Customer Churn Analysis Dashboard

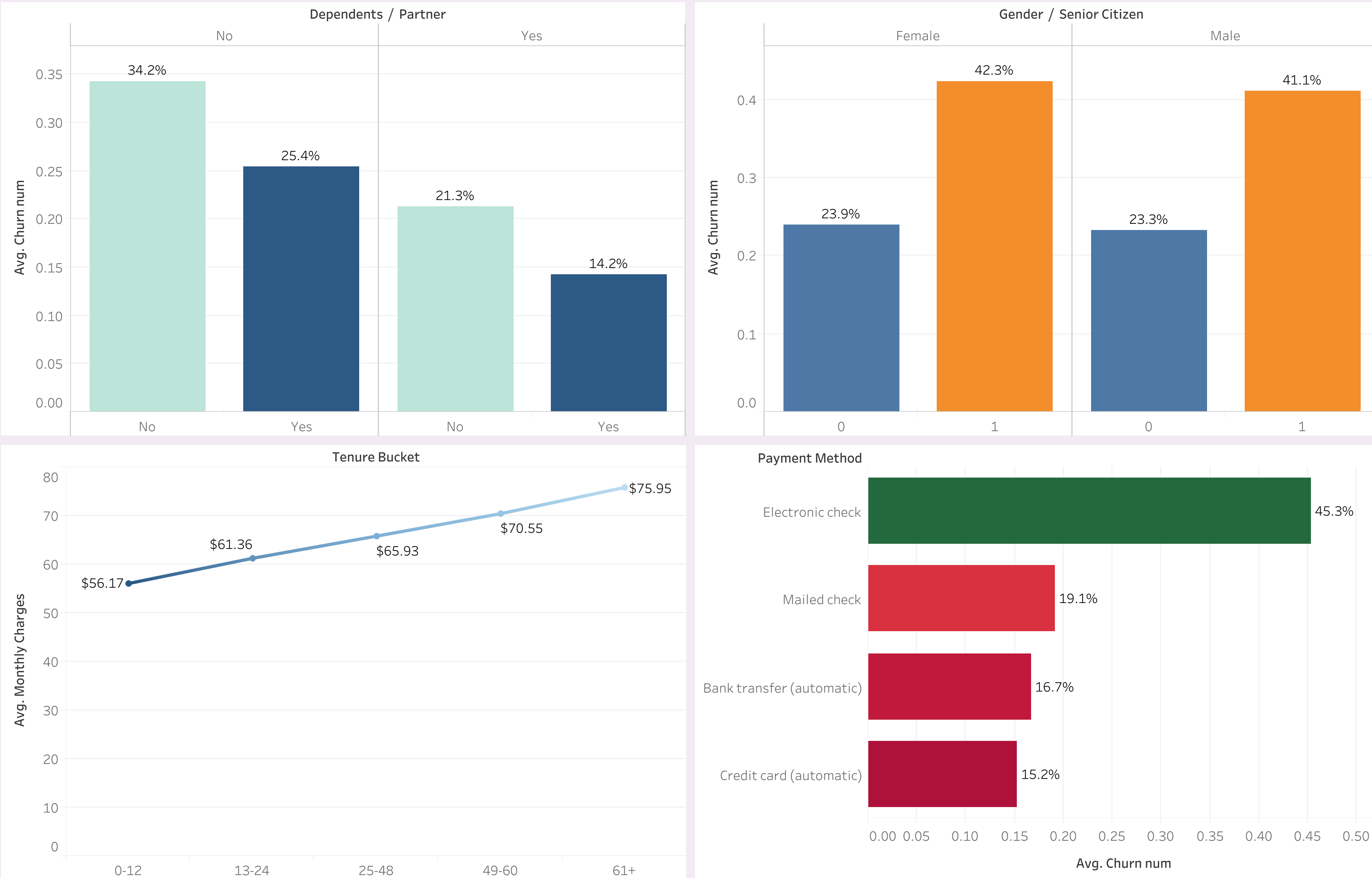
Exploring Key Drivers of Attrition and Predictive Model Insights
An interactive visual exploration of factors influencing customer churn, behavioral patterns, and model performance using statistical and machine learning techniques.
SPRINGBOARD DATA SCIENCE TRACK | AUGUST 2025

Created by: Shayma Remy
Tools Used: Python (Preprocessing & Modeling), Tableau Public (Visualization)
Models: Logistic Regression, Decision Tree
Key Metrics: Churn Rate, Customer Profile Breakdown, Risk Scores, ROC Curve, Feature Importance
Objective: To analyze and predict customer churn using machine learning models and uncover key drivers behind customer retention and attrition.

Dataset:
Telco Customer Churn Dataset (simulated telecom customer data with demographics, services, and churn behavior)

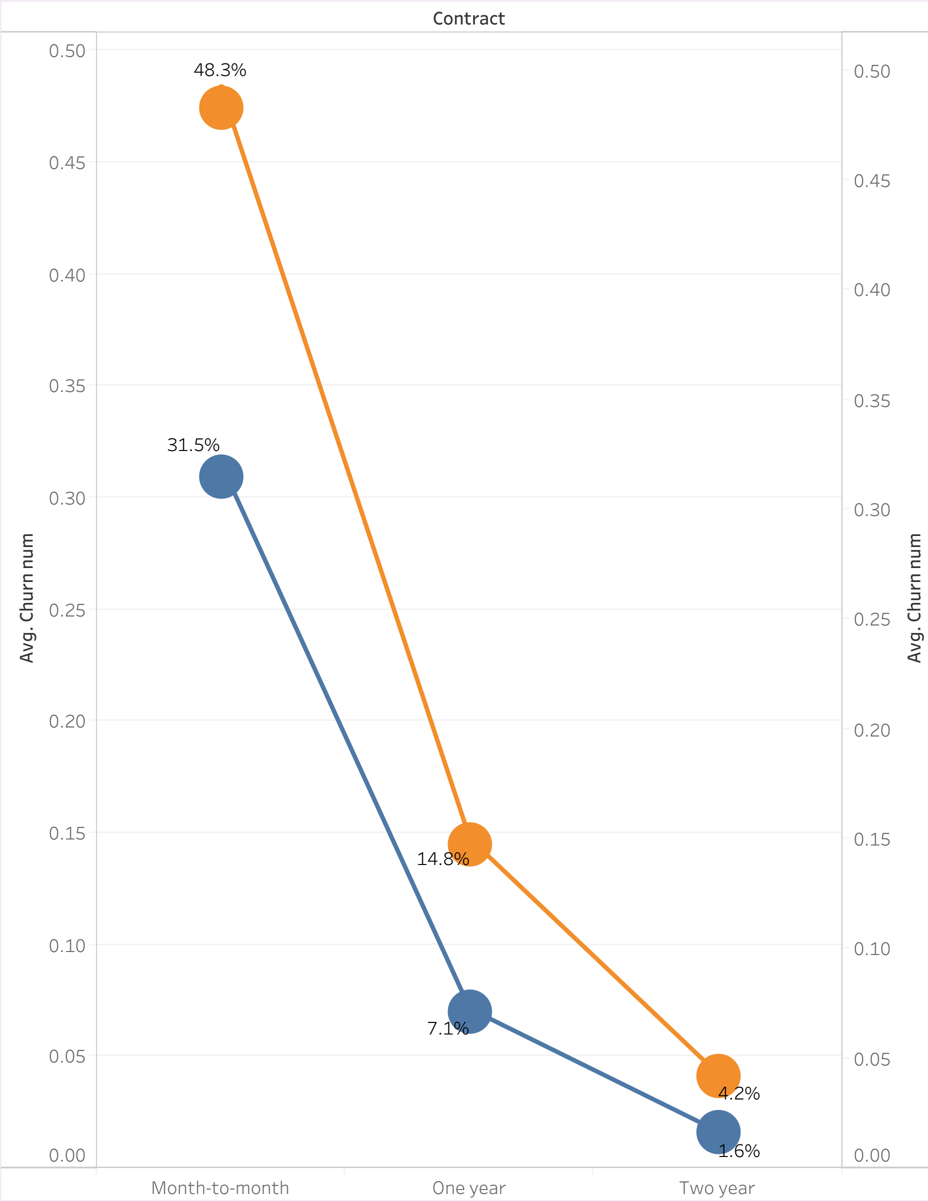
Understanding Customer Demographics & Behavior

