Causal Impact of Contract Type on Customer Churn

Telco Customer Analysis Using IPW and Doubly Robust Estimation

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Background & Research Question

Introduction

Customer churn is a major challenge in subscription-based industries, especially telecommunications, where profitability depends on retaining existing customers rather than acquiring new ones.

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The Motivation

Contract type—month-to-month vs. long-term—is a controllable business decision that may influence churn through pricing, commitment, and switching costs.

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The Challenge

Customers self-select into contract types based on tenure, service usage, and billing behavior, making simple churn comparisons misleading.

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The Method

Using observational Telco data, we apply propensity score methods and doubly robust estimation to isolate true causal impact.

Why It Matters?

Churn directly reduces recurring revenue and increases acquisition costs. Even small reductions in churn lead to large gains in customer lifetime value (CLV).

Causal Inference allows us:

Design Better Offers

Price and structure contracts more effectively

Target High-Impact Customers

Identify which customers benefit most from contract migration

Quantify CLV Returns

Measure incremental value of different contract enrollment

> This shifts focus from **predicting who will churn** to **understanding which interventions actually reduce churn**, supporting data-driven retention strategy.

Research Question

What is the causal effect of being on a long-term contract (1-2 years) versus a month-to-month contract on a customer's probability to churn?

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Data Overview

Data Structure & Cleaning

Data Source

Telco customer churn: IBM dataset from Kaggle (https://www.kaggle.com/datasets/yeanzc/telco-customer-churn-ibm-dataset)

Sample & unit of observation

7,043 residential customers from a single telecom provider; each row is one customer at one point in time.

Time frame & structure

Single cross-sectional snapshot, with observed customer characteristics and churn status. The study is observational, not experimental—customers self-select into contract types.

Data Cleaning

- Found 11 missing TotalCharges values, all with tenure = 0; set these to 0 and converted TotalCharges to numeric.
- For multi-category variables (InternetService, Contract, PaymentMethod, etc.), applied one-hot encoding with drop_first=True to avoid multicollinearity.
- Converted all dummy variables from True/False to integers and dropped non-modeling fields like customerID.

Key Variables

Outcome Y: Churn (1 = customer churned, 0 = stayed)

Treatment D: Contract type (**1 = long-term**: one or two-year contract; **0 = short term**; month-to-month)

Covariates X:

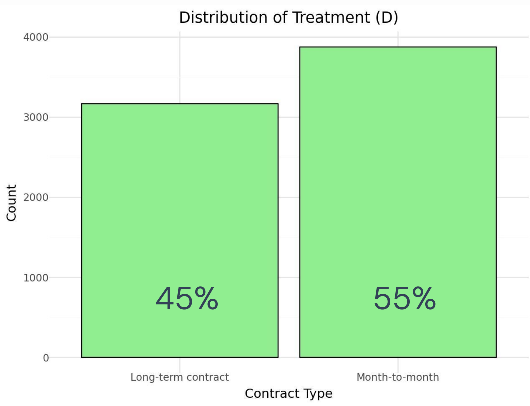
Demographics: gender, SeniorCitizen, Partner, Dependents.

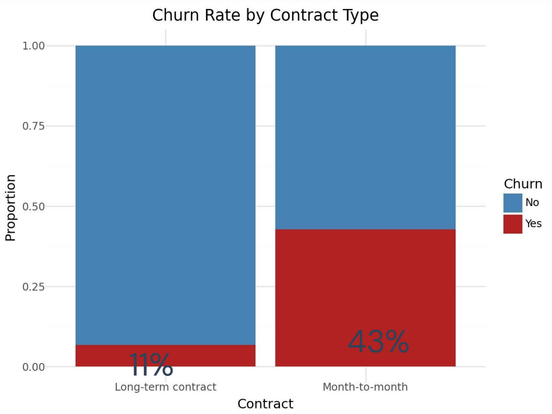
Tenure & pricing: tenure, MonthlyCharges, TotalCharges.

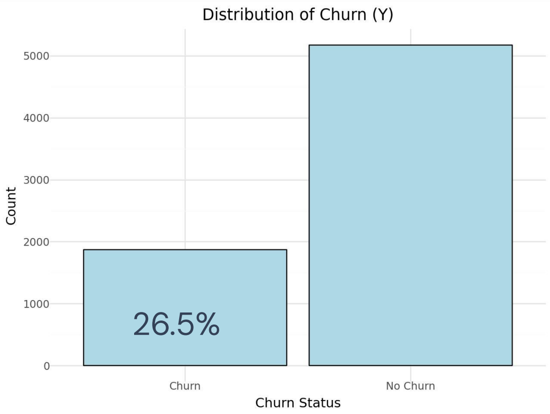
Service mix: PhoneService, MultipleLines, InternetService, OnlineSecurity, OnlineBackup, DeviceProtection, TechSupport, StreamingTV, StreamingMovies.

