TASK 2

import libraries and read data into dataframe

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

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

Out[3]:

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

In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 264834 entries, 0 to 264833
Data columns (total 12 columns):
 #   Column            Non-Null Count   Dtype  
---  ------            --------------   -----  
 0   LYLTY_CARD_NBR    264834 non-null  int64  
 1   DATE              264834 non-null  object 
 2   STORE_NBR         264834 non-null  int64  
 3   TXN_ID            264834 non-null  int64  
 4   PROD_NBR          264834 non-null  int64  
 5   PROD_NAME         264834 non-null  object 
 6   PROD_QTY          264834 non-null  int64  
 7   TOT_SALES         264834 non-null  float64
 8   PACK_SIZE         264834 non-null  int64  
 9   BRAND             264834 non-null  object 
 10  LIFESTAGE         264834 non-null  object 
 11  PREMIUM_CUSTOMER  264834 non-null  object 
dtypes: float64(1), int64(6), object(5)
memory usage: 19.2+ MB
```

In [5]:
```
df['DATE'] = pd.to_datetime(df['DATE'])
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 264834 entries, 0 to 264833
Data columns (total 12 columns):
 #   Column            Non-Null Count   Dtype         
---  ------            --------------   -----         
 0   LYLTY_CARD_NBR    264834 non-null  int64         
 1   DATE              264834 non-null  datetime64[ns]
 2   STORE_NBR         264834 non-null  int64         
 3   TXN_ID            264834 non-null  int64         
 4   PROD_NBR          264834 non-null  int64         
 5   PROD_NAME         264834 non-null  object        
 6   PROD_QTY          264834 non-null  int64         
 7   TOT_SALES         264834 non-null  float64       
 8   PACK_SIZE         264834 non-null  int64         
 9   BRAND             264834 non-null  object        
 10  LIFESTAGE         264834 non-null  object        
 11  PREMIUM_CUSTOMER  264834 non-null  object        
dtypes: datetime64[ns](1), float64(1), int64(6), object(4)
memory usage: 20.2+ MB
```

Add a new month ID column in the data with the format yyyymm

In [6]:

```
# Extract the year and month from the 'DATE' column and format it as "yyyymm"
df['YEARMONTH'] = df['DATE'].dt.strftime('%Y%m')

# Display the DataFrame with the new 'YEARMONTH' column
df.head(10)
```

Out[6]:

	LYLTY_CARD_NBR	DATE	STORE_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_SALES	PACK_SIZE
0	1000	2018-10-17	1	1	5	Natural Chip Compny SeaSalt175g	2	6.0	175
1	1002	2018-09-16	1	2	58	Red Rock Deli Chikn&Garlic Aioli 150g	1	2.7	150
2	1003	2019-03-07	1	3	52	Grain Waves Sour Cream&Chives 210G	1	3.6	210
3	1003	2019-03-08	1	4	106	Natural ChipCo Hony Soy Chckn175g	1	3.0	175
4	1004	2018-11-02	1	5	96	WW Original Stacked Chips 160g	1	1.9	160
5	1005	2018-12-28	1	6	86	Cheetos Puffs 165g	1	2.8	165
6	1007	2018-12-04	1	7	49	Infuzions SourCream&Herbs Veg Strws 110g	1	3.8	110
7	1007	2018-12-05	1	8	10	RRD SR Slow Rst Pork Belly 150g	1	2.7	150
8	1009	2018-11-20	1	9	20	Doritos Cheese Supreme 330g	1	5.7	330
9	1010	2018-09-09	1	10	51	Doritos Mexicana 170g	2	8.8	170

Next, we define the measure calculations to use during the analysis. calculate for each store and month calculate total sales, number of customers, transactions per customer, chips per customer and the average price per unit.

In [7]:

```
# Assuming you have a DataFrame named 'data' with 'STORE_NUM', 'YEARMONTH', 'TOT_SALES',

# Calculate total sales per store and month
total_sales = df.groupby(['STORE_NBR', 'YEARMONTH'])['TOT_SALES'].sum().reset_index()

# Calculate the number of customers per store and month (unique count of transactions)
num_customers = df.groupby(['STORE_NBR', 'YEARMONTH'])['TXN_ID'].nunique().reset_index()

# Calculate transactions per customer per store and month
transactions_per_customer = total_sales['TOT_SALES'] / num_customers['TXN_ID']

# Calculate chips per customer per store and month (assuming chips are identified by the
chips_per_customer = df[df['PROD_NAME'].str.contains('chips', case=False, na=False)].grou

# Calculate the average price per unit per store and month
avg_price_per_unit = total_sales['TOT_SALES'] / df.groupby(['STORE_NBR', 'YEARMONTH'])['PR

# Create a new DataFrame with all the calculated measures
measure_over_time = pd.DataFrame({
    'STORE_NBR': total_sales['STORE_NBR'],
    'YEARMONTH': total_sales['YEARMONTH'],
    'totSales': total_sales['TOT_SALES'],
    'nCustomers': num_customers['TXN_ID'],
    'nTxnPerCust': transactions_per_customer,
    'nChipsPerTxn': chips_per_customer['PROD_QTY'],
    'avgPricePerUnit': avg_price_per_unit
})

# Display the resulting DataFrame
print(measure_over_time.shape)
measure_over_time.head()
```

```
(3169, 7)
```

Out[7]:

	STORE_NBR	YEARMONTH	totSales	nCustomers	nTxnPerCust	nChipsPerTxn	avgPricePerUnit
0	1	201807	206.9	52	3.978846	15.0	3.337097
1	1	201808	176.1	43	4.095349	7.0	3.261111
2	1	201809	278.8	62	4.496774	20.0	3.717333
3	1	201810	188.1	45	4.180000	11.0	3.243103
4	1	201811	192.6	47	4.097872	16.0	3.378947

Filter to the pre-trial period and stores with full observation

In [8]:

```
# Convert 'YEARMONTH' column to integer for comparison
measure_over_time['YEARMONTH'] = measure_over_time['YEARMONTH'].astype(int)

# Find stores with a full observation period (12 months)
stores_with_full_obs = measure_over_time.groupby('STORE_NBR')['YEARMONTH'].nunique() == 12
full_obs_stores = stores_with_full_obs[stores_with_full_obs].index.tolist()

# Filter to the pre-trial period (before February 2019) and stores with full observation p
pre_trial_measures = measure_over_time[(measure_over_time['YEARMONTH'] < 201902) & (measur

# Display the resulting DataFrame
print(pre_trial_measures.shape)
pre_trial_measures.head()
```

```
(1820, 7)
```

Out[8]:

	STORE_NBR	YEARMONTH	totSales	nCustomers	nTxnPerCust	nChipsPerTxn	avgPricePerUnit
0	1	201807	206.9	52	3.978846	15.0	3.337097
1	1	201808	176.1	43	4.095349	7.0	3.261111
2	1	201809	278.8	62	4.496774	20.0	3.717333
3	1	201810	188.1	45	4.180000	11.0	3.243103
4	1	201811	192.6	47	4.097872	16.0	3.378947

Create a function to calculate correlation for a measure, looping through each control store.

Create a function to calculate a standardised magnitude distance for a measure, looping through each control store

Use the function you created to calculate correlations and magnitude against store 77 using total sales and number of customers.

In [9]:

```
from scipy.stats import pearsonr

# Function to calculate correlation
def calculate_correlation(input_table, metric_col, store_comparison):
    calc_corr_table = pd.DataFrame(columns=['Store1', 'Store2', 'corr_measure'])
    store_numbers = input_table['STORE_NBR'].unique()

    for i in store_numbers:
        if i != store_comparison:
            trial_store_data = input_table[input_table['STORE_NBR'] == store_comparison][r
            control_store_data = input_table[input_table['STORE_NBR'] == i][metric_col]
            corr_measure, _ = pearsonr(trial_store_data, control_store_data)
            calculated_measure = pd.DataFrame({'trial_store_data': [store_comparison], 'co
            calculated_measure['Store1'] = [store_comparison]
            calculated_measure['Store2'] = [i]
            calculated_measure['corr_measure'] = [corr_measure]
            calc_corr_table = pd.concat([calc_corr_table, calculated_measure])

    return calc_corr_table


# Function to calculate magnitude distance
def calculate_magnitude_distance(input_table, metric_col, store_comparison):
    magnitude_table = pd.DataFrame(columns=["Store1", "Store2", "YEARMONTH", "magnitude_me
    store_numbers = input_table["STORE_NBR"].unique()

    for i in store_numbers:
        magnitude_measure = pd.DataFrame({
            "Store1": [store_comparison],
            "Store2": [i],
            "YEARMONTH": input_table[input_table["STORE_NBR"] == store_comparison]["YEARMO
            "magnitude_measure": abs(input_table[(input_table["STORE_NBR"] == store_compar
                                 - input_table[input_table["STORE_NBR"] == i][metric_col].value
        })
        magnitude_table = pd.concat([magnitude_table, magnitude_measure], ignore_index=Tru

    # Standardize the magnitude distance
    min_max_dist = magnitude_table.groupby(["Store1", "YEARMONTH"])["magnitude_measure"].a
    dist_table = magnitude_table.merge(min_max_dist, on=["Store1", "YEARMONTH"])
    dist_table["magnitudeMeasure"] = 1 - (dist_table["magnitude_measure"] - dist_table["mi
```

```python
    final_dist_table = dist_table.groupby(["Store1", "Store2"])["magnitudeMeasure"].mean()
    final_dist_table.rename(columns={"magnitudeMeasure": "mag_measure"}, inplace=True)

    return final_dist_table

# Trial store and metric column
trial_store = 77
metric_col_sales = 'totSales'
metric_col_customers = 'nCustomers'

# Calculate correlations for total sales and number of customers
corr_nSales = calculate_correlation(pre_trial_measures, metric_col_sales, trial_store)
corr_nCustomers = calculate_correlation(pre_trial_measures, metric_col_customers, trial_st

# Calculate magnitude distances for total sales and number of customers
magnitude_nSales = calculate_magnitude_distance(pre_trial_measures, metric_col_sales, tria
magnitude_nCustomers = calculate_magnitude_distance(pre_trial_measures, metric_col_custome

# Display the resulting DataFrames
print("Correlation for Total Sales:")
print(corr_nSales)

print("Correlation for Number of Customers:")
print(corr_nCustomers)

print("Magnitude Distance for Total Sales:")
print(magnitude_nSales)

print("Magnitude Distance for Number of Customers:")
print(magnitude_nCustomers)
```

```
Correlation for Total Sales:
   Store1 Store2  corr_measure  trial_store_data  control_store_data
0      77      1      0.075218              77.0                 1.0
0      77      2     -0.263079              77.0                 2.0
0      77      3      0.806644              77.0                 3.0
0      77      4     -0.263300              77.0                 4.0
0      77      5     -0.110652              77.0                 5.0
..    ...    ...           ...               ...                 ...
0      77    268      0.344757              77.0               268.0
0      77    269     -0.315730              77.0               269.0
0      77    270      0.315430              77.0               270.0
0      77    271      0.355487              77.0               271.0
0      77    272      0.117622              77.0               272.0

[259 rows x 5 columns]
Correlation for Number of Customers:
   Store1 Store2  corr_measure  trial_store_data  control_store_data
0      77      1      0.363018              77.0                 1.0
0      77      2     -0.360042              77.0                 2.0
0      77      3      0.903701              77.0                 3.0
0      77      4     -0.148594              77.0                 4.0
0      77      5      0.434635              77.0                 5.0
..    ...    ...           ...               ...                 ...
0      77    268      0.437141              77.0               268.0
0      77    269     -0.413574              77.0               269.0
0      77    270      0.295337              77.0               270.0
0      77    271      0.240728              77.0               271.0
0      77    272      0.145939              77.0               272.0

[259 rows x 5 columns]
Magnitude Distance for Total Sales:
     Store1  Store2  mag_measure
0        77       1     0.932426
1        77       2     0.890259
```

```
2          77       3      0.316822
3          77       4      0.170851
4          77       5      0.612748
..        ...     ...           ...
255        77     268      0.945280
256        77     269      0.484967
257        77     270      0.499399
258        77     271      0.504059
259        77     272      0.897550

[260 rows x 3 columns]
Magnitude Distance for Number of Customers:
     Store1  Store2  mag_measure
0        77       1     0.976744
1        77       2     0.891473
2        77       3     0.356589
3        77       4     0.201550
4        77       5     0.496124
..      ...     ...          ...
255      77     268     0.976744
256      77     269     0.356589
257      77     270     0.364341
258      77     271     0.441860
259      77     272     0.976744

[260 rows x 3 columns]
```

Create a combined score composed of correlation and magnitude, by first merging the correlations table with the magnitude table.

In [10]:

```python
# Merge correlations and magnitude tables for sales
score_nSales = pd.merge(corr_nSales, magnitude_nSales, on=['Store1', 'Store2'], how='inner

# Calculate the final score for total sales as the simple average
score_nSales['scoreNSales'] = (score_nSales['corr_measure'] + score_nSales['mag_measure'])

# Merge correlations and magnitude tables for customers
score_nCustomers = pd.merge(corr_nCustomers, magnitude_nCustomers, on=['Store1', 'Store2']

# Calculate the final score for number of customers as the simple average
score_nCustomers['scoreNCust'] = (score_nCustomers['corr_measure'] + score_nCustomers['mag

# Sort the scores for total sales in descending order
score_nSales = score_nSales.sort_values(by='scoreNSales', ascending=False)

# Display the sorted scores for total sales
print("Sorted Scores for Total Sales:")
print(score_nSales)

# Sort the scores for number of customers in descending order
score_nCustomers = score_nCustomers.sort_values(by='scoreNCust', ascending=False)

# Display the sorted scores for number of customers
print("Sorted Scores for Number of Customers:")
print(score_nCustomers)
```

```
Sorted Scores for Total Sales:
    Store1 Store2  corr_measure  trial_store_data  control_store_data  \
220     77    233      0.903774              77.0               233.0
46      77     50      0.763866              77.0                50.0
38      77     41      0.783232              77.0                41.0
15      77     17      0.842668              77.0                17.0
107     77    115      0.689159              77.0               115.0
..     ...    ...           ...               ...                 ...
22      77     24     -0.718112              77.0                24.0
```