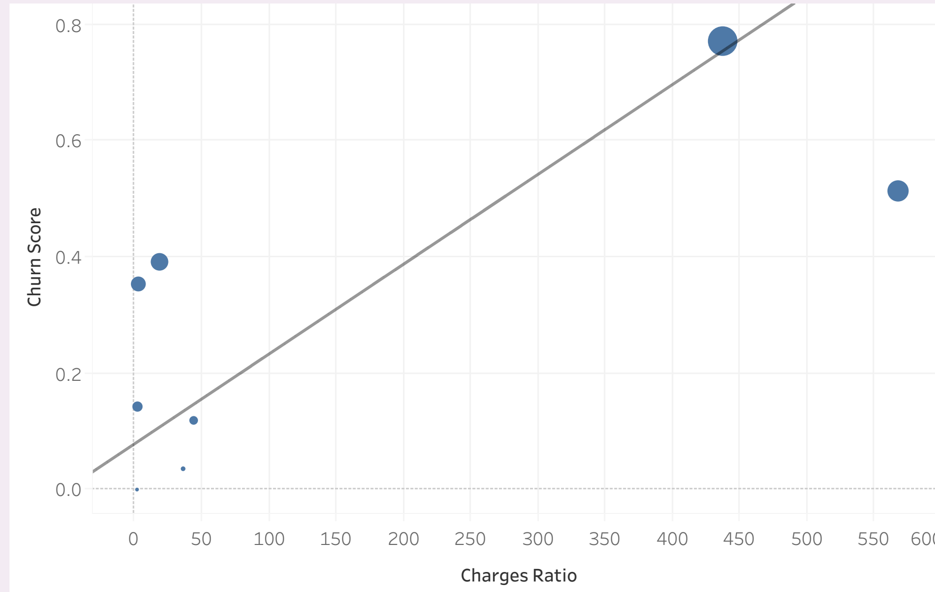
How do customer demographics and payment behaviors relate to churn risk?

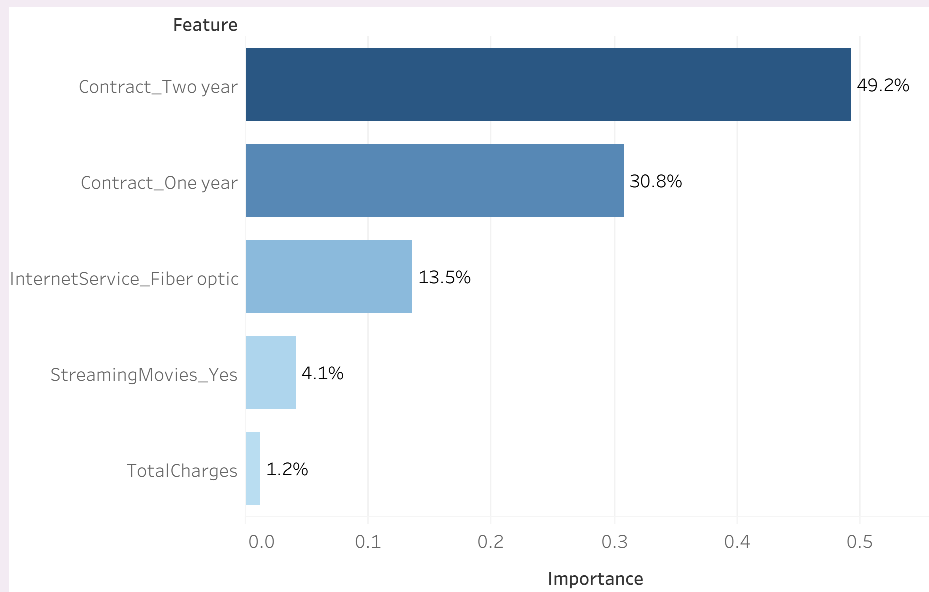


Key Predictors of Churn

Which variables most influence whether a customer stays or leaves?

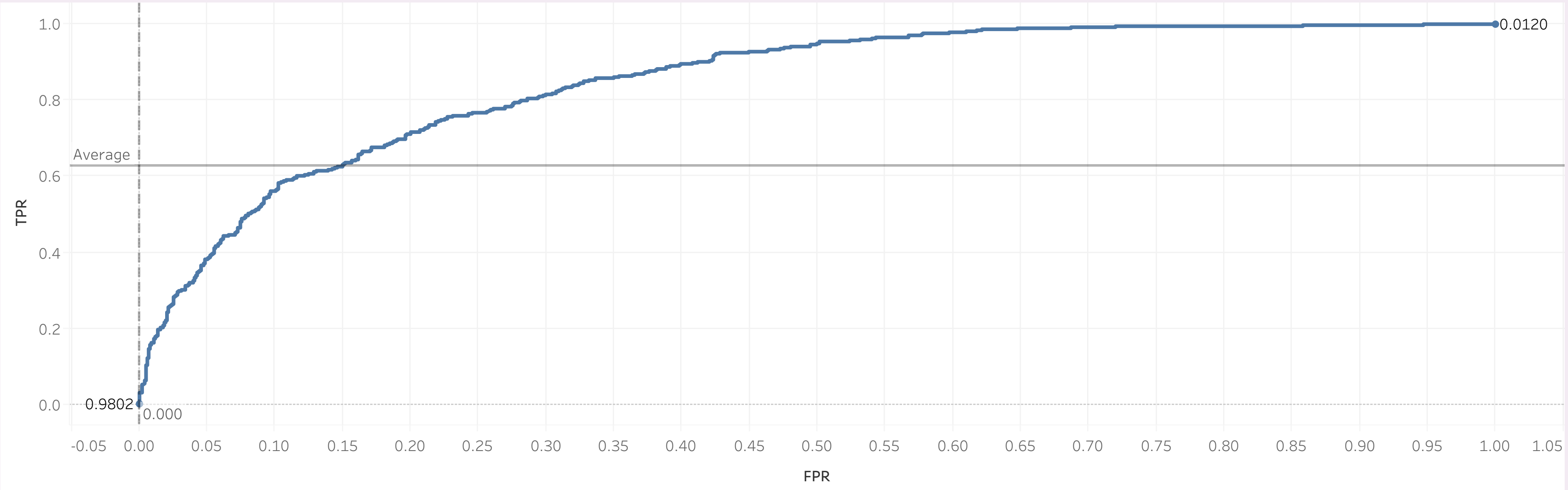






Evaluating Predictive Model Performance

How well do our models predict churn, and what are their strengths and weaknesses?

