Understanding the Modern Shopper:

Strategic Analysis of Promotional Effectiveness

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Meet The Dunnhumby Team

Our team of experts brings a diverse set of skills in advanced analytics, business intelligence, technology, marketing, finance, and strategic communication. Together, we combine deep industry experience with data-driven thinking to deliver holistic and actionable recommendations for BigBox.

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About Us & Business Objectives

We Help Companies Put Customers At The Center

dunnhumby

Dunnhumby serves **60+ retailers** and **1,250+ CPGs**, helping them understand their customer base and make smarter decisions using data

Dunnhumby offers **personalized marketing, product assortment, pricing,** and **promotion strategies** through analytics and AI

Coca-Cola · L'ORÉAL · gsk GlaxoSmithKline · Nestlé · Unilever · DANONE · Mondelēz International

9 billion
data records processed every week

1.3 billion
global shopper insights generated

$600 billion
worldwide retail sales analyzed

Highly Competitive Retail Space Requires a Data-Driven Approach to Driving Customer Value

Situation

Retailers are struggling to capture customer attention and build loyalty in a fragmented landscape

Client

BigBox wants to better understand customer behavior and its coupon marketing strategy

Goal

Use data-driven insights to identify who to target, how to reach them, and what to promote

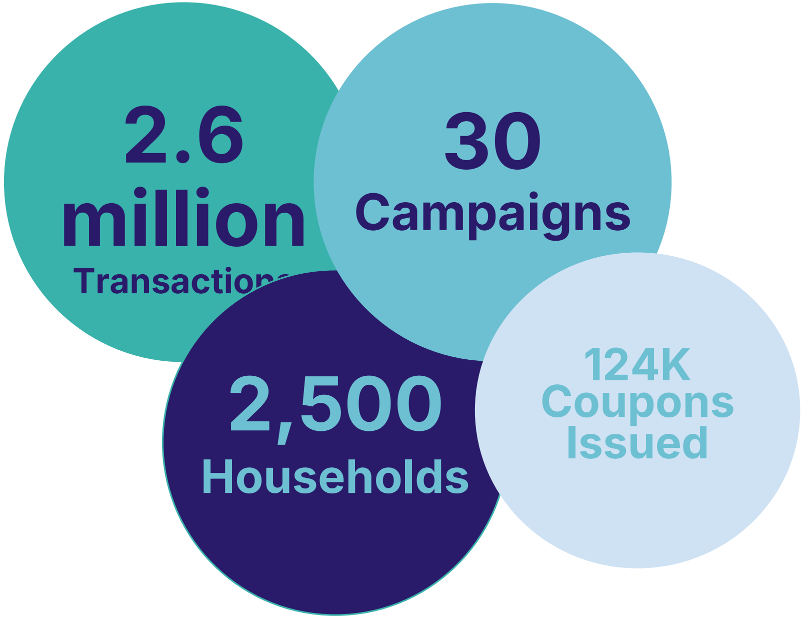
Our Approach Will Explore Marketing Strategies, Coupon Redemption, and Customer Behavior to Drive Engagement and Basket Size

How can BigBox drive greater returns with an improved coupon targeting strategy?

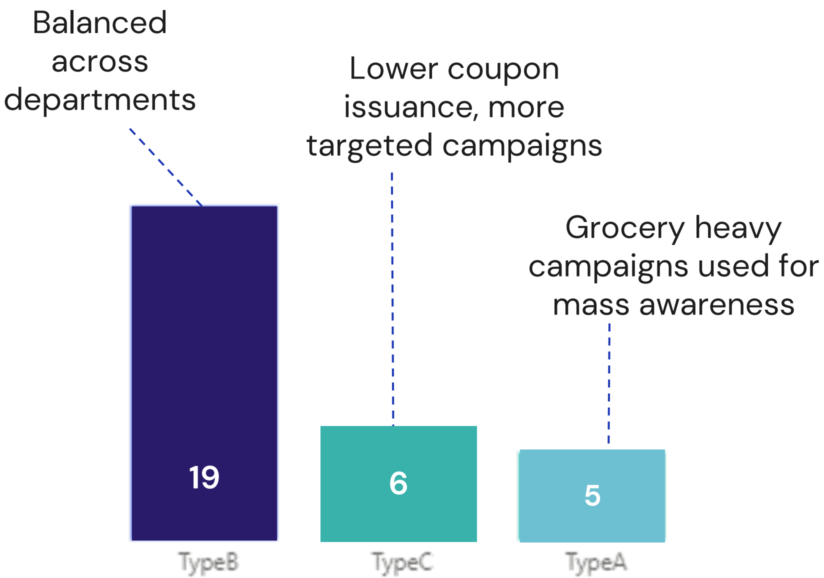
- Which customer segments are most likely to redeem coupons?
- Does a customer’s level of engagement impact their redemption behavior?
- Does coupon redemption grow basket size, and which departments drive the most lift?
- How can BigBox leverage additional advertising strategies to boost campaign reach?

The Dataset

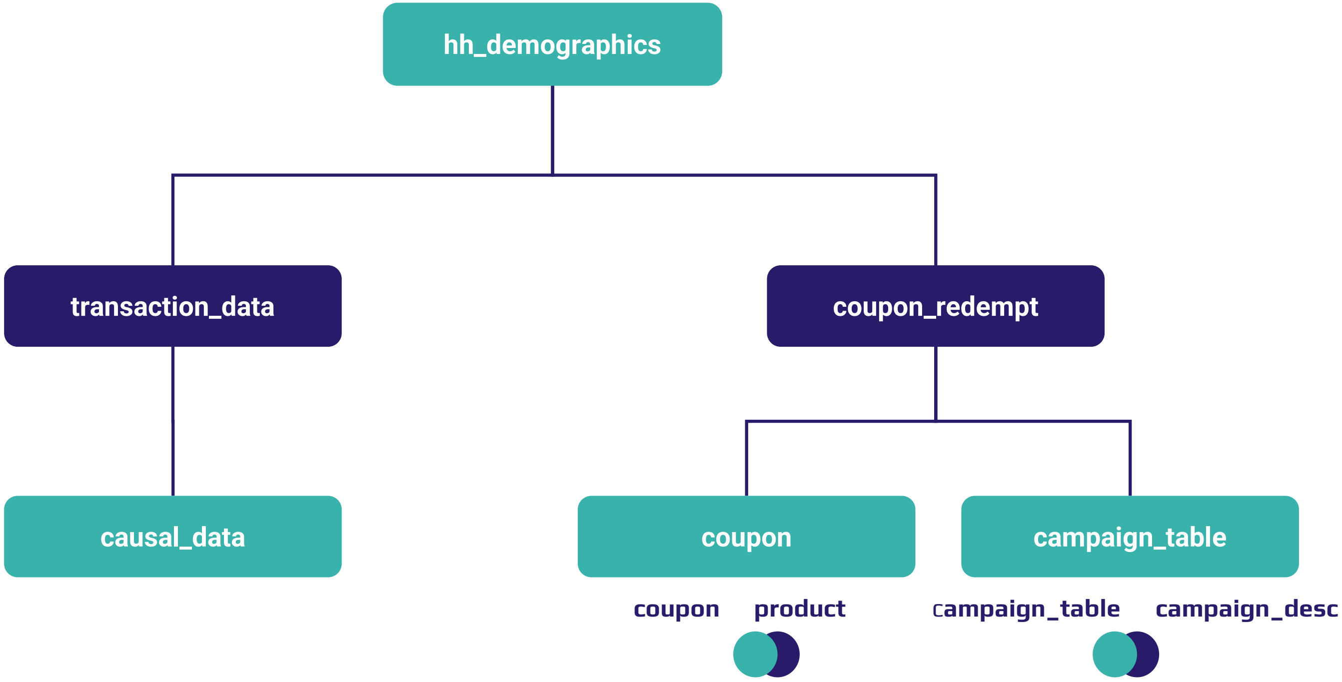
BigBox's Rich Dataset Unlocks an Opportunity to Understand Customer Behavior and Campaign Impact at Scale



Campaigns spanned across 3 Types



Household Data Is the Link Between Transactions and Campaigns



Several Challenges & Data Complexities Were Addressed Throughout the Analysis

Merging Disparate Tables
Multiple joins across tables resulted in significant data volume and structure complexity

Defining Key Metrics with Business Logic

Highly Unbalanced Redemption Classes

Managing Data with Integrity
Many demographic records were missing or unreliable. Incomplete rows were removed to protect analysis quality and focus on usable, trustworthy data

Analysis Based on Practical Assumptions
Estimates were used to fill gaps in cost data, and gross margin used external benchmarks

Model Overview

We Modeled Customer-Level Engagement and Redemption Likelihood as Value Drivers

Do our customers have different levels of engagement?

Who is more likely to redeem a coupon?

Does issuing coupons create value?

Logistic & Linear Regressions Are Ideal to Answer Key Business Questions

Data Preparation: Table Joins | Outlier Detection | Missing Values | One-Hot Encoding

Feature Selection: RFM Analysis | VIF Scores | SMOTE | Statistical Analysis

Modeling: Linear Regression | Logistic Regression | Random Forest | GBDT | Grid Search CV

Power BI

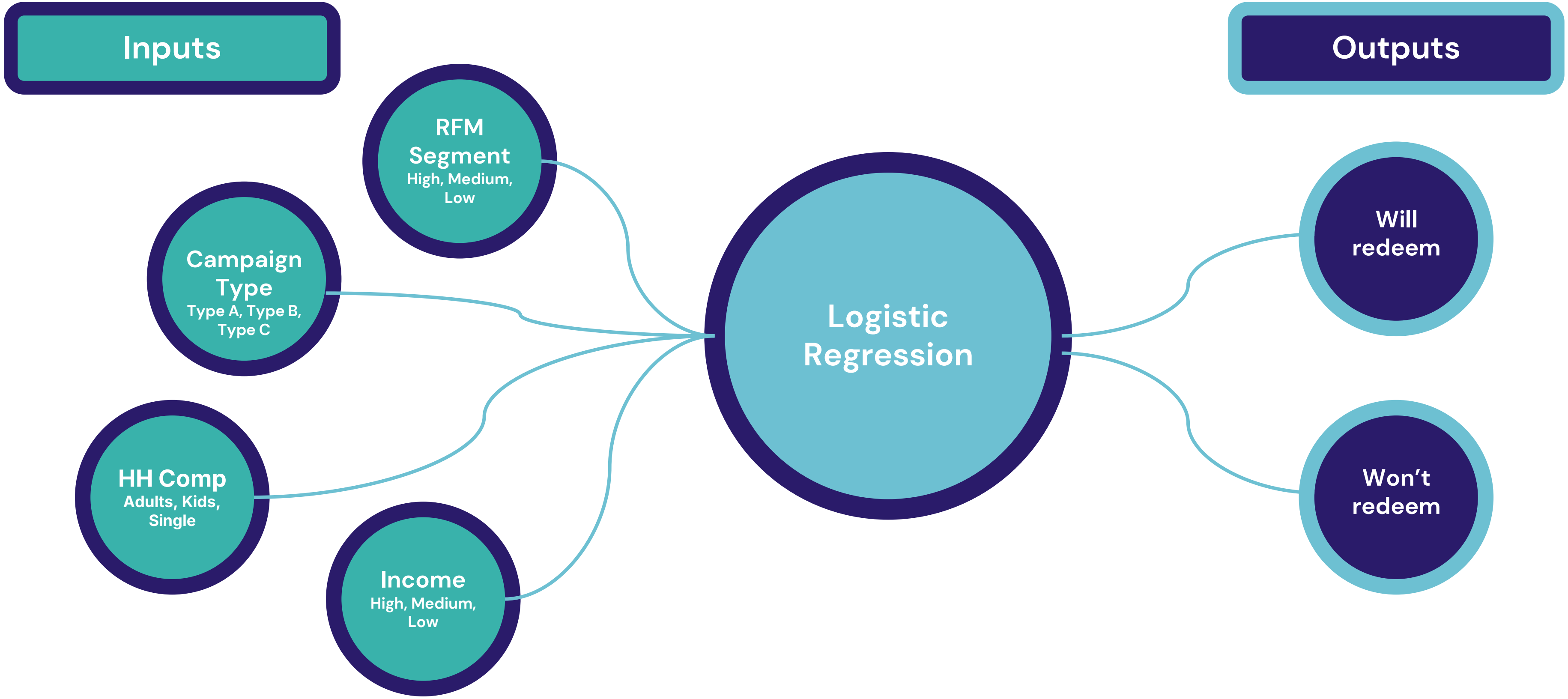
Excel

Python

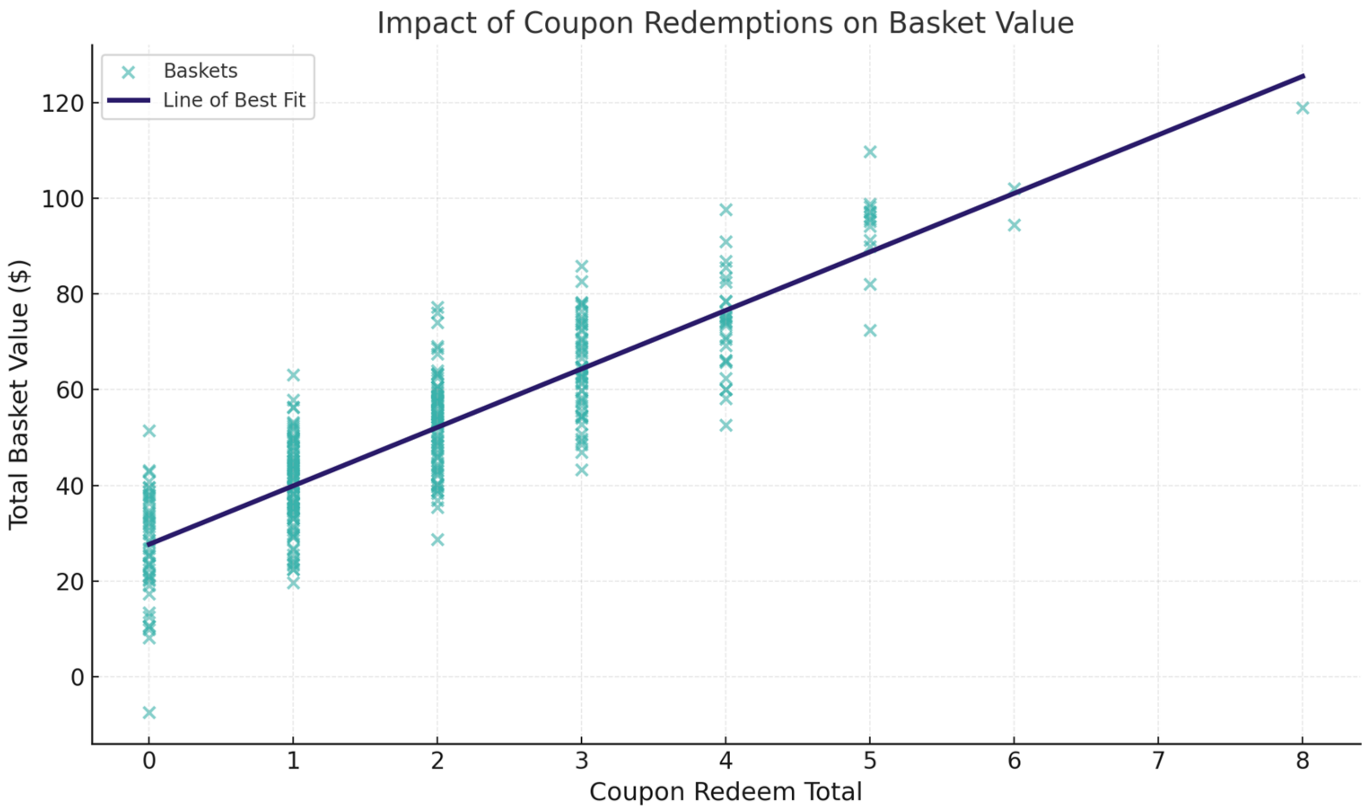
Recency, Frequency, and Monetary Value Analysis Was Used to Find the Most Valuable Segments

- Enables **data-driven segmentation** of customers into tiers by value / priority
- Design to support targeted marketing efforts, such as **personalized coupon offers**
- Provides foundational structure for prioritizing customer engagement strategies and **maximizing ROI** from promotions

Binary Classification Model Predicts Coupon Redemption Likelihood



Define the Line of Best Fit to Understand Basket Expansion Impact



Key Insights & Learnings

Lower-Income, Multi-Adult Households Are Most Likely to Redeem

Income Impact

Lower income households were more likely to redeem, with high earners not showing significant engagement

Household Type Drives Engagement

Although families with kids had high engagement, multi-adult households were more likely to make a redemption

Age Is Not A Factor

Age had no measurable effect on redemption behavior and was removed from the final model

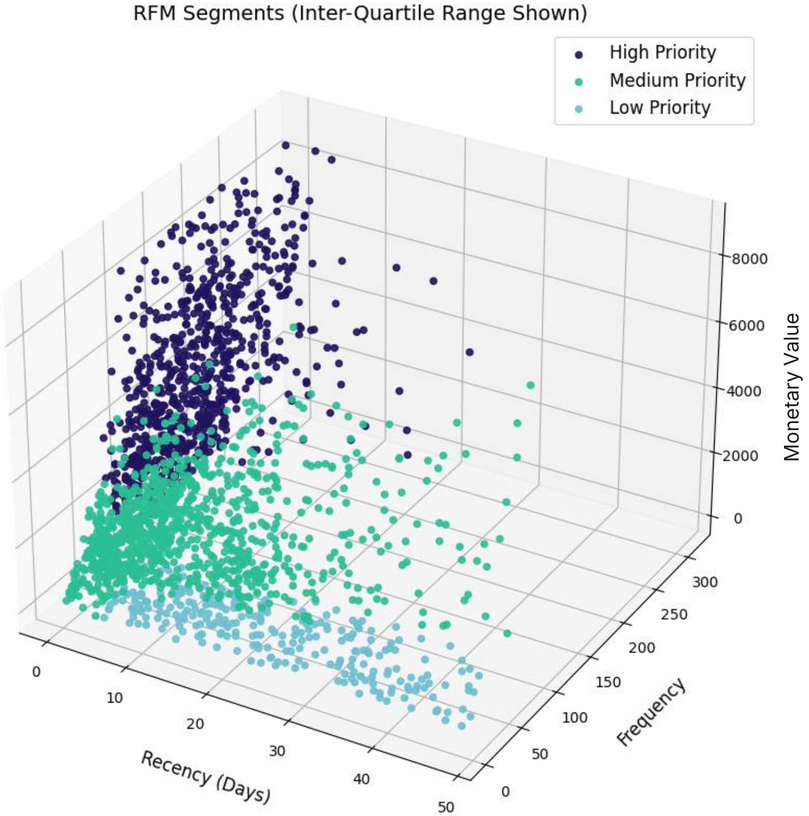
High-RFM Households Are the Best Targets for Coupons

High-RFM segments statistically more likely to redeem

Low and Middle-RFM segments show little response to coupons

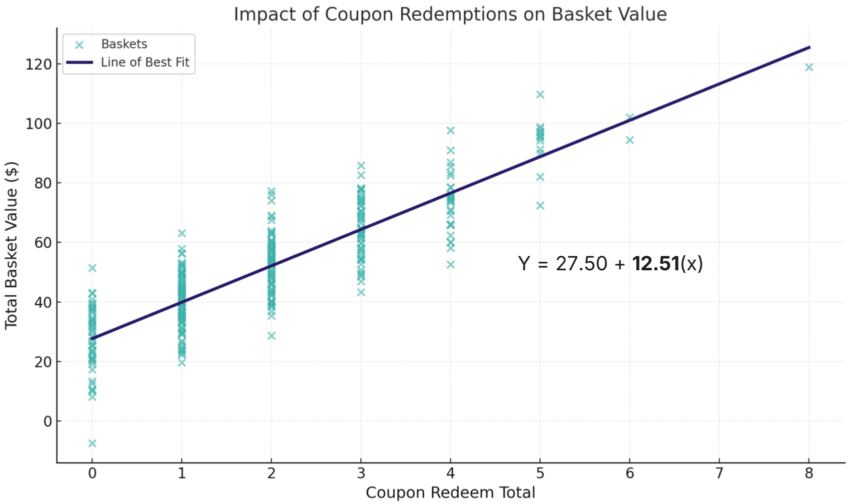
Generally engaged customers, with most purchasing within 100 days

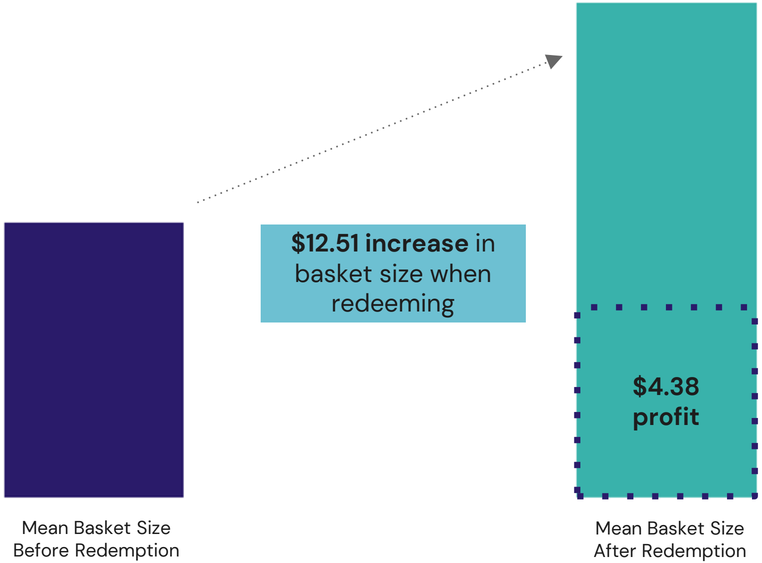
Most spent <$5K, with few driving the biggest spend



Coupon Redemption Increases Basket Size by $12.51

Coupon redemption has a statistically significant effect on basket size using a linear regression





When coupons are redeemed, the basket size increases and so does the profit, as seen in the coefficient for **coupon_redeem_total**, which returned a value of 12.5095.

