In [2]:
```
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import numpy as np
```

In [4]:
```
qvi = pd.read_csv(r"D:\Documents\PowerBi Projects\Quantim\QVI_data.csv")
qvi.head()
```

Out[4]:

| | LYLTY_CARD_NBR | DATE | STORE_NBR | TXN_ID | PROD_NBR | PROD_NAME | PROD_QTY | TOT_SALES | PACK_SIZE | BRAND | LIFESTAGE | PREMIUM_CUSTOMER |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1000 | 2018-10-17 | 1 | 1 | 5 | Natural Chip Compny SeaSalt175g | 2 | 6.0 | 175 | NATURAL | YOUNG SINGLES/COUPLES | Premium |
| **1** | 1002 | 2018-09-16 | 1 | 2 | 58 | Red Rock Deli Chikn&Garlic Aioli 150g | 1 | 2.7 | 150 | RRD | YOUNG SINGLES/COUPLES | Mainstream |
| **2** | 1003 | 2019-03-07 | 1 | 3 | 52 | Grain Waves Sour Cream&Chives 210G | 1 | 3.6 | 210 | GRNWVES | YOUNG FAMILIES | Budget |
| **3** | 1003 | 2019-03-08 | 1 | 4 | 106 | Natural ChipCo Hony Soy Chckn175g | 1 | 3.0 | 175 | NATURAL | YOUNG FAMILIES | Budget |
| **4** | 1004 | 2018-11-02 | 1 | 5 | 96 | WW Original Stacked Chips 160g | 1 | 1.9 | 160 | WOOLWORTHS | OLDER SINGLES/COUPLES | Mainstream |

In [6]:
```
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
 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
```

In [8]:
```
qvi["DATE"] = pd.to_datetime(qvi["DATE"])
qvi["YEARMONTH"] = qvi["DATE"].dt.strftime("%Y%m").astype("int")
```

Compile each store's monthly: 1. Total sales 2. Number of customers, 3. Average transactions per customer 4. Average chips per customer 5. Average price per unit

In [10]:
```
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", "avgPricePerUnit"]
    return metrics
```

In [12]:
```
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   int32
 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), int32(1), int64(2)
memory usage: 161.1 KB
```

Pre-Trial Observation as this filter only stores with full 12 months observation

In [14]:
```
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)]
```

```python
pretrial_full_observ = full_observ[full_observ["YEARMONTH"] < 201902]

pretrial_full_observ.head(8)
```

Out[14]:

| | 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 [16]:

```python
def calcCorrTable(metricCol, storeComparison, inputTable=pretrial_full_observ):
  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].reset_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"] == storeComparison]["YEARMONTH"])
    corrs = pd.concat([corrs, concat_df])
  return corrs
```

In [22]:

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

# corr_table.head(8)
```

In [32]:

```python
import pandas as pd
import warnings

# Suppress FutureWarnings
warnings.simplefilter(action='ignore', category=FutureWarning)

# Define your functions here (e.g., calcCorrTable)

# Initialize an empty DataFrame for correlations
corr_table = pd.DataFrame()

# Loop through trial numbers and calculate the correlation tables
for trial_num in [77, 86, 88]:
    try:
        # Calculate the correlation table for the current trial number
        new_corr_data = calcCorrTable(["TOT_SALES", "nCustomers", "nTxnPerCust", "nChipsPerTxn", "avgPricePerUnit"], trial_num)

        # Check if the new correlation data is valid (not empty and contains non-NA values)
        if new_corr_data is not None and not new_corr_data.empty and not new_corr_data.isnull().all().all():
            corr_table = pd.concat([corr_table, new_corr_data], ignore_index=True)  # Concatenate if valid
        else:
            print(f"No valid data for trial number {trial_num}.")  # Optional: log this information

    except Exception as e:
        print(f"An error occurred while processing trial number {trial_num}: {e}")  # Handle and log exceptions

# Display the first 8 rows of the combined correlation table
# print(corr_table.head(8))
corr_table.head(8)
```

Out[32]:

| | 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 |
| **7** | 201807 | 77 | 2 | 0.142957 |

In [34]:

```
def calculateMagnitudeDistance(metricCol, storeComparison, inputTable=pretrial_full_observ):
    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 [36]:

```
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[36]:

| | 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 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **2** | 0.207554 | 0.286822 | 0.462846 | 0.779879 | 0.923887 | 201809 | 88 | 272 | 0.532198 |
| **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 [38]:

```
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 [40]:

```
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 [42]:

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

Determining the top five highest composite score for each trial based on Total sales

In [44]:
```
grouped_comparison_table1 = compare_metrics_table1.groupby(["Trial_Str", "Ctrl_Str"]).mean().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      YEARMONTH  Corr_Score  magnitude  CompScore
218         77       233  201822.571429         1.0   0.986477   0.993238
239         77       255  201822.571429         1.0   0.979479   0.989739
177         77       188  201822.571429         1.0   0.977663   0.988831
49          77        53  201822.571429         1.0   0.976678   0.988339
120         77       131  201822.571429         1.0   0.976267   0.988134

     Trial_Str  Ctrl_Str      YEARMONTH  Corr_Score  magnitude  CompScore
356         86       109  201822.571429         1.0   0.966783   0.983391
401         86       155  201822.571429         1.0   0.965876   0.982938
464         86       222  201822.571429         1.0   0.962280   0.981140
467         86       225  201822.571429         1.0   0.960512   0.980256
471         86       229  201822.571429         1.0   0.951704   0.975852