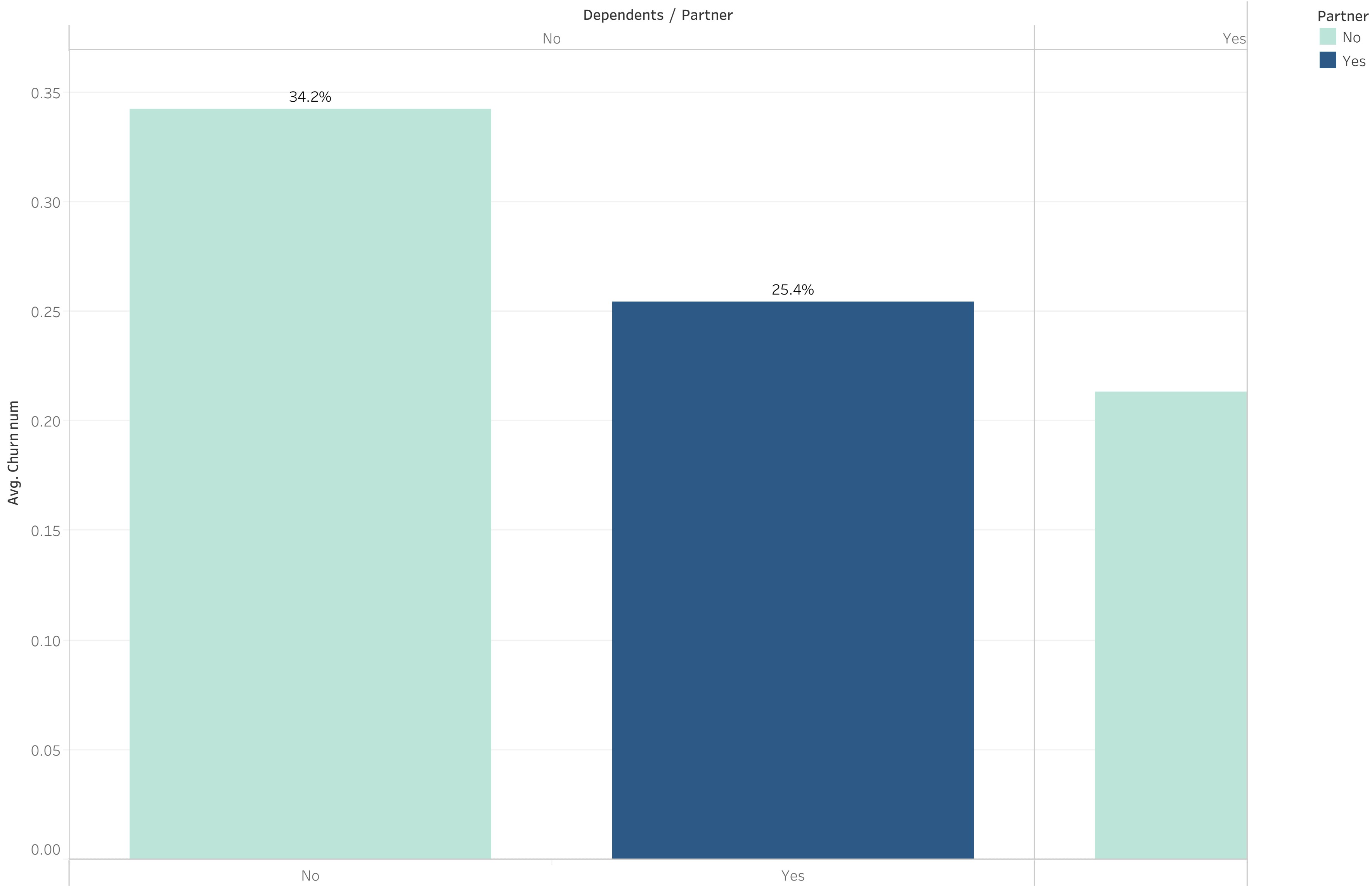


	LogReg Predicted	
Actual	0	1
0	739	296
1	73	301

	Tree Predicted	
Actual	0	1
0	591	444
1	45	329

Impact of Partner and Dependents on Customer Churn

How does a customer's partner status and presence of dependents, both individually and together, affect their likelihood to churn?



Customers with neither a partner nor dependents churn at the highest rate (34.2%). Adding a partner alone reduces churn to 25.4%. Introducing dependents further lowers risk—churn falls to 21.3% for customers with dependents but no partner, and to just 14.2% for those with both a partner and dependents—highlighting that family ties correlate with markedly better retention.

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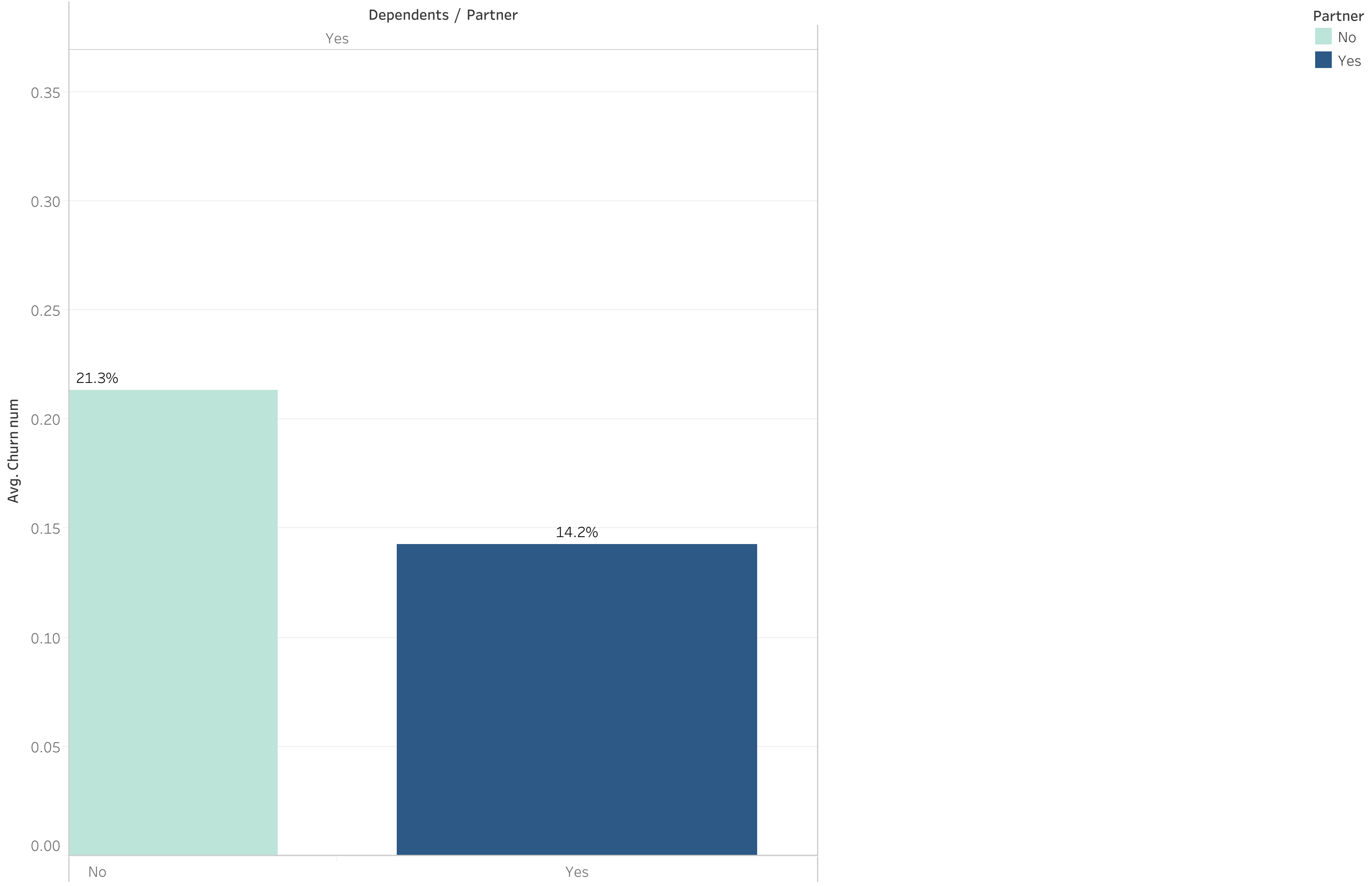

