```python
    Parameters:
                data: (dataframe) It takes dataframe contaning store number, months, sales and number o
f customers
                trialStore: (integer) It takes the trial store number from which we need to compare all
 stores

    Return: It returns a dataframe with store number and correlation score corresponding to that store
 and the trail store
    """

    df = data[["STORE_NBR","MonthID","nCustomers"]]
    storeNBR = df["STORE_NBR"].unique()
    corr = list()

    ts = df[df["STORE_NBR"] == trialStore].iloc[:,-1]
    for n in storeNBR:
        cs = df[df["STORE_NBR"] == n].iloc[:,-1]
        corr.append(np.corrcoef(ts,cs)[0,1])

    corrCustDf = pd.DataFrame({"STORE_NBR":storeNBR,"corrCust":corr})

    return corrCustDf
```

In [13]:
```python
def magDistSales(data, trialStore):
    """
    It calculates the the absoulte distance of each store to the trial store based on monthly sales.

    Parameters:
                data: (dataframe) It takes dataframe contaning store number, months, sales and number o
f customers
                trialStore: (integer) It takes the trial store number from which we need to compare all
 stores

    Return: It returns a dataframe with store number and absolute distance corresponding to that store
 and the trail store
    """
    df = data[["STORE_NBR","MonthID","totSales"]]
    storeNBR = df["STORE_NBR"].unique()
    dist = list()

    ts = np.array(df[df["STORE_NBR"] == trialStore].iloc[:,-1])
    for n in storeNBR:
        cs = np.array(df[df["STORE_NBR"] == n].iloc[:,-1])
        d = sum(np.abs(ts - cs))
        dist.append(d)

    magDistSalesDf = pd.DataFrame({"STORE_NBR":storeNBR,"distSales":dist})

    return magDistSalesDf
```

In [14]:
```python
def magDistCust(data, trialStore):
    """
    It calculates the the absoulte distance of each store to the trial store based on number of custome
rs.

    Parameters:
                data: (dataframe) It takes dataframe contaning store number, months, sales and number o
f customers
                trialStore: (integer) It takes the trial store number from which we need to compare all
 stores

    Return: It returns a dataframe with store number and absolute distance corresponding to that store
 and the trail store
    """
    df = data[["STORE_NBR","MonthID","nCustomers"]]
    storeNBR = df["STORE_NBR"].unique()
    dist = list()

    ts = np.array(df[df["STORE_NBR"] == trialStore].iloc[:,-1])
    for n in storeNBR:
        cs = np.array(df[df["STORE_NBR"] == n].iloc[:,-1])
        d = sum(np.abs(ts - cs))
        dist.append(d)

    magDistCustDf = pd.DataFrame({"STORE_NBR":storeNBR,"distCust":dist})

    return magDistCustDf
```

In [15]:
```python
def stdMagDis(data, colList):
    """
    It standarizes the absolute distance so that the measure ranges from 0 to 1.
    Parameters:
                data: (dataframe) It takes dataframe contaning absolute distance score
                colList: (list) It takes the list of columns which needs to be standardized.
                        To standardize, it uses MinMaxScalar from sckit-learn library

    Return: It returns the dataframe with (1 - standardized distance) and all other given columns
    """
    df = data.copy()

    from sklearn.preprocessing import MinMaxScaler
    minMaxScalar = MinMaxScaler()

    df[colList] = minMaxScalar.fit_transform(df[colList])

    for col in colList:
        df.loc[:, col] = 1 - df.loc[:, col]

    return df
```

In [16]:
```python
def controlStores(data, trialStore):
    """
    It returns a dataframe with all 4 scores correlation score for sales and number of customers, absol
ute difference score
    for sales and number of customers of each store to the given trial store.

    It merge all 4 dataframes returned from different functions into one single dataframe.

    Parameters:
                data: (dataframe) It takes dataframe contaning store number, months, sales and number o
f customers
                trailStore: (integer) It takes the trial store number from which we need to compare all
 stores

    """
    controlStoresDf = corrSales(data, trialStore)

    #merging corrSales and corrCust -> controlStoresDf
    controlStoresDf = controlStoresDf.merge(right=corrCust(data, trialStore), how="inner", on="STORE_NB
R")

    #merging controlStoresDf and magDistSales -> controlStoresDf
    controlStoresDf = controlStoresDf.merge(right=magDistSales(data, trialStore), how="inner", on="STOR
E_NBR")

    #merging controlStoresDf and magDistCust -> controlStoresDf
    controlStoresDf = controlStoresDf.merge(right=magDistCust(data, trialStore), how="inner", on="STORE
_NBR")

    #Standardising the magnitude distance so that the measure ranges from 0 to 1
    controlStoresDf = stdMagDis(controlStoresDf, ["distSales","distCust"])

    #creating a column to show the compared trial store number
    controlStoresDf.loc[:, "trialStore"] = trialStore

    #returning final dataframe
    return controlStoresDf
```

Let's see all four score corrosponding to Trial Store (77)

In [17]:
```python
controlStores77 = controlStores(preTrialMeasures, 77)

controlStores77
```

Out[17]:

	STORE_NBR	corrSales	corrCust	distSales	distCust	trialStore
0	1	0.075218	0.322168	0.950903	0.938744	77
1	2	-0.263079	-0.572051	0.933198	0.921899	77
2	3	0.806644	0.834207	0.317676	0.318530	77
3	4	-0.263300	-0.295639	0.130226	0.157734	77
4	5	-0.110652	0.370659	0.526858	0.460949	77
...	...	...	...	...	...	...
255	268	0.344757	0.369517	0.958964	0.937213	77
256	269	-0.315730	-0.474293	0.418570	0.315467	77
257	270	0.315430	-0.131259	0.414653	0.333844	77
258	271	0.355487	0.019629	0.523884	0.459418	77
259	272	0.117622	0.223217	0.877596	0.946401	77

260 rows × 6 columns

Let's see all four score corrosponding to Trial Store (86)

In [18]:
```python
controlStores86 = controlStores(preTrialMeasures, 86)

controlStores86
```

Out[18]:

	STORE_NBR	corrSales	corrCust	distSales	distCust	trialStore
0	1	0.445632	0.485831	0.212664	0.433681	86
1	2	-0.403835	-0.086161	0.169679	0.366617	86
2	3	-0.261284	-0.353786	0.766059	0.912072	86
3	4	-0.039035	-0.169608	0.499755	0.773472	86
4	5	0.235159	-0.253229	0.924119	0.922504	86
...	...	...	...	...	...	...
255	268	-0.452182	-0.034273	0.239638	0.414307	86
256	269	0.697055	-0.098587	0.899881	0.918033	86
257	270	-0.730679	-0.767267	0.836892	0.891207	86
258	271	0.527637	0.267393	0.919228	0.932936	86
259	272	0.004926	-0.353815	0.438479	0.411326	86

260 rows × 6 columns

Let's see all four score corrosponding to Trial Store (88)

In [19]:
```python
controlStores88 = controlStores(preTrialMeasures, 88)

controlStores88
```

Out[19]:

	STORE_NBR	corrSales	corrCust	distSales	distCust	trialStore
0	1	0.813636	0.305334	0.137831	0.340749	88
1	2	-0.067927	-0.452379	0.109972	0.288056	88
2	3	-0.507847	0.522884	0.799738	0.840749	88
3	4	-0.745566	-0.361503	0.897187	0.923888	88
4	5	0.190330	-0.025320	0.607131	0.731850	88
...	...	...	...	...	...	...
255	268	-0.021429	0.672672	0.155314	0.325527	88
256	269	-0.172578	-0.274781	0.706839	0.843091	88
257	270	-0.723272	-0.103032	0.710445	0.829040	88
258	271	-0.103037	-0.018831	0.609869	0.733021	88
259	272	-0.772772	0.026909	0.284186	0.323185	88

