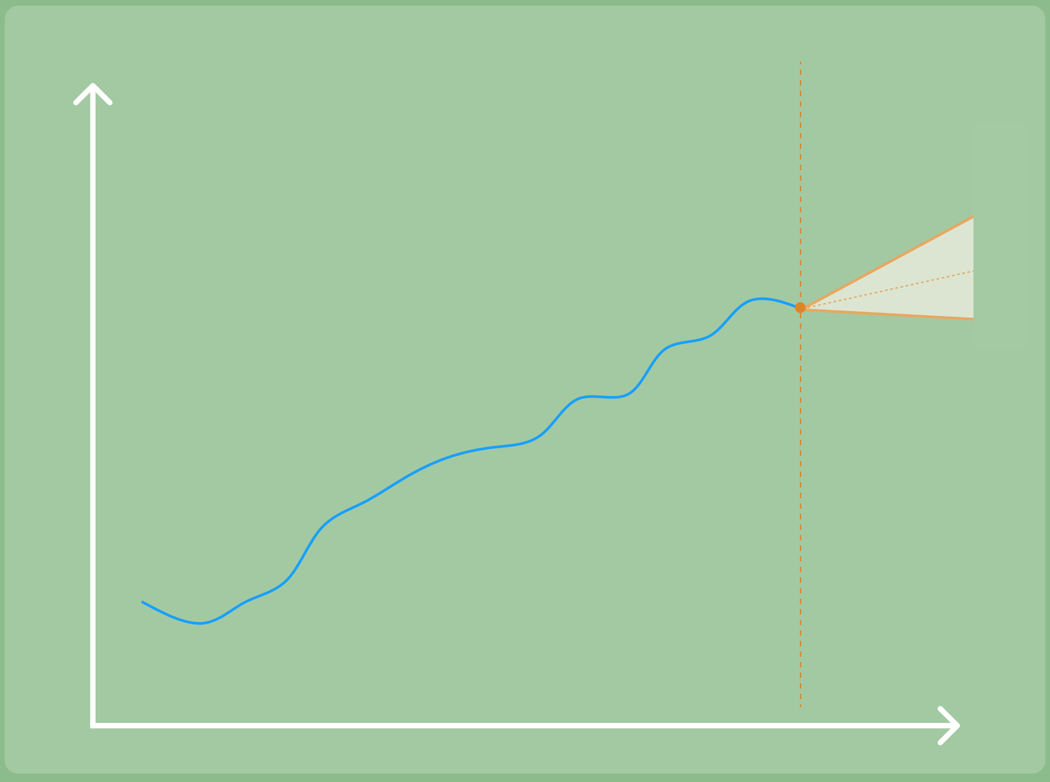
Credit Risk Forecasting Framework

Time Series Analysis of Charge-Offs and Recoveries Using Holt-Winters and ARIMA Models

Ian Moore | 8/30/2025

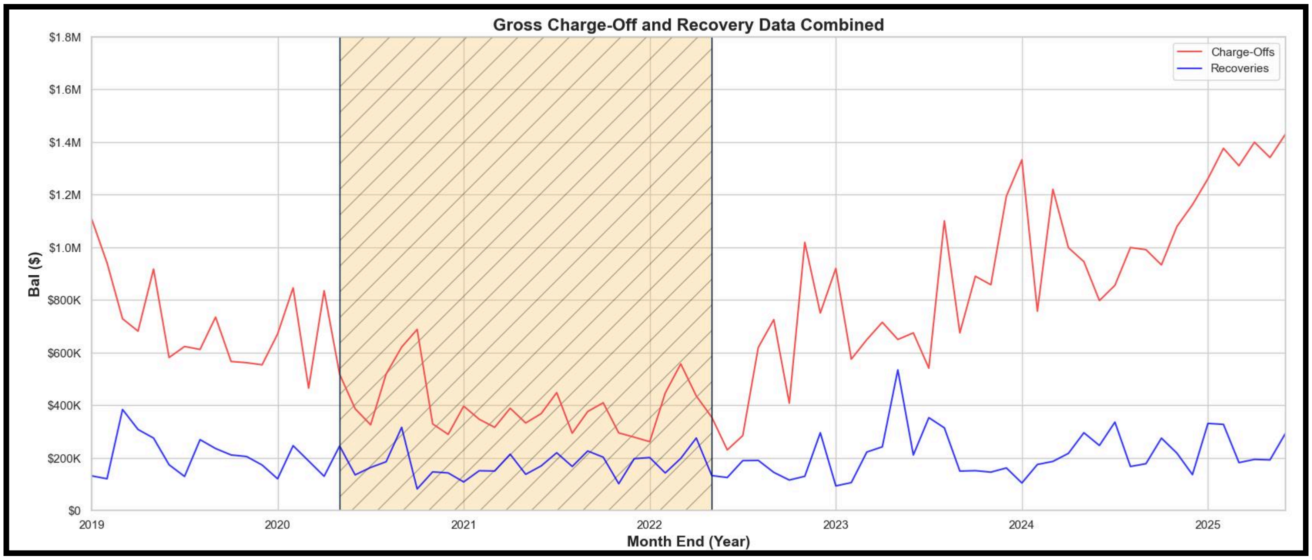
github.com/imoore99/TIME_SERIES_FORECASTING