```
234      77    247     -0.631050              77.0                247.0
3        77      4     -0.263300              77.0                  4.0
51       77     55     -0.666782              77.0                 55.0
71       77     75     -0.806751              77.0                 75.0

     mag_measure  scoreNSales
220     0.995415     0.949595
46      0.986771     0.875318
38      0.939567     0.861399
15      0.858013     0.850340
107     0.953322     0.821241
..           ...          ...
22      0.682502    -0.017805
234     0.582381    -0.024334
3       0.170851    -0.046224
51      0.554420    -0.056181
71      0.401909    -0.202421

[259 rows x 7 columns]
Sorted Scores for Number of Customers:
    Store1 Store2  corr_measure  trial_store_data  control_store_data  \
220     77    233      0.958422              77.0               233.0
38      77     41      0.843928              77.0                41.0
240     77    254      0.865382              77.0               254.0
15      77     17      0.808263              77.0                17.0
107     77    115      0.768323              77.0               115.0
..     ...    ...           ...               ...                 ...
234     77    247     -0.552421              77.0               247.0
79      77     86     -0.556984              77.0                86.0
129     77    138     -0.651739              77.0               138.0
138     77    147     -0.737568              77.0               147.0
71      77     75     -0.641599              77.0                75.0

     mag_measure  scoreNCust
220     0.992248    0.975335
38      0.961240    0.902584
240     0.937984    0.901683
15      0.984496    0.896379
107     0.992248    0.880286
..           ...         ...
234     0.449612   -0.051404
79      0.449612   -0.053686
129     0.503876   -0.073932
138     0.589147   -0.074211
71      0.457364   -0.092117

[259 rows x 7 columns]
```

Combine scores across the drivers by first merging our sales scores and customer scores into a single table

In [11]:

```python
# Merge sales and customer scores into a single table
score_Control = pd.merge(score_nSales, score_nCustomers, on=['Store1', 'Store2'], how='inn

# Calculate the final control store score as a weighted average (0.5 for each score)
score_Control['finalControlScore'] = 0.5 * score_Control['scoreNSales'] + 0.5 * score_Cont

# Sort the stores by final control score in descending order
score_Control = score_Control.sort_values(by='finalControlScore', ascending=False)

# Display the sorted control store scores
print("Sorted Control Store Scores:")
score_Control.head()
```

```
Sorted Control Store Scores:
```

Out[11]:

	Store1	Store2	corr_measure_x	trial_store_data_x	control_store_data_x	mag_measure_x	scoreNSales	corr_measur
0	77	233	0.903774	77.0	233.0	0.995415	0.949595	0.958
2	77	41	0.783232	77.0	41.0	0.939567	0.861399	0.843
3	77	17	0.842668	77.0	17.0	0.858013	0.850340	0.808
4	77	115	0.689159	77.0	115.0	0.953322	0.821241	0.768
5	77	167	0.657110	77.0	167.0	0.954525	0.805818	0.678

The store with the highest score is then selected as the control store since it is most similar to the trial store.

Select control stores based on the highest matching store (closest to 1 but

not the store itself, i.e. the second ranked highest store)

Select the most appropriate control store for trial store 77 by finding the store with the highest final score.

In [12]:

```
# Filter the scores for the trial store
trial_store_scores = score_Control[score_Control['Store1'] == trial_store]

# Sort the scores in descending order
trial_store_scores = trial_store_scores.sort_values(by='finalControlScore', ascending=Fals

# Select the second highest ranked store (closest to 1 but not the store itself)
control_store = trial_store_scores.iloc[0]['Store2']

# Display the selected control store
print("Selected Control Store:", control_store)
```

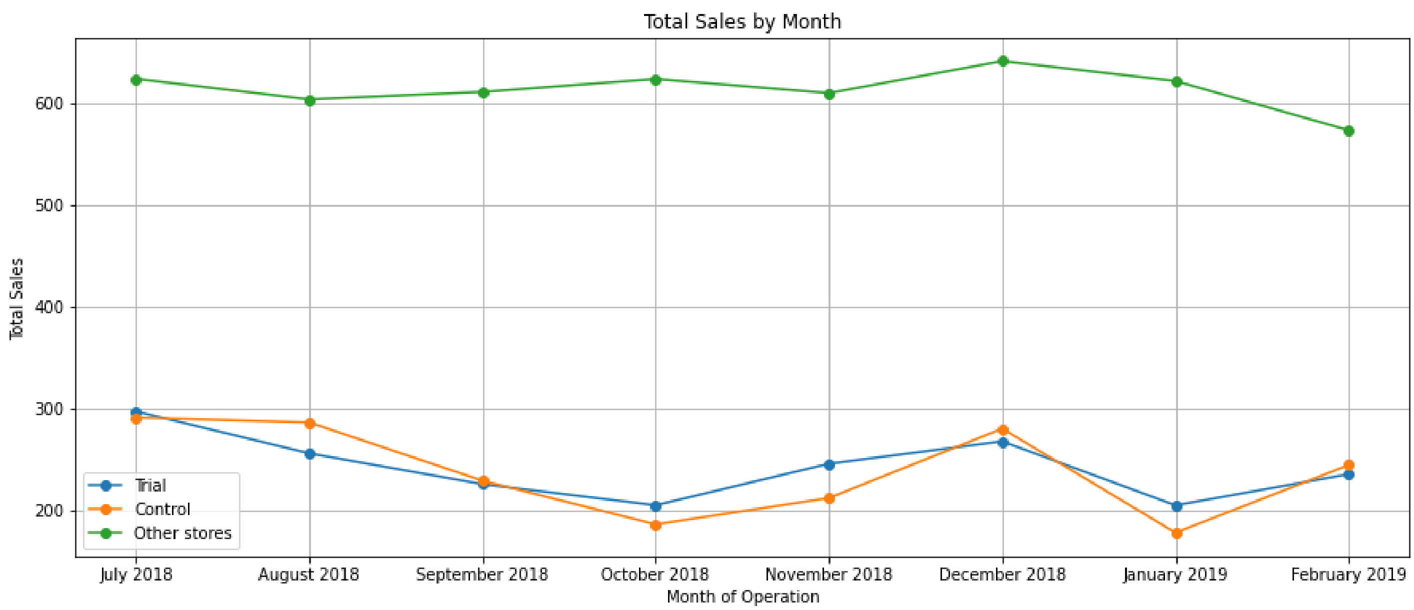
```
Selected Control Store: 233
```

Now that we have found a control store, let's check visually if the drivers are indeed similar in the period before the trial. We'll look at total sales first.

In [13]:

```
# Create a new DataFrame with store types
measure_over_time['Store_type'] = measure_over_time['STORE_NBR'].apply(lambda x: 'Trial' i

# Calculate the mean total sales by month and store type
pastSales = measure_over_time.groupby(['YEARMONTH', 'Store_type'])['totSales'].mean().rese

# Convert YEARMONTH to TransactionMonth as a date
pastSales['TransactionMonth'] = pd.to_datetime(pastSales['YEARMONTH'].astype(str), format=

# Convert TransactionMonth to "Month Year" format
pastSales['TransactionMonth'] = pastSales['TransactionMonth'].dt.strftime('%B %Y')

# Filter data for months before March 2019
pastSales = pastSales[pastSales['YEARMONTH'] < 201903]

# Create a line plot
plt.figure(figsize=(15, 6))
plt.plot(pastSales[pastSales['Store_type'] == 'Trial']['TransactionMonth'], pastSales[past
plt.plot(pastSales[pastSales['Store_type'] == 'Control']['TransactionMonth'], pastSales[pa
plt.plot(pastSales[pastSales['Store_type'] == 'Other stores']['TransactionMonth'], pastSal

# Set labels and title
plt.xlabel('Month of Operation')
plt.ylabel('Total Sales')
plt.title('Total Sales by Month')
```

```
plt.legend()
plt.grid(True)

# Show the plot
plt.show()
```

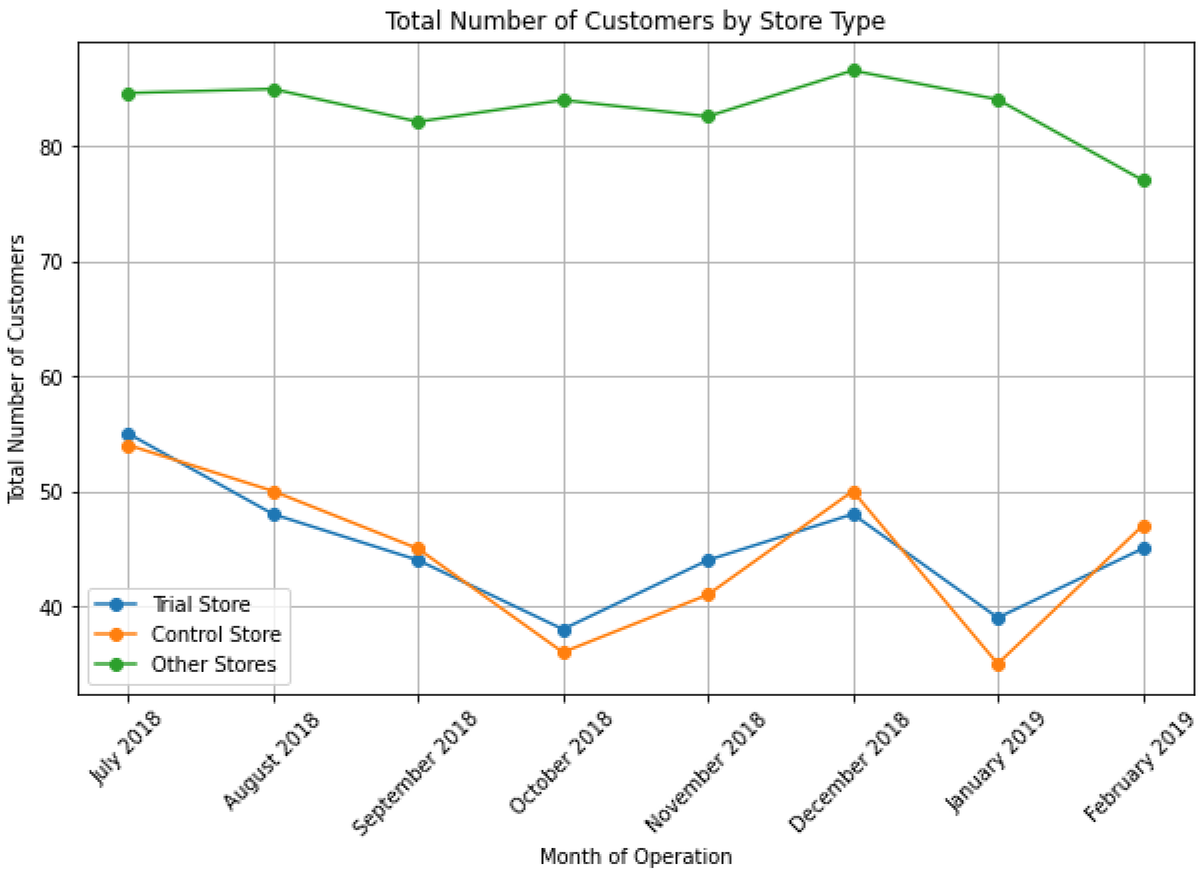


Next, number of customers,

Conduct visual checks on customer count trends by comparing the trial store to the control store and other stores.

In [15]:

```
# Create a 'Store_type' column based on trial_store and control_store
measure_over_time['Store_type'] = measure_over_time['STORE_NBR'].apply(
    lambda x: 'Trial' if x == trial_store else ('Control' if x == control_store else 'Othe
)

# Calculate the mean number of customers by YEARMONTH and Store_type
pastCustomers = measure_over_time.groupby(['YEARMONTH', 'Store_type'])['nCustomers'].mean

# Filter data for months before March 2019
pastCustomers = pastCustomers[pastCustomers['YEARMONTH'] < 201903]

# Convert YEARMONTH to a date format
pastCustomers['TransactionMonth'] = pd.to_datetime(pastCustomers['YEARMONTH'], format='%Y%

# Convert TransactionMonth to "Month Year" format
pastCustomers['TransactionMonth'] = pastCustomers['TransactionMonth'].dt.strftime('%B %Y')

# Plot customer count trends
plt.figure(figsize=(10, 6))
plt.plot(pastCustomers[pastCustomers['Store_type'] == 'Trial']['TransactionMonth'],
         pastCustomers[pastCustomers['Store_type'] == 'Trial']['nCustomers'], label='Trial
plt.plot(pastCustomers[pastCustomers['Store_type'] == 'Control']['TransactionMonth'],
         pastCustomers[pastCustomers['Store_type'] == 'Control']['nCustomers'], label='Con
plt.plot(pastCustomers[pastCustomers['Store_type'] == 'Other stores']['TransactionMonth'],
         pastCustomers[pastCustomers['Store_type'] == 'Other stores']['nCustomers'], label

plt.xlabel('Month of Operation')
plt.ylabel('Total Number of Customers')
plt.title('Total Number of Customers by Store Type')
plt.xticks(rotation=45)
plt.legend()
plt.grid(True)
plt.show()
```



The trial period goes from the start of February 2019 to April 2019. We now want to see if there has been an uplift in overall chip sales. We'll start with scaling the control store's sales to a level similar to control for any differences between the two stores outside of the trial period.

Scale pre-trial control sales to match pre-trial trial store sales

In [16]:

```
# Calculate the scaling factor for control store sales
trial_store_sales = pre_trial_measures[(pre_trial_measures['STORE_NBR'] == trial_store) &
control_store_sales = pre_trial_measures[(pre_trial_measures['STORE_NBR'] == control_store

scaling_factor = trial_store_sales / control_store_sales

# Apply the scaling factor
measure_over_time_sales = measure_over_time
scaledControlSales = measure_over_time_sales[measure_over_time_sales['STORE_NBR'] == contr
scaledControlSales['controlSales'] = scaledControlSales['totSales'] * scaling_factor
```

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.

Calculate the percentage difference between scaled control sales and trial sales

In [18]:

```
#  Merge the DataFrames on 'YEARMONTH' column
merged_sales = pd.merge(scaledControlSales[['YEARMONTH', 'controlSales']], measure_over_ti

# Calculate the percentage difference
merged_sales['percentageDiff'] = abs(merged_sales['controlSales'] - merged_sales['totSales

merged_sales.head()
```

Out[18]:

	YEARMONTH	controlSales	totSales	percentageDiff
0	201807	297.565550	296.8	0.002573

	YEARMONTH	controlSales	totSales	percentageDiff
1	201808	292.652187	255.5	0.126950
2	201809	233.998916	225.2	0.037602
3	201810	190.085733	204.5	0.075830
4	201811	216.597421	245.3	0.132516

Let's see if the difference is significant!

As our null hypothesis is that the trial period is the same as the pre-trial period, let's take the standard deviation based on the scaled percentage difference in the pre-trial period

In [19]:

```
# Get the percentageDiff DataFrame for the pre-trial period
pre_trial_percentage_df = merged_sales[['percentageDiff','YEARMONTH']]
```

In [20]:

```
# Filter the percentageDiff DataFrame for the pre-trial period
pre_trial_percentage_diff = pre_trial_percentage_df[pre_trial_percentage_df['YEARMONTH'] <

# Calculate the standard deviation
std_dev = np.std(pre_trial_percentage_diff['percentageDiff'])
std_dev
```

Out[20]:

```
0.046236161851401746
```

Note that there are 8 months in the pre-trial period

hence 8 - 1 = 7 degrees of freedom

In [21]:

```
# Number of data points
n = 8

# Degrees of freedom
degrees_of_freedom = n - 1
degrees_of_freedom
```

Out[21]:

```
7
```

We will test with a null hypothesis of there being 0 difference between trial and control stores.

Calculate the t-values for the trial months. After that, find the 95th percentile of the t distribution with the appropriate degrees of freedom

to check whether the hypothesis is statistically significant.

In [22]:

```
percentageDiff = merged_sales[['percentageDiff','YEARMONTH', 'totSales','controlSales']]
```

In [23]:

```
from scipy.stats import t

# Calculate the standard deviation based on the scaled percentage difference in the pre-tı
std_dev = np.std(percentageDiff[percentageDiff['YEARMONTH'] < 201902]['percentageDiff'])

# Degrees of freedom (number of months in the pre-trial period - 1)
degrees_of_freedom = 7
```

```
# Calculate the t-values for the trial months
percentageDiff['tValue'] = (percentageDiff['percentageDiff'] - 0) / std_dev
percentageDiff['TransactionMonth'] = pd.to_datetime(percentageDiff['YEARMONTH'].astype(st

# Filter for the trial months
trial_months = percentageDiff[(percentageDiff['YEARMONTH'] < 201905) & (percentageDiff['YE

# Find the 95th percentile of the t-distribution
alpha = 0.05  # Significance level
t_critical = t.ppf(1 - alpha / 2, degrees_of_freedom)

print("Critical t-value for a 95% confidence interval:", t_critical)
print(trial_months[['TransactionMonth', 'tValue']])
```

```
C:\Users\DELL\AppData\Local\Temp/ipykernel_1980/1941313700.py:10: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_gu
ide/indexing.html#returning-a-view-versus-a-copy
  percentageDiff['tValue'] = (percentageDiff['percentageDiff'] - 0) / std_dev
C:\Users\DELL\AppData\Local\Temp/ipykernel_1980/1941313700.py:11: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_gu
ide/indexing.html#returning-a-view-versus-a-copy
  percentageDiff['TransactionMonth'] = pd.to_datetime(percentageDiff['YEARMONTH'].astype(s
tr), format='%Y%m')
Critical t-value for a 95% confidence interval: 2.3646242510102993
  TransactionMonth     tValue
7       2019-02-01   1.278363
8       2019-03-01   7.927151
9       2019-04-01  13.476023
```

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.

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

In [37]:

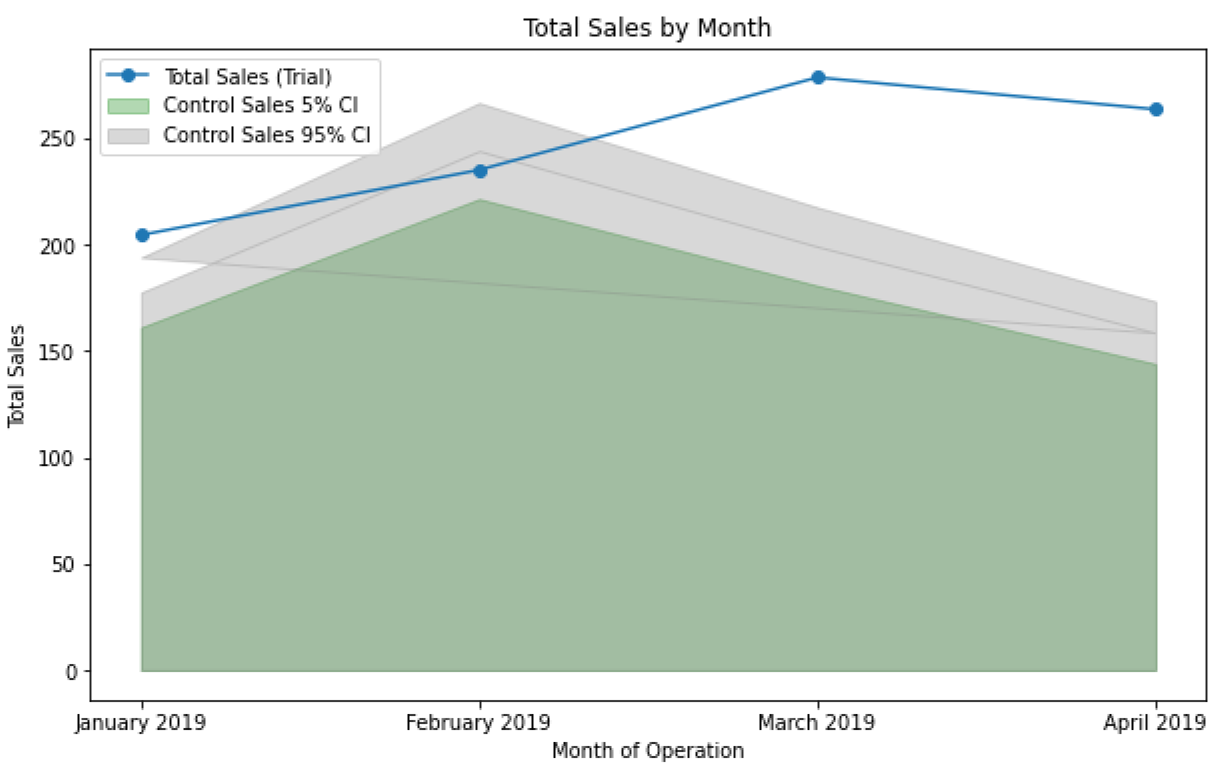
```
# Create a new column Store_type
measure_over_time['Store_type'] = 'Other stores'
measure_over_time.loc[measure_over_time['STORE_NBR'] == trial_store, 'Store_type'] = 'Tria
measure_over_time.loc[measure_over_time['STORE_NBR'] == control_store, 'Store_type'] = 'Co

# Calculate mean total sales by YEARMONTH and Store_type
pastSales = measure_over_time[measure_over_time['Store_type'].isin(['Trial', 'Control'])]
pastSales = pastSales.groupby(['YEARMONTH', 'Store_type'])['totSales'].mean().reset_index

# Convert YEARMONTH to TransactionMonth
pastSales['TransactionMonth'] = pd.to_datetime(pastSales['YEARMONTH'], format='%Y%m')

stdDev = np.std(percentageDiff[percentageDiff['YEARMONTH'] < 201902]['percentageDiff'])
# Control store 95th percentile
pastSales_Controls95 = pastSales[pastSales['Store_type'] == 'Control'].copy()
pastSales_Controls95['totSales'] = pastSales_Controls95['totSales'] * (1 + stdDev * 2)
pastSales_Controls95['Store_type'] = 'Control 95th % confidence interval'

# Control store 5th percentile
pastSales_Controls5 = pastSales[pastSales['Store_type'] == 'Control'].copy()
pastSales_Controls5['totSales'] = pastSales_Controls5['totSales'] * (1 - stdDev * 2)
pastSales_Controls5['Store_type'] = 'Control 5th % confidence interval'
```

```
# Update 'Store_type' for 95th and 5th percentiles
pastSales.loc[pastSales['Store_type'] == 'Control', 'Store_type'] = 'Control 95th % confic
pastSales.loc[pastSales['Store_type'] == 'Control 5th % confidence interval', 'Store_type'

# Concatenate the DataFrames
trialAssessment = pd.concat([pastSales, pastSales_Controls95, pastSales_Controls5], ignore

# Filter the data for the specified date range
filtered_data = trialAssessment[(trialAssessment['TransactionMonth'] >= '2019-01-01') & (t

# Convert TransactionMonth to "Month Year" format
filtered_data.loc[:, 'TransactionMonth'] = filtered_data['TransactionMonth'].dt.strftime('
```

Create a plot

In [40]:

```
plt.figure(figsize=(10, 6))
#plt.plot(filtered_data['TransactionMonth'], filtered_data['totSales'], label='Total Sales
for store_type, data in filtered_data.groupby('Store_type'):
    if store_type == 'Trial':
        plt.plot(data['TransactionMonth'], data['totSales'], marker='o', label='Total Sale
    elif store_type == 'Control':
        plt.plot(data['TransactionMonth'], data['totSales'], marker='o', label='Total Sale
    elif store_type == 'Control 95th % confidence interval':
        plt.fill_between(data['TransactionMonth'], data['totSales'], alpha=0.3, color='gra
    elif store_type == 'Control 5th % confidence interval':
        plt.fill_between(data['TransactionMonth'], data['totSales'], alpha=0.3, color='gre
    else:
        plt.plot(data['TransactionMonth'], data['totSales'], label=f'Total Sales ({store_t

plt.xlabel('Month of Operation')
plt.ylabel('Total Sales')
plt.title('Total Sales by Month')
plt.legend()
plt.show()
```



The results show that the trial in store 77 is significantly different to its control store in the trial period as the trial store performance lies outside the 5% to 95% confidence interval of the control store in two of the three trialmonths.

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

This would be a repeat of the steps before for total sales

Scale pre-trial control customers to match pre-trial trial store customers

Over to you! Compute a scaling factor to align control store customer counts to our trial store.

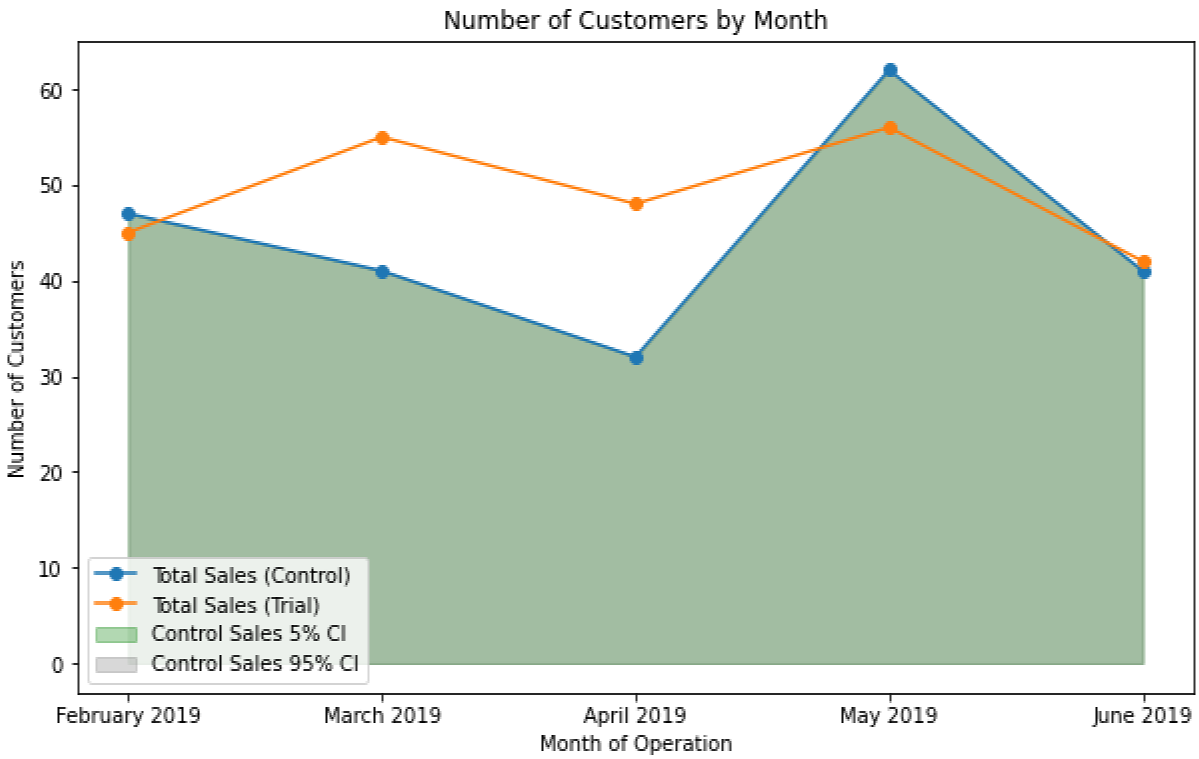
Then, apply the scaling factor to control store customer counts.

Finally, calculate the percentage difference between scaled control store customers and trial customers.

In [39]:

```
# Compute a scaling factor to align control store customer counts to the trial store
scalingFactorForControlCust = measure_over_time[measure_over_time['STORE_NBR'] == trial_st

# Apply the scaling factor to control store customer counts
measure_over_time['scaledControlCustomers'] = measure_over_time['nCustomers'] * scalingFac

# Calculate the percentage difference between scaled control store customers and trial cus
measure_over_time['percentageDiff'] = abs(measure_over_time['scaledControlCustomers'] - me

# Standard deviation based on the scaled percentage difference in the pre-trial period
stdDev = measure_over_time[measure_over_time['YEARMONTH'] < 201902]['percentageDiff'].std

# Degrees of freedom
degreesOfFreedom = 7

# Trial and control store number of customers
pastCustomers = measure_over_time[measure_over_time['Store_type'].isin(['Trial', 'Control'
pastCustomers = pastCustomers.groupby(['YEARMONTH', 'Store_type'])['nCustomers'].mean().re

pastCustomers['TransactionMonth'] = pd.to_datetime(pastSales['YEARMONTH'], format='%Y%m')

# Control store 95th percentile
pastCustomers_Controls95 = pastCustomers[pastCustomers['Store_type'] == 'Control'].copy()
pastCustomers_Controls95['nCustomers'] = pastCustomers_Controls95['nCustomers'] * (1 + std
pastCustomers_Controls95['Store_type'] = 'Control 95th % confidence interval'

# Control store 5th percentile
pastCustomers_Controls5 = pastCustomers[pastCustomers['Store_type'] == 'Control'].copy()
pastCustomers_Controls5['nCustomers'] = pastCustomers_Controls5['nCustomers'] * (1 - stdDe
pastCustomers_Controls5['Store_type'] = 'Control 5th % confidence interval'

# Concatenate the DataFrames
trialCusAssessment = pd.concat([pastCustomers, pastCustomers_Controls95, pastCustomers_Con

# Filter the data for the specified date range
filtered_Cus_data = trialCusAssessment[(trialCusAssessment['TransactionMonth'] >= '2019-02

filtered_Cus_data.loc[:, 'TransactionMonth'] = filtered_Cus_data['TransactionMonth'].dt.st

plt.figure(figsize=(10, 6))
for store_type, data in filtered_Cus_data.groupby('Store_type'):
    if store_type == 'Trial':
        plt.plot(data['TransactionMonth'], data['nCustomers'], marker='o', label='Total Sa
    elif store_type == 'Control':
        plt.plot(data['TransactionMonth'], data['nCustomers'], marker='o', label='Total Sa
    elif store_type == 'Control 95th % confidence interval':
        plt.fill_between(data['TransactionMonth'], data['nCustomers'], alpha=0.3, color='g
    elif store_type == 'Control 5th % confidence interval':
        plt.fill_between(data['TransactionMonth'], data['nCustomers'], alpha=0.3, color='g
```

```
    else:
        plt.plot(data['TransactionMonth'], data['nCustomers'], label=f'Total Sales ({store
plt.xlabel('Month of Operation')
plt.ylabel('Number of Customers')
plt.title('Number of Customers by Month')
plt.legend()
plt.show()
```



Let's repeat finding the control store and assessing the impact of the trial for each of the other two trial stores.

Trial store 86

In [41]:

```
from scipy.stats import pearsonr

# Function to calculate correlation
def calculate_correlation(input_table, metric_col, store_comparison):
    calc_corr_table = pd.DataFrame(columns=['Store1', 'Store2', 'corr_measure'])
    store_numbers = input_table['STORE_NBR'].unique()

    for i in store_numbers:
        if i != store_comparison:
            trial_store_data = input_table[input_table['STORE_NBR'] == store_comparison][r
            control_store_data = input_table[input_table['STORE_NBR'] == i][metric_col]
            corr_measure, _ = pearsonr(trial_store_data, control_store_data)
            calculated_measure = pd.DataFrame({'trial_store_data': [store_comparison], 'co
            calculated_measure['Store1'] = [store_comparison]
            calculated_measure['Store2'] = [i]
            calculated_measure['corr_measure'] = [corr_measure]
            calc_corr_table = pd.concat([calc_corr_table, calculated_measure])

    return calc_corr_table


# Function to calculate magnitude distance
def calculate_magnitude_distance(input_table, metric_col, store_comparison):
    magnitude_table = pd.DataFrame(columns=["Store1", "Store2", "YEARMONTH", "magnitude_me
    store_numbers = input_table["STORE_NBR"].unique()
```

```
    for i in store_numbers:
        magnitude_measure = pd.DataFrame({
            "Store1": [store_comparison],
            "Store2": [i],
            "YEARMONTH": input_table[input_table["STORE_NBR"] == store_comparison]["YEARMO
            "magnitude_measure": abs(input_table[(input_table["STORE_NBR"] == store_compar
                            - input_table[input_table["STORE_NBR"] == i][metric_col].value
        })
        magnitude_table = pd.concat([magnitude_table, magnitude_measure], ignore_index=Tru

    # Standardize the magnitude distance
    min_max_dist = magnitude_table.groupby(["Store1", "YEARMONTH"])["magnitude_measure"].a
    dist_table = magnitude_table.merge(min_max_dist, on=["Store1", "YEARMONTH"])
    dist_table["magnitudeMeasure"] = 1 - (dist_table["magnitude_measure"] - dist_table["mi

    final_dist_table = dist_table.groupby(["Store1", "Store2"])["magnitudeMeasure"].mean()
    final_dist_table.rename(columns={"magnitudeMeasure": "mag_measure"}, inplace=True)

    return final_dist_table

# Trial store and metric column
trial_store = 86
metric_col_sales = 'totSales'
metric_col_customers = 'nCustomers'

# Calculate correlations for total sales and number of customers
corr_nSales = calculate_correlation(pre_trial_measures, metric_col_sales, trial_store)
corr_nCustomers = calculate_correlation(pre_trial_measures, metric_col_customers, trial_st

# Calculate magnitude distances for total sales and number of customers
magnitude_nSales = calculate_magnitude_distance(pre_trial_measures, metric_col_sales, tria
magnitude_nCustomers = calculate_magnitude_distance(pre_trial_measures, metric_col_custome

# Display the resulting DataFrames
print("Correlation for Total Sales:")
print(corr_nSales)

print("Correlation for Number of Customers:")
print(corr_nCustomers)

print("Magnitude Distance for Total Sales:")
print(magnitude_nSales)

print("Magnitude Distance for Number of Customers:")
print(magnitude_nCustomers)
```

```
Correlation for Total Sales:
   Store1 Store2  corr_measure  trial_store_data  control_store_data
0      86      1      0.445632              86.0                 1.0
0      86      2     -0.403835              86.0                 2.0
0      86      3     -0.261284              86.0                 3.0
0      86      4     -0.039035              86.0                 4.0
0      86      5      0.235159              86.0                 5.0
..    ...    ...           ...               ...                 ...
0      86    268     -0.452182              86.0               268.0
0      86    269      0.697055              86.0               269.0
0      86    270     -0.730679              86.0               270.0
0      86    271      0.527637              86.0               271.0
0      86    272      0.004926              86.0               272.0

[259 rows x 5 columns]
Correlation for Number of Customers:
   Store1 Store2  corr_measure  trial_store_data  control_store_data
0      86      1      0.095038              86.0                 1.0
0      86      2      0.126654              86.0                 2.0
```

```
0      86      3     -0.528883              86.0              3.0
0      86      4      0.245200              86.0              4.0
0      86      5     -0.186157              86.0              5.0
..    ...    ...           ...               ...              ...
0      86    268     -0.358962              86.0            268.0
0      86    269      0.536756              86.0            269.0
0      86    270     -0.718733              86.0            270.0
0      86    271      0.503830              86.0            271.0
0      86    272      0.029710              86.0            272.0

[259 rows x 5 columns]
Magnitude Distance for Total Sales:
     Store1  Store2  mag_measure
0        86       1     0.226524
1        86       2     0.163205
2        86       3     0.646163
3        86       4     0.426975
4        86       5     0.909481
..      ...     ...          ...
255      86     268     0.245824
256      86     269     0.898646
257      86     270     0.920316
258      86     271     0.927314
259      86     272     0.481828

[260 rows x 3 columns]
Magnitude Distance for Number of Customers:
     Store1  Store2  mag_measure
0        86       1     0.403226
1        86       2     0.314516
2        86       3     0.903226
3        86       4     0.741935
4        86       5     0.951613
..      ...     ...          ...
255      86     268     0.403226
256      86     269     0.903226
257      86     270     0.911290
258      86     271     0.991935
259      86     272     0.403226

[260 rows x 3 columns]
```

In [42]:

```python
# Merge correlations and magnitude tables for sales
score_nSales = pd.merge(corr_nSales, magnitude_nSales, on=['Store1', 'Store2'], how='inner

# Calculate the final score for total sales as the simple average
score_nSales['scoreNSales'] = (score_nSales['corr_measure'] + score_nSales['mag_measure'])

# Merge correlations and magnitude tables for customers
score_nCustomers = pd.merge(corr_nCustomers, magnitude_nCustomers, on=['Store1', 'Store2']

# Calculate the final score for number of customers as the simple average
score_nCustomers['scoreNCust'] = (score_nCustomers['corr_measure'] + score_nCustomers['mag

# Sort the scores for total sales in descending order
score_nSales = score_nSales.sort_values(by='scoreNSales', ascending=False)

# Display the sorted scores for total sales
print("Sorted Scores for Total Sales:")
print(score_nSales)

# Sort the scores for number of customers in descending order
score_nCustomers = score_nCustomers.sort_values(by='scoreNCust', ascending=False)

# Display the sorted scores for number of customers
```

```
print("Sorted Scores for Number of Customers:")
print(score_nCustomers)
```

```
Sorted Scores for Total Sales:
    Store1  Store2  corr_measure  trial_store_data  control_store_data  \
146     86     155      0.877882              86.0               155.0
101     86     109      0.788300              86.0               109.0
209     86     222      0.795075              86.0               222.0
129     86     138      0.759864              86.0               138.0
106     86     114      0.734415              86.0               114.0
..     ...     ...           ...               ...                 ...
47      86      51     -0.736441              86.0                51.0
240     86     254     -0.793506              86.0               254.0
39      86      42     -0.745720              86.0                42.0
111     86     120     -0.872693              86.0               120.0
137     86     146     -0.775127              86.0               146.0

     mag_measure  scoreNSales
146     0.963431     0.920656
101     0.990745     0.889522
209     0.940858     0.867967
129     0.921219     0.840541
106     0.940406     0.837411
..           ...          ...
47      0.124153    -0.306144
240     0.169526    -0.311990
39      0.023815    -0.360952
111     0.104402    -0.384146
137     0.006546    -0.384291

[259 rows x 7 columns]
Sorted Scores for Number of Customers:
    Store1  Store2  corr_measure  trial_store_data  control_store_data  \
129     86     138      0.819280              86.0               138.0
234     86     247      0.718834              86.0               247.0
45      86      49      0.690542              86.0                49.0
157     86     166      0.765179              86.0               166.0
138     86     147      0.799353              86.0               147.0
..     ...     ...           ...               ...                 ...
47      86      51     -0.742888              86.0                51.0
111     86     120     -0.778269              86.0               120.0
48      86      52     -0.603873              86.0                52.0
152     86     161     -0.620881              86.0               161.0
137     86     146     -0.756025              86.0               146.0

     mag_measure  scoreNCust
129     0.943548    0.881414
234     1.000000    0.859417
45      0.991935    0.841239
157     0.903226    0.834202
138     0.854839    0.827096
..           ...         ...
47      0.241935   -0.250476
111     0.209677   -0.284296
48      0.024194   -0.289840
152     0.024194   -0.298344
137     0.008065   -0.373980

[259 rows x 7 columns]
```

In [43]:

```
# Merge sales and customer scores into a single table
score_Control = pd.merge(score_nSales, score_nCustomers, on=['Store1', 'Store2'], how='inn

# Calculate the final control store score as a weighted average (0.5 for each score)
score_Control['finalControlScore'] = 0.5 * score_Control['scoreNSales'] + 0.5 * score_Cont
```

```
# Sort the stores by final control score in descending order
score_Control = score_Control.sort_values(by='finalControlScore', ascending=False)

# Display the sorted control store scores
print("Sorted Control Store Scores:")
score_Control.head()
```

Sorted Control Store Scores:

Out[43]:

	Store1	Store2	corr_measure_x	trial_store_data_x	control_store_data_x	mag_measure_x	scoreNSales	corr_measur
0	86	155	0.877882	86.0	155.0	0.963431	0.920656	0.642
3	86	138	0.759864	86.0	138.0	0.921219	0.840541	0.819
2	86	222	0.795075	86.0	222.0	0.940858	0.867967	0.596
4	86	114	0.734415	86.0	114.0	0.940406	0.837411	0.660
8	86	247	0.538935	86.0	247.0	0.955079	0.747007	0.718

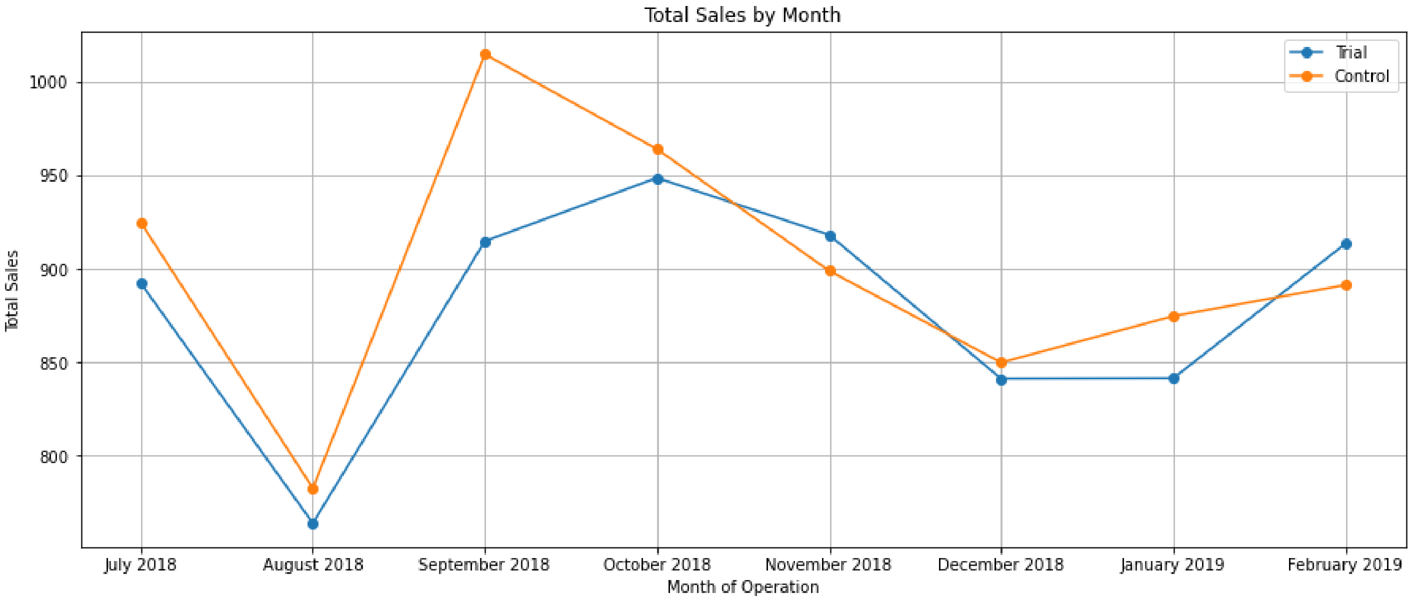
In [44]:

```
# Filter the scores for the trial store
trial_store_scores = score_Control[score_Control['Store1'] == trial_store]