260 rows × 6 columns

Let's concatenate scores corrosponding to all three trial stores into a single dataframe

In [20]:
```python
controlStoresAll = pd.concat([controlStores77,controlStores86,controlStores88],axis=0).reset_index(drop
=True)

controlStoresAll
```

Out[20]:

	STORE_NBR	corrSales	corrCust	distSales	distCust	trialStore
0	1	0.075218	0.322168	0.950903	0.938744	77
1	2	-0.263079	-0.572051	0.933198	0.921899	77
2	3	0.806644	0.834207	0.317676	0.318530	77
3	4	-0.263300	-0.295639	0.130226	0.157734	77
4	5	-0.110652	0.370659	0.526858	0.460949	77
...	...	...	...	...	...	...
775	268	-0.021429	0.672672	0.155314	0.325527	88
776	269	-0.172578	-0.274781	0.706839	0.843091	88
777	270	-0.723272	-0.103032	0.710445	0.829040	88
778	271	-0.103037	-0.018831	0.609869	0.733021	88
779	272	-0.772772	0.026909	0.284186	0.323185	88

780 rows × 6 columns

Combining all 4 scores to get a single score

We'll now combine all 4 scores to get a single score for each store to a trail store. This will be the final score to decide the control store.

We will be assigning equal weightage to all four drivers and combine them i.e. we will be taking simple average of all scores.

In [21]:
```python
#taking average of correlation and absoulte difference difference scores for sales
controlStoresAll["scoreNSales"] = (0.5 * controlStoresAll["corrSales"]) + (0.5 * controlStoresAll["dist
Sales"])

#taking average of correlation and absoulte difference difference scores for number of customers
controlStoresAll["scoreNCust"] = (0.5 * controlStoresAll["corrCust"]) + (0.5 * controlStoresAll["distCu
st"])

#we are taking average of sales and number of customers scores
controlStoresAll["finalControlScore"] = (0.5 * controlStoresAll["scoreNSales"]) + (0.5 * controlStoresA
ll["scoreNCust"])
```

In [22]:
```python
controlStoresAll
```

Out[22]:

	STORE_NBR	corrSales	corrCust	distSales	distCust	trialStore	scoreNSales	scoreNCust	finalControlScore
0	1	0.075218	0.322168	0.950903	0.938744	77	0.513060	0.630456	0.571758
1	2	-0.263079	-0.572051	0.933198	0.921899	77	0.335060	0.174924	0.254992
2	3	0.806644	0.834207	0.317676	0.318530	77	0.562160	0.576369	0.569264
3	4	-0.263300	-0.295639	0.130226	0.157734	77	-0.066537	-0.068953	-0.067745
4	5	-0.110652	0.370659	0.526858	0.460949	77	0.208103	0.415804	0.311954
...	...	...	...	...	...	...	...	...	...
775	268	-0.021429	0.672672	0.155314	0.325527	88	0.066942	0.499099	0.283021
776	269	-0.172578	-0.274781	0.706839	0.843091	88	0.267131	0.284155	0.275643
777	270	-0.723272	-0.103032	0.710445	0.829040	88	-0.006413	0.363004	0.178295
778	271	-0.103037	-0.018831	0.609869	0.733021	88	0.253416	0.357095	0.305256
779	272	-0.772772	0.026909	0.284186	0.323185	88	-0.244293	0.175047	-0.034623

780 rows × 9 columns

Control Store for Trial Store (77)

The store with the Highest score (other than trial store itself) will be selected as the control store since it is most similar to the trial store.

In [23]:
```python
controlStoresAll[controlStoresAll["trialStore"] == 77].sort_values("finalControlScore",ascending=False)
```

Out[23]:

	STORE_NBR	corrSales	corrCust	distSales	distCust	trialStore	scoreNSales	scoreNCust	finalControlScore
72	77	1.000000	1.000000	1.000000	1.000000	77	1.000000	1.000000	1.000000
221	233	0.903774	0.990358	0.984567	0.992343	77	0.944171	0.991350	0.967761
38	41	0.783232	0.844219	0.962834	0.973966	77	0.873033	0.909093	0.891063
15	17	0.842668	0.747308	0.872450	0.961715	77	0.857559	0.854511	0.856035
241	254	0.577108	0.916208	0.917168	0.934150	77	0.747138	0.925179	0.836159
...	...	...	...	...	...	...	...	...	...
3	4	-0.263300	-0.295639	0.130226	0.157734	77	-0.066537	-0.068953	-0.067745
130	138	-0.585174	-0.534877	0.458558	0.358346	77	-0.063308	-0.088266	-0.075787
235	247	-0.631050	-0.621034	0.498955	0.402757	77	-0.066047	-0.109139	-0.087593
95	102	-0.550834	-0.652527	0.462890	0.372129	77	-0.043972	-0.140199	-0.092086
71	75	-0.806751	-0.590735	0.266465	0.307810	77	-0.270143	-0.141463	-0.205803

260 rows × 9 columns

> ***Store 233 is the Control Store corresponding to Trial Store 77 because it has the highest score among all other stores***

Control Store for Trial Store (86)

The store with the Highest score (other than trial store itself) will be selected as the control store since it is most similar to the trial store.

In [24]:
```python
controlStoresAll[controlStoresAll["trialStore"] == 86].sort_values("finalControlScore",ascending=False)
```

Out[24]:

	STORE_NBR	corrSales	corrCust	distSales	distCust	trialStore	scoreNSales	scoreNCust	finalControlScore
340	86	1.000000	1.000000	1.000000	1.000000	86	1.000000	1.000000	1.000000
407	155	0.877882	0.942876	0.962197	0.985097	86	0.920039	0.963986	0.942013
362	109	0.788300	0.770778	0.963195	0.965723	86	0.875747	0.868250	0.871999
367	114	0.734415	0.855339	0.919935	0.934426	86	0.827175	0.894883	0.861029
390	138	0.759864	0.749701	0.923802	0.926975	86	0.841833	0.838338	0.840085
...	...	...	...	...	...	...	...	...	...
361	108	-0.840413	-0.697245	0.329577	0.327869	86	-0.255418	-0.184688	-0.220053
308	52	-0.601629	-0.594459	0.024254	0.020864	86	-0.288688	-0.286798	-0.287743
372	120	-0.872693	-0.815097	0.160064	0.357675	86	-0.356315	-0.228711	-0.292513
299	42	-0.745720	-0.664952	0.009233	0.019374	86	-0.368243	-0.322789	-0.345516
398	146	-0.775127	-0.654598	0.008268	0.005961	86	-0.383430	-0.324319	-0.353874

260 rows × 9 columns

> ***Store 155 is the Control Store corresponding to Trial Store 86 because it has the highest score among all other stores***

Control Store for Trial Store (88)

The store with the Highest (other than trial store itself) score will be selected as the control store since it is most similar to the trial store.

