# CUSTOMER OPTIMIZATION

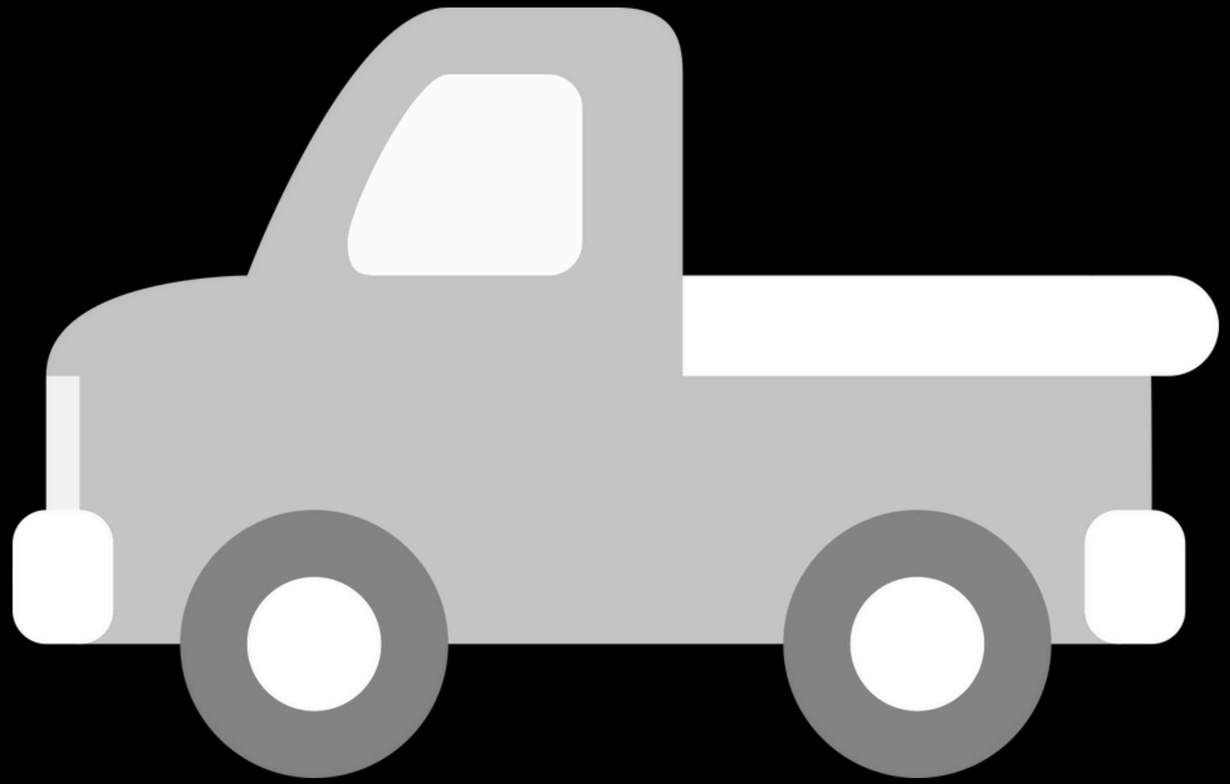
IS 6813 Capstone

Andy Spendlove, Dan Powell, Jessica Kersey,
Melissa Messervy, Tommaso Pascucci

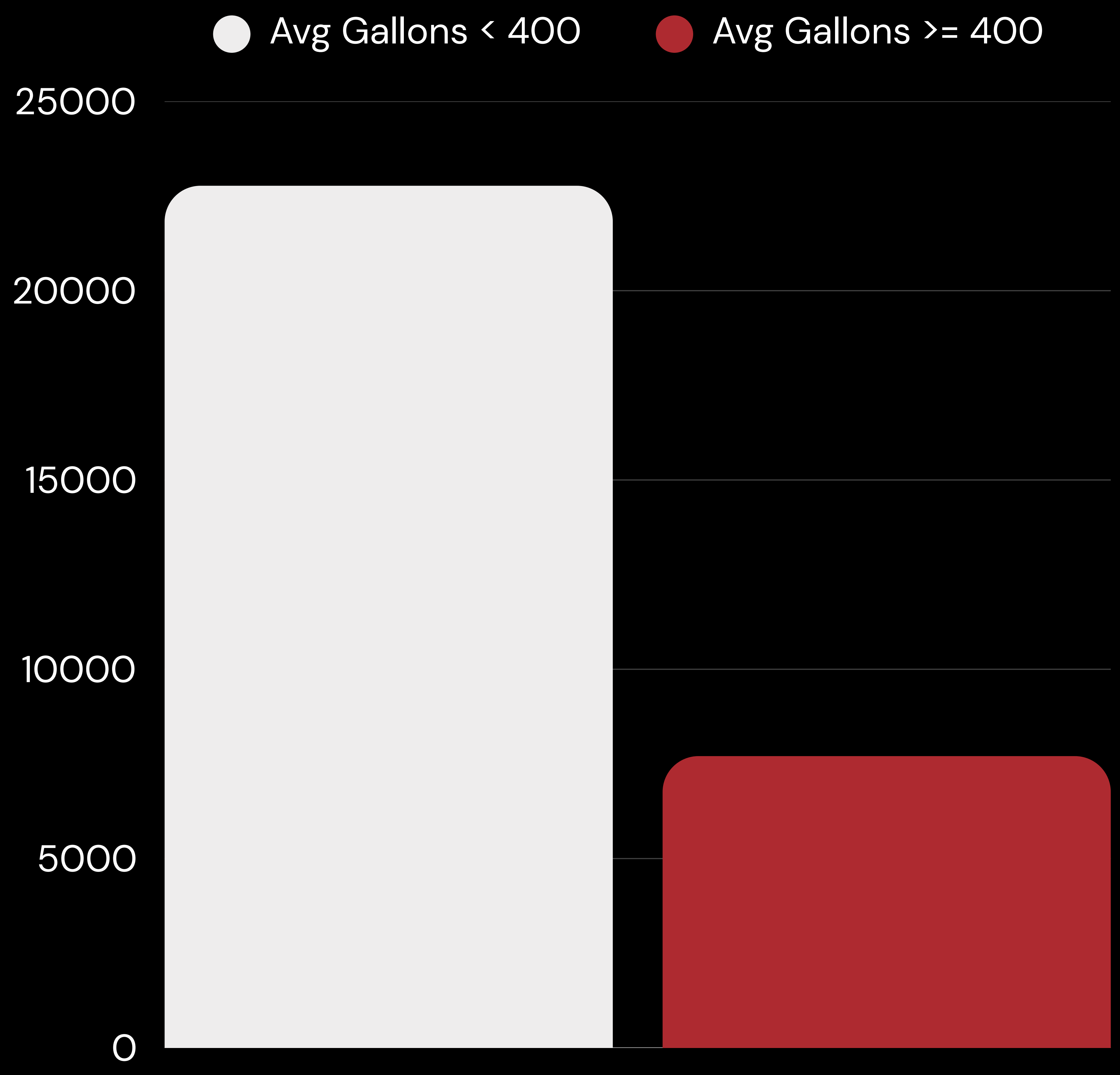
# Overview

# Project Background

400 gallons



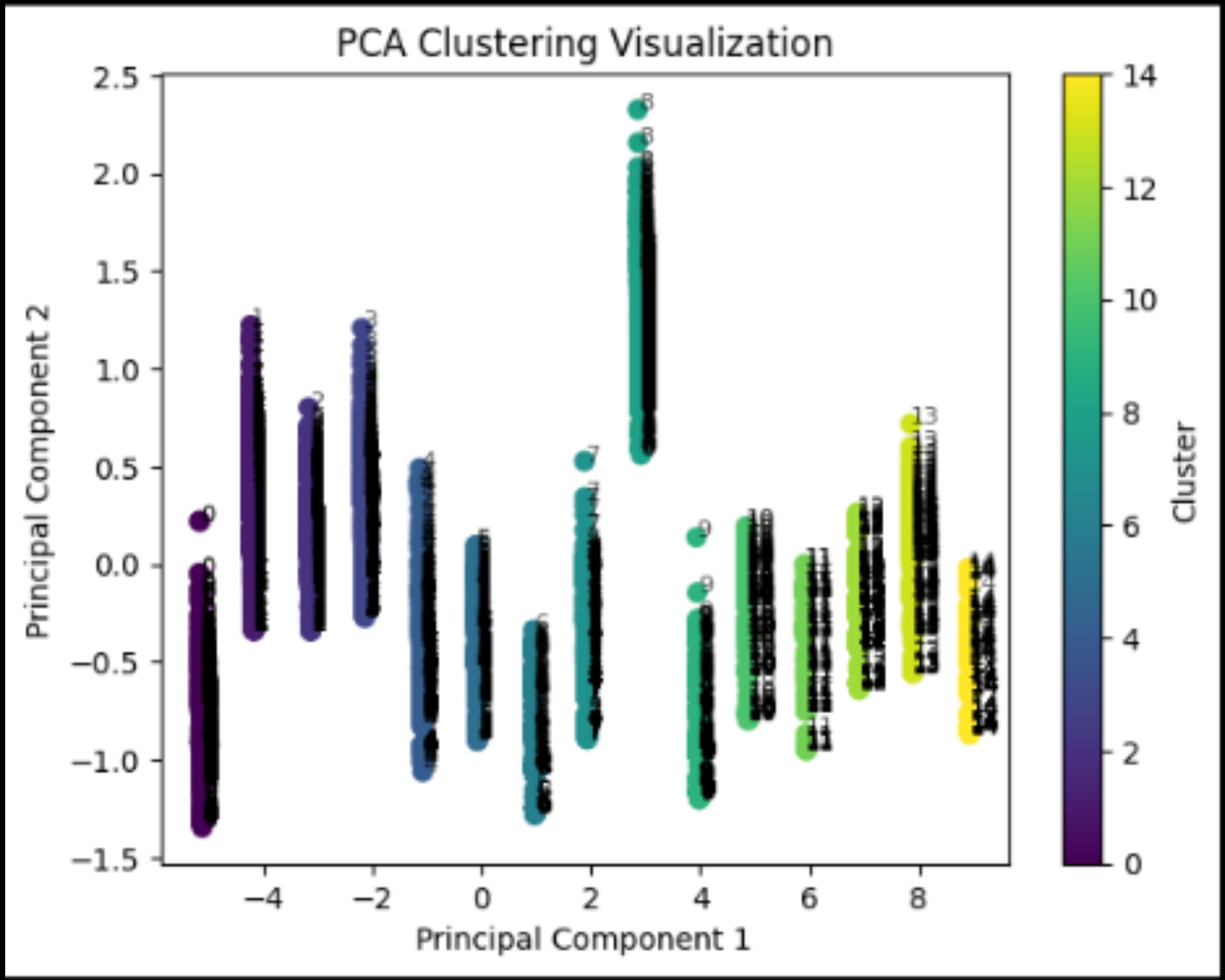
# Current Threshold



# Overview

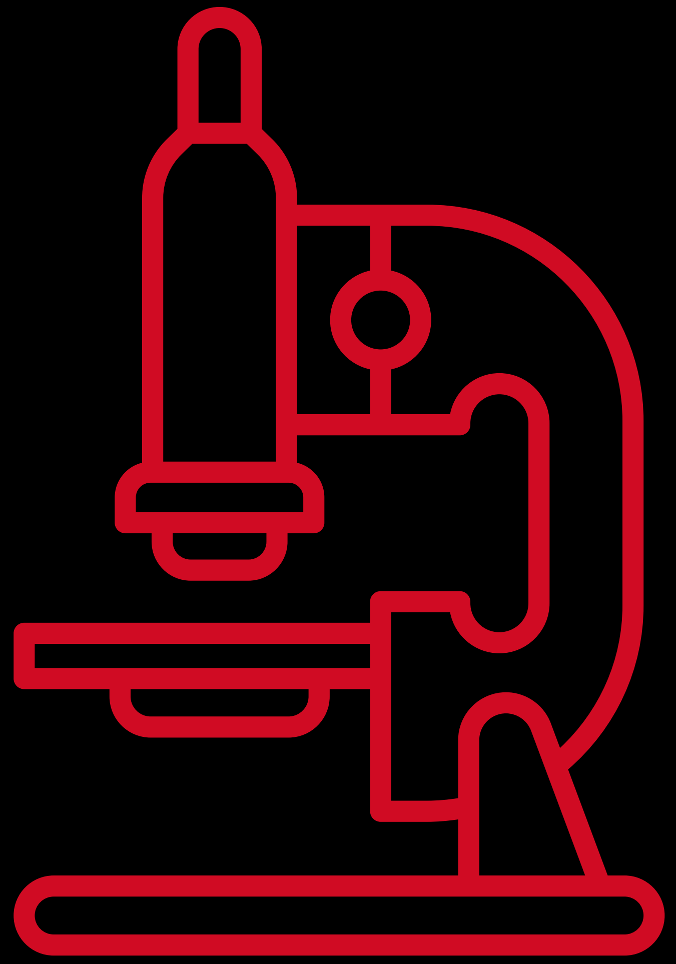
# Initial Approach

- Frequent order type associated with growth in initial models
- Sales reps with frequent order type clustered in high-growth group



# Refined Approach

- Modeled customers below 400 gallons / year
- Causal Inference to estimate Heterogenous Treatment Effect
- Target = Avg Gallons Ordered Per Year
- Treatment = Frequent Order Type: Sales Rep



# Overview

- Project Background
- Approach
- Immediate Impact
- Targeted Intervention
- Moving Forward

## Customers Projected to Exceed 400 Gallons With Intervention

# 41 OR 0.4%

# Overview

Project Background

Approach

Immediate Impact

Targeted Intervention

Moving Forward

# Targeted Intervention

| CUSTOMER NUMBER | FREQUENT ORDER TYPE | TREATMENT EFFECT |
| --- | --- | --- |
| 501676519 | MYCOKE360 | 170 |
| 501697621 | MYCOKE360 | 170 |
| 600058076 | CALL CENTER | 169 |
| 501121328 | MYCOKE LEGACY | 164 |
| 600266259 | CALL CENTER | 159 |
| 600558267 | MYCOKE LEGACY | 154 |
| 600567852 | MYCOKE LEGACY | 154 |
| 501284653 | MYCOKE LEGACY | 151 |