While Coupon Redemption Was Strongest for Produce, Sales Lift Was Highest in Groceries

Did spending change?

Coupon **redemption** increased mean basket size by **$12.51**

Which coupons are the best?

Produce* coupons Mean basket size increase of **$16.60**

Where did customers spend more?

Groceries* purchases drove 96% of basket expansion

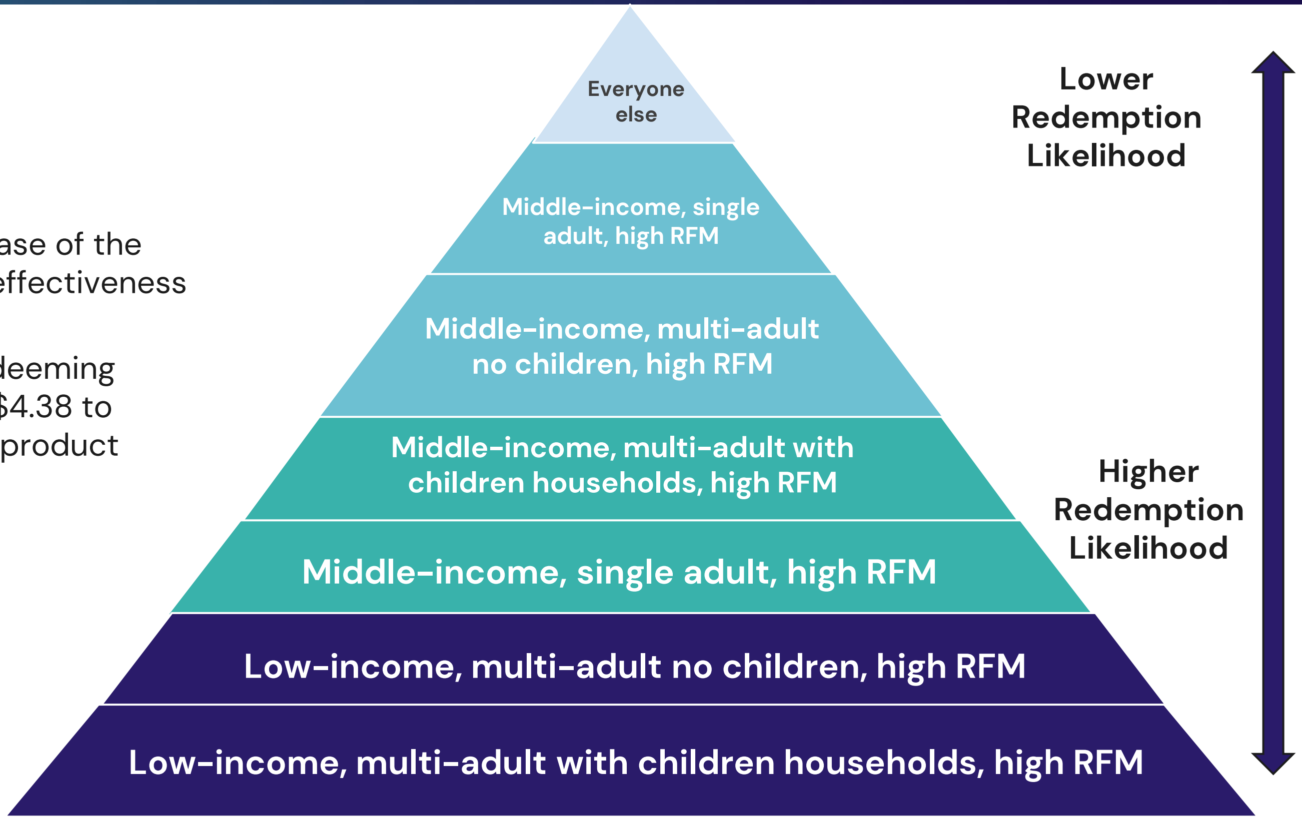
*Produce defined as perishable goods non-animal products. Groceries defined as non-perishable.

Strategic Recommendations

Targeting Should be Focused on Lower-Income, Multi-Adult Households with High Engagement

Increase investment to the base of the pyramid to boost campaign effectiveness

Cap cost of campaign per redeeming customer to no greater than $4.38 to maintain profitability without product targeting



BigBox Should Target Households with Likelihood of Redemption Above 8% to Maximize ROI

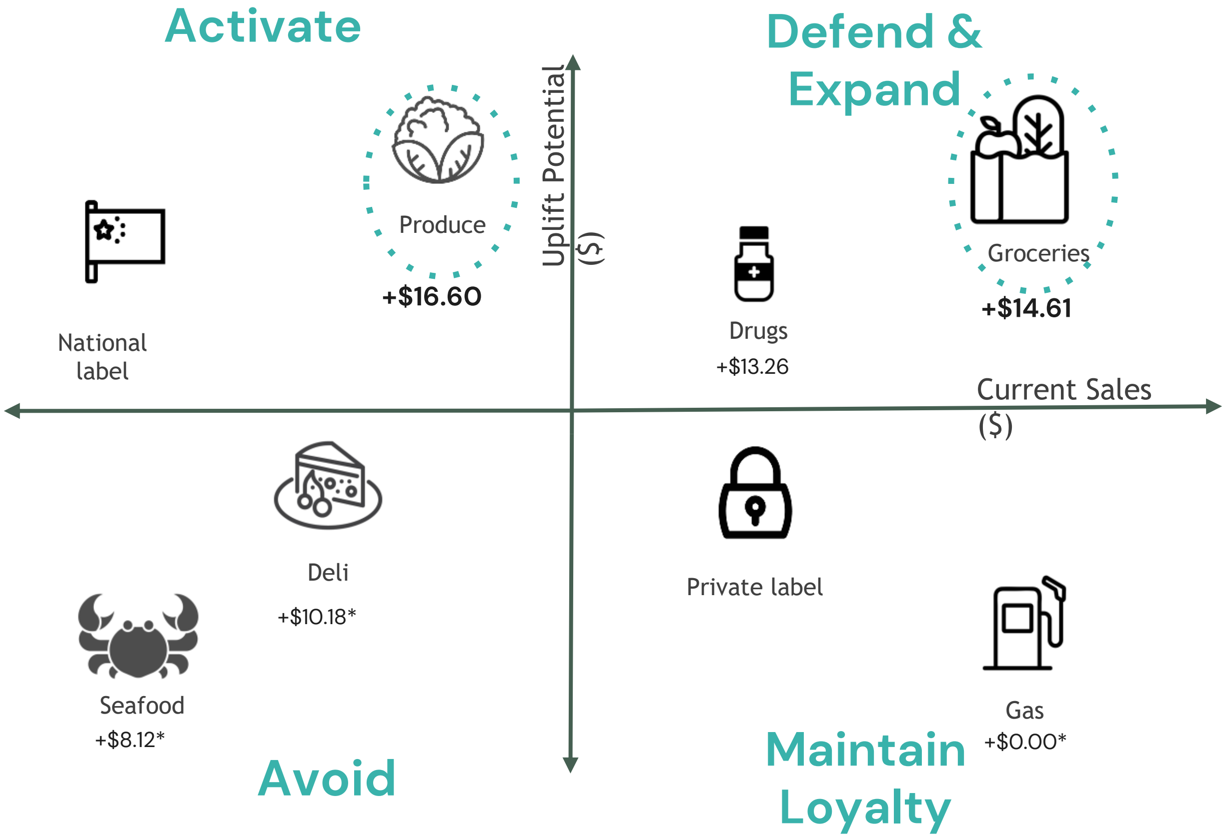
$$\text{Cutoff} = \frac{\text{Campaign Cost}}{\text{Contribution Margin}} \rightarrow \frac{\$0.35}{\$4.38} \approx 0.0799$$

Estimated average campaign cost per basket

Estimated contribution margin (i.e., incremental profit) per basket

	Pessimistic	Baseline	Optimistic
PARAMETERS	15% higher costs from tariffs, 10% less demand from market conditions	Current cost and demand levels	20–25% higher demand from optimized in-store displays and mailers, steady cost
CUTOFF VALUE	~11% – 14%	~8%	~6.4% – 6.7%

BigBox Should Prioritize Categories with the Most Uplift Potential



* Statistically insignificant

Match Promotional Channels to Category Potential to Boost Lift

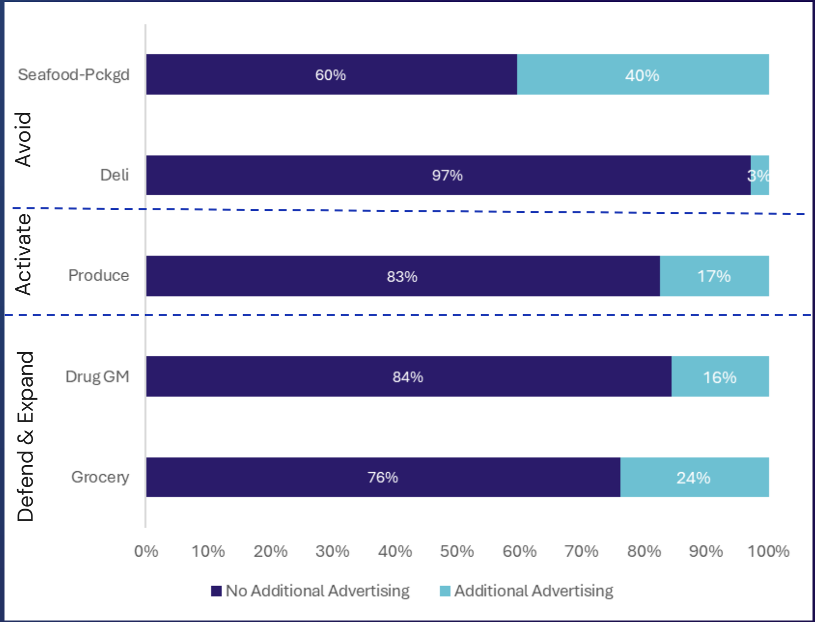
Activate Use Mailer + Display to boost awareness of National brands that are not widely purchased