In [25]:
```python
controlStoresAll[controlStoresAll["trialStore"] == 88].sort_values("finalControlScore",ascending=False)
```

Out[25]:

	STORE_NBR	corrSales	corrCust	distSales	distCust	trialStore	scoreNSales	scoreNCust	finalControlScore
602	88	1.000000	1.000000	1.000000	1.000000	88	1.000000	1.000000	1.000000
745	237	0.308479	0.947326	0.955903	0.987119	88	0.632191	0.967223	0.799707
690	178	0.731857	0.939466	0.693901	0.818501	88	0.712879	0.878984	0.795931
585	69	0.450029	0.815792	0.706057	0.867681	88	0.578043	0.841737	0.709890
626	113	0.495763	0.862632	0.680855	0.781030	88	0.588309	0.821831	0.705070
...	...	...	...	...	...	...	...	...	...
604	90	-0.662427	-0.503735	0.175513	0.310304	88	-0.243457	-0.096715	-0.170086
765	258	0.087493	-0.825850	0.008248	0.001171	88	0.047871	-0.412339	-0.182234
653	141	-0.690590	-0.547399	0.195038	0.286885	88	-0.247776	-0.130257	-0.189016
747	239	-0.642329	-0.660672	0.247620	0.291569	88	-0.197355	-0.184552	-0.190953
559	42	-0.519338	-0.282575	0.005984	0.015222	88	-0.256677	-0.133676	-0.195177

260 rows × 9 columns

> ***Store 237 is the Control Store corresponding to Trial Store 88 because it has the highest score among all other stores***

Assessment of Control Stores prior Trial Period

(July 2018 - January 2019)

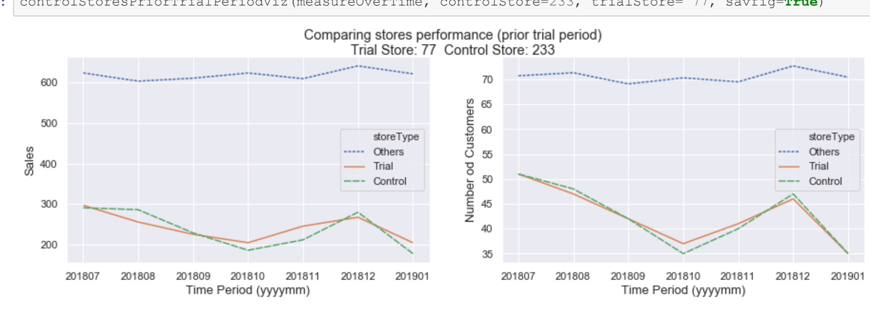
Now that we have found a control store, let's check visually if the drivers are indeed similar in the period before the trial for control store, trial store and other stores(taking all other stores together).

Let us define a function to reduce our efforts

In [26]:
```python
def controlStoresPriorTrialPeriodViz(data,controlStore,trialStore,savfig=False):
    """
    It create two line plots, one for sales and another for number of customers for the given control a
nd trial store to check
    visually if the drivers are indeed similar in the period before the trial.

    Parameters:
                data: (dataframe) It takes dataframe with store number, months, sales and number of cus
tomers for all stores
                controlStore: (integer) It takes control store number
                trialStore: (integer) It takes corrosponding trial store number
                savfig: (boolean) It asks for saving the figure on the local system or not, by default
 it is False.

    It creates a single line for stores other than control and trial store by aggregating values by mea
n
    """
    df = data.copy()

    df["storeType"] = df["STORE_NBR"].apply(lambda x: "Control" if x==controlStore else "Others")
    df.loc[df["STORE_NBR"]==trialStore,"storeType"] = "Trial"
    df = df[df["MonthID"] < 201902]
    df["MonthID"] = df["MonthID"].astype(str)

    plt.figure(figsize=(15,4))
    plt.subplot(1,2,1)
    sns.lineplot(data=df, x="MonthID", y="totSales", hue="storeType", estimator="mean", err_style=None,
 style="storeType",\
                dashes=[(2,1),(1,0),(5,1)])
    plt.xlabel("Time Period (yyyymm)",size=13)
    plt.ylabel("Sales",size=13)

    plt.subplot(1,2,2)
    sns.lineplot(data=df, x="MonthID", y="nCustomers", hue="storeType", estimator="mean", err_style=Non
e, style="storeType",\
                dashes=[(2,1),(1,0),(5,1)])
    plt.xlabel("Time Period (yyyymm)",size=13)
    plt.ylabel("Number od Customers",size=13)

    plt.suptitle(f"Comparing stores performance (prior trial period)\nTrial Store: {trialStore}  Contro
l Store: {controlStore}")

    if savfig==True:
        path="C:/Users/amitm/Jupyter Notebools/Quantium/Task 2/"+"Stores Performance ("+str(trialStore)
+").jpeg"
        plt.savefig(path,dpi=500)
```

Visualizing stores performance in the period before the trial for Control Store (233) and Trial Store (77)

```
In [27]: controlStoresPriorTrialPeriodViz(measureOverTime, controlStore=233, trialStore= 77, savfig=True)
```



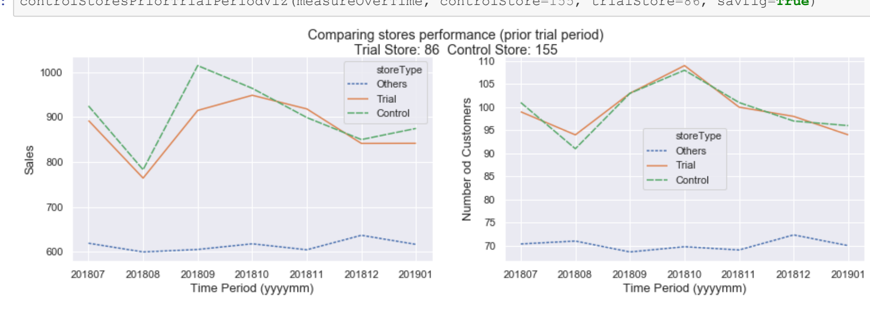
Insights:

- We can see that lines are almost over lapping each other in both charts for control store and trial store and others store line is way far from trial store
- This shows that the choosen control store (233) is correct and have very similar performance to the trial store (77) in terms of our choosen drivers

Note: *Measures are aggregated by mean for other stores*

Let's visualise stores performance in the period before the trial for Control Store (155) and Trial Store (86)

```
In [28]: controlStoresPriorTrialPeriodViz(measureOverTime, controlStore=155, trialStore=86, savfig=True)
```



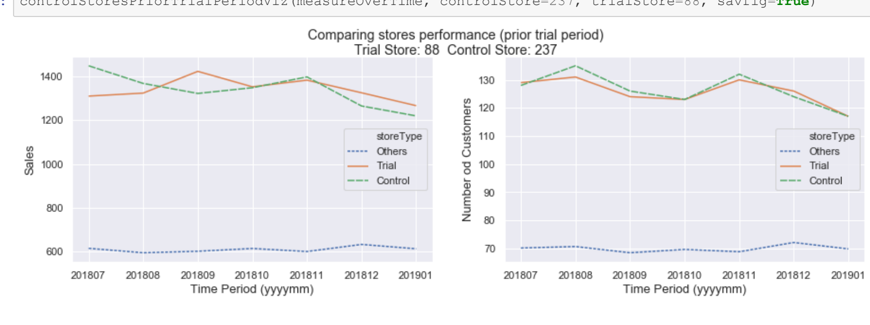
Insights:

- We can see that lines are almost over lapping each other in both charts for control store and trial store and others store line is way far from trial store
- This shows that the choosen control store (155) is correct and have very similar performance to the trial store (86) in terms of our choosen drivers

Note: *Measures are aggregated by mean for other stores*

Let's visualise stores performance in the period before the trial for Control Store (237) and Trial Store (88)

```
In [29]: controlStoresPriorTrialPeriodViz(measureOverTime, controlStore=237, trialStore=88, savfig=True)
```



Insights:

- We can see that lines are almost over lapping each other in both charts for control store and trial store and others store line is way far from trial store
- This shows that the choosen control store (237) is correct and have very similar performance to the trial store (88) in terms of our choosen drivers

Note: *Measures are aggregated by mean for other stores*

Phase 2: Assessment of Trial Stores during the Trial Period

(February 2019 - April 2020)

Our goal is to see if there has been an uplift in overall chip sales in trail stores. We now have control stores to compare compare the results and make conclusion.

