Quantium Data Analytics Task 2: Experimentation and Uplift Testing

Testing the impact of a new store layout for the Chips Category on sales performance

Whats going on? -> A major retail chain wanted to know: **"If we redesign the chip aisle layout, will we sell more chips?"**

For that they ran a experiment as changing all their stores at once would have been too risky.

THE EXPERIMENT

In ** Feb 2019**, the company rolled out a brand new store layout for the chips in three stores:

- Store 77
- Store 86
- Store 88

They let this new layout run for **3 months(Feb through April 2019)** to see what would happen.

THE PROBLEM

Lets say Store 77's chip sales went up 20% during those 3 months. First thought, **"WOW IT WORKED"**, BUT **"IT MAY NOT BE WHAT IT SEEMS"**

Maybe the sales went up because:

- The season (People preferring chips in the Spring)
- There was a big promotion
- The economy was doing well

How can we be sure that the rise in sales was because of the layout not because of the other factors?

THE SOLUTION: FINDING "TWIN" STORES

We need to find stores that are like "twins" to our trial stores -stores that:

- Sold similar amounts of chips before the trial
- Had similar customer patterns before the trial

- Were in the similar market conditions
- But **did NOT get the new layout**

These "twin" stores are called **Control Stores**. We can call it a reference store.

This controlled store carry great significance here, as witH0ut the control store, any data or analysis of trial store would have not made any sense.

What are we going to do?

Right now, we have not the data called merged_df(cleaned, and merged dataset of both **QVI_transaction_data** and **QVI_purchase_behaviour_data**) Now the process we are going to follow:

1. Identify which stores have data from July 2018 to June 2019 (Full observation period)
2. Seperate the pre trial period and trial period.
3. Use pretrial period to find the twin stores for the trial stores (77,86,& 88)
4. Once we find the twin stores, we'll compare the trial period of trial stores and control stores.
5. Then only, we will conclude whether the new layout was effective or not.

BOTTOM LINE:

We're trying to answer: **"Did the new layout work,or would sales have gone up anyway?"** Control stores helps to answer that with confidence.

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly as px
```

In [2]:
```
store_df=pd.read_csv('merged_data.csv')
```

In [3]:
```
store_df.head(5)
```

Out[3]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	P
0	2019-06-06	34	34057	31150	102	Kettle Mozzarella Basil & Pesto	
1	2019-03-04	245	245223	247682	102	Kettle Mozzarella Basil & Pesto	
2	2019-06-25	160	160226	161580	102	Kettle Mozzarella Basil & Pesto	
3	2019-04-10	65	65122	62177	102	Kettle Mozzarella Basil & Pesto	
4	2018-09-22	91	91070	89505	102	Kettle Mozzarella Basil & Pesto	

Client have selected store 77,86, and 88 as trial stores and want control stores that are operational for the entire observation period.

In [4]:

```
store_df[store_df['STORE_NBR'].isin([77,86,88])].head(4)
```

Out[4]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME
94	2018-12-23	88	88340	87908	102	Kettle Mozzarella Basil & Pesto
116	2019-03-21	88	88092	86672	102	Kettle Mozzarella Basil & Pesto
132	2019-03-17	86	86006	84180	102	Kettle Mozzarella Basil & Pesto
201	2018-12-26	88	88187	87149	102	Kettle Mozzarella Basil & Pesto

Trial Period- Feb 2019- End of April 2019

We would want to match trial stores(77,86,88) to the control stores (the stores that are similar to the trial stores prior to the trial period of Feb 2019)

KPI of this comparisions:

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

In [5]:
```
store_df['DATE']=pd.to_datetime(store_df['DATE'])
store_df['Month_ID']=store_df['DATE'].dt.year*100+store_df['DATE'].dt.
```

In [6]:
```
store_df.head(4)
```

Out[6]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	P
0	2019-06-06	34	34057	31150	102	Kettle Mozzarella Basil & Pesto	
1	2019-03-04	245	245223	247682	102	Kettle Mozzarella Basil & Pesto	
2	2019-06-25	160	160226	161580	102	Kettle Mozzarella Basil & Pesto	
3	2019-04-10	65	65122	62177	102	Kettle Mozzarella Basil & Pesto	

Metrics for comparison of control stores and trial stores

For each store and each month we need to calculate total sales, number of customers, transactions per customers, chips per customer and the average price per customers.

In [7]:
```
monthly_metrics=store_df.groupby(['STORE_NBR','Month_ID']).agg(
    {
    'TOT_SALES':'sum', # total sales
    'LYLTY_CARD_NBR':'nunique', #number of customers
    'TXN_ID':'count', # Total numner of transaction
    'PROD_QTY':'sum' # Total chips/product sold

    }). reset_index()
monthly_metrics.columns=['STORE_NBR','MONTH_ID','TOTAL_SALES','NUMBER_
'TOTAL_CHIPS']
monthly_metrics.head(4)
```

Out[7]:

	STORE_NBR	MONTH_ID	TOTAL_SALES	NUMBER_CUSTOMERS	TOTAL_TRA
0	1	201807	188.9	47	
1	1	201808	168.4	41	
2	1	201809	268.1	57	
3	1	201810	175.4	39	

In [8]:
```
# Derive metrics
monthly_metrics['TXN_PER_CUSTOMERS']=(monthly_metrics['TOTAL_TRANSACTI
monthly_metrics['CHIPS_PER_CUSTOMER']=(monthly_metrics['TOTAL_CHIPS']/
monthly_metrics['AVG_PRICE_PER_CUSTOMER']=(monthly_metrics['TOTAL_SALE
```

In [9]:
```
monthly_metrics.head()
```

Out[9]:

	STORE_NBR	MONTH_ID	TOTAL_SALES	NUMBER_CUSTOMERS	TOTAL_TRA
0	1	201807	188.9	47	
1	1	201808	168.4	41	
2	1	201809	268.1	57	
3	1	201810	175.4	39	
4	1	201811	184.8	44	

The pre trial period is upto Feb 2019 and the full is from july 2018 to June 2019

First lets figure out the stores that were operational in the entire periods.

In [10]:
```
all_month=monthly_metrics['MONTH_ID'].nunique()
all_month
```

Out[10]: 12

In [11]:
```
store_months_counts=monthly_metrics.groupby("STORE_NBR")['MONTH_ID'].n
operational_stores=store_months_counts[store_months_counts==12].index.
```

In [12]:
```
monthly_metrics['STORE_NBR'].nunique()
```

Out[12]: 271

In [13]:
```
len(operational_stores)
```

Out[13]: 259

Out of 271 stores, only 259 were operationally active through out the entire period.

In [14]:
```
operational_stores_monthly_metrics=monthly_metrics[monthly_metrics['ST
```

In [15]:
```
monthly_metrics.size
```

Out[15]: 28485

In [16]:
```
operational_stores_monthly_metrics.size
```

Out[16]: 27972

Around 513 row of data was removed.

Seperating Pre- Trial data (Data before February 2019)
and Trial data (Data from Febraury 2019- April 2019)

In [17]:
```
pre_trial_data=operational_stores_monthly_metrics[operational_stores_m
pre_trial_data.tail()
```

Out[17]:

	STORE_NBR	MONTH_ID	TOTAL_SALES	NUMBER_CUSTOMERS	TOTAL_T
3155	272	201809	294.5	31	
3156	272	201810	405.1	41	
3157	272	201811	355.8	39	
3158	272	201812	363.1	43	
3159	272	201901	392.4	44	

In [18]:
```
trial_data=operational_stores_monthly_metrics[(operational_stores_mont
trial_data.tail()
```

Out[18]:

	STORE_NBR	MONTH_ID	TOTAL_SALES	NUMBER_CUSTOMERS	TOTAL_T
3149	271	201903	699.6	76	
3150	271	201904	700.8	79	
3160	272	201902	385.3	44	
3161	272	201903	421.9	48	
3162	272	201904	445.1	54	

Note: Trial data is the data of the stores on the trial period. It is where we are trying a new store layout and this data is where we are doing monthly_metrics of the analysis. The pretrial_store is the store we are using to just check and validate our results.

Seperating trial and potential control stores

Trial Stores 76,86,88, Now we have to figure out the control stores. The way of figuring out the control store is to calculate H0w correlated the performance of each store is to the trial store.

In [19]:
```
trial_stores_trial_data=trial_data[trial_data['STORE_NBR'].isin([77,86
trial_stores_trial_data.head()
```

Out[19]:

	STORE_NBR	MONTH_ID	TOTAL_SALES	NUMBER_CUSTOMERS	TOTAL_TI
887	77	201902	211.6	40	
888	77	201903	255.1	46	
889	77	201904	258.1	47	
984	86	201902	872.8	105	
985	86	201903	945.4	108	

In [20]:
```
trial_stores_pretrial_data=pre_trial_data[pre_trial_data['STORE_NBR'].
trial_stores_pretrial_data.head()
```

Out[20]:

	STORE_NBR	MONTH_ID	TOTAL_SALES	NUMBER_CUSTOMERS	TOTAL_TI
880	77	201807	268.4	47	
881	77	201808	247.5	46	
882	77	201809	216.8	40	
883	77	201810	194.3	36	
884	77	201811	224.9	39	

In [21]:
```
Potential_control_stores=pre_trial_data[~pre_trial_data['STORE_NBR'].i
```

In [22]:
```
Potential_control_stores
```

Out[22]:

	STORE_NBR	MONTH_ID	TOTAL_SALES	NUMBER_CUSTOMERS	TOTAL_T
0	1	201807	188.9	47	
1	1	201808	168.4	41	
2	1	201809	268.1	57	
3	1	201810	175.4	39	
4	1	201811	184.8	44	
...	...	...	...	...	
3155	272	201809	294.5	31	
3156	272	201810	405.1	41	
3157	272	201811	355.8	39	
3158	272	201812	363.1	43	
3159	272	201901	392.4	44	

1792 rows × 9 columns

Finding the twin (control store)

Metrics: Transactions per customers [TXN_PER_CUSTOMERS]

Monthly overall sales revnue[TOTAL_SALES]

Monthly_overall_customers[NUMBER_CUSTOMERS]

Correlation

In [23]:

```
def find_control_stores(trial_stores_pretrial_data,potential_control_s
    """
    Find the best control stores for each trial store based on correla

    Parameters:
    trial_stores_pretrial_data: Dataframe
    Pre_trial data for trial stores(77,86,88)

    potential_control_stores: DataFrame
    Pre_trial data for all non_trial stores

    visualize=True
    It calls the visualize_correlation function

    Returns:
    DataFrame with control store recommendation for each trial_stores
    """
```

```
trial_stores=[77,86,88]
metrics=['TOTAL_SALES','NUMBER_CUSTOMERS','TXN_PER_CUSTOMERS']

potential_control_stores_list=potential_control_stores['STORE_NBR'

#store all results
all_results=[]

for trial_store in trial_stores:
   # print(f"\n{'='*70}")
    #print(f"Finding control stores for trial store {trial_store}"
    #print(f"\n{'='*70}")

    trial_data=trial_stores_pretrial_data[
        trial_stores_pretrial_data['STORE_NBR']==trial_store].sort

    #store correlations for each control stores
    store_correlations={}

    for control_store in potential_control_stores_list:
        #Getting the control store data
        control_data=potential_control_stores[
            potential_control_stores['STORE_NBR']==control_store
        ].sort_values('MONTH_ID').reset_index(drop=True)

        #store correlation for each metrics:
        correlations={}


        for metric in metrics:
            #MERGE on Month_ID
            trial_metric=trial_data[['MONTH_ID',metric]].rename(co
            control_metric=control_data[['MONTH_ID',metric]].renam
            merged=trial_metric.merge(control_metric, on='MONTH_ID

            #calculate correlation
            if len(merged)>=2:
                if merged['trial'].std()>0 and merged['control'].s
                    corr=merged['trial'].corr(merged['control'])
                    correlations[metric]=corr
                else:
                    correlations[metric]=None

        #Calculate the average correlation of all metrics

        valid_corrs=[va for va in correlations.values() if va is n
        if valid_corrs:
            avg_corr=sum(valid_corrs)/len(valid_corrs)
            store_correlations[control_store]={
                'corr_sales':correlations['TOTAL_SALES'],
                'corr_customers':correlations['NUMBER_CUSTOMERS'],
                'corr_txn':correlations['TXN_PER_CUSTOMERS'],
```

