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Causal Effects of Communication Channels in Bank Telemarketing Campaigns: Evidence from Interpretable Causal Machine Learning Models

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ABSTRACT

This study examines the causal effect of communication channel choice on customer subscription decisions in bank telemarketing campaigns. While existing studies rely heavily on predictive machine learning models to assess campaign success, these approaches are often limited in supporting causal decision-making processes. To address this gap, this study adopts a causal machine learning framework using an open-access bank marketing dataset. The dataset consists of approximately 41,000 observations, with communication channel mobile phone communication channel (cellular) or telephone (landline phone communication channel) treated as a binary strategic intervention variable. Mean Treatment Effect (ATE) is estimated using Dual Machine Learning, while Conditional Mean Treatment Effects (CATE) are analyzed through a Causal Forest model to capture customer-level heterogeneity. The results show that although the mean effect of the communication channel is modest, significant heterogeneity exists among customer segments. To interpret the sources of treatment effect heterogeneity, a SHAP-based explainability analysis is performed on a high-accuracy surrogate model that approximately represents the CATE estimates. The findings reveal that macroeconomic indicators such as employment levels (np.employed) and interest rates, along with campaign-related features, play a critical role in shaping the effectiveness of communication channels. Mobile communication has strong positive effects for certain customer groups, while its impact is weak or even negative for others. Overall, this study contributes to the bank telemarketing literature by moving beyond predictive accuracy and towards a causal and interpretable decision support framework. The results highlight the importance of designing marketing strategies that account for customer-level heterogeneity and contextual factors, rather than relying solely on average effects.

Keywