScaledNcust", "t_STORE_NB
R", "t_nCustomers"]
scaledncust_vs_trial["nCust_Percentage_Diff"] = (scaledncust_vs_trial["t_nCustomers"] - s
caledncust_vs_trial["c_ScaledNcust"]) / (((scaledncust_vs_trial["t_nCustomers"] + scaledn
cust_vs_trial["c_ScaledNcust"])/2))

scaledncust_vs_trial["trial_period"] = scaledncust_vs_trial["YEARMONTH"].apply(lambda cel
l: label_period(cell))
scaledncust_vs_trial[scaledncust_vs_trial["trial_period"] == "trial"]
```

Out[34]:

	c_STORE_NBR	YEARMONTH	c_ScaledNcust	t_STORE_NBR	t_nCustomers	nCust_Percentage_Diff	trial_period
7	233	201902	45.151007	77	45	-0.003350	trial
8	233	201903	40.134228	77	50	0.218913	trial
9	233	201904	30.100671	77	47	0.438370	trial
19	155	201902	95.000000	86	107	0.118812	trial
20	155	201903	94.000000	86	115	0.200957	trial
21	155	201904	99.000000	86	105	0.058824	trial
31	40	201902	127.610209	88	124	-0.028697	trial
32	40	201903	120.464037	88	134	0.106388	trial

33	c_STORE_NBR	YEARMONTH	c_ScaledNcust	t_STORE_NBR	t_nCustomers	nCust_Percentage_Diff	trial_period

Check significance of Trial minus Control stores nCustomers Percentage Difference Pre-Trial vs Trial.

- **Step 1: Check null hypothesis of 0 difference between control store's Pre-Trial and Trial period performance.**
- **Step 2: Proof control and trial stores are similar statistically**
- **Step 3: After checking Null Hypothesis of first 2 step to be true, we can check Null Hypothesis of Percentage Difference between Trial and Control stores during pre-trial is the same as during trial.**

In [35]:

```
# Step 1
for num in [40, 155, 233]:
    print("Store", num)
    print(ttest_ind(pretrial_scaled_ncust_control_stores[pretrial_scaled_ncust_control_st
ores["STORE_NBR"] == num]["ScaledNcust"],
                   trial_scaled_ncust_control_stores[trial_scaled_ncust_control_stores["
STORE_NBR"] == num]["ScaledNcust"],
                   equal_var=False), '\n')

alpha = 0.05
print("Critical t-value for 95% confidence interval:")
print(t.ppf((alpha/2, 1-alpha/2), df=min([len(pretrial_scaled_ncust_control_stores[pretr
ial_scaled_ncust_control_stores["STORE_NBR"] == num]),
                       len(trial_scaled_ncust_control_stores[trial_scaled_ncust_control_
stores["STORE_NBR"] == num])])-1))
```

```
Store 40
Ttest_indResult(statistic=0.644732693420032, pvalue=0.5376573016017127)

Store 155
Ttest_indResult(statistic=1.3888888888888882, pvalue=0.204345986327886)

Store 233
Ttest_indResult(statistic=0.8442563765225701, pvalue=0.4559280037660254)

Critical t-value for 95% confidence interval:
[-4.30265273  4.30265273]
```

In [36]:

```
# Step 2
for trial, cont in trial_control_dic.items():
    print("Trial store:", trial, ", Control store:", cont)
    print(ttest_ind(pretrial_full_observ[pretrial_full_observ["STORE_NBR"] == trial]["nC
ustomers"],
                   pretrial_scaled_ncust_control_stores[pretrial_scaled_ncust_control_st
ores["STORE_NBR"] == cont]["ScaledNcust"],
                   equal_var=True), '\n')

alpha = 0.05
print("Critical t-value for 95% confidence interval:")
print(t.ppf((alpha/2, 1-alpha/2), df=len(pretrial_full_observ[pretrial_full_observ["STOR
E_NBR"] == trial])-1))
```

```
Trial store: 77 , Control store: 233
Ttest_indResult(statistic=0.0, pvalue=1.0)

Trial store: 86 , Control store: 155
Ttest_indResult(statistic=0.0, pvalue=1.0)

Trial store: 88 , Control store: 40
Ttest_indResult(statistic=-7.648483953264653e-15, pvalue=0.9999999999999994)

Critical t-value for 95% confidence interval:
[-2.44691185  2.44691185]
```

In [37]:

```
# Step 3
```

```
# Step 5
for trial, cont in trial_control_dic.items():
    print("Trial store:", trial, ", Control store:", cont)
    temp_pre = scaledncust_vs_trial[(scaledncust_vs_trial["c_STORE_NBR"] == cont) & (scaledncust_vs_trial["trial_period"]=="pre")]
    std = temp_pre["nCust_Percentage_Diff"].std()
    mean = temp_pre["nCust_Percentage_Diff"].mean()
    #print(std, mean)
    for t_month in scaledncust_vs_trial[scaledncust_vs_trial["trial_period"] == "trial"]["YEARMONTH"].unique():
        pdif = scaledncust_vs_trial[(scaledncust_vs_trial["YEARMONTH"] == t_month) & (scaledncust_vs_trial["t_STORE_NBR"] == trial)]["nCust_Percentage_Diff"]
        print(t_month,":",(float(pdif)-mean)/std)
    print('\n')

print("Critical t-value for 95% confidence interval:")
conf_intv_95 = t.ppf(0.95, df=len(temp_pre)-1)
print(conf_intv_95)
```

```
Trial store: 77 , Control store: 233
201902 : -0.19886295797440687
201903 : 8.009609025380932
201904 : 16.114474772873923


Trial store: 86 , Control store: 155
201902 : 6.220524882227514
201903 : 10.52599074274189
201904 : 3.0763575852842706


Trial store: 88 , Control store: 40
201902 : -0.3592881735131531
201903 : 1.2575196020616801
201904 : 0.6092905590514273


Critical t-value for 95% confidence interval:
1.9431802803927816
```

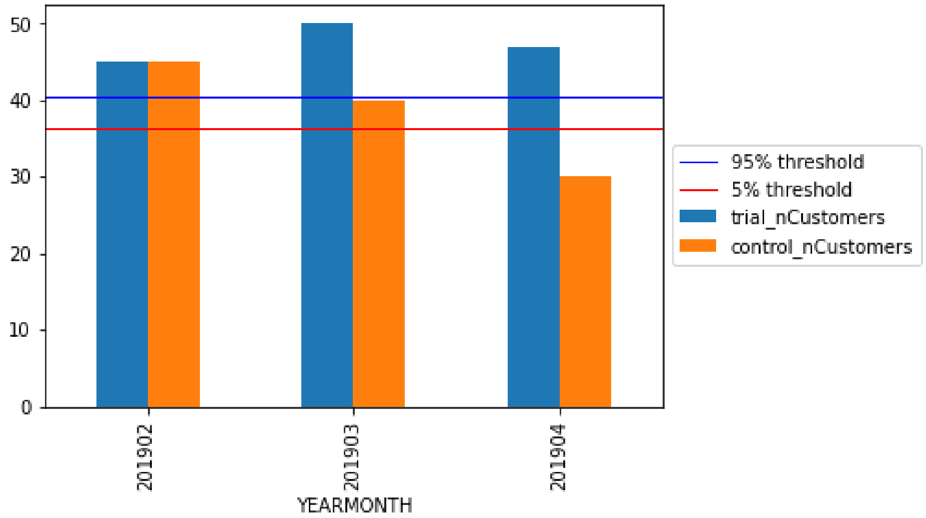
There are 5 months' increase in performance that are statistically significant (Above the 95% confidence interval t-score):

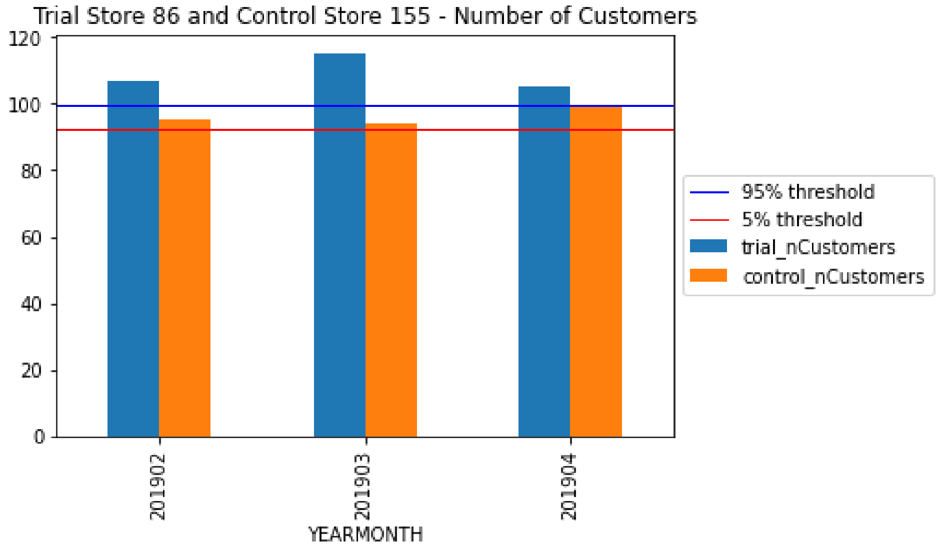
- **March and April trial months for trial store 77**
- **Feb, March and April trial months for trial store 86**

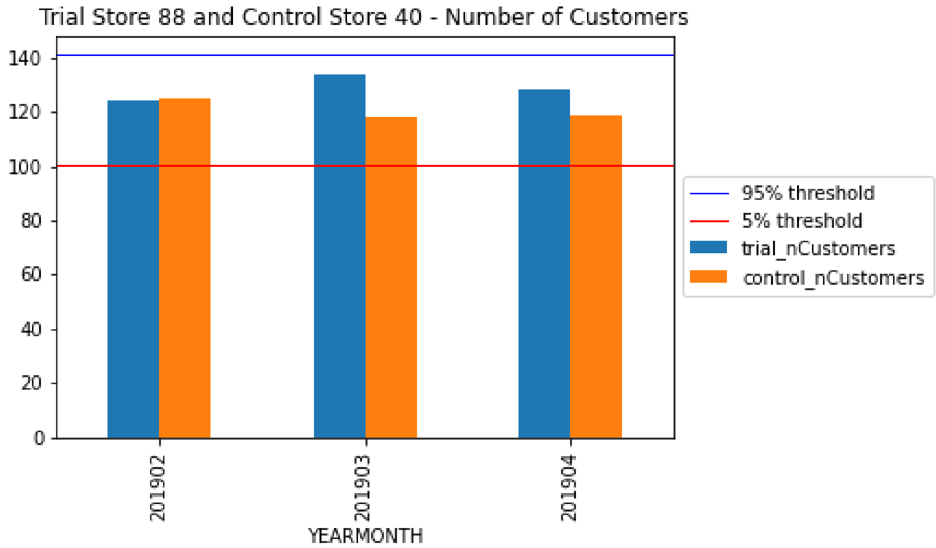
In [38]:

```
for trial, control in trial_control_dic.items():
    a = trial_scaled_ncust_control_stores[trial_scaled_ncust_control_stores["STORE_NBR"] == control].rename(columns={"nCustomers": "control_nCustomers"})
    b = trial_full_observ[trial_full_observ["STORE_NBR"] == trial][["STORE_NBR", "YEARMONTH", "nCustomers"]].rename(columns={"nCustomers": "trial_nCustomers"})
    comb = b[["YEARMONTH", "trial_nCustomers"]].merge(a[["YEARMONTH", "control_nCustomers"]],on="YEARMONTH").set_index("YEARMONTH")
    comb.plot.bar()
    cont_sc_ncust = trial_scaled_ncust_control_stores[trial_scaled_ncust_control_stores["STORE_NBR"] == control]["nCustomers"]
    std = scaledncust_vs_trial[(scaledncust_vs_trial["c_STORE_NBR"] == control) & (scaledncust_vs_trial["trial_period"]=="pre")]["nCust_Percentage_Diff"].std()
    thresh95 = cont_sc_ncust.mean() + (cont_sc_ncust.mean() * std * 2)
    thresh5 = cont_sc_ncust.mean() - (cont_sc_ncust.mean() * std * 2)
    plt.axhline(y=thresh95,linewidth=1, color='b', label="95% threshold")
    plt.axhline(y=thresh5,linewidth=1, color='r', label="5% threshold")
    plt.legend(loc='center left', bbox_to_anchor=(1.0, 0.5))
    plt.title("Trial Store "+str(trial)+" and Control Store "+str(control)+" - Number of Customers")
    plt.savefig("TS {} and CS {} - nCustomers.png".format(trial,control), bbox_inches="tight")
```

Trial Store 77 and Control Store 233 - Number of Customers







We can see that Trial store 77 sales for Feb, March, and April exceeds 95% threshold of control store. Same goes to store 86 sales for all 3 trial months.

- **Trial store 77: Control store 233**
- **Trial store 86: Control store 155**
- **Trial store 88: Control store 40**
- **Both trial store 77 and 86 showed significant increase in Total Sales and Number of Customers during trial period. But not for trial store 88. Perhaps the client knows if there's anything about trial 88 that differs it from the other two trial.**
- **Overall the trial showed positive significant result.**