# Sort the scores in descending order
trial_store_scores = trial_store_scores.sort_values(by='finalControlScore', ascending=Fals

# Select the second highest ranked store (closest to 1 but not the store itself)
control_store = trial_store_scores.iloc[0]['Store2']

# Display the selected control store
print("Selected Control Store:", control_store)
```

Selected Control Store: 155

In [47]:

```
# Extract relevant data
pastSales = measure_over_time.copy()

# Create a new DataFrame with store types
pastSales['Store_type'] = pastSales['STORE_NBR'].apply(lambda x: 'Trial' if x == trial_sto

# Calculate the mean total sales by month and store type
pastSales['totSales'] = pastSales.groupby(['YEARMONTH', 'Store_type'])['totSales'].transfo
#pastSales = pastSales[pastSales['Store_type'].isin(['Trial', 'Control'])]
pastSales['TransactionMonth'] = pd.to_datetime(pastSales['YEARMONTH'].astype(str), format=

# Filter data for months before March 2019
pastSales = pastSales[pastSales['TransactionMonth'] < '2019-03-01']
pastSales.loc[:, 'TransactionMonth'] = pastSales['TransactionMonth'].dt.strftime('%B %Y')

# Create a line plot
plt.figure(figsize=(15, 6))
plt.plot(pastSales[pastSales['Store_type'] == 'Trial']['TransactionMonth'], pastSales[past
plt.plot(pastSales[pastSales['Store_type'] == 'Control']['TransactionMonth'], pastSales[pa
#plt.plot(pastSales[pastSales['Store_type'] == 'Other stores']['TransactionMonth'], pastSa

# Add labels and legend
plt.xlabel('Month of Operation')
plt.ylabel('Total Sales')
plt.title('Total Sales by Month')
plt.legend()
plt.grid(True)
plt.show()
```

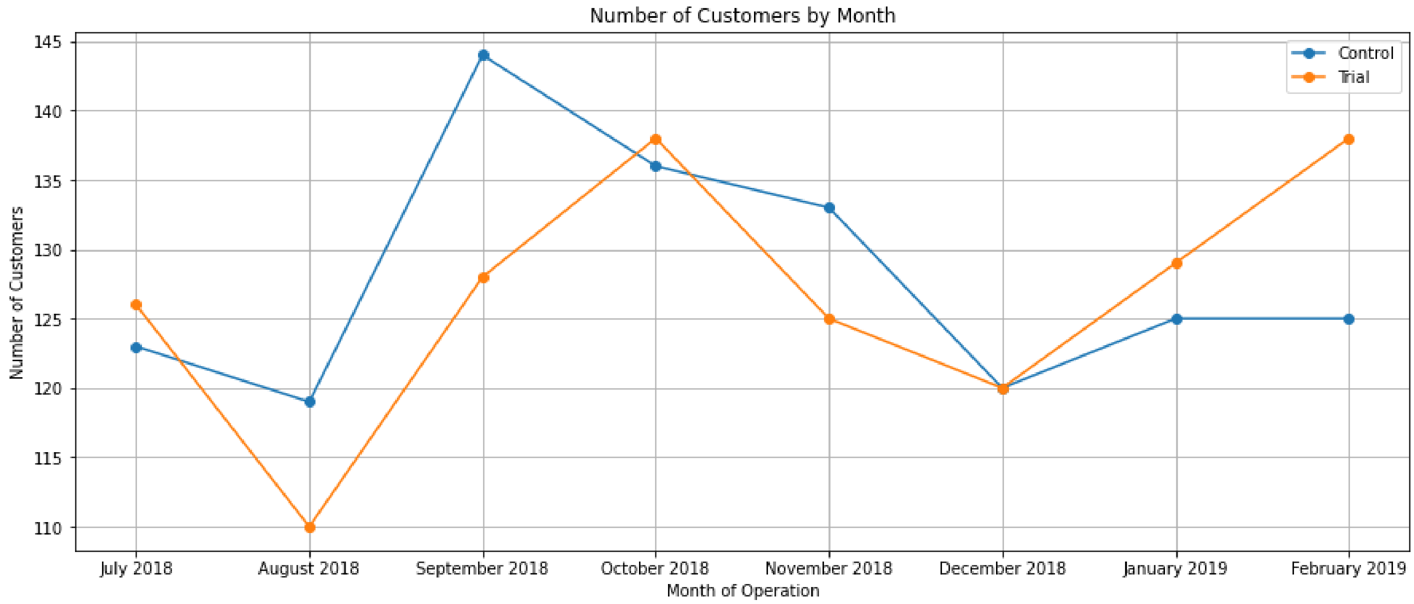


Great, sales are trending in a similar way.

Next, number of customers

In [51]:

```
# Extract relevant data
pastCustomers = measure_over_time.copy()
pastCustomers['Store_type'] = pastCustomers['STORE_NBR'].apply(lambda x: 'Trial' if x == t
pastCustomers['numberCustomers'] = pastCustomers.groupby(['YEARMONTH', 'Store_type'])['nCu
pastCustomers = pastCustomers[pastCustomers['Store_type'].isin(['Trial', 'Control','other_
pastCustomers['TransactionMonth'] = pd.to_datetime(pastCustomers['YEARMONTH'].astype(str),

# Filter data for months before March 2019
pastCustomers = pastCustomers[pastCustomers['TransactionMonth'] < '2019-03-01']
pastCustomers.loc[:, 'TransactionMonth'] = pastCustomers['TransactionMonth'].dt.strftime('

# Create a line plot
plt.figure(figsize=(15, 6))
for store_type, group_data in pastCustomers.groupby('Store_type'):
    plt.plot(group_data['TransactionMonth'], group_data['numberCustomers'], label=store_ty

# Add labels and legend
plt.xlabel('Month of Operation')
plt.ylabel('Number of Customers')
plt.title('Number of Customers by Month')
plt.legend()
plt.grid(True)
plt.show()
```



Good, the trend in number of customers is also similar.

Let's now assess the impact of the trial on sales.

In [53]:

```
# Assuming you have already defined trial_store and control_store
trial_store = 86
control_store = 155

# Calculate the scaling factor for control store sales
trial_store_sales = pre_trial_measures[(pre_trial_measures['STORE_NBR'] == trial_store) &
control_store_sales = pre_trial_measures[(pre_trial_measures['STORE_NBR'] == control_store

scalingFactorForControlSales = trial_store_sales / control_store_sales

# Apply the scaling factor
measure_over_time_sales = measure_over_time
scaledControlSales = measure_over_time_sales[measure_over_time_sales['STORE_NBR'] == contr
scaledControlSales['controlSales'] = scaledControlSales['totSales'] * scalingFactorForCont

#  Calculate the percentage difference between scaled control sales and trial sales
percentageDifference = pd.merge(scaledControlSales[['YEARMONTH', 'controlSales']],measure_

# Calculate the percentage difference
percentageDifference['percentageDiff'] = abs(percentageDifference['controlSales'] -percent

percentageDifference.head()

# Filter the percentageDiff DataFrame for the pre-trial period
pre_trial_period_df = percentageDifference[['percentageDiff','YEARMONTH']]
pre_trial_percentage_diffr = pre_trial_period_df[pre_trial_period_df['YEARMONTH'] < 201902

# Calculate the standard deviation
std_dev = np.std(pre_trial_percentage_diffr['percentageDiff'])
std_dev

from scipy.stats import t

# Calculate the standard deviation based on the scaled percentage difference in the pre-tr
std_dev = np.std(percentageDifference[percentageDifference['YEARMONTH'] < 201902]['percent

# Degrees of freedom (number of months in the pre-trial period - 1)
degrees_of_freedom = 7

# Calculate the t-values for the trial months
percentageDifference['tValue'] = (percentageDifference['percentageDiff'] - 0) / std_dev
```

```
percentageDifference['TransactionMonth'] = pd.to_datetime(percentageDifference['YEARMONTH'

# Filter for the trial months
trial_months = percentageDifference[(percentageDifference['YEARMONTH'] < 201905) & (percer

# Find the 95th percentile of the t-distribution
alpha = 0.05  # Significance level
t_critical = t.ppf(1 - alpha / 2, degrees_of_freedom)

print("Critical t-value for a 95% confidence interval:", t_critical)
print(trial_months[['TransactionMonth', 'tValue']])
```

```
Critical t-value for a 95% confidence interval: 2.3646242510102993
  TransactionMonth     tValue
7       2019-02-01   2.354174
8       2019-03-01  13.206585
9       2019-04-01   1.473915
```

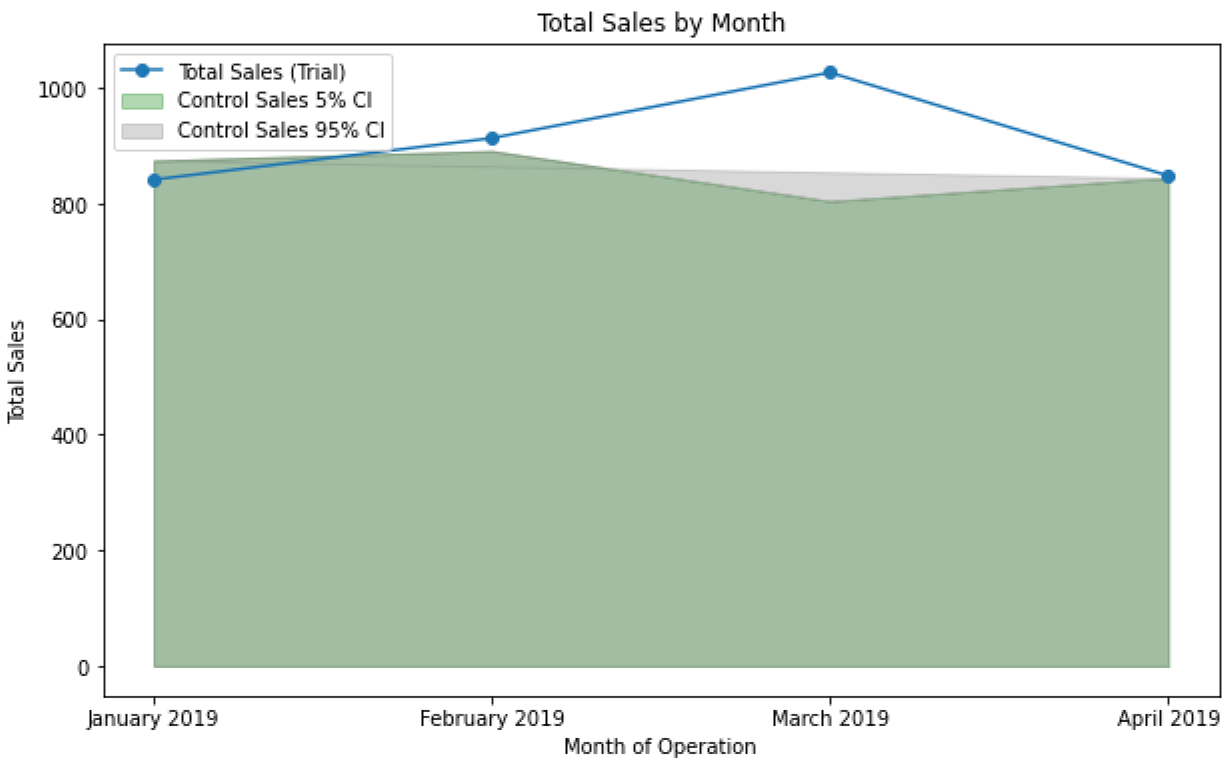
We can observe that the t-value is much larger than the 95th percentile value of the t-distribution for March only - i.e. the increase in sales in the trial store 86 in March is statistically greater than in the control store.

Calculate the 5th and 95th percentile for control store sales

In [57]:

```
# Create a new column Store_type
measure_over_time['Store_type'] = 'Other stores'
measure_over_time.loc[measure_over_time['STORE_NBR'] == trial_store, 'Store_type'] = 'Tria
measure_over_time.loc[measure_over_time['STORE_NBR'] == control_store, 'Store_type'] = 'Co

# Calculate mean total sales by YEARMONTH and Store_type
pastSales = measure_over_time[measure_over_time['Store_type'].isin(['Trial', 'Control'])]
pastSales = pastSales.groupby(['YEARMONTH', 'Store_type'])['totSales'].mean().reset_index

# Convert YEARMONTH to TransactionMonth
pastSales['TransactionMonth'] = pd.to_datetime(pastSales['YEARMONTH'], format='%Y%m')

std_dev = np.std(percentageDifference[percentageDifference['YEARMONTH'] < 201902]['percent
# Control store 95th percentile
pastSales_Controls95 = pastSales[pastSales['Store_type'] == 'Control'].copy()
pastSales_Controls95['totSales'] = pastSales_Controls95['totSales'] * (1 + stdDev * 2)
pastSales_Controls95['Store_type'] = 'Control 95th % confidence interval'

# Control store 5th percentile
pastSales_Controls5 = pastSales[pastSales['Store_type'] == 'Control'].copy()
pastSales_Controls5['totSales'] = pastSales_Controls5['totSales'] * (1 - stdDev * 2)
pastSales_Controls5['Store_type'] = 'Control 5th % confidence interval'

# Update 'Store_type' for 95th and 5th percentiles
pastSales.loc[pastSales['Store_type'] == 'Control', 'Store_type'] = 'Control 95th % confic
pastSales.loc[pastSales['Store_type'] == 'Control 5th % confidence interval', 'Store_type'

# Concatenate the DataFrames
trial86Assessment = pd.concat([pastSales, pastSales_Controls95, pastSales_Controls5], ignc

# Filter the data for the specified date range
trial86Assessment = trial86Assessment[(trial86Assessment['TransactionMonth'] >= '2019-01-(

# Convert TransactionMonth to "Month Year" format
trial86Assessment.loc[:, 'TransactionMonth'] = trial86Assessment['TransactionMonth'].dt.st

#Create a plot
plt.figure(figsize=(10, 6))
#plt.plot(filtered_data['TransactionMonth'], filtered_data['totSales'], label='Total Sales
for store_type, data in trial86Assessment.groupby('Store_type'):
    if store_type == 'Trial':
        plt.plot(data['TransactionMonth'], data['totSales'], marker='o', label='Total Sale
```