     Trial_Str  Ctrl_Str      YEARMONTH  Corr_Score  magnitude  CompScore
551         88        40  201822.571429         1.0   0.941165   0.970582
538         88        26  201822.571429         1.0   0.904377   0.952189
582         88        72  201822.571429         1.0   0.903800   0.951900
517         88         4  201822.571429         1.0   0.903466   0.951733
568         88        58  201822.571429         1.0   0.891678   0.945839
```

In [46]:
```
compare_metrics_table2 = pd.DataFrame()
for trial_num in [77, 86, 88]:
    compare_metrics_table2 = pd.concat([compare_metrics_table2, combine_corr_dist(["nCustomers"], trial_num)])
```

Determining the top five highest composite score for each trial based on no. of customers

In [48]:
```
grouped_comparison_table2 = compare_metrics_table2.groupby(["Trial_Str", "Ctrl_Str"]).mean().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')
```

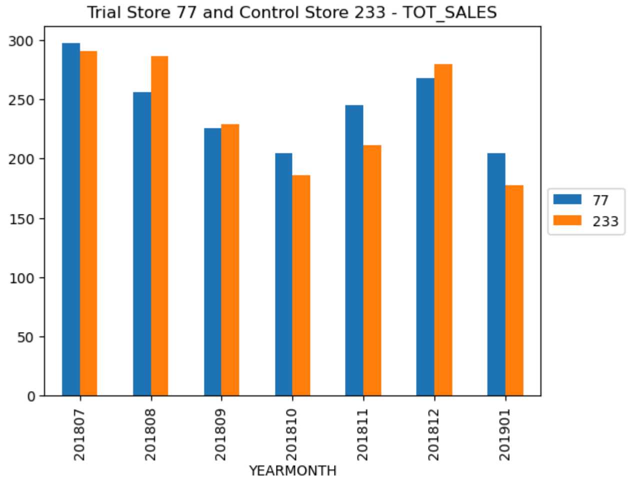
```
     Trial_Str  Ctrl_Str      YEARMONTH  Corr_Score  magnitude  CompScore
218         77       233  201822.571429         1.0   0.993132   0.996566
38          77        41  201822.571429         1.0   0.976648   0.988324
101         77       111  201822.571429         1.0   0.968407   0.984203
105         77       115  201822.571429         1.0   0.967033   0.983516
15          77        17  201822.571429         1.0   0.965659   0.982830

     Trial_Str  Ctrl_Str      YEARMONTH  Corr_Score  magnitude  CompScore
401         86       155  201822.571429         1.0   0.986772   0.993386
467         86       225  201822.571429         1.0   0.969577   0.984788
356         86       109  201822.571429         1.0   0.969577   0.984788
471         86       229  201822.571429         1.0   0.964286   0.982143
293         86        39  201822.571429         1.0   0.961640   0.980820

     Trial_Str  Ctrl_Str      YEARMONTH  Corr_Score  magnitude  CompScore
736         88       237  201822.571429         1.0   0.987818   0.993909
705         88       203  201822.571429         1.0   0.944629   0.972315
551         88        40  201822.571429         1.0   0.942414   0.971207
668         88       165  201822.571429         1.0   0.935770   0.967885
701         88       199  201822.571429         1.0   0.932447   0.966224
```

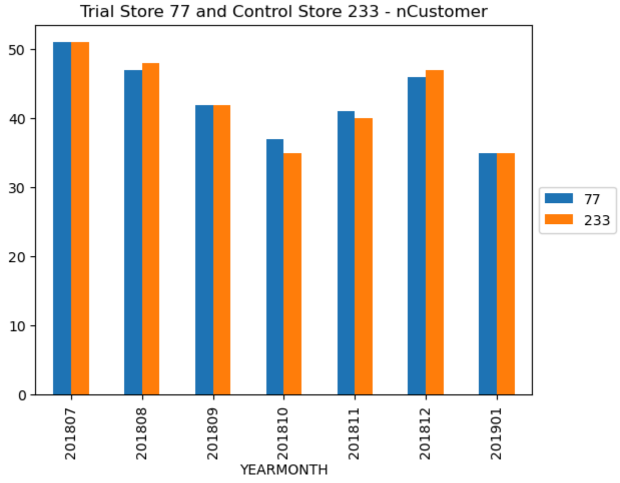
In [50]:
```
for trial_num in compare_metrics_table2["Trial_Str"].unique():
    a = grouped_comparison_table1[grouped_comparison_table1["Trial_Str"] == trial_num].sort_values(ascending=False, by="CompScore").set_index(["Trial_Str", "Ctrl_Str"])["CompScore"]
    b = grouped_comparison_table2[grouped_comparison_table2["Trial_Str"] == trial_num].sort_values(ascending=False, by="CompScore").set_index(["Trial_Str", "Ctrl_Str"])["CompScore"]
    print((pd.concat([a,b], axis=1).sum(axis=1)/2).sort_values(ascending=False).head(3), '\n')
```

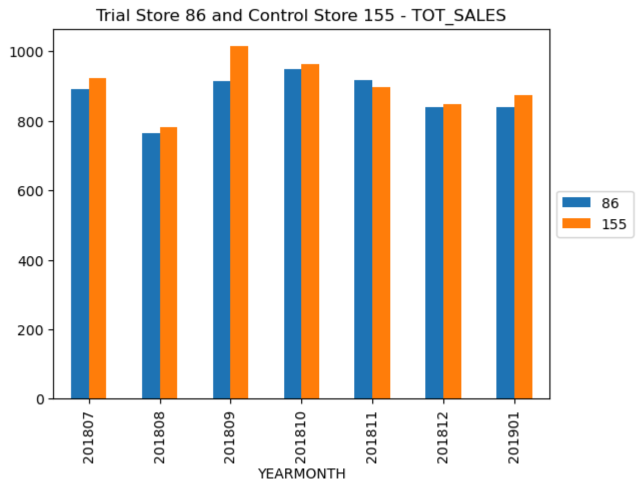
```
Trial_Str  Ctrl_Str
77         233         0.994902
           41          0.986020
           46          0.984762
dtype: float64

