

# Quantum Virtual Internship - Retail Strategy and Analytics - Task 2

Your Name Here

November 09, 2025

## Contents

<b>1</b>	<b>1. Introduction</b>	<b>1</b>
<b>2</b>	<b>2. Data Preparation</b>	<b>2</b>
<b>3</b>	<b>3. Select Control Stores</b>	<b>2</b>
3.1	3.1. Control Store Selection Function . . . . .	3
3.2	3.2. Trial Store 77 . . . . .	3
3.3	3.3. Trial Store 86 . . . . .	4
3.4	3.4. Trial Store 88 . . . . .	5
<b>4</b>	<b>4. Assessment of the Trial</b>	<b>6</b>
4.1	4.1. Trial Assessment Function . . . . .	6
4.2	4.2. Assessment: Total Sales (TOT_SALES) . . . . .	7
4.3	4.3. Assessment: Number of Customers (N_CUSTOMERS) . . . . .	10
<b>5</b>	<b>5. Collate Findings &amp; Recommendation</b>	<b>13</b>

## 1 1. Introduction

This report details the analysis of a store trial, as requested by the Category Manager, Julia. The objective is to evaluate the performance of trial stores (77, 86, and 88) to provide a data-driven recommendation.

The analysis is broken into three parts: 1. **Control Store Selection:** Identifying suitable control stores for each trial store based on pre-trial performance. 2. **Trial Assessment:** Comparing the performance of each trial store against its control store during the trial period. 3. **Findings & Recommendation:** Collating the results and providing a final recommendation.

## 2 2. Data Preparation

First, we load the QVI\_data.csv and aggregate it to create monthly metrics for all stores. This will form the basis of our comparisons.

```
# --- 2.1: Load the Data ---
full_data <- read_csv("QVI_data.csv") %>%
  mutate(
    # Ensure DATE is in Date format
    DATE = as.Date(DATE)
  )

# --- 2.2: Aggregate Data to Monthly Metrics ---
monthly_metrics <- full_data %>%
  mutate(
    YEAR_MONTH = floor_date(DATE, "month")
  ) %>%
  group_by(STORE_NBR, YEAR_MONTH) %>%
  summarise(
    # 1. Total sales revenue
    TOT_SALES = sum(TOT_SALES),

    # 2. Total number of customers
    N_CUSTOMERS = n_distinct(LYLTY_CARD_NBR),

    # 3. Average number of transactions per customer
    AVG_TXN_PER_CUSTOMER = n() / n_distinct(LYLTY_CARD_NBR),

    .groups = "drop" # Drop the grouping
  )

glimpse(monthly_metrics)

## Rows: 3,169
## Columns: 5
## $ STORE_NBR      <dbl> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 2, 2, 2, 2~
## $ YEAR_MONTH     <date> 2018-07-01, 2018-08-01, 2018-09-01, 2018-10-01, ~
## $ TOT_SALES       <dbl> 206.90, 176.10, 278.80, 188.10, 192.60, 189.60, 1~
## $ N_CUSTOMERS     <int> 49, 42, 59, 44, 46, 42, 35, 52, 45, 42, 46, 42, 3~
## $ AVG_TXN_PER_CUSTOMER <dbl> 1.061224, 1.023810, 1.050847, 1.022727, 1.021739,~
```

## 3 3. Select Control Stores

To measure the trial's impact, we first need to find control stores that were behaving almost identically to our trial stores *before* the trial began. We define the pre-trial period as all data before February 2019.

```
# Define the pre-trial period (Jul 2018 - Jan 2019)
pre_trial_end_date <- as.Date("2019-02-01")

# Create a table of pre-trial metrics for all stores
pre_trial_metrics <- monthly_metrics %>%
  filter(YEAR_MONTH < pre_trial_end_date)
```