```
    elif store_type == 'Control':
        plt.plot(data['TransactionMonth'], data['totSales'], marker='o', label='Total Sale
    elif store_type == 'Control 95th % confidence interval':
        plt.fill_between(data['TransactionMonth'], data['totSales'], alpha=0.3, color='gra
    elif store_type == 'Control 5th % confidence interval':
        plt.fill_between(data['TransactionMonth'], data['totSales'], alpha=0.3, color='gre
    else:
        plt.plot(data['TransactionMonth'], data['totSales'], label=f'Total Sales ({store_t

plt.xlabel('Month of Operation')
plt.ylabel('Total Sales')
plt.title('Total Sales by Month')
plt.legend()
plt.show()
```



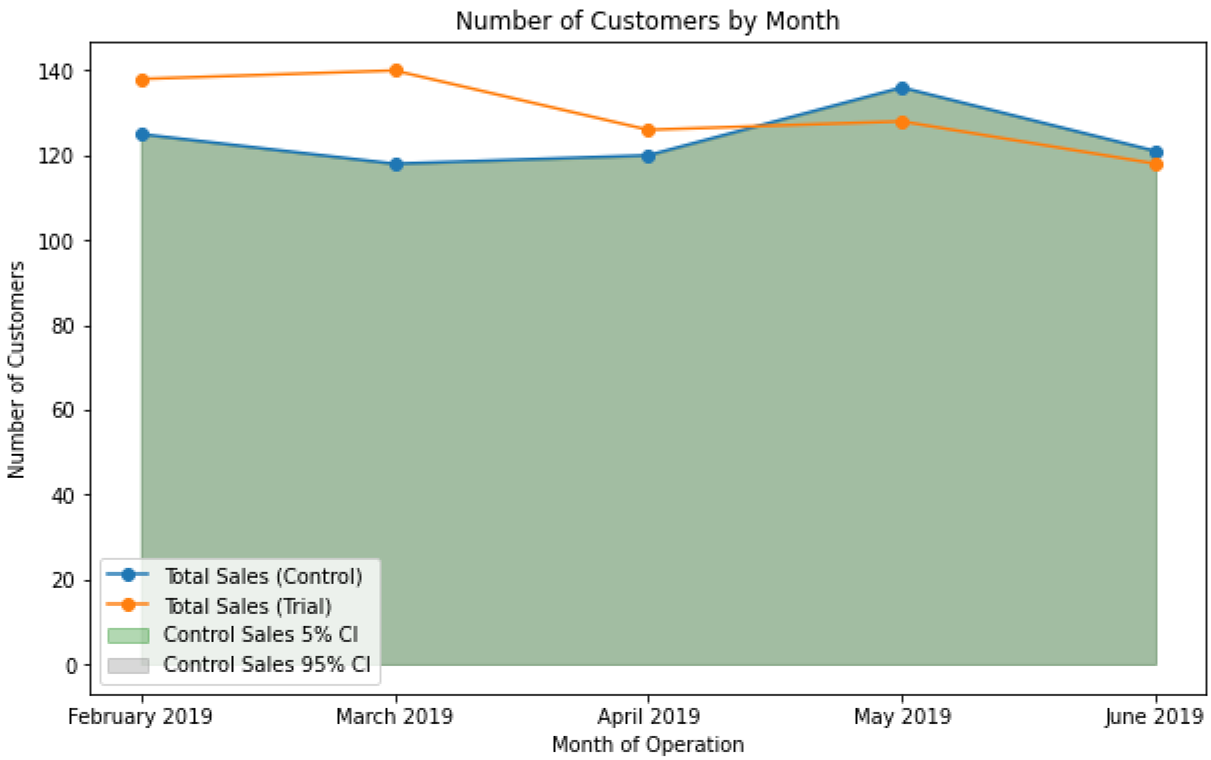
The results show that the trial in store 86 is not significantly different to its control store in the trial period as the trial store performance lies inside the 5% to 95% confidence interval of the control store in two of the three trial months.

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

In [65]:
```
# Assuming you have already defined trial_store and control_store
trial_store = 86
control_store = 155

# Calculate the scaling factor for control store sales
trial_store_cust = pre_trial_measures[(pre_trial_measures['STORE_NBR'] == trial_store) &
control_store_cust = pre_trial_measures[(pre_trial_measures['STORE_NBR'] == control_store)

scalingFactorForControlCust = trial_store_cust / control_store_cust

# Apply the scaling factor
measure_over_time_custs = measure_over_time
measure_over_time_custs['scaledControlCustomers'] = measure_over_time_custs['nCustomers']

# Calculate the percentage difference between scaled control store customers and trial cus
measure_over_time_custs['percentageDiff'] = abs(measure_over_time_custs['scaledControlCust

# Standard deviation based on the scaled percentage difference in the pre-trial period
```

```python
stdDev = measure_over_time_custs[measure_over_time_custs['YEARMONTH'] < 201902]['percentag

# Degrees of freedom
degreesOfFreedom = 7

# Trial and control store number of customers
pastCustomers = measure_over_time_custs[measure_over_time_custs['Store_type'].isin(['Trial
pastCustomers = pastCustomers.groupby(['YEARMONTH', 'Store_type'])['nCustomers'].mean().re

pastCustomers['TransactionMonth'] = pd.to_datetime(pastSales['YEARMONTH'], format='%Y%m')

# Control store 95th percentile
pastCustomers_Controls95 = pastCustomers[pastCustomers['Store_type'] == 'Control'].copy()
pastCustomers_Controls95['nCustomers'] = pastCustomers_Controls95['nCustomers'] * (1 + std
pastCustomers_Controls95['Store_type'] = 'Control 95th % confidence interval'

# Control store 5th percentile
pastCustomers_Controls5 = pastCustomers[pastCustomers['Store_type'] == 'Control'].copy()
pastCustomers_Controls5['nCustomers'] = pastCustomers_Controls5['nCustomers'] * (1 - stdDe
pastCustomers_Controls5['Store_type'] = 'Control 5th % confidence interval'

# Concatenate the DataFrames
trialC86Assessment = pd.concat([pastCustomers, pastCustomers_Controls95, pastCustomers_Con
#trialC86Assessment['YEARMONTH'] = trialC86Assessment['YEARMONTH'].astype(int)
trialC86Assessment['TransactionMonth'] = pd.to_datetime(trialC86Assessment['YEARMONTH'], f

# Filter the data for the specified date range
filtered_Cus86_data = trialC86Assessment[(trialC86Assessment['TransactionMonth'] >= '2019-

filtered_Cus86_data.loc[:, 'TransactionMonth'] = filtered_Cus86_data['TransactionMonth'].d

#Create a plot
plt.figure(figsize=(10, 6))
for store_type, data in filtered_Cus86_data.groupby('Store_type'):
    if store_type == 'Trial':
        plt.plot(data['TransactionMonth'], data['nCustomers'], marker='o', label='Total Sa
    elif store_type == 'Control':
        plt.plot(data['TransactionMonth'], data['nCustomers'], marker='o', label='Total Sa
    elif store_type == 'Control 95th % confidence interval':
        plt.fill_between(data['TransactionMonth'], data['nCustomers'], alpha=0.3, color='g
    elif store_type == 'Control 5th % confidence interval':
        plt.fill_between(data['TransactionMonth'], data['nCustomers'], alpha=0.3, color='g
    else:
        plt.plot(data['TransactionMonth'], data['nCustomers'], label=f'Total Sales ({store

plt.xlabel('Month of Operation')
plt.ylabel('Number of Customers')
plt.title('Number of Customers by Month')
plt.legend()
plt.show()
```

```
C:\Users\DELL\anaconda3\lib\site-packages\pandas\core\indexing.py:1773: SettingWithCopyWar
ning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_gu
ide/indexing.html#returning-a-view-versus-a-copy
  self._setitem_single_column(ilocs[0], value, pi)
```



It looks like the number of customers is significantly higher in all of the three months. This seems to suggest that the trial had a significant impact on increasing the number of customers in trial store 86 but as we saw, sales were not significantly higher.

Trial store 88

Use the functions from earlier to calculate the correlation of the sales and number of customers of each potential control store to the trial store

Use the functions from earlier to calculate the magnitude distance of the sales and number of customers of each potential control store to the trial store

Create a combined score composed of correlation and magnitude by merging the correlations table and the magnitudes table, for each driver.

In [68]:

```
from scipy.stats import pearsonr

# Function to calculate correlation
def calculate_correlation(input_table, metric_col, store_comparison):
    calc_corr_table = pd.DataFrame(columns=['Store1', 'Store2', 'corr_measure'])
    store_numbers = input_table['STORE_NBR'].unique()

    for i in store_numbers:
        if i != store_comparison:
            trial_store_data = input_table[input_table['STORE_NBR'] == store_comparison][r
            control_store_data = input_table[input_table['STORE_NBR'] == i][metric_col]
            corr_measure, _ = pearsonr(trial_store_data, control_store_data)
            calculated_measure = pd.DataFrame({'trial_store_data': [store_comparison], 'co
            calculated_measure['Store1'] = [store_comparison]
            calculated_measure['Store2'] = [i]
            calculated_measure['corr_measure'] = [corr_measure]
            calc_corr_table = pd.concat([calc_corr_table, calculated_measure])

    return calc_corr_table


# Function to calculate magnitude distance
```

```python
def calculate_magnitude_distance(input_table, metric_col, store_comparison):
    magnitude_table = pd.DataFrame(columns=["Store1", "Store2", "YEARMONTH", "magnitude_me
    store_numbers = input_table["STORE_NBR"].unique()

    for i in store_numbers:
        magnitude_measure = pd.DataFrame({
            "Store1": [store_comparison],
            "Store2": [i],
            "YEARMONTH": input_table[input_table["STORE_NBR"] == store_comparison]["YEARMO
            "magnitude_measure": abs(input_table[(input_table["STORE_NBR"] == store_compar
                                - input_table[input_table["STORE_NBR"] == i][metric_col].value
        })
        magnitude_table = pd.concat([magnitude_table, magnitude_measure], ignore_index=Tru

    # Standardize the magnitude distance
    min_max_dist = magnitude_table.groupby(["Store1", "YEARMONTH"])["magnitude_measure"].a
    dist_table = magnitude_table.merge(min_max_dist, on=["Store1", "YEARMONTH"])
    dist_table["magnitudeMeasure"] = 1 - (dist_table["magnitude_measure"] - dist_table["mi

    final_dist_table = dist_table.groupby(["Store1", "Store2"])["magnitudeMeasure"].mean()
    final_dist_table.rename(columns={"magnitudeMeasure": "mag_measure"}, inplace=True)

    return final_dist_table

# Trial store and metric column
trial_store = 88
metric_col_sales = 'totSales'
metric_col_customers = 'nCustomers'

# Calculate correlations for total sales and number of customers
corr_nSales = calculate_correlation(pre_trial_measures, metric_col_sales, trial_store)
corr_nCustomers = calculate_correlation(pre_trial_measures, metric_col_customers, trial_st

# Calculate magnitude distances for total sales and number of customers
magnitude_nSales = calculate_magnitude_distance(pre_trial_measures, metric_col_sales, tria
magnitude_nCustomers = calculate_magnitude_distance(pre_trial_measures, metric_col_custome

# Display the resulting DataFrames
print("Correlation for Total Sales:")
print(corr_nSales)

print("Correlation for Number of Customers:")
print(corr_nCustomers)

print("Magnitude Distance for Total Sales:")
print(magnitude_nSales)

print("Magnitude Distance for Number of Customers:")
print(magnitude_nCustomers)
```

```
Correlation for Total Sales:
   Store1 Store2  corr_measure  trial_store_data  control_store_data
0      88      1      0.813636              88.0                 1.0
0      88      2     -0.067927              88.0                 2.0
0      88      3     -0.507847              88.0                 3.0
0      88      4     -0.745566              88.0                 4.0
0      88      5      0.190330              88.0                 5.0
..    ...    ...           ...               ...                 ...
0      88    268     -0.021429              88.0               268.0
0      88    269     -0.172578              88.0               269.0
0      88    270     -0.723272              88.0               270.0
0      88    271     -0.103037              88.0               271.0
0      88    272     -0.772772              88.0               272.0

[259 rows x 5 columns]
```

```
Correlation for Number of Customers:
   Store1 Store2  corr_measure  trial_store_data  control_store_data
0      88      1      0.540631              88.0                 1.0
0      88      2     -0.220174              88.0                 2.0
0      88      3      0.028485              88.0                 3.0
0      88      4     -0.393173              88.0                 4.0
0      88      5     -0.325467              88.0                 5.0
..    ...    ...           ...               ...                 ...
0      88    268      0.416857              88.0               268.0
0      88    269     -0.410442              88.0               269.0
0      88    270     -0.483987              88.0               270.0
0      88    271     -0.391527              88.0               271.0
0      88    272     -0.401536              88.0               272.0

[259 rows x 5 columns]
Magnitude Distance for Total Sales:
     Store1  Store2  mag_measure
0        88       1     0.153935
1        88       2     0.110907
2        88       3     0.920003
3        88       4     0.931048
4        88       5     0.618040
..      ...     ...          ...
255      88     268     0.167050
256      88     269     0.748428
257      88     270     0.733701
258      88     271     0.728946
259      88     272     0.327428

[260 rows x 3 columns]
Magnitude Distance for Number of Customers:
     Store1  Store2  mag_measure
0        88       1     0.331126
1        88       2     0.258278
2        88       3     0.900662
3        88       4     0.966887
4        88       5     0.781457
..      ...     ...          ...
255      88     268     0.331126
256      88     269     0.900662
257      88     270     0.894040
258      88     271     0.827815
259      88     272     0.331126

[260 rows x 3 columns]
```

In [69]:

```
# Merge correlations and magnitude tables for sales
score_nSales = pd.merge(corr_nSales, magnitude_nSales, on=['Store1', 'Store2'], how='inner

# Calculate the final score for total sales as the simple average
score_nSales['scoreNSales'] = (score_nSales['corr_measure'] + score_nSales['mag_measure'])

# Merge correlations and magnitude tables for customers
score_nCustomers = pd.merge(corr_nCustomers, magnitude_nCustomers, on=['Store1', 'Store2']

# Calculate the final score for number of customers as the simple average
score_nCustomers['scoreNCust'] = (score_nCustomers['corr_measure'] + score_nCustomers['mag

# Sort the scores for total sales in descending order
score_nSales = score_nSales.sort_values(by='scoreNSales', ascending=False)

# Display the sorted scores for total sales
print("Sorted Scores for Total Sales:")
print(score_nSales)
```

```
# Sort the scores for number of customers in descending order
score_nCustomers = score_nCustomers.sort_values(by='scoreNCust', ascending=False)