Defend & Expand Use Mailers to reinforce high-volume, high-value categories like Grocery and Drugs

Maintain Loyalty Use Mailers selectively for retention efforts, and avoid over-investing in promotional support

Avoid Skip promotions for categories that have low uplift and sales potential

Product Marketing by Department
% Share of Coupon Redeemed Transactions

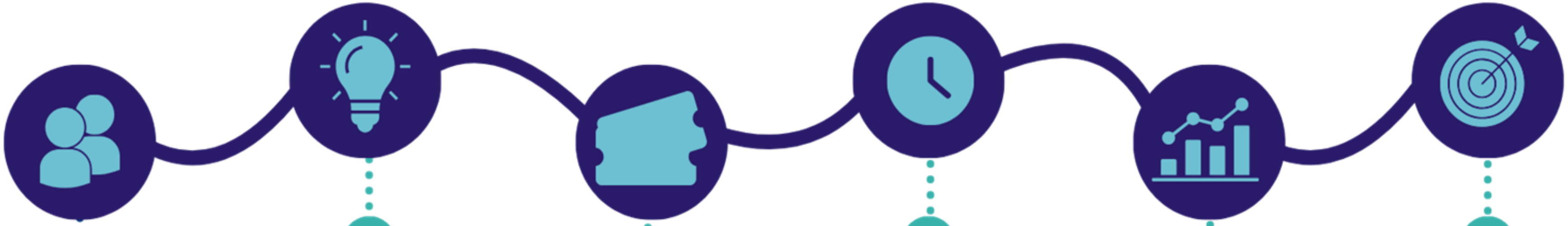


We Propose a 6-Step Campaign Roadmap to Success

Pre-Campaign
4-6 weeks

Run Campaign
6-8 weeks

Post-Campaign
3-4 weeks



1. Determine who to target
2. Evaluate competitor coupon strategy
3. Select product-level coupons, send dates, and expiration
4. Run campaign per predefined calendar and launch strategy
5. Implement tracking system
6. Evaluate long-term impact

The Analysis Doesn't Stop Here!

Campaigns

- Campaign type and basket size relationship
- Ineffective campaigns
- Seasonality

Customers

- Household
- Basket expansion
- Pain of paying

Products

- Product selection
- Virtuous or hedonic products
- Cross-selling and bundling

Real-World Applications & Reflection

Reflecting on Our MSBA Journey

Learned strategies to help clients address their data challenges both on supply and demand sides – Jungmin Cho

Transferred ML learnings into real world B2B SaaS churn model – Brett Gottschalk

Understand and navigate the complexities of determining the most important datasets – Sarah Lynch

Learned to filter noise and align diverse perspectives to stay focused on the key business question – Gabriel Menezes

The best questions aren't always the first ones, they evolve as more insights are uncovered – Sabrina Noriega

“Marketing without data is like driving with your eyes closed.”

- *Dan Zarrella*

Appendix

About the Data (Resources)

We will use data from **BigBox's recent marketing campaigns** to generate our recommendations. Our dataset contains **household level transactions** over two years from a group of **2,500 households** who are frequent shoppers at BigBox. It includes each household's full purchases from BigBox, and for some households, demographic information and direct marketing contact history as well.

There are eight files to aid our analysis, which can be joined through various keys:

Table Name	Description
transaction_data	Contains all products purchased by households within the study. Each line is like a line from a store receipt.
campaign_table	Lists campaigns received by each household in the study. Each household received a different set of campaigns.
campaign_desc	Provides length of time for which a campaign runs. Coupons received are valid within the dates contained in this table.
product	Contains information on each product sold, such as type of product, national or private label, and a brand identifier.
coupon	Lists all coupons sent to customers as part of a campaign, as well as the products for which each coupon is redeemable.
coupon_redempt	Identifies the coupons that each household redeemed.
causal_data	Indicates whether a given product was featured in a weekly mailer or was part of an in-store display.
hh_demographic	Contains demographic information for a portion of households.

Entity Relationship Diagram

This ERD visualizes key relationships across eight dataset tables, automatically inferred via overlapping key fields. Edge thickness represents relationship strength, based on column value overlap (20%, 50%, 80%).

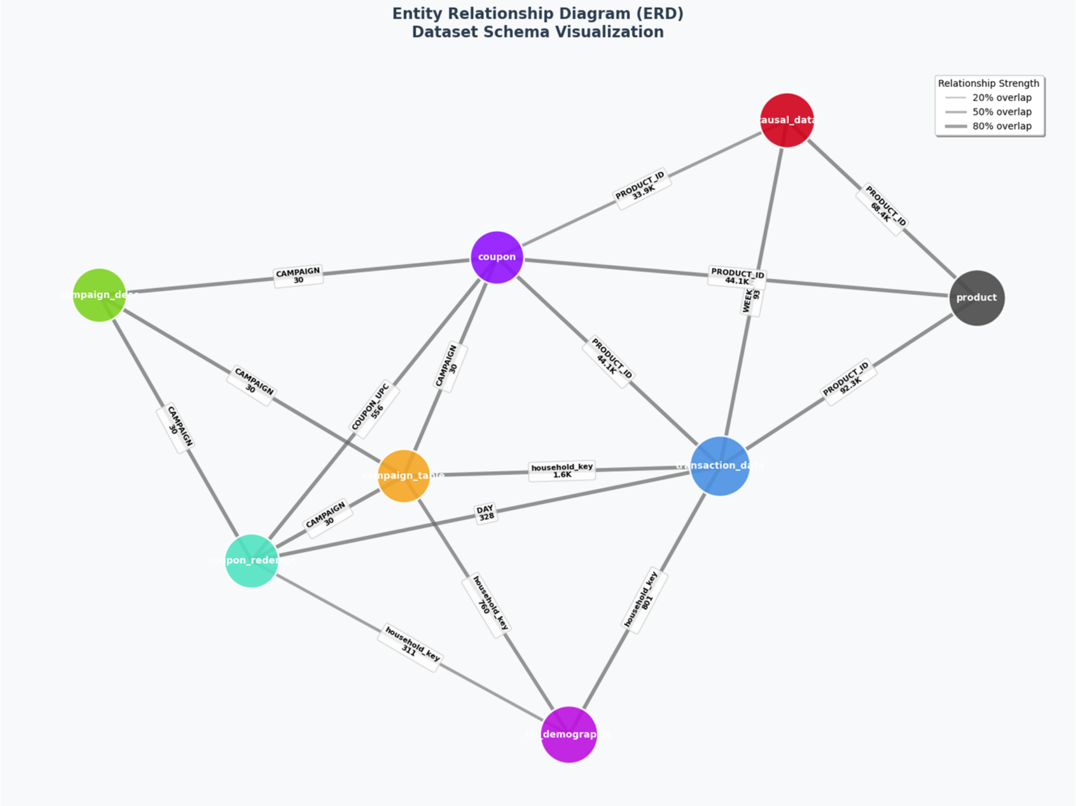
Central Node: transaction_data connects heavily with product, coupon, demographic, and causal_data, indicating its role as a transactional hub.

Shared Keys:

- household_key links user-level data (transaction_data, demographic).
- product_id connects transaction_data, product, causal_data, and coupon.
- campaign fields link promotional tables: coupon, campaign_table, and campaign_desc.

Insights: High overlaps suggest strong referential integrity. Product and coupon usage can be analyzed across transactions, demographics, and marketing campaigns.

This mapping enables robust join strategies for downstream analysis in customer behavior, promotion effectiveness, and attribution modeling.



Hypothesis Testing

Variable	Hypothesis	Results
Age	H1 = Age is a statistically significant predictor of coupon redemption likelihood H0 = Age does not impact a household's coupon redemption likelihood	**Reject the null for most age groups**; we grouped age into four categories (25-34, 35-44, 55-64, and 65+). The ranges 25-34, 35-44,and 65+ returned p-values that were statistically significant (p ~0.000-0.015), whereas 55-64 returned a p-value (0.131) that was greater than the 0.05 threshold. All coefficients were negative. Age groups were removed due to statistical insignificance and lack of predictive power, depending on the model.
Household Income	H1 = Household Income is a statistically significant predictor of coupon redemption likelihood H0 = Household Income does not impact a household's coupon redemption likelihood	**Reject the null** ($p<0.000$); we grouped household income income into three brackets (High, Medium, and Low). We found that High income had a p-value greater than 0.05. Medium income group, however, tend to drive redemption likelihood (ß=0.5705). Low Income is the most prominent driver and is included in the base case.
Household Size	H1 = Household Size is a statistically significant predictor of coupon redemption likelihood H0 = Household Size does not impact a household's coupon redemption likelihood	**Reject the null** ($p<0.000$); the probability that single-adult households redeem a coupon was lower in comparison to families who are more inclined to redeem coupons. We saw that as number of household members go up, the likelihood to redeem a coupon also went up, with the most significant predictor being a multi-adult household.
RFM Segmentation of HH	H1 = RFM Segmentation is a statistically significant predictor of coupon redemption likelihood H0 = RFM Segmentation does not impact a household's coupon redemption likelihood	**Reject the null** ($p<0.000$); we included the medium value group from the RFM analysis as a feature in our refined logistic regression model and removed Low Value due to statistical insignificance. Higher RFM value results in higher likelihood to redeem a coupon.