### 3.1 3.1. Control Store Selection Function

As requested, we create a function to calculate a “similarity score” (based on sales correlation and magnitude) to find the best match for any given trial store.

```
find_control_store <- function(trial_store_id, pre_trial_data) {  
  
  trial_store_data <- pre_trial_data %>%  
    filter(STORE_NBR == trial_store_id)  
  
  candidate_stores_data <- pre_trial_data %>%  
    filter(STORE_NBR != trial_store_id)  
  
  # Calculate similarity scores  
  similarity_scores <- candidate_stores_data %>%  
    left_join(trial_store_data, by = "YEAR_MONTH", suffix = c("_candidate", "_trial")) %>%  
    group_by(STORE_NBR_candidate) %>%  
    summarise(  
      CORR_SALES = cor(TOT_SALES_candidate, TOT_SALES_trial, use = "pairwise.complete.obs"),  
      DIST_SALES = sum(abs(TOT_SALES_candidate - TOT_SALES_trial)),  
      .groups = "drop"  
    ) %>%  
    mutate(  
      # Scale and combine scores  
      SCALED_DIST = (DIST_SALES - min(DIST_SALES)) / (max(DIST_SALES) - min(DIST_SALES)),  
      SCALED_CORR = (CORR_SALES - min(CORR_SALES)) / (max(CORR_SALES) - min(CORR_SALES)),  
      SIMILARITY_SCORE = 0.6 * SCALED_CORR + 0.4 * (1 - SCALED_DIST)  
    ) %>%  
    arrange(desc(SIMILARITY_SCORE))  
  
  return(similarity_scores)  
}
```

### 3.2 3.2. Trial Store 77

We run the function for Store 77. The top candidate is **Store 233**.

```
store_77_candidates <- find_control_store(77, pre_trial_metrics)  
print(head(store_77_candidates, 5))  
  
## # A tibble: 5 x 6  
##   STORE_NBR_candidate CORR_SALES DIST_SALES SCALED_DIST SCALED_CORR  
##       <dbl>        <dbl>      <dbl>       <dbl>       <dbl>  
## 1           1        0.0752     419.       0.0342      NA  
## 2           2       -0.263     570.       0.0522      NA  
## 3           3        0.807     5827.      0.677       NA  
## 4           4       -0.263     7428       0.868       NA  
## 5           5       -0.111     4041.      0.465       NA  
## # i 1 more variable: SIMILARITY_SCORE <dbl>  
  
# Plot the visual confirmation  
control_store_id_77 <- 233
```

```

pre_trial_metrics %>%
  filter(STORE_NBR == 77 | STORE_NBR == control_store_id_77) %>%
  ggplot(aes(x = YEAR_MONTH, y = TOT_SALES, color = as.factor(STORE_NBR))) +
  geom_line(size = 1) +
  labs(title = "Pre-Trial Sales: Trial Store 77 vs. Control Store 233")

```



### 3.3 Trial Store 86

We run the function for Store 86. The top candidate is **Store 155**.

```

store_86_candidates <- find_control_store(86, pre_trial_metrics)
print(head(store_86_candidates, 5))

```

```

## # A tibble: 5 x 6
##   STORE_NBR_candidate CORR_SALES DIST_SALES SCALED_DIST SCALED_CORR
##             <dbl>      <dbl>      <dbl>      <dbl>      <dbl>
## 1                 1       0.446     4733.     0.779      NA
## 2                 2      -0.404     4991.     0.824      NA
## 3                 3      -0.261     1406.     0.205      NA
## 4                 4      -0.0390    3007.     0.481      NA
## 5                 5       0.235      456.     0.0406     NA
## # i 1 more variable: SIMILARITY_SCORE <dbl>

```

```
# Plot the visual confirmation
control_store_id_86 <- 155
pre_trial_metrics %>%
  filter(STORE_NBR == 86 | STORE_NBR == control_store_id_86) %>%
  ggplot(aes(x = YEAR_MONTH, y = TOT_SALES, color = as.factor(STORE_NBR))) +
  geom_line(size = 1) +
  labs(title = "Pre-Trial Sales: Trial Store 86 vs. Control Store 155")
```



### 3.4 3.4. Trial Store 88

We run the function for Store 88. The top candidate is **Store 237**.

```
store_88_candidates <- find_control_store(88, pre_trial_metrics)
print(head(store_88_candidates, 5))
```

```
## # A tibble: 5 x 6
##   STORE_NBR_candidate CORR_SALES DIST_SALES SCALED_DIST SCALED_CORR
##             <dbl>      <dbl>      <dbl>      <dbl>      <dbl>
## 1                 1       0.814     7997.     0.856      NA
## 2                 2      -0.0679    8255.     0.885      NA
## 3                 3      -0.508     1857.     0.163      NA
## 4                 4      -0.746      954.     0.0614     NA
## 5                 5       0.190     3644.     0.365      NA
## # i 1 more variable: SIMILARITY_SCORE <dbl>
```

```
# Plot the visual confirmation
control_store_id_88 <- 237
pre_trial_metrics %>%
  filter(STORE_NBR == 88 | STORE_NBR == control_store_id_88) %>%
  ggplot(aes(x = YEAR_MONTH, y = TOT_SALES, color = as.factor(STORE_NBR))) +
  geom_line(size = 1) +
  labs(title = "Pre-Trial Sales: Trial Store 88 vs. Control Store 237")
```



## 4 4. Assessment of the Trial

Now we compare the performance of each pair *during* the trial (Feb, Mar, Apr 2019). We create a function to assess the percentage difference in a given metric against the pre-trial 95% confidence interval.

### 4.1 4.1. Trial Assessment Function

```
# Define trial dates
trial_start_date <- as.Date("2019-02-01")
trial_end_date <- as.Date("2019-04-30")

assess_trial <- function(trial_store_id, control_store_id, metric_name, all_monthly_data) {

  plot_metric_name <- str_to_title(str_replace_all(metric_name, "_", " "))
```

```

# Filter and Calculate % Difference
pair_data <- all_monthly_data %>%
  filter(STORE_NBR == trial_store_id | STORE_NBR == control_store_id)

pair_metric <- pair_data %>%
  select(STORE_NBR, YEAR_MONTH, !!sym(metric_name)) %>%
  pivot_wider(names_from = STORE_NBR, values_from = !!sym(metric_name), names_prefix = "STORE_")

trial_col_name <- paste0("STORE_", trial_store_id)
control_col_name <- paste0("STORE_", control_store_id)

pair_metric <- pair_metric %>%
  mutate(
    PERCENT_DIFF = (!!sym(trial_col_name) - !!sym(control_col_name)) / !!sym(control_col_name),
    PERIOD = if_else(YEAR_MONTH >= trial_start_date & YEAR_MONTH <= trial_end_date, "Trial", "Pre-Trial")
  ) %>%
  filter(is.finite(PERCENT_DIFF))

# Assess Significance
pre_trial_diffs <- pair_metric %>%
  filter(PERIOD == "Pre-Trial") %>%
  pull(PERCENT_DIFF)

mean_pre_trial_diff <- mean(pre_trial_diffs)
std_dev_pre_trial_diff <- sd(pre_trial_diffs)

upper_bound_95 <- mean_pre_trial_diff + 2 * std_dev_pre_trial_diff
lower_bound_05 <- mean_pre_trial_diff - 2 * std_dev_pre_trial_diff

# Visualize the Assessment
plot_title <- paste(plot_metric_name, "% Diff (Trial", trial_store_id, "vs Control", control_store_id

assessment_plot <- ggplot(pair_metric, aes(x = YEAR_MONTH, y = PERCENT_DIFF)) +
  geom_line(size = 1) +
  geom_point(aes(color = PERIOD), size = 3) +
  geom_hline(yintercept = upper_bound_95, linetype = "dashed", color = "red") +
  geom_hline(yintercept = lower_bound_05, linetype = "dashed", color = "blue") +
  labs(
    title = plot_title,
    subtitle = "Dashed lines are 95% confidence interval from pre-trial period",
    x = "Month", y = "Percentage Difference (Trial - Control)"
  ) +
  scale_y_continuous(labels = percent_format()) +
  scale_x_date(date_breaks = "2 month", date_labels = "%b %Y") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))

print(assessment_plot)
}