```
                    'avg_correlation':avg_corr
                }
        #convert to Dataframe
        corr_df=pd.DataFrame.from_dict(store_correlations,orient='inde
        corr_df['CONTROL_STORE']=corr_df.index
        corr_df=corr_df.reset_index(drop=True)

        corr_df=corr_df.sort_values('avg_correlation',ascending=False)

        corr_df['TRIAL_STORE']=trial_store

        #Reorder columns
        corr_df=corr_df[['TRIAL_STORE','CONTROL_STORE','corr_sales','c

        #print(f"\nTop 3  control store candidates:")
        #print(corr_df.head(3).to_string(index=False))



        #STORE RESULTS
        all_results.append(corr_df)

    final_results=pd.concat(all_results,ignore_index=True)

    if visualize:
        visualize_correlations(final_results)

    return final_results
```

In [24]:

```
def visualize_correlations(final_results):
    """
    It is an internal function to create correlation visualization for
    Parameter:
    final_results: DataFrame
    """
    trial_stores=final_results['TRIAL_STORE'].unique()
    fig,axes=plt.subplots(len(trial_stores),1,figsize=(10,5*len(trial_

    for idx,trial_store in enumerate(trial_stores):
        # Filter data for this trial store
        trial_data=final_results[final_results['TRIAL_STORE']==trial_s

        #Get top stores
        top_stores=trial_data.nlargest(3,'avg_correlation')

        # Prepare the data for heatmap
        heatmap_data=top_stores[['corr_sales','corr_customers','corr_t
        heatmap_data.columns=[f"Store {int(x)}" for x in top_stores['C
```

```
        heatmap_data.index=['Sales','Customers','Txn/Customer']

        #empty row with Nan values that will be masked
        spacer_row=pd.DataFrame([[np.nan]*len(heatmap_data.columns)],
                                columns=heatmap_data.columns,
                                index=[''])

        #add average correlations as a row
        avg_row=pd.DataFrame([top_stores['avg_correlation'].values],
                             columns=heatmap_data.columns,
                             index=['Avg Correlation'])

        heatmap_data=pd.concat([heatmap_data,spacer_row,avg_row])

        #create mask for the spacer row only
        mask= pd.DataFrame(False,index=heatmap_data.index,columns=heat
        mask.loc['']= True

        #Ensure no Nan or None values
        heatmap_data=heatmap_data.fillna(0)

        # create heatmap
        ax=axes[idx]
        sns.heatmap(heatmap_data,annot=True, cmap='RdYlGn', vmin=-1, v
                    cbar_kws={'label':'Correlation Coefficient' }, ax=
                    linecolor='white',mask=mask)


        # Add a H0rizontal line to seperate average from individual st
        ax.hlines([3],*ax.get_xlim(),colors='black',linewidth=3)
        ax.set_title(f'Trial store:{trial_store}-- Top 3 Control Store
        ax.set_ylabel('Metrics', fontsize=11)
        ax.set_xlabel('Control Store Number', fontsize=11)

    plt.tight_layout()
    plt.show()
```

In [25]:

```
results_corr=find_control_stores(trial_stores_pretrial_data,Potential_
results_corr
```


Trial store:77-- Top 3 Control Stores by Correlation
Metrics
Sales
Customers
Txn/Customer
Avg Correlation
0.78
0.67
0.86
0.92
0.85
0.81
0.57
0.54
0.35
0.76
0.69
0.67
Store 119
Store 84
Store 162
Control Store Number
Correlation Coefficient
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00


Trial store:86-- Top 3 Control Stores by Correlation
Metrics
Sales
Customers
Txn/Customer
Avg Correlation
0.58
0.8
0.83
0.76
0.62
0.75
0.79
0.69
0.51
0.71
0.7
0.7
Store 176
Store 138
Store 260
Control Store Number
Correlation Coefficient
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00


Trial store:88-- Top 3 Control Stores by Correlation
Metrics
Sales
Customers
Txn/Customer
Avg Correlation
0.48
0.87
0.94
0.97
0.46
0.25
0
0
0
0.72
0.67
0.59
Store 14
Store 204
Store 159
Control Store Number
Correlation Coefficient
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00

Out[25]:

	TRIAL_STORE	CONTROL_STORE	corr_sales	corr_customers	corr_txn
0	77	119	0.775571	0.919064	0.571447
1	77	84	0.666157	0.851521	0.543934
2	77	162	0.857584	0.811532	0.345759
3	77	3	0.660447	0.755249	0.424751
4	77	233	0.973643	0.965682	-0.162093
...	...	...	...	...	...
763	88	8	-0.634070	-0.377091	-0.484478
764	88	270	-0.695938	-0.074695	-0.892528
765	88	175	-0.831593	-0.368608	-0.476383
766	88	23	-0.891573	-0.157431	-0.732566
767	88	133	-0.627136	-0.571400	-0.822184

768 rows × 6 columns

Best Matched control store for each trial store

In [26]:

```
best_match=results_corr.groupby('TRIAL_STORE').first().reset_index()
best_match
```

Out[26]:

	TRIAL_STORE	CONTROL_STORE	corr_sales	corr_customers	corr_txn	avg
0	77	119	0.775571	0.919064	0.571447	
1	86	176	0.582468	0.756402	0.794317	
2	88	14	0.479135	0.967364	0.386764	

In [27]:

```
print(best_match[['TRIAL_STORE','CONTROL_STORE','avg_correlation']].to
```

```
TRIAL_STORE  CONTROL_STORE  avg_correlation
         77            119         0.755361
         86            176         0.711063
         88             14         0.723249
```

Absolute Difference

In [28]:

```
def calculate_magnitude_difference(trial_stores_pretrial_data,potentia
    """
    Finding the best control stores for each trial store based on the
    Flow:
```

```
    Find the value difference between different values of the metrics
    and controlled stored, then normalize it and then give the value,
    magnitude of the difference

    Parameters:
    trial_stores_pretrial_data: DataFrame
    pre_trial data for trial stores(77,86,88)

    potential_control_stores: DataFrame
    pre_trial data for all non_trial stores

    Returns: DataFrame
    Control store recommendation for each trial_store based on magnitu

    Visualization
    """
    trial_stores=[77,86,88]
    metrics=['TOTAL_SALES','NUMBER_CUSTOMERS','TXN_PER_CUSTOMERS']

    potential_control_stores_list=potential_control_stores['STORE_NBR'

    #Store allresults
    complete_results=[]

    for trial_store in trial_stores:
        #print(f"\n{"="*100}")
        #print(f"Finding control stores for each trial store {trial_st
        #print(f"\n{"="*100}")

        trial_data=trial_stores_pretrial_data[
                    trial_stores_pretrial_data['STORE_NBR']==trial_sto

        #First Pass: collect all differences for normalizaiton
        all_diffs_by_metric={}
        control_store_raw_diffs={}

        for metric in metrics:
            all_diffs_by_metric[metric]=[]

            #control store
            for control_store in potential_control_stores_list:
                control_data=potential_control_stores[
                            potential_control_stores['STORE_NBR']==con
                            ].sort_values('MONTH_ID').reset_index(drop

                #Merge on MONTH_ID
                trial_metric=trial_data[['MONTH_ID',metric]].rename(co
                control_metric=control_data[['MONTH_ID',metric]].renam
                merged=trial_metric.merge(control_metric,on='MONTH_ID'

                if len(merged)>0:
                    merged['abs_diff']=abs(merged['trial']-merged['con
```

```
                #store for this control store
                if control_store not in control_store_raw_diffs:
                    control_store_raw_diffs[control_store]={}
                control_store_raw_diffs[control_store][metric]=mer

                #Collect all the differences for this metric
                all_diffs_by_metric[metric].extend(merged['abs_dif
                #extend helps to put all the data in one scale and
                #individual items not as an entire list of one ite


        #Second Pass: Normalize and calculate distances
        store_distances={}
        for control_store in potential_control_stores_list:
            if control_store not in control_store_raw_diffs:
                continue

            #store normalized distances for each metric
            distances={}

            for metric in metrics:
                if metric in control_store_raw_diffs[control_store]:
                    store_diffs= control_store_raw_diffs[control_store

                    # Get min and max for this metric across all store
                    min_diff=min(all_diffs_by_metric[metric])
                    max_diff=max(all_diffs_by_metric[metric])

                    #Normalize:(value-min)/(max-min)

                    if max_diff > min_diff:
                        store_diffs['normalized']=(store_diffs['abs_di
                    else:
                        store_diffs['normalized']=0

                    # Average normalized distance across all months
                    avg_normalized_dist=store_diffs['normalized'].mean
                    distances[metric]=avg_normalized_dist
                else:
                    distances[metric]=None

            valid_dists=[va for va in distances.values() if va is not

            if valid_dists:
                avg_dist=sum(valid_dists)/len(valid_dists)
                store_distances[control_store]={
                    'dist_sales':distances['TOTAL_SALES'],
                    'dist_customers':distances['NUMBER_CUSTOMERS'],
                    'dist_txn':distances['TXN_PER_CUSTOMERS'],
                    'avg_magnitude_distance': avg_dist
                }
```

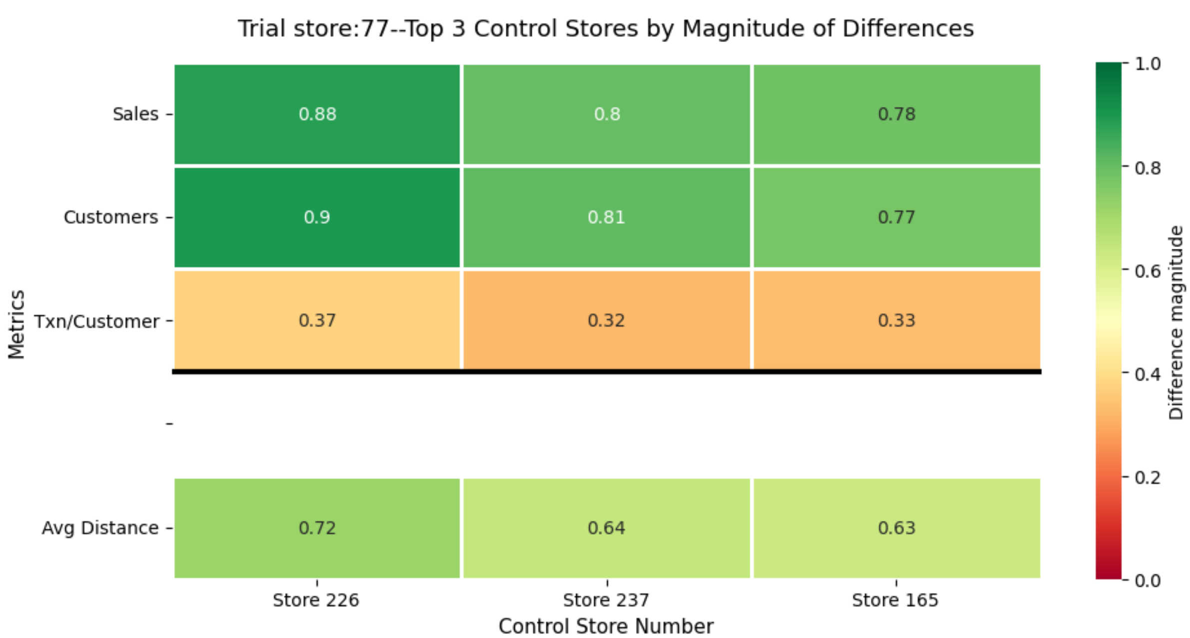
```
        #Convert to DataFrame
        dist_df=pd.DataFrame.from_dict(store_distances,orient='index')
        dist_df['CONTROL_STORE']=dist_df.index
        dist_df=dist_df.reset_index(drop=True)
        dist_df=dist_df.sort_values('avg_magnitude_distance',ascending
        dist_df['TRIAL_STORE']=trial_store

        #Reordering the columns
        dist_df=dist_df[['TRIAL_STORE','CONTROL_STORE','dist_sales','d
                         'dist_txn','avg_magnitude_distance']]

        #print(f"\n Top 3 control store candidates (smallest distance)
        #print(dist_df.head(3).to_string(index=False))