Billing & payment: PaperlessBilling, PaymentMethod.

Descriptive Statistics & EDA







Treatment distribution:

- **45%** of customers are on **long-term contracts (1–2 years)**
- **55%** are on **month-to-month contracts**

Churn by contract type:

- Long-term contract customers have a **low churn rate (~11%)**
- Month-to-month customers have a **much higher churn rate (~43%)**

Overall churn:

- Across the full sample, the **average churn rate is ~26.5%**

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Identification Strategy & Methods

Identification Strategy

Because our data are observational, we use a propensity score approach, specifically Inverse Probability Weighting (IPW) and doubly robust estimator, to approximate the kind of comparison we would get from a randomized experiment.

KEY ASSUMPTIONS

1 Unconfoundedness

After controlling for demographics, tenure, service mix, and pricing, contract type is "as good as random."

$$(Y(0), Y(1)) \perp D \mid X$$

2 Overlap

For most values of X, customers have a positive probability of being in either group

3 SUTVA

Each customer's churn outcome depends only on their own contract type, not on other customers' contracts.

4 Correct specification of at least one model (DR)

For the doubly robust estimator to be consistent, either the propensity score model or the outcome models must be correctly specified.

Methodologies

Propensity Score Model

We estimate each customer's probability of being on a long-term contract,

$$e(X)=P(D=1 \mid X)$$

using a machine-learning model (Logistic Regression & Random Forest) on pre-treatment covariates.

IPW

1. We clip propensity scores to [0.01, 0.99] to avoid extreme IPW weights and stabilize the estimator.
2. We then apply Inverse Probability Weighting (IPW) to reweight customers.

Doubly Robust Estimator

1. We estimate potential churn under long-term vs month-to-month contracts with separate outcome models m1(X) and m0(X).
2. We then add an IPW-based correction term using the clever covariate Hi to adjust for residual selection into contract type.

Why these methods fit the question?

IPW addresses selection on observables by reweighting customers so that long-term and month-to-month groups are balanced on observed covariates, approximating a randomized experiment.
DR adds robustness, making our conclusions less sensitive to the exact functional form of either the propensity score model or the outcome model.

Diagnostic Checks

Propensity score overlap	Plot the distribution of estimated propensity scores for long-term (D=1) vs. month-to-month (D=0) customers to check common support.
Covariate balance	Compute Standardized Mean Differences (SMDs) for all covariates in the raw data and in the IPW-weighted sample.
Model diagnostics (for DR)	Compare the DR ATE to the pure IPW ATE → similar estimates increase confidence that our conclusions are not driven by a single modeling choice.
Bootstrap	To calculate the standard error and assess the variability of the ATE estimate.

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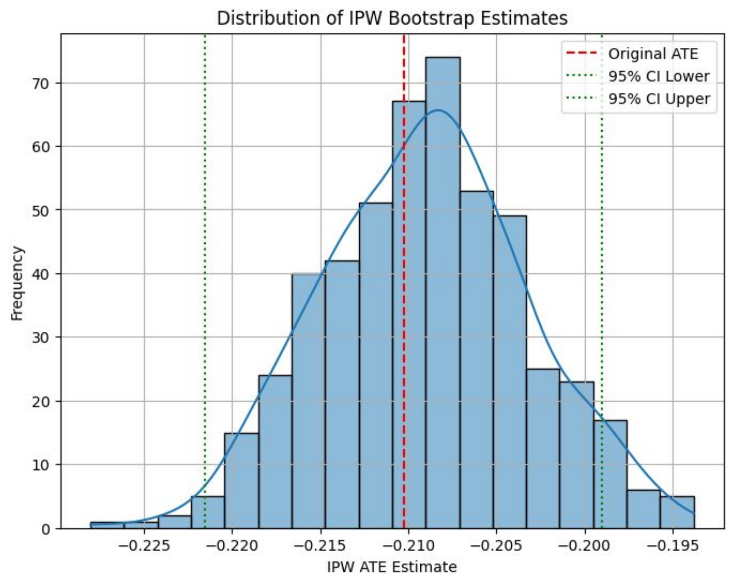
Result & Next Steps

Results - IPW Estimator

ATE: -0.2102
Bootstrap SE: 0.0057
95% CI: [-0.2215, -0.1990]

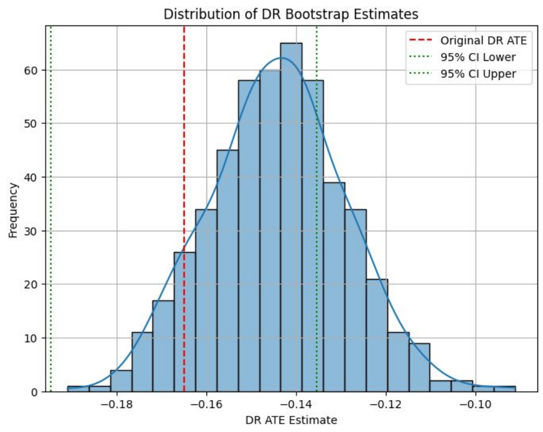


Insights

- Long-term contracts reduce churn probability by ~21 percentage points.
- Strong evidence (tight CI), effect is large relative to baseline churn (~26.5%).
- Bootstrap distribution is centered and symmetric → estimator is stable.

