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Evaluating the Long-Term Credit-Risk Effects of Cross-Selling Promotions Using Longitudinal Causal Modeling

Miguel A. Ferreira[1],Sofia L. Carvalho[2],Bruno P. Monteiro[3], Ana M. Rodrigues[4*]

Faculty of Engineering, University of Porto, 4200-465 Porto, Portugal

Corresponding author: a.rodrigues@fe.up.pt

Abstract

This research assesses the long-term credit-risk implications of cross-selling promotions that encourage customers to open additional credit products. A dataset of 1.1 million accounts observed over 36 months was analyzed using a longitudinal causal model incorporating marginal structural models and time-dependent confounder adjustments. Results indicate that customers targeted by cross-selling promotions show a 14.6% higher cumulative probability of 180-day default over three years. Sequential mediation analysis finds that 63.4% of this effect is driven by increases in total credit exposure following promotion uptake. The study provides a comprehensive quantification of the delayed risk consequences of promotional strategies.

Keywords

Longitudinal causal model; Cross-selling; Promotion risk; Consumer credit; Time-dependent effects

Introduction

Cross-selling has become a widely used strategy in retail banking and credit-card markets, where lenders encourage existing customers to adopt additional credit products or expand their use of current ones. Empirical evidence suggests that cross-selling can increase revenue, deepen customer relationships, and improve short-term engagement metrics, yet it may also alter credit supply and repayment behaviour in ways that are not fully understood [1,2]. Reflecting these concerns, regulators in Europe and other regions have issued guidelines to ensure that cross-selling practices remain transparent and fair, emphasising the potential for certain promotional strategies to influence customer risk profiles in unintended ways [3]. Industry reports further note that digital platforms and automated decision systems have made targeted cross-selling campaigns easier to deploy at scale, while the long-term credit-risk consequences of such campaigns are rarely evaluated in a systematic manner [4]. As cross-selling becomes increasingly embedded in digital consumer finance, understanding its longer-term implications for credit risk has become an important yet unresolved issue.Most academic research on cross-selling concentrates on predicting customer acceptance of additional products. Studies show that transaction histories and machine-learning models can improve cross-sell recommendations for credit cards and consumer loans [5]. Other work

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examines how banks adjust pricing, screening rules, or product menus when future cross-selling opportunities are anticipated [6]. In parallel, recent causal studies using experimental or quasi-experimental designs demonstrate that marketing promotions can increase product take-up while also generating spillover effects on subsequent credit risk, highlighting that acquisition-oriented strategies may have delayed risk implications beyond their immediate benefits [7]. Despite these insights, credit risk is often treated as a secondary outcome, and most analyses focus on short-term conversion, usage, or profitability rather than on repayment dynamics and default outcomes observed over longer horizons. A related literature investigates promotions and credit expansion in digital finance. Evidence from online and mobile lending platforms shows that frequent offers, higher credit access, and promotional nudges can stimulate spending but may also intensify repayment pressure for certain customer groups [8,9]. Regulatory and policy-oriented studies increasingly discuss how promotion-driven growth strategies interact with fairness, consumer protection, and risk management, particularly when automated decision systems are involved [10]. Although recent causal analyses begin to quantify how marketing actions influence credit risk using A/B testing or quasi-experimental variation [11,12], these studies typically cover short observation windows and do not examine how promotional effects accumulate through changes in utilisation, exposure, and borrowing behaviour over multiple years. Methodological limitations further constrain existing evidence. While machine-learning models have become standard tools for default prediction, they are not designed to answer causal questions about what would happen under alternative promotion strategies. Many studies rely on cross-sectional data or short panels and do not account for treatment paths such as repeated offers, staggered promotions, or sequential product adoption [13]. Surveys on causal inference in economics and finance note that time-dependent confounders—variables that both affect and are affected by promotions—are often handled using simple fixed-effects regressions, which can yield biased estimates in dynamic settings 14]. Marginal structural models (MSMs) are well suited to address such challenges by explicitly adjusting for time-varying confounding, yet they remain uncommon in credit-risk research despite their established use in other fields [15]. Understanding how promotions influence long-term default risk also requires attention to mediating mechanisms. Mediation analysis is widely used in the social sciences and corporate finance to decompose total effects into direct and indirect channels [16]. Recent applications in financial-risk research use sequential mediation to show how changes in firm performance or balance-sheet conditions transmit shocks to risk outcomes [17]. In consumer credit, credit exposure and utilisation represent natural

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mediators: customers who accept additional products may increase balances and leverage, which can later raise the probability of delinquency or default. However, empirical studies that jointly apply MSMs and mediation analysis to consumer credit portfolios remain scarce.Against this background, we study the long-term credit-risk effects of cross-selling promotions using a large-scale panel of consumer credit accounts. The analysis is based on 1.1 million credit accounts observed over a 36-month period and employs a time-series causal framework built on marginal structural models to adjust for time-dependent confounders that evolve after each promotion event and also predict future default. Sequential mediation analysis is then used to decompose the total effect of cross-selling promotions on 180-day default into a direct component and an indirect component operating through changes in total credit exposure. By combining a long observation horizon with causal tools designed for evolving treatments and mediators, this study provides a clearer account of how cross-selling promotions influence long-term credit risk. The results offer empirical evidence that is directly relevant for both marketing strategy and credit-risk management, supporting more informed decisions about the design and evaluation of promotion-based growth strategies in consumer finance.