ianmooreanalytics.com



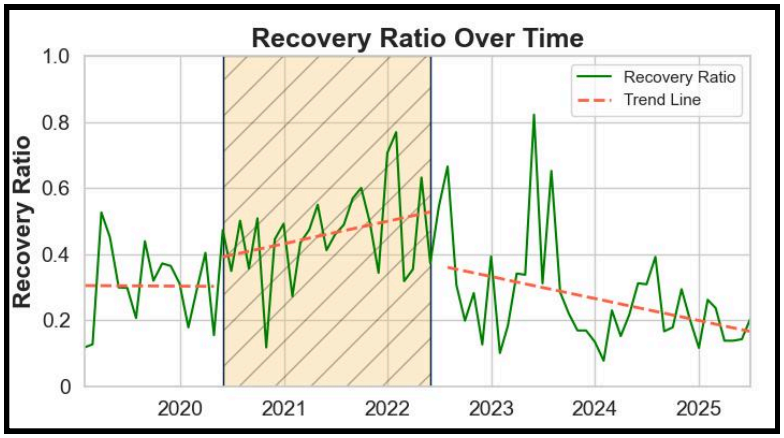
Section 1: Business Context and Opportunity

- **Issue:** The loan portfolio is experiencing fundamental risk profile deterioration with charge-offs surging 500% from the COVID trough ($230K to $1.4M+) while recoveries remain flat around $200K. As a result, this created an unsustainable loss trajectory that threatens portfolio profitability and capital adequacy.
- **Critical Pattern:** Post-COVID divergence between charge-offs and recoveries reveals systematic problem - charge-offs increasing aggressively while collection capacity appears constrained. Recovery ratios have collapsed from 30% historical norms to 15-20% as current levels face continued downward pressure.
- **Strategic Gap:** The organization lacks systematic and consistent forecasting capabilities which hinder their ability to anticipate portfolio deterioration or optimize resource allocation. Current reactive approach provides no early warning system for risk management or capacity planning.
- **Financial Impact:** Without a predictive framework, management cannot proactively adjust reserves, collection strategies, or operational capacity. Declining collection effectiveness directly reduces cash flow and increases regulatory capital requirements.
- **Opportunity:** Advanced time series modeling will provide a 12-month forecasting horizon for both charge-offs and recoveries. This will enable proactive risk management and strategic resource allocation to restore portfolio performance.



Section 2: Strategic Approach

Recovery Ratio Assessment: The recovery ratio analysis reveals the core strategic challenge facing the organization. Collection effectiveness has deteriorated from 30% historical norms to current levels of 15-20%. It appears the COVID period created artificial distortions that peaked near 80% before the dramatic collapse. this proves the need for systematic and consistent forecasting to ensure adequate proactive planning.



Root Cause Analysis: Decomposing the ratio deterioration reveals that both chargeoffs and recoveries are contributing to the crisis, but in fundamentally different ways. Charge-offs have resumed aggressive growth patterns, surging from $230K pandemic lows to over $1.4M - a 500% increase that reflects broader macroeconomic pressures including elevated interest rates and inflationary impacts on borrower payment capacity. However, recoveries remained static around $200K throughout the entire period. This suggests operational constraints rather than market dynamics are the limiting factor.

This distinction is critical for strategic focus. While charge-off growth may be partially driven by external economic conditions affecting the entire sector, the recovery flatness indicates internal capacity constraints that are directly addressable through operational improvements. The framework must therefore provide reliable charge-off forecasts for reserve planning while identifying recovery optimization opportunities that could dramatically improve collection effectiveness within management's direct control.