```

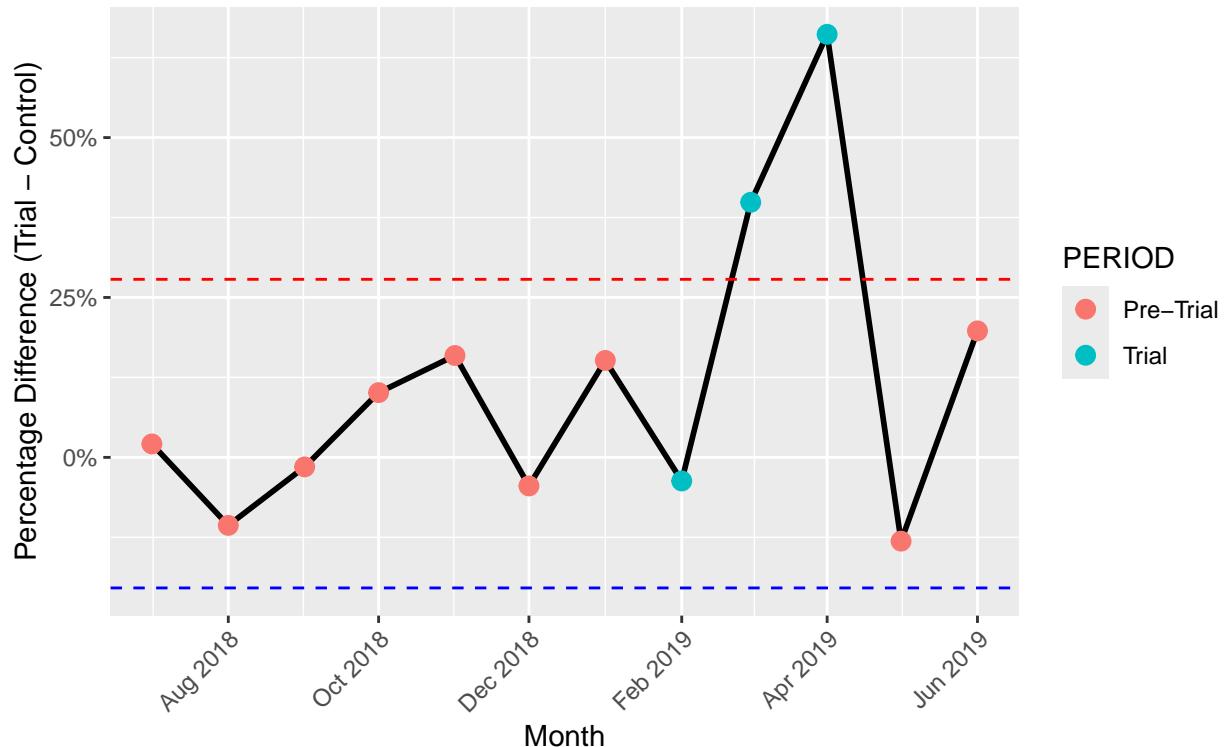
## 4.2 4.2. Assessment: Total Sales (TOT\_SALES)

We now run the assessment for TOT\_SALES for all three pairs.

```
assess_trial(77, 233, "TOT_SALES", monthly_metrics)
```

