In [2]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import datetime
from scipy import stats
```

In [3]:
```
df = pd.read_csv('QVI_data.csv')
df
```

Out[3]:

	LYLTY_CARD_NBR	DATE	STORE_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_SALES	PACK_SIZE	BRAND	L
0	1000	2018-10-17	1	1	5	Natural Chip Compny SeaSalt175g	2	6.0	175	NATURAL	SINGLES/
1	1002	2018-09-16	1	2	58	Red Rock Deli Chikn&Garlic Aioli 150g	1	2.7	150	RRD	SINGLES/
2	1003	2019-03-07	1	3	52	Grain Waves Sour Cream&Chives 210G	1	3.6	210	GRNWVES	YOUNG
3	1003	2019-03-08	1	4	106	Natural ChipCo Hony Soy Chckn175g	1	3.0	175	NATURAL	YOUNG
4	1004	2018-11-02	1	5	96	WW Original Stacked Chips 160g	1	1.9	160	WOOLWORTHS	SINGLES/
...	...	...	...	...	...	...	...	...	...	...	
264829	2370701	2018-12-08	88	240378	24	Grain Waves Sweet Chilli 210g	2	7.2	210	GRNWVES	YOUNG
264830	2370751	2018-10-01	88	240394	60	Kettle Tortilla ChpsFeta&Garlic 150g	2	9.2	150	KETTLE	YOUNG
264831	2370961	2018-10-24	88	240480	70	Tyrrells Crisps Lightly Salted 165g	2	8.4	165	TYRRELLS	OLDER
264832	2370961	2018-10-27	88	240481	65	Old El Paso Salsa Dip Chnky Tom Ht300g	2	10.2	300	OLD	OLDER
264833	2373711	2018-12-14	88	241815	16	Smiths Crinkle Chips Salt & Vinegar 330g	2	11.4	330	SMITHS	SINGLES/

264834 rows × 12 columns

The client has selected store numbers 77, 86 and 88 as trial stores with a trial period of Feb 2019 to April 2019. The client also wants control stores to be established stores that are operational for the entire observation period.

We would want to match trial stores to control stores that are similar to the trial store prior to the trial period of Feb 2019 in terms of:

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

To choose the control stores, we will create the metrics of interest and filter to stores that are present throughout the pre-trial period.

First, we want to add a column with the year/month of the transaction.

In [4]:
```
# Change DATE column to store dates as datetimes
df['DATE'] = pd.to_datetime(df['DATE'])

# Then add a YEARMONTH column
df['YEARMONTH'] = df['DATE'].dt.strftime('%Y%m').astype('int64')
df
```

Out[4]:

	LYLTY_CARD_NBR	DATE	STORE_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_SALES	PACK_SIZE	BRAND	L
0	1000	2018-10-17	1	1	5	Natural Chip Compny SeaSalt175g	2	6.0	175	NATURAL	SINGLES/
1	1002	2018-09-16	1	2	58	Red Rock Deli Chikn&Garlic Aioli 150g	1	2.7	150	RRD	SINGLES/
2	1003	2019-03-07	1	3	52	Grain Waves Sour Cream&Chives 210G	1	3.6	210	GRNWVES	YOUNG
3	1003	2019-03-08	1	4	106	Natural ChipCo Hony Soy Chckn175g	1	3.0	175	NATURAL	YOUNG
4	1004	2018-11-02	1	5	96	WW Original Stacked Chips 160g	1	1.9	160	WOOLWORTHS	SINGLES/
...	...	...	...	...	...	...	...	...	...	...	
264829	2370701	2018-12-08	88	240378	24	Grain Waves Sweet Chilli 210g	2	7.2	210	GRNWVES	YOUNG
264830	2370751	2018-10-01	88	240394	60	Kettle Tortilla ChpsFeta&Garlic 150g	2	9.2	150	KETTLE	YOUNG
264831	2370961	2018-10-24	88	240480	70	Tyrrells Crisps Lightly Salted 165g	2	8.4	165	TYRRELLS	OLDER
264832	2370961	2018-10-27	88	240481	65	Old El Paso Salsa Dip Chnky Tom Ht300g	2	10.2	300	OLD	OLDER
264833	2373711	2018-12-14	88	241815	16	Smiths Crinkle Chips Salt & Vinegar 330g	2	11.4	330	SMITHS	SINGLES/

264834 rows × 13 columns

Next, we want to create a function that will be able to calculate the total sales, number of customers, transactions per customer, chips per customer and the average price per unit for each store and month.

In [20]:
```
grouped_df = df.groupby(["STORE_NBR", "YEARMONTH"])
tot_sales = grouped_df.TOT_SALES.sum()
tot_sales
# tot_sales.sum("STORE_NBR"==273)
```

Out[20]:
```
STORE_NBR  YEARMONTH
1          201807       206.9
           201808       176.1
           201809       278.8
           201810       188.1
           201811       192.6
                        ...
272        201902       395.5
           201903       442.3
           201904       445.1
           201905       314.6
           201906       312.1
Name: TOT_SALES, Length: 3169, dtype: float64
```

In [21]:
```
numberOfCustomers = grouped_df.LYLTY_CARD_NBR.nunique()
numberOfCustomers
```

Out[21]:
```
STORE_NBR  YEARMONTH
1          201807       49
           201808       42
           201809       59
           201810       44
           201811       46
                        ..
272        201902       45
           201903       50
           201904       54
           201905       34
           201906       34
Name: LYLTY_CARD_NBR, Length: 3169, dtype: int64
```

In [23]:
```
numberOfTransactions_perCust = grouped_df.TXN_ID.size()/numberOfCustomers
numberOfTransactions_perCust
```

Out[23]:
```
STORE_NBR  YEARMONTH
1          201807       1.061224
           201808       1.023810
           201809       1.050847
           201810       1.022727
           201811       1.021739
                          ...
272        201902       1.066667
           201903       1.060000
           201904       1.037037
           201905       1.176471
           201906       1.088235
Length: 3169, dtype: float64
```

In [25]:
```
numberOfChipsPerTransaction = grouped_df.PROD_QTY.sum()/grouped_df.TXN_ID.size()
numberOfChipsPerTransaction
```

Out[25]:
```
STORE_NBR  YEARMONTH
1          201807       1.192308
           201808       1.255814
           201809       1.209677
           201810       1.288889
           201811       1.212766
                          ...
272        201902       1.895833
           201903       1.905660
           201904       1.875000
           201905       1.775000
           201906       1.891892
Length: 3169, dtype: float64
```

In [26]:
```
avg_priceperunit = tot_sales/grouped_df.PROD_QTY.sum()
avg_priceperunit
```

Out[26]:
```
STORE_NBR  YEARMONTH
1          201807       3.337097
           201808       3.261111
           201809       3.717333
           201810       3.243103
           201811       3.378947
                          ...
272        201902       4.346154
           201903       4.379208
           201904       4.239048
           201905       4.430986
           201906       4.458571
Length: 3169, dtype: float64
```

In [29]:
```
# Put the metrics together in an array
metric_arrays = [tot_sales, numberOfCustomers, numberOfTransactions_perCust, numberOfChipsPerTransaction, avg_priceperunit

# Create the metrics table fro mthe array
metrics_df = pd.concat(metric_arrays, axis=1)
# Give the columns labels
metrics_df.columns = ['tot_sales', 'n_cust', 'ntrans_percust', 'nchips_pertrans', 'avg_priceperunit']
metrics_df = metrics_df.reset_index()
metrics_df
```

Out[29]:

	STORE_NBR	YEARMONTH	tot_sales	n_cust	ntrans_percust	nchips_pertrans	avg_priceperunit
0	1	201807	206.9	49	1.061224	1.192308	3.337097
1	1	201808	176.1	42	1.023810	1.255814	3.261111
2	1	201809	278.8	59	1.050847	1.209677	3.717333
3	1	201810	188.1	44	1.022727	1.288889	3.243103
4	1	201811	192.6	46	1.021739	1.212766	3.378947
...	...	...	...	...	...	...	...
3164	272	201902	395.5	45	1.066667	1.895833	4.346154
3165	272	201903	442.3	50	1.060000	1.905660	4.379208
3166	272	201904	445.1	54	1.037037	1.875000	4.239048
3167	272	201905	314.6	34	1.176471	1.775000	4.430986
3168	272	201906	312.1	34	1.088235	1.891892	4.458571

3169 rows × 7 columns

In [30]:
```
# Filter to select the stores with full observation periods
month_counts = metrics_df.groupby('STORE_NBR').YEARMONTH.nunique().reset_index()
stores_fullobs = month_counts[month_counts.YEARMONTH ==12].STORE_NBR
pretrial_metrics = metrics_df[metrics_df['STORE_NBR'].isin(stores_fullobs)]

# Then filter to keep only the pre-trial period data
pretrial_metrics = pretrial_metrics.loc[pretrial_metrics.YEARMONTH < 201902]
pretrial_metrics
```

Out[30]:

	STORE_NBR	YEARMONTH	tot_sales	n_cust	ntrans_percust	nchips_pertrans	avg_priceperunit
0	1	201807	206.9	49	1.061224	1.192308	3.337097
1	1	201808	176.1	42	1.023810	1.255814	3.261111
2	1	201809	278.8	59	1.050847	1.209677	3.717333
3	1	201810	188.1	44	1.022727	1.288889	3.243103
4	1	201811	192.6	46	1.021739	1.212766	3.378947
...	...	...	...	...	...	...	...
3159	272	201809	304.7	32	1.125000	1.972222	4.291549
3160	272	201810	430.6	44	1.159091	1.941176	4.349495
3161	272	201811	376.2	41	1.097561	1.933333	4.324138
3162	272	201812	403.9	47	1.000000	1.893617	4.538202
3163	272	201901	423.0	46	1.086957	1.920000	4.406250

1820 rows × 7 columns

Now we need to work out a way of ranking how similar each potential control store is to the trial store. We can calculate how correlated the performance of each potential control store is to the trial store.

In [31]:
```
# Write a function to calculate the correlation between a trial store and all possible control stores
# Inputs:
    # trial (int) : the trial store to test
    # metric_col (str) : the label of the metric column to correlate
    # input_table (df) : the full data table of metrics to obtain the correlations with
# Output:
    # corr_table (df) : a data frame with the year-month, trial store, control store and their correlation