Framework Design: Based on this dual-factor analysis, the forecasting framework employs a consistent methodology that recognizes charge-offs and recoveries as fundamentally different phenomena requiring distinct analytical approaches. Rather than applying generic time series models, the framework tailors methodological selection to each series' underlying statistical properties and business characteristics.

Model Selection Process: The analysis begins with comprehensive statistical testing to understand data behavior. Charge-off data exhibits non-stationary trending patterns with seasonal components, while recovery data demonstrates mean-reverting volatility around stable long-term averages. This distinction drives the selection of appropriate forecasting techniques - trend-based exponential smoothing for charge-offs versus uncertainty-aware approaches for recoveries.

Validation Framework:

- **Out-of-sample testing:** Rigorous train/test splits prevent overfitting and ensure reliable performance
- **Multiple performance metrics:** MAPE, R-squared, and confidence interval coverage provide comprehensive evaluation
- **Business interpretation:** Forecasts must translate into actionable operational intelligence

Implementation Design: The framework provides 12-month forecasting horizons with monthly refresh capability, confidence intervals for scenario planning, and direct integration with reserve planning and capacity allocation decisions. This operational focus ensures the analytical sophistication serves practical business needs rather than academic exercises.

Section 3: Data Insights & Model Selection

The distinct statistical characteristics identified above require separate analytical approaches for charge-off and recovery forecasting. Both series will be evaluated using ARIMA and Holt-Winters methodologies, with model selection based on out-of-sample performance using R-squared and MAPE metrics to ensure reliable forecasting accuracy.

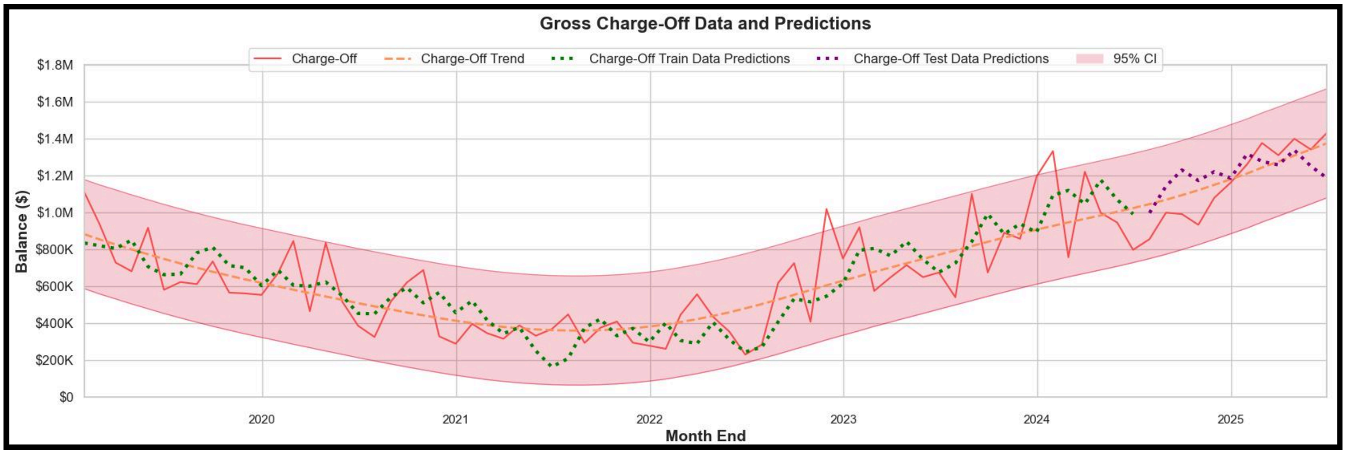
Section 3.1: Charge-Off Analysis & Model Testing

Data Characteristics & Statistical Testing: Charge-offs failed the stationarity test (p-value: 0.989), indicating they follow trends and can continue growing or declining without reverting to a typical level. In addition, they showed clear seasonal patterns (seasonality strength: 0.306), further indicating the need for trend-based forecasting methods. This means charge-offs don’t have a stable long-term average they return to - they can drift upward or downward and stay at those new levels. This reveals that charge-offs will require a model that can handle ongoing trends and growth patterns.

Model Performance Summary:

In-Sample Results: The Holt-Winters model demonstrated strong training performance with perfect mean alignment ($619,944 actual vs. fitted) and appropriate volatility smoothing. The additive trend and seasonal configuration achieved an R^2 of 0.602 and MAPE of 22.93%, effectively capturing the U-shaped recovery pattern from COVID lows through current growth trajectory.