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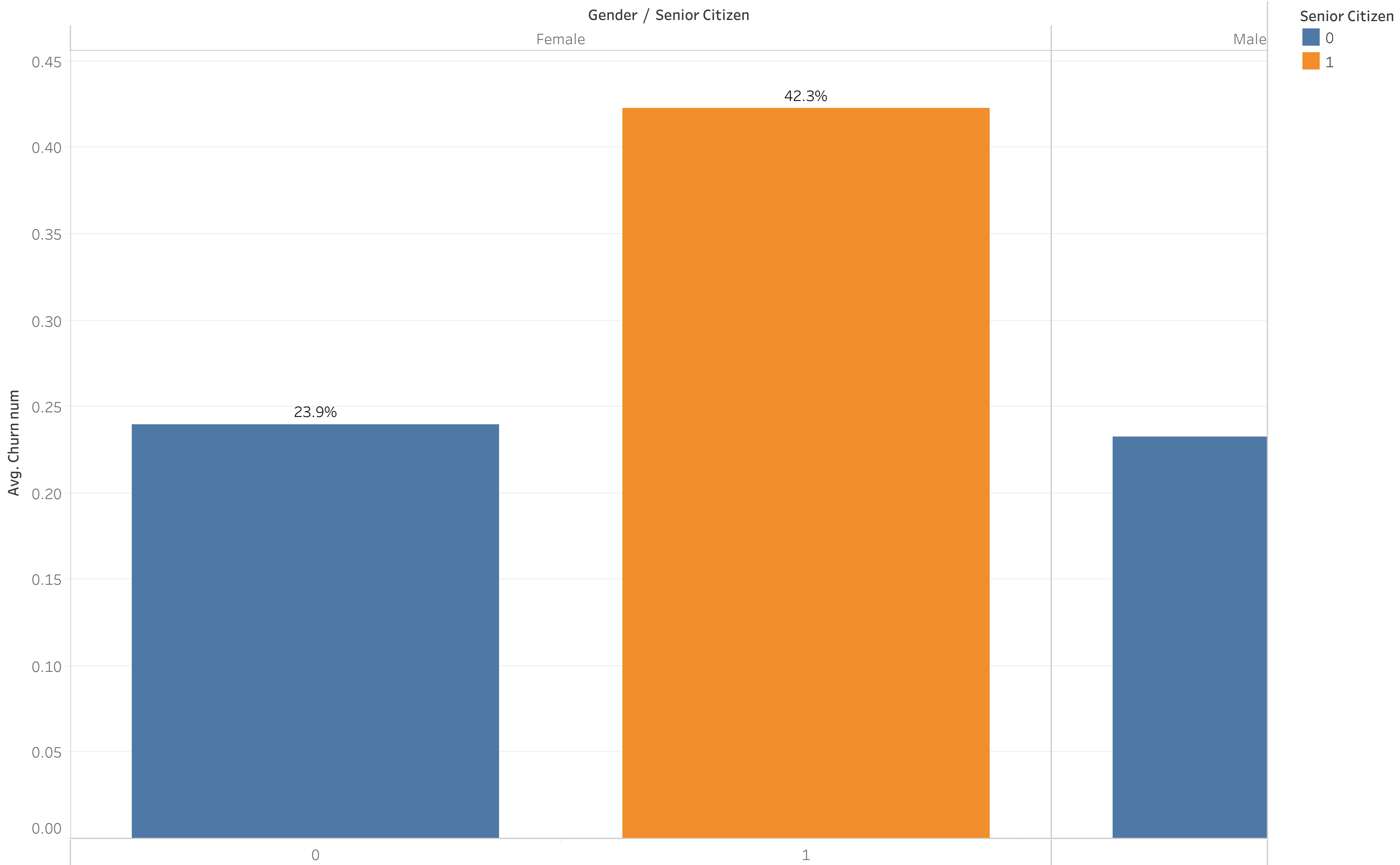
Churn Rates by Gender and Senior Citizen Status

How does being a senior citizen affect churn rates for male and female customers?



Senior citizens churn at a dramatically higher rate (~42%) than non-seniors (~24%), and this pattern holds for both women and men. Gender alone has little effect on churn among non-seniors (23.9% vs. 23.3%) or seniors (42.3% vs. 41.1%), indicating that age is a far stronger predictor of attrition than gender.

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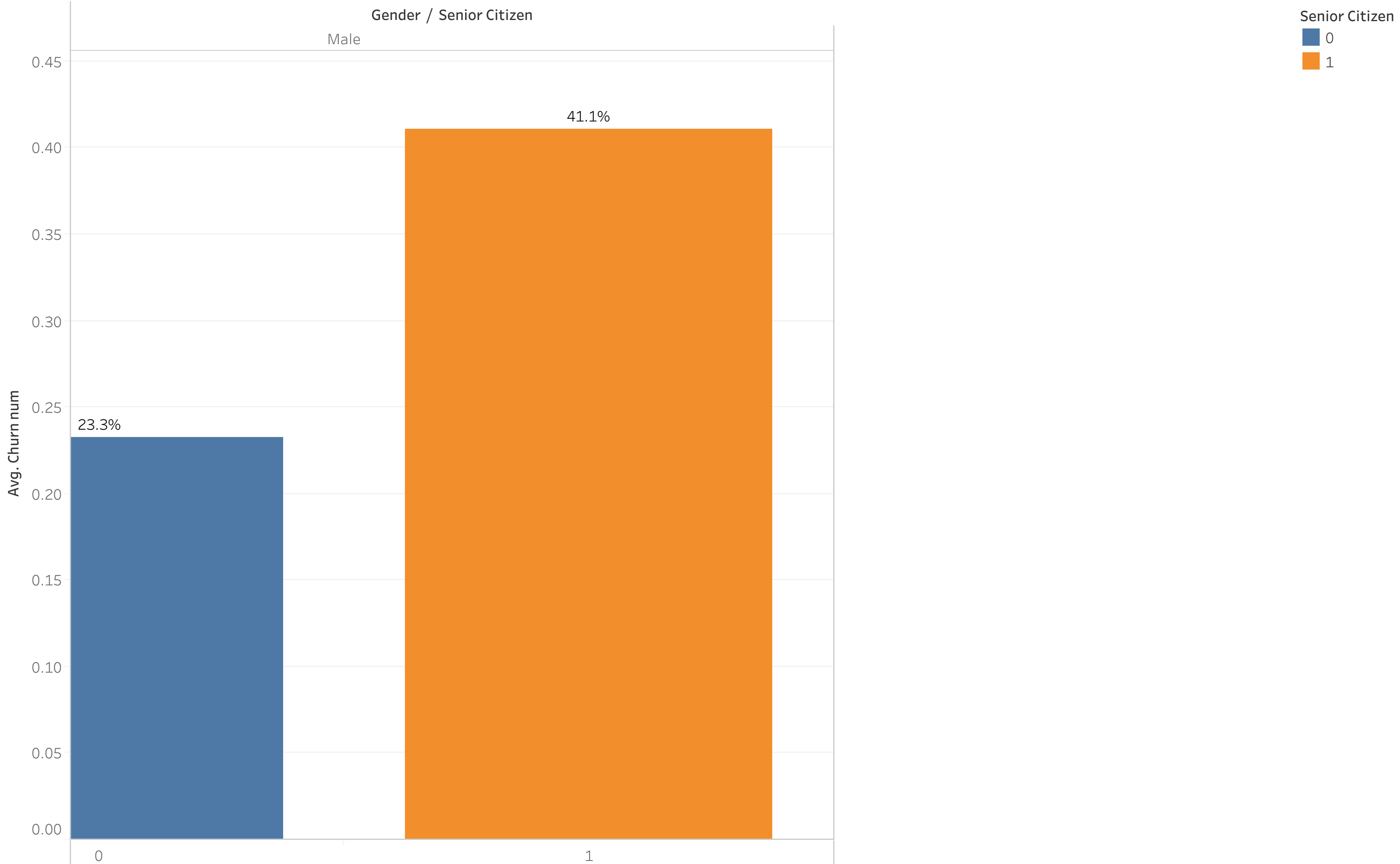