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
```

Similarities based on total sales: 1. Trial store 77: Store 233, 255, 188 2. Trial store 86: Store 109, 155, 222 3. Trial store 88: Store 40, 26, 72 Similarities based on No. of Customers: 1. Trial store 77: Store 233, 41, 111 2. Trial store 86: Store 155, 225, 109 3. Trial store 88: Store 237, 203, 40 Final SImilarities based on Highest average of both features combined: 1. Trial store 77: Store 233 2. Trial store 86: Store 155 3. Trial store 88: Store 40

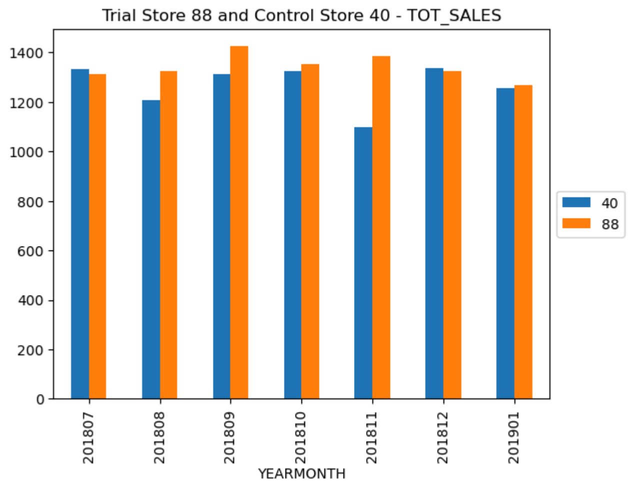
In [54]:
```
trial_control_dic = {77:233, 86:155, 88:40}
for key, val in trial_control_dic.items():
    pretrial_full_observ[pretrial_full_observ["STORE_NBR"].isin([key, val])].groupby(
        ["YEARMONTH", "STORE_NBR"]).sum()["TOT_SALES"].unstack().plot.bar()
    plt.legend(loc='center left', bbox_to_anchor=(1.0, 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')
```

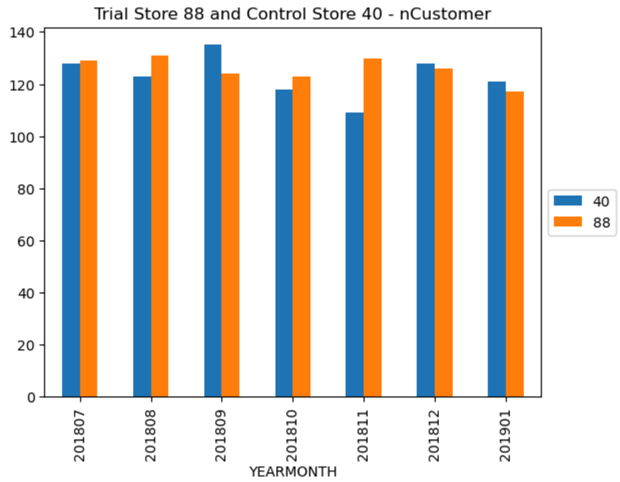



Trial Store 86 and Control Store 155 - TOT_SALES
1000
800
600
400
200
0
201807
201808
201809
201810
201811
201812
201901
YEARMONTH
86
155


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



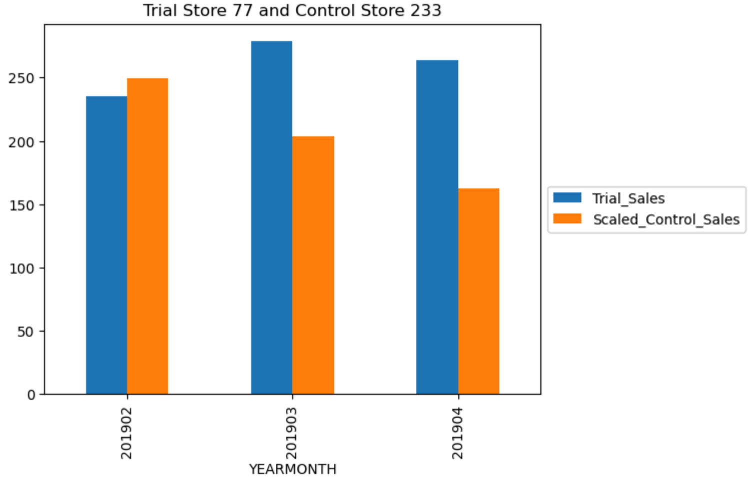



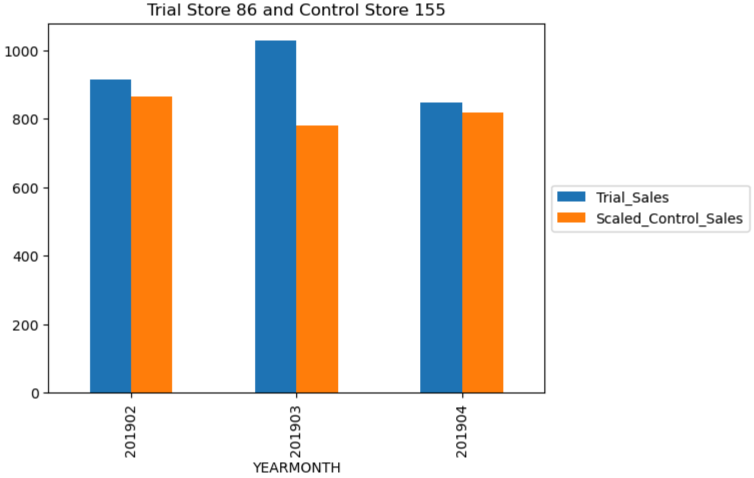

Next we'll compare the performance of Trial stores to Control stores during the trial period. To ensure their performance is comparable during Trial period, we need to scale (multiply to ratio of trial / control) all of Control stores' performance to Trial store's performance during pre-trial. Starting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

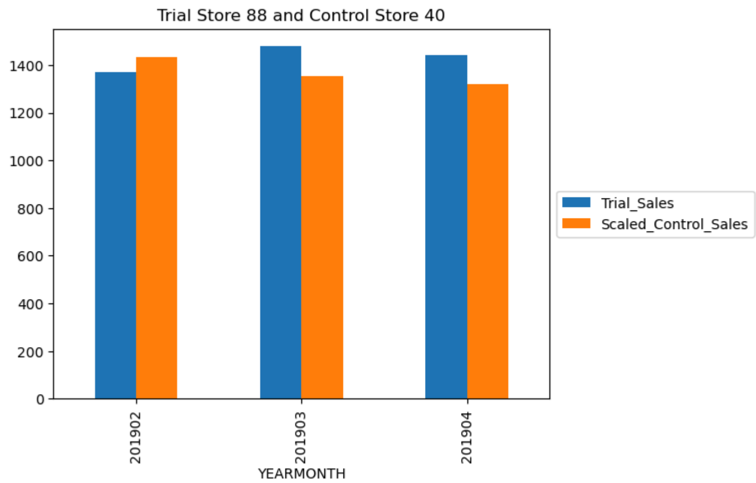
In [56]:
```
#Ratio of Store 77 and its Control store.
sales_ratio_77 = pretrial_full_observ[pretrial_full_observ["STORE_NBR"] == 77]["TOT_SALES"].sum() / pretrial_full_observ[pretrial_full_observ["STORE_NBR"] == 233]["TOT_SALES"].sum()

