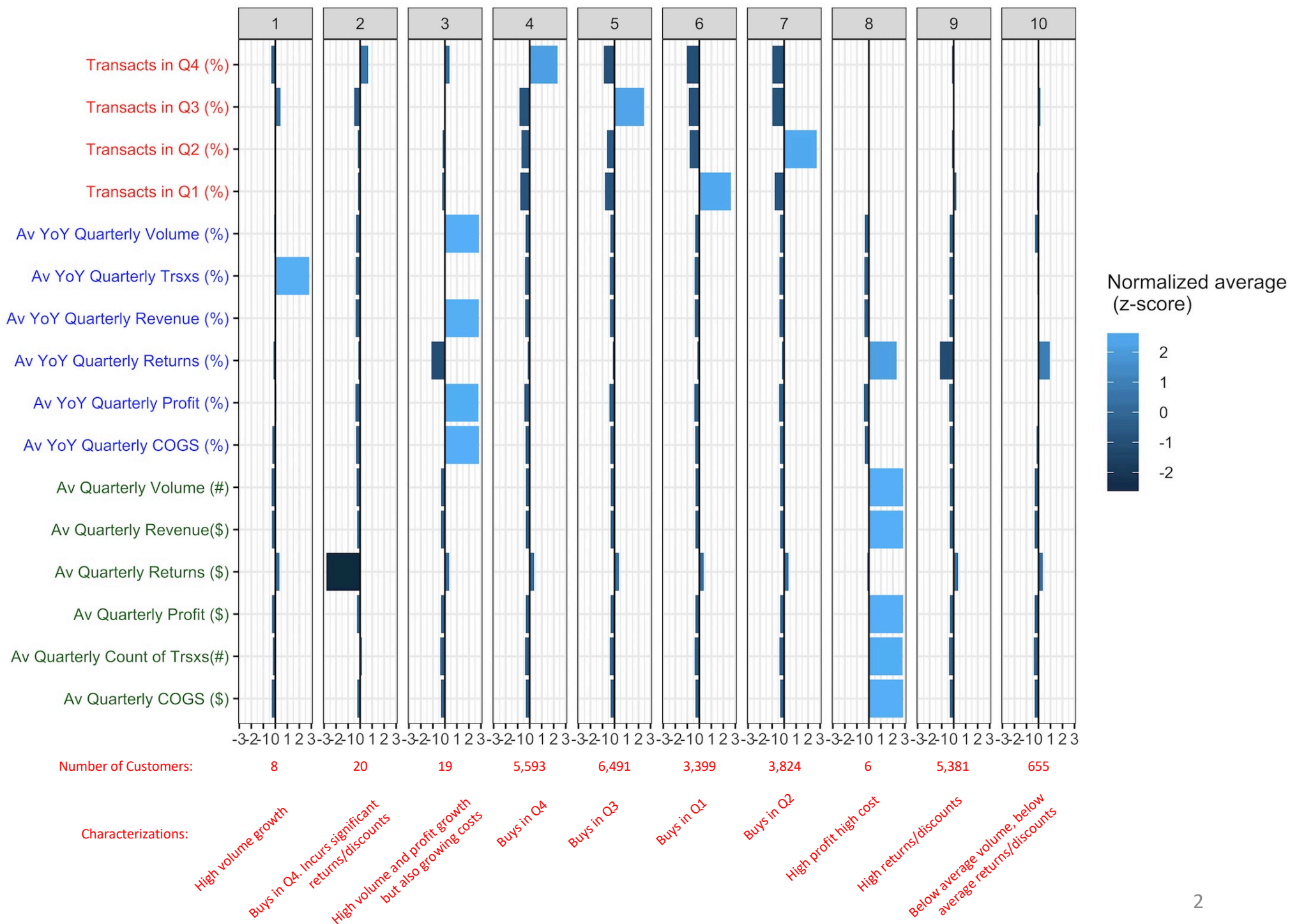


Summary

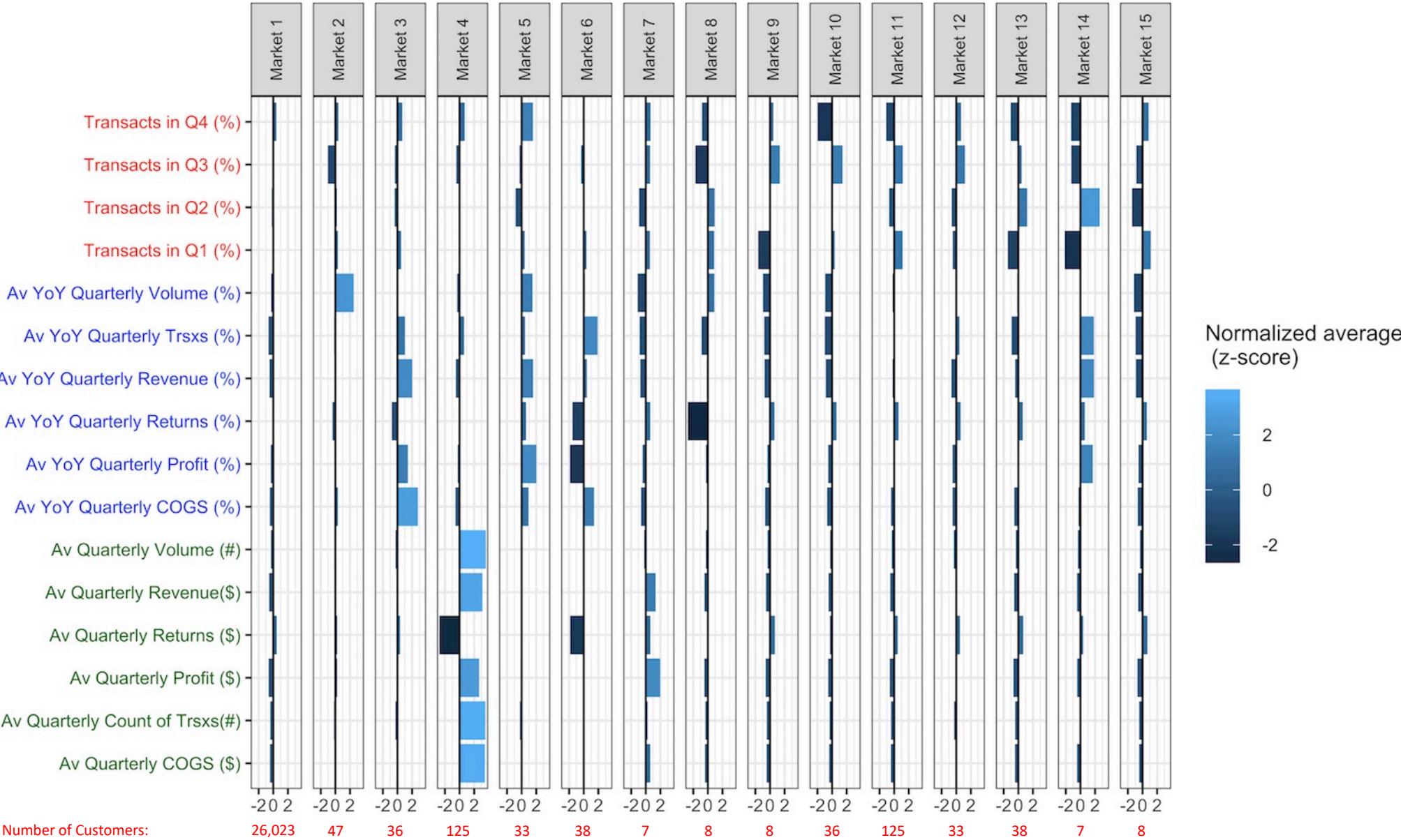
1. The current practice of “End Market” classification fails because “Market 1” makes up >98% of all customers
2. By segmenting customers based on purchasing behavior (e.g., how much, how often, when, where) we can identify like-groupings of customers
3. Targeting underperforming customers may result in incremental revenue and cost improvement
4. Back-of-the-envelope analysis suggests ~700K in potential annual savings:
 - \$333K in potential annual revenue headroom at 25% under-performer lift rate
 - \$361K in potential annual cost reduction at 25% under-performer lift rate
5. Additional areas for exploration:
 - Implement a targeted sales function (BAU: engineers solely responsible for sales)
 - Plant optimization / reduce redundancy
 - Seasonality of purchasing (consolidation, targeting)
 - How sensitive are customers to price increases?
 - Which customers/markets are most influenced by regulations?
 - Target customers based on likelihood of gains (predictive modeling)