Out-of-Sample Results: Critical testing revealed significant performance differences between model configurations. While multiplicative models showed superior in-sample metrics (R^2: 0.67), they failed dramatically during validation with negative R^2 values and systematic over-forecasting. The additive configuration delivered strong generalization performance with 11.65% MAPE and R^2 of 0.408, representing a 45% improvement in forecast accuracy over the multiplicative approach.



Model Selection Conclusion: Holt-Winters with additive trend and seasonal components, were selected for charge-off forecasting based on validated out-of-sample performance. The model will provide reliable 12-month forecasting capability with appropriate confidence intervals for risk management planning.

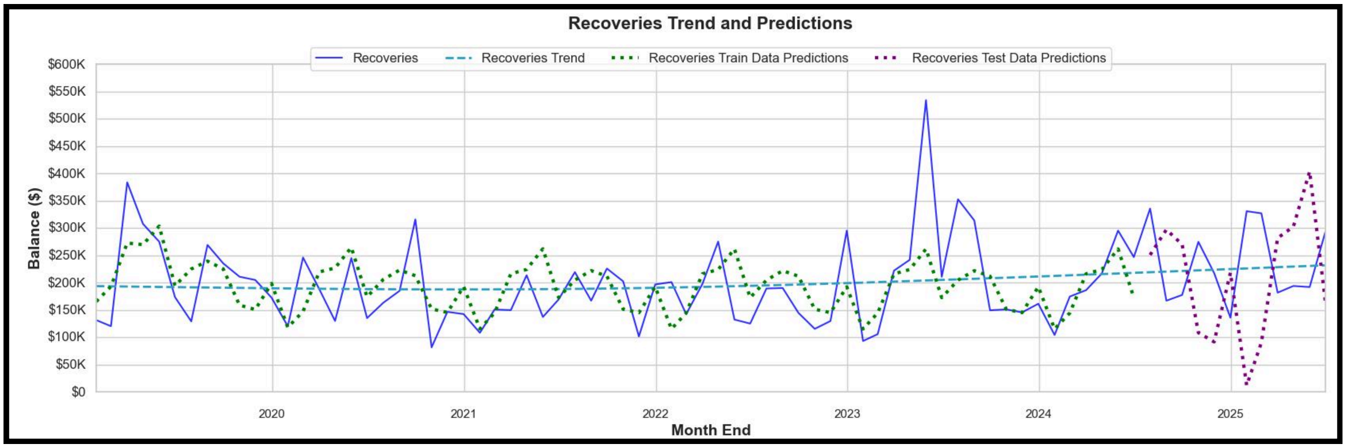
Section 3.2: Recovery Analysis & Model Testing

Data Characteristics & Statistical Testing: Recovery data exhibited stationary behavior (ADF test p-value: 0.000) with high volatility around a stable mean of $200K. Unlike charge-offs, recoveries demonstrated mean-reverting characteristics with no underlying trend patterns, requiring a fundamentally different modeling approach.

Model Performance Summary:

In-Sample Results: The Holt-Winters model showed significant over-smoothing with fitted standard deviation representing only 57% of actual volatility. While maintaining perfect mean alignment, the model failed to capture the substantial month-to-month fluctuations that characterize recovery operations, resulting in poor R-squared performance (0.308) despite unbiased predictions.