Data Preprocessing

Data Cleaning

1. Merged Coupon, Redemption, and HH Demographic tables
2. Dropped 42% of rows that had missing demographic data
3. ***Classified households into low, middle and high income brackets to improve model interpretability**
4. ***Classified households by High, Medium, Low value according to Recency, Frequency and Monetary (RFM) scores to improve model performance through customer segmentation**
5. Created redemption label
6. Removed redundant/non descriptive columns
7. One hot encoded categorical variables
8. Tested for multicollinearity using VIF. Dropped select collinear features
9. Addressed class imbalance with SMOTE
10. Split into train/test

Classification

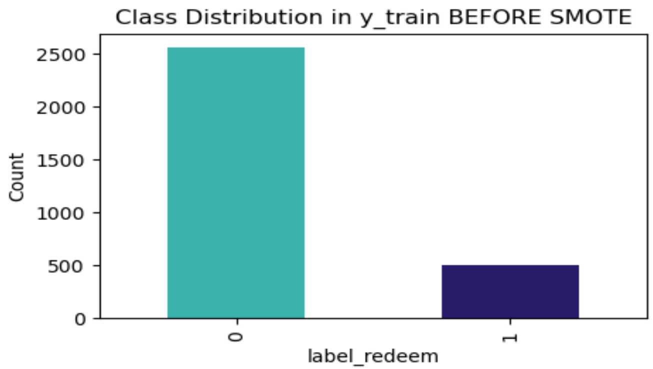
The categorical variables were one-hot encoded into binary values (this included variables campaign desc, age dec, income desc, homeowner desc, HH comp desc, HH size desc)

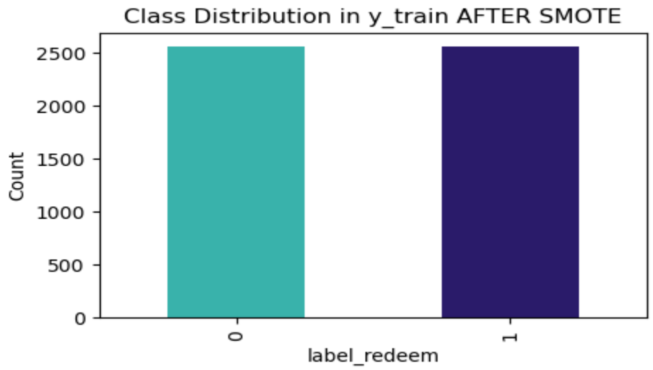
Target Variable and Features

The target variable we used was called label_redeem: 1 or 0 and the features included the following: demographics (age, income, household composition) and campaign type (A, B, and C)

*New data preprocessing that was incorporated

Class Distribution





Before SMOTE

- Class distribution checked to ensure balance
- Redemption classes were heavily unbalanced, with 2563 in the non-redempt group and 499 in the redemption group

After SMOTE

- Synthetic Minority Over-sampling Technique (SMOTE) was used to address the imbalance of the 1 class
- Synthetic samples now rebalanced the classes to 2563 across groups

Addressing Missing Data Using Synthetic Data Generation & Industry Benchmarks

Creating a Balanced Dataset for Model Training & Testing

A balanced dataset with approximately equal observations in each class is crucial to training a well-performing classifier model. As is the case in most retail scenarios, Bigbox data has a much smaller sample for coupon redemption than non-redemption, requiring balancing of the dataset. We used **SMOTE (Synthetic Minority Oversampling Technique)** to balance the size of the two classes within our dataset. Additional detail were discussed in slide 10.

Addressing Missing Cost Data for Return on Marketing Investment (ROMI) Calculation

Cost data (coupon campaign cost, contribution margin of products) is required to build robust and holistic business recommendations for Bigbox's management team. We augmented our initial dataset with additions from several sources:

- Gross profit, net profit, fixed costs, and variable costs for retailers (of similar scale, reach, and product mix as Bigbox) were imputed from industry benchmarks and used to calculate the contribution margin:
  - NYU Stern School of Business – Aswath Damodaran, "Margins by Sector (US)"
  - Vena Solutions, "What's the Average Profit Margin by Industry?"
  - Statista, "Average Gross Profit Margin of Retail Stores Worldwide by Category"
  - National Grocers Association (2021) – "How Is a Retail Price Calculated?", Ted Mason; January 28, 2021 (NGA Foundation Technical Assistance Center)
- Coupon campaign costs were imputed from industry average CPM (Cost per Mille) for direct mail marketing:
  - Top Draw Inc., "Is Online Advertising Expensive? Online Advertising Costs in 2025"

The resulting Return on Marketing Investment (ROMI) value was further compared against industry benchmarks to test the reasonableness of our analysis.

Who is most likely to redeem a coupon?

We ran multiple binary classification models, balancing predictive accuracy with campaign insight. The data was split into 80% training data and 20% testing data to help it learn patterns and identify patterns. The variable **“label_redeem”** was stratified to maintain the class proportions.

Models Evaluated

Recency, Frequency, Monetary Segmentation

Logistic Regression

Interpretability and statistical inference

Random Forest

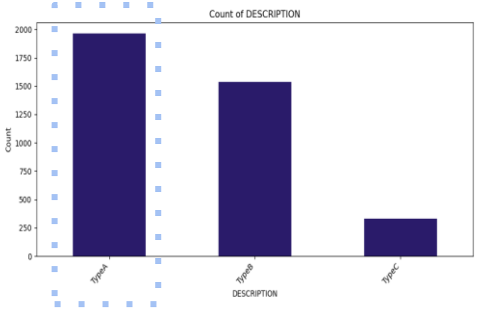
Non-linear interactions and feature importance

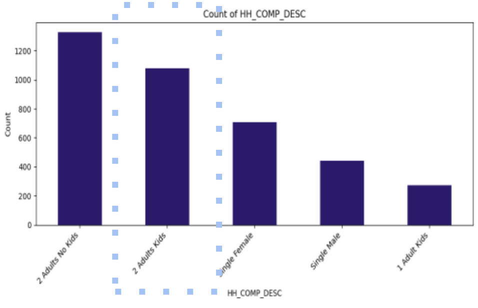
Gradient Boosted Decision Tree

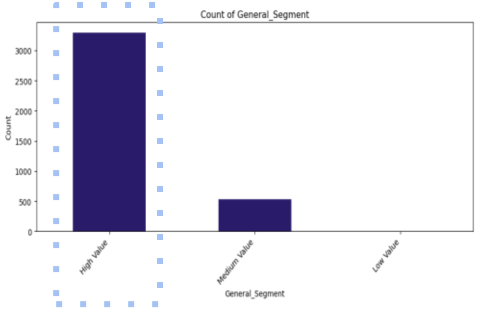
Maximum accuracy when classes are imbalanced

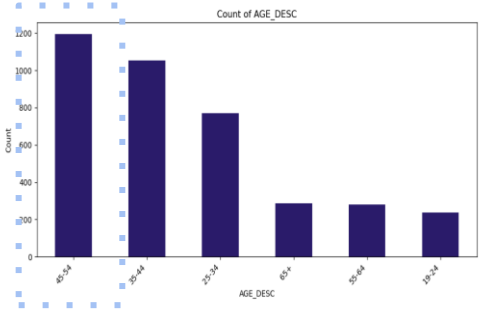
Logistic Regression Base Case Selection

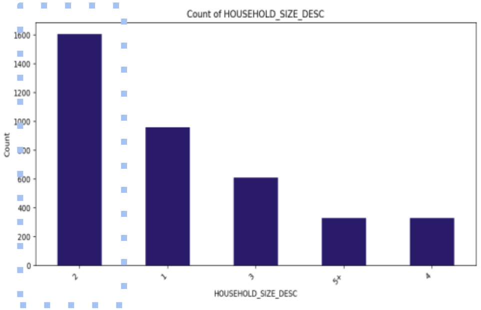
Base/Reference case selection made based on frequency of variable observations and coefficient statistical significance

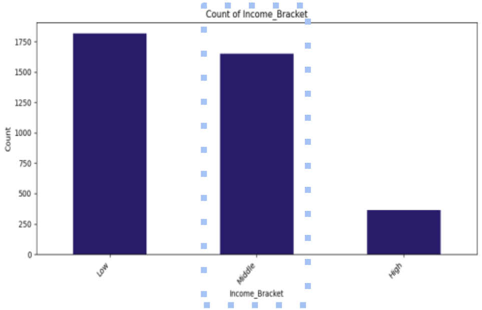












Model Performance Comparisons

Inclusion of RFM segmentation improved model Accuracy and Precision at the expense of Recall and AUC

Non-Optimized Models				
Model	**Accuracy**	**Precision**	**Recall**	**AUC**
Logistic Regression	0.6397	0.2525	0.6160	0.6567
Random Forest	0.6501	0.2560	0.6000	0.6413
XGBoost	0.6305	0.2500	0.6320	0.6471

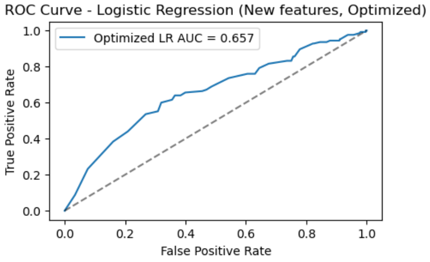
Optimized Models				
Model	**Accuracy**	**Precision**	**Recall**	**AUC**
Logistic Regression	0.6358	0.2548	0.6400	0.6573
Random Forest	0.6501	0.2560	0.6000	0.6414
XGBoost	0.6501	0.2560	0.6000	0.6439

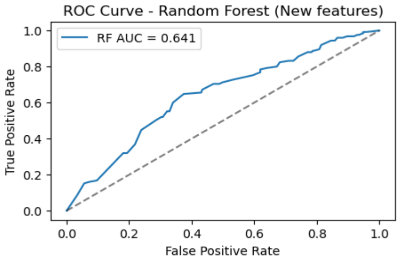
Comparative Analysis

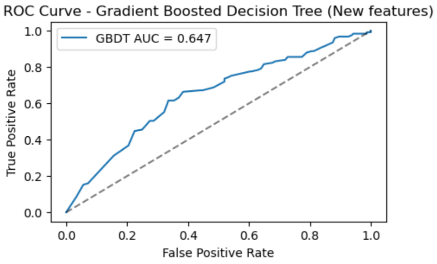
Logistic Regression

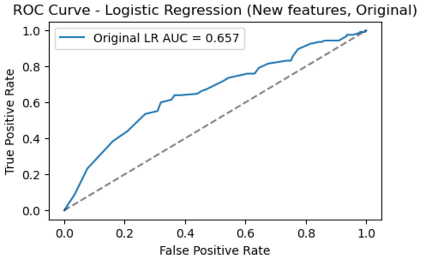
Random Forest

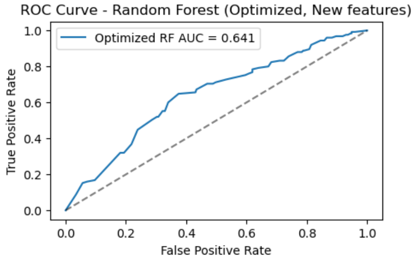
XGBoost

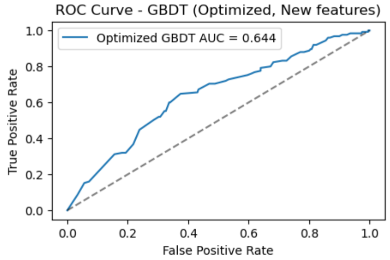












**We chose the optimized logistic regression model because it had the best interpretability out of the three optimized models, with an AUC of 0.657.*
***Model choice should be based on the business need for accuracy, precision or recall*