To do that, ***first we need to scale the control store's sales to a level similar to control for any differences between the two stores outside of the trial period.***

Assessment of sales of Trial Store (77)

Calculating Scaling Factor for Control Store's Sale

$$ScalingFactor = \frac{\sum Trial\ Store's\ Sales\ (prior\ trial\ period)}{\sum Control\ Store's\ Sales\ (prior\ trial\ period)}$$

```
In [30]: scalingFactorForControlSales = preTrialMeasures[preTrialMeasures["STORE_NBR"]==77]["totSales"].sum()/ p
reTrialMeasures[\
                                                  preTrialMeasures["STORE_NBR"]==233]["totSales"].sum()

scalingFactorForControlSales
```

```
Out[30]: 1.023617303289553
```

Creating a dataframe with control store's data only for all months

```
In [31]: scaledControlSales = measureOverTime[measureOverTime["STORE_NBR"]==233][["STORE_NBR","MonthID","totSale
s"]]

scaledControlSales
```

Out[31]:

	STORE_NBR	MonthID	totSales
2699	233	201807	290.7
2700	233	201808	285.9
2701	233	201809	228.6
2702	233	201810	185.7
2703	233	201811	211.6
2704	233	201812	279.8
2705	233	201901	177.5
2706	233	201902	244.0
2707	233	201903	199.1
2708	233	201904	158.6
2709	233	201905	344.4
2710	233	201906	221.0

Scaling control store's sales

$$controlSales = Control\ Store's\ Sales * Scaling\ Factor$$

```
In [32]: scaledControlSales["controlSales"] = scaledControlSales["totSales"] * scalingFactorForControlSales

scaledControlSales
```

Out[32]:

	STORE_NBR	MonthID	totSales	controlSales
2699	233	201807	290.7	297.565550
2700	233	201808	285.9	292.652187
2701	233	201809	228.6	233.998916
2702	233	201810	185.7	190.085733
2703	233	201811	211.6	216.597421
2704	233	201812	279.8	286.408121
2705	233	201901	177.5	181.692071
2706	233	201902	244.0	249.762622
2707	233	201903	199.1	203.802205
2708	233	201904	158.6	162.345704
2709	233	201905	344.4	352.533799
2710	233	201906	221.0	226.219424

Merging trial store's sales in the same dataframe

```
In [33]: trialSales = measureOverTime[measureOverTime["STORE_NBR"]==77][["MonthID","totSales"]]

scaledControlSales = scaledControlSales.merge(trialSales,on="MonthID")

scaledControlSales.rename(columns={"totSales_x":"totSales","totSales_y":"trialSales"},inplace=True)

scaledControlSales
```

Out[33]:

	STORE_NBR	MonthID	totSales	controlSales	trialSales
0	233	201807	290.7	297.565550	296.8
1	233	201808	285.9	292.652187	255.5
2	233	201809	228.6	233.998916	225.2
3	233	201810	185.7	190.085733	204.5
4	233	201811	211.6	216.597421	245.3
5	233	201812	279.8	286.408121	267.3
6	233	201901	177.5	181.692071	204.4
7	233	201902	244.0	249.762622	235.0
8	233	201903	199.1	203.802205	278.5
9	233	201904	158.6	162.345704	263.5
10	233	201905	344.4	352.533799	299.3
11	233	201906	221.0	226.219424	264.7

Calculating Percentage Difference in Sales

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 [34]: scaledControlSales["percentageDiff"] = np.abs(scaledControlSales["controlSales"] - scaledControlSales[
"trialSales"]) /\
                                    scaledControlSales["controlSales"]

scaledControlSales
```

Out[34]:

	STORE_NBR	MonthID	totSales	controlSales	trialSales	percentageDiff
0	233	201807	290.7	297.565550	296.8	0.002573
1	233	201808	285.9	292.652187	255.5	0.126950
2	233	201809	228.6	233.998916	225.2	0.037602
3	233	201810	185.7	190.085733	204.5	0.075830
4	233	201811	211.6	216.597421	245.3	0.132516
5	233	201812	279.8	286.408121	267.3	0.066716
6	233	201901	177.5	181.692071	204.4	0.124980
7	233	201902	244.0	249.762622	235.0	0.059107
8	233	201903	199.1	203.802205	278.5	0.366521
9	233	201904	158.6	162.345704	263.5	0.623080
10	233	201905	344.4	352.533799	299.3	0.151003
11	233	201906	221.0	226.219424	264.7	0.170103

Check if the difference is significant!

We need to check and confirm this statistically, and we will do hypothesis testing. Our hyothesis will be,

Null Hypothesis: There is no difference in sales in trial and pre-trial period

Alternate Hypothesis: There is a difference in sales in trial and pre-trial period

Let's calculate the standard deviation based on the scaled percentage difference in the pre-trial period

```
In [35]: stdDev = scaledControlSales[scaledControlSales["MonthID"] < 201902]["percentageDiff"].std()

stdDev
```

```
Out[35]: 0.049940762641425544
```

Let's calculate the t-value

Our focus will be for trial period only

We are testing with a null hypothesis of there being 0 difference between trial and control stores, that's why we have subtracted zero,

$$t-value = \frac{Percentage\ Difference - 0}{Standard\ Deviation}$$

```
In [36]: scaledControlSales["tValue"] = (scaledControlSales["percentageDiff"] - 0) / stdDev

scaledControlSales
```

Out[36]:

	STORE_NBR	MonthID	totSales	controlSales	trialSales	percentageDiff	tValue
0	233	201807	290.7	297.565550	296.8	0.002573	0.051515
1	233	201808	285.9	292.652187	255.5	0.126950	2.542011
2	233	201809	228.6	233.998916	225.2	0.037602	0.752940
3	233	201810	185.7	190.085733	204.5	0.075830	1.518406
4	233	201811	211.6	216.597421	245.3	0.132516	2.653459
5	233	201812	279.8	286.408121	267.3	0.066716	1.335911
6	233	201901	177.5	181.692071	204.4	0.124980	2.502571
7	233	201902	244.0	249.762622	235.0	0.059107	1.183534
8	233	201903	199.1	203.802205	278.5	0.366521	7.339116
9	233	201904	158.6	162.345704	263.5	0.623080	12.476373
10	233	201905	344.4	352.533799	299.3	0.151003	3.023650
11	233	201906	221.0	226.219424	264.7	0.170103	3.406093

The 95th percentile of the t-distribution with the appropriate degrees of freedom to check whether the hypothesis is statistically significant.

Since there are 7 months in the pre-trial period

Hence, *degrees of freedom = 6 (7 - 1)*

```
In [37]: #0.95 taken because we are interested to know 95 percentile of t-distribution
degreesOfFreedom = 6
stats.t.ppf(0.95,df=degreesOfFreedom)
```

```
Out[37]: 1.9431802803927816
```

Comparing t-value and 95th percentile of the t-distribution for trial period