Results - DR Estimator

ATE: -0.1650
Bootstrap SE: 0.0151
95% CI: [-0.1947, -0.1353]

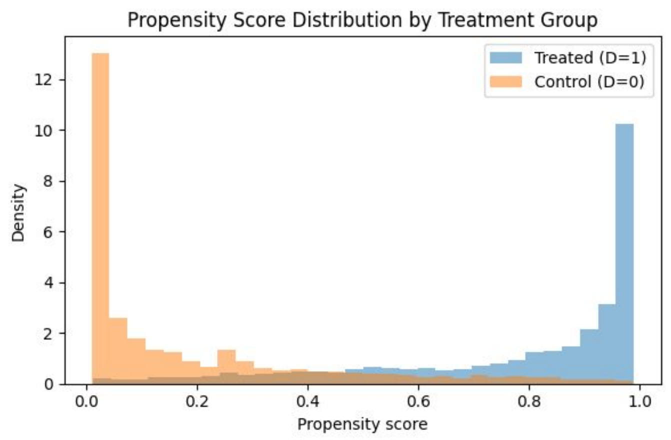


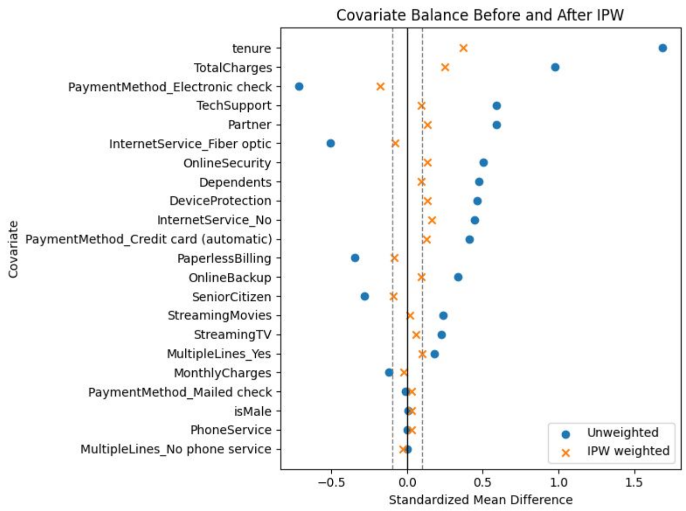
Insights

- DR estimate also shows a large and negative impact (–0.16).
- Slightly more conservative than IPW → typical for DR.
- Agreement between IPW & DR strengthens credibility of the causal effect.

Both IPW and DR estimators consistently show that long-term contracts significantly reduce customer churn, confirming a robust causal effect across methods.

Diagnostics





Propensity Score Distribution

- Month-to-month customers (orange) mostly have very low propensity scores while long-term customers (blue) mostly have very high propensity scores.
- Despite clipping, we still see lack of overlapping areas near the extremes

Covariate Balance

- After applying IPW, standardized mean differences for most of the covariates fall below the 0.1 threshold.
- IPW drastically reduces imbalance, but **tenure** and **TotalCharges** still have |SMD| ≈ 0.37 and 0.25, so those dimensions are not fully balanced.

Limitations

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Unobserved Confounding

- Factors like customer satisfaction, loyalty, or motivation are not observed.
- These may influence both contract choice and churn, potentially biasing estimates.

02

Selection Bias in Treatment Assignment

- Customers who choose long-term contracts may differ systematically (e.g., risk tolerance, stability, budget constraints).
- Variables like MonthlyCharges are precise, but other categorical fields (like service level or payment type) might be imperfect proxies for customer behavior.

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Diagnostics

- Lack of perfect common support in the overlap plot (Average Treatment Effect on the Overlap Population instead of entire population)
- A few covariates falling outside the 0.1 threshold in SMD plot (model might need more complex functional forms like interactions or polynomials to account for that)

Conclusion

Insights

Customers on long-term contracts churn significantly less than monthly customers. Using causal inference (IPW + Doubly Robust), we estimate that long-term contract reduce churn by ~16-21%

Recommendation

Target monthly customer segments with incentives to transition to long term contracts to reduce churn and increase retention.

Next-steps

- Implement more causal methods like DML to address high dimensionality
- Addressing the current limitations like lack of good common support and covariate imbalance etc.

Q & A