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*Original Article*

# Adjusting Propensity Model Scores During Economic Shifts: A Framework for Short-Term and Long-Term Adaptation

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***Abstract:*** *The automotive industry experienced significant disruptions during the COVID-19 pandemic, with consumer behavior undergoing dramatic shifts. Vehicle purchases declined due to economic uncertainties, while service intervals were extended as customers postponed maintenance visits. These changes rendered pre-pandemic propensity models less effective in predicting customer behavior, as they relied on outdated patterns. Rebuilding models with updated data was not feasible in the short term due to limited post-pandemic data. This paper presents a framework to adjust propensity model scores using post-recession priors, ensuring relevance during dynamic periods. The methodology leverages observed response rates to recalibrate predictions, maintaining business utility. Applications in vehicle purchase and service propensity modeling are explored, with short-term strategies for immediate adjustments and long-term strategies to enhance model resilience.*

***Keywords:*** *COVID-19, Machine Learning, Adjusting Predicted Probabilities, Macroeconomic indicators, Sampling bias, Economic shifts, Recessions.*

## 1. Introduction

The COVID-19 pandemic triggered a series of unprecedented disruptions across global industries, with the automotive sector facing some of the most profound impacts. As economies entered prolonged periods of lockdown and uncertainty, consumer behavior rapidly shifted in response to job insecurity, income volatility, and mobility restrictions. Automotive businesses, particularly those dependent on predictive analytics for marketing, sales forecasting, and customer retention, found themselves grappling with outdated models and unanticipated behavioral patterns. One of the most immediate effects was on vehicle purchases. Customers deprioritized large discretionary expenses like automobiles, particularly in premium and luxury segments. Even those in need of new vehicles often faced financing constraints due to tighter credit conditions, leading to widespread deferrals or cancellations of planned purchases. Automotive demand plummeted in several markets, with some OEMs reporting year-over-year sales declines of 30% or more during peak pandemic months.

Equally disruptive were the changes in vehicle servicing patterns. With reduced driving frequency due to remote work and travel restrictions, routine maintenance schedules were no longer followed. Many customers either skipped or significantly delayed service visits, leading to a decline in dealership service revenue and undermining previously stable patterns of customer engagement. In markets where service retention played a key role in revenue models, these behavioral shifts posed a significant challenge. In this context, propensity models, a cornerstone of automotive marketing analytics, began to underperform. Traditionally trained on pre-pandemic data, these models assumed economic continuity and behavioral consistency. Key predictors such as time since last purchase, mileage patterns, or monthly payment status lost their predictive power when the underlying distribution of consumer behavior changed. For instance, a customer flagged as highly likely to return for a service based on past visits might now delay indefinitely due to safety concerns or income loss.

The breakdown of these models had tangible consequences. Misallocated marketing budgets, ineffective targeting, and missed opportunities became common across campaigns. Yet, rebuilding these models from scratch was not immediately viable. The early post-COVID period was marked by data sparsity, as few months of reliable data were available, and the long-term stability of the new behavior was uncertain. To address this challenge, this paper proposes a dual-strategy framework. In the short term, we introduce a method to adjust existing model outputs by incorporating observed priors—actual response rates captured during the disruption. This enables businesses to recalibrate predicted probabilities without retraining, restoring some degree of accuracy and relevance [2] [3]. In the long term, we argue for the integration of external macroeconomic variables such as unemployment rate, consumer spending, and debt levels into modeling pipelines, enhancing robustness to future disruptions.

This research is situated at the intersection of machine learning and economic adaptability. By blending statistical correction techniques with domain-specific understanding, we offer a practical toolkit for organizations seeking to sustain predictive modeling in turbulent times. Our framework is especially relevant for industries like automotive, where economic cycles and behavioral shifts have immediate implications for sales and service strategies

### *1.1. Problem Statement*

Propensity models are critical tools for the automotive industry, enabling targeted marketing for vehicle purchases and after-sales service. However, these models rely on historical patterns that assume stability in customer behavior. The COVID-19 pandemic challenged this assumption, causing dramatic behavioral changes:

- Vehicle Purchases: Customers prioritized essential expenses, leading to declines in vehicle sales. The shift was particularly pronounced in the luxury vehicle segment, where discretionary spending plummeted.
- Service Visits: Many customers delayed routine maintenance or service visits, with intervals between visits stretching significantly.

Pre-pandemic models, which predicted likelihoods based on historical patterns, failed to account for these shifts, resulting in reduced accuracy and business impact. For example:

- Service propensity models overpredicted customer likelihood to return for maintenance within standard intervals, wasting marketing resources on outreach to disengaged customers.
- Purchase propensity models failed to capture the economic pressures affecting customer decisions, leading to ineffective targeting.