        #store results
        complete_results.append(dist_df)

    complete_results = pd.concat(complete_results, ignore_index=True)

    if visualize:
        visualize_differences(complete_results)

    return complete_results
```

In [29]:

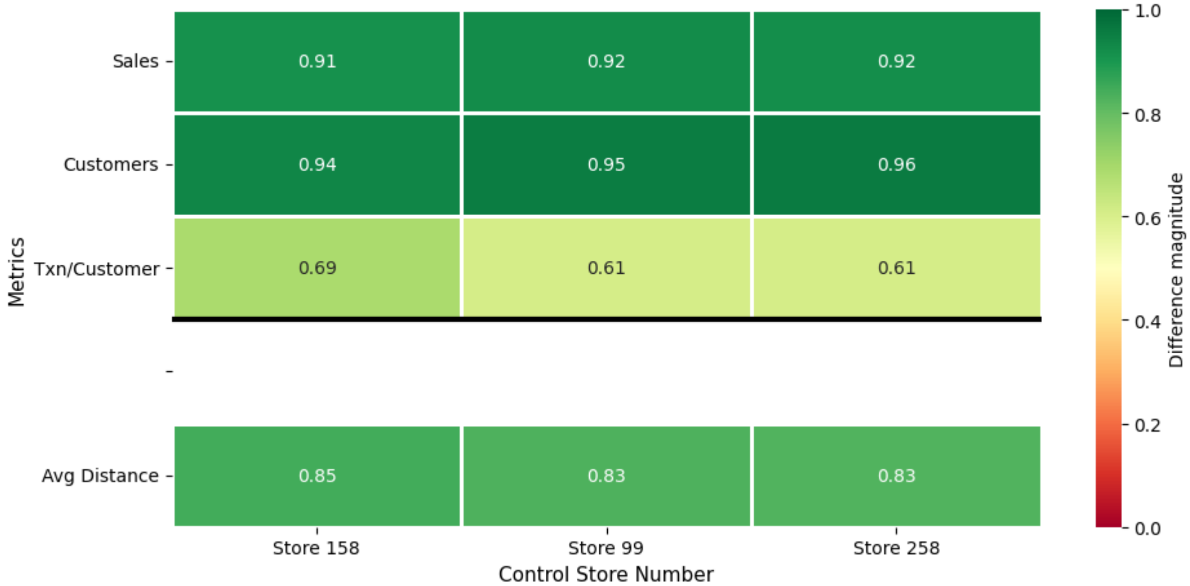
```
def visualize_differences(complete_results):
    """
    It is an internal function to create differnces visualization for
    Parameter
    complete_results: DataFrame
    """
    trial_stores=complete_results['TRIAL_STORE'].unique()
    fig,axes=plt.subplots(len(trial_stores),1,figsize=(10,5*len(trial_

    for idx,trial_store in enumerate(trial_stores):
        # Filter data for this trial store
        trial_data=complete_results[complete_results['TRIAL_STORE']==t

        #Get top_stores
        top_stores=trial_data.nlargest(3,'avg_magnitude_distance')

        # Prepare the data for the heatmap
        heatmap_data=top_stores[['dist_sales','dist_customers','dist_t
        heatmap_data.columns=[f"Store {int(x)}" for x in top_stores['C
        heatmap_data.index=['Sales','Customers','Txn/Customer']

        #spacer row
        spacer_row=pd.DataFrame([[np.nan]*len(heatmap_data.columns)],
                                columns=heatmap_data.columns,
                                index=[''])

        #add average magnitude distance as a row
```

```
        avg_row=pd.DataFrame([top_stores['avg_magnitude_distance'].val
                             columns=heatmap_data.columns,
                             index=['Avg Distance'])

        heatmap_data=pd.concat([heatmap_data,spacer_row,avg_row])

        # creating a mask for spacer row
        mask=pd.DataFrame(False,index=heatmap_data.index,columns=heatm
        mask.loc['']=True

        # Ensure no Nan or None values
        heatmap_data=heatmap_data.fillna(0)

        # create heatmap
        ax=axes[idx]
        sns.heatmap(heatmap_data,annot=True, cmap='RdYlGn',vmin=0,vmax
                    cbar_kws={'label':'Difference magnitude'},ax=ax, l
                    linecolor='white',mask=mask)

        #Add a H0rizontal line to seperate
        ax.hlines([3],*ax.get_xlim(),colors='black',linewidth=3)
        ax.set_title(f'Trial store:{trial_store}--Top 3 Control Stores
        ax.set_ylabel('Metrics',fontsize=11)
        ax.set_xlabel('Control Store Number', fontsize=11)

    plt.tight_layout()
    plt.show()
```

In [30]:
```
results_diff=calculate_magnitude_difference(trial_stores_pretrial_data
results_diff
```



Trial store:88--Top 3 Control Stores by Magnitude of Differences



Out[30]:

	TRIAL_STORE	CONTROL_STORE	dist_sales	dist_customers	dist_txn	a
0	77	233	0.013298	0.008487	0.093993	
1	77	176	0.033114	0.060820	0.056273	
2	77	46	0.024989	0.039604	0.089402	
3	77	145	0.055457	0.042433	0.057358	
4	77	111	0.034755	0.045262	0.082460	
...	...	...	...	...	...	
763	88	146	0.918106	0.951220	0.607083	
764	88	198	0.919323	0.955865	0.607083	
765	88	258	0.918159	0.958188	0.607083	
766	88	99	0.923757	0.953542	0.607083	
767	88	158	0.913640	0.937282	0.688715	

768 rows × 6 columns

Merger of Correlation and Magnitude

In [31]:

```
corr_results=find_control_stores(trial_stores_pretrial_data,Potential_
corr_results
```

Out[31]:

	TRIAL_STORE	CONTROL_STORE	corr_sales	corr_customers	corr_txn
0	77	119	0.775571	0.919064	0.571447
1	77	84	0.666157	0.851521	0.543934
2	77	162	0.857584	0.811532	0.345759
3	77	3	0.660447	0.755249	0.424751
4	77	233	0.973643	0.965682	-0.162093
...	...	...	...	...	...
763	88	8	-0.634070	-0.377091	-0.484478
764	88	270	-0.695938	-0.074695	-0.892528
765	88	175	-0.831593	-0.368608	-0.476383
766	88	23	-0.891573	-0.157431	-0.732566
767	88	133	-0.627136	-0.571400	-0.822184

768 rows × 6 columns

In [32]:

```
magnitude_results=calculate_magnitude_difference(trial_stores_pretrial
magnitude_results
```

Out[32]:

	TRIAL_STORE	CONTROL_STORE	dist_sales	dist_customers	dist_txn	a
0	77	233	0.013298	0.008487	0.093993	
1	77	176	0.033114	0.060820	0.056273	
2	77	46	0.024989	0.039604	0.089402	
3	77	145	0.055457	0.042433	0.057358	
4	77	111	0.034755	0.045262	0.082460	
...	...	...	...	...	...	
763	88	146	0.918106	0.951220	0.607083	
764	88	198	0.919323	0.955865	0.607083	
765	88	258	0.918159	0.958188	0.607083	
766	88	99	0.923757	0.953542	0.607083	
767	88	158	0.913640	0.937282	0.688715	

768 rows × 6 columns

In [33]:

```
corr_mag_df=corr_results.merge(magnitude_results,on=['TRIAL_STORE','CO
```

```
corr_mag_df
```

Out[33]:

	TRIAL_STORE	CONTROL_STORE	corr_sales	corr_customers	corr_txn
0	77	119	0.775571	0.919064	0.571447
1	77	84	0.666157	0.851521	0.543934
2	77	162	0.857584	0.811532	0.345759
3	77	3	0.660447	0.755249	0.424751
4	77	233	0.973643	0.965682	-0.162093
...	...	...	...	...	...
763	88	8	-0.634070	-0.377091	-0.484478
764	88	270	-0.695938	-0.074695	-0.892528
765	88	175	-0.831593	-0.368608	-0.476383
766	88	23	-0.891573	-0.157431	-0.732566
767	88	133	-0.627136	-0.571400	-0.822184

768 rows × 10 columns

Note: The measurement of goodness is in opposite direction in the case of correlation and in the case of magnitude of differences

i.e. In correlation the value close to 1 is considered is considered great, whereas in the magnitude of differences its considered bad

and The scale of measurement is also different
Correlation: -1 to 1 Magnitude_difference: 0-1 Hence Normalization is very essential here

In [34]:

```
corr_mag_df['corr_normalized']=(corr_mag_df['avg_correlation']+1)/2
"""
Original Correlation                        Normalized Correlation
-1 <- worst                                 0 <- Worst
0<- No correlation                          0.5 <- No correlation
+1 <-- Best Correaltion                     +1 <- Best correlation

"""

corr_mag_df['dist_normalized']=1-corr_mag_df['avg_magnitude_distance']

#Both are now on [0,1] scale where higher=better
corr_mag_df['combined_score']=(corr_mag_df['corr_normalized']+
                               corr_mag_df['dist_normalized'])/2
```

In [35]:
```
corr_mag_df.head()
```

Out[35]:

	TRIAL_STORE	CONTROL_STORE	corr_sales	corr_customers	corr_txn	avg
0	77	119	0.775571	0.919064	0.571447	
1	77	84	0.666157	0.851521	0.543934	
2	77	162	0.857584	0.811532	0.345759	
3	77	3	0.660447	0.755249	0.424751	
4	77	233	0.973643	0.965682	-0.162093	

In [36]:
```
#selecting the control store based on highest combined_store
control_stores_of_trial_stores=corr_mag_df.sort_values(['TRIAL_STORE',
                                                        ascending=[True
```

In [37]:
```
print(control_stores_of_trial_stores[['TRIAL_STORE','CONTROL_STORE','c
```