def calc_corr(trial, metric_col, input_table = pretrial_metrics):
    trial_stores = [77, 86, 88]
    control_stores = stores_fullobs[~stores_fullobs.isin(trial_stores)] # all stores but trial stores
    # Keep the trial store values to perform correlation with
    trial_vals = input_table[input_table["STORE_NBR"] == trial][metric_col].reset_index()
    corr_table = pd.DataFrame(columns = ['YEARMONTH', 'trial_store', 'control_store', 'correlation'])
    # Find the correlation for each control store
    for control in control_stores:
        # Keep the control store values to perform correlation with
        control_vals = input_table[input_table["STORE_NBR"] == control][metric_col].reset_index()
        corr_row = pd.DataFrame(columns = ['YEARMONTH', 'trial_store', 'control_store', 'correlation'])
        corr_row.YEARMONTH = list(input_table.loc[input_table.STORE_NBR == control]["YEARMONTH"])
        corr_row.trial_store = trial
        corr_row.control_store = control
        corr_row.correlation = control_vals.corrwith(trial_vals, axis=1)
        corr_table = pd.concat([corr_table, corr_row]) # add each store's block to the dataframe
    return (corr_table)
```

In [32]:
```
trial_stores = [77, 86, 88]
corr_table = pd.DataFrame(columns = ['YEARMONTH', 'trial_store', 'control_store', 'correlation'])
for store in trial_stores:
    corr_section = calc_corr(store, ['tot_sales', 'n_cust', 'ntrans_percust', 'nchips_pertrans', 'avg_priceperunit'] )
    corr_table = pd.concat([corr_table, corr_section])
```

In [33]:
```
corr_table
```

Out[33]:

	YEARMONTH	trial_store	control_store	correlation
0	201807	77	1	0.070544
1	201808	77	1	0.027332
2	201809	77	1	0.002472
3	201810	77	1	-0.019991
4	201811	77	1	0.030094
...	...	...	...	...
2	201809	88	272	0.533160
3	201810	88	272	0.591056
4	201811	88	272	0.566378
5	201812	88	272	0.594442
6	201901	88	272	0.621775

5397 rows × 4 columns

Apart from correlation, we can also calculate a standardised metric based on the absolute difference between the trial store's performance and each control store's performance. Write a function to calculate the magnitude distance.

In [34]:
```
# Inputs:
    # trial (int) : the trial store to test
    # metric_col (str) : the label of the metric column to correlate
    # input_table (df) : the full data table of metrics to obtain the correlations with
# Output:
    # corr_table (df) : a data frame with the year-month, trial store, control store and their normalised distance

def calc_magdist(trial, metric_col, input_table = pretrial_metrics):
    trial_stores = [77, 86, 88]
    control_stores = stores_fullobs[~stores_fullobs.isin(trial_stores)] # all stores but the trials
    dist_table = pd.DataFrame() # to store the distances for each store and month
    for control in control_stores: # calculate for each control store
        dist_row = pd.DataFrame()
        # Calculate the distance as an absolute value
        dist_row = abs(input_table[input_table["STORE_NBR"] == trial].reset_index()[metric_col]\
                       - input_table[input_table["STORE_NBR"] == control].reset_index()[metric_col])
        dist_row.insert(0,'YEARMONTH', list(input_table.loc[input_table.STORE_NBR == trial]["YEARMONTH"]))
        dist_row.insert(1,'trial_store', trial)
        dist_row.insert(2,'control_store', control)
        dist_table = pd.concat([dist_table, dist_row])

    for col in metric_col: # then loop over each column to find the max and min distances to normalise
        maxdist = dist_table[col].max()
        mindist = dist_table[col].min()
        dist_table[col] = 1-(dist_table[col] - mindist)/(maxdist-mindist) # normalised distance measure
        # also give an average magnitude over all metrics per month and store pair
    dist_table['mag_measure'] = dist_table[metric_col].mean(axis=1)
    return (dist_table)
```

Now we will use the functions to find the control stores! 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. So we will need to use our functions to get four scores, two for each of total sales and total customers.

In [35]:
```
# Write a function to generate a table of averaged correlations, distance and scores over the pretrial months for each sto
# Inputs:
    # trial (int) : the trial store to test
    # metric_col (str) : the metric label to calculate the scores for
    # input_table (df) : the data to calculate the scores with in the pre-trial period
# Output:
    # avg_corrmag (df) : a table with the correlations, distance and scores averaged over the pretrial months for each sto
def calc_corrdist_score (trial, metric_col, input_table=pretrial_metrics):
    # Calculate the correlations and magnitudes for all months
    corr_vals = calc_corr(trial, metric_col, input_table)
    mag_vals = calc_magdist(trial, metric_col, input_table)
    mag_vals = mag_vals.drop(metric_col, axis=1) # For one metric, the two columns will be duplicates so drop one

    # Combine correlations and magnitudes together to one df
    combined_corr_dist = pd.merge(corr_vals, mag_vals, on=["YEARMONTH", "trial_store", "control_store"])

    # Average correlations and distances over the pre-trial months
    avg_corrmag = combined_corr_dist.groupby(["trial_store", "control_store"]).mean().reset_index()

    # Find a combined score by taking the weighted average of the correlations and magnitudes
    corr_weight = 0.5
    avg_corrmag['combined_score'] = corr_weight*avg_corrmag['correlation'] + (1-corr_weight)*avg_corrmag['mag_measure']

    return(avg_corrmag)
```

In [36]:
```
# Write a function to output the 5 stores with the highest averaged scores combining the tot_sales and n_cust metrics
# for a given trial store over the pre-trial period
# Inputs:
    # trial (int) : the trial store to test
# Output:
    # scores (df) : a sorted table with the 5 highest composite scores of possible control stores

def find_highestscore(trial):
    # Obtain the scores for the tot_sales and n_cust metrics separately
    scores_tot_sales = calc_corrdist_score (trial, ['tot_sales'])
    scores_n_cust = calc_corrdist_score (trial, ['n_cust'])
    # Create a data table to store the composite results in - stores are also
    scores_control = pd.DataFrame()
    scores_control['control_store'] = scores_tot_sales.control_store
    # Calculate the composite scores
    scores_control['correlation'] = 0.5*scores_tot_sales.correlation + 0.5*scores_n_cust.correlation
    scores_control['mag_measure'] = 0.5*scores_tot_sales.mag_measure + 0.5*scores_n_cust.mag_measure
    scores_control['scores'] = 0.5*scores_tot_sales.combined_score + 0.5*scores_n_cust.combined_score
    return(scores_control.sort_values(by = 'scores', ascending = False).reset_index(drop = True).head(5))
```

In [37]:
```python
# Now find the control stores with the highest scores for each of the trial stores
trial_stores = [77, 86, 88]
for trial in trial_stores:
    print('Trial store: ', trial)
    print(find_highestscore(trial))
    print()
```

```
Trial store:  77

C:\Users\user\AppData\Local\Temp\ipykernel_11636\266015848.py:18: FutureWarning: The default value of numeric_only in Dat
aFrameGroupBy.mean is deprecated. In a future version, numeric_only will default to False. Either specify numeric_only or
select only columns which should be valid for the function.
  avg_corrmag = combined_corr_dist.groupby(["trial_store", "control_store"]).mean().reset_index()
C:\Users\user\AppData\Local\Temp\ipykernel_11636\266015848.py:18: FutureWarning: The default value of numeric_only in Dat
aFrameGroupBy.mean is deprecated. In a future version, numeric_only will default to False. Either specify numeric_only or
select only columns which should be valid for the function.
  avg_corrmag = combined_corr_dist.groupby(["trial_store", "control_store"]).mean().reset_index()

   control_store  correlation  mag_measure    scores
0            233          1.0     0.989804  0.994902
1             41          1.0     0.972041  0.986020
2             46          1.0     0.969523  0.984762
3             53          1.0     0.968421  0.984211
4            111          1.0     0.967981  0.983991

Trial store:  86

C:\Users\user\AppData\Local\Temp\ipykernel_11636\266015848.py:18: FutureWarning: The default value of numeric_only in Dat
aFrameGroupBy.mean is deprecated. In a future version, numeric_only will default to False. Either specify numeric_only or
select only columns which should be valid for the function.
  avg_corrmag = combined_corr_dist.groupby(["trial_store", "control_store"]).mean().reset_index()
C:\Users\user\AppData\Local\Temp\ipykernel_11636\266015848.py:18: FutureWarning: The default value of numeric_only in Dat
aFrameGroupBy.mean is deprecated. In a future version, numeric_only will default to False. Either specify numeric_only or
select only columns which should be valid for the function.
  avg_corrmag = combined_corr_dist.groupby(["trial_store", "control_store"]).mean().reset_index()

   control_store  correlation  mag_measure    scores
0            155          1.0     0.976324  0.988162
1            109          1.0     0.968180  0.984090
2            225          1.0     0.965044  0.982522
3            229          1.0     0.957995  0.978997
4            101          1.0     0.945394  0.972697

Trial store:  88

C:\Users\user\AppData\Local\Temp\ipykernel_11636\266015848.py:18: FutureWarning: The default value of numeric_only in Dat
aFrameGroupBy.mean is deprecated. In a future version, numeric_only will default to False. Either specify numeric_only or
select only columns which should be valid for the function.
  avg_corrmag = combined_corr_dist.groupby(["trial_store", "control_store"]).mean().reset_index()

   control_store  correlation  mag_measure    scores
0             40          1.0     0.941789  0.970895
1             26          1.0     0.917859  0.958929
2             72          1.0     0.908157  0.954079
3             58          1.0     0.900435  0.950217
4             81          1.0     0.887572  0.943786