```
In [38]: scaledControlSales[scaledControlSales["MonthID"].isin([201902,201903,201904])]
```

Out[38]:

	STORE_NBR	MonthID	totSales	controlSales	trialSales	percentageDiff	tValue
7	233	201902	244.0	249.762622	235.0	0.059107	1.183534
8	233	201903	199.1	203.802205	278.5	0.366521	7.339116
9	233	201904	158.6	162.345704	263.5	0.623080	12.476373

Observation:

We can observe that the t-value 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 in March and April is statistically greater than in the control store.

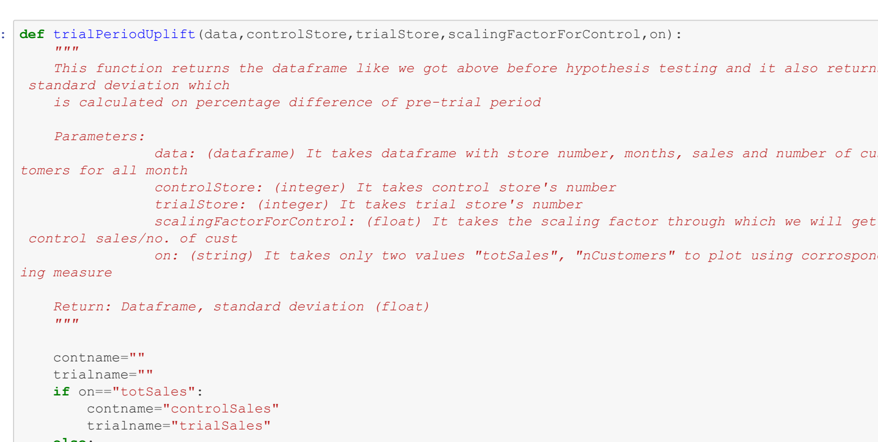
Visualizing the Sales of Trial and Control Store

Let's create a more visual version of this by plotting the sales of the control store, trial store, other stores and the 5% and 95% confidence level of control store's sales.

Let's define a function for this which we can use for other stores also

```
In [39]: def controlStoreViz(data,controlStore,trialStore,stdDev,on,savfig=False):
    """
    It plots a line plot sales/ number of customers of Trail Store, Control Store, and Others Store alo
ng with 5% and 95%
    percentile confidence level of control store's sales/ number of customers over the whole type perio
d.

    Parameters:
                data: (dataframe) It takes dataframe with store number, months, sales and number of cus
tomers for all month
                controlStore: (integer) It takes control store's number
                trialStore: (integer) It takes trial store's number
                stdDev: (float) It takes the standard deviation which is used in hypothesis testing
                on: (string) It takes only two values "totSales", "nCustomers" to plot using corrospond
ing measure
                savefig: (boolean) It asks to save the chart on the local system ot not, by default it
 is False

    It creates a single line for stores other than control and trial store by aggregating values by mea
n
    """
    df = data[["STORE_NBR","MonthID",on]]

    df["storeType"] = df["STORE_NBR"].apply(lambda x: "Control" if x==controlStore else "Others")
    df.loc[df["STORE_NBR"]==trialStore,"storeType"] = "Trial"


    Controls95 = pd.DataFrame(columns=["STORE_NBR","MonthID",on,"storeType"])
    Controls95[on] = df[df["STORE_NBR"]==controlStore][on] * (1 + 2 * stdDev)
    Controls95["STORE_NBR"] = df[df["STORE_NBR"]==controlStore]["STORE_NBR"]
    Controls95["MonthID"] = df[df["STORE_NBR"]==controlStore]["MonthID"]
    Controls95["storeType"] = ["Control 95th % confidence interval"] * len(df[df["STORE_NBR"]==controlS
tore])


    Controls05 = Controls95.copy()
    Controls05[on] = df[df["STORE_NBR"]==controlStore][on] * (1 - 2 * stdDev)
    Controls05.loc[:,"storeType"] = "Control 5th % confidence interval"

    df = df.append(Controls95,ignore_index=True)
    df = df.append(Controls05,ignore_index=True)

    df["MonthID"] = df["MonthID"].astype(str)

    name=""
    if on == "totSales":
        name="Sales"
    else:
        name="Number of customers"

    plt.figure(figsize=(15,6))
    sns.lineplot(data=df, x="MonthID", y=on, hue="storeType", estimator="mean", err_style=None, style=
"storeType",\
                dashes=[(1,0),(1,0),(1,0),(3,1),(3,1)])
    plt.xlabel("Time Period (yyyymm)",size=15)
    plt.ylabel(name,size=15)

    areaMax = df.groupby(["MonthID","storeType"])[on].mean().max()
    plt.fill_between(["201902","201904"],[areaMax],color="skyblue", alpha=0.5)

    ytext = df[df["storeType"]=="Others"].groupby(["MonthID"])[on].mean().min() - 20
    plt.text("201902",y=ytext,s="        Trial Period",color="blue",size=15)
    plt.title(f"\nTrial Store: {trialStore}  Control Store: {controlStore}",size=15)

    plt.suptitle(name+" over the period",size=20)

    if savfig==True:
        path="C:/Users/amitm/Jupyter Notebools/Quantium/Task 2/"+name+" All ("+str(trialStore)+").jpeg"
        plt.savefig(path,dpi=500)
```

```
In [40]: controlStoreViz(measureOverTime, controlStore=233, trialStore=77, stdDev=stdDev, on="totSales", savfig=
True)
```



Observation:

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% and 95% confidence interval of the control store in **two of the three trial months**.

Assessment of Number of Customers of Trial Store (77)

Let's now see if there has been an uplift in number of customers in trail stores during trial period.

To do this, we need perform the same calculations we did above on sales, but now on number of customers.

Let's define a function for all this, it will help in assessing other trial stores also and it will save our lot of time

```
In [41]: def trialPeriodUplift(data,controlStore,trialStore,scalingFactorForControl,on):
    """
    This function returns the dataframe like we got above before hypothesis testing and it also returns
 standard deviation which
    is calculated on percentage difference of pre-trial period

    Parameters:
                data: (dataframe) It takes dataframe with store number, months, sales and number of cus
tomers for all month
                controlStore: (integer) It takes control store's number
                trialStore: (integer) It takes trial store's number
                scalingFactorForControl: (float) It takes the scaling factor through which we will get
 control sales/no. of cust
                on: (string) It takes only two values "totSales", "nCustomers" to plot using corrospond
ing measure

    Return: Dataframe, standard deviation (float)
    """

    contname=""
    trialname=""
    if on=="totSales":
        contname="controlSales"
        trialname="trialSales"
    else:
        contname="controlCust"
        trialname="trialCust"


    scaledControl = data[data["STORE_NBR"]==controlStore][["STORE_NBR","MonthID",on]]

    scaledControl[contname] = scaledControl[on] * scalingFactorForControl


    trial = data[data["STORE_NBR"]==trialStore][["MonthID",on]]
    trial.rename(columns={on:trialname},inplace=True)

    scaledControl = scaledControl.merge(trial,on="MonthID")

    scaledControl["percentageDiff"] = np.abs(scaledControl[contname] - scaledControl[trialname]) / scal
edControl[contname]

    stdDev = scaledControl[scaledControl["MonthID"] < 201902]["percentageDiff"].std()

    scaledControl["tValue"] = (scaledControl["percentageDiff"] - 0) / stdDev

    return scaledControl, stdDev
```

Calculating Scaling Factor for Control Store's Number of Customers

```
In [42]: scalingFactor= preTrialMeasures[preTrialMeasures["STORE_NBR"]==77]["nCustomers"].sum()/ preTrialMeasure
s[\
                                                  preTrialMeasures["STORE_NBR"]==233]["nCustomers"].sum()
scalingFactor
```