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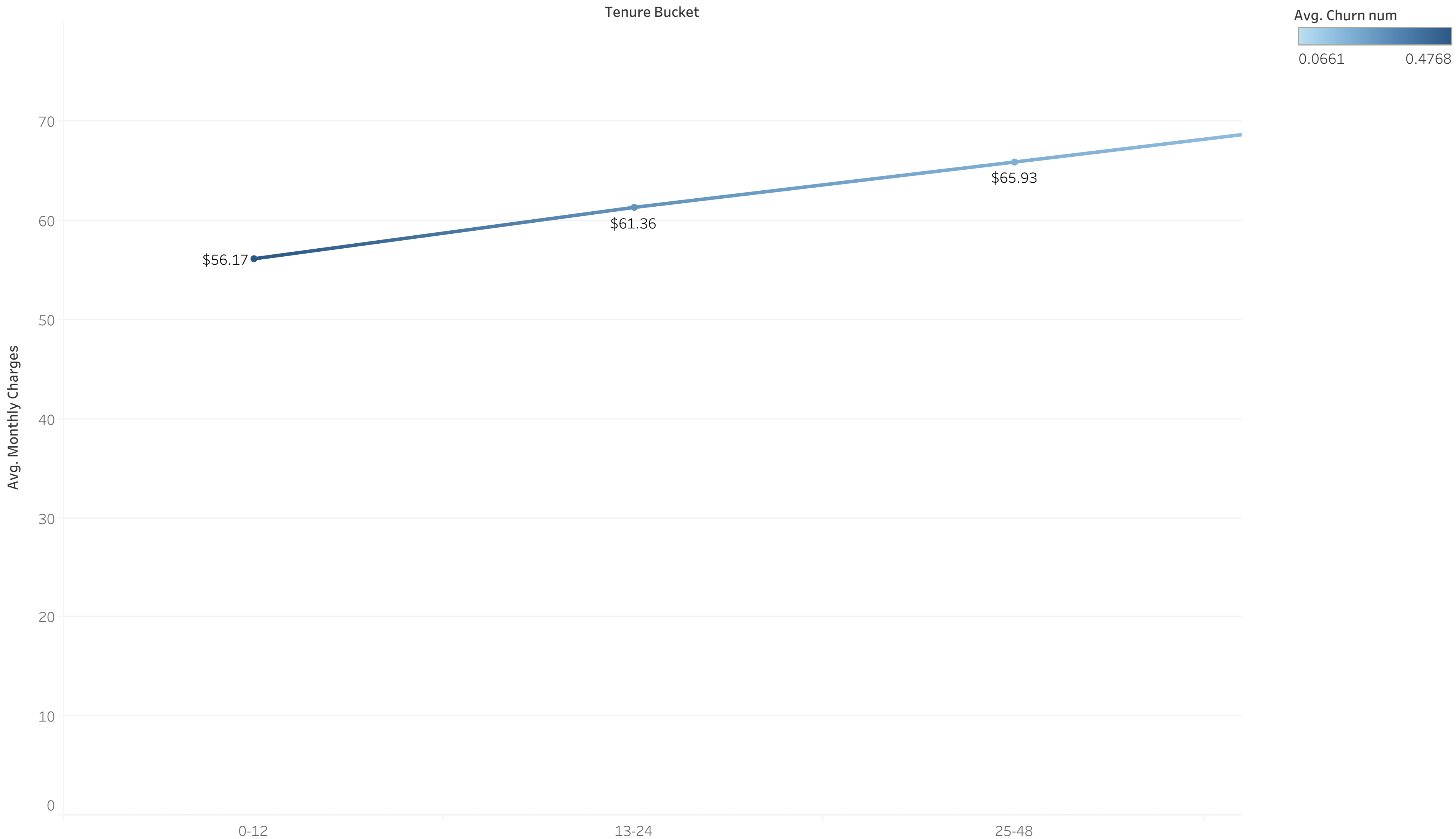
Average Monthly Charges by Tenure Bucket

How do customers' average monthly charges vary across different tenure buckets?



This line graph visualizes the average monthly charges across different tenure buckets. Customers with longer tenure tend to pay higher monthly charges. Those in the 0–12 month range pay an average of $56.17, gradually increasing to $75.95 for those with 61+ months of tenure. This upward trend may reflect increased service usage or upgraded plans over time, indicating that long-term customers are more financially valuable — but also potentially more sensitive to price increases.

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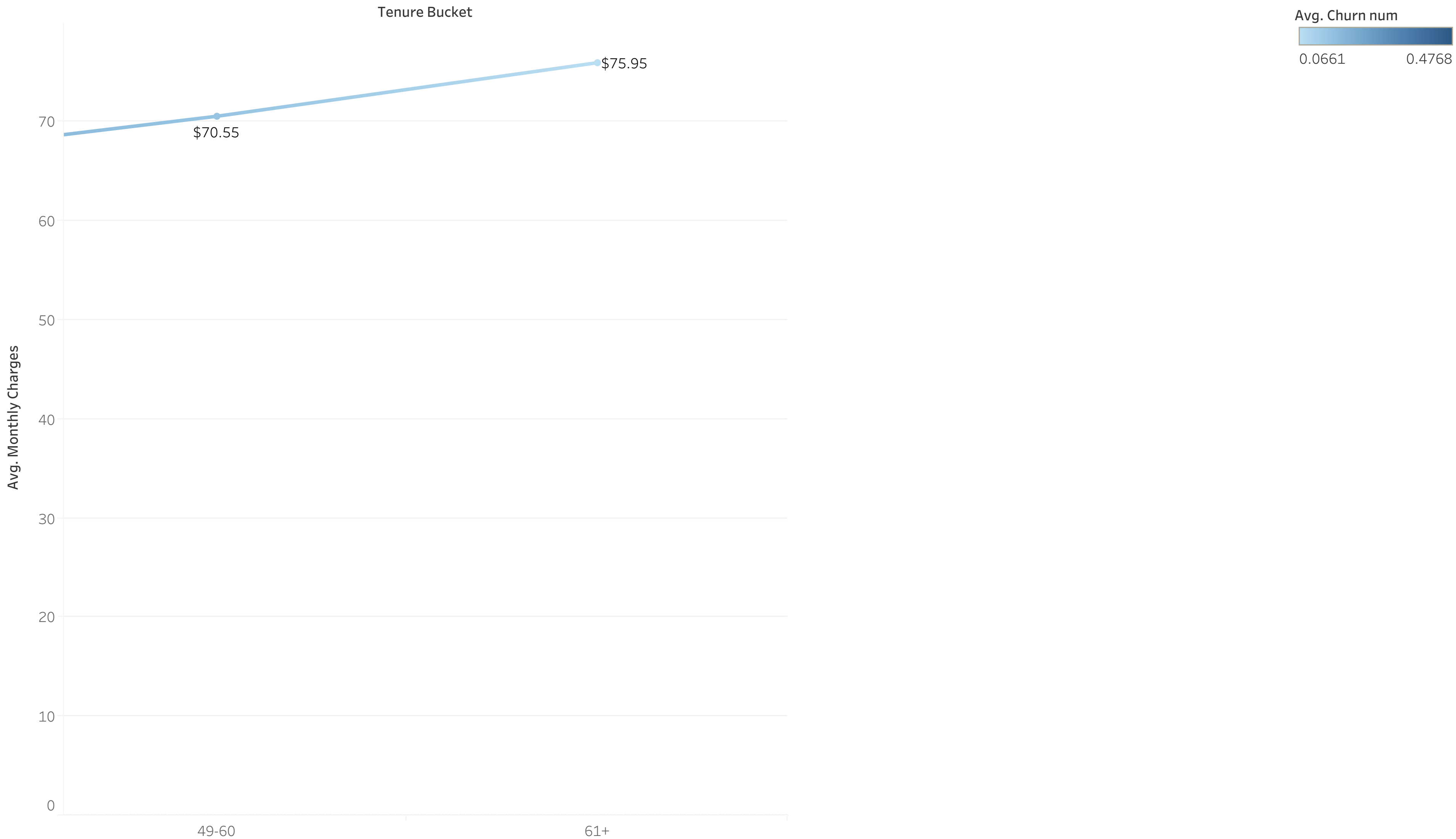