C:\Users\user\AppData\Local\Temp\ipykernel_11636\266015848.py:18: FutureWarning: The default value of numeric_only in Dat
aFrameGroupBy.mean is deprecated. In a future version, numeric_only will default to False. Either specify numeric_only or
select only columns which should be valid for the function.
  avg_corrmag = combined_corr_dist.groupby(["trial_store", "control_store"]).mean().reset_index()
```

From the above output, the stores with the highest scores are:

- Store 233 for trial store 77
- Store 155 for trial store 86
- Store 40 for trial stre 88

Note that the combined store for the control cases of trial store 88 are lower than those of stores 77 and 86. This may suggest that the control stores may not match store 88 as well as for the other trial stores.

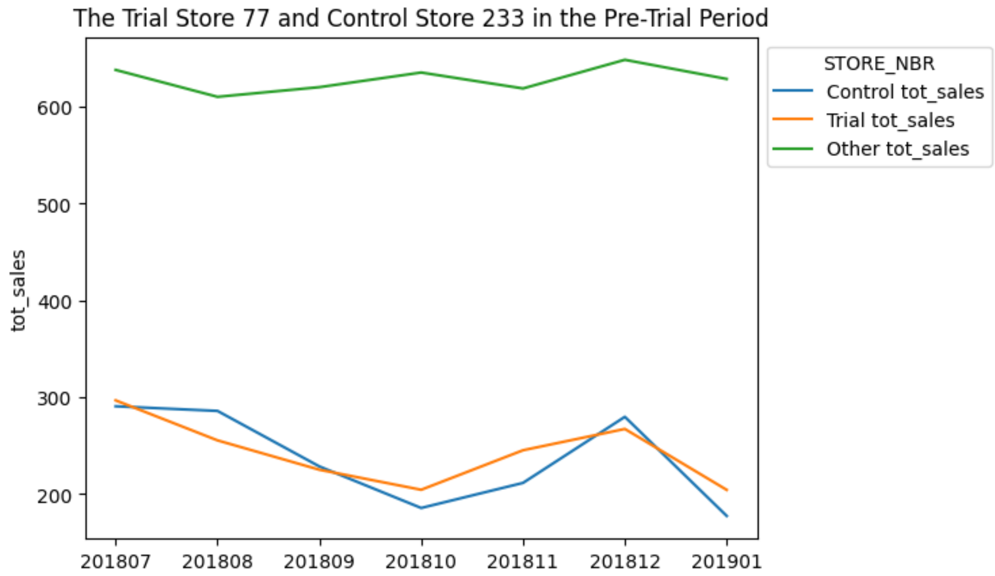
Now that we have found the control stores, we can visually check if the drivers are similar between these and the trial stores in the pre-trial period.

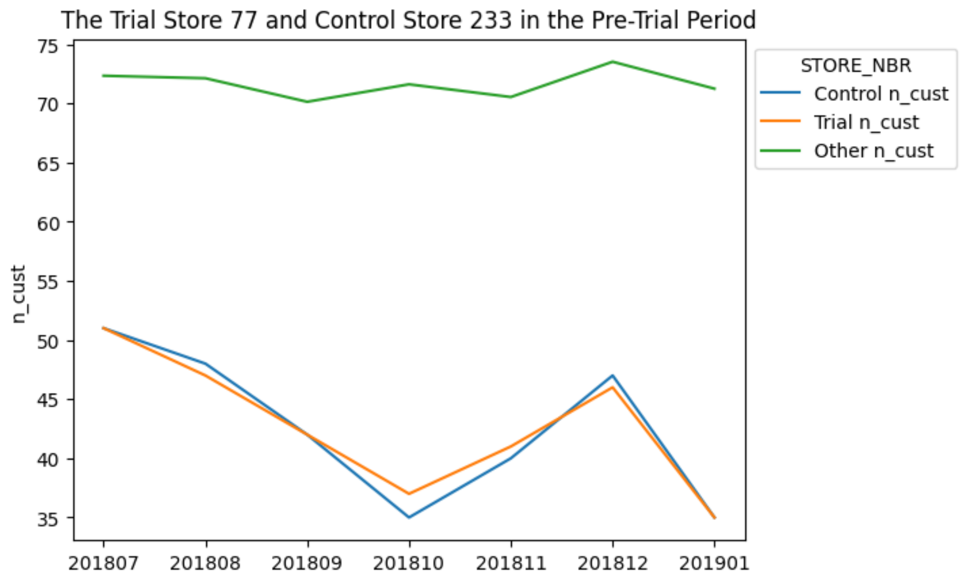
In [38]:
```
def make_plots(storepair, metric_col):
    trial = storepair[0]
    control = storepair[1]
    trial_plot = pretrial_metrics[pretrial_metrics.STORE_NBR == trial][['YEARMONTH', 'STORE_NBR', metric_col]]
    trial_plot = trial_plot.rename(columns = {metric_col: metric_col+'_trial'})
    control_plot = pretrial_metrics[pretrial_metrics.STORE_NBR == control][['YEARMONTH', 'STORE_NBR', metric_col]]
    control_plot = control_plot.rename(columns = {metric_col: metric_col+'_control'})

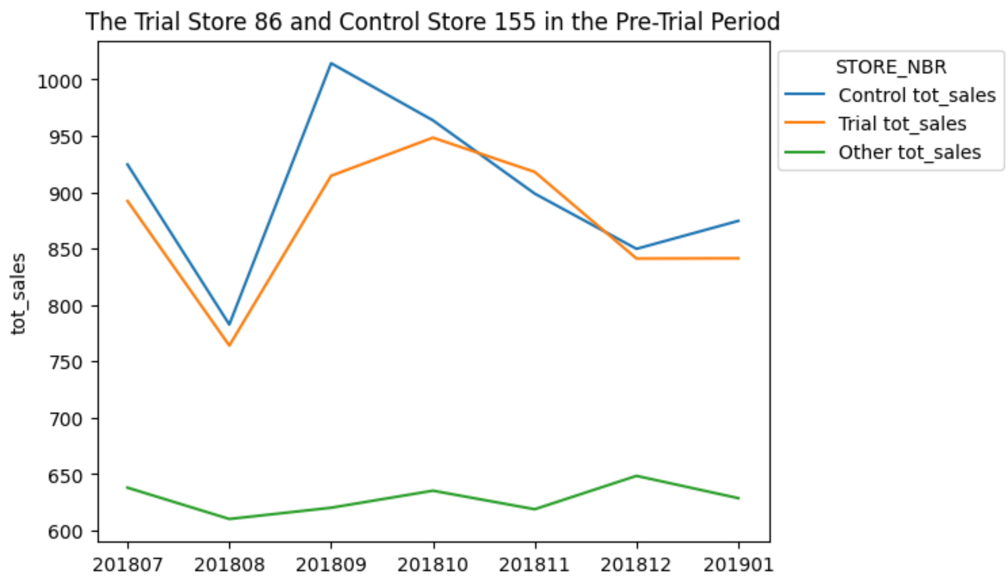
    other_stores = pretrial_metrics.loc[(pretrial_metrics.STORE_NBR != 77)][['YEARMONTH', 'STORE_NBR', metric_col]]
    other_stores = other_stores.loc[(pretrial_metrics.STORE_NBR != 233)]
    plot_other = other_stores.groupby('YEARMONTH')[metric_col].mean()