```
Out[42]: 1.0033557046979866
```

```
In [43]: scaledControlCust, stdDev = trialPeriodUplift(measureOverTime,controlStore=233, trialStore=77, \
                                            scalingFactorForControl=scalingFactor, on="nCustomers")

scaledControlCust
```

Out[43]:

	STORE_NBR	MonthID	nCustomers	controlCust	trialCust	percentageDiff	tValue
0	233	201807	51	51.171141	51	0.003344	0.183352
1	233	201808	48	48.161074	47	0.024108	1.321664
2	233	201809	42	42.140940	42	0.003344	0.183352
3	233	201810	35	35.117450	37	0.053607	2.938874
4	233	201811	40	40.134228	41	0.021572	1.182622
5	233	201812	47	47.157718	46	0.024550	1.345883
6	233	201901	35	35.117450	35	0.003344	0.183352
7	233	201902	45	45.151007	45	0.003344	0.183352
8	233	201903	40	40.134228	50	0.245819	13.476388
9	233	201904	30	30.100671	47	0.561427	30.778725
10	233	201905	57	57.191275	55	0.038315	2.100509
11	233	201906	41	41.137584	41	0.003344	0.183352

The 95th percentile of the t-distribution with the appropriate degrees of freedom to check whether the hypothesis is statistically significant.

Since there are 7 months in the pre-trial period

Hence, degrees of freedom = 6 (7 - 1)

```
In [44]: degreesOfFreedom = 7
stats.t.ppf(0.95,df=degreesOfFreedom)
```

```
Out[44]: 1.894578605061305
```

Comparing t-value and 95th percentile of the t-distribution for trial period

```
In [45]: scaledControlCust[scaledControlCust["MonthID"].isin([201902,201903,201904])]
```

Out[45]:

	STORE_NBR	MonthID	nCustomers	controlCust	trialCust	percentageDiff	tValue
7	233	201902	45	45.151007	45	0.003344	0.183352
8	233	201903	40	40.134228	50	0.245819	13.476388
9	233	201904	30	30.100671	47	0.561427	30.778725

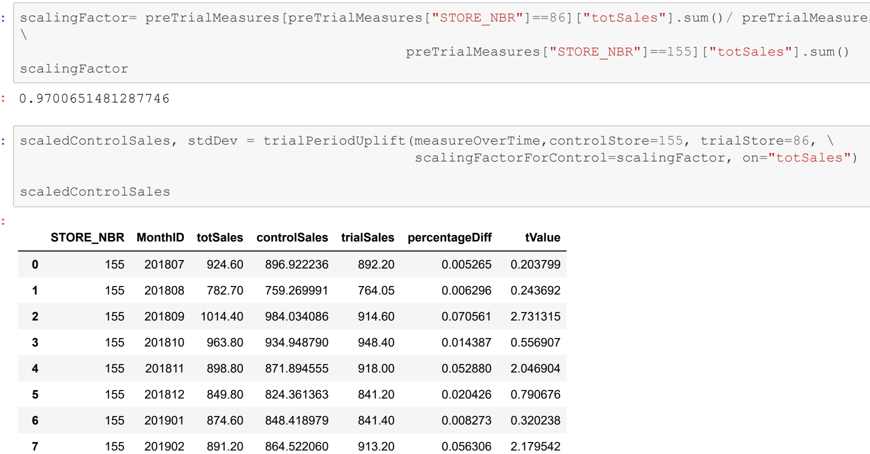
Observation:

We can observe that the **t-value is much larger** than the 95th percentile value of the t-distribution for March and April - i.e. the **increase in customers** in the trial store in March and April is statistically greater than in the control store.

Visualizing the Number of Customers of Trial and Control Store

Let's create a more visual version of this by plotting the number of customers of the control store, trial store, other stores and the 5% and 95% confidence level of control store's number of customers.

```
In [46]: controlStoreViz(measureOverTime, controlStore=233, trialStore=77, stdDev=stdDev, on="nCustomers", savfi
g=True)
```



Observation:

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% and 95% confidence interval of the control store in **two of the three trial months**.

Assessment of Sales of Trial Store (86)

Calculating Scaling Factor for Control Store's Sale

```
In [47]: scalingFactor= preTrialMeasures[preTrialMeasures["STORE_NBR"]==86]["totSales"].sum()/ preTrialMeasures[
\
                                                  preTrialMeasures["STORE_NBR"]==155]["totSales"].sum()
scalingFactor
```

```
Out[47]: 0.9700651481287746
```

```
In [48]: scaledControlSales, stdDev = trialPeriodUplift(measureOverTime,controlStore=155, trialStore=86, \
                                            scalingFactorForControl=scalingFactor, on="totSales")

scaledControlSales
```

Out[48]:

	STORE_NBR	MonthID	totSales	controlSales	trialSales	percentageDiff	tValue
0	155	201807	924.60	896.922236	892.20	0.005265	0.203799
1	155	201808	782.70	759.269991	764.05	0.006296	0.243692
2	155	201809	1014.40	984.034086	914.60	0.070561	2.731315
3	155	201810	963.80	934.948790	948.40	0.014387	0.556907
4	155	201811	898.80	871.894555	918.00	0.052880	2.046904
5	155	201812	849.80	824.361363	841.20	0.020426	0.790676
6	155	201901	874.60	848.418979	841.40	0.008273	0.320238
7	155	201902	891.20	864.522060	913.20	0.056306	2.179542
8	155	201903	804.40	780.320405	1026.80	0.315870	12.226922
9	155	201904	844.60	819.317024	848.20	0.035253	1.364580
10	155	201905	922.85	895.224622	889.30	0.006618	0.256176
11	155	201906	857.20	831.539845	838.00	0.007769	0.300725

The 95th percentile of the t-distribution with the appropriate degrees of freedom to check whether the hypothesis is statistically significant.

Since there are 7 months in the pre-trial period

Hence, degrees of freedom = 6 (7 - 1)

```
In [49]: degreesOfFreedom = 7
stats.t.ppf(0.95,df=degreesOfFreedom)
```

```
Out[49]: 1.894578605061305
```

Comparing t-value and 95th percentile of the t-distribution for trial period

```
In [50]: scaledControlSales[scaledControlSales["MonthID"].isin([201902,201903,201904])]
```

Out[50]:

	STORE_NBR	MonthID	totSales	controlSales	trialSales	percentageDiff	tValue
7	155	201902	891.2	864.522060	913.2	0.056306	2.179542
8	155	201903	804.4	780.320405	1026.8	0.315870	12.226922
9	155	201904	844.6	819.317024	848.2	0.035253	1.364580

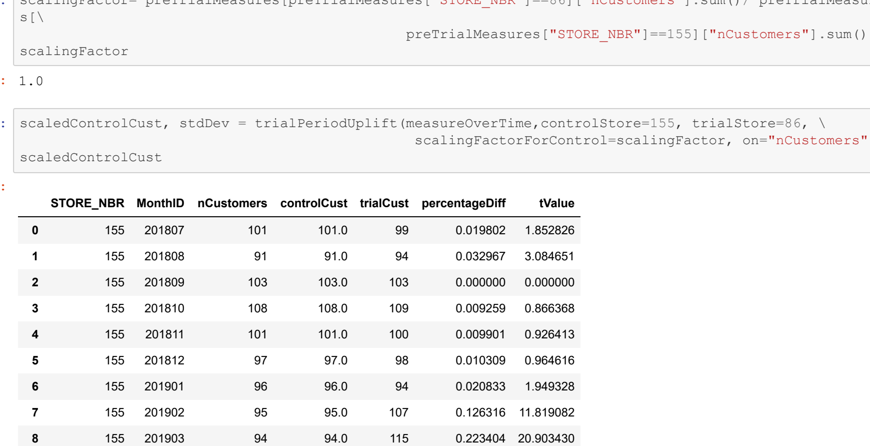
Observation:

We can observe that the **t-value is larger** than the 95th percentile value of the t-distribution for **February and March** - i.e. the **increase in sales** in the trial store in February and March is statistically greater than in the control store.

Visualizing the Sales of Trial and Control Store

Let's create a more visual version of this by plotting the sales of the control store, trial stores, other stores and the 5% and 95% confidence level of control store's sales.