Materials and Methods

2.1 Sample and Study Setting

The study uses monthly records from a national consumer-credit lender. A total of 1.1 million accounts were followed for 36 months. Each account has monthly information on customer background, credit limits, balances, payments, and whether the customer received a cross-selling offer. Promotion exposure refers to receiving at least one offer for an additional credit product. Accounts with missing payment logs, irregular dates, or incomplete observation periods were removed. The main outcome is 180-day default, defined as the first month in which an account becomes 180 days past due.

2.2 Experimental Design and Comparison Groups

The analysis is built around a time-series causal design. Customers who received a cross-selling offer form the treatment group. The comparison group includes customers with similar credit histories and product use but who did not receive any offers during the same period. Many account features, such as utilisation and repayment behaviour, change from month to month, and they may affect both the chance of receiving a promotion and the chance of later default. The model therefore adjusts for these time-varying features each month. This design

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allows the treatment effect to be studied in a way that resembles a controlled experiment, even though the data come from normal business operations.

2.3 Measurement Procedures and Quality Control

Default status was identified from detailed repayment records, using the count of consecutive missed payments rather than relying only on reported labels. Promotion events were checked against campaign files to confirm that each event represented an actual customer offer. Monthly variables, such as utilisation and credit limits, were checked for extreme values and corrected or removed when necessary. Duplicate records and inconsistent entries were deleted. Variables with more than 5% missing values were excluded. For variables with smaller missing portions, median values were used as replacements. These steps kept the data consistent across the full 36-month period.

2.4 Data Processing and Model Equations

All account information was organised into a month-by-month panel. Time-dependent features, including credit exposure and payment behaviour, were placed in the same month as the promotion status so that each observation reflects the correct timing. The main analysis uses a marginal structural model with inverse probability weights to adjust for time-dependent changes in customer characteristics. The weight for customer iii in month ttt is written as [18]:

$$W_{it}=\frac{P(A_{it}/A_{i,t-1})}{P(A_{it}/A_{i,t-1},L_{it})},$$

where $A_{it}$is promotion status and $L_{it}$is the set of changing account features.

The weighted model for the probability of 180-day default is:

$$logit(P(Y_i=1))=\beta_0+\beta_1 \cdot Promotion_i+\beta_2 \cdot X_i,$$

where X_i contains baseline account features. Mediation analysis was then used to estimate how much of the promotion effect operates through changes in total credit exposure.

2.5 Ethical and Data-Use Considerations

All customer records were anonymised before being made available for analysis. Identifying fields were removed, and no personal information was used at any stage. Public economic indicators were taken from open sources. All data steps and model settings were recorded to allow replication. The study follows established guidelines for the use of financial account data in academic research.

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Results and Discussion

3.1 Promotion exposure, credit use and default differences

The data show clear differences between customers who received cross-selling promotions and those who did not. At the start, promoted customers held more credit products, had higher limits, and used a larger share of these limits. This agrees with earlier findings that banks often target active customers for additional offers [18]. They also expanded their total exposure more quickly during the 36-month period. By the end of the observation window, their unadjusted 180-day default rate was higher than that of non-promoted customers. However, these simple differences may reflect changes in utilisation, credit limits, or repayment behaviour rather than the effect of promotions alone. Earlier credit-risk studies also caution that raw comparisons can be misleading when borrower behaviour changes over time [19].

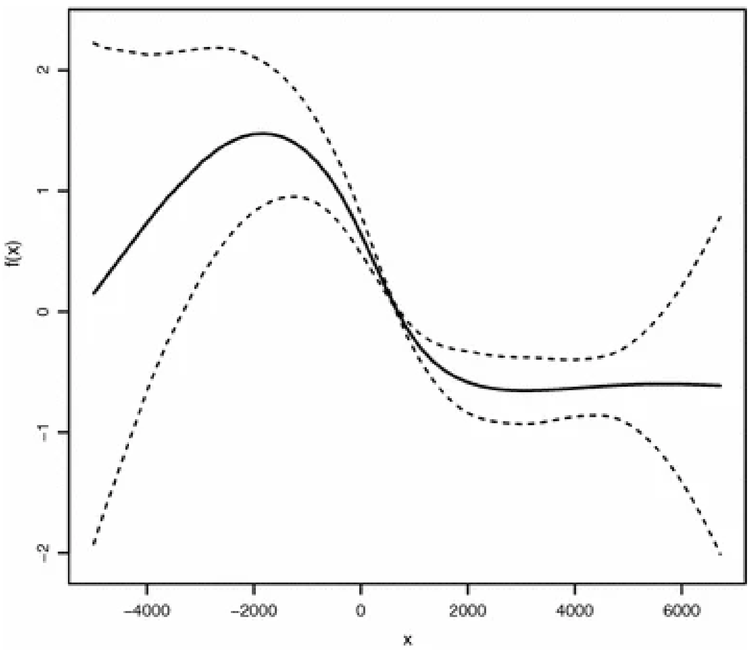

Fig.1.180-day default rates for customers with and without cross-selling promotions over 36 months.