```
   TRIAL_STORE  CONTROL_STORE  combined_score
0           77            233        0.878806
1           86            138        0.886573
2           88            201        0.810178
```

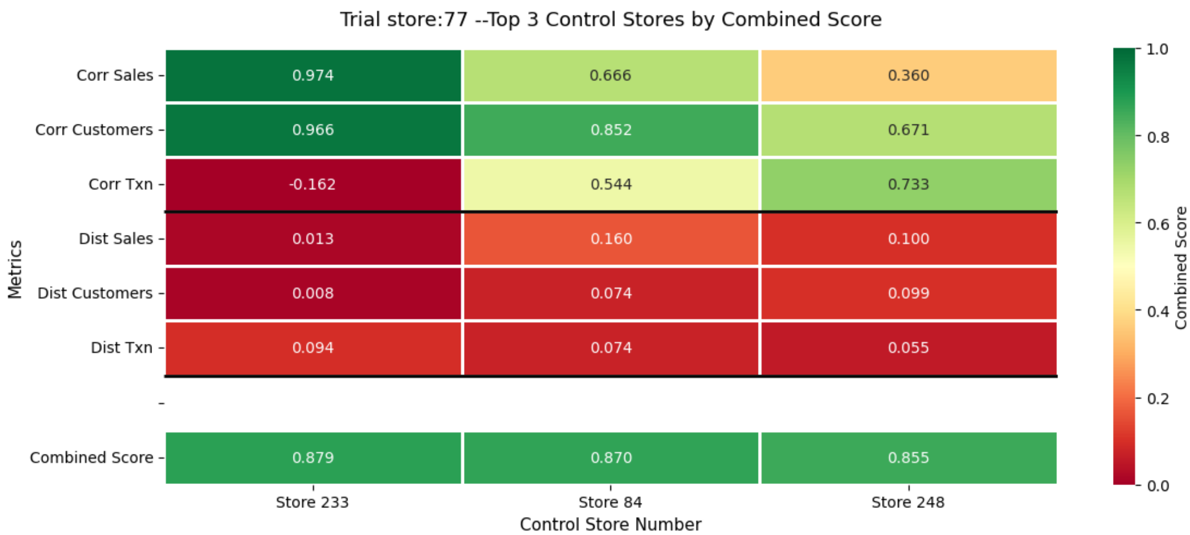
The twin (Control Store of)

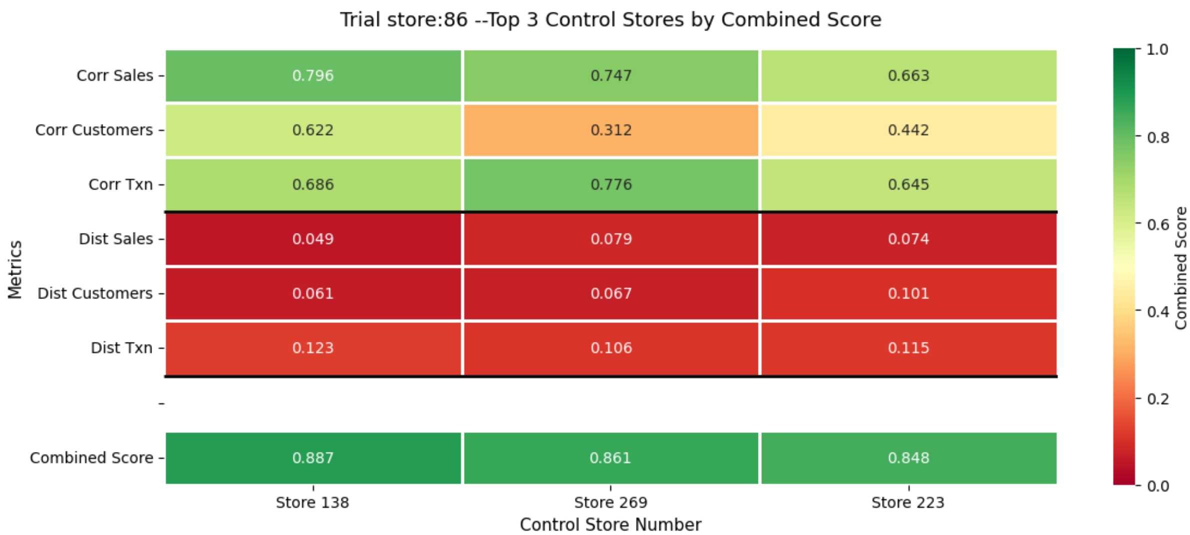
1. TRIAL STORE 77 -> STORE 233
2. TRIAL STORE 86 --> STORE 138
3. TRIAL STORE 88 --> STORE 201

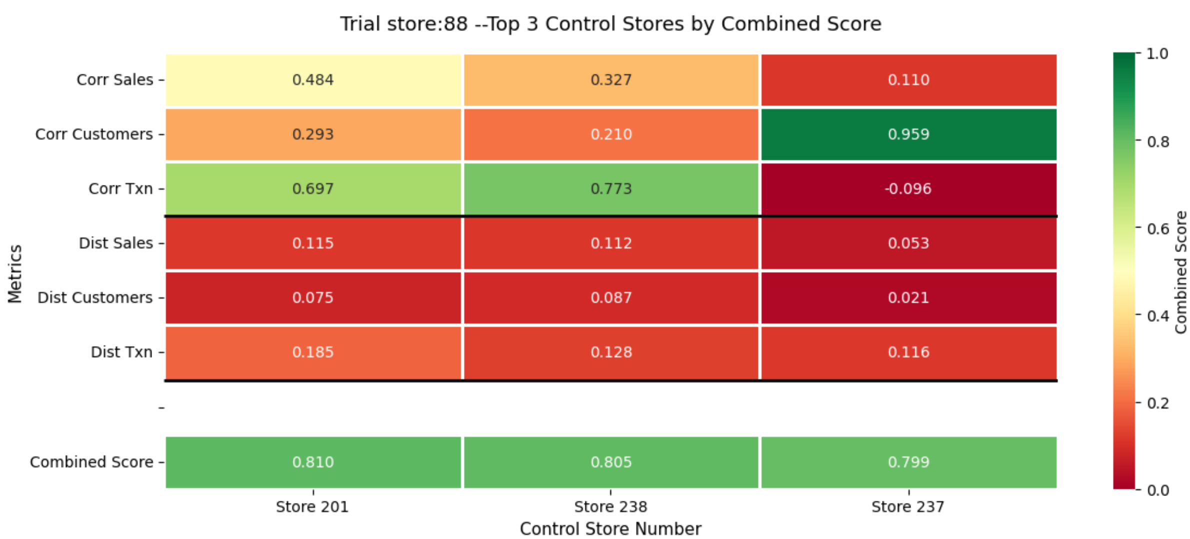
VISUALIZING THE COMBINED SCORE

In [38]:
```
trial_stores=corr_mag_df['TRIAL_STORE'].unique()
fig,axes=plt.subplots(len(trial_stores),1,figsize=(12, 5*len(trial_sto

for idx,trial_store in enumerate(trial_stores):
    trial1_data=corr_mag_df[corr_mag_df['TRIAL_STORE']==trial_store].c
    top_stores=trial1_data.nlargest(3,'combined_score')

    heatmap_data=top_stores[['corr_sales','corr_customers','corr_txn',
    heatmap_data.columns=[f"Store {int(x)}" for x in top_stores['CONTR
    heatmap_data.index=['Corr Sales','Corr Customers','Corr Txn','Dist
                        'Dist Customers','Dist Txn']

    spacer_row=pd.DataFrame([[np.nan]*len(heatmap_data.columns)],
```

```
                                columns=heatmap_data.columns,
                                index=[''])

    # Add combined score as a row
    combined_row=pd.DataFrame([top_stores['combined_score'].values],
                                columns=heatmap_data.columns,
                                index=['Combined Score'])

    heatmap_data=pd.concat([heatmap_data,spacer_row,combined_row])

    # creating a mask for spacer row
    mask=pd.DataFrame(False, index=heatmap_data.index,columns=heatmap_
    mask.loc['']=True

    # Create heatmap
    ax=axes[idx]
    sns.heatmap(heatmap_data,annot=True, fmt='.3f',cmap='RdYlGn', vmin
                cbar_kws={'label':'Combined Score'},ax=ax, linewidths=

    # Add H0rizontal lines to seperate sections
    ax.hlines([3,6],*ax.get_xlim(),colors='black',linewidth=2)
    ax.set_title(f'Trial store:{trial_store} --Top 3 Control Stores by
    ax.set_ylabel('Metrics', fontsize=11)
    ax.set_xlabel('Control Store Number', fontsize=11)
plt.tight_layout()
plt.show()
```







Checking the pre trial data of store 77 and store 233 to see H0w close it is

In [39]:
```
store_77=pre_trial_data[pre_trial_data['STORE_NBR']==77][['MONTH_ID','
store_77=store_77.rename(columns={'TOTAL_SALES':'77_TOTAL_SALES','NUMB
store_77
```

Out[39]:

	MONTH_ID	77_TOTAL_SALES	77_NUMBER_CUSTOMERS	77_TOTAL_TRAN
880	201807	268.4	47	
881	201808	247.5	46	
882	201809	216.8	40	
883	201810	194.3	36	
884	201811	224.9	39	
885	201812	255.2	43	
886	201901	188.4	31	

In [40]:
```
store_233=pre_trial_data[pre_trial_data['STORE_NBR']==233][['MONTH_ID'
store_233=store_233.rename(columns={'TOTAL_SALES':'233_TOTAL_SALES','N
store_233
```

Out[40]:

	MONTH_ID	233_TOTAL_SALES	233_NUMBER_CUSTOMERS	233_TOTAL_
2695	201807	271.2	47	
2696	201808	260.7	44	
2697	201809	220.9	40	
2698	201810	159.3	32	
2699	201811	206.5	39	
2700	201812	265.4	43	
2701	201901	150.5	31	

In [41]:
```
store_77_233=store_77.merge(store_233,on='MONTH_ID',how='inner')
store_77_233['MONTH_ID']=pd.to_datetime(store_77_233['MONTH_ID'],forma
store_77_233
```

Out[41]:

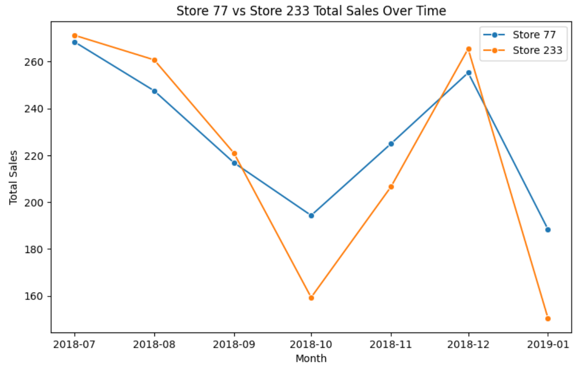
	MONTH_ID	77_TOTAL_SALES	77_NUMBER_CUSTOMERS	77_TOTAL_TRANSA(
0	2018-07-01	268.4	47	
1	2018-08-01	247.5	46	
2	2018-09-01	216.8	40	
3	2018-10-01	194.3	36	
4	2018-11-01	224.9	39	
5	2018-12-01	255.2	43	
6	2019-01-01	188.4	31	

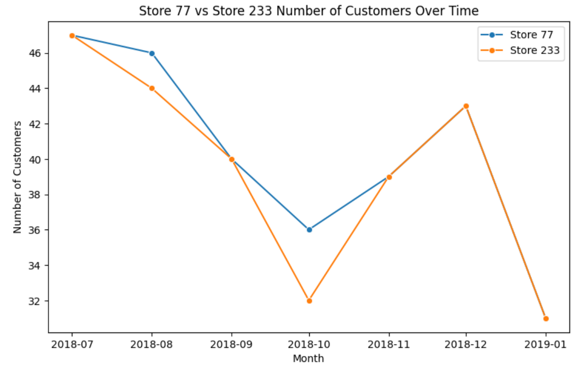
In [42]:

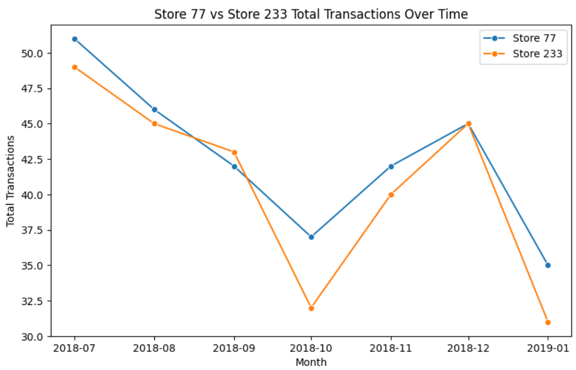
```
fig, axes=plt.subplots(2,2,figsize=(20,12))
ax=axes.flatten()
sns.lineplot(data=store_77_233, x='MONTH_ID', y='77_TOTAL_SALES', mark
sns.lineplot(data=store_77_233, x='MONTH_ID', y='233_TOTAL_SALES', mar
ax[0].set_xlabel('Month')
ax[0].set_ylabel('Total Sales')
ax[0].set_title('Store 77 vs Store 233 Total Sales Over Time')
ax[0].legend()

sns.lineplot(data=store_77_233, x='MONTH_ID', y='77_NUMBER_CUSTOMERS',
sns.lineplot(data=store_77_233, x='MONTH_ID', y='233_NUMBER_CUSTOMERS'
ax[1].set_xlabel('Month')
ax[1].set_ylabel('Number of Customers')
ax[1].set_title('Store 77 vs Store 233 Number of Customers Over Time')
ax[1].legend()

sns.lineplot(data=store_77_233, x='MONTH_ID', y='77_TOTAL_TRANSACTIONS
sns.lineplot(data=store_77_233, x='MONTH_ID', y='233_TOTAL_TRANSACTION
ax[2].set_xlabel('Month')
ax[2].set_ylabel('Total Transactions')
ax[2].set_title('Store 77 vs Store 233 Total Transactions Over Time')
ax[2].legend()

ax[3].set_visible(False)
plt.suptitle('METRICS COMPARISION OF STORE 77 & STORE 233',fontsize='1
```

Out[42]: `Text(0.5, 0.98, 'METRICS COMPARISION OF STORE 77 & STORE 233')`

METRICS COMPARISION OF STORE 77 & STORE 233







Checking the pre trial data of store 86 and store 138 to see H0w close it is

In [43]:
```
store_86=pre_trial_data[pre_trial_data['STORE_NBR']==86][['MONTH_ID','
store_86=store_86.rename(columns={'TOTAL_SALES':'86_TOTAL_SALES','NUMB
store_86
```

Out[43]:

	MONTH_ID	86_TOTAL_SALES	86_NUMBER_CUSTOMERS	86_TOTAL_TRAI
977	201807	851.00	94	
978	201808	726.85	92	
979	201809	855.00	100	
980	201810	898.80	105	
981	201811	851.20	95	
982	201812	812.20	93	
983	201901	800.60	89	

In [44]:
```
store_138=pre_trial_data[pre_trial_data['STORE_NBR']==138][['MONTH_ID'
store_138=store_138.rename(columns={'TOTAL_SALES':'138_TOTAL_SALES','N
store_138
```

Out[44]:

	MONTH_ID	138_TOTAL_SALES	138_NUMBER_CUSTOMERS	138_TOTAL_T
1588	201807	778.2	87	
1589	201808	660.3	81	
1590	201809	869.8	108	
1591	201810	910.8	103	
1592	201811	906.4	101	
1593	201812	806.4	97	
1594	201901	880.0	95	

In [45]:

```
store_86_138=store_86.merge(store_138,on='MONTH_ID',how='inner')
store_86_138['MONTH_ID']=pd.to_datetime(store_86_138['MONTH_ID'],forma
store_86_138
```

Out[45]:

	MONTH_ID	86_TOTAL_SALES	86_NUMBER_CUSTOMERS	86_TOTAL_TRANS
0	2018-07-01	851.00	94	
1	2018-08-01	726.85	92	
2	2018-09-01	855.00	100	
3	2018-10-01	898.80	105	
4	2018-11-01	851.20	95	
5	2018-12-01	812.20	93	
6	2019-01-01	800.60	89	

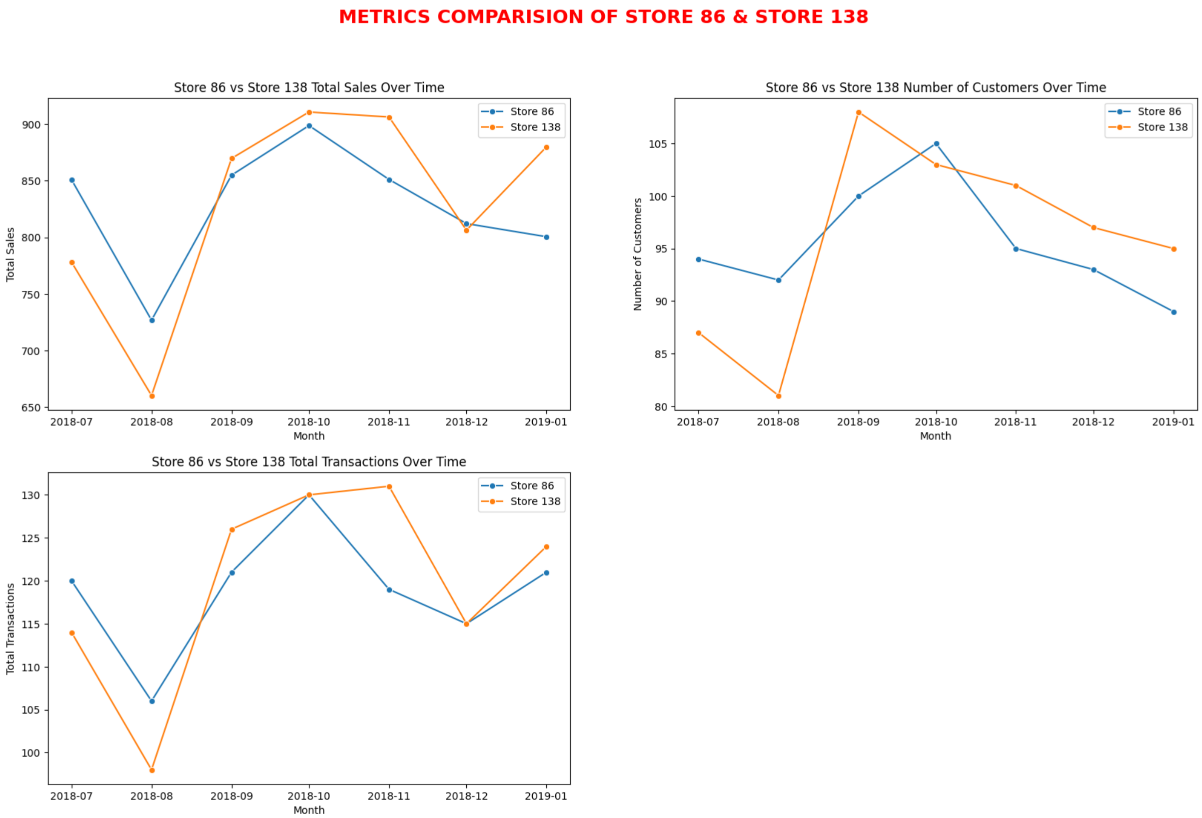
In [46]:

```
fig, axes=plt.subplots(2,2,figsize=(20,12))
ax=axes.flatten()
sns.lineplot(data=store_86_138, x='MONTH_ID', y='86_TOTAL_SALES', mark
sns.lineplot(data=store_86_138, x='MONTH_ID', y='138_TOTAL_SALES', mar
ax[0].set_xlabel('Month')
ax[0].set_ylabel('Total Sales')
ax[0].set_title('Store 86 vs Store 138 Total Sales Over Time')
ax[0].legend()

sns.lineplot(data=store_86_138, x='MONTH_ID', y='86_NUMBER_CUSTOMERS',
sns.lineplot(data=store_86_138, x='MONTH_ID', y='138_NUMBER_CUSTOMERS'
ax[1].set_xlabel('Month')
ax[1].set_ylabel('Number of Customers')
ax[1].set_title('Store 86 vs Store 138 Number of Customers Over Time')
ax[1].legend()
```

```
sns.lineplot(data=store_86_138, x='MONTH_ID', y='86_TOTAL_TRANSACTIONS
sns.lineplot(data=store_86_138, x='MONTH_ID', y='138_TOTAL_TRANSACTION
ax[2].set_xlabel('Month')
ax[2].set_ylabel('Total Transactions')
ax[2].set_title('Store 86 vs Store 138 Total Transactions Over Time')
ax[2].legend()

ax[3].set_visible(False)
plt.suptitle('METRICS COMPARISION OF STORE 86 & STORE 138',fontsize='1
```

Out[46]:

```
Text(0.5, 0.98, 'METRICS COMPARISION OF STORE 86 & STORE 138')
```



Checking the pre trial data of store 88 and store 201 to see H0w close it is

In [47]:

```
store_88=pre_trial_data[pre_trial_data['STORE_NBR']==88][['MONTH_ID','
store_88=store_88.rename(columns={'TOTAL_SALES':'88_TOTAL_SALES','NUMB
store_88
```

Out[47]:

	MONTH_ID	88_TOTAL_SALES	88_NUMBER_CUSTOMERS	88_TOTAL_TRA
1001	201807	1218.2	124	
1002	201808	1242.2	125	
1003	201809	1361.8	121	
1004	201810	1270.8	120	
1005	201811	1311.4	123	
1006	201812	1213.0	120	
1007	201901	1215.4	115	

In [48]:
```
store_201=pre_trial_data[pre_trial_data['STORE_NBR']==201][['MONTH_ID'
store_201=store_201.rename(columns={'TOTAL_SALES':'201_TOTAL_SALES','N
store_201
```

Out[48]:

	MONTH_ID	201_TOTAL_SALES	201_NUMBER_CUSTOMERS	201_TOTAL_
2334	201807	1046.0	115	
2335	201808	1057.7	107	
2336	201809	1099.0	103	
2337	201810	1142.6	117	
2338	201811	1208.1	124	
2339	201812	1110.7	113	
2340	201901	1082.5	106	

In [49]:
```
store_88_201=store_88.merge(store_201,on='MONTH_ID',how='inner')
store_88_201['MONTH_ID']=pd.to_datetime(store_88_201['MONTH_ID'],forma
store_88_201
```

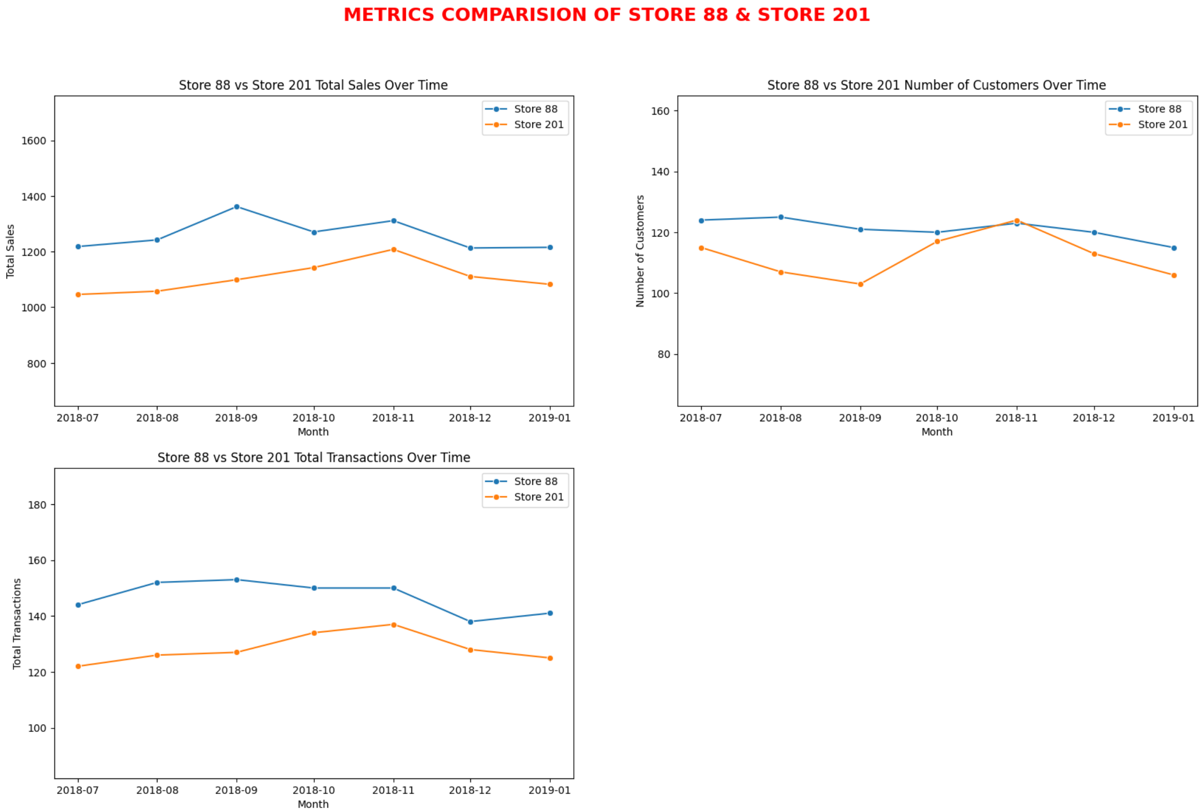
Out[49]:

	MONTH_ID	88_TOTAL_SALES	88_NUMBER_CUSTOMERS	88_TOTAL_TRANS
0	2018-07-01	1218.2	124	
1	2018-08-01	1242.2	125	
2	2018-09-01	1361.8	121	
3	2018-10-01	1270.8	120	
4	2018-11-01	1311.4	123	
5	2018-12-01	1213.0	120	
6	2019-01-01	1215.4	115	

In [50]:

```
fig, axes=plt.subplots(2,2,figsize=(20,12))
ax=axes.flatten()
sns.lineplot(data=store_88_201, x='MONTH_ID', y='88_TOTAL_SALES', mark
sns.lineplot(data=store_88_201, x='MONTH_ID', y='201_TOTAL_SALES', mar
ax[0].set_xlabel('Month')
ax[0].set_ylabel('Total Sales')
ax[0].set_title('Store 88 vs Store 201 Total Sales Over Time')
ax[0].legend()
sales_min = min(store_88_201['88_TOTAL_SALES'].min(), store_88_201['20
sales_max = max(store_88_201['88_TOTAL_SALES'].max(), store_88_201['20
ax[0].set_ylim(sales_min - 400, sales_max + 400)

sns.lineplot(data=store_88_201, x='MONTH_ID', y='88_NUMBER_CUSTOMERS',
sns.lineplot(data=store_88_201, x='MONTH_ID', y='201_NUMBER_CUSTOMERS'
ax[1].set_xlabel('Month')
ax[1].set_ylabel('Number of Customers')
ax[1].set_title('Store 88 vs Store 201 Number of Customers Over Time')
ax[1].legend()
customers_min = min(store_88_201['88_NUMBER_CUSTOMERS'].min(), store_8
customers_max = max(store_88_201['88_NUMBER_CUSTOMERS'].max(), store_8
ax[1].set_ylim(customers_min - 40, customers_max + 40)

sns.lineplot(data=store_88_201, x='MONTH_ID', y='88_TOTAL_TRANSACTIONS
sns.lineplot(data=store_88_201, x='MONTH_ID', y='201_TOTAL_TRANSACTION
ax[2].set_xlabel('Month')
ax[2].set_ylabel('Total Transactions')
ax[2].set_title('Store 88 vs Store 201 Total Transactions Over Time')
ax[2].legend()
txn_min = min(store_88_201['88_TOTAL_TRANSACTIONS'].min(), store_88_20
txn_max = max(store_88_201['88_TOTAL_TRANSACTIONS'].max(), store_88_20
ax[2].set_ylim(txn_min - 40, txn_max + 40)

ax[3].set_visible(False)
plt.suptitle('METRICS COMPARISION OF STORE 88 & STORE 201',fontsize='1
```