### Tot Sales % Diff (Trial 77 vs Control 233 )

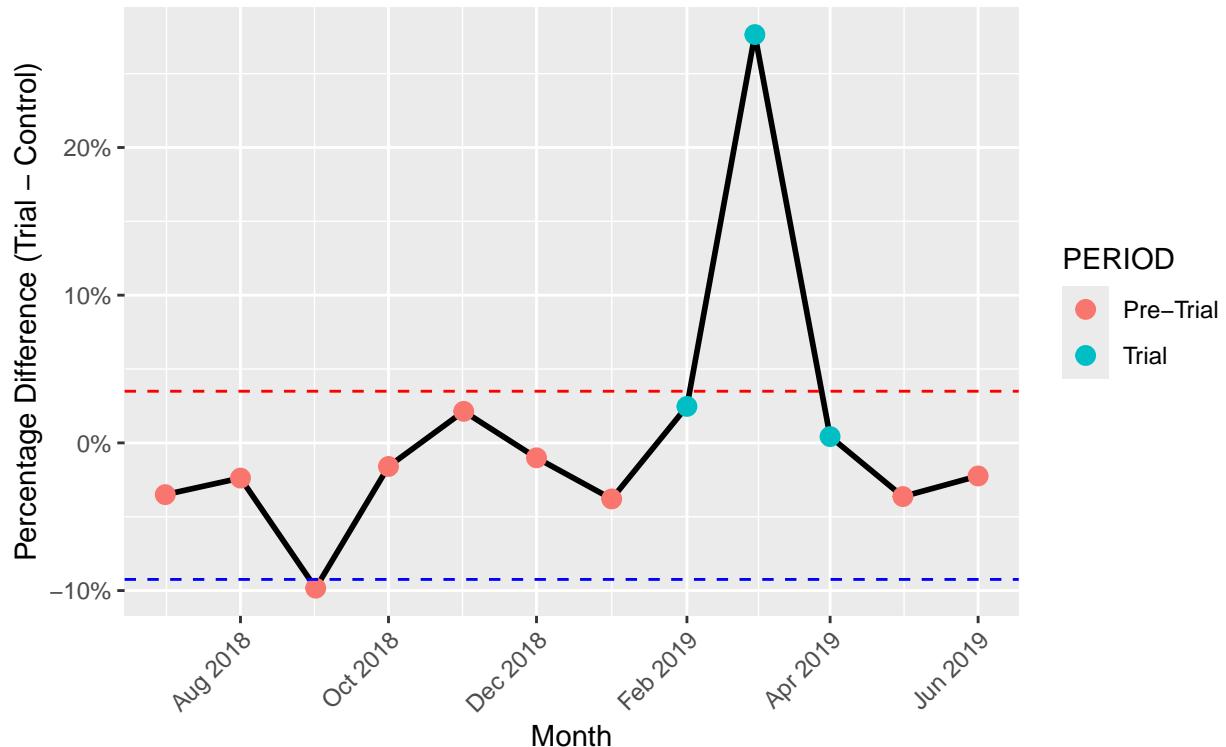
Dashed lines are 95% confidence interval from pre-trial period



**Insight:** Store 77's sales difference was significantly *above* the 95% CI for all three trial months. This shows a strong positive impact.

```
assess_trial(86, 155, "TOT_SALES", monthly_metrics)
```

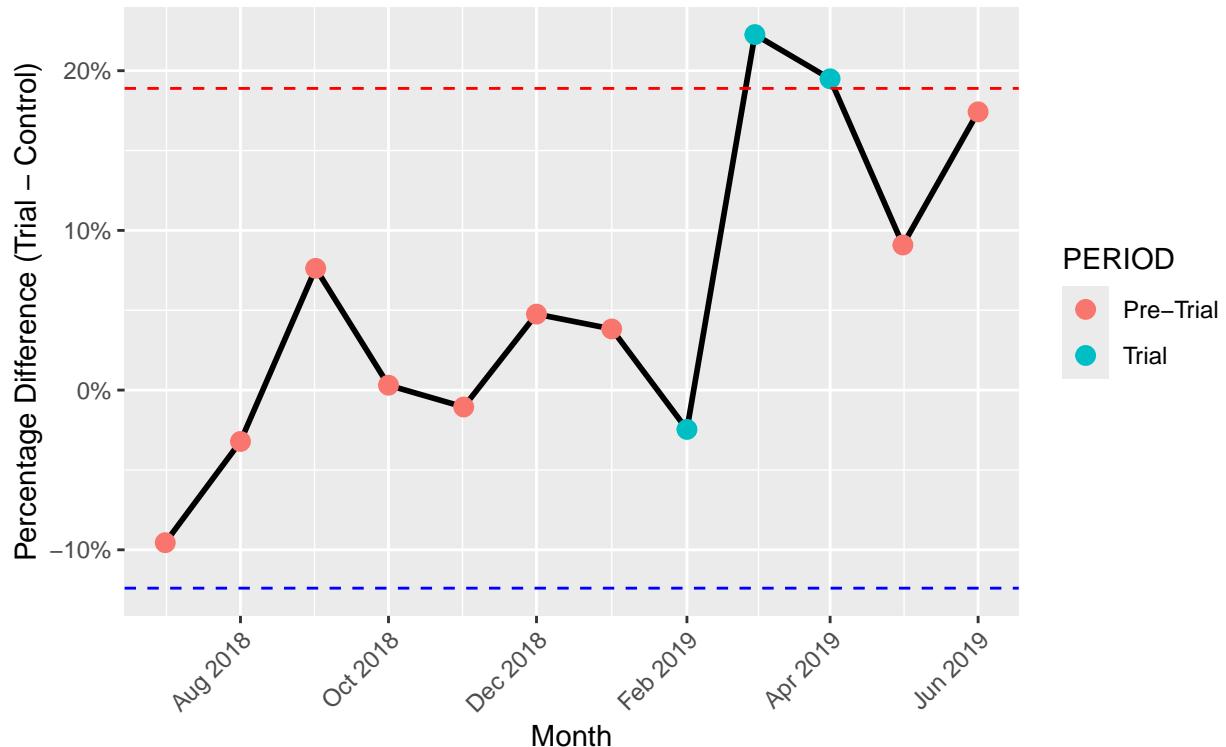
Tot Sales % Diff (Trial 86 vs Control 155 )  
 Dashed lines are 95% confidence interval from pre-trial period