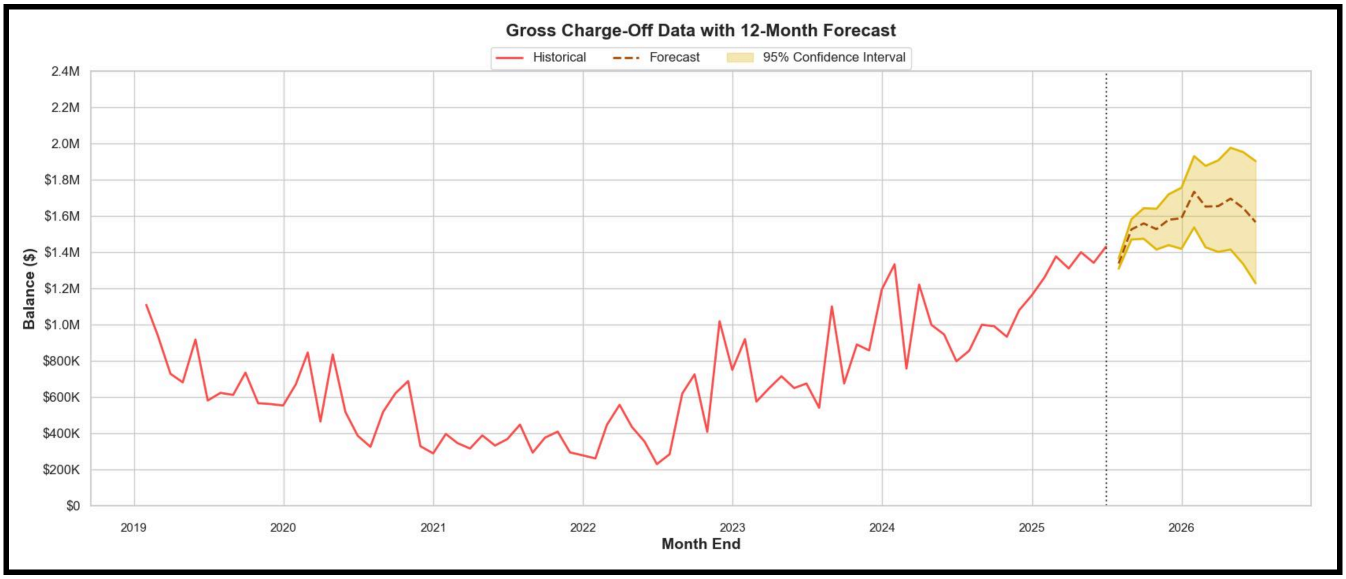
Out-of-Sample Results: Testing revealed Holt-Winters model failure with 64% MAPE and R^2: -4.665, indicating forecasts performed nearly five times worse than simply using the historical mean. The model produced unusable predictions, including forecasts dropping to near zero, demonstrating fundamental inappropriateness for volatile, stationary data.



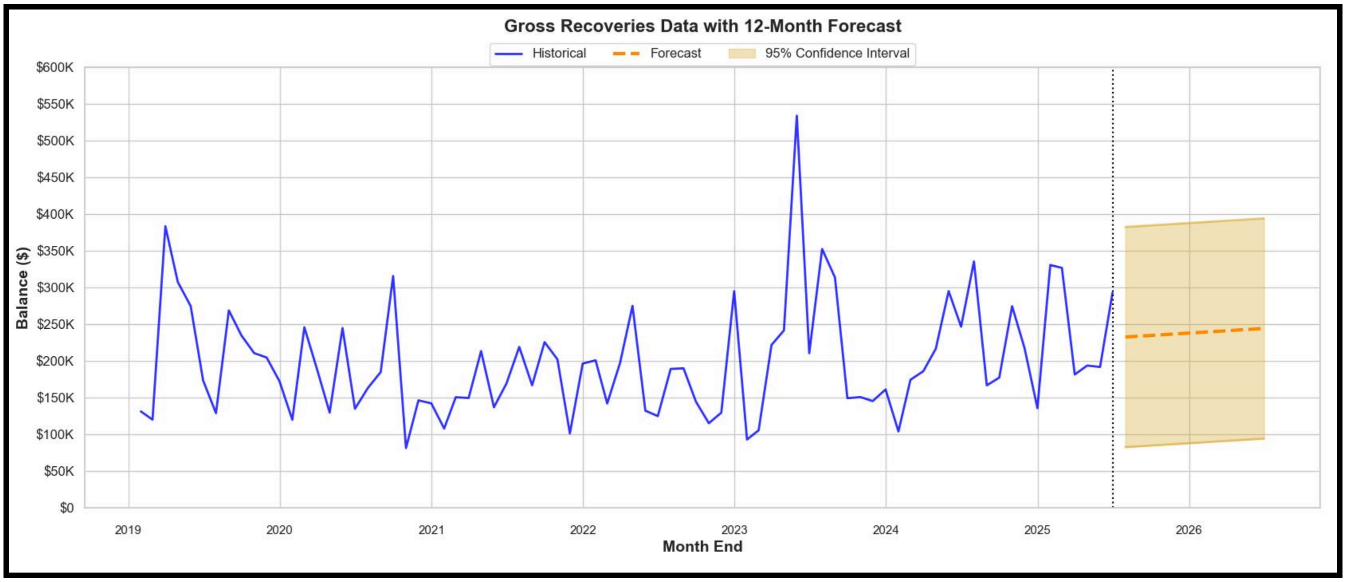
Model Selection Conclusion: Holt-Winters methodology proved fundamentally inappropriate for recovery data. The alternative approaches including ARIMA (22.74% MAPE) and SARIMA (30.57% MAPE) showed marginal improvements but still failed to provide realistic forecasts. In the end, the HP Filter trend-based approach was ultimately selected given the mean-reverting and static nature of recoveries.