```
In [51]: controlStoreViz(measureOverTime, controlStore=155, trialStore=86, stdDev=stdDev, on="totSales", savfig=
True)
```



Observation:

The results show that the trial in store 86 is **not significantly different** to its control store in the trial period as the trial store performance **lies inside** the 5% to 95% confidence interval of the control store in **two of the three trial months.**

Assessment of Number of Customers of Trial Store (86)

Calculating Scaling Factor for Control Store's Number of Customers

```
In [52]: scalingFactor= preTrialMeasures[preTrialMeasures["STORE_NBR"]==86]["nCustomers"].sum()/ preTrialMeasure
s[\
                                                  preTrialMeasures["STORE_NBR"]==155]["nCustomers"].sum()
scalingFactor
```

```
Out[52]: 1.0
```

```
In [53]: scaledControlCust, stdDev = trialPeriodUplift(measureOverTime,controlStore=155, trialStore=86, \
                                            scalingFactorForControl=scalingFactor, on="nCustomers")
scaledControlCust
```

Out[53]:

	STORE_NBR	MonthID	nCustomers	controlCust	trialCust	percentageDiff	tValue
0	155	201807	101	101.0	99	0.019802	1.852826
1	155	201808	91	91.0	94	0.032967	3.084651
2	155	201809	103	103.0	103	0.000000	0.000000
3	155	201810	108	108.0	109	0.009259	0.866368
4	155	201811	101	101.0	100	0.009901	0.926413
5	155	201812	97	97.0	98	0.010309	0.964616
6	155	201901	96	96.0	94	0.020833	1.949328
7	155	201902	95	95.0	107	0.126316	11.819082
8	155	201903	94	94.0	115	0.223404	20.903430
9	155	201904	99	99.0	105	0.060606	5.670772
10	155	201905	106	106.0	104	0.018868	1.765429
11	155	201906	95	95.0	98	0.031579	2.954771

The 95th percentile of the t-distribution with the appropriate degrees of freedom to check whether the hypothesis is statistically significant.

Since there are 7 months in the pre-trial period

Hence, degrees of freedom = 6 (7 - 1)

```
In [54]: degreesOfFreedom = 7
stats.t.ppf(0.95,df=degreesOfFreedom)
```

```
Out[54]: 1.894578605061305
```

Comparing t-value and 95th percentile of the t-distribution for trial period