Characteristics of Cluster Groups



“End Market” Segmentation Fails because 98% of customers are labeled “Market 1”

Characteristics of End Market Groups



Characterizations:

Entire Portfolio,
mostly unremarkable

...?

...?

...?

Targeting Customers for Interventions

Process:

- Assign a cluster to each customer along with information about common cluster behavior (e.g., average profit, average cost, etc.)
- Identify customers that are under-performing relative to their cluster
- Target customers in order of potential upside (delta from group mean)
- For future exploration: Target customers based on *likelihood of incremental gain (predictive modeling)*

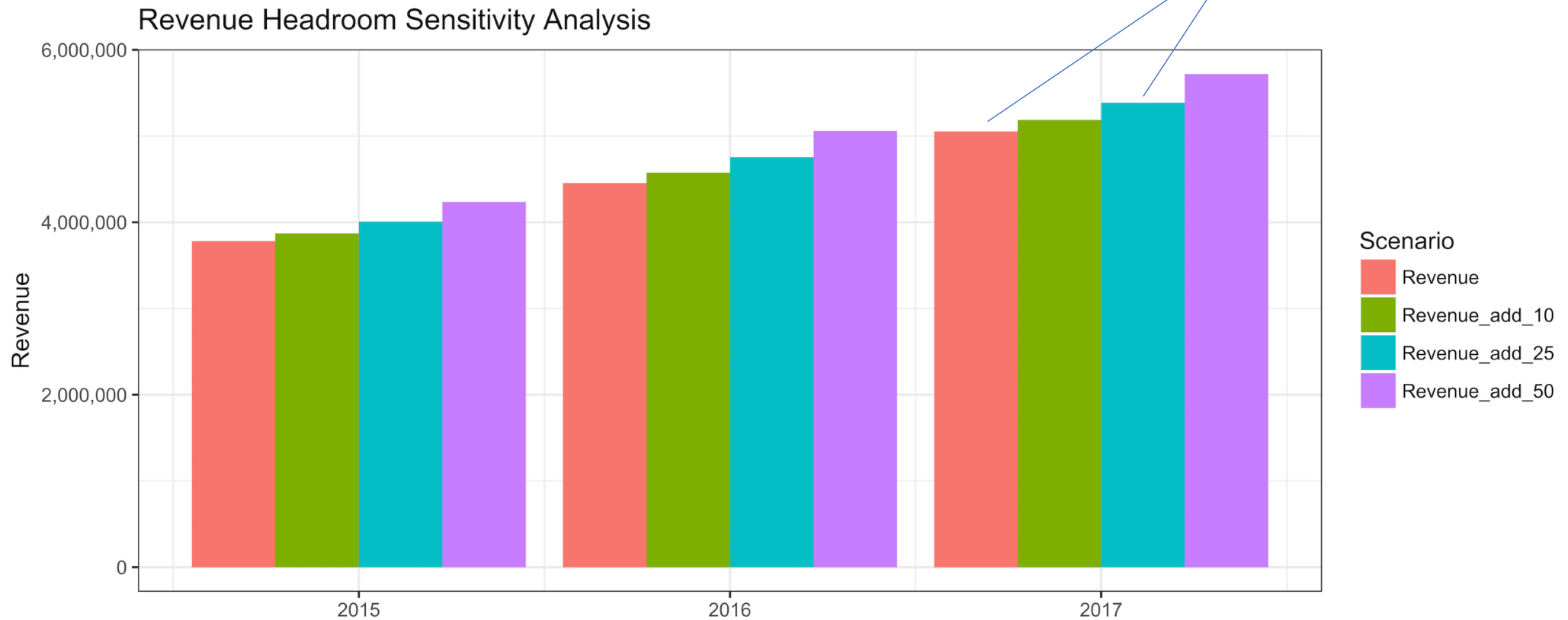
Example: Top 10 Underperforming Customers by profit:

| Customer | Cust. Av Quarterly Profit | Cluster Av Quarterly Profit | Delta |
|----------------|---------------------------|-----------------------------|-----------|
| Customer 243 | \$13,192 | \$20,595 | \$(7,402) |
| Customer 126 | \$13,422 | \$20,595 | \$(7,173) |
| Customer 21670 | \$18,175 | \$20,595 | \$(2,420) |
| Customer 10569 | \$20 | \$433 | \$(413) |
| Customer 76 | \$20,256 | \$20,595 | \$(339) |
| Customer 11669 | \$40 | \$361 | \$(321) |
| Customer 6118 | \$51 | \$361 | \$(310) |
| Customer 12692 | \$70 | \$361 | \$(292) |
| Customer 6108 | \$100 | \$361 | \$(262) |
| Customer 8197 | \$169 | \$361 | \$(193) |

Potential Upside: Increasing Revenues

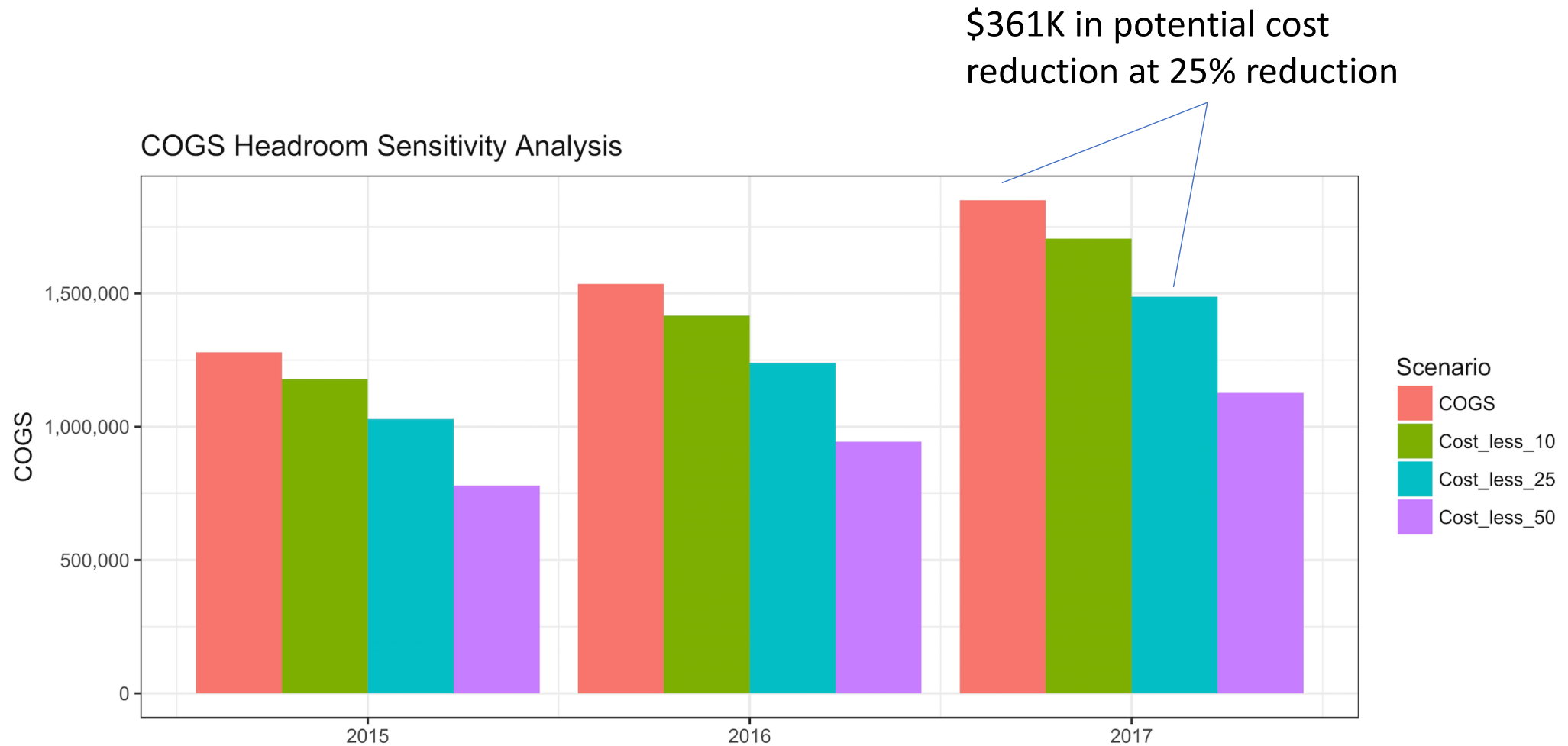
If we increased underperformer revenues by 10%-50%, how much would that be worth?