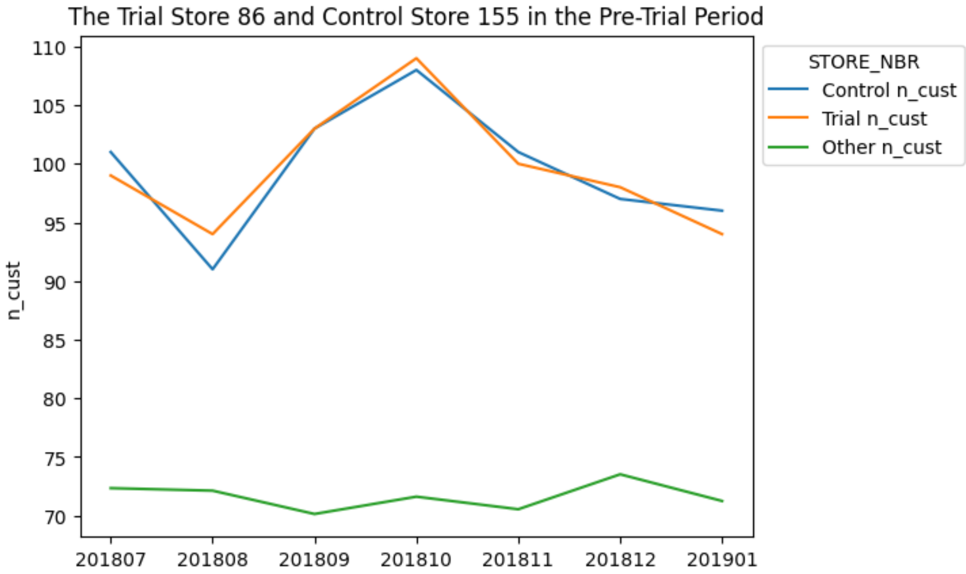
    ax = control_plot.plot.line(x = "YEARMONTH", y = metric_col+'_control', use_index=False, label = 'Control '+metric_col
    ax_trial = trial_plot.plot.line(x = "YEARMONTH", y = metric_col+'_trial', use_index=False, ax=ax, label = 'Trial '+met
    ax_other = plot_other.plot.line(use_index = False, ax=ax, label = 'Other '+ metric_col)
    ax.set_ylabel(metric_col)
    plt.legend(title = 'STORE_NBR', loc = "upper left",bbox_to_anchor=(1.0, 1.0))
    positions = (0,1,2,3,4,5,6)
    labels = ("201807", '201808', '201809', '201810', '201811', '201812', '201901')
    plt.xticks (positions, labels)
    titlestr = 'The Trial Store ' + str(storepair[0]) + ' and Control Store ' + str(storepair[1]) + ' in the Pre-Trial Per
    ax.set_title(titlestr)
```

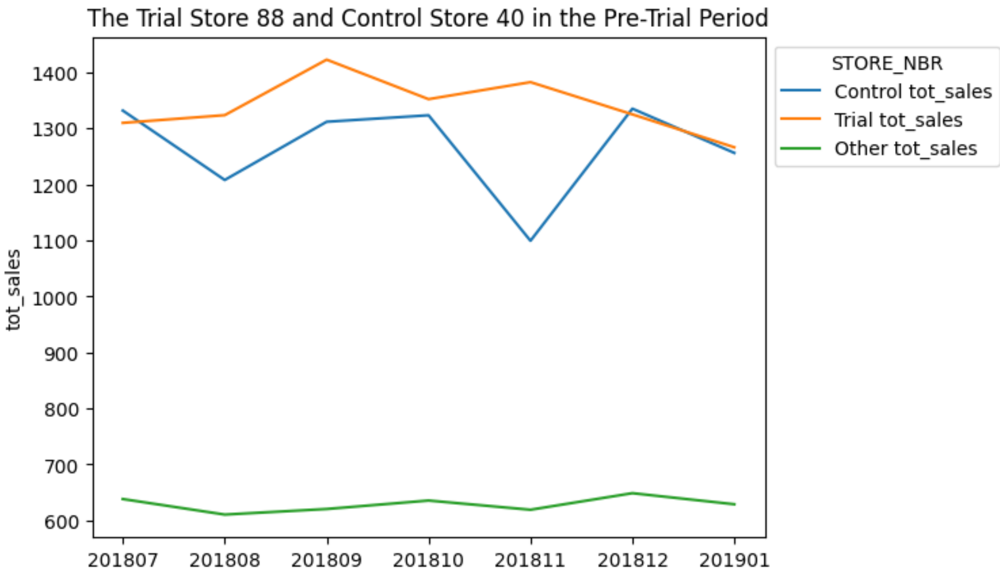
In [39]:
```
storepair = [[77, 233], [86, 155], [88, 40]]
metric_col = ['tot_sales', 'n_cust']
for pair in storepair:
    for metric in metric_col:
        make_plots(pair, metric)
```

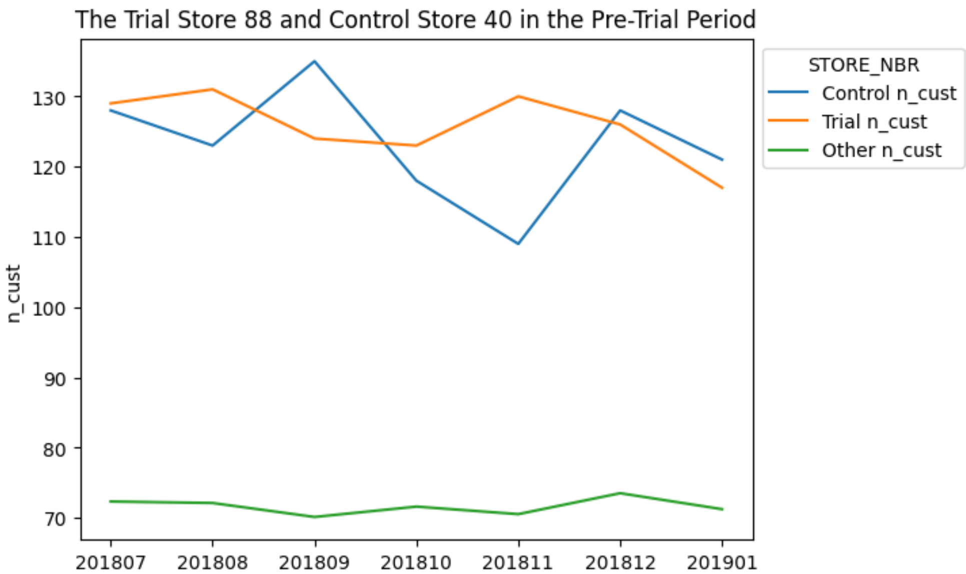












The metrics of the control and trial stores look reasonably similar in the pre-trial period.

Now, we want to see if there has been an uplift in overall chip sales. We'll start with scaling the control store's sales to a level similar to control for any differences between the two stores outside of the trial period.

In [40]:
```
# Calculate the scaling factor for the store pairs
scale_store77 = pretrial_metrics[pretrial_metrics.STORE_NBR == 77]['tot_sales'].sum()/pretrial_metrics[pretrial_metrics.ST
scale_store86 = pretrial_metrics[pretrial_metrics.STORE_NBR == 86]['tot_sales'].sum()/pretrial_metrics[pretrial_metrics.ST
scale_store88 = pretrial_metrics[pretrial_metrics.STORE_NBR == 88]['tot_sales'].sum()/pretrial_metrics[pretrial_metrics.ST
```

In [41]:
```
# Extract the control store data from the df and scale according to the store
scaled_control233 = metrics_df[metrics_df.STORE_NBR.isin([233])][['STORE_NBR', "YEARMONTH", 'tot_sales']]
scaled_control233.tot_sales *= scale_store77
scaled_control155 = metrics_df[metrics_df.STORE_NBR.isin([155])][['STORE_NBR', "YEARMONTH", 'tot_sales']]
scaled_control155.tot_sales *= scale_store86
scaled_control40 = metrics_df[metrics_df.STORE_NBR.isin([40])][['STORE_NBR', "YEARMONTH", 'tot_sales']]
scaled_control40.tot_sales *= scale_store88

# Combine the scaled control stores to a single df
scaledsales_control = pd.concat([scaled_control233, scaled_control155, scaled_control40]).reset_index(drop = True)
scaledsales_control = scaledsales_control.rename(columns = {'tot_sales':'scaled_tot_sales', 'STORE_NBR': 'CONTROL_NBR'})
# Get the trial period of scaled control stores
scaledsales_control_trial = scaledsales_control[(scaledsales_control.YEARMONTH>=201902) & (scaledsales_control.YEARMONTH<=

# Get the trial period of the trial stores
trialsales = metrics_df[metrics_df.STORE_NBR.isin([77,86,88])][['STORE_NBR', "YEARMONTH", 'tot_sales']].reset_index(drop =
trialsales = trialsales.rename(columns = {'STORE_NBR': 'TRIAL_NBR'})
trialsales_trial = trialsales[(trialsales.YEARMONTH >= 201902) & (trialsales.YEARMONTH <= 201904)].reset_index(drop = True
```

Now that we have comparable sales figures for the control store, we can calculate the percentage difference between the scaled control sales and the trial store's sales during the trial period.

In [42]:
```
# Calculate the percentage difference between the control and trial store pairs for each month over the year
percentdiff = scaledsales_control.copy()
percentdiff[['TRIAL_NBR', 'tot_sales_t']] = trialsales[['TRIAL_NBR', 'tot_sales']]
percentdiff = percentdiff.rename(columns = {'scaled_tot_sales' : 'scaled_sales_c'})
percentdiff['sales_percent_diff'] = (percentdiff.tot_sales_t-percentdiff.scaled_sales_c)\
                                    /(0.5*((percentdiff.scaled_sales_c+percentdiff.tot_sales_t)))
percentdiff.head()
```

Out[42]:

	CONTROL_NBR	YEARMONTH	scaled_sales_c	TRIAL_NBR	tot_sales_t	sales_percent_diff
0	233	201807	297.565550	77	296.8	-0.002576
1	233	201808	292.652187	77	255.5	-0.135554
2	233	201809	233.998916	77	225.2	-0.038323
3	233	201810	190.085733	77	204.5	0.073060
4	233	201811	216.597421	77	245.3	0.124281

Let's see if the difference is significant using a t-test. Our null hypothesis is that the trial period is the same as the pre-trial period; we will test with a null hypothesis that there is a 0-percent between the trial and control stores.

In [43]:

```
# As our null hypothesis is that the trial period is the same as the pre-trial period,
# let's take the standard deviation based on the scaled percentage difference in the pre-trial period.
pretrial_percentdiff = percentdiff[percentdiff.YEARMONTH < 201902]
pretrial_percentdiff_std = pretrial_percentdiff.groupby(['TRIAL_NBR'])['sales_percent_diff'].agg('std').reset_index()
dof = 6 # 7 months of data - 1

for stores in storepair: # stores numbers are stored as [trial, control] in storepair
    trialstore = stores[0]
    controlstore = stores[1]
    pretrial = percentdiff[(percentdiff.YEARMONTH < 201902) & (percentdiff.TRIAL_NBR == trialstore)]
    std = pretrial['sales_percent_diff'].agg('std')
    mean =  pretrial['sales_percent_diff'].agg('mean')
    trialperiod = percentdiff[(percentdiff.YEARMONTH >= 201902) & (percentdiff.YEARMONTH <= 201904) \
                              & (percentdiff.TRIAL_NBR == trialstore)]
    print("Trial store -", trialstore, "; control store -", controlstore)
    print("Month : t-statistic")
    for month in trialperiod.YEARMONTH.unique():
        xval = trialperiod[trialperiod.YEARMONTH == month]['sales_percent_diff'].item()
        tstat = ((xval - mean)/std)
        print(str(month), ' : ', tstat)
    print()

# Generate the t-statistic for the 95% percentile with 6 dof
print ('95th percentile value:', stats.t.ppf(1-0.05, 6))
```

```
Trial store - 77 ; control store - 233
Month : t-statistic
201902  :  -0.7171038288055838
201903  :  3.035317928855674
201904  :  4.708944418758219

Trial store - 86 ; control store - 155
Month : t-statistic
201902  :  1.4133618775921597
201903  :  7.123063846042147
201904  :  0.8863824572944234

Trial store - 88 ; control store - 40
Month : t-statistic
201902  :  -0.5481633746817577
201903  :  1.0089992743637823
201904  :  0.9710006270463672