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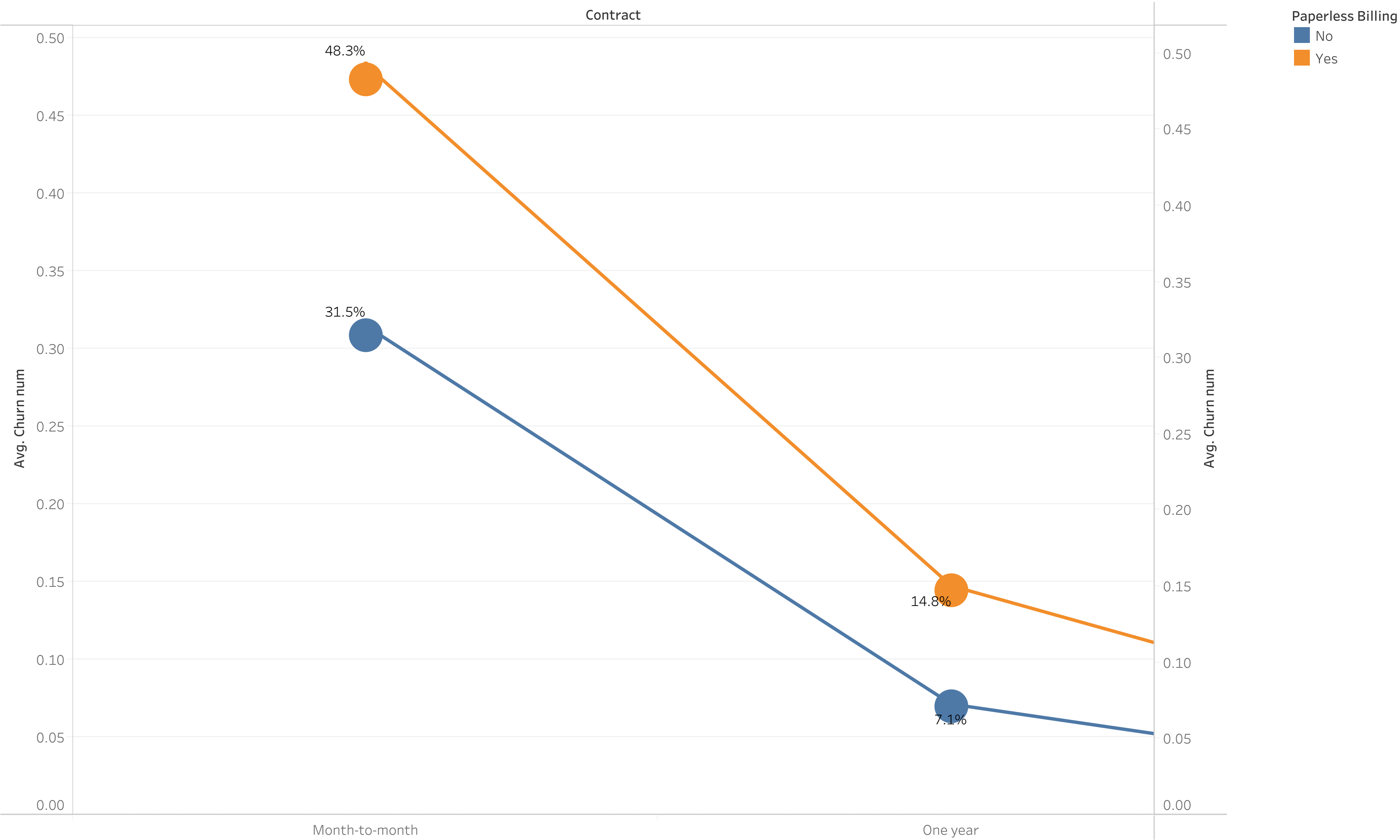
Churn Rate by Contract Type & Paperless Billing Status

How do different contract terms (month-to-month, one-year, two-year) and the use of paperless billing impact customer churn rates?



Churn decreases sharply as contract length increases: month-to-month customers churn at 31.5% (no paperless billing) and 48.3% (with paperless), one-year at 7.1% vs. 14.8%, and two-year at just 1.7% vs. 4.2%. At every contract tier, customers using paperless billing exhibit roughly 1.5× higher churn—highlighting both the protective effect of longer-term commitments and the elevated risk among paperless-billing subscribers.

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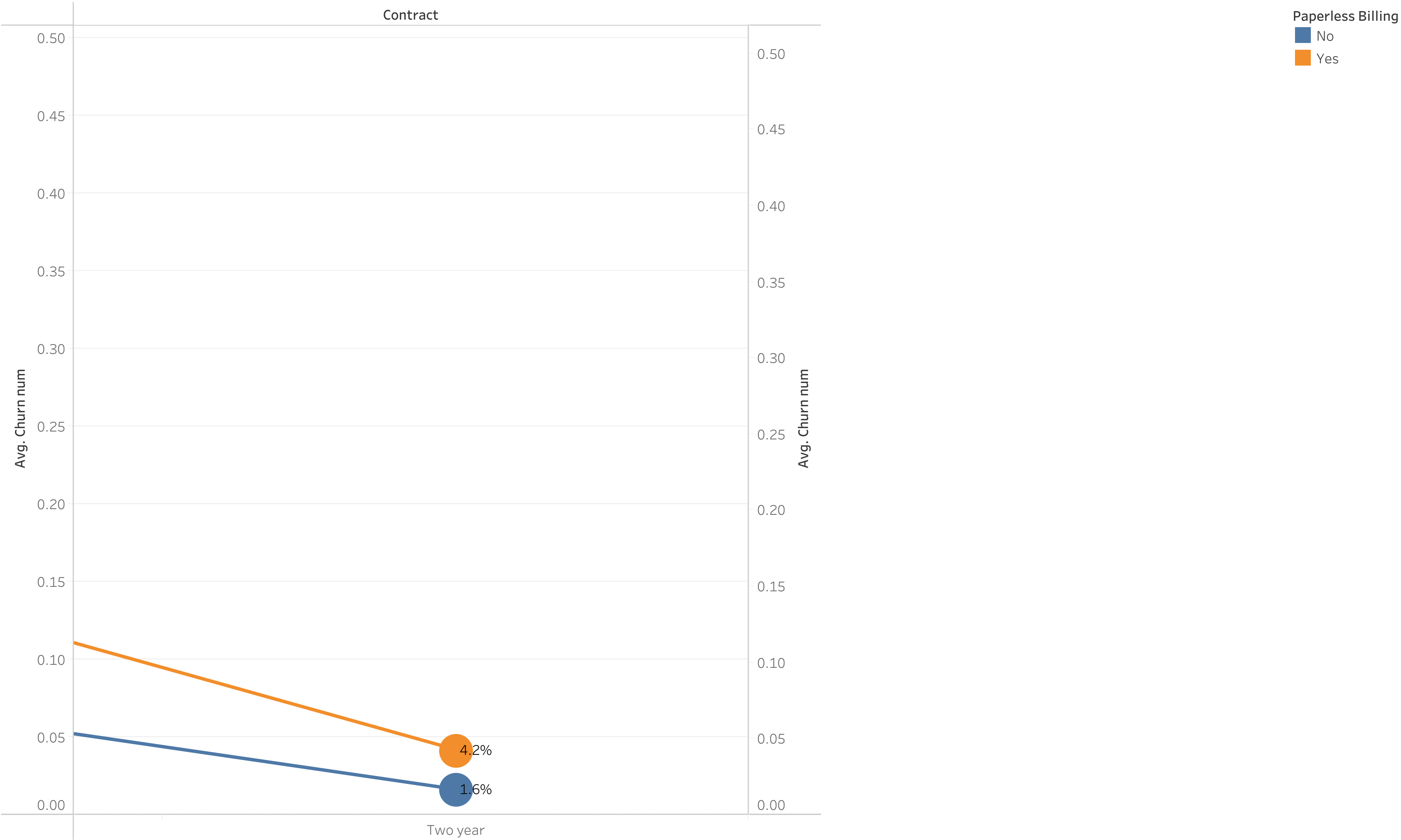