# Conditional Average Treatment Effects

## All Customers

+10

Avg Gallons per year

## Subset

+6

Avg Gallons per year

# Conditional Average Treatment Effects

## Sub-Trade Channel: Middle School

**+92**

Avg Gallons per year

## Cold Drink Channel: Wellness

**+55**

Avg Gallons per year

# Overview

# Moving Forward

## Recommendation

- Refine the sales rep models
- Utilize HTE modeling
- Model other interventions

## Outcome

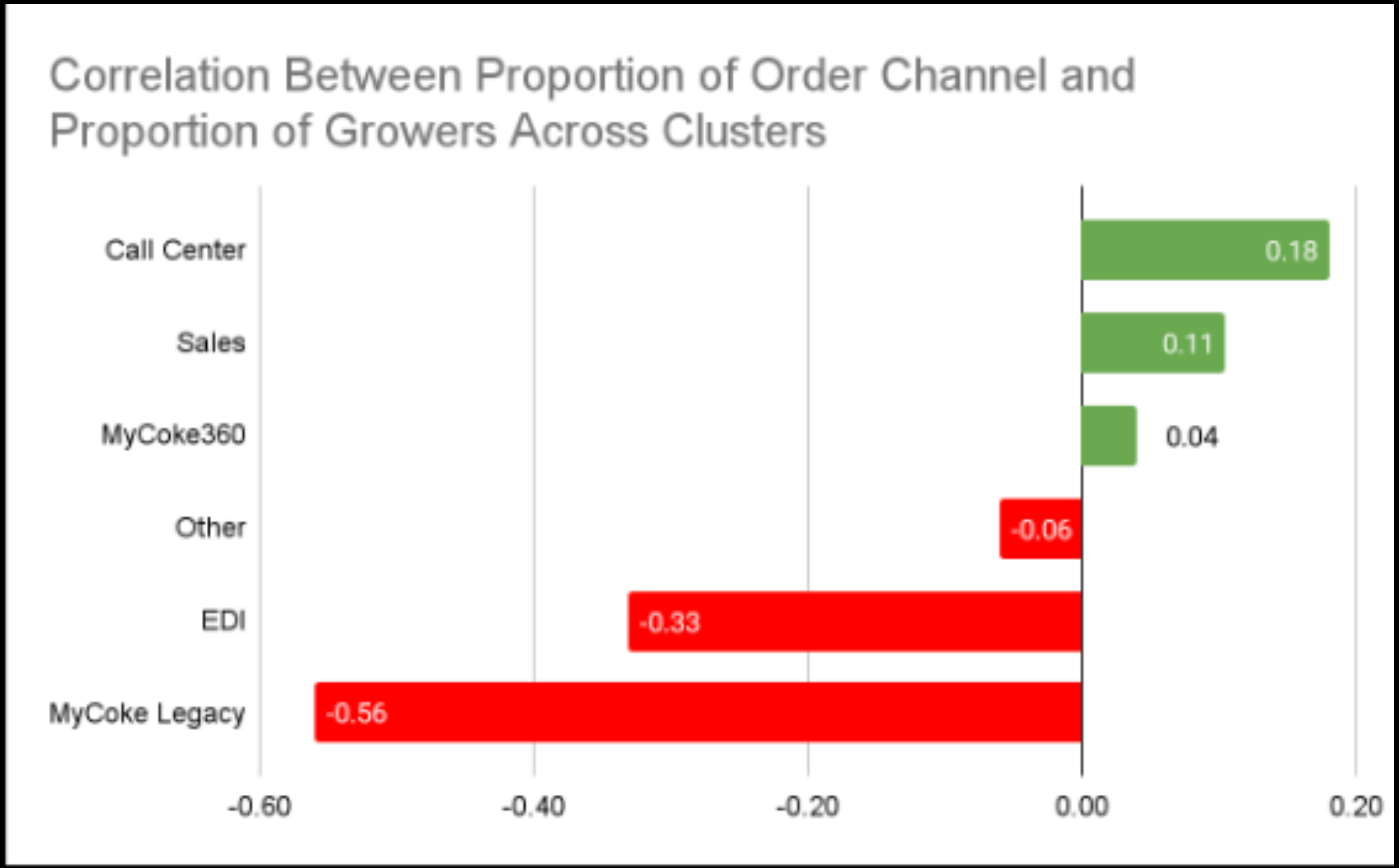
- Boost overall sales
- Retain Red Truck customers
- Unlock growth opportunities

# QUESTIONS?

# APPENDIX

# Clustering Models

- Looked at clusters with high proportions of customers that grew (2023-2024)
- Examined characteristics of clusters
  - Highest proportions of growers and declining businesses
- Examined Correlations
  - Proportion of growing companies in a cluster and characteristics
- Customers included in model: 17,281