#Ratio of Store 86 and its Control store.
sales_ratio_86 = pretrial_full_observ[pretrial_full_observ["STORE_NBR"] == 86]["TOT_SALES"].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_SALES"].sum() / pretrial_full_observ[pretrial_full_observ["STORE_NBR"] == 40]["TOT_SALES"].sum()
```

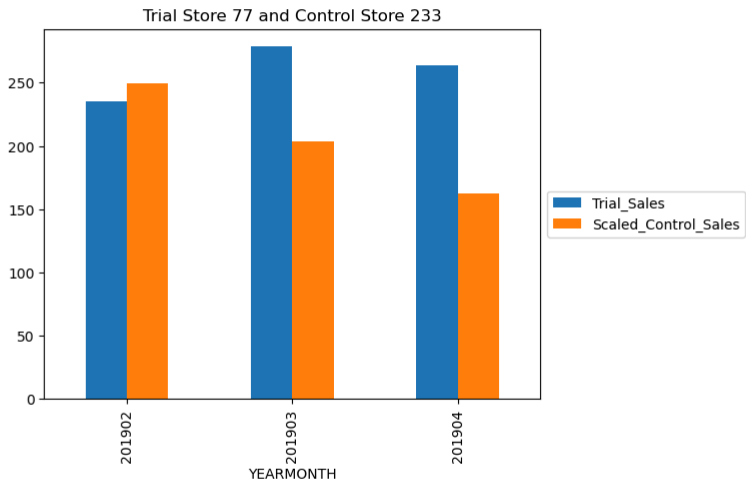
In [62]:
```
trial_full_observ = full_observ[(full_observ["YEARMONTH"] >= 201902) & (full_observ["YEARMONTH"] <= 201904)]
scaled_sales_control_stores = full_observ[full_observ["STORE_NBR"].isin([233, 155, 40])][["STORE_NBR", "YEARMONTH", "TOT_SALES"]]

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_stores["YEARMONTH"] >= 201902) & (scaled_sales_control_stores["YEARMONTH"] <= 201904)]
pretrial_scaled_sales_control_stores = scaled_sales_control_stores[scaled_sales_control_stores["YEARMONTH"] < 201902]

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", "YEARMONTH", "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))
    plt.show()
    print('\n')
```

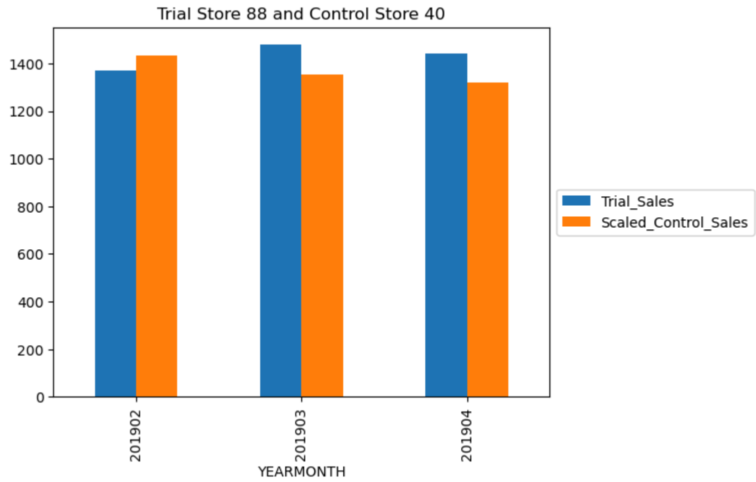


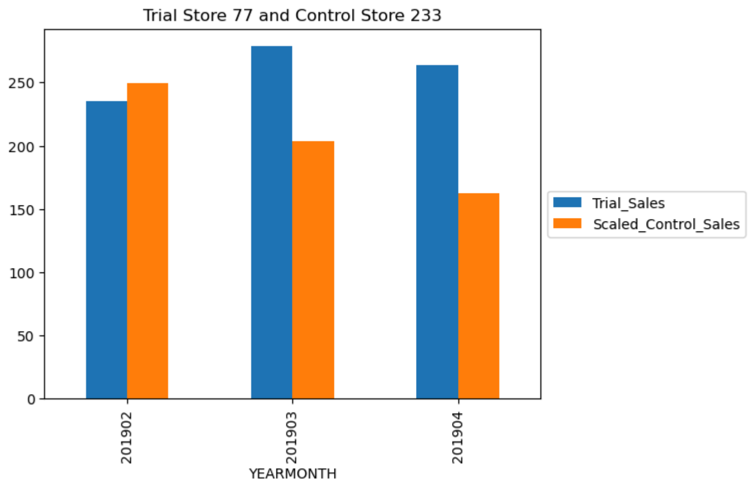



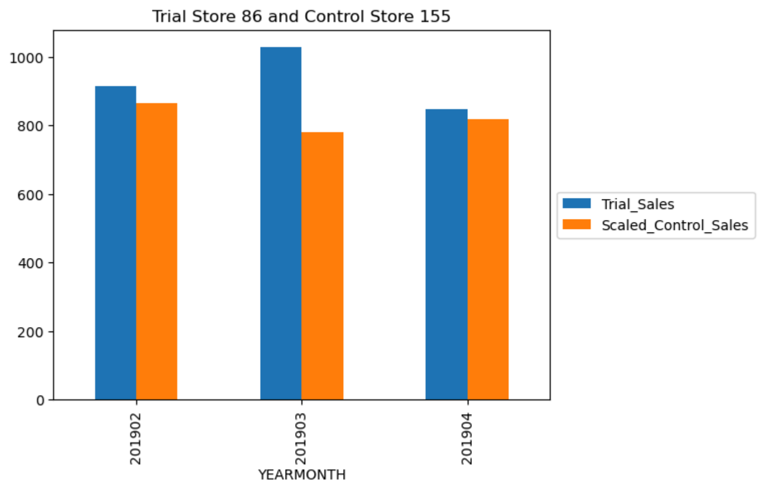

Trial Store 88 and Control Store 40
1400
1200
1000
800
600
400
200
0
201902
201903
201904
YEARMONTH
Trial_Sales
Scaled_Control_Sales

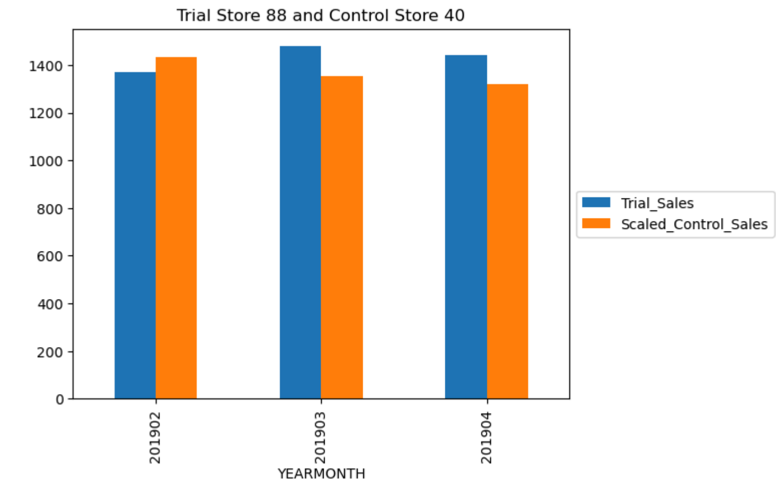

Trial Store 77 and Control Store 233
250
200
150
100
50
0
201902
201903
201904
YEARMONTH
Trial_Sales
Scaled_Control_Sales


Trial Store 86 and Control Store 155
1000
800
600
400
200
0
201902
201903
201904
YEARMONTH
Trial_Sales
Scaled_Control_Sales


Trial Store 88 and Control Store 40
1400
1200
1000
800
600
400
200
0
201902
201903
201904
YEARMONTH
Trial_Sales
Scaled_Control_Sales


Trial Store 77 and Control Store 233
250
200
150
100
50
0
201902
201903
201904
YEARMONTH
Trial_Sales
Scaled_Control_Sales


Trial Store 86 and Control Store 155
1000
800
600
400
200
0
201902
201903
201904
YEARMONTH
Trial_Sales
Scaled_Control_Sales




In [64]:
```
percentage_diff
```

Out[64]: {77: 1.2615468650086281, 86: 1.1315014357363697, 88: 1.043458345854219}

In [66]:
```
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_NBR", "t_TOT_SALES"]
scaledsales_vs_trial["Sales_Percentage_Diff"] = (scaledsales_vs_trial["t_TOT_SALES"] - scaledsales_vs_trial["c_ScaledSales"]) / (((scaledsales_vs_trial["t_TOT_SALES"] + scaledsales_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 cell: label_period(cell))
scaledsales_vs_trial[scaledsales_vs_trial["trial_period"] == "trial"]
```

Out[66]:

| | 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 [68]:
```
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_stores["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"]))
```