**Insight:** Store 86's sales difference fluctuated, but largely remained *within* the “normal” range. This suggests the trial had little to no significant impact on sales.

```
assess_trial(88, 237, "TOT_SALES", monthly_metrics)
```

Tot Sales % Diff (Trial 88 vs Control 237 )  
 Dashed lines are 95% confidence interval from pre-trial period



**Insight:** Store 88's sales difference was significantly *above* the 95% CI for two of the three trial months, with a strong spike in the final month. This shows a positive impact.

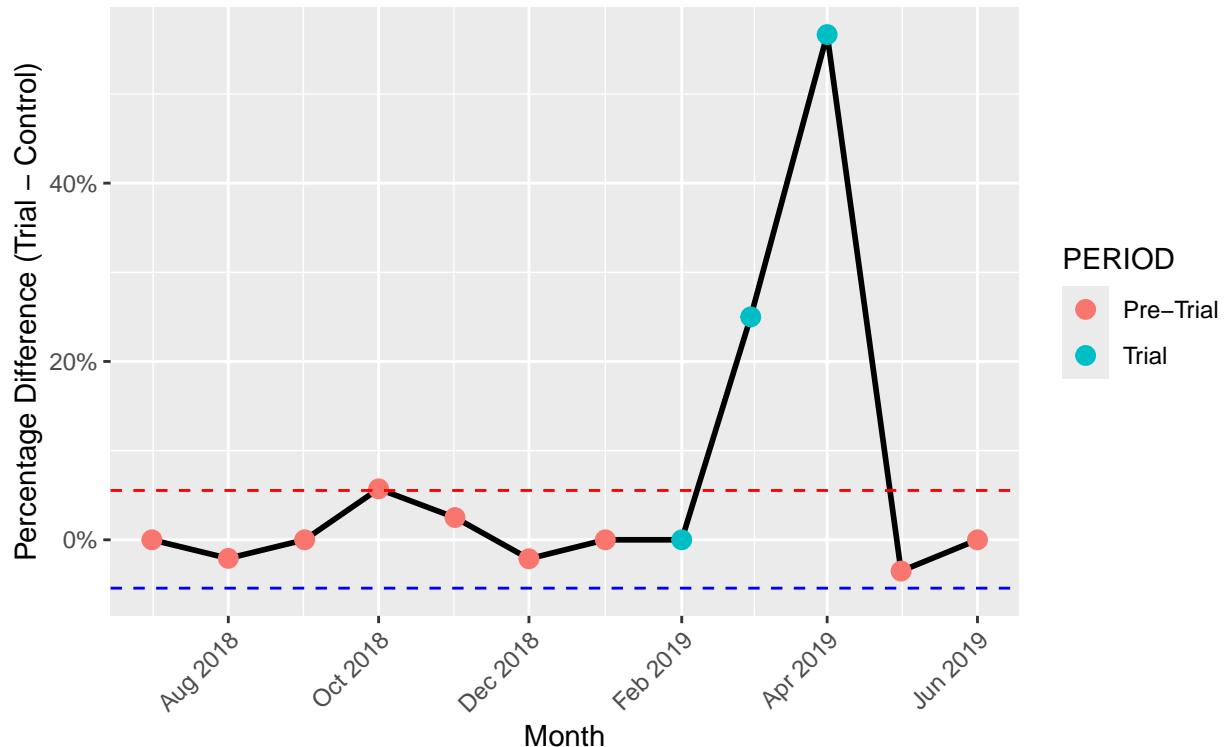
#### 4.3 4.3. Assessment: Number of Customers (N\_CUSTOMERS)