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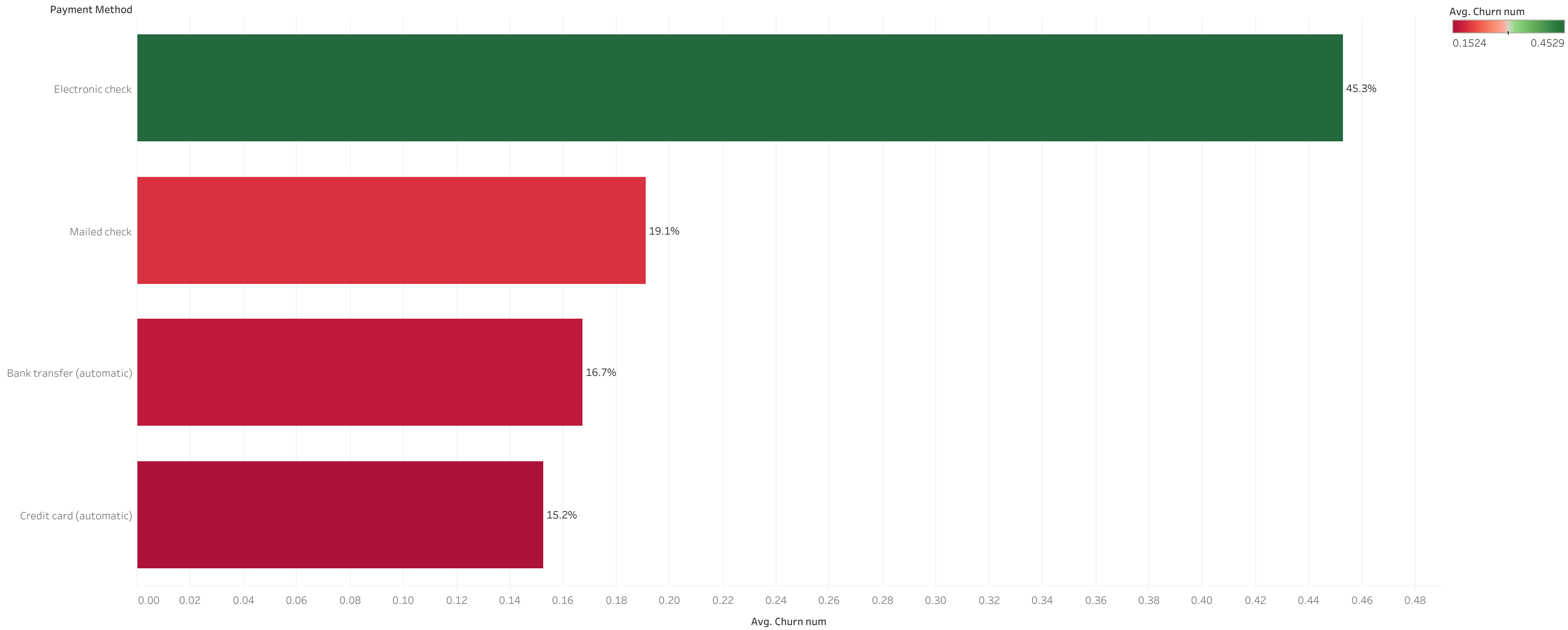
Customer Churn by Payment Method

How does a customer's chosen payment method influence their likelihood to churn?



Electronic check users churn at a striking 45%, far above all other groups. Mailed check customers churn at 19%, while automatic payment methods show the greatest stability: bank transfer (automatic) churns at almost 17%, and credit card (automatic) at only 15%. This pattern underscores payment method as a powerful predictor of churn risk—particularly highlighting the elevated vulnerability of electronic-check users.

Confusion Matrix – Logistic Regression Model

How well does the logistic regression model classify customer churn?

	LogReg Predicted
Actual	0
0	
1	

count

73 739

This confusion matrix visualizes the classification performance of the logistic regression model. Most churn predictions align with actual outcomes, demonstrating strong recall in identifying customers who are likely to churn. However, the model produces a notable number of false positives—predicting churn where it does not occur—resulting in lower precision. This tradeoff suggests the model is more sensitive than specific, favoring early churn detection even at the cost of occasional misclassification.

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Confusion Matrix – Decision Tree Model

How accurately does the decision tree model detect customer churn?

	Tree Predicted
Actual	0
0	
1	

count

45 591

This confusion matrix shows how the decision tree model performs in predicting churn. The model demonstrates high recall, successfully identifying most customers who actually churned. However, it also generates a substantially higher number of false positives than the logistic regression model, leading to lower precision and reduced overall accuracy. This suggests the decision tree is highly sensitive to churn but often misclassifies non-churners, making it more aggressive in its churn prediction strategy.

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0	444
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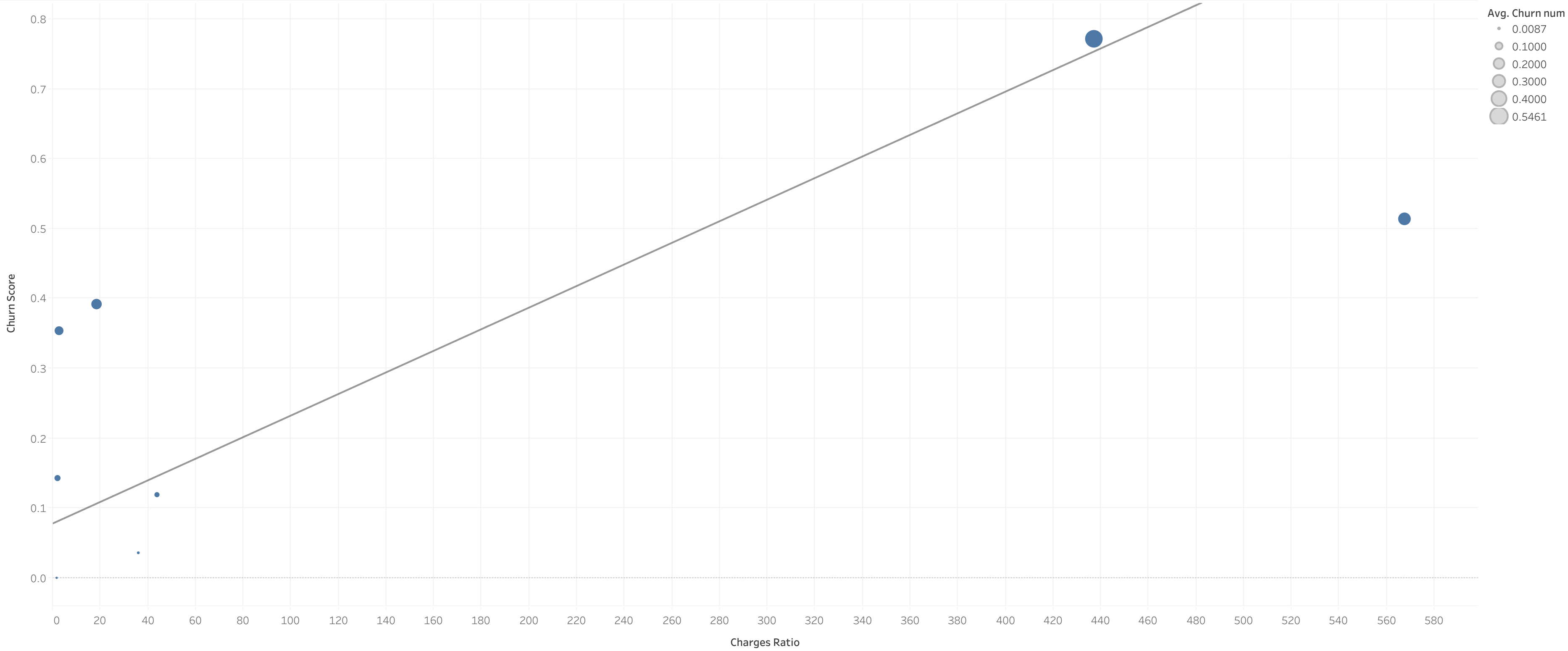
The Relationship Between Churn Score and Charges Ratio