```
In [55]: scaledControlCust[scaledControlCust["MonthID"].isin([201902,201903,201904])]
```

Out[55]:

	STORE_NBR	MonthID	nCustomers	controlCust	trialCust	percentageDiff	tValue
7	155	201902	95	95.0	107	0.126316	11.819082
8	155	201903	94	94.0	115	0.223404	20.903430
9	155	201904	99	99.0	105	0.060606	5.670772

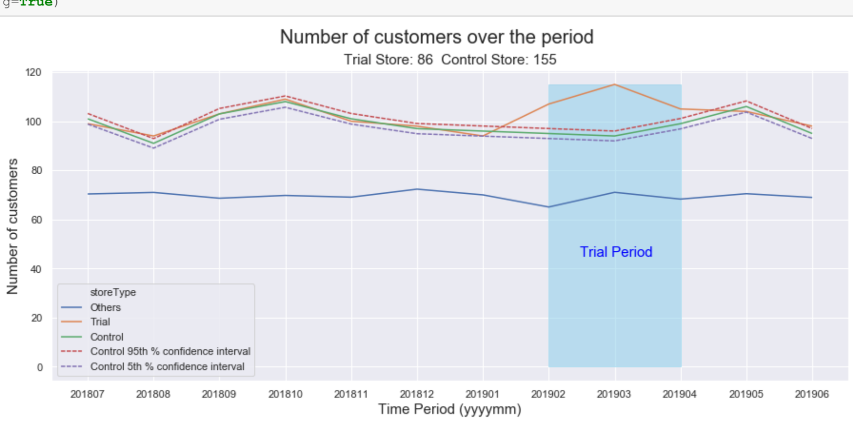
Observation:

We can observe that the t-value is **much larger** than the 95th percentile value of the t-distribution for **all three trial months** - i.e. the **increase in number of customers** in the trial store in all three trial months is statistically greater than in the control store.

Visualizing the Number of Customers of Trial and Control Store

Let's create a more visual version of this by plotting the number of customers of the control store, trial stores, other stores and the 5% and 95% confidence level of control store's number of customers.

In [56]:
```
controlStoreViz(measureOverTime, controlStore=155, trialStore=86, stdDev=stdDev, on="nCustomers", savfi
g=True)
```



Observation:

The results show that the trial in store 86 is **significantly different** to its control store in the trial period as the trial store performance **lies outside** the 5% and 95% confidence interval of the control store in **all three trial months.**

Assessment of Sales of Trial Store (88)

Calculating Scaling Factor for Control Store's Sale

In [57]:
```
scalingFactor= preTrialMeasures[preTrialMeasures["STORE_NBR"]==88]["totSales"].sum()/ preTrialMeasures[
\
                                        preTrialMeasures["STORE_NBR"]==237]["totSales"].sum()
scalingFactor
```

Out[57]: `1.0015583306649594`

In [58]:
```
scaledControlSales, stdDev = trialPeriodUplift(measureOverTime,controlStore=237, trialStore=88, \
                                        scalingFactorForControl=scalingFactor, on="totSales")
scaledControlSales
```

Out[58]:

	STORE_NBR	MonthID	totSales	controlSales	trialSales	percentageDiff	tValue
0	237	201807	1448.4	1450.657086	1310.00	0.096961	2.897136
1	237	201808	1367.8	1369.931485	1323.80	0.033674	1.006168
2	237	201809	1322.2	1324.260425	1423.00	0.074562	2.227870
3	237	201810	1348.3	1350.401097	1352.40	0.001480	0.044228
4	237	201811	1397.6	1399.777923	1382.80	0.012129	0.362408
5	237	201812	1265.0	1266.971288	1325.20	0.045959	1.373227
6	237	201901	1219.7	1221.600696	1266.40	0.036673	1.095756
7	237	201902	1404.8	1406.989143	1370.20	0.026147	0.781270
8	237	201903	1208.2	1210.082775	1477.20	0.220743	6.595668
9	237	201904	1204.6	1206.477165	1439.40	0.193060	5.768527
10	237	201905	1199.3	1201.168906	1308.25	0.089147	2.663672
11	237	201906	1153.6	1155.397690	1354.60	0.172410	5.151513

The 95th percentile of the t-distribution with the appropriate degrees of freedom to check whether the hypothesis is statistically significant.

Since there are 7 months in the pre-trial period

Hence, degrees of freedom = 6 (7 - 1)

In [59]:
```
degreesOfFreedom = 7
stats.t.ppf(0.95,df=degreesOfFreedom)
```

Out[59]: `1.894578605061305`

Comparing t-value and 95th percentile of the t-distribution for trial period

In [60]:
```
scaledControlSales[scaledControlSales["MonthID"].isin([201902,201903,201904])]
```

Out[60]:

	STORE_NBR	MonthID	totSales	controlSales	trialSales	percentageDiff	tValue
7	237	201902	1404.8	1406.989143	1370.2	0.026147	0.781270
8	237	201903	1208.2	1210.082775	1477.2	0.220743	6.595668
9	237	201904	1204.6	1206.477165	1439.4	0.193060	5.768527

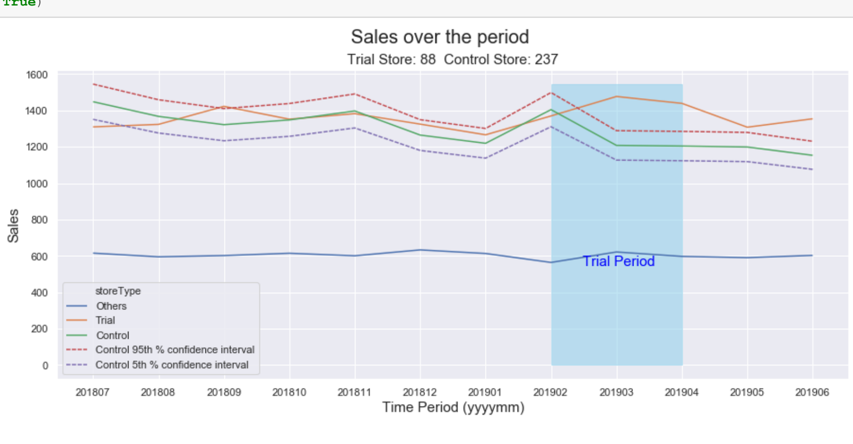
Observation:

We can observe that the **t-value is larger** than the 95th percentile value of the t-distribution for **March and April** - i.e. the **increase in sales** in the trial store in March and April is statistically greater than in the control store.

Visualizing the Sales of Trial and Control Store

Let's create a more visual version of this by plotting the sales of the control store, trial stores, other stores and the 5% and 95% confidence level of control store's sales.

In [61]:
```
controlStoreViz(measureOverTime, controlStore=237, trialStore=88, stdDev=stdDev, on="totSales", savfig=
True)
```



Observation:

The results show that the trial in store 88 is **significantly different** to its control store in the trial period as the trial store performance **lies outside** the 5% and 95% confidence interval of the control store in **two of the three trial months.**

Assessment of Number of Customers of Trial Store (88)

Calculating Scaling Factor for Control Store's Number of Customers

In [62]:
```
scalingFactor= preTrialMeasures[preTrialMeasures["STORE_NBR"]==88]["nCustomers"].sum()/ preTrialMeasure
s[\
                                        preTrialMeasures["STORE_NBR"]==237]["nCustomers"].sum()
scalingFactor
```

Out[62]: `0.9943502824858758`

In [63]:
```
scaledControlCust, stdDev = trialPeriodUplift(measureOverTime,controlStore=237, trialStore=88, \
                                        scalingFactorForControl=scalingFactor, on="nCustomers")
scaledControlCust
```

Out[63]:

	STORE_NBR	MonthID	nCustomers	controlCust	trialCust	percentageDiff	tValue
0	237	201807	128	127.276836	129	0.013539	1.827026
1	237	201808	135	134.237288	131	0.024116	3.254435
2	237	201809	126	125.288136	124	0.010281	1.387456
3	237	201810	123	122.305085	123	0.005682	0.766752
4	237	201811	132	131.254237	130	0.009556	1.289537
5	237	201812	124	123.299435	126	0.021902	2.955705
6	237	201901	117	116.338983	117	0.005682	0.766752
7	237	201902	126	125.288136	124	0.010281	1.387456
8	237	201903	119	118.327684	134	0.132448	17.873693
9	237	201904	120	119.322034	128	0.072727	9.814423
10	237	201905	129	128.271186	128	0.002114	0.285303
11	237	201906	119	118.327684	121	0.022584	3.047677

The 95th percentile of the t-distribution with the appropriate degrees of freedom to check whether the hypothesis is statistically significant.

Since there are 7 months in the pre-trial period

Hence, degrees of freedom = 6 (7 - 1)

In [64]:
```
degreesOfFreedom = 7
stats.t.ppf(0.95,df=degreesOfFreedom)
```

Out[64]: `1.894578605061305`

Comparing t-value and 95th percentile of the t-distribution for trial period

In [65]:
```
scaledControlCust[scaledControlCust["MonthID"].isin([201902,201903,201904])]
```

Out[65]:

	STORE_NBR	MonthID	nCustomers	controlCust	trialCust	percentageDiff	tValue
7	237	201902	126	125.288136	124	0.010281	1.387456
8	237	201903	119	118.327684	134	0.132448	17.873693
9	237	201904	120	119.322034	128	0.072727	9.814423

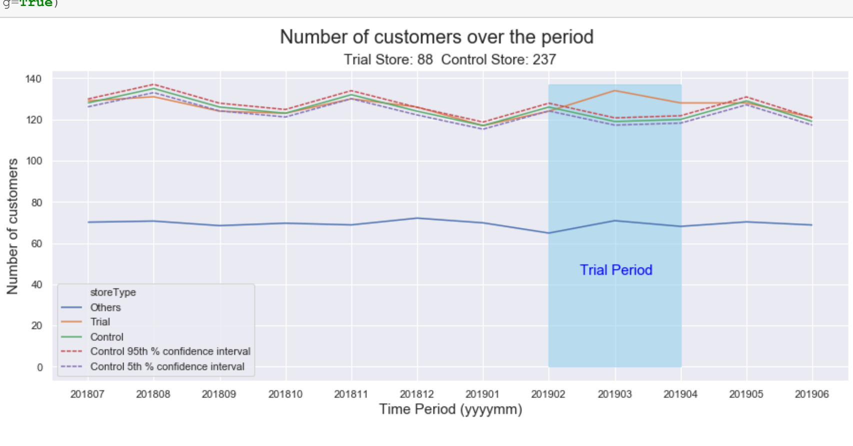
Observation:

We can observe that the t-value is **much larger** than the 95th percentile value of the t-distribution for **March and April** - i.e. the **increase in number of customers** in the trial store in March and April is statistically greater than in the control store.

Visualizing the Sales of Trial and Control Store

Let's create a more visual version of this by plotting the number of customers of the control store, trial stores, other stores and the 5% and 95% confidence level of control store's number of customers.

In [66]:
```
controlStoreViz(measureOverTime, controlStore=237, trialStore=88, stdDev=stdDev, on="nCustomers", savfi
g=True)
```



Observation:

The results show that the trial in store 88 is **significantly different** to its control store in the trial period as the trial store performance **lies outside** the 5% and 95% confidence interval of the control store in **two of the three trial months.**

Conclusion

First we found control stores for trial stores using pre-trial period data

- Control store 233 for trial store 77
- Control store 155 for trial store 86
- Control store 237 for trial store 88

Then we assessed trial store's performance in trial period

- We found there was a significant difference in the sales and number of customers for two out of three trial months for trial stores 77 and 88
  - Sales and number of customers increased for those months
- However, for trial store 86 there was no significant difference in the sales but there was significant difference in the number of customers
  - Number of customers were increased for all three trial months
  - Sales was inceasd for one out of three trial months
- This shows that, trial store 86 was able to attract significantly more customers in trial period than pre-trial period however, sales did not increased significantly. We need to check with the category manager, if some different startegy was applied at this store.

Overall, impact of the new trial layouts at trial stores shows a significant increase in sales.

We can tell the Category Manger that the trial layout was successful in creating an impact on sales, and therefore it can be rolled out to all their stores as well.