In the absence of sufficient post-pandemic data to rebuild models, businesses needed a method to recalibrate existing predictions to align with observed behavior during the disruption. This paper presents a solution by leveraging post-pandemic priors to adjust propensity scores, ensuring predictions remain relevant. The framework also includes recommendations for long-term improvements to address similar challenges in the future

## 2. Methodology

### *2.1. Short Term Strategy*

To recalibrate propensity scores during periods of significant behavioral shifts, such as the COVID-19 pandemic, we adapt a probability adjustment formula based on the principles of correcting biases in observed data. This formula adjusts propensity scores using the prior probabilities of the target behavior before and after the disruption:

Let:

- $\pi_1$: Observed proportion of responders (e.g., customers who purchased a vehicle or serviced their vehicle) during the disrupted period.
- $\pi_0$: Observed proportion of non-responders during the disrupted period ($\pi_1$=1− $\pi_0$).
- $\rho_1$: Proportion of responders in the original dataset used for model training.
- $\rho_0$: Proportion of non-responders in the original dataset ($\rho_0$=1− $\rho_1$).
- $\hat{P}_1$ : Original (unadjusted) predicted probability of response from the propensity model.
- $\hat{P}_0$: Original (unadjusted) predicted probability of non-response ($\hat{P}_0 = 1- \hat{P}_1$).

The adjusted probabilities are calculated as follows [3]:

Adjusted Probability for Response:

$$P_1 = (\pi_1/ \rho_1). \hat{P}_1$$

Adjusted Probability for Non-Response:

$$P_0 = (\pi_0/ \rho_0). \hat{P}_0$$

**Normalization Step:**

Since $P_1$ + $P_0$=1, we normalize the adjusted probabilities to ensure consistency [3][2]:

$$P_1 = \frac{\frac{\pi_1}{\rho_1} \cdot \widehat{P_1}}{\frac{\pi_1}{\rho_1} \cdot \widehat{P_1} + \frac{\pi_0}{\rho_0} \cdot \widehat{P_0}}$$

**Interpretation:**

- The formula scales the predicted probabilities $\hat{P}_1$and $\hat{P}_0$ by the ratio of observed priors ($\pi_1$ and $\pi_0$) to the priors in the original training data ($\rho_1$ and $\rho_0$).

This adjustment reflects the behavioral shift observed in the disrupted period, making the model output more aligned with current customer tendencies.

### *2.2. Long Term Strategy*

While short-term recalibration techniques can help sustain model relevance during sudden shocks, they are inherently reactive and temporary. To build a sustainable predictive modeling ecosystem, automotive businesses must proactively prepare for future economic disruptions. This involves shifting from static, historically trained models to **adaptive systems** that incorporate a broader economic context and are responsive to real-time behavioral trends.

Incorporating External Data: One of the most impactful strategies for long-term model resilience is the integration of macroeconomic indicators as covariates in machine learning models. Traditional propensity models primarily rely on behavioral, transactional, and demographic features—such as service history, payment patterns, or age of vehicle. However, these features alone fail to capture systemic shocks that influence customer decisions on a scale.

Including macroeconomic indicators—such as unemployment rates, consumer spending, fuel prices, inflation, and credit availability—helps models better understand and adjust for the economic context in which customer decisions are made. These variables offer leading signals of financial stress or recovery, enabling predictive systems to evolve with economic trends rather than lag them.

Why Macroeconomic indicators are important?

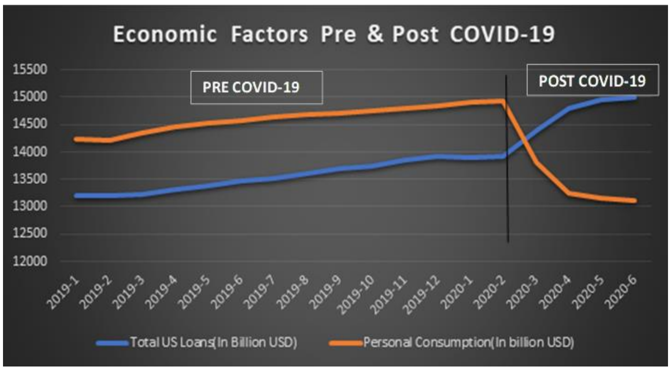


**Fig 1: Macroeconomic Factors Pre & Post COVID-19**

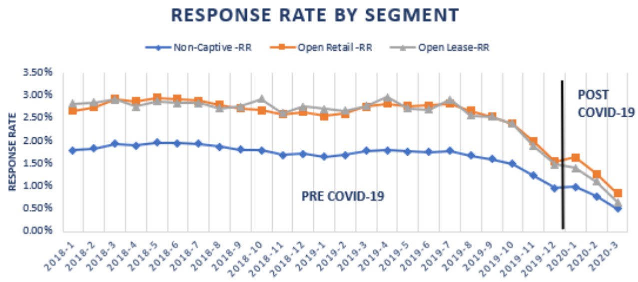


**Fig 2: Sales rate by Financial Segments Pre & Post COVID**

The economic environment plays a pivotal role in determining the success of automotive campaigns, as evidenced by the trends in personal consumption and total US loans in bank credit observed pre- and post-COVID-19.