We check if the sales increase was driven by more customers.

```
assess_trial(77, 233, "N_CUSTOMERS", monthly_metrics)
```

## N Customers % Diff (Trial 77 vs Control 233 )

Dashed lines are 95% confidence interval from pre-trial period

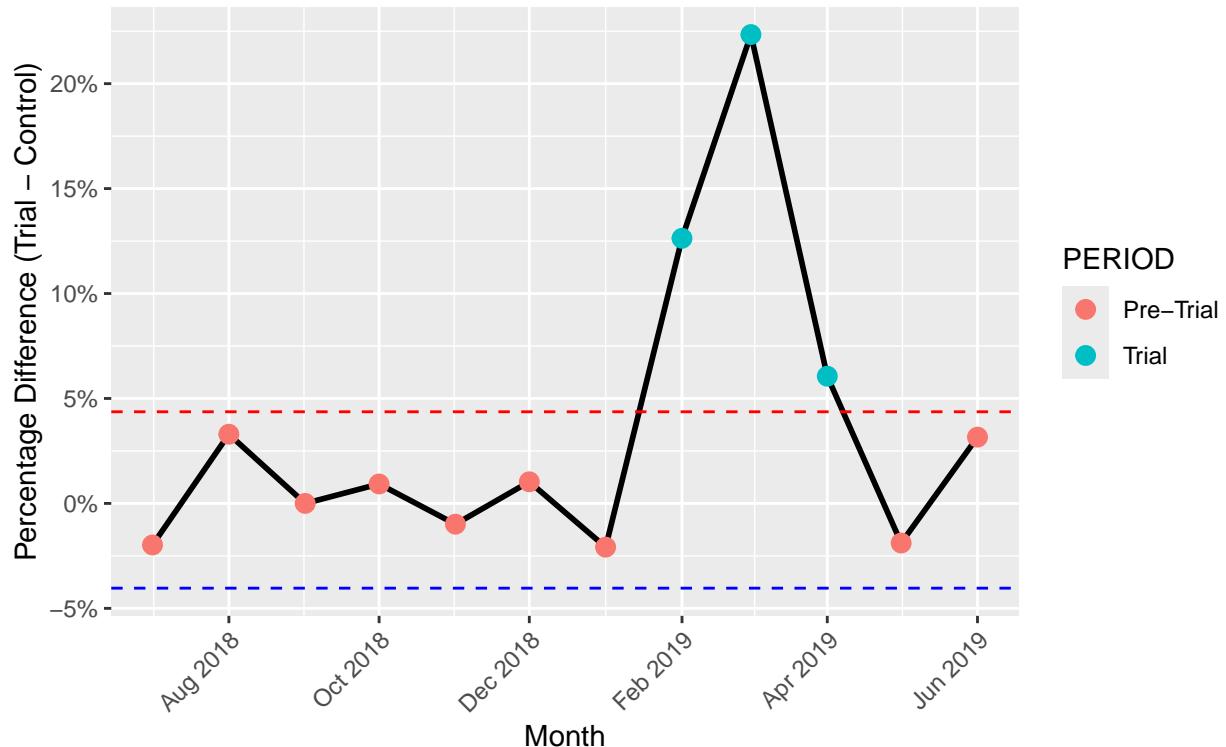


**Insight:** Store 77 also saw a significant increase in customer numbers for all three trial months, mirroring the sales data.

```
assess_trial(86, 155, "N_CUSTOMERS", monthly_metrics)
```