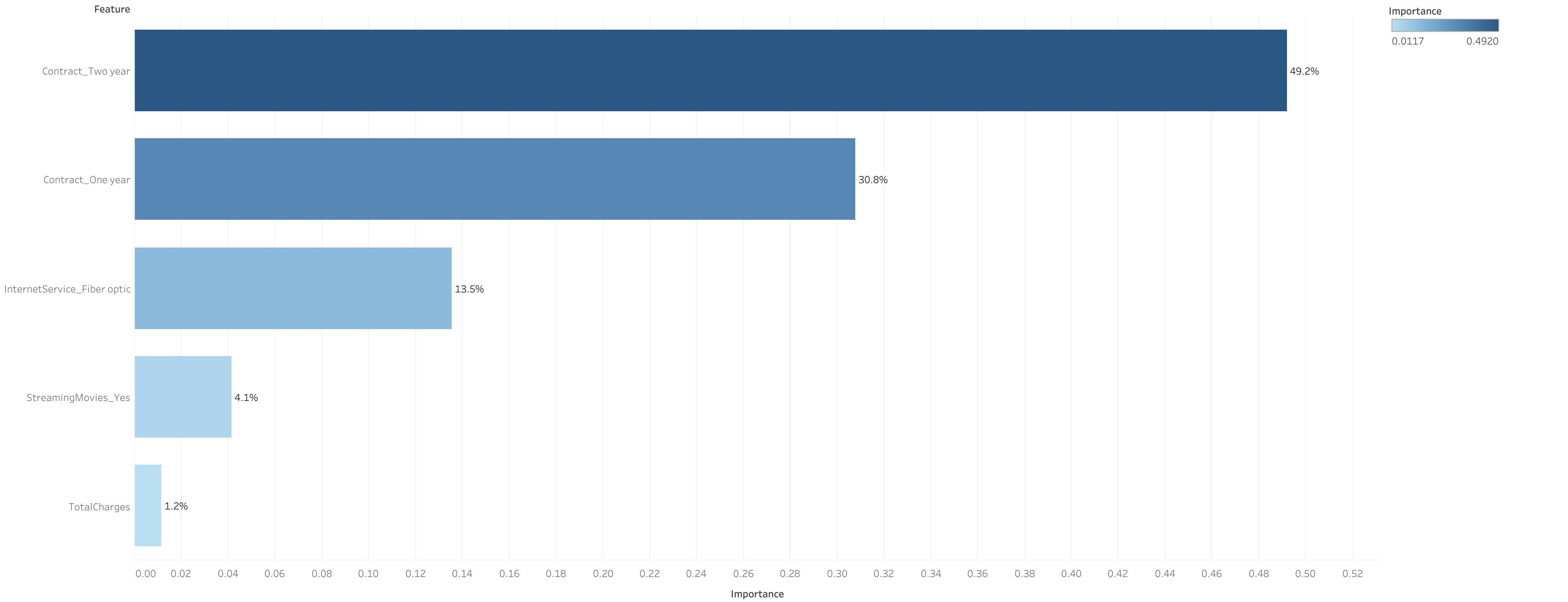
What is the relationship between a customer’s charges ratio and their predicted churn score?



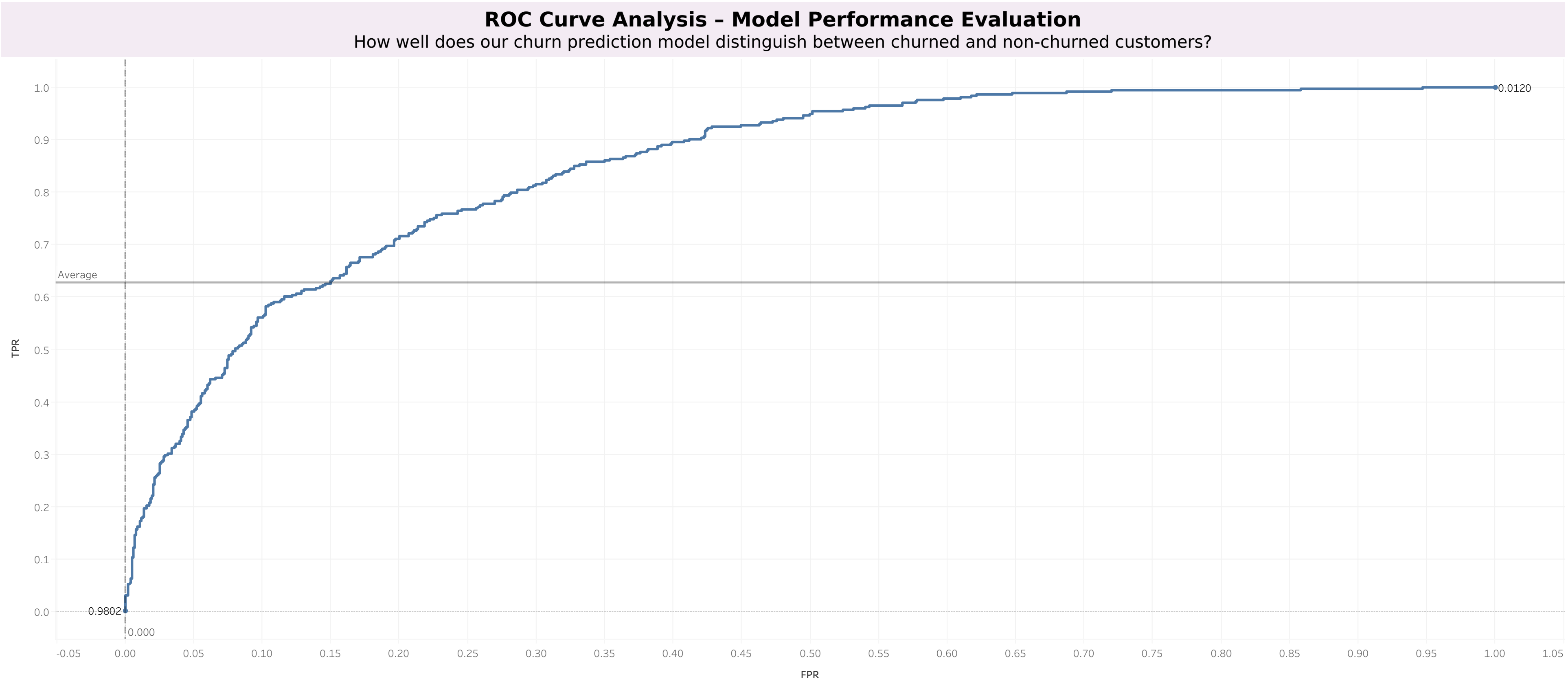
This scatter plot reveals only a weak positive correlation between charges ratio and churn score (p = 0.02982), suggesting that customers with higher charges ratios tend to have slightly higher churn scores—but the effect is minimal. Billing burden alone does not strongly predict churn risk, indicating that other factors play a larger role in determining a customer’s likelihood to leave.

Top 5 Drivers of Churn

What are the primary factors that most significantly influence a customer's likelihood of churning?



Contract term dominates churn risk, with two-year contracts (49.2%, 0.492) and one-year contracts (30.8%, 0.3077) accounting for the bulk of predictive power. Fiber Internet Service contributes 13.5% (0.1354), Streaming Movies 4.1% (0.0414), and Total Charges 1.2% (0.0117). These top five features explain over 99% of the model's churn prediction.



This ROC curve illustrates the performance of our churn prediction model by plotting the True Positive Rate (sensitivity) against the False Positive Rate. The Area Under the Curve (AUC) is 0.836, indicating strong model performance. AUC values closer to 1 suggest better predictive accuracy. The curve demonstrates that the model distinguishes effectively between customers likely to churn and those who are not, making it a reliable tool for churn risk assessment.

FINAL RECOMMENDATIONS

Data-driven actions to reduce churn

Incentivize Long-Term Contracts

Estimated churn drop: 10–12%

Offer 10–15% discount to convert MTM customers to 1–2 year plans.

Shift E-Check Users to Autopay

Electronic check churn: 46% → target 20%

Provide billing credit or loyalty points to customers who switch to credit card or bank transfer autopay.

Target High-Risk Customers

Top 15% flagged for outreach

Contact high churn_score customers with personalized retention offers (bundles, credits).

Projected impact: If adopted at current scale, expected reduction ≈ 10–12% overall churn; estimated ~5,000 customers retained/year.