\$333K in potential incremental revenue at 25% increase



Potential Upside: Decreasing COGS

If we decreased underperformer costs by 10%-50%, how much would that be worth?



Appendix

Future Topics:

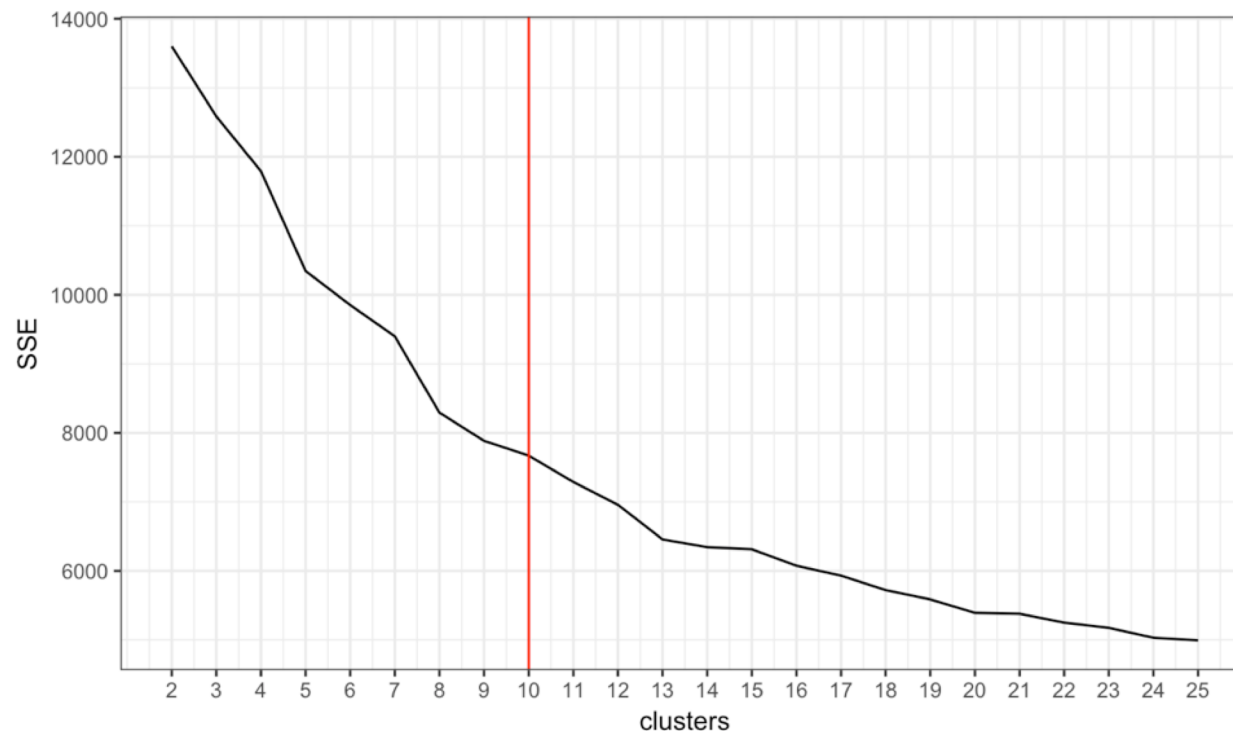
- Employ predictive modeling to target customers based on things like:
 - Predicted sensitivity to increased prices
 - Likelihood of attrition
 - Likelihood to consolidate plants/products
 - Additional data to enhance models:
 - Price of eventual goods sold by customers using our parts
 - Part classifications (materials, intended use, etc.)
 - Factory locations and customer locations
- Network Analysis
 - Which products are antecedents of other products?
 - Opportunities for cross selling?
- Optimization of product mix / manufacturing output
 - What is the exact right mix of products to produce so as to:
 - Maximize revenue
 - Minimize cost
 - Maximize LTV of customer
- Plant optimization
 - Redundancy in plants
 - Consolidation
 - Logistics optimization
 - “Data Envelopment Analysis” to determine relative efficiency of plants