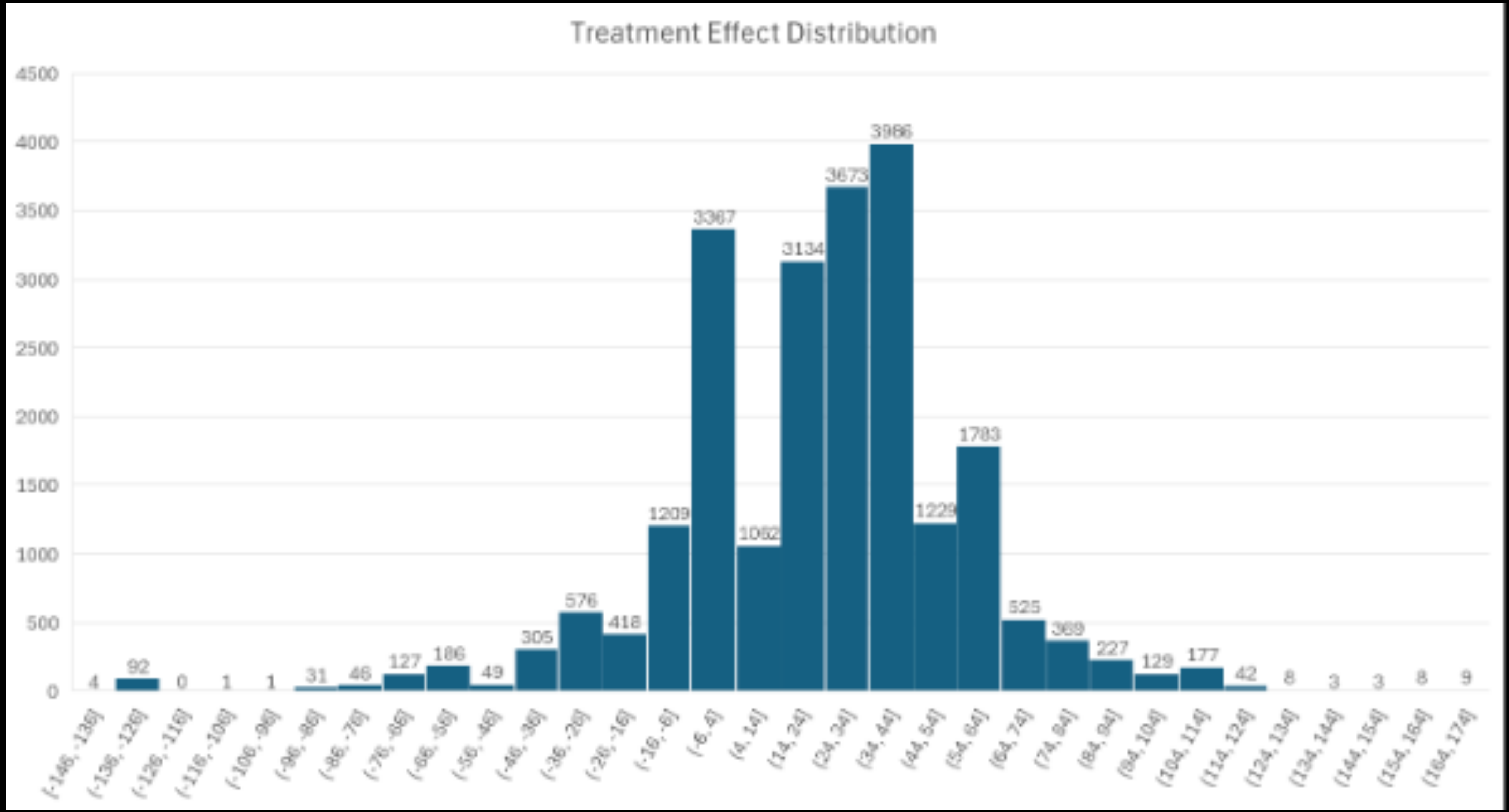

*Removed customers with NA values

# Summary of HTE Modeling

- Heterogeneous Treatment Effect (HTE)
  - Treatment effects that vary across individuals or subgroups in a sample
  - Idea: model potential outcomes (factual and counterfactual) for each individual to estimate ITE
- Conditional Average Treatment Effect (CATE)
  - Treatment effects conditional on a covariate feature
- Individual Treatment Effect (ITE)
  - CATE down to the individual level; treatment effect conditional on being CUSTOMER NUMBER x