```python
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[pretrial_scaled_sales_control_stores["STORE_NBR"] == num]),
                       len(trial_scaled_sales_control_stores[trial_scaled_sales_control_stores["STORE_NBR"] == num])])-1))
```

```
Store 40
TtestResult(statistic=-0.5958372343168558, pvalue=0.5722861621434027, df=6.228548324256264)

Store 155
TtestResult(statistic=1.4291956879290917, pvalue=0.1972705865160342, df=6.794437403919926)

Store 233
TtestResult(statistic=1.191102601097452, pvalue=0.2944500606486209, df=4.355475642590669)

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

In [70]:
```python
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"] == 40]["ScaledSales"]
```

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

In [72]:
```python
# 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]["TOT_SALES"],
                    pretrial_scaled_sales_control_stores[pretrial_scaled_sales_control_stores["STORE_NBR"] == cont]["ScaledSales"],
                    equal_var=True), '\n')
    #print(len(pretrial_full_observ[pretrial_full_observ["STORE_NBR"] == trial]["TOT_SALES"]),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["STORE_NBR"] == trial])-1))
```

```
Trial store: 77 , Control store: 233
TtestResult(statistic=-1.2533353315065932e-15, pvalue=0.999999999999999, df=12.0)

Trial store: 86 , Control store: 155
TtestResult(statistic=3.1048311203382156e-15, pvalue=0.9999999999999976, df=12.0)

Trial store: 88 , Control store: 40
TtestResult(statistic=-5.69358613974361e-15, pvalue=0.9999999999999956, df=12.0)

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.

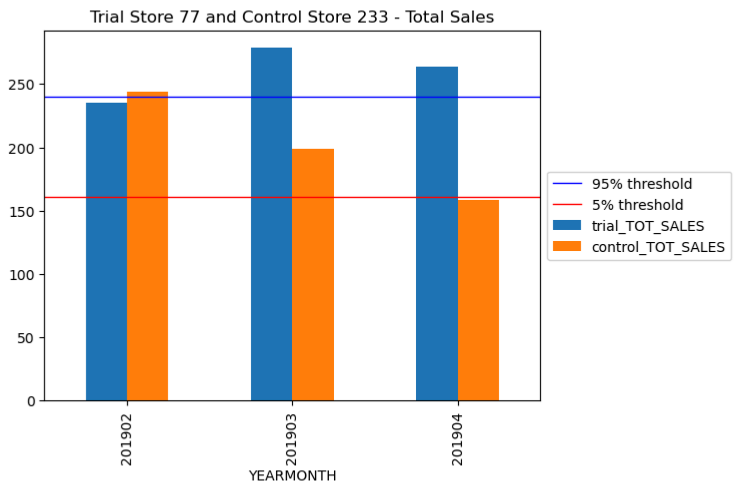
In [74]:
```python
# Step 3
for trial, cont in trial_control_dic.items():
    print("Trial store:", trial, ", Control store:", cont)
    temp_pre = scaledsales_vs_trial[(scaledsales_vs_trial["c_STORE_NBR"] == cont) & (scaledsales_vs_trial["trial_period"]=="pre")]
    std = temp_pre["Sales_Percentage_Diff"].std()
    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)
```

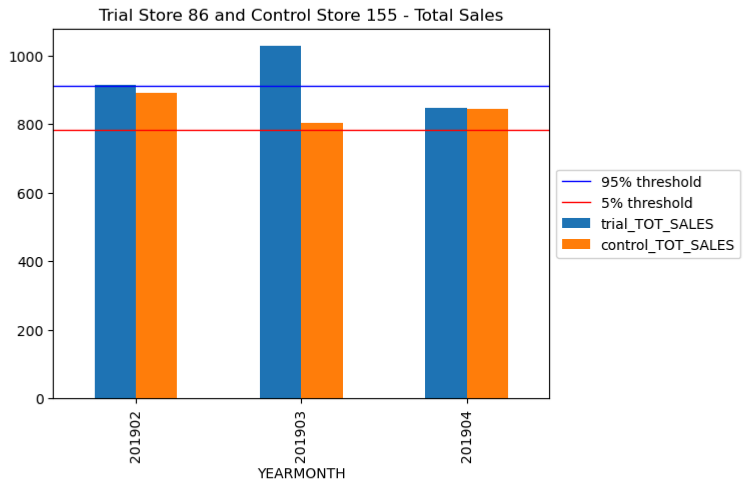
```
Trial store: 77 , Control store: 233
201902 : -0.7171038288055838
201903 : 3.035317928855674
201904 : 4.708944418758219