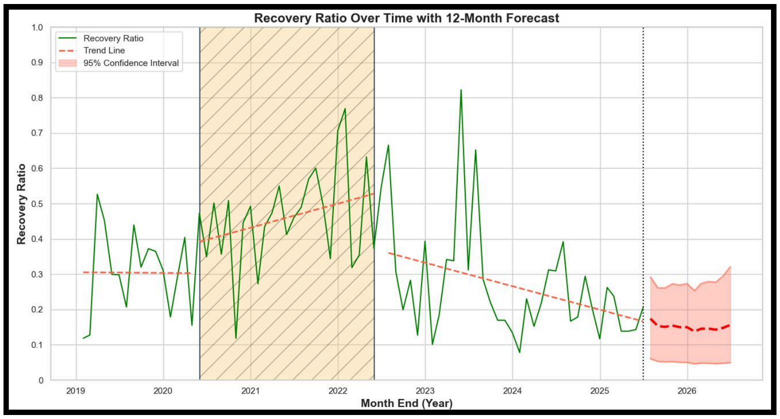
Section 4: Forecasting Results and Business Impact

Charge-Off Projections: The validated forecasting models project continued portfolio deterioration over the next 12 months, with charge-offs rising from current levels of $1.4M to approximately $1.7M by mid-2026 - a 21% increase that will further strain collection operations and capital reserves. The 95% confidence intervals span $1.4M to $1.9M by period end, providing management with realistic planning scenarios while acknowledging inherent forecasting uncertainty.



Recovery Forecasting Results: Recovery projections demonstrate the operational constraint challenge, with forecasts remaining stable around $240K monthly throughout the 12-month horizon. The HP Filter approach provides realistic uncertainty bounds spanning $80K to $400K, reflecting the inherent volatility of collection operations while acknowledging that recovery capacity appears constrained at current operational levels.





Immediate Business Implications: The combination of rising charge-offs and constrained recoveries projects continued deterioration in collection effectiveness. The forecasted recovery ratios will decline from today's 15-17% to an estimated 12-14% range, threatening cash flow and signaling fundamental capacity misalignment between loss generation and collection infrastructure.

Strategic Window: The 12-month forecasting horizon provides sufficient lead time for operational capacity expansion. Delaying collection infrastructure investments will result in continued ratio deterioration, reduced profitability, and potential regulatory scrutiny. The model's validated accuracy (11.65% MAPE) ensures reliable planning foundation for resource allocation decisions.

Financial Impact: Without intervention, the organization faces approximately $50K monthly in incremental losses due to declining collection effectiveness. Conservative estimates suggest annual impact exceeding $600K in reduced recoveries, making collection capacity expansion not just operationally necessary but financially imperative for portfolio sustainability.

Section 5: Implementation Roadmap

Immediate Actions (0-3 months): Deploy the validated forecasting framework into monthly portfolio planning processes to provide consistent early warning capability. Conduct comprehensive assessment of current collection team capacity against projected 12-month workload increases. Establish automated 30/60/90-day delinquency intervention protocols to prevent accounts from reaching charge-off status.

Operational Improvements (3-6 months): Streamline collection workflows to handle projected volume increases efficiently while maintaining quality standards. Invest in automated dialing systems and digital payment solutions to scale operations without proportional staffing increases. Restructure performance metrics to prioritize recovery effectiveness over contact volume, aligning incentives with business outcomes rather than activity levels.

Strategic Capacity Expansion (6-12 months): Develop risk-based collection strategies that prioritize resources on highest-recovery-probability accounts using segmentation analytics. Evaluate third-party collection partnerships to provide overflow capacity for projected volume surges. Expand predictive analytics capabilities to include early intervention modeling and customer propensity scoring for proactive risk management.

Ongoing Monitoring Framework: Refresh forecasting models monthly with actual performance data to maintain accuracy and detect trend changes. Track recovery ratio performance against forecast benchmarks to measure intervention effectiveness. Conduct quarterly strategic reviews comparing collection capacity against projected portfolio needs, adjusting resource allocation proactively.

Expected Outcomes: Implementation of this roadmap should stabilize recovery ratios above 20% within 12 months, improve cash flow predictability through accurate forecasting, and establish scalable collection infrastructure aligned with portfolio growth projections. Success metrics include sustained recovery ratio improvement, reduced forecast variance, and proactive capacity management.