Purchase Likelihood - Log. Regression

```
Statistical significance of coefficients (statsmodels, new features, original LR):
                           Logit Regression Results
==============================================================================
Dep. Variable:           label_redeem   No. Observations:                 5126
Model:                          Logit   Df Residuals:                     5117
Method:                           MLE   Df Model:                            8
Date:                Mon, 04 Aug 2025   Pseudo R-squ.:                  0.1007
Time:                        22:56:38   Log-Likelihood:                -3195.3
converged:                       True   LL-Null:                       -3553.1
Covariance Type:            nonrobust   LLR p-value:                 3.106e-149
===================================================================================================
                                    coef    std err          z      P>|z|      [0.025      0.975]
---------------------------------------------------------------------------------------------------
const                             0.8821      0.068     13.024      0.000       0.749       1.015
DESCRIPTION_TypeC                -1.2407      0.122    -10.191      0.000      -1.479      -1.002
DESCRIPTION_TypeB                -1.3072      0.067    -19.479      0.000      -1.439      -1.176
HH_COMP_DESC_Single Male         -1.0938      0.114     -9.599      0.000      -1.317      -0.870
HH_COMP_DESC_2 Adults No Kids    -0.3489      0.074     -4.733      0.000      -0.493      -0.204
HH_COMP_DESC_Single Female       -0.5735      0.089     -6.448      0.000      -0.748      -0.399
HH_COMP_DESC_1 Adult Kids        -0.9438      0.142     -6.648      0.000      -1.222      -0.666
General_Segment_Medium Value     -1.4898      0.114    -13.024      0.000      -1.714      -1.266
Income_Bracket_Low                0.2438      0.061      4.019      0.000       0.125       0.363
===================================================================================================
```

Basket Size - Linear Regression

Based on our analysis, we found that when coupons are redeemed, the basket size increases, and therefore so does profit. This was evident in the coefficient for **coupon_redeem_total**, which returned a value of 12.5095. Generally, coupon redemption increases basket size by $12.51. This indicates that the company should focus on increasing coupon redemption rates using the marketing materials that resonate the most with their audience in order to maximize profit.

```
 OLS Regression Results
==============================================================================
Dep. Variable:      total_sales_value   R-squared:                       0.083
Model:                            OLS   Adj. R-squared:                  0.083
Method:                 Least Squares   F-statistic:                 2.489e+04
Date:                Thu, 17 Jul 2025   Prob (F-statistic):               0.00
Time:                        19:29:26   Log-Likelihood:            -1.3720e+06
No. Observations:              276484   AIC:                         2.744e+06
Df Residuals:                  276482   BIC:                         2.744e+06
Df Model:                           1
Covariance Type:            nonrobust
=======================================================================================
                          coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------------
const                  27.4947      0.067    412.919      0.000      27.364      27.625
coupon_redeem_total    12.5095      0.079    157.755      0.000      12.354      12.665
==============================================================================
Omnibus:               183705.223   Durbin-Watson:                   1.948
Prob(Omnibus):              0.000   Jarque-Bera (JB):          3392489.919
Skew:                       2.954   Prob(JB):                         0.00
Kurtosis:                  19.111   Cond. No.                         1.27
==============================================================================
```

Basket Size - Coupon Redemption Two Sample T-Test

Department	Baskets with Redeemed Coupon	Mean Basket Size	mean_basket_size_nonredeem	mean_diff	t_stat_x	p_value_x	t_stat_y	p_value_y
PASTRY	38	$ 34.66	$ 17.00	$ 17.66	4.07	0.00	4.07	0.00
MEAT	29	$ 39.17	$ 21.74	$ 17.43	3.52	0.00	3.52	0.00
PRODUCE	412	$ 35.61	$ 19.01	$ 16.60	14.19	0.00	14.19	-
COUP/STR & MFG	22	$ 27.32	$ 11.42	$ 15.90	4.48	0.00	4.48	0.00
GROCERY	11,347	$ 26.20	$ 11.59	$ 14.61	77.23	-	77.23	-
DRUG GM	3,340	$ 26.82	$ 13.56	$ 13.26	34.40	0.00	34.40	-
MEAT-PCKGD	1,089	$ 35.00	$ 21.76	$ 13.24	18.26	0.00	18.26	-
NUTRITION	186	$ 32.80	$ 21.75	$ 11.05	6.26	0.00	6.26	-
DELI	159	$ 29.36	$ 19.18	$ 10.18	5.79	0.00	5.79	-
SEAFOOD-PCKGD	138	$ 34.88	$ 26.76	$ 8.12	3.96	0.00	3.96	0.00
COSMETICS	100	$ 25.79	$ 19.66	$ 6.13	3.13	0.00	3.13	0.00
MISC. TRANS.	2	$ 7.50	$ 19.10	$ (11.60)	(18.47)	0.00	(18.47)	0.00
FLORAL	9	$ 17.89	$ 13.38	$ 4.51	1.29	0.23	1.29	0.23
UNKNOWN	4,945	$ 23.84	$ 24.18	$ (0.34)	(0.69)	0.49	(0.69)	0.49
PHOTO	3	$ 24.33	$ 40.36	$ (16.03)	(2.06)	0.06	(2.06)	0.06

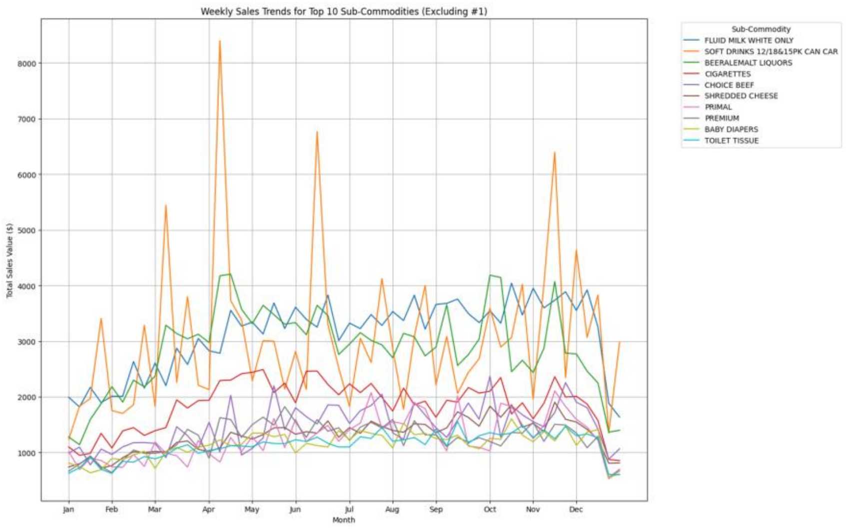
Basket Size - Spend Two Sample T-Test

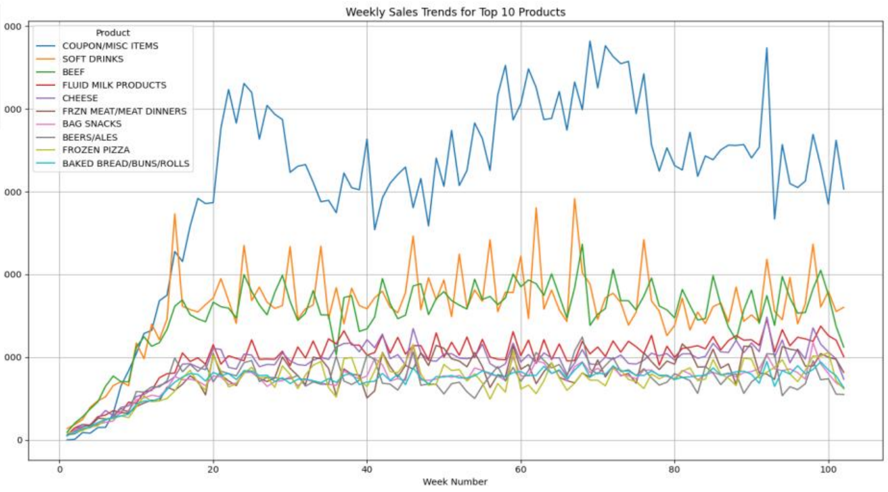
Department	No Coupon Mean	With Coupon Mean	Difference	t-stat	p-value
GROCERY	12.99	31.14	18.16	62.93	-
DRUG GM	3.57	4.38	0.81	8.11	0.00
RESTAURANT	0.01	-	(0.01)	(14.15)	0.00
CHEF SHOPPE	0.01	-	(0.01)	(25.39)	0.00
TRAVEL & LEISUR	0.01	-	(0.01)	(26.33)	0.00
GARDEN CENTER	0.03	-	(0.03)	(14.63)	0.00
MISC. TRANS.	0.04	0.00	(0.04)	(8.69)	0.00
COSMETICS	0.11	0.05	(0.06)	(9.88)	0.00
SPIRITS	0.08	-	(0.08)	(35.76)	0.00
SEAFOOD	0.11	-	(0.11)	(42.49)	-
SALAD BAR	0.11	-	(0.11)	(74.25)	-
FLORAL	0.14	0.00	(0.14)	(38.18)	-
SEAFOOD-PCKGD	0.23	0.06	(0.16)	(21.49)	0.00
NUTRITION	0.35	0.09	(0.26)	(25.44)	0.00
PASTRY	0.44	0.01	(0.43)	(92.98)	-
MISC SALES TRAN	0.44	-	(0.44)	(51.11)	-
MEAT-PCKGD	1.46	0.72	(0.74)	(25.72)	0.00
DELI	0.94	0.11	(0.84)	(68.94)	-
PRODUCE	2.01	0.29	(1.72)	(87.26)	-
MEAT	1.99	0.03	(1.97)	(150.75)	-
KIOSK-GAS	1.98	-	(1.98)	(137.37)	-

* No change in mean basket size excluded

Early Signs of Seasonality

We observe some subtle signs of seasonality in sales, localized to specific products. We will explore this potential relationship between sales and time of year in our future, continued collaboration with BigBox





Scenarios

Good

Improved targeting increases campaign efficiency and overall performance.

Better

High value customers deepen relationship with BigBox, new customers are acquired and retained economically.