Trial store: 86 , Control store: 155
201902 : 1.4133618775921597
201903 : 7.123063846042147
201904 : 0.8863824572944234


Trial store: 88 , Control store: 40
201902 : -0.5481633746817577
201903 : 1.0089992743637823
201904 : 0.9710006270463672


Critical t-value for 95% confidence interval:
1.9431802805153022
```

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

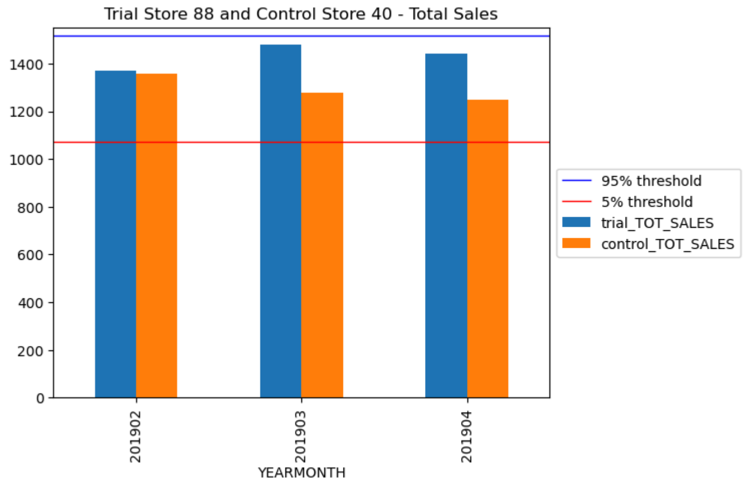
In [78]:

```
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")
    plt.show()
    print('\n')
```

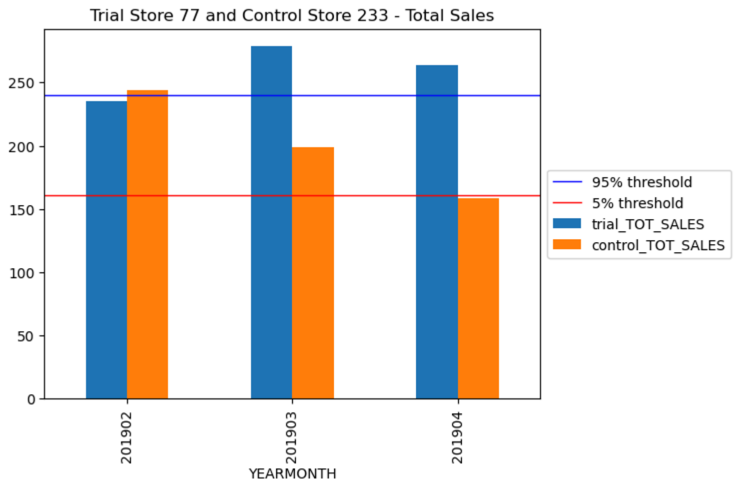


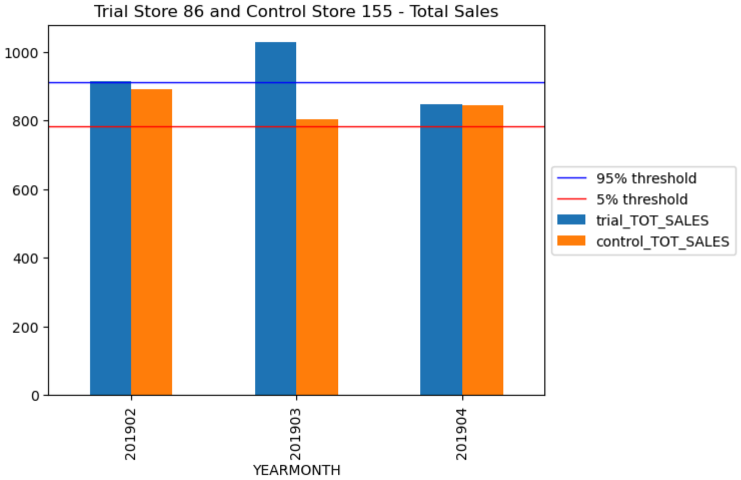


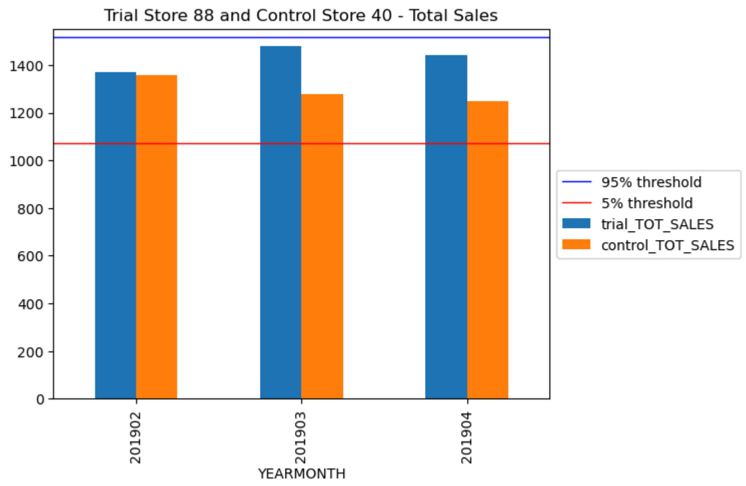
Trial Store 86 and Control Store 155 - Total Sales
1000
800
600
400
200
0
201902
201903
201904
YEARMONTH
95% threshold
5% threshold
trial_TOT_SALES
control_TOT_SALES

Trial Store 88 and Control Store 40 - Total Sales
1400
1200
1000
800
600
400
200
0
201902
201903
201904
YEARMONTH
95% threshold
5% threshold
trial_TOT_SALES
control_TOT_SALES

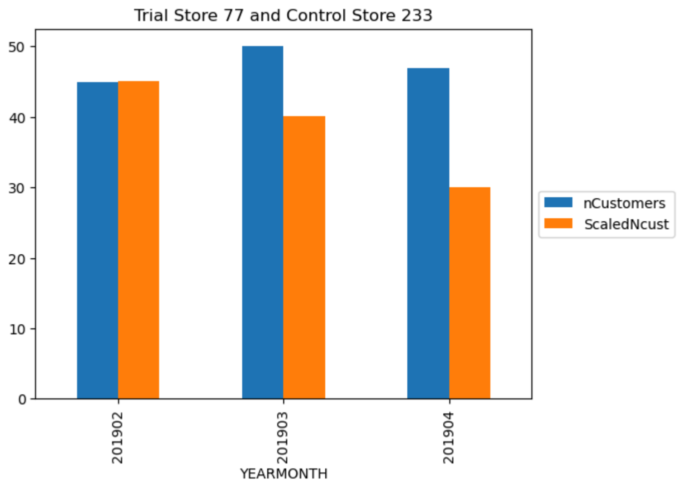

Trial Store 77 and Control Store 233 - Total Sales
250
200
150
100
50
0
201902
201903
201904
YEARMONTH
95% threshold
5% threshold
trial_TOT_SALES
control_TOT_SALES

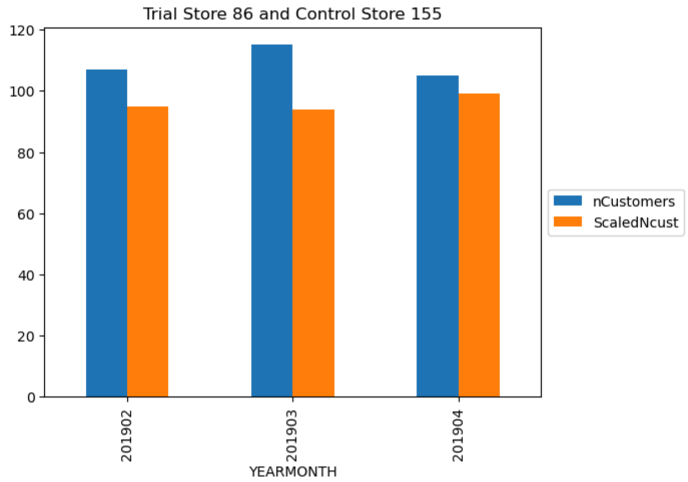

Trial Store 86 and Control Store 155 - Total Sales
1000
800
600
400
200
0
201902
201903
201904
YEARMONTH
95% threshold
5% threshold
trial_TOT_SALES
control_TOT_SALES

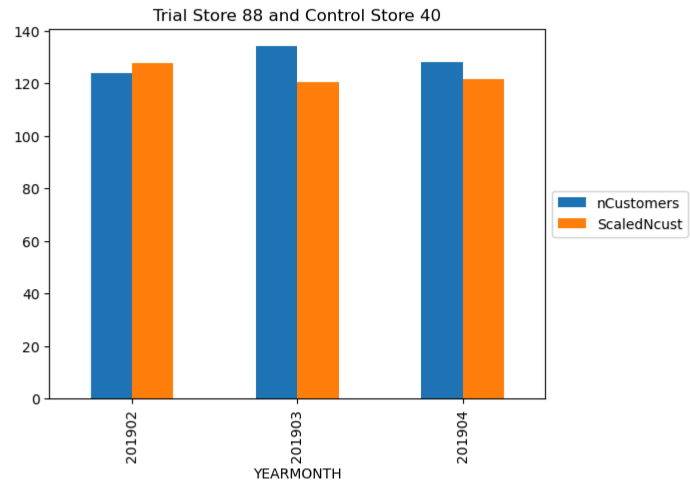



In [80]:
```
#Ratio of Store 77 and its Control store.
ncust_ratio_77 = pretrial_full_observ[pretrial_full_observ["STORE_NBR"] == 77]["nCustomers"].sum() / pretrial_full_observ[pretrial_full_observ["STORE_NBR"] == 233]["nCustomers"].sum()

#Ratio of Store 86 and its Control store.
ncust_ratio_86 = pretrial_full_observ[pretrial_full_observ["STORE_NBR"] == 86]["nCustomers"].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]["nCustomers"].sum() / pretrial_full_observ[pretrial_full_observ["STORE_NBR"] == 40]["nCustomers"].sum()
```

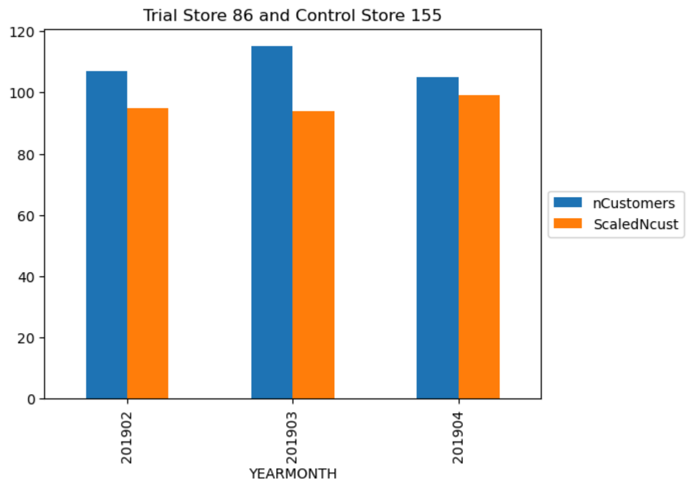
In [86]:
```
#trial_full_observ = full_observ[(full_observ["YEARMONTH"] >= 201902) & (full_observ["YEARMONTH"] <= 201904)]
scaled_ncust_control_stores = full_observ[full_observ["STORE_NBR"].isin([233, 155, 40])][["STORE_NBR", "YEARMONTH", "nCustomers"]]