Appendix

Why choose 10 clusters?

- “Elbow” method reveals 10 clusters is optimal
- Few enough to be understandable, and increasing group size incrementally decreases the Sum of Squared Errors within clusters

Within-Cluster Sum of Squared Errors for kmeans across different k



Appendix

Cluster Averages:

| Characteristics | Clusters: | | | | | | | | | |
|--------------------------------|-----------|---------|--------|-------|-------|-------|-------|-----------|-------|-------|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| count | 8 | 20 | 19 | 5,593 | 6,491 | 3,399 | 3,824 | 6 | 5,381 | 655 |
| Av Quarterly Volume (#) | 6,674 | 11,208 | 2,970 | 322 | 328 | 415 | 378 | 1,156,063 | 2,375 | 1,408 |
| Av Quarterly Revenue(\$) | \$619 | \$1,009 | \$104 | \$44 | \$41 | \$47 | \$43 | \$41,876 | \$156 | \$136 |
| Av Quarterly Profit (\$) | \$361 | \$433 | \$77 | \$33 | \$31 | \$36 | \$33 | \$20,595 | \$107 | \$102 |
| Av Quarterly COGS (\$) | \$258 | \$576 | \$27 | \$11 | \$10 | \$11 | \$11 | \$21,281 | \$48 | \$34 |
| Av Quarterly Count of Trxs (#) | 111 | 318 | 4 | 3 | 3 | 3 | 3 | 1,829 | 6 | 8 |
| Av Quarterly Returns (\$) | -416% | -44022% | -246% | -65% | -50% | -68% | -54% | -7095% | -136% | -214% |
| Av YoY Quarterly Volume (%) | 4387% | 22% | 57103% | 18% | 6% | -40% | -70% | 6% | 119% | 967% |
| Av YoY Quarterly Revenue (%) | 590% | 27% | 5918% | 1% | 0% | 0% | -5% | 11% | 45% | 551% |
| Av YoY Quarterly Profit (%) | 649% | 26% | 4027% | -35% | -7% | 0% | -3% | 8% | 41% | 536% |
| Av YoY Quarterly COGS (%) | 1355% | 47% | 44506% | 21% | 17% | 8% | 13% | 16% | 238% | 2543% |
| Av YoY Quarterly Trxs (%) | 2843% | 32% | 310% | 0% | -2% | 0% | 0% | 14% | 26% | 268% |
| Av YoY Quarterly Returns (%) | 0% | 0% | -5% | 0% | 0% | 0% | 0% | 13% | -5% | 6% |
| Transacts in Q1 (%) | 22% | 18% | 16% | 1% | 1% | 94% | 2% | 24% | 29% | 20% |
| Transacts in Q2 (%) | 22% | 18% | 17% | 4% | 6% | 1% | 95% | 24% | 19% | 21% |
| Transacts in Q3 (%) | 35% | 12% | 26% | 3% | 84% | 2% | 0% | 24% | 25% | 28% |
| Transacts in Q4 (%) | 21% | 48% | 40% | 91% | 6% | 2% | 4% | 28% | 26% | 31% |