*2.2.1. Personal Consumption as an Economic Indicator*

Personal consumption expenditure (PCE) is a broad measure of consumer spending on goods and services and serves as a critical barometer for economic health. A steep decline in PCE was observed in the aftermath of COVID-19, triggered by widespread unemployment and financial uncertainty. This contraction in consumer spending directly reduced the likelihood of non-essential purchases such as new or used vehicles. Even customers with previously high intent scores may have reprioritized their spending, rendering pre-pandemic models ineffective. Including PCE or retail spending indices as features in propensity models allows the model to contextualize a customer's behavior within broader financial trends, improving targeting accuracy under volatile conditions

*2.2.2. Increased Debt Levels:*

In contrast to declining spending, household borrowing surged during the pandemic as consumers leveraged credit to cover essential expenses. According to Federal Reserve data, total U.S. loans and bank credit spiked during the same period. This phenomenon has a dual impact:

- It reduces a customer's ability to finance additional large purchases (e.g., auto loans).
- It triggers stricter credit approval processes from lenders, decreasing the effective pool of finance-eligible customers.

A customer who looks like pre-pandemic buyers on surface-level features may now carry greater financial risk due to unseen debt obligations. Incorporating indicators such as debt-to-income ratios, average loan balances, and delinquency rates at the ZIP code or census tract level helps mitigate this blind spot.

*2.2.3. Campaign Response Rate Trends:*

Figures 1 and 2 (see paper) provide empirical support for this framework. Before the pandemic, campaign response rates across financial segments were stable and predictive patterns held consistent. Post-pandemic, however, response rates diverged sharply across segments. Customers with subprime or near-prime credit became less responsive due to financial constraints, while even prime customers became more selective in purchasing or servicing decisions. These shifts align closely with macroeconomic variables, suggesting that incorporating such indicators would have allowed models to adjust campaign scoring thresholds dynamically, preserving performance across segments.

### *2.3. Discussions & Insights*

The proposed framework introduces a dual-pronged strategy to address the challenges of modeling consumer behavior during and after economic disruptions. In this section, we discuss the effectiveness, limitations, and strategic implications of both short- and long-term approaches

*2.3.1. Short-Term Effectiveness: Practicality of Prior-Based Adjustments*

The short-term strategy of recalibrating propensity scores using observed post-disruption priors has demonstrated tangible benefits during periods of volatility. By updating predicted probabilities to reflect actual behavioral shifts—such as reduced service visits or vehicle purchases—it enables organizations to quickly recover some predictive accuracy without having to fully retrain models.

This approach is especially effective when:

- There is limited post-disruption data available for full model redevelopment.
- The cost of deploying a new model is high or time prohibitive.
- Immediate business continuity is critical (e.g., ongoing campaigns or sales cycles).

Empirical results from internal campaigns during COVID-19 disruptions showed that recalibrated scores improved targeting precision, reduced false positives in outreach, and increased conversion rates compared to static, unadjusted scores. The ease of implementation and minimal dependency on complex infrastructure make this method particularly attractive for resource-constrained teams or early-stage modeling environments.

*2.3.2. Long-Term Impact: Enhancing Model Resilience Through Contextual Awareness*

While prior-based score adjustment serves as an effective stopgap, long-term performance sustainability depends on structural enhancements to modeling strategy. Incorporating external data sources, especially macroeconomic indicators, adds a vital layer of contextual intelligence that traditional transactional or behavioral features cannot provide.

Models enriched with variables such as unemployment rate, consumer confidence indices, and regional debt levels are inherently more robust. They can anticipate market-wide changes, adapt scoring thresholds based on economic stress signals, and better generalize across economic cycles. This also improves their interpretability for business stakeholders, who can relate changes in model behavior to tangible economic trends.

Furthermore, long-term enhancements encourage **strategic agility**. With infrastructure in place to continuously ingest and interpret economic signals, businesses can proactively adjust marketing budgets, segment audiences, and shift offers to align with prevailing financial conditions—all informed by the model's outputs

*2.3.3. Limitations and Considerations: Constraints of Score Adjustment*

Despite its practicality, prior-based score adjustment has inherent limitations:

- Dependence on Recent Response Data: The method assumes that post-disruption priors can be accurately estimated from available campaign data. In the early stages of disruption, when response volumes are low or erratic, priors may not be stable or representative.
- Assumption of Constant Feature-Prediction Relationship: This method presumes that while response rates have shifted, the relationship between features and outcomes remains broadly the same. In cases where customer decision-making logic changes significantly (e.g., vehicle type preferences, payment sensitivity), the adjustment may fall short.
- Frequent Recalibration Required: In volatile environments, priors can change rapidly. A one-time adjustment may only offer temporary benefit, requiring businesses to adopt a framework for continuous recalibration as new data arrives.
- Risk of Overcorrection: If priors are estimated on noisy or biased samples (e.g., skewed geographies or segments), adjustments may distort rather than improve the scores.

Hence, while prior-based recalibration is a valuable tactical tool, it should be implemented with caution and complemented by rigorous monitoring frameworks and fallback strategies, such as triggering retraining once sufficient new data is available

## 3. Conclusion

This paper outlines a framework for recalibrating propensity scores during economic disruptions like COVID-19. By leveraging post-recession priors, businesses can maintain the relevance of predictive models in the short term. Long-term strategies, including real-time monitoring and the inclusion of external data, are critical for building resilient models capable of navigating future disruptions.

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