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_stores["YEARMONTH"] >= 201902) & (scaled_ncust_control_stores["YEARMONTH"] <= 201904)]
pretrial_scaled_ncust_control_stores = scaled_ncust_control_stores[scaled_ncust_control_stores["YEARMONTH"] < 201902]

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", "YEARMONTH", "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))
    plt.show()
    print('\n')
```

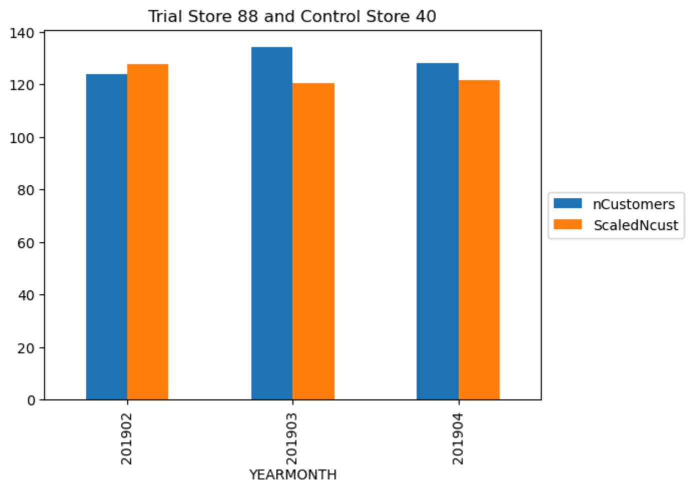

Trial Store 77 and Control Store 233
50
40
30
20
10
0
201902
201903
201904
YEARMONTH
nCustomers
ScaledNcust


Trial Store 86 and Control Store 155
120
100
80
60
40
20
0
201902
201903
201904
YEARMONTH
nCustomers
ScaledNcust


Trial Store 88 and Control Store 40
0
20
40
60
80
100
120
140
201902
201903
201904
YEARMONTH
nCustomers
ScaledNcust


Trial Store 77 and Control Store 233
0
10
20
30
40
50
201902
201903
201904
YEARMONTH
nCustomers
ScaledNcust




In [88]:
```
ncust_percentage_diff
```

Out[88]: {77: 1.2306529009742622, 86: 1.1354166666666667, 88: 1.0444876946258161}

In [90]:
```
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_NBR", "t_nCustomers"]
scaledncust_vs_trial["nCust_Percentage_Diff"] = (scaledncust_vs_trial["t_nCustomers"] - scaledncust_vs_trial["c_ScaledNcust"]) / (((scaledncust_vs_trial["t_nCustomers"] + scaledncust_vs_trial["c_ScaledNcust"])/2))

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

Out[90]:

| | 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** | 40 | 201904 | 121.484919 | 88 | 128 | 0.052228 | trial |

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 [92]:

```
# Step 1
for num in [40, 155, 233]:
    print("Store", num)
    print(ttest_ind(pretrial_scaled_ncust_control_stores[pretrial_scaled_ncust_control_stores["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[pretrial_scaled_ncust_control_stores["STORE_NBR"] == num]),
                        len(trial_scaled_ncust_control_stores[trial_scaled_ncust_control_stores["STORE_NBR"] == num])])-1))
```

```
Store 40
TtestResult(statistic=0.644732693420032, pvalue=0.5376573016017127, df=7.7735551763644395)

Store 155
TtestResult(statistic=1.3888888888888882, pvalue=0.204345986327886, df=7.572528547077964)

Store 233
TtestResult(statistic=0.8442563765225701, pvalue=0.4559280037660254, df=3.2638055826510652)

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

In [94]:

```
# 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]["nCustomers"],
                    pretrial_scaled_ncust_control_stores[pretrial_scaled_ncust_control_stores["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["STORE_NBR"] == trial])-1))
```

```
Trial store: 77 , Control store: 233
TtestResult(statistic=0.0, pvalue=1.0, df=12.0)

Trial store: 86 , Control store: 155
TtestResult(statistic=0.0, pvalue=1.0, df=12.0)

Trial store: 88 , Control store: 40
TtestResult(statistic=-7.648483953264653e-15, pvalue=0.9999999999999994, df=12.0)

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

In [96]:

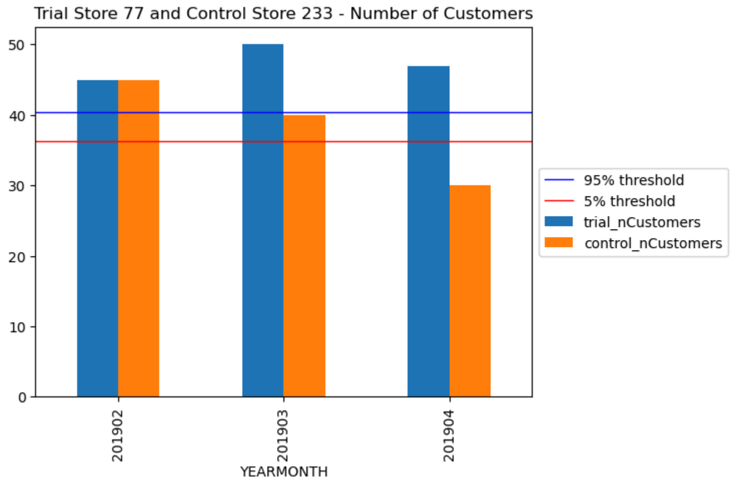
```
# Step 3
for trial, cont in trial_control_dic.items():
    print("Trial store:", trial, ", Control store:", cont)
    temp_pre = scaledncust_vs_trial[(scaledncust_vs_trial["c_STORE_NBR"] == cont) & (scaledncust_vs_trial["trial_period"]=="pre")]
    std = temp_pre["nCust_Percentage_Diff"].std()
    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:
1.9431802805153022
```

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 [98]:
```
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")
    plt.show()
    print('\n')
```





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. 1. Trial store 77: Control store 233 2. Trial store 86: Control store 155 3. Trial store 88: Control store 40 4. 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. 5. Overall the trial showed positive significant result.