95th percentile value: 1.9431802803927816
```

We can observe that the t-value for the trial store 77 is much larger than the 95th percentile value of the t-distribution for March and April - i.e. the increase in sales in the trial store 77 in March and April is statistically greater than in the control store. This can also be seen for March of trial store 86.

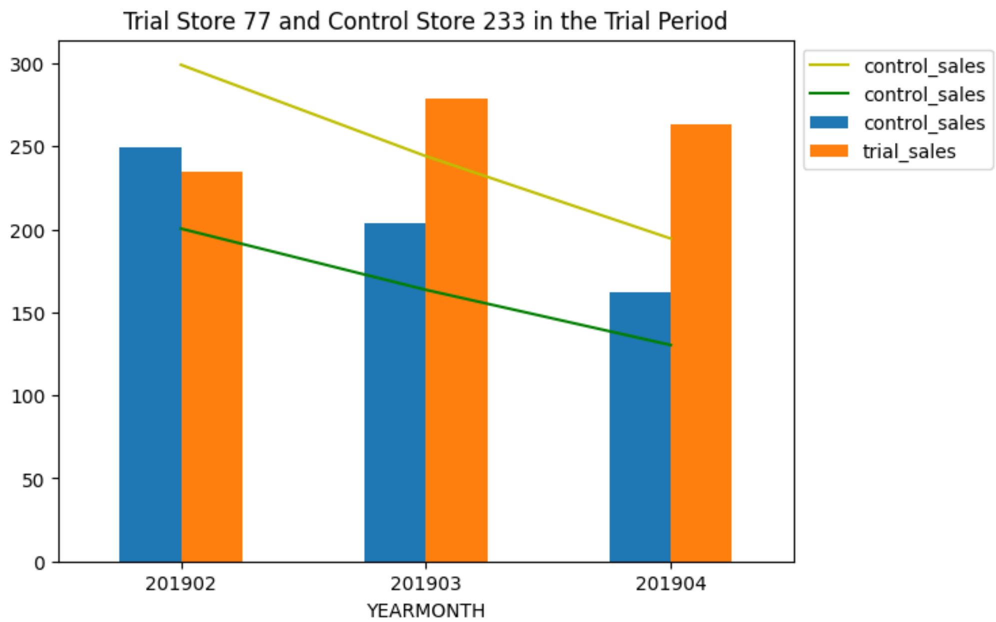
Let's create a more visual version of this by plotting the sales of the control store, the sales of the trial stores and the 95th percentile value of sales of the control store.

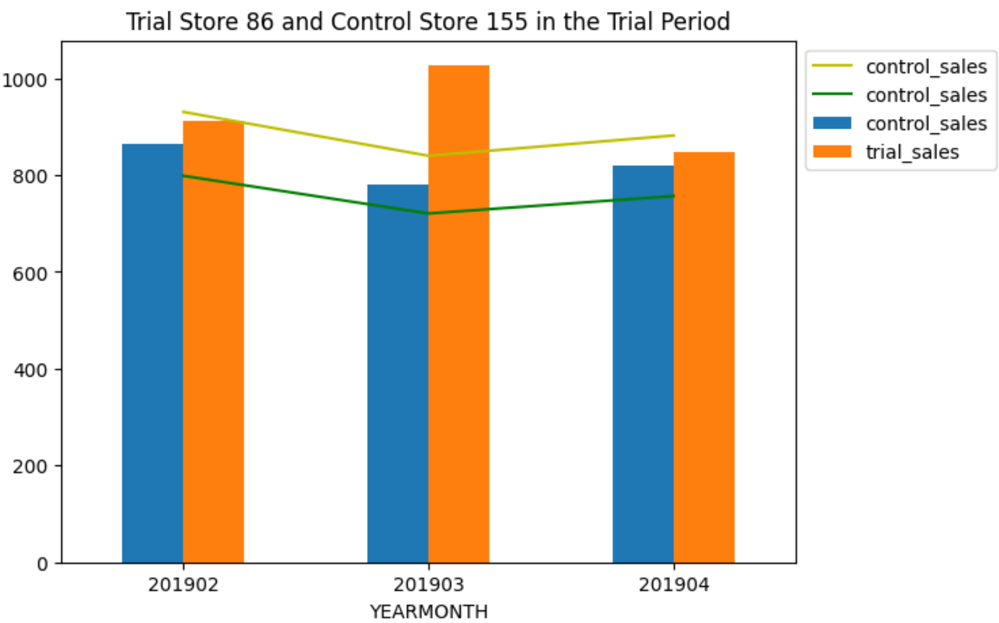
In [45]:
```
# First do bar graphs during the trial period
storepair = [[77, 233], [86, 155], [88, 40]]
for stores in storepair: # stores numbers are stored as [trial, control] in storepair
    trial = stores[0]
    control = stores[1]

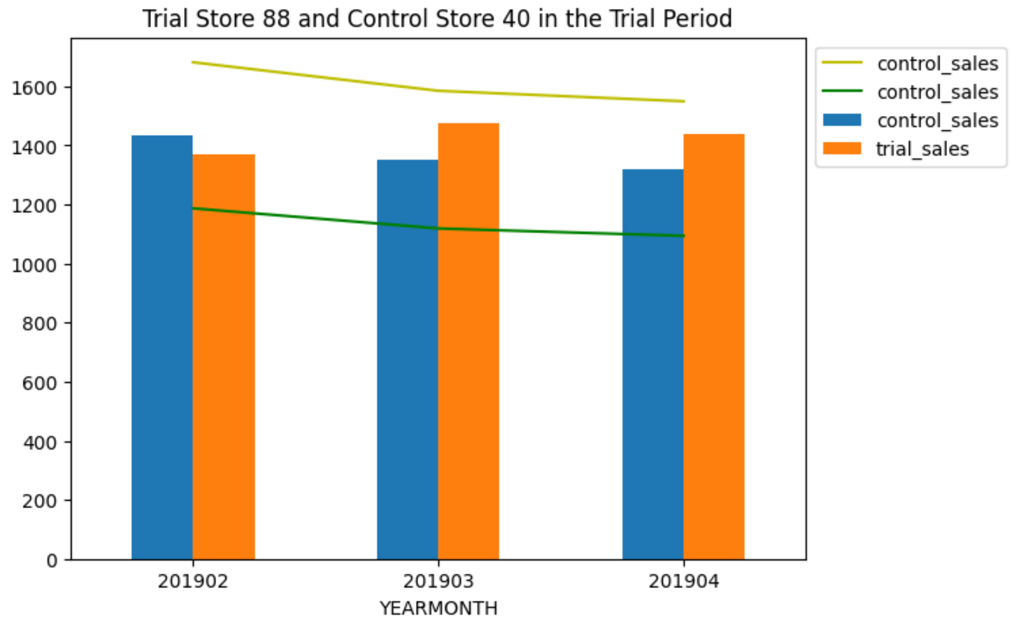
    # Plot the bar chart of sales performance
    plot_control = percentdiff[(percentdiff['CONTROL_NBR'] == control) & (percentdiff.YEARMONTH >= 201902) & (percentdiff.
                    [['YEARMONTH', 'CONTROL_NBR', 'scaled_sales_c']]
    plot_control = plot_control.rename(columns = {"CONTROL_NBR" : "STORE_NBR", "scaled_sales_c": "control_sales"})
    plot_trial = percentdiff[(percentdiff['TRIAL_NBR'] == trial) & (percentdiff.YEARMONTH >= 201902) & (percentdiff.YEARMO
                    [['YEARMONTH', 'TRIAL_NBR', 'tot_sales_t']]
    plot_trial = plot_trial.rename(columns = {"TRIAL_NBR" : "STORE_NBR", "tot_sales_t": "trial_sales"})
    toplot = plot_control[["YEARMONTH", "control_sales"]].merge(plot_trial[["YEARMONTH", "trial_sales"]],on="YEARMONTH").s
    ax = toplot.plot(kind = 'bar',  figsize=(7, 5))


    # plot the thresholds as lines
    std = percentdiff[(percentdiff['CONTROL_NBR'] == control) & (percentdiff.YEARMONTH < 201902)]['sales_percent_diff'].st
    threshold95 = plot_control.reset_index()[['YEARMONTH', 'control_sales']]
    threshold95.control_sales = threshold95.control_sales*(1+std*2)
    threshold5 = plot_control.reset_index()[['YEARMONTH', 'control_sales']]
    threshold5.control_sales = threshold5.control_sales*(1-std*2)
    ax95 = threshold95.plot.line(x = 'YEARMONTH', y = 'control_sales',color='y', figsize=(7, 5), use_index=False, ax = ax)
    ax5 = threshold5.plot.line(x = 'YEARMONTH', y = 'control_sales', color='g', figsize=(7, 5), use_index=False, ax = ax)

    # Other plot features
    plt.legend(loc = "upper left",bbox_to_anchor=(1.0, 1.0))
    titlestr = 'Trial Store ' + str(trial) + ' and Control Store ' + str(control) + ' in the Trial Period'
    ax.set_title(titlestr)
    plt.show()
```






Trial Store 88 and Control Store 40 in the Trial Period
1600
1400
1200
1000
800
600
400
200
0
201902
201903
201904
YEARMONTH
control_sales
control_sales
control_sales
trial_sales

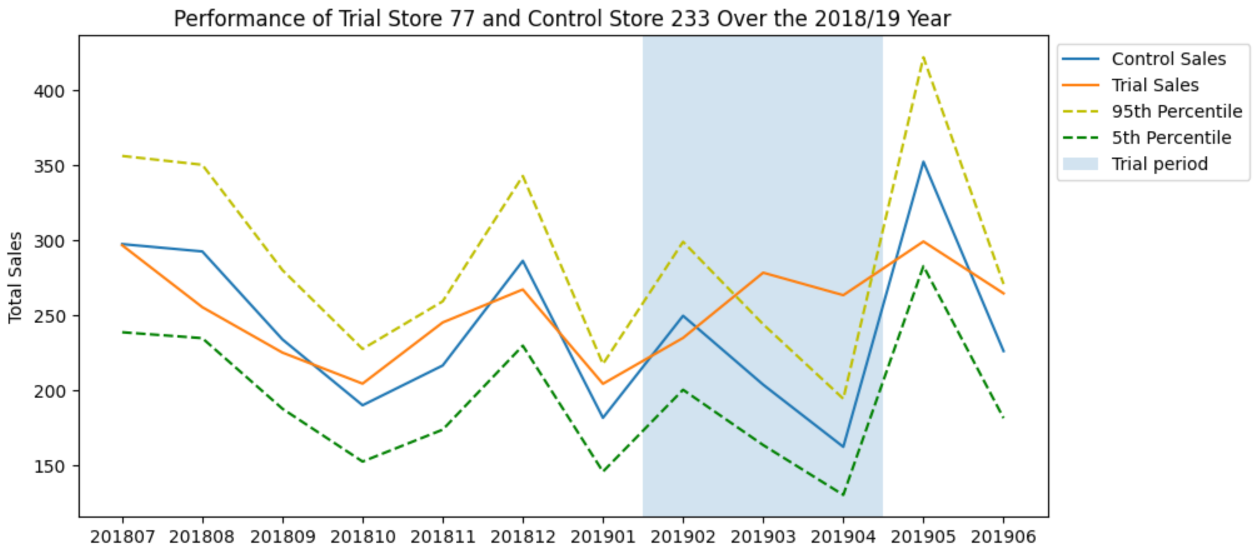
In [46]:
```
# Then do line graphs during the whole year - for the report
from matplotlib.patches import Rectangle
storepair = [[77, 233], [86, 155], [88, 40]]
for stores in storepair: # stores numbers are stored as [trial, control] in storepair
    trial = stores[0]
    control = stores[1]