## N Customers % Diff (Trial 86 vs Control 155 )

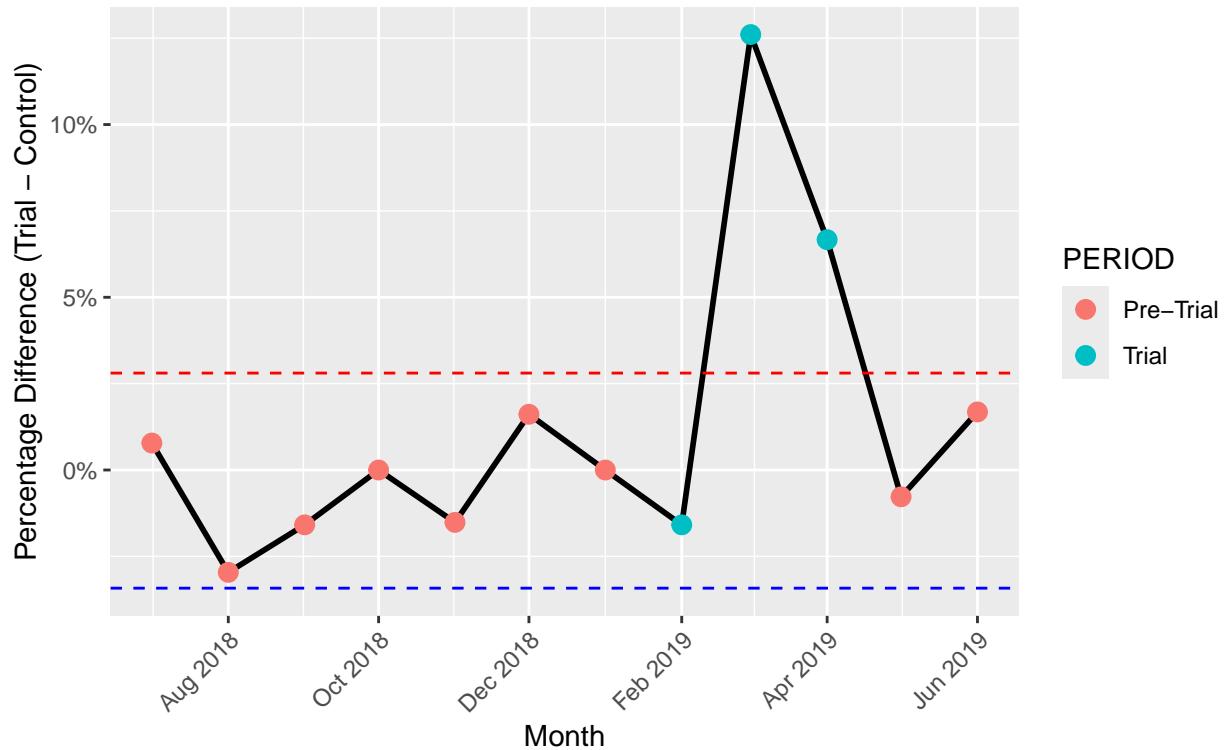
Dashed lines are 95% confidence interval from pre-trial period



**Insight:** Store 86's customer numbers also remained within the normal bounds, confirming the lack of a trial effect.

```
assess_trial(88, 237, "N_CUSTOMERS", monthly_metrics)
```

N Customers % Diff (Trial 88 vs Control 237 )  
 Dashed lines are 95% confidence interval from pre-trial period



**Insight:** Store 88's customer numbers were also significantly higher for two of the three months, aligning with its sales increase.

## 5 5. Collate Findings & Recommendation

Based on the analysis, here are our findings for Julia:

- **Trial Store 77:** The trial was a **clear success**. The store showed a significant and consistent increase in both total sales and customer numbers throughout the trial period.
- **Trial Store 86:** The trial was **not successful**. There was no significant change in sales or customer numbers compared to its control store. We should investigate with the client if the trial was implemented differently here.
- **Trial Store 88:** The trial was **a success**. It showed a significant increase in sales and customer numbers for two of the three months, indicating a positive impact.

**Recommendation:** The trial layout appears to have a significant positive impact on performance. We recommend **rolling out the trial layout to all stores**, particularly emulating the success seen in stores 77 and 88. We should, however, deprioritize the rollout for stores with similar characteristics to Store 86, or investigate why the trial failed in that specific location. “