# Display the sorted scores for number of customers
print("Sorted Scores for Number of Customers:")
print(score_nCustomers)
```

```
Sorted Scores for Total Sales:
    Store1  Store2  corr_measure  trial_store_data  control_store_data  \
193     88     203      0.508001              88.0               203.0
169     88     178      0.731857              88.0               178.0
98      88     106      0.644724              88.0               106.0
6       88       7      0.649657              88.0                 7.0
116     88     125      0.624109              88.0               125.0
..     ...     ...           ...               ...                 ...
83      88      90     -0.662427              88.0                90.0
39      88      42     -0.519338              88.0                42.0
7       88       8     -0.816296              88.0                 8.0
176     88     185     -0.705768              88.0               185.0
48      88      52     -0.569312              88.0                52.0

     mag_measure  scoreNSales
193     0.966866     0.737434
169     0.725418     0.728637
98      0.795061     0.719893
6       0.781178     0.715418
116     0.792760     0.708434
..           ...          ...
83      0.175794    -0.243316
39      0.016183    -0.251578
7       0.287928    -0.264184
176     0.168277    -0.268746
48      0.016950    -0.276181

[259 rows x 7 columns]
Sorted Scores for Number of Customers:
    Store1  Store2  corr_measure  trial_store_data  control_store_data  \
6       88       7      0.946829              88.0                 7.0
114     88     123      0.906737              88.0               123.0
224     88     237      0.723230              88.0               237.0
105     88     113      0.693233              88.0               113.0
193     88     203      0.573341              88.0               203.0
..     ...     ...           ...               ...                 ...
177     88     186     -0.625444              88.0               186.0
222     88     235     -0.820958              88.0               235.0
226     88     239     -0.806828              88.0               239.0
244     88     258     -0.529150              88.0               258.0
132     88     141     -0.937860              88.0               141.0

     mag_measure  scoreNCust
6       0.781457    0.864143
114     0.821192    0.863965
224     0.940397    0.831814
105     0.860927    0.777080
193     0.927152    0.750247
..           ...         ...
177     0.205298   -0.210073
222     0.370861   -0.225048
226     0.278146   -0.264341
244     0.000000   -0.264575
132     0.271523   -0.333168

[259 rows x 7 columns]
```

In [70]:

```
# Merge sales and customer scores into a single table
```

```
score_Control = pd.merge(score_nSales, score_nCustomers, on=['Store1', 'Store2'], how='inn

# Calculate the final control store score as a weighted average (0.5 for each score)
score_Control['finalControlScore'] = 0.5 * score_Control['scoreNSales'] + 0.5 * score_Cont

# Sort the stores by final control score in descending order
score_Control = score_Control.sort_values(by='finalControlScore', ascending=False)

# Display the sorted control store scores
print("Sorted Control Store Scores:")
score_Control.head()
```

```
Sorted Control Store Scores:
```

Out[70]:

	Store1	Store2	corr_measure_x	trial_store_data_x	control_store_data_x	mag_measure_x	scoreNSales	corr_measu
3	88	7	0.649657	88.0	7.0	0.781178	0.715418	0.94
0	88	203	0.508001	88.0	203.0	0.966866	0.737434	0.57
13	88	123	0.399761	88.0	123.0	0.843074	0.621418	0.90
1	88	178	0.731857	88.0	178.0	0.725418	0.728637	0.60
17	88	237	0.308479	88.0	237.0	0.893849	0.601164	0.72

Select control stores based on the highest matching store

(closest to 1 but not the store itself, i.e. the second ranked highest store)

Select control store for trial store 88

In [81]:

```
# Filter the scores for the trial store
trial_store_scores = score_Control[score_Control['Store1'] == 88]

# Sort the scores in descending order
trial_store_scores = trial_store_scores.sort_values(by='finalControlScore', ascending=Fals

# Select the second highest ranked store (closest to 1 but not the store itself)
control_store = trial_store_scores.iloc[1]['Store2']

# Display the selected control store
print("Selected Control Store:", control_store)
```

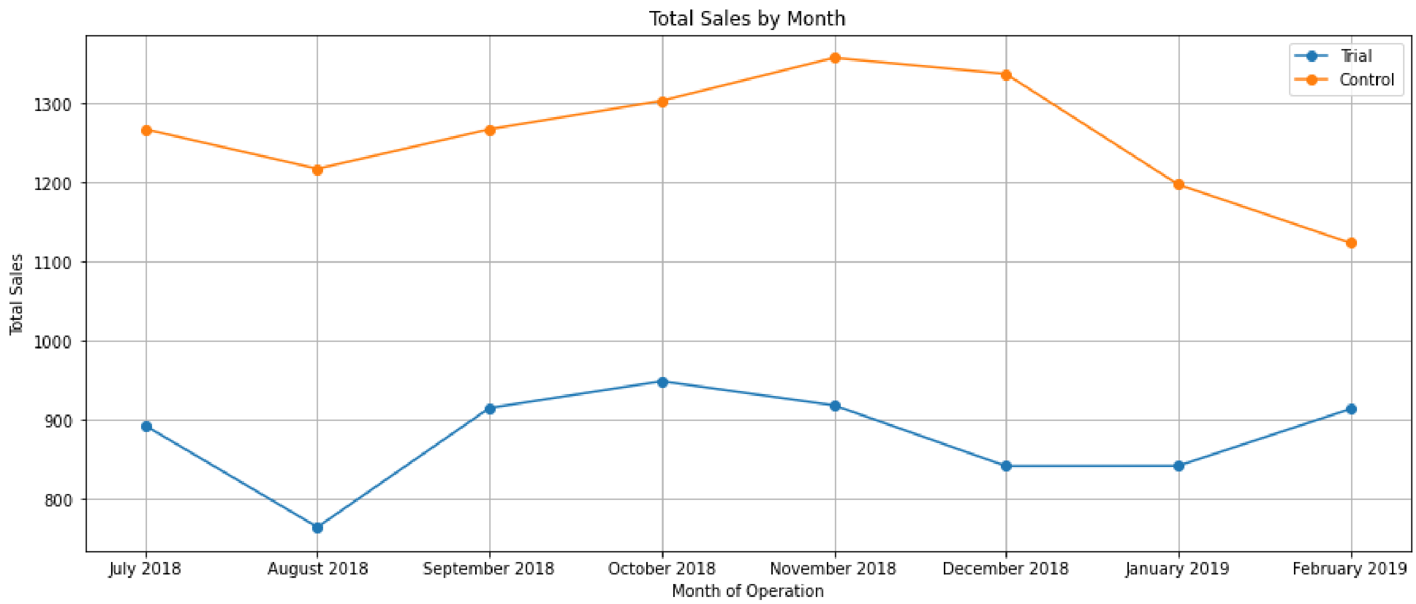
```
Selected Control Store: 203
```

We've now found store 237 to be a suitable control store for trial store 88. Again, let's check visually if the drivers are indeed similar in the period before the trial. We'll look at total sales first.

In [82]:

```
# Extract relevant data
pastSales88 = measure_over_time.copy()

# Create a new DataFrame with store types
pastSales88['Store_type'] = pastSales88['STORE_NBR'].apply(lambda x: 'Trial' if x == trial

# Calculate the mean total sales by month and store type
pastSales88['totSales'] = pastSales88.groupby(['YEARMONTH', 'Store_type'])['totSales'].tra
#pastSales = pastSales[pastSales['Store_type'].isin(['Trial', 'Control'])]
pastSales88['TransactionMonth'] = pd.to_datetime(pastSales88['YEARMONTH'].astype(str), for

# Filter data for months before March 2019
pastSales88 = pastSales88[pastSales88['TransactionMonth'] < '2019-03-01']
pastSales88.loc[:, 'TransactionMonth'] = pastSales88['TransactionMonth'].dt.strftime('%B %
```

```
# Create a line plot
plt.figure(figsize=(15, 6))
plt.plot(pastSales88[pastSales88['Store_type'] == 'Trial']['TransactionMonth'], pastSales8
plt.plot(pastSales88[pastSales88['Store_type'] == 'Control']['TransactionMonth'], pastSale
#plt.plot(pastSales[pastSales['Store_type'] == 'Other stores']['TransactionMonth'], pastSa

# Add labels and legend
plt.xlabel('Month of Operation')
plt.ylabel('Total Sales')
plt.title('Total Sales by Month')
plt.legend()
plt.grid(True)
plt.show()
```



Great, the trial and control stores have similar total sales.

Next, number of customers.

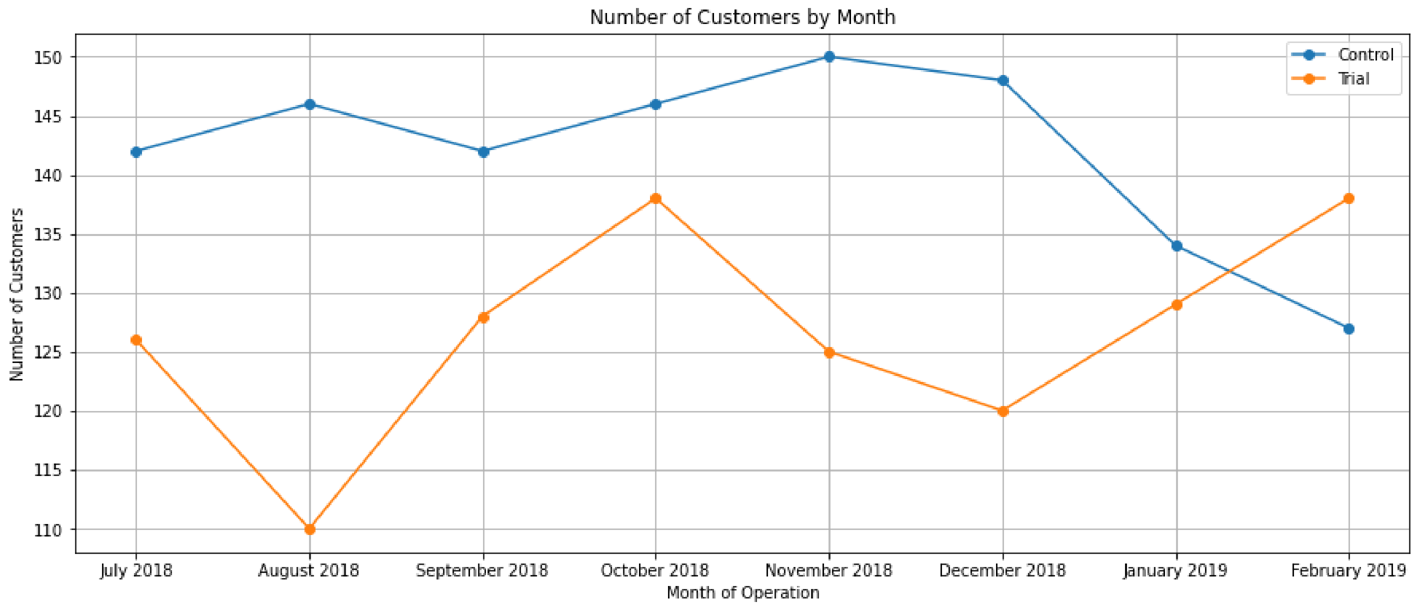
Visual checks on trends based on the drivers

For the period before the trial, create a graph with customer counts of thetrial store for each month, compared to the control store and other stores

In [83]:

```
# Extract relevant data
pastCustomers88 = measure_over_time.copy()
pastCustomers88['Store_type'] = pastCustomers88['STORE_NBR'].apply(lambda x: 'Trial' if x
pastCustomers88['numberCustomers'] = pastCustomers88.groupby(['YEARMONTH', 'Store_type'])
pastCustomers88 = pastCustomers88[pastCustomers88['Store_type'].isin(['Trial', 'Control',
pastCustomers88['TransactionMonth'] = pd.to_datetime(pastCustomers88['YEARMONTH'].astype(s

# Filter data for months before March 2019
pastCustomers88 = pastCustomers88[pastCustomers88['TransactionMonth'] < '2019-03-01']
pastCustomers88.loc[:, 'TransactionMonth'] = pastCustomers88['TransactionMonth'].dt.strfti

# Create a line plot
plt.figure(figsize=(15, 6))
for store_type, group_data in pastCustomers88.groupby('Store_type'):
    plt.plot(group_data['TransactionMonth'], group_data['numberCustomers'], label=store_ty

# Add labels and legend
plt.xlabel('Month of Operation')
plt.ylabel('Number of Customers')
plt.title('Number of Customers by Month')
plt.legend()
```

```
plt.grid(True)
plt.show()
```



Total number of customers of the control and trial stores are also similar.

Let's now assess the impact of the trial on sales.

In [88]:

```
# Assuming you have already defined trial_store and control_store
trial_store = 88
control_store = 237

# Calculate the scaling factor for control store sales
trial_store_sales = pre_trial_measures[(pre_trial_measures['STORE_NBR'] == trial_store) &
control_store_sales = pre_trial_measures[(pre_trial_measures['STORE_NBR'] == control_store

scalingFactorForControlSales = trial_store_sales / control_store_sales

# Apply the scaling factor
measure_over_time_sales = measure_over_time
scaledControlSales = measure_over_time_sales[measure_over_time_sales['STORE_NBR'] == contr
scaledControlSales['controlSales'] = scaledControlSales['totSales'] * scalingFactorForCont

#  Calculate the percentage difference between scaled control sales and trial sales
percentageDifference = pd.merge(scaledControlSales[['YEARMONTH', 'controlSales']],measure_

# Calculate the percentage difference
percentageDifference['percentageDiff'] = abs(percentageDifference['controlSales'] -percent

percentageDifference.head()

# Filter the percentageDiff DataFrame for the pre-trial period
pre_trial_period_df = percentageDifference[['percentageDiff','YEARMONTH']]
pre_trial_percentage_diffr = pre_trial_period_df[pre_trial_period_df['YEARMONTH'] < 201902

# Calculate the standard deviation
std_dev = np.std(pre_trial_percentage_diffr['percentageDiff'])
std_dev

from scipy.stats import t

# Calculate the standard deviation based on the scaled percentage difference in the pre-tr
std_dev = np.std(percentageDifference[percentageDifference['YEARMONTH'] < 201902]['percent