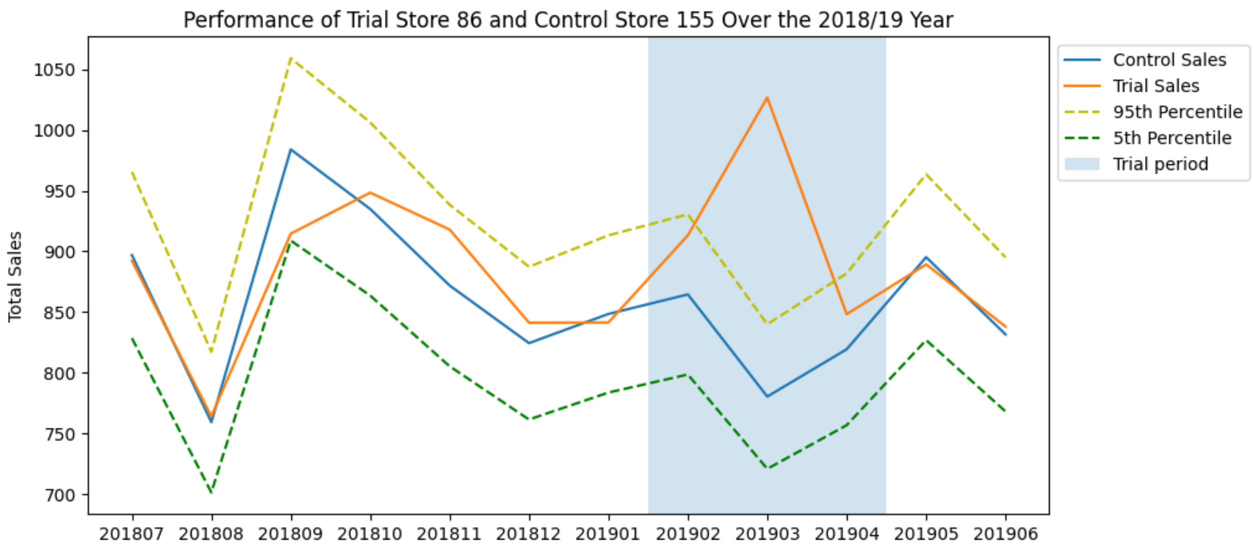
    # Plot the line graph of sales performance
    plot_control = percentdiff[(percentdiff['CONTROL_NBR'] == control)][['YEARMONTH', 'CONTROL_NBR', 'scaled_sales_c']]
    plot_control = plot_control.rename(columns = {"CONTROL_NBR" : "STORE_NBR", "scaled_sales_c": "control_sales"})
    plot_trial = percentdiff[(percentdiff['TRIAL_NBR'] == trial)][['YEARMONTH', 'TRIAL_NBR', 'tot_sales_t']]
    plot_trial = plot_trial.rename(columns = {"TRIAL_NBR" : "STORE_NBR", "tot_sales_t": "trial_sales"})

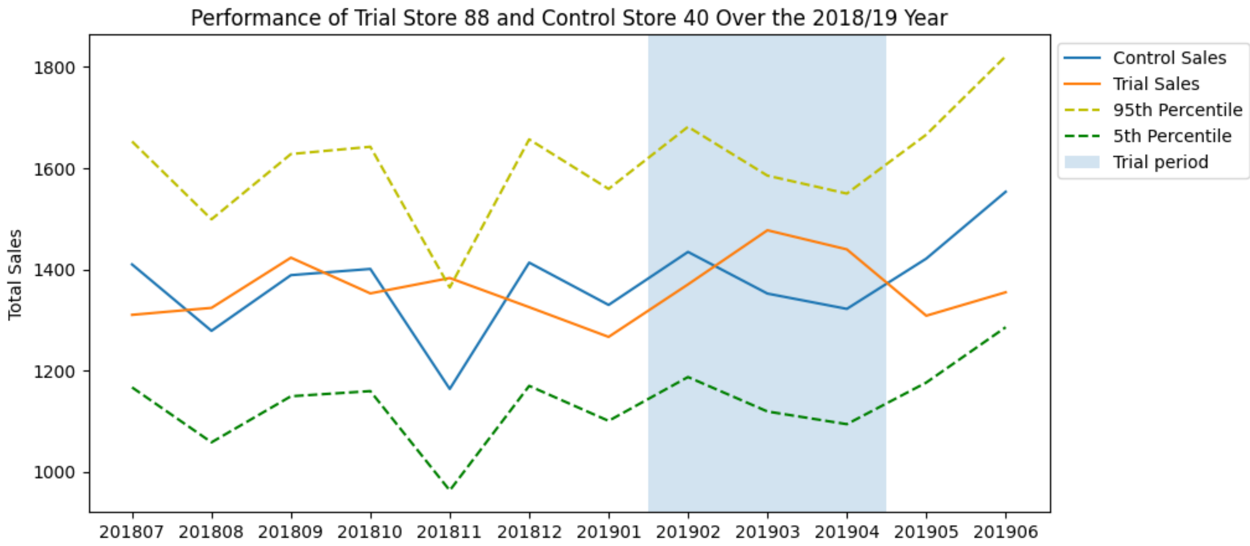
    ax = plot_control.plot.line(x = "YEARMONTH", y = 'control_sales', use_index=False, label = 'Control Sales')
    ax_trial = plot_trial.plot.line(x = "YEARMONTH", y = 'trial_sales', use_index=False, ax=ax, label = 'Trial Sales')


    # plot the thresholds as lines
    std = percentdiff[(percentdiff['CONTROL_NBR'] == control) & (percentdiff.YEARMONTH < 201902)]['sales_percent_diff'].st
    threshold95 = plot_control.reset_index()[['YEARMONTH', 'control_sales']]
    threshold95.control_sales = threshold95.control_sales*(1+std*2)
    threshold5 = plot_control.reset_index()[['YEARMONTH', 'control_sales']]
    threshold5.control_sales = threshold5.control_sales*(1-std*2)
    ax95 = threshold95.plot.line(x = 'YEARMONTH', y = 'control_sales',color='y', linestyle = '--', figsize=(10, 5), use_in
    ax5 = threshold5.plot.line(x = 'YEARMONTH', y = 'control_sales', color='g',  linestyle = '--', figsize=(10, 5), use_in
    ax.add_patch(Rectangle((6.5, 0), 3, 2000, alpha = 0.2, label = 'Trial period'))

    # Other plot features
    ax.set_ylabel('Total Sales')
    plt.legend(loc = "upper left",bbox_to_anchor=(1.0, 1.0))
    titlestr = 'Performance of Trial Store ' + str(trial) + ' and Control Store ' + str(control) + ' Over the 2018/19 Year
    positions = (0,1,2,3,4,5,6,7,8,9, 10, 11)
    labels = ("201807", '201808', '201809', '201810', '201811', '201812', '201901', '201902', '201903', '201904', '201905'
    plt.xticks (positions, labels)
    ax.set_title(titlestr)
    plt.show()
```







The results show 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 in two of the three trial months.

For store 86, we can see that the trial in March is significantly different to the control store with the total sales performance outside of the 5% to 95% confidence interval. However, there is no significant difference in February's and April's performance.

The results for store 88 show no significant difference between the trial and control stores during this period.

Let's have a look at assessing this for number of customers as well.

In [48]:
```
# Calculate the scaling factor for the store pairs
scale_store77 = pretrial_metrics[pretrial_metrics.STORE_NBR == 77]['n_cust'].sum()/pretrial_metrics[pretrial_metrics.STORE
scale_store86 = pretrial_metrics[pretrial_metrics.STORE_NBR == 86]['n_cust'].sum()/pretrial_metrics[pretrial_metrics.STORE
scale_store88 = pretrial_metrics[pretrial_metrics.STORE_NBR == 88]['n_cust'].sum()/pretrial_metrics[pretrial_metrics.STORE
```

In [49]:
```
# Extract the control store data from the df and scale according to the store
scaled_control233 = metrics_df[metrics_df.STORE_NBR.isin([233])][['STORE_NBR', "YEARMONTH", 'n_cust']]
scaled_control233.n_cust *= scale_store77
scaled_control155 = metrics_df[metrics_df.STORE_NBR.isin([155])][['STORE_NBR', "YEARMONTH", 'n_cust']]
scaled_control155.n_cust *= scale_store86
scaled_control40 = metrics_df[metrics_df.STORE_NBR.isin([40])][['STORE_NBR', "YEARMONTH", 'n_cust']]
scaled_control40.n_cust *= scale_store88

# Combine the scaled control stores to a single df
scaledncust_control = pd.concat([scaled_control233, scaled_control155, scaled_control40]).reset_index(drop = True)
scaledncust_control = scaledncust_control.rename(columns = {'n_cust':'scaled_n_cust', 'STORE_NBR': 'CONTROL_NBR'})
# Get the trial period of scaled control stores
scaledncust_control_trial = scaledncust_control[(scaledsales_control.YEARMONTH>=201902) & (scaledsales_control.YEARMONTH<=

# Get the trial period of the trial stores
trialncust = metrics_df[metrics_df.STORE_NBR.isin([77,86,88])][['STORE_NBR', "YEARMONTH", 'n_cust']].reset_index(drop = Tr
trialncust = trialncust.rename(columns = {'STORE_NBR': 'TRIAL_NBR'})
trialncust_trial = trialncust[(trialncust.YEARMONTH >= 201902) & (trialsales.YEARMONTH <= 201904)].reset_index(drop = True
```

In [50]:
```
# Calculate the percentage difference between the control and trial store pairs for each month over the year
percentdiff = scaledncust_control.copy()
percentdiff[['TRIAL_NBR', 'n_cust_t']] = trialncust[['TRIAL_NBR', 'n_cust']]
percentdiff = percentdiff.rename(columns = {'scaled_n_cust' : 'scaled_n_cust_c'})
percentdiff['cust_percent_diff'] = (percentdiff.n_cust_t-percentdiff.scaled_n_cust_c)\
                                    /(0.5*((percentdiff.scaled_n_cust_c+percentdiff.n_cust_t)))
percentdiff.head()
```

Out[50]:

	CONTROL_NBR	YEARMONTH	scaled_n_cust_c	TRIAL_NBR	n_cust_t	cust_percent_diff
0	233	201807	51.171141	77	51	-0.003350
1	233	201808	48.161074	77	47	-0.024402
2	233	201809	42.140940	77	42	-0.003350
3	233	201810	35.117450	77	37	0.052208
4	233	201811	40.134228	77	41	0.021342

In [51]:

```
# As our null hypothesis is that the trial period is the same as the pre-trial period,
# let's take the standard deviation based on the scaled percentage difference in the pre-trial period.
pretrial_percentdiff = percentdiff[percentdiff.YEARMONTH < 201902]
pretrial_percentdiff_std = pretrial_percentdiff.groupby(['TRIAL_NBR'])['cust_percent_diff'].agg('std').reset_index()
dof = 6 # 7 months of data - 1

for stores in storepair: # stores numbers are stored as [trial, control] in storepair
    trialstore = stores[0]
    controlstore = stores[1]
    pretrial = percentdiff[(percentdiff.YEARMONTH < 201902) & (percentdiff.TRIAL_NBR == trialstore)]
    std = pretrial['cust_percent_diff'].agg('std')
    mean =  pretrial['cust_percent_diff'].agg('mean')
    trialperiod = percentdiff[(percentdiff.YEARMONTH >= 201902) & (percentdiff.YEARMONTH <= 201904) \
                              & (percentdiff.TRIAL_NBR == trialstore)]
    print("Trial store -", trialstore, "; control store -", controlstore)
    print("Month : t-statistic")
    for month in trialperiod.YEARMONTH.unique():
        xval = trialperiod[trialperiod.YEARMONTH == month]['cust_percent_diff'].item()
        tstat = ((xval - mean)/std)
        print(str(month), ' : ', tstat)
    print()

# Generate the t-statistic for the 95% percentile with 6 dof
print ('95th percentile value:', stats.t.ppf(1-0.05, 6))
```

```
Trial store - 77 ; control store - 233
Month : t-statistic
201902  :  -0.19886295797440687
201903  :  8.009609025380932
201904  :  16.114474772873923

Trial store - 86 ; control store - 155
Month : t-statistic
201902  :  6.220524882227514
201903  :  10.52599074274189
201904  :  3.0763575852842706

Trial store - 88 ; control store - 40
Month : t-statistic
201902  :  -0.3592881735131531
201903  :  1.2575196020616801
201904  :  0.6092905590514273

95th percentile value: 1.9431802803927816
```

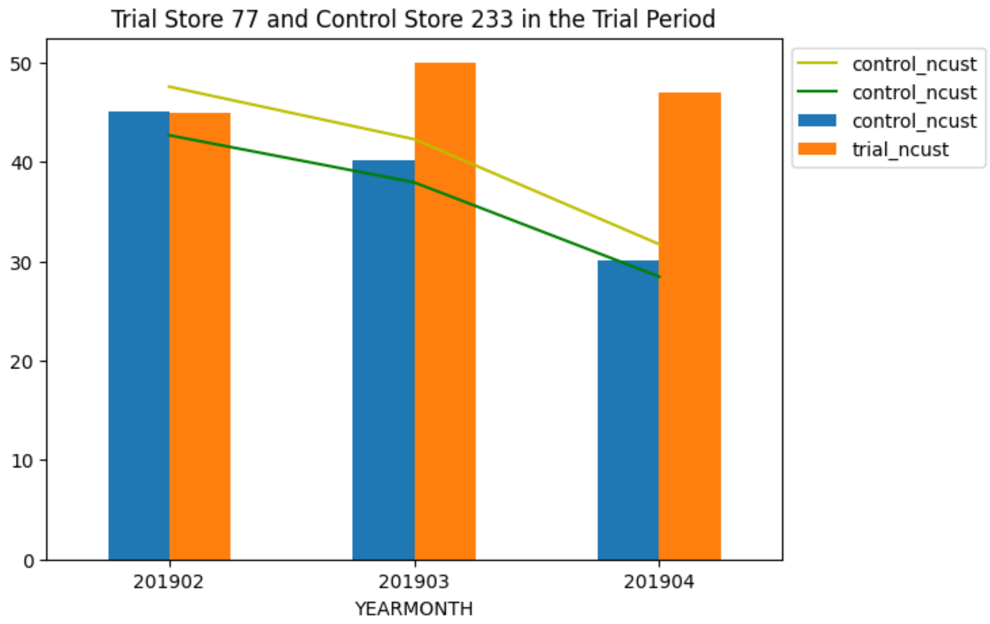
We can see from the above results that similar to the total sales metric, there are statistically significant increases in the number of customers in stores 77 and 86 in at least 2 months during the trial period. However, there is no significant increase in store 88.

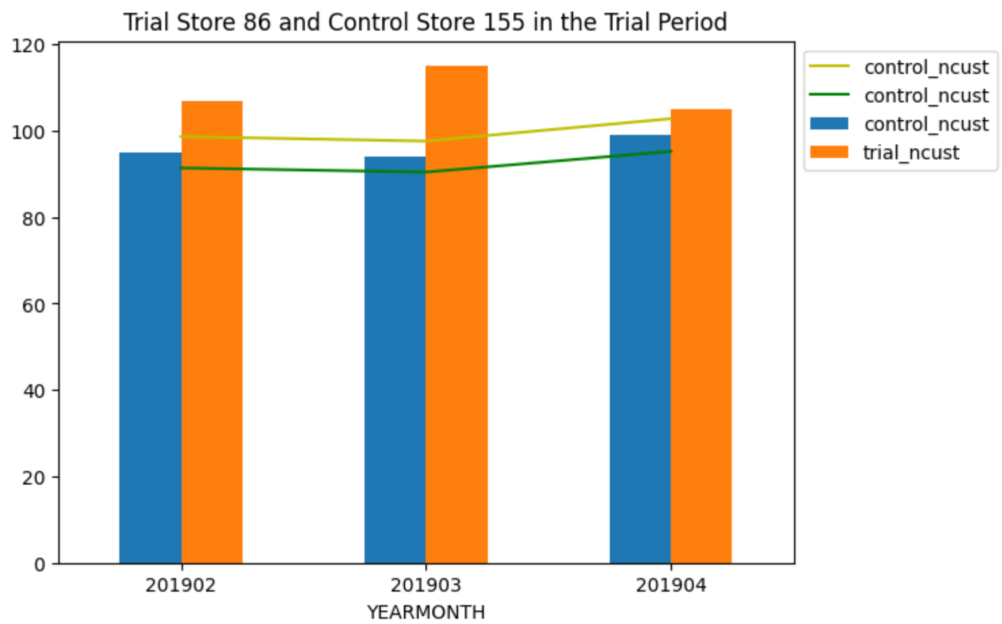
Let's create a more visual version of this by plotting the sales of the control store, the sales of the trial stores and the 95th percentile value of sales of the control store.

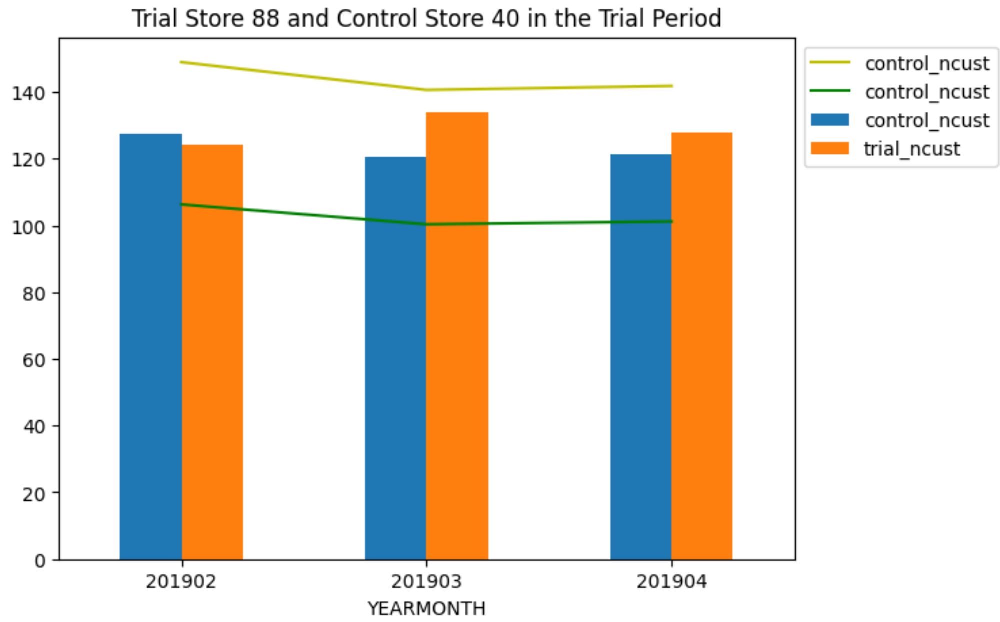
In [53]:
```
# First do bar charts to focus on the trial period
storepair = [[77, 233], [86, 155], [88, 40]]
for stores in storepair: # stores numbers are stored as [trial, control] in storepair
    trial = stores[0]
    control = stores[1]
    plot_control = percentdiff[(percentdiff['CONTROL_NBR'] == control) & (percentdiff.YEARMONTH >= 201902) & (percentdiff.
                    [['YEARMONTH', 'CONTROL_NBR', 'scaled_n_cust_c']]
    plot_control = plot_control.rename(columns = {"CONTROL_NBR" : "STORE_NBR", "scaled_n_cust_c": "control_ncust"})
    plot_trial = percentdiff[(percentdiff['TRIAL_NBR'] == trial) & (percentdiff.YEARMONTH >= 201902) & (percentdiff.YEARMO
                    [['YEARMONTH', 'TRIAL_NBR', 'n_cust_t']]
    plot_trial = plot_trial.rename(columns = {"TRIAL_NBR" : "STORE_NBR", "n_cust_t": "trial_ncust"})
    toplot = plot_control[["YEARMONTH", "control_ncust"]].merge(plot_trial[["YEARMONTH", "trial_ncust"]],on="YEARMONTH").s
    ax = toplot.plot(kind = 'bar',  figsize=(7, 5))


    # plot the thresholds as lines
    std = percentdiff[(percentdiff['CONTROL_NBR'] == control) & (percentdiff.YEARMONTH < 201902)]['cust_percent_diff'].std
    threshold95 = plot_control.reset_index()[['YEARMONTH', 'control_ncust']]
    threshold95.control_ncust = threshold95.control_ncust*(1+std*2)
    threshold5 = plot_control.reset_index()[['YEARMONTH', 'control_ncust']]
    threshold5.control_ncust = threshold5.control_ncust*(1-std*2)
    ax95 = threshold95.plot.line(x = 'YEARMONTH', y = 'control_ncust',color='y', figsize=(7, 5), use_index=False, ax = ax)
    ax5 = threshold5.plot.line(x = 'YEARMONTH', y = 'control_ncust', color='g', figsize=(7, 5), use_index=False, ax = ax)