```
Out[50]: Text(0.5, 0.98, 'METRICS COMPARISION OF STORE 88 & STORE 201')
```



Conclusion: Visually all three control stores, decided by the combined store seems to be accurate.

Checking if the total sales, Number of Customers and Total Transactions Over time have increased in the trial store or not

Null Hypothesis: In trial period all the metrics of trial store will be similar to that of control stores.
Alternative Hypothesis: In Trial period, trial stores metrics will be greater than that of pre trial period.

STORE 77 AND 233

```
In [51]: store_77_trial=trial_data[trial_data['STORE_NBR']==77][['MONTH_ID','TO
         store_77_trial=store_77_trial.rename(columns={'TOTAL_SALES':'77_TOTAL_
```

```
store_77_trial
```

Out[51]:

	MONTH_ID	77_TOTAL_SALES	77_NUMBER_CUSTOMERS	77_TOTAL_TRAN
887	201902	211.6	40	
888	201903	255.1	46	
889	201904	258.1	47	

In [52]:
```
store_233_trial=trial_data[trial_data['STORE_NBR']==233][['MONTH_ID','
store_233_trial=store_233_trial.rename(columns={'TOTAL_SALES':'233_TOT
store_233_trial
```

Out[52]:

	MONTH_ID	233_TOTAL_SALES	233_NUMBER_CUSTOMERS	233_TOTAL_
2702	201902	220.7	42	
2703	201903	180.6	35	
2704	201904	144.2	27	

In [53]:
```
store_77_233_trial=store_77_trial.merge(store_233_trial,on='MONTH_ID',
store_77_233_trial['MONTH_ID']=pd.to_datetime(store_77_233_trial['MONT
store_77_233_trial
```

Out[53]:

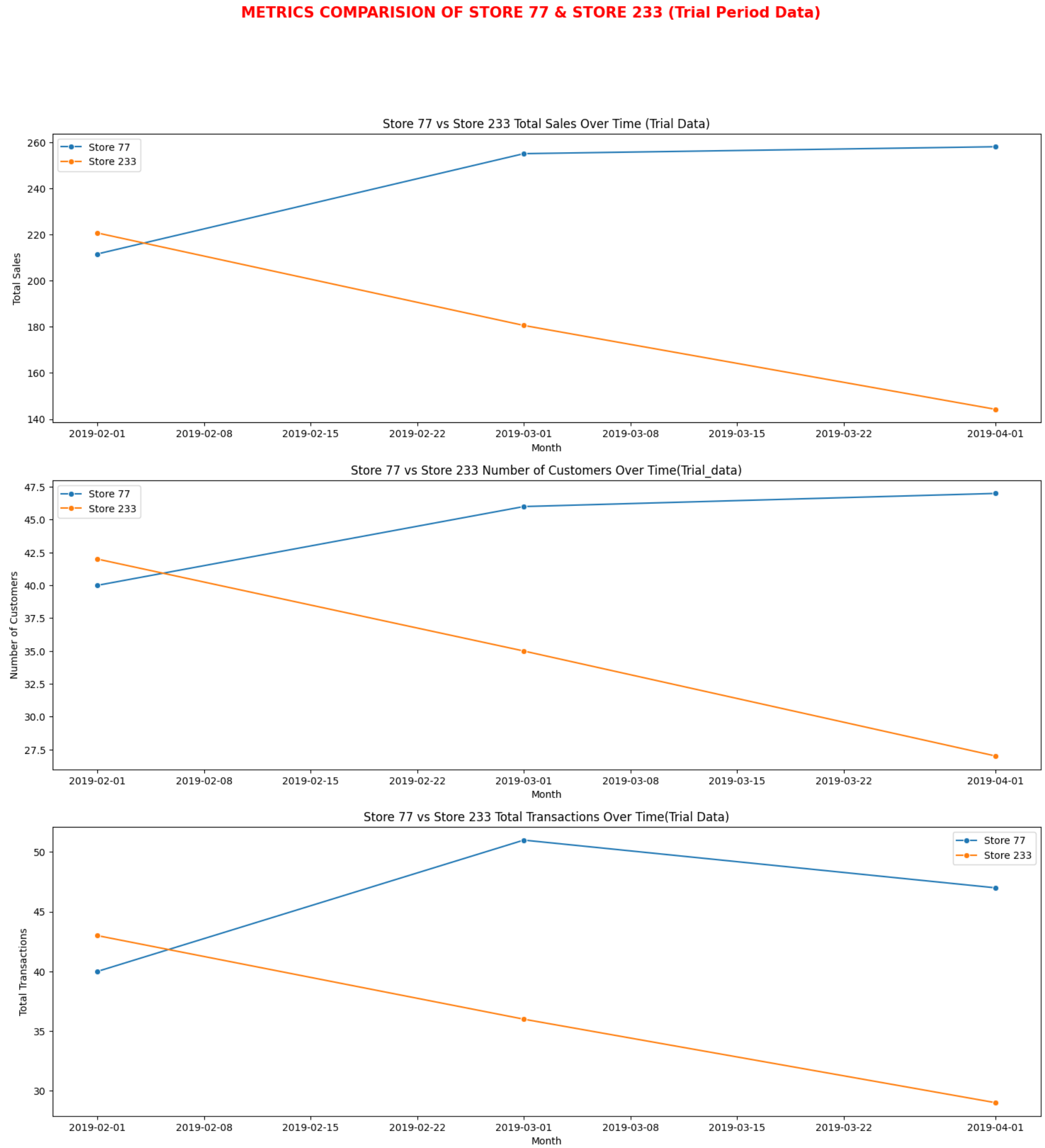
	MONTH_ID	77_TOTAL_SALES	77_NUMBER_CUSTOMERS	77_TOTAL_TRANSA
0	2019-02-01	211.6	40	
1	2019-03-01	255.1	46	
2	2019-04-01	258.1	47	

In [68]:
```
fig, axes=plt.subplots(3,1,figsize=(18,18))
ax=axes.flatten()
sns.lineplot(data=store_77_233_trial, x='MONTH_ID', y='77_TOTAL_SALES'
sns.lineplot(data=store_77_233_trial, x='MONTH_ID', y='233_TOTAL_SALES
ax[0].set_xlabel('Month')
ax[0].set_ylabel('Total Sales')
ax[0].set_title('Store 77 vs Store 233 Total Sales Over Time (Trial Da
ax[0].legend()

sns.lineplot(data=store_77_233_trial, x='MONTH_ID', y='77_NUMBER_CUSTO
sns.lineplot(data=store_77_233_trial, x='MONTH_ID', y='233_NUMBER_CUST
ax[1].set_xlabel('Month')
ax[1].set_ylabel('Number of Customers')
ax[1].set_title('Store 77 vs Store 233 Number of Customers Over Time(T
ax[1].legend()
```

```
sns.lineplot(data=store_77_233_trial, x='MONTH_ID', y='77_TOTAL_TRANSA
sns.lineplot(data=store_77_233_trial, x='MONTH_ID', y='233_TOTAL_TRANS
ax[2].set_xlabel('Month')
ax[2].set_ylabel('Total Transactions')
ax[2].set_title('Store 77 vs Store 233 Total Transactions Over Time(Tr
ax[2].legend()


plt.suptitle('METRICS COMPARISION OF STORE 77 & STORE 233 (Trial Perio
```

Out[68]:

```
Text(0.5, 0.98, 'METRICS COMPARISION OF STORE 77 & STORE 233 (Trial P
eriod Data)')
```



Visually the new format seem to work.

Lets back this visualization statistically

In [55]:
```
from scipy import stats
```

In [56]:
```
print("="*100)
print("HYPOTHESIS TEST: STORE 77 (TRIAL) Vs STORE 233 (CONTROL)")
print("="*100)
print("\n Null Hypothesis(H0)): Trial store metric = Control store met
print("\n Alternative Hypothesis(H1): Trial store metrics > Control st
print("\n")
store_77_trial=trial_data[trial_data['STORE_NBR']==77][['MONTH_ID','TO
store_233_trial=trial_data[trial_data['STORE_NBR']==233][['MONTH_ID','

# One tailed Independent Samples T test
print("\n One-TAILED INDEPENDENT SAMPLES T-TEST")
#because h1 says "greater than", not just different
print("="*100)

#Test 1: Total SALES
t_stat_sales, p_value_sales_two=stats.ttest_ind(store_77_trial['TOTAL_
                                                store_233_trial['TOTAL
p_value_sales=p_value_sales_two/2 if t_stat_sales >0 else 1 - (p_value
print(f"\n1. TOTAL SALES")
print(f"Store 77 {((store_77_trial['TOTAL_SALES'].mean()/store_233_tri
print(f"T_statistic:{t_stat_sales:.4f}")
print(f"p_value(one-tailed):{p_value_sales:.4f}")
if t_stat_sales > 0 and p_value_sales <0.05:
    print(f"Reject H0: Store 77 sales are significantly greater than s
elif t_stat_sales > 0:
    print(f"Fail to Reject H0: Store 77 sales sales are higher but Not
else:
    print(f"Fail to Reject H0: Store 77 sales are Lower than store 233

# Test 2: Number Of Customers
t_stat_cust, p_value_cust_two=stats.ttest_ind(store_77_trial['NUMBER_C
                                                store_233_trial['NUMBE
p_value_cust= p_value_cust_two/ 2 if t_stat_cust > 0 else 1 - (p_value

print(f"\n2. NUMBER OF CUSTOMERS:")
print(f"Store 77{((store_77_trial['NUMBER_CUSTOMERS'].mean()/store_233
print(f"t-statistic:{t_stat_cust:.4f}")
print(f"p-value(one-tailed): {p_value_cust:.4f}")
if t_stat_cust > 0 and p_value_cust < 0.05:
    print(f" REJECT H0: Store 77 customers are Significantly Greater t
elif t_stat_cust > 0:
    print(f"Fail to Reject H0: Store 77 customers are higher but not s
else:
    print(f"Fail to Reject H0: Store 77 customers are Lower than store

#Test 3: Total_Transactions
t_stat_trans, p_value_trans_two=stats.ttest_ind(store_77_trial['TOTAL_
                                              store_233_trial['TOTAL_TRA
```

```
p_value_trans=p_value_trans_two/2 if t_stat_trans > 0 else 1 - (p_valu

print(f"\n3. Total Transactions")
print(f"Store 77 is {((store_77_trial['TOTAL_TRANSACTIONS'].mean()/sto
print(f"t_statistic:{t_stat_trans:.4f}")
print(f"p_value (one_tailed):{p_value_trans:.4f}")
if t_stat_trans > 0 and p_value_trans < 0.05:
    print(f"Reject H0: Store 77 transactions are SIGNIFICANTLY GREATER
elif t_stat_trans > 0:
    print(f"Fail to Reject H0: Store 77 transactions are higher but NO
else:
    print(f"Fail to Reject H0: Store 77 trnasactions are Lower than st
```

```
======================================================================
=============================
HYPOTHESIS TEST: STORE 77 (TRIAL) Vs STORE 233 (CONTROL)
======================================================================
=============================

 Null Hypothesis(H0)): Trial store metric = Control store metric in Tri
al period

 Alternative Hypothesis(H1): Trial store metrics > Control store metric
in Trial Period



 One-TAILED INDEPENDENT SAMPLES T-TEST
======================================================================
=============================

1. TOTAL SALES
Store 77 +32.87% vs Store 233
T_statistic:2.2370
p_value(one-tailed):0.0445
Reject H0: Store 77 sales are significantly greater than store 233(p<0.
05)

2. NUMBER OF CUSTOMERS:
Store 77+27.88% vs Store 233
t-statistic:1.9917
p-value(one-tailed): 0.0586
Fail to Reject H0: Store 77 customers are higher but not significantly
(p>=0.05)