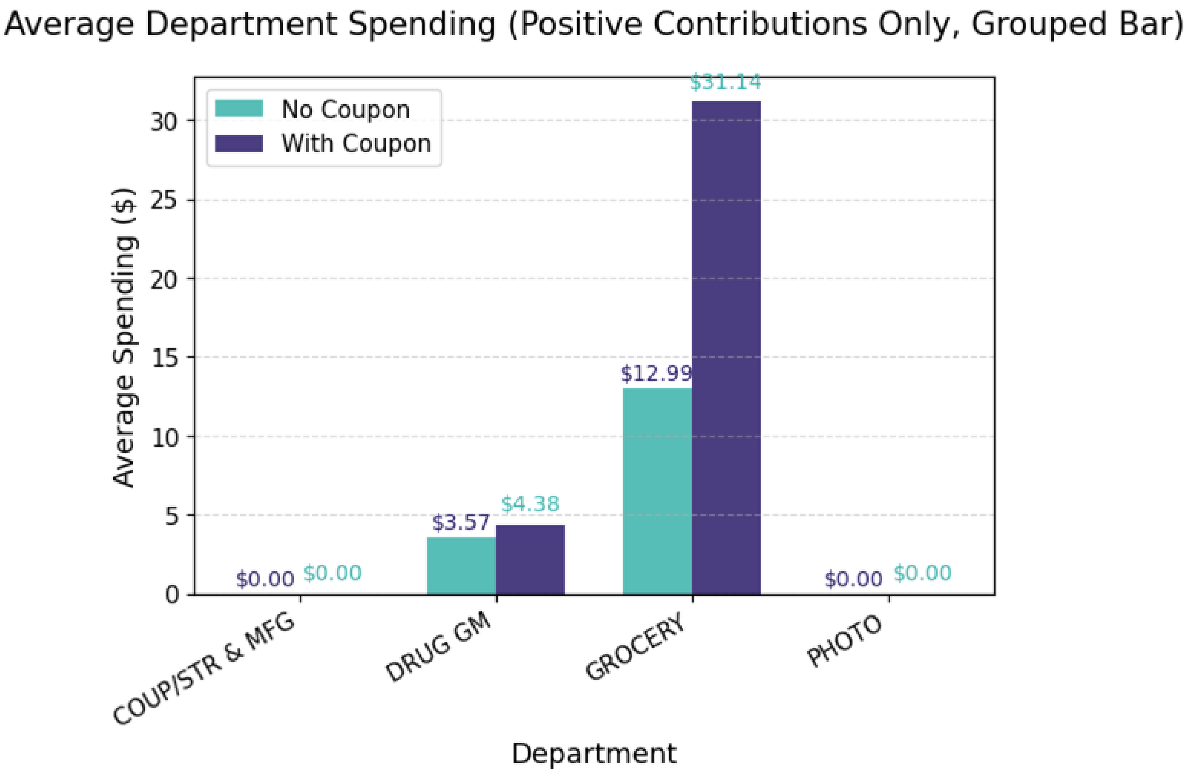
Best

Customers redeem the coupons, basket size increases, and overall profit increases as a result.

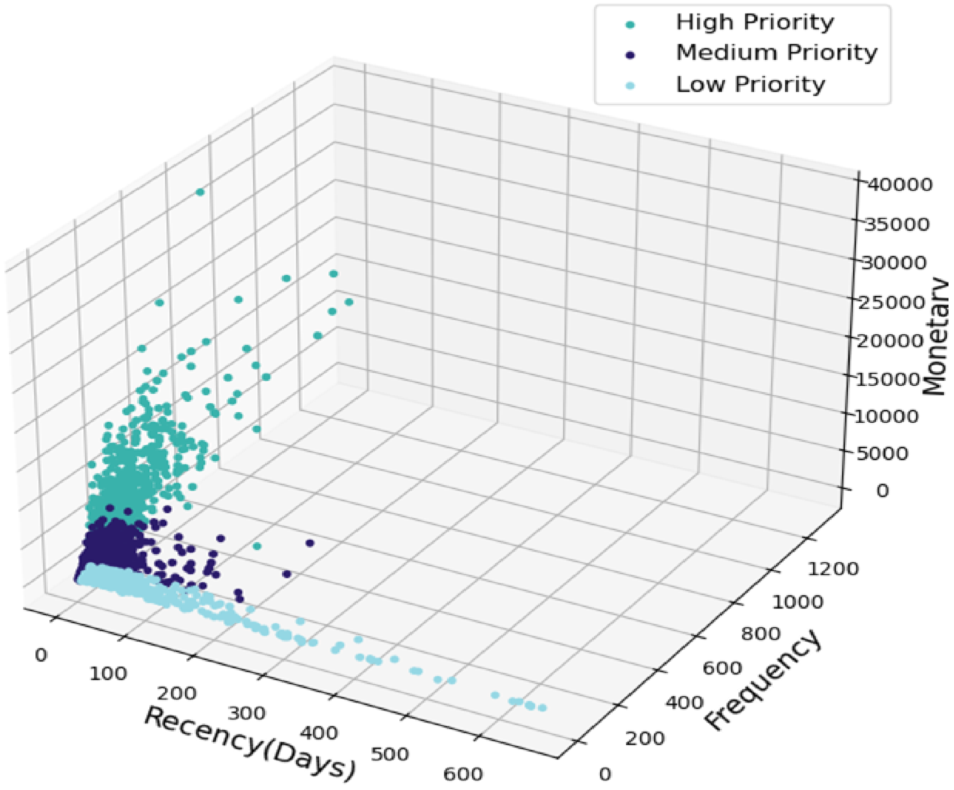
Produce and Grocery Departments are Most Promising for Basket Size Expansion

* Statistically insignificant

Customers Spend More on Non-Perishable Groceries, While Spending Less in Other Areas

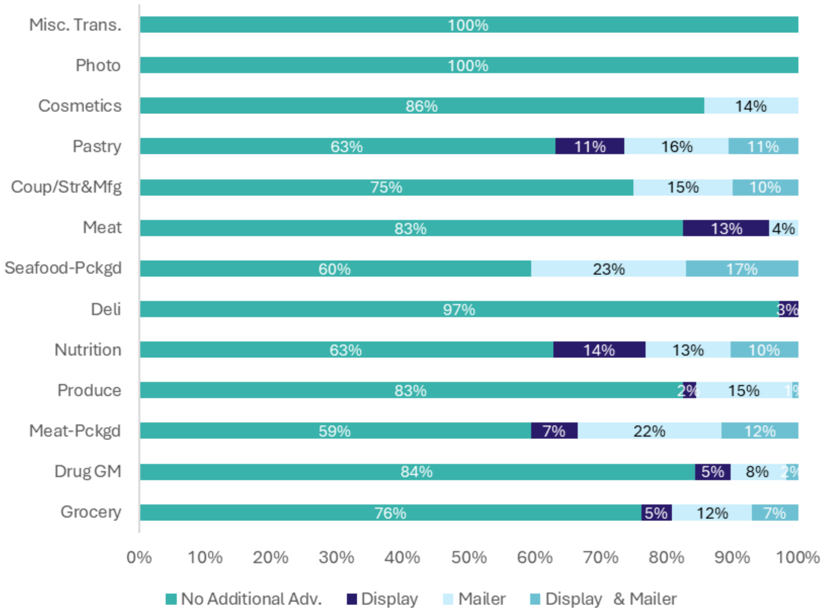


Full RFM Segmentation Contains Some Outlier Households that Fell Out of the IQR



Mailer-Based Marketing Contributed to Redemption Success

Product Marketing by Department
% Share of Coupon Redeemed Transactions



Coupon redemption activity coincided with weekly mailer campaigns, especially in food-related departments

Grocery led departments with over 4K products promoted with display and/or mailers

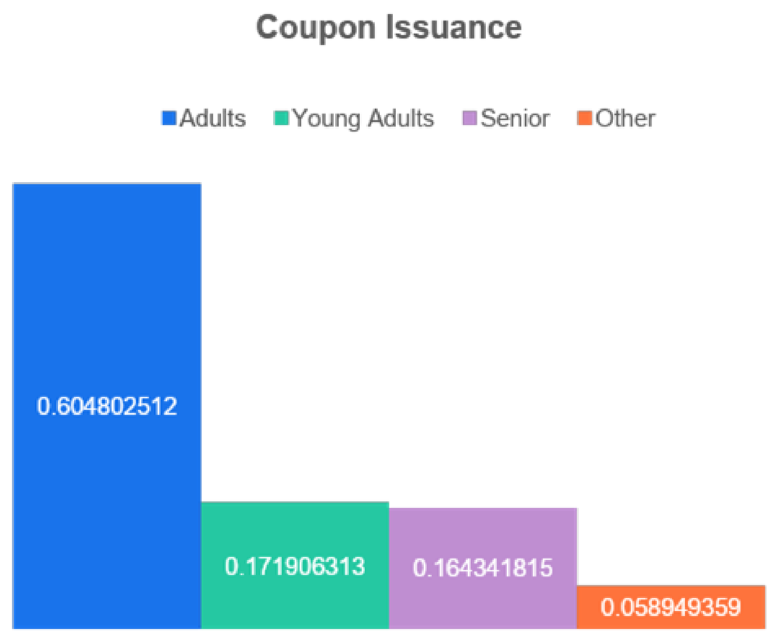
Non-essentials like photo and misc. were less likely to have additional advertising support

Age Group Coupon Analysis

Coupon Issuance by Age Group (Adult Bucket)

- The largest share of coupon redemptions came from the Adult age group, with over 37.3 million issuances.
- Young Adults and Seniors followed closely, with 10.6M and 10.1M respectively.
- The "Other" category accounted for only 3.6M, showing campaigns are primarily focused on core adult demographics.

Ps: Once again reinforcing that adults households are the main target of coupons campaigns.



Income Group Coupon Analysis

Coupon Issuance by Income Group

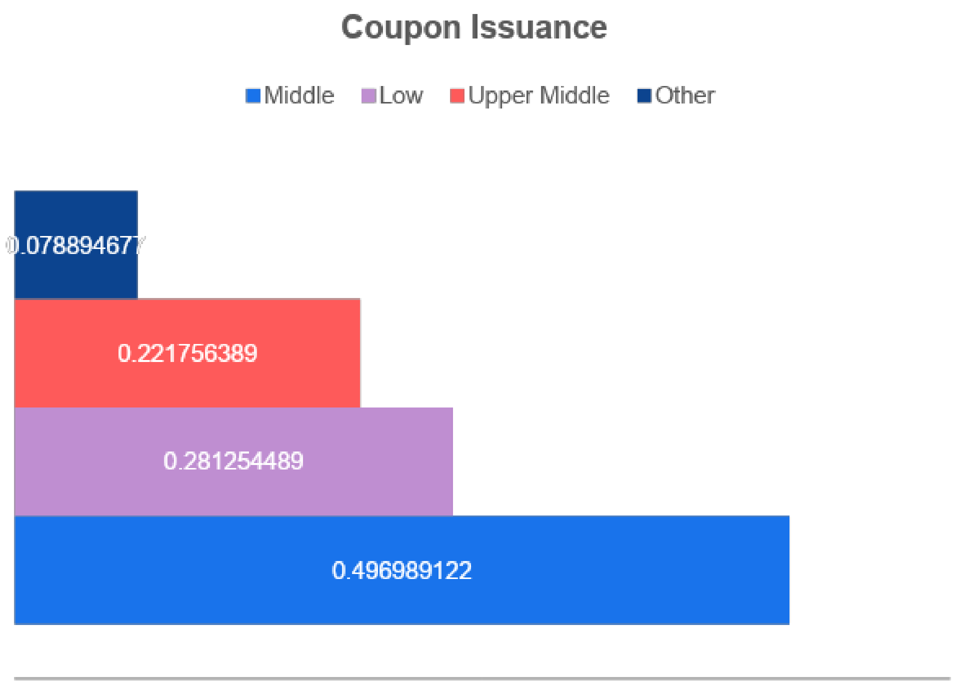
The majority of coupons were issued to Middle-income households (28.4M), followed by Low-income (16.1M) and Upper Middle-income (12.7M).