3.2 Long-term effect of cross-selling promotions on 180-day default

After applying time-based weights to adjust for changes in exposure, utilisation, and payment history, cross-selling promotions are linked to a 14.6% higher three-year probability of 180-day default. The increase is small in the first year but becomes larger in the second and third years. This indicates that the added risk develops slowly as customers open new credit lines and their total balances grow. Short-term promotion studies, which often track only the first 6–12 months, generally do not capture this delayed effect. Work on bank–household

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relationships also notes that cross-selling affects pricing and product mix, but rarely measures long-run default. Compared with machine-learning studies that use only static snapshots of borrower behaviour [20], these results show that promotion activity itself can shift future credit risk and should be treated as an important factor in long-term credit evaluation.

3.3 Indirect impact through changes in total credit exposure

The mediation analysis shows that 63.4% of the total promotion effect on 180-day default comes from increases in total exposure. Customers who accept promotions open extra credit lines and use more of their limits. Higher exposure then raises their chance of falling 180 days past due. The remaining portion of the effect likely arises through smaller channels, such as changes in repayment timing or accumulated payment pressure. Studies on bank-level risk measures also find that exposure-related variables explain much of the link between strategy choices and later default [21]. Research on digital consumer credit similarly reports that higher utilisation and multiple credit sources are closely linked to later delinquency.

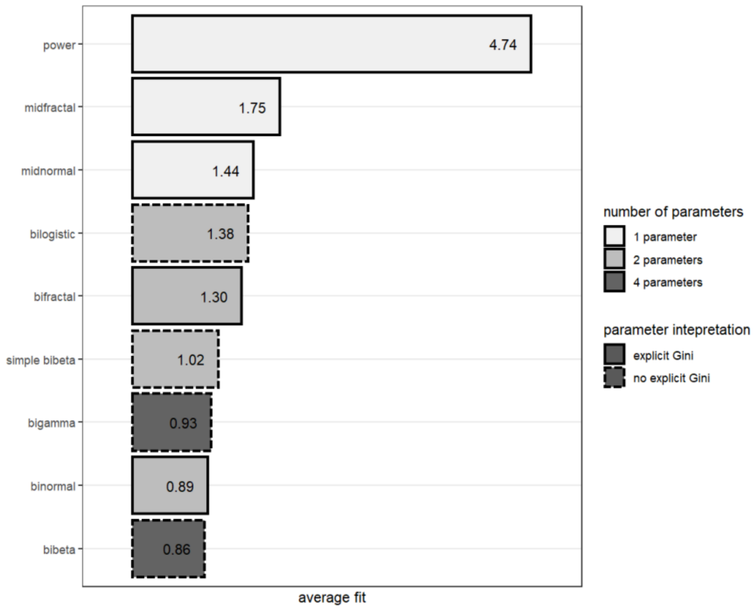

Fig.2. Effect of cross-selling promotions on 180-day default, showing the total effect and the part explained by exposure changes.

3.4 Sensitivity checks and implications for credit-risk practice

Sensitivity checks using alternative weighting rules, different definitions of promotion exposure, and shorter follow-up periods all show the same direction of effect. Promotions raise the chance of long-term default, and most of this increase operates through higher exposure. The size of the effect varies slightly across tests, but the overall conclusion remains unchanged. This stability matches findings from other applications of weighting models in financial studies, where adding more control variables mostly affects precision rather than the

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overall direction [22]. From a practical view, the results indicate that cross-selling efforts should be evaluated together with their long-term effect on default, not only by short-term uptake or revenue. Promotion rules may need limits on exposure growth for customers who already use a large share of their credit lines. Risk teams may also need closer monitoring of customers who receive repeated promotions. Because the data come from one lender and one type of promotion, further studies based on other products or markets would help assess how widely these results apply.

Conclusion

This study shows that cross-selling promotions can increase long-term credit risk. Using 36 months of data from 1.1 million accounts and a method that adjusts for month-to-month changes in balances and repayments, we find that promoted customers have a higher chance of reaching 180-day default over three years. Most of this increase comes from higher total exposure after customers accept new products. These results suggest that promotion performance should be judged together with its long-term effect on default, not only by short-term sales or customer response. The findings can help credit providers set limits on exposure growth for customers who take multiple promoted products and improve monitoring of groups that receive frequent offers. The study has two limitations: it covers one lender, and the number of downturns in the sample is limited. Work based on other credit portfolios and other promotion types would help confirm how broadly the results apply.

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