3. Total Transactions
Store 77 is +27.78% vs Store 233
t_statistic:1.9365
p_value (one_tailed):0.0624
Fail to Reject H0: Store 77 transactions are higher but NOT significant
ly (p >=0.05)
```

OVERALL CONCLUSION:

The new store layout was successful in increasing sales. Store 77 performed significantly better than its control store (Store 233) in terms of sales during the trial period. However, the increase in customer count and transactions, while positive, were not statistically significant at the α=0.05 level.

Business Interpretation:

- The layout change worked- it drove higher sales.
- The higher sales might be due to:
    1. Store layout pursading customer to buy more things and spend more.
    2. Slightly more customers(Make sense as layout won't increase the customers by itself)
    3. Better product placement leading to higher-value purchases.

Recommendation: Implement the new layout based on the significant sales increase. The fact that customers and transactions showed positive trends (even if not statistically significant) is also encouraging and suggests the layout had an overall positive impact.

Store 86 vs Store 138

In [57]:
```
store_86_trial=trial_data[trial_data['STORE_NBR']==86][['MONTH_ID','TO
store_86_trial=store_86_trial.rename(columns={'TOTAL_SALES':'86_TOTAL_
store_86_trial
```

Out[57]:

	MONTH_ID	86_TOTAL_SALES	86_NUMBER_CUSTOMERS	86_TOTAL_TRAI
984	201902	872.8	105	
985	201903	945.4	108	
986	201904	804.0	99	

In [58]:
```
store_138_trial=trial_data[trial_data['STORE_NBR']==138][['MONTH_ID','
store_138_trial=store_138_trial.rename(columns={'TOTAL_SALES':'138_TOT
store_138_trial
```

Out[58]:

	MONTH_ID	138_TOTAL_SALES	138_NUMBER_CUSTOMERS	138_TOTAL_T
1595	201902	683.8	83	
1596	201903	888.8	102	
1597	201904	776.6	100	

In [59]:

```
store_86_138_trial=store_86_trial.merge(store_138_trial,on='MONTH_ID',
store_86_138_trial['MONTH_ID']=pd.to_datetime(store_86_138_trial['MONT
store_86_138_trial
```

Out[59]:

	MONTH_ID	86_TOTAL_SALES	86_NUMBER_CUSTOMERS	86_TOTAL_TRANSA
0	2019-02-01	872.8	105	
1	2019-03-01	945.4	108	
2	2019-04-01	804.0	99	

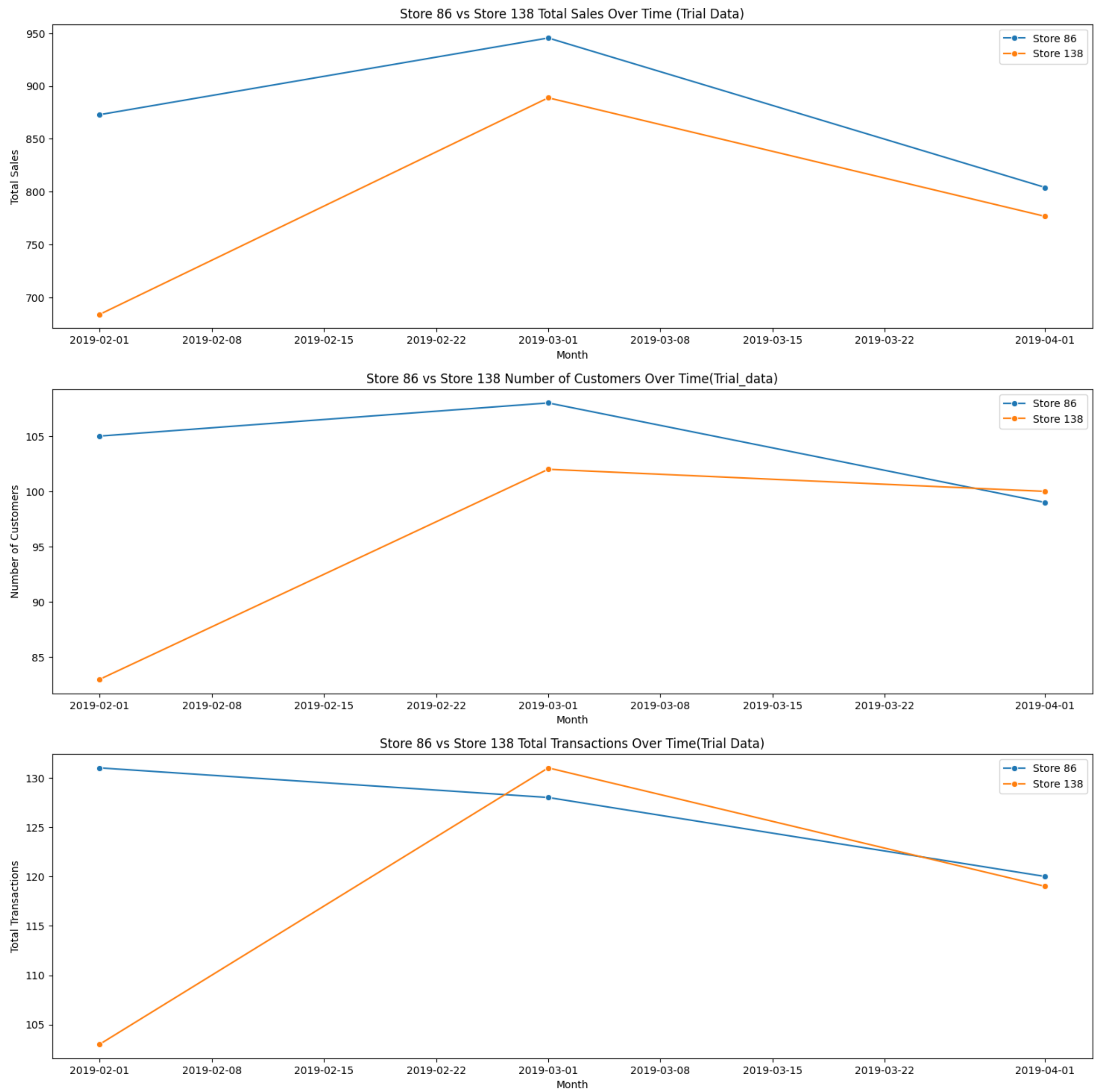
In [67]:

```
fig, axes=plt.subplots(3,1,figsize=(18,18))
ax=axes.flatten()
sns.lineplot(data=store_86_138_trial, x='MONTH_ID', y='86_TOTAL_SALES'
sns.lineplot(data=store_86_138_trial, x='MONTH_ID', y='138_TOTAL_SALES
ax[0].set_xlabel('Month')
ax[0].set_ylabel('Total Sales')
ax[0].set_title('Store 86 vs Store 138 Total Sales Over Time (Trial Da
ax[0].legend()

sns.lineplot(data=store_86_138_trial, x='MONTH_ID', y='86_NUMBER_CUSTO
sns.lineplot(data=store_86_138_trial, x='MONTH_ID', y='138_NUMBER_CUST
ax[1].set_xlabel('Month')
ax[1].set_ylabel('Number of Customers')
ax[1].set_title('Store 86 vs Store 138 Number of Customers Over Time(T
ax[1].legend()

sns.lineplot(data=store_86_138_trial, x='MONTH_ID', y='86_TOTAL_TRANSA
sns.lineplot(data=store_86_138_trial, x='MONTH_ID', y='138_TOTAL_TRANS
ax[2].set_xlabel('Month')
ax[2].set_ylabel('Total Transactions')
ax[2].set_title('Store 86 vs Store 138 Total Transactions Over Time(Tr
ax[2].legend()


plt.suptitle('METRICS COMPARISION OF STORE 86 & STORE 138 (Trial Perio
```

Out[67]:

```
Text(0.5, 0.98, 'METRICS COMPARISION OF STORE 86 & STORE 138 (Trial P
eriod Data)')
```

METRICS COMPARISION OF STORE 86 & STORE 138 (Trial Period Data)



Visually the total Sales seems to be high in STORE 86, but is it significant statistically? We need to check it

In [61]:
```
print("="*100)
print("HYPOTHESIS TEST: STORE 86 (TRIAL) Vs STORE 138 (CONTROL)")
print("="*100)
print("\n Null Hypothesis(H0)): Trial store metric = Control store met
print("\n Alternative Hypothesis(H1): Trial store metrics > Control st
print("\n")
store_86_trial=trial_data[trial_data['STORE_NBR']==86][['MONTH_ID','TO
store_138_trial=trial_data[trial_data['STORE_NBR']==138][['MONTH_ID','

# One tailed Independent Samples T test
print("\n One-TAILED INDEPENDENT SAMPLES T-TEST")
```

```
#because h1 says "greater than", not just different
print("="*100)

#Test 1: Total SALES
t_stat_sales, p_value_sales_two=stats.ttest_ind(store_86_trial['TOTAL_
                                                store_138_trial['TOTAL
p_value_sales=p_value_sales_two/2 if t_stat_sales >0 else 1 - (p_value
print(f"\n1. TOTAL SALES")
print(f"Store 86 {((store_86_trial['TOTAL_SALES'].mean()/store_138_tri
print(f"T_statistic:{t_stat_sales:.4f}")
print(f"p_value(one-tailed):{p_value_sales:.4f}")
if t_stat_sales > 0 and p_value_sales <0.05:
    print(f"Reject H0: Store 86 sales are significantly greater than s
elif t_stat_sales > 0:
    print(f"Fail to Reject H0: Store 86 sales sales are higher but Not
else:
    print(f"Fail to Reject H0: Store 86 sales are Lower than store 138

# Test 2: Number Of Customers
t_stat_cust, p_value_cust_two=stats.ttest_ind(store_86_trial['NUMBER_C
                                                store_138_trial['NUMBE
p_value_cust= p_value_cust_two/ 2 if t_stat_cust > 0 else 1 - (p_value

print(f"\n2. NUMBER OF CUSTOMERS:")
print(f"Store 86{((store_86_trial['NUMBER_CUSTOMERS'].mean()/store_138
print(f"t-statistic:{t_stat_cust:.4f}")
print(f"p-value(one-tailed): {p_value_cust:.4f}")
if t_stat_cust > 0 and p_value_cust < 0.05:
    print(f" REJECT H0: Store 86 customers are Significantly Greater t
elif t_stat_cust > 0:
    print(f"Fail to Reject H0: Store 86 customers are higher but not s
else:
    print(f"Fail to Reject H0: Store 86 customers are Lower than store

#Test 3: Total_Transactions
t_stat_trans, p_value_trans_two=stats.ttest_ind(store_86_trial['TOTAL_
                                              store_138_trial['TOTAL_TRA
p_value_trans=p_value_trans_two/2 if t_stat_trans > 0 else 1 - (p_valu

print(f"\n3. Total Transactions")
print(f"Store 86 is {((store_86_trial['TOTAL_TRANSACTIONS'].mean()/sto
print(f"t_statistic:{t_stat_trans:.4f}")
print(f"p_value (one_tailed):{p_value_trans:.4f}")
if t_stat_trans > 0 and p_value_trans < 0.05:
    print(f"Reject H0: Store 86 transactions are SIGNIFICANTLY GREATER
elif t_stat_trans > 0:
    print(f"Fail to Reject H0: Store 86 transactions are higher but NO
else:
    print(f"Fail to Reject H0: Store 86 transactions are Lower than st
```

```
================================================================================
==============================
HYPOTHESIS TEST: STORE 86 (TRIAL) Vs STORE 138 (CONTROL)
================================================================================
==============================

 Null Hypothesis(H0)): Trial store metric = Control store metric in Tri
al period

 Alternative Hypothesis(H1): Trial store metrics > Control store metric
in Trial Period



 One-TAILED INDEPENDENT SAMPLES T-TEST
================================================================================
==============================

1. TOTAL SALES
Store 86 +11.62% vs Store 138
T_statistic:1.2645
p_value(one-tailed):0.1374
Fail to Reject H0: Store 86 sales sales are higher but Not significantl
y (p >=0.05)

2. NUMBER OF CUSTOMERS:
Store 86+9.47% vs Store 138
t-statistic:1.3672
p-value(one-tailed): 0.1217
Fail to Reject H0: Store 86 customers are higher but not significantly
(p>=0.05)