The "Other" group received significantly fewer coupons (4.5M), possibly due to unclear or missing income data.

Ps: Middle-income households are the core target for coupon campaigns.

Low-income households also represent a major share, supporting the idea that coupons are being used to drive affordability and loyalty.

Upper Middle-income groups are still targeted but at lower rates.



Insights on Brands by Campaign Type

Top Manufacturers by Campaign Type

Type A campaigns had the highest issuance overall, with top manufacturers like Manufacturer 13 (29,312 coupons) and Manufacturer 3 (15,394 coupons) standing out.

Type B campaigns were led by Manufacturer 13 again, though at a lower volume (3,583 coupons), followed by Manufacturer 3 and Manufacturer 22.

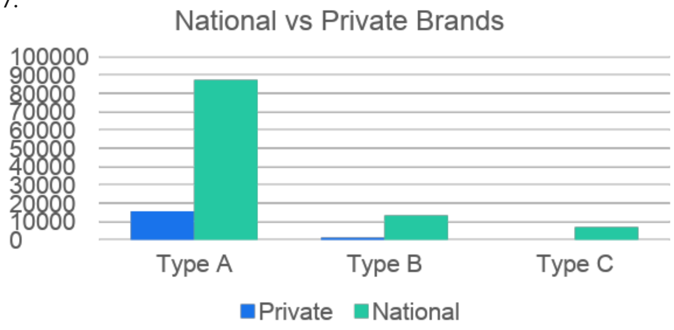
Type C campaigns had limited activity, with Manufacturer 13 issuing the most (3,651 coupons), suggesting it plays a key role across all campaign types.

Ps: looks like Manufacturer 13 is important to our strategy regardless of each campaign type.

National vs. Private Brands by Campaign Type

National brands dominate coupon issuance across all campaign types.

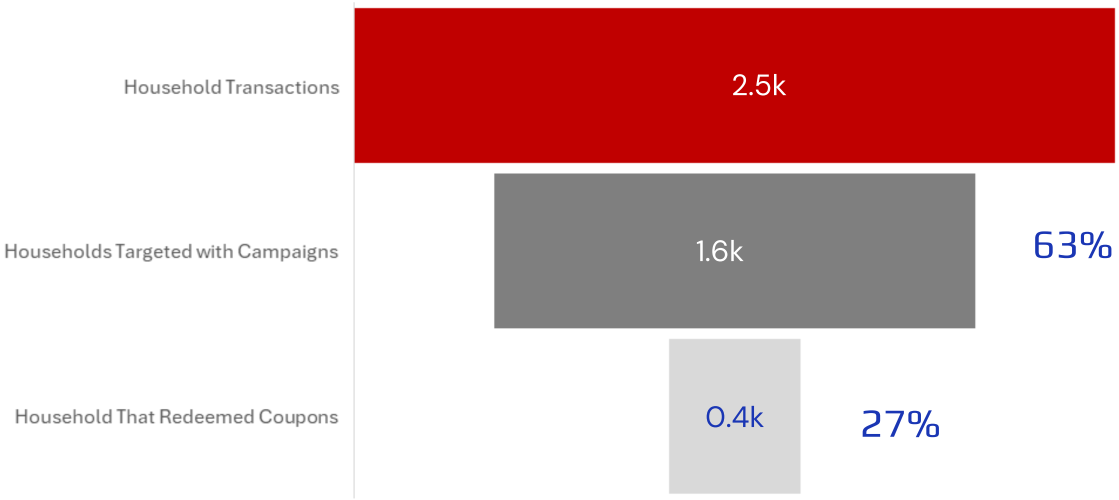
- In Type A campaigns, 87,336 coupons were issued for National brands vs. 15,557 for Private labels.
- In Type B, the gap remains with 13,365 National vs. 1,256 Private.
- In Type C, National brands issued 7,007 coupons, while Private labels had only 27.



Household Coupon Conversions

1.6k households were targeted with Big Box marketing campaigns, with 27% of those targeted redeeming a coupon

Conversion Funnel



- There were 30 campaigns in total, 5 Type A, 19 Type B, 6 Type C
- Households were cross-exposed to multiple campaign Types; 96% of HHs targeted were exposed to Type A, 65% to Type B, 25% to Type C
- Households redeemed multiple Types; 383 HHs redeemed Type A, 141 Type B, 38 Type C

Insights by Campaign Type

Campaign Reach and Classification

Mass: Over 1000 households (ie: Campaigns 13,18,8)

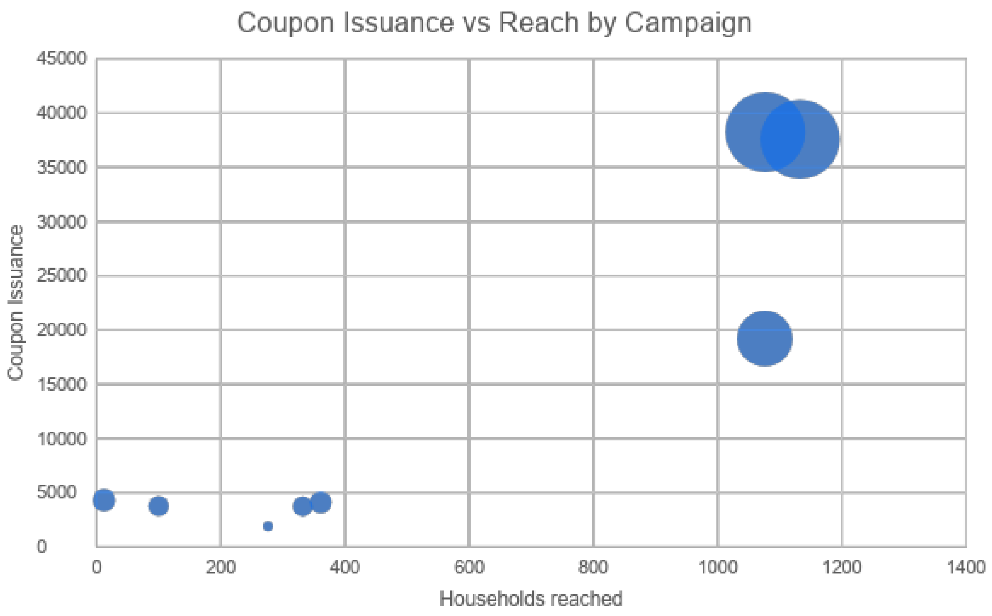
Mid-size: 200-1000 households (ie: Campaigns 30,26,14)

Targeted: Under 200 households (ie: Campaigns 27,24,16)

Mass campaigns drive the highest volume of coupon issuance, making them powerful for broad exposure.

Targeted and Mid-size campaigns also show strong issuance-to-reach ratios, indicating potential for higher personalization and efficiency per household.

Mass campaign to build awareness and targeted campaigns to drive loyalty or influence specific segments



Sales Value

Sales driven by frequently replenished household and grocery items, while all other categories contributed much smaller share

Redeemed Coupons Sales Value by Top Departments		
Department	Sales Value	% Share (by Sales Value)
Grocery	$39,579	82%
Drug GM	$4,183	7%
Meat-Pckgd	$2,694	6%
Produce	$751	2%

Redeemed Coupons Sales Value by Top Products		
Product	Sales Value	% Share (by Sales Value)
Refrigerated Dough	$2,532	5%
Laundry Detergents	$2,424	5%
Frozen Pizza	$2,110	4%
Bath Tissues	$2,075	4%

Drug GM, at its higher price point, has an opportunity to boost total sales value

Grocery and household essentials were most frequently redeemed, driving up sales value

Advertising Method

National brands drive coupon redemptions while private label sees minimal advertising support

Product Marketing by Brand Type

Coupon Redeemed				
	None	Display	Mailer	Display & Mailer
National	17,591	1,112	2,854	1,541
Private	96	9	19	18

No Coupon Redeemed				
	None	Display	Mailer	Display & Mailer
National	1,847,944	131,255	271,748	129,137
Private	258,025,398	67,933	139,063	51,440

National brands were more likely to appear in mailers and/or in-store displays, boosting coupon redemption rates

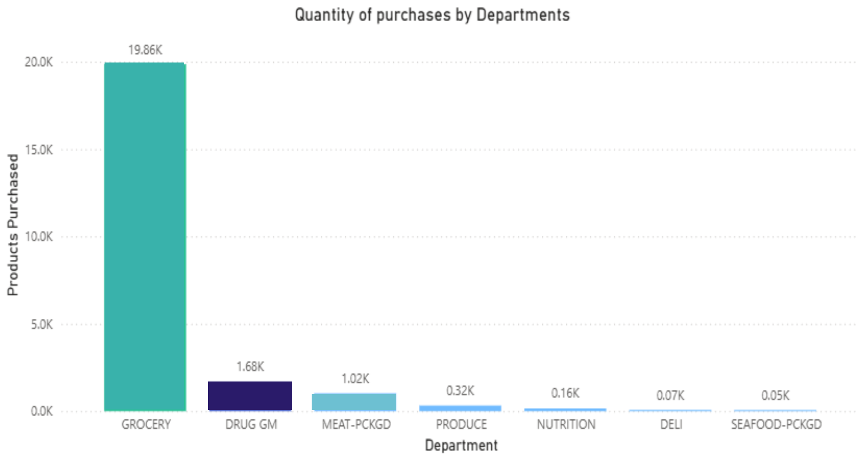
Private label items were less heavily advertised

Private label dominated sales volume when no coupon was redeemed but lacks visibility in terms of ad support, a large portion driven by gas sales

Sales Volume

Among those who redeemed coupons, Grocery Campaigns reached more customers and generated the most profit

The Drug department had around 1700 coupons redeemed, but with an impressive profit considering the quantity of purchases.



Redeemed Coupons Sales Volume by Top Products		
Product	**Sales Volume**	**% Share (by Sales Volume)**
Refrigerated Dough	1,559	7%
Soup	1,443	6%
Frozen Pizza	904	4%
Frz Meat/ Meat Dinner	791	3%