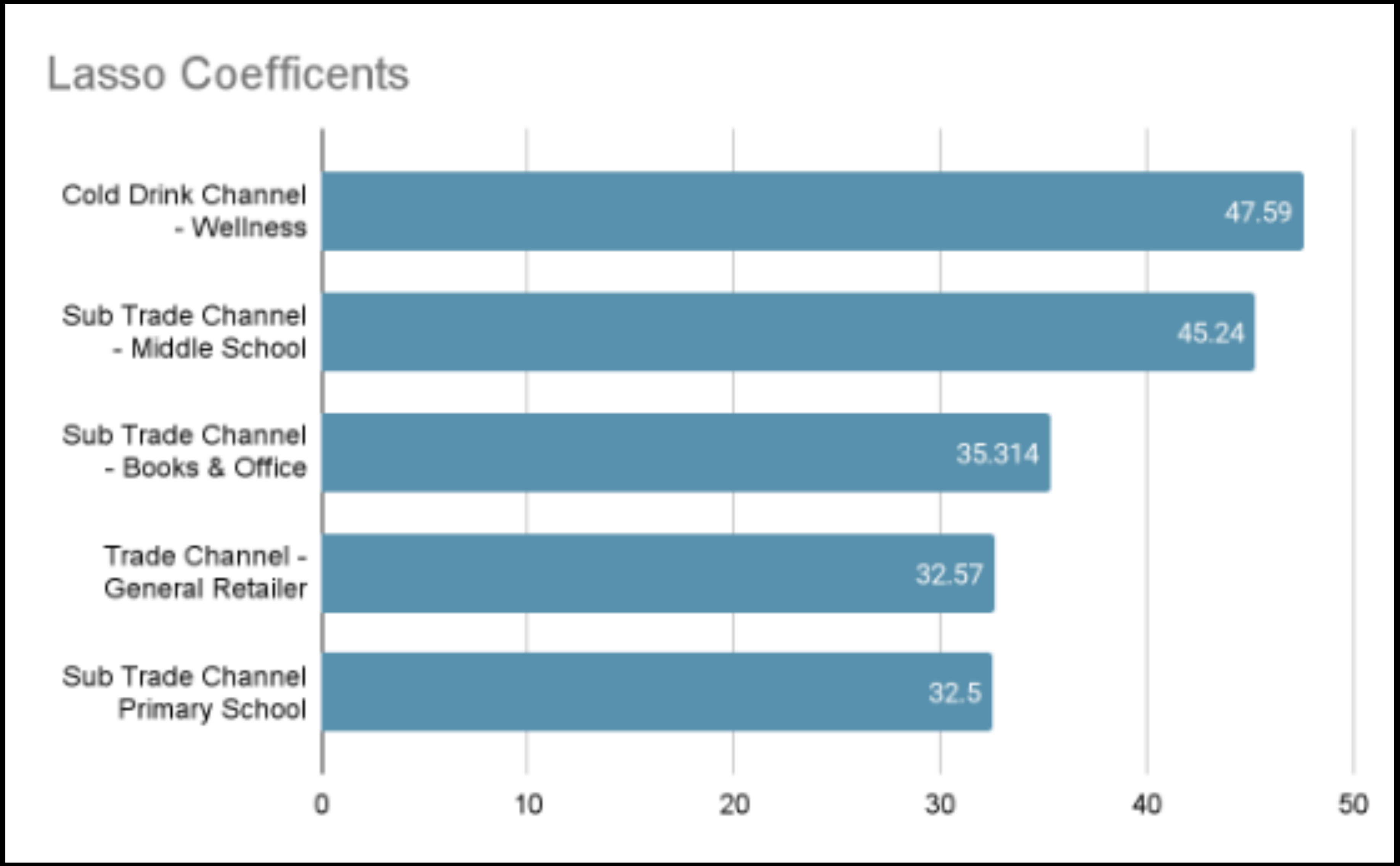
# HTE Modeling - T-learner

- Trains Two Random Forest Models
  - Treatment (Sales Rep)
  - Non-Treatment (Not Sales Rep)
- Gets predictions for treatment effect using the treated and untreated models
- Calculates ITE
  - ITE = $\hat{Y}1 - \hat{Y}0$
- R^2 of models:
  - Untreated learner: 0.109
  - Treated learner: 0.235
- Mean CATE: 22.44
- Customers included in model: 22779



# Modeling Results - Lasso

- Conducted Lasso Regression on Treatment Effect using characteristics
- R2: 0.460
- Gave insight into magnitude and direction of selected features' impact on treatment effect



# Attempted Models

## High-Growth Feature Analysis

- Logistic Regression
- Lasso
- Ridge
- Clustering
- Causal Forest
- Random Forest
- K-Means Clustering
- K-Medoid Clustering
- XG Boost
- DBSCAN

## Treatment effects

- T-learner
  - Sales Rep
  - MyCoke360
- Causal forest
  - Sales Rep - All Customers
  - Sales Rep - Subset

## Treatment Effect Feature Importance

- Lasso
- Random Forest