3. Total Transactions
Store 86 is +7.37% vs Store 138
t_statistic:0.9905
p_value (one_tailed):0.1890
Fail to Reject HO: Store 86 transactions are higher but NOT significant
ly (p >=0.05)
```

OVERALL CONCLUSION:

The new store layout did not have statistically significnat impact on Store 86's performance. While all metrics(sales, customers, transactions) showed positive increases compared to the control store (Store 138), none of these increases were large enough to be considered statistically significant at the α=0.05 level.

Business Interpretation:

- The layout change showed weak/inconclusive results for Store 86.
- The improvements could be due to random chance rather than the layout change

- This result contradicts store 77, which showed sales improvement.

Possible Reasons for Different Results

- Store-specific factor(location, customer demographics, store size)
- Implementation differences
- Local market conditions
- The layout change may work better in some store types than other

Recommendation

- We should further investigate why store 77 succeeded but store 86 didn't
- We should analyze if store 88 shows similar pattern to 77 or 86.

Store 88 vs Store 201

In [62]:
```
store_88_trial=trial_data[trial_data['STORE_NBR']==88][['MONTH_ID','TO
store_88_trial=store_88_trial.rename(columns={'TOTAL_SALES':'88_TOTAL_
store_88_trial
```

Out[62]:

	MONTH_ID	88_TOTAL_SALES	88_NUMBER_CUSTOMERS	88_TOTAL_TRA
1008	201902	1339.6	122	
1009	201903	1467.0	133	
1010	201904	1317.0	119	

In [63]:
```
store_201_trial=trial_data[trial_data['STORE_NBR']==201][['MONTH_ID','
store_201_trial=store_201_trial.rename(columns={'TOTAL_SALES':'201_TOT
store_201_trial
```

Out[63]:

	MONTH_ID	201_TOTAL_SALES	201_NUMBER_CUSTOMERS	201_TOTAL_
2341	201902	1006.6	101	
2342	201903	1328.5	128	
2343	201904	1205.8	121	

In [64]:
```
store_88_201_trial=store_88_trial.merge(store_201_trial,on='MONTH_ID',
store_88_201_trial['MONTH_ID']=pd.to_datetime(store_88_201_trial['MONT
store_88_201_trial
```

Out[64]:

	MONTH_ID	88_TOTAL_SALES	88_NUMBER_CUSTOMERS	88_TOTAL_TRANS/
0	2019-02-01	1339.6	122	
1	2019-03-01	1467.0	133	
2	2019-04-01	1317.0	119	

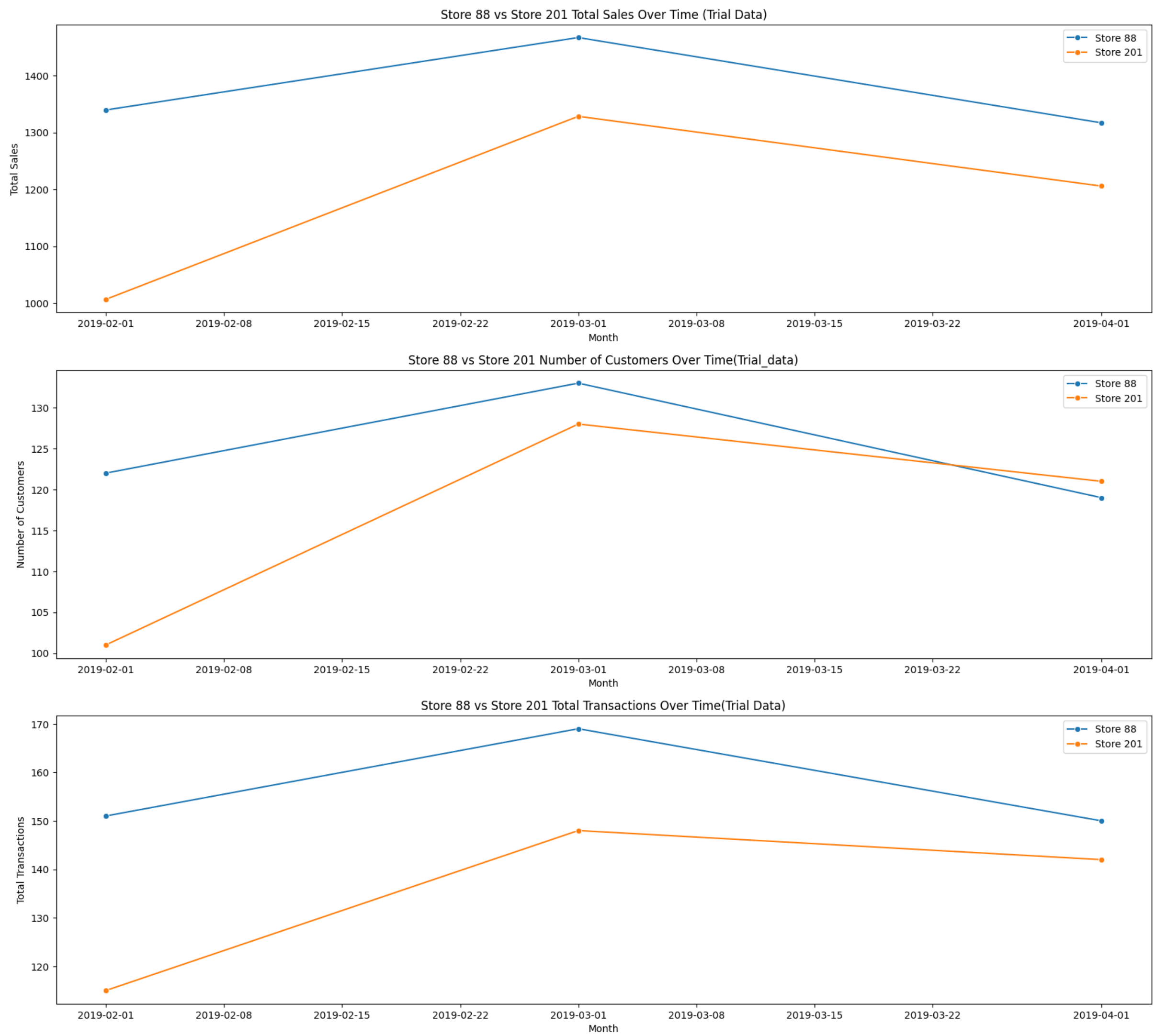
In [65]:

```
fig, axes=plt.subplots(3,1,figsize=(20,18))
ax=axes.flatten()
sns.lineplot(data=store_88_201_trial, x='MONTH_ID', y='88_TOTAL_SALES'
sns.lineplot(data=store_88_201_trial, x='MONTH_ID', y='201_TOTAL_SALES
ax[0].set_xlabel('Month')
ax[0].set_ylabel('Total Sales')
ax[0].set_title('Store 88 vs Store 201 Total Sales Over Time (Trial Da
ax[0].legend()

sns.lineplot(data=store_88_201_trial, x='MONTH_ID', y='88_NUMBER_CUSTO
sns.lineplot(data=store_88_201_trial, x='MONTH_ID', y='201_NUMBER_CUST
ax[1].set_xlabel('Month')
ax[1].set_ylabel('Number of Customers')
ax[1].set_title('Store 88 vs Store 201 Number of Customers Over Time(T
ax[1].legend()

sns.lineplot(data=store_88_201_trial, x='MONTH_ID', y='88_TOTAL_TRANSA
sns.lineplot(data=store_88_201_trial, x='MONTH_ID', y='201_TOTAL_TRANS
ax[2].set_xlabel('Month')
ax[2].set_ylabel('Total Transactions')
ax[2].set_title('Store 88 vs Store 201 Total Transactions Over Time(Tr
ax[2].legend()


plt.suptitle('METRICS COMPARISION OF STORE 88 & STORE 201 (Trial Perio
```

Out[65]:

```
Text(0.5, 0.98, 'METRICS COMPARISION OF STORE 88 & STORE 201 (Trial P
eriod Data)')
```

METRICS COMPARISION OF STORE 88 & STORE 201 (Trial Period Data)



Visually, the store 88 (trial store seems to perform well, lets prove it statistically)

In [66]:
```
print("="*100)
print("HYPOTHESIS TEST: STORE 88 (TRIAL) Vs STORE 201 (CONTROL)")
print("="*100)
print("\n Null Hypothesis(H0)): Trial store metric = Control store met
print("\n Alternative Hypothesis(H1): Trial store metrics > Control st
print("\n")
store_88_trial=trial_data[trial_data['STORE_NBR']==88][['MONTH_ID','TO
store_201_trial=trial_data[trial_data['STORE_NBR']==201][['MONTH_ID','

# One tailed Independent Samples T test
print("\n One-TAILED INDEPENDENT SAMPLES T-TEST")
#because h1 says "greater than", not just different
print("="*100)
```

```
#Test 1: Total SALES
t_stat_sales, p_value_sales_two=stats.ttest_ind(store_88_trial['TOTAL_
                                                store_201_trial['TOTAL
p_value_sales=p_value_sales_two/2 if t_stat_sales >0 else 1 - (p_value
print(f"\n1. TOTAL SALES")
print(f"Store 88 {((store_88_trial['TOTAL_SALES'].mean()/store_201_tri
print(f"T_statistic:{t_stat_sales:.4f}")
print(f"p_value(one-tailed):{p_value_sales:.4f}")
if t_stat_sales > 0 and p_value_sales <0.05:
    print(f"Reject H0: Store 88 sales are significantly greater than s
elif t_stat_sales > 0:
    print(f"Fail to Reject H0: Store 88 sales sales are higher but Not
else:
    print(f"Fail to Reject H0: Store 88 sales are Lower than store 201

# Test 2: Number Of Customers
t_stat_cust, p_value_cust_two=stats.ttest_ind(store_88_trial['NUMBER_C
                                                store_201_trial['NUMBE
p_value_cust= p_value_cust_two/ 2 if t_stat_cust > 0 else 1 - (p_value

print(f"\n2. NUMBER OF CUSTOMERS:")
print(f"Store 88{((store_88_trial['NUMBER_CUSTOMERS'].mean()/store_201
print(f"t-statistic:{t_stat_cust:.4f}")
print(f"p-value(one-tailed): {p_value_cust:.4f}")
if t_stat_cust > 0 and p_value_cust < 0.05:
    print(f" REJECT H0: Store 88 customers are Significantly Greater t
elif t_stat_cust > 0:
    print(f"Fail to Reject H0: Store 88 customers are higher but not s
else:
    print(f"Fail to Reject H0: Store 88 customers are Lower than store

#Test 3: Total_Transactions
t_stat_trans, p_value_trans_two=stats.ttest_ind(store_88_trial['TOTAL_
                                            store_201_trial['TOTAL_TRA
p_value_trans=p_value_trans_two/2 if t_stat_trans > 0 else 1 - (p_valu

print(f"\n3. Total Transactions")
print(f"Store 88 is {((store_88_trial['TOTAL_TRANSACTIONS'].mean()/sto
print(f"t_statistic:{t_stat_trans:.4f}")
print(f"p_value (one_tailed):{p_value_trans:.4f}")
if t_stat_trans > 0 and p_value_trans < 0.05:
    print(f"Reject H0: Store 88 transactions are SIGNIFICANTLY GREATER
elif t_stat_trans > 0:
    print(f"Fail to Reject H0: Store 88 transactions are higher but NO
else:
    print(f"Fail to Reject H0: Store 88 transactions are Lower than st
```

```
================================================================================
=============================
HYPOTHESIS TEST: STORE 88 (TRIAL) Vs STORE 201 (CONTROL)
================================================================================
=============================

 Null Hypothesis(H0)): Trial store metric = Control store metric in Tri
al period

 Alternative Hypothesis(H1): Trial store metrics > Control store metric
in Trial Period



 One-TAILED INDEPENDENT SAMPLES T-TEST
================================================================================
=============================

1. TOTAL SALES
Store 88 +16.46% vs Store 201
T_statistic:1.8538
p_value(one-tailed):0.0687
Fail to Reject H0: Store 88 sales sales are higher but Not significantl
y (p >=0.05)

2. NUMBER OF CUSTOMERS:
Store 88+6.86% vs Store 201
t-statistic:0.8752
p-value(one-tailed): 0.2154
Fail to Reject H0: Store 88 customers are higher but not significantly
(p>=0.05)

3. Total Transactions
Store 88 is +16.05% vs Store 201
t_statistic:1.8239
p_value (one_tailed):0.0711
Fail to Reject H0: Store 88 transactions are higher but NOT significant
ly (p >=0.05)
```

Overall conclusions for store 88

The new store layout did Not have a statistically significant impact on Store 88's performance at the $\alpha=0.05$ significance level.

Key Observations:

- Boderine results: Sales ($p=0.0687$) and Transactions ($p=0.0711$) were VERY close to being significnat.
- All metrics showed positive trends (all increase between 6-16%)
- The improvements were not strong enough to conclusively attribute them to the layout change rather than random variation.

Comparsion Across All Stores:

- Store 77: significnat sucess (sales p=0.0445)
- Store 86: Not significant (all p_values > 0.10)
- Store 88: Borderline but not significant (p-values ~0.07)

Overall conclusion:

In all the three trial stores we see a postive increase in sales, number of customers and total transactions. In store 77 the growth is significant as backed by the statistic. In other stores the growth is not as significant but the p-values are at borderline level showing some positive indications.

So, from this we can understand couple of things

- Store layout works well for store 77
- Its inconclusive for Store 88 and no clear benefit for store 86 (even if in some months the growth is significant, in an averge it is inconclusive.)
- We can confidently implement the new layout in store 77 but for other trial store, there are no evidences(certain evidence of efectiveness)
- More stores and longer trial periods can guarantee more conclusive results.