    # Other plot features
    plt.legend(loc = "upper left",bbox_to_anchor=(1.0, 1.0))
    titlestr = 'Trial Store ' + str(trial) + ' and Control Store ' + str(control) + ' in the Trial Period'
    ax.set_title(titlestr)
    plt.show()
```





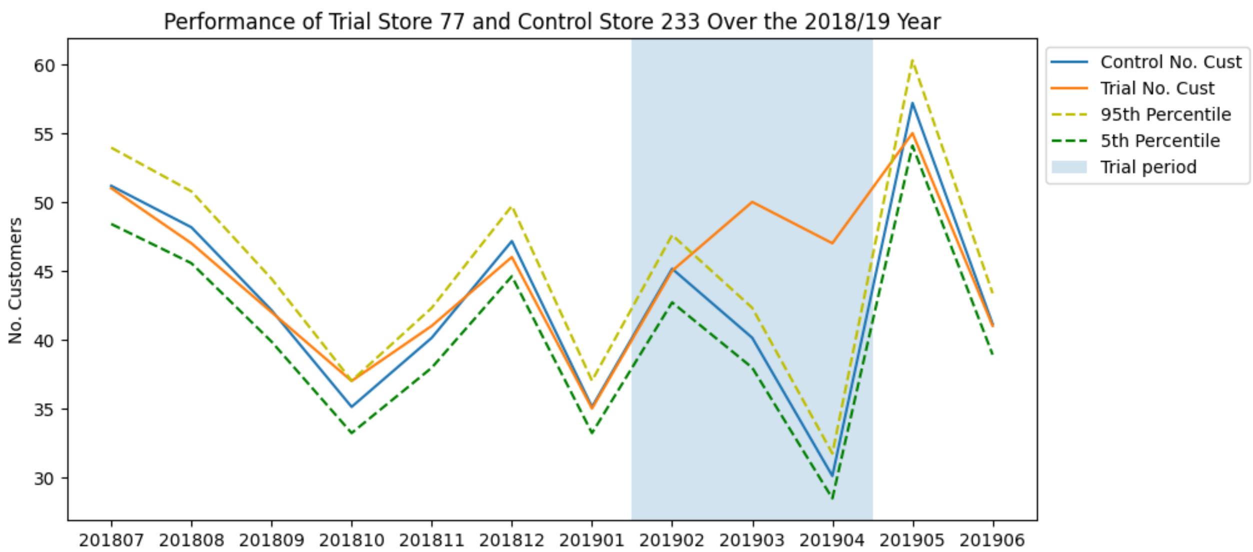

Trial Store 88 and Control Store 40 in the Trial Period
140
120
100
80
60
40
20
0
201902
201903
201904
YEARMONTH
control_ncust
control_ncust
control_ncust
trial_ncust

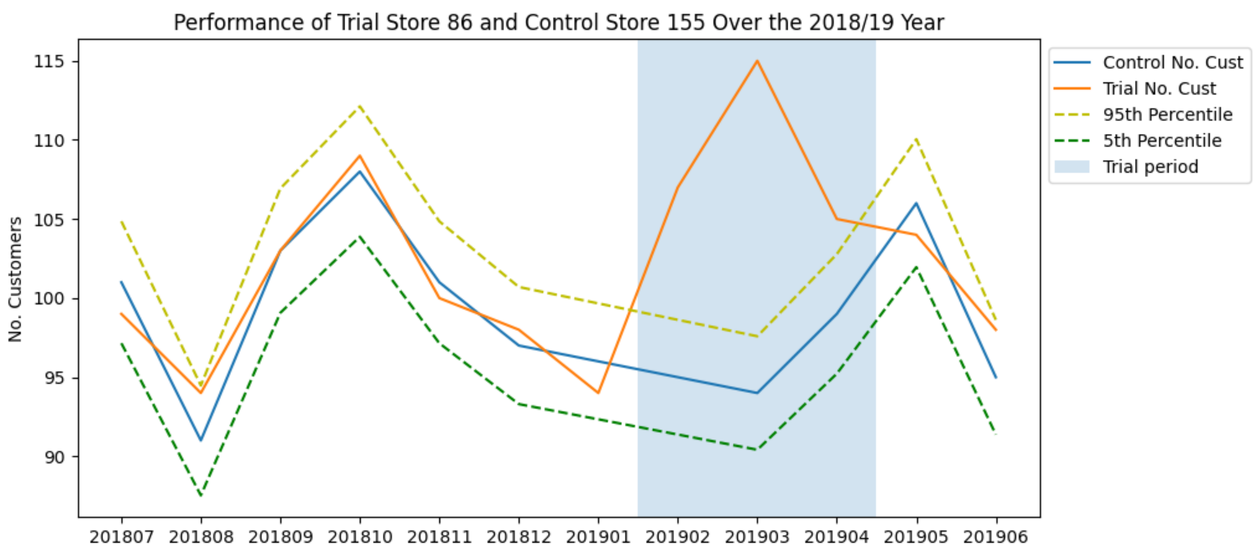
In [54]:
```
# Then do line graphs to show a full year's trend
storepair = [[77, 233], [86, 155], [88, 40]]
for stores in storepair: # stores numbers are stored as [trial, control] in storepair
    trial = stores[0]
    control = stores[1]
    plot_control = percentdiff[(percentdiff['CONTROL_NBR'] == control)]\
                    [['YEARMONTH', 'CONTROL_NBR', 'scaled_n_cust_c']]
    plot_control = plot_control.rename(columns = {"CONTROL_NBR" : "STORE_NBR", "scaled_n_cust_c": "control_ncust"})
    plot_trial = percentdiff[(percentdiff['TRIAL_NBR'] == trial)]\
                    [['YEARMONTH', 'TRIAL_NBR', 'n_cust_t']]
    plot_trial = plot_trial.rename(columns = {"TRIAL_NBR" : "STORE_NBR", "n_cust_t": "trial_ncust"})

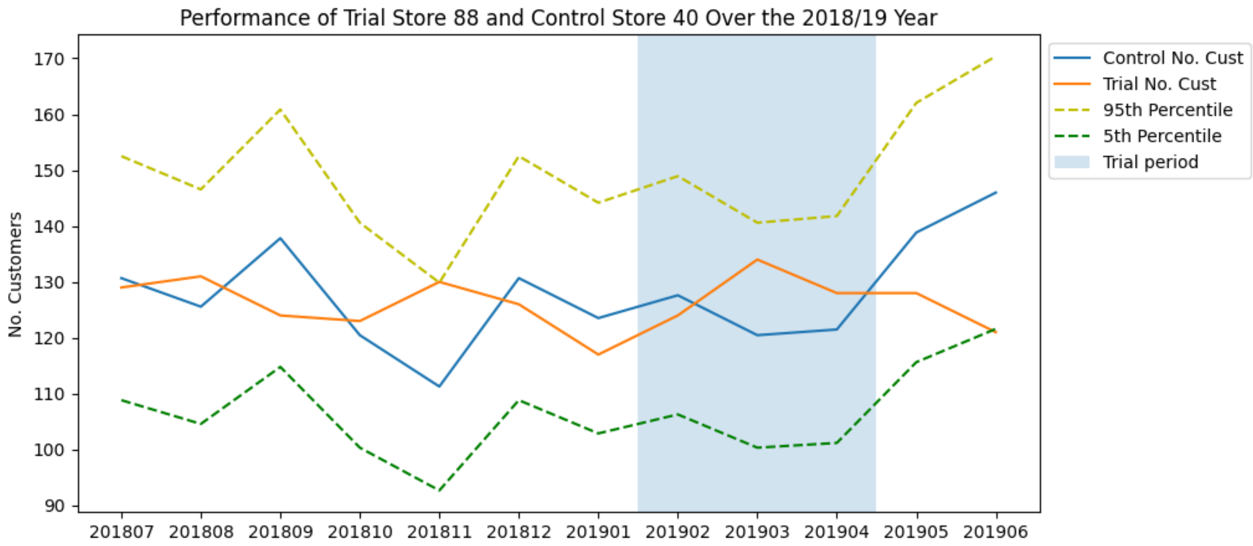
    ax = plot_control.plot.line(x = "YEARMONTH", y = 'control_ncust', use_index=False, label = 'Control No. Cust')
    ax_trial = plot_trial.plot.line(x = "YEARMONTH", y = 'trial_ncust', use_index=False, ax=ax, label = 'Trial No. Cust')

    # plot the thresholds as lines
    std = percentdiff[(percentdiff['CONTROL_NBR'] == control) & (percentdiff.YEARMONTH < 201902)]['cust_percent_diff'].std
    threshold95 = plot_control.reset_index()[['YEARMONTH', 'control_ncust']]
    threshold95.control_ncust = threshold95.control_ncust*(1+std*2)
    threshold5 = plot_control.reset_index()[['YEARMONTH', 'control_ncust']]
    threshold5.control_ncust = threshold5.control_ncust*(1-std*2)
    ax95 = threshold95.plot.line(x = 'YEARMONTH', y = 'control_ncust',color='y', linestyle = '--', figsize=(10, 5), use_in
    ax5 = threshold5.plot.line(x = 'YEARMONTH', y = 'control_ncust', color='g',  linestyle = '--', figsize=(10, 5), use_in
    ax.add_patch(Rectangle((6.5, 0), 3, 2000, alpha = 0.2, label = 'Trial period'))

    # Other plot features
    ax.set_ylabel('No. Customers')
    plt.legend(loc = "upper left",bbox_to_anchor=(1.0, 1.0))
    titlestr = 'Performance of Trial Store ' + str(trial) + ' and Control Store ' + str(control) + ' Over the 2018/19 Year
    positions = (0,1,2,3,4,5,6,7,8,9, 10, 11)
    labels = ("201807", '201808', '201809', '201810', '201811', '201812', '201901', '201902', '201903', '201904', '201905'
    plt.xticks (positions, labels)
    ax.set_title(titlestr)
    plt.show()
```







It looks like the number of customers is significantly higher in all of the three months for store 77 and 86. This seems to suggest that the trial had a significant impact on increasing the number of customers in trial store 86 but as we saw, the statistical significance in the total sales were not as large, compared to store 77. We should check with the Category Manager if there were special deals in the trial store that were may have resulted in lower prices, impacting the results. Likewise to when considering the total sales, there appears to be no significant different in the number of customers between the control and trial stores for store 88 over the trial period.

Conclusion ¶

In this task, we found that the results for trial stores 77 and 86 showed a statistically significant difference in at least two stores of the three months of the trial period. However, this was not the case for store 88. We can check to see if the trial was implemented differently in store 88 but even so, we have been able to see that the trial has resulted in a significant increase in sales.

```
In [ ]:
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