# Degrees of freedom (number of months in the pre-trial period - 1)
degrees_of_freedom = 7
```

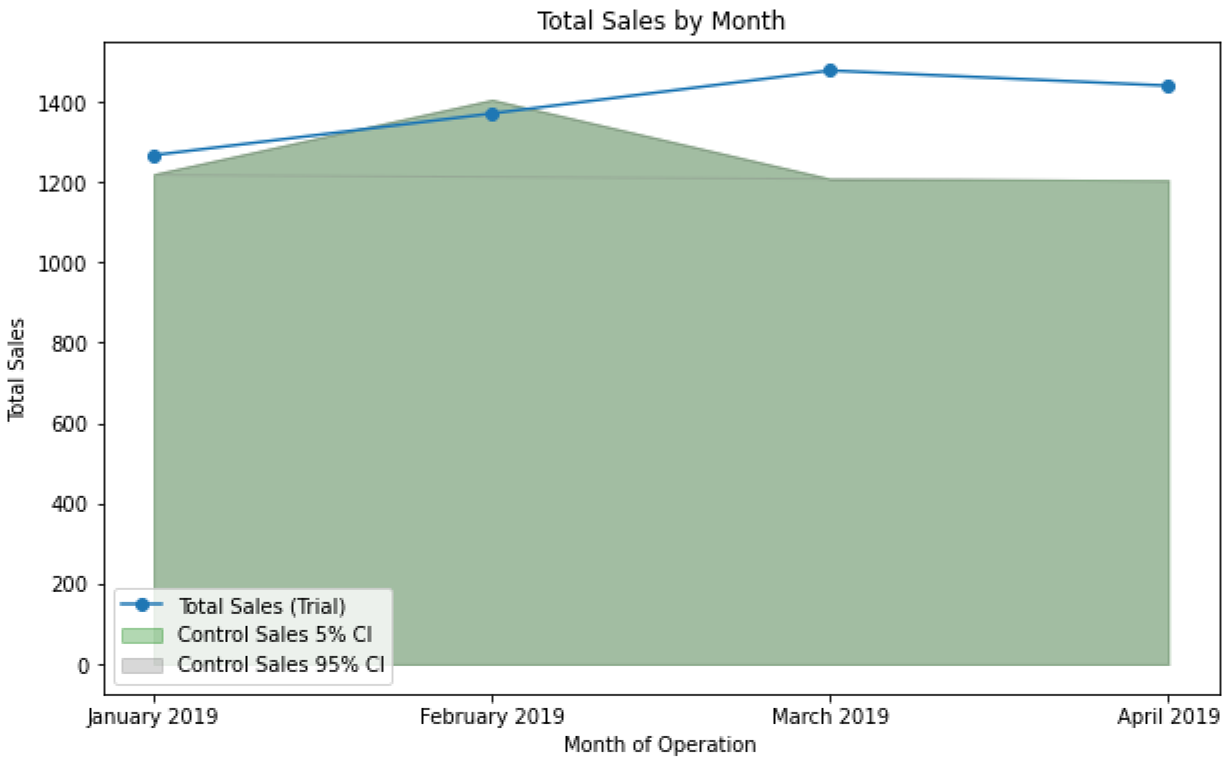
```
# Calculate the t-values for the trial months
percentageDifference['tValue'] = (percentageDifference['percentageDiff'] - 0) / std_dev
percentageDifference['TransactionMonth'] = pd.to_datetime(percentageDifference['YEARMONTH'

# Filter for the trial months
trial_months = percentageDifference[(percentageDifference['YEARMONTH'] < 201905) & (percen

# Find the 95th percentile of the t-distribution
alpha = 0.05  # Significance level
t_critical = t.ppf(1 - alpha / 2, degrees_of_freedom)

print("Critical t-value for a 95% confidence interval:", t_critical)
print(trial_months[['TransactionMonth', 'tValue']])
```

```
Critical t-value for a 95% confidence interval: 2.3646242510102993
  TransactionMonth    tValue
7       2019-02-01  0.843868
8       2019-03-01  7.124136
9       2019-04-01  6.230721
```

In [89]:

```
# Create a new column Store_type
measure_over_time['Store_type'] = 'Other stores'
measure_over_time.loc[measure_over_time['STORE_NBR'] == trial_store, 'Store_type'] = 'Tria
measure_over_time.loc[measure_over_time['STORE_NBR'] == control_store, 'Store_type'] = 'Co

# Calculate mean total sales by YEARMONTH and Store_type
pastSales = measure_over_time[measure_over_time['Store_type'].isin(['Trial', 'Control'])]
pastSales = pastSales.groupby(['YEARMONTH', 'Store_type'])['totSales'].mean().reset_index

# Convert YEARMONTH to TransactionMonth
pastSales['TransactionMonth'] = pd.to_datetime(pastSales['YEARMONTH'], format='%Y%m')

std_dev = np.std(percentageDifference[percentageDifference['YEARMONTH'] < 201902]['percent
# Control store 95th percentile
pastSales_Controls95 = pastSales[pastSales['Store_type'] == 'Control'].copy()
pastSales_Controls95['totSales'] = pastSales_Controls95['totSales'] * (1 + stdDev * 2)
pastSales_Controls95['Store_type'] = 'Control 95th % confidence interval'

# Control store 5th percentile
pastSales_Controls5 = pastSales[pastSales['Store_type'] == 'Control'].copy()
pastSales_Controls5['totSales'] = pastSales_Controls5['totSales'] * (1 - stdDev * 2)
pastSales_Controls5['Store_type'] = 'Control 5th % confidence interval'

# Update 'Store_type' for 95th and 5th percentiles
pastSales.loc[pastSales['Store_type'] == 'Control', 'Store_type'] = 'Control 95th % confic
pastSales.loc[pastSales['Store_type'] == 'Control 5th % confidence interval', 'Store_type'

# Concatenate the DataFrames
trial88Assessment = pd.concat([pastSales, pastSales_Controls95, pastSales_Controls5], ignc

# Filter the data for the specified date range
trial88Assessment = trial88Assessment[(trial88Assessment['TransactionMonth'] >= '2019-01-(

# Convert TransactionMonth to "Month Year" format
trial88Assessment.loc[:, 'TransactionMonth'] = trial88Assessment['TransactionMonth'].dt.st

#Create a plot
plt.figure(figsize=(10, 6))
#plt.plot(filtered_data['TransactionMonth'], filtered_data['totSales'], label='Total Sales
for store_type, data in trial88Assessment.groupby('Store_type'):
    if store_type == 'Trial':
        plt.plot(data['TransactionMonth'], data['totSales'], marker='o', label='Total Sale
    elif store_type == 'Control':
        plt.plot(data['TransactionMonth'], data['totSales'], marker='o', label='Total Sale
```

```
    elif store_type == 'Control 95th % confidence interval':
        plt.fill_between(data['TransactionMonth'], data['totSales'], alpha=0.3, color='gra
    elif store_type == 'Control 5th % confidence interval':
        plt.fill_between(data['TransactionMonth'], data['totSales'], alpha=0.3, color='gre
    else:
        plt.plot(data['TransactionMonth'], data['totSales'], label=f'Total Sales ({store_t

plt.xlabel('Month of Operation')
plt.ylabel('Total Sales')
plt.title('Total Sales by Month')
plt.legend()
plt.show()
```



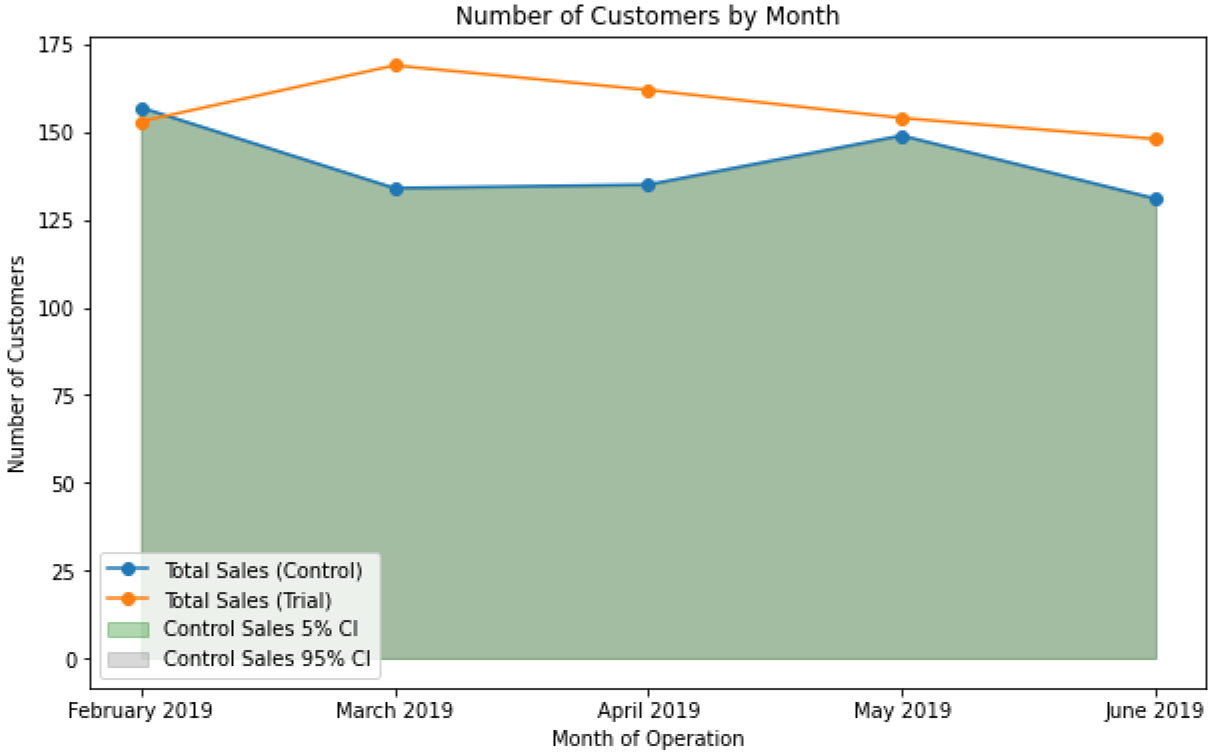
The results show that the trial in store 88 is significantly different to its control store in the trial period as the trial store performance lies outside of the 5% to 95% confidence interval of the control store in two of the three trial months.

In [92]:

```
# Assuming you have already defined trial_store and control_store
trial_store = 88
control_store = 237

# Calculate the scaling factor for control store sales
trial_store_cust = pre_trial_measures[(pre_trial_measures['STORE_NBR'] == trial_store) &
control_store_cust = pre_trial_measures[(pre_trial_measures['STORE_NBR'] == control_store)

scalingFactorForControlCust = trial_store_cust / control_store_cust

# Apply the scaling factor
measure_over_time_custs = measure_over_time
measure_over_time_custs['scaledControlCustomers'] = measure_over_time_custs['nCustomers']

# Calculate the percentage difference between scaled control store customers and trial cus
measure_over_time_custs['percentageDiff'] = abs(measure_over_time_custs['scaledControlCust

# Standard deviation based on the scaled percentage difference in the pre-trial period
stdDev = measure_over_time_custs[measure_over_time_custs['YEARMONTH'] < 201902]['percentag

# Degrees of freedom
degreesOfFreedom = 7
```

```python
# Trial and control store number of customers
pastCustomers = measure_over_time_custs[measure_over_time_custs['Store_type'].isin(['Trial
pastCustomers = pastCustomers.groupby(['YEARMONTH', 'Store_type'])['nCustomers'].mean().re

pastCustomers['TransactionMonth'] = pd.to_datetime(pastSales['YEARMONTH'], format='%Y%m')

# Control store 95th percentile
pastCustomers_Controls95 = pastCustomers[pastCustomers['Store_type'] == 'Control'].copy()
pastCustomers_Controls95['nCustomers'] = pastCustomers_Controls95['nCustomers'] * (1 + std
pastCustomers_Controls95['Store_type'] = 'Control 95th % confidence interval'

# Control store 5th percentile
pastCustomers_Controls5 = pastCustomers[pastCustomers['Store_type'] == 'Control'].copy()
pastCustomers_Controls5['nCustomers'] = pastCustomers_Controls5['nCustomers'] * (1 - stdDe
pastCustomers_Controls5['Store_type'] = 'Control 5th % confidence interval'

# Concatenate the DataFrames
trialC88Assessment = pd.concat([pastCustomers, pastCustomers_Controls95, pastCustomers_Con
trialC88Assessment['TransactionMonth'] = pd.to_datetime(trialC88Assessment['YEARMONTH'], f

# Filter the data for the specified date range
filtered_Cus88_data = trialC88Assessment[(trialC88Assessment['TransactionMonth'] >= '2019-

filtered_Cus88_data.loc[:, 'TransactionMonth'] = filtered_Cus88_data['TransactionMonth'].c

#Create a plot
plt.figure(figsize=(10, 6))
for store_type, data in filtered_Cus88_data.groupby('Store_type'):
    if store_type == 'Trial':
        plt.plot(data['TransactionMonth'], data['nCustomers'], marker='o', label='Total Sa
    elif store_type == 'Control':
        plt.plot(data['TransactionMonth'], data['nCustomers'], marker='o', label='Total Sa
    elif store_type == 'Control 95th % confidence interval':
        plt.fill_between(data['TransactionMonth'], data['nCustomers'], alpha=0.3, color='g
    elif store_type == 'Control 5th % confidence interval':
        plt.fill_between(data['TransactionMonth'], data['nCustomers'], alpha=0.3, color='g
    else:
        plt.plot(data['TransactionMonth'], data['nCustomers'], label=f'Total Sales ({store

plt.xlabel('Month of Operation')
plt.ylabel('Number of Customers')
plt.title('Number of Customers by Month')
plt.legend()
plt.show()
```

```
C:\Users\DELL\anaconda3\lib\site-packages\pandas\core\indexing.py:1773: SettingWithCopyWar
ning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_gu
ide/indexing.html#returning-a-view-versus-a-copy
  self._setitem_single_column(ilocs[0], value, pi)
```



Total number of customers in the trial period for the trial store is significantly higher than the control store for two out of three months, which indicates a positive trial effect.

Conclusion

We've found control stores 233, 155, 237 for trial stores 77, 86 and 88 respectively. The results for trial stores 77 and 88 during the trial period show a significant difference in at least two of the three trial months but this is not the case for trial store 86. We can check with the client if the implementation of the trial was different in trial store 86 but overall, the trial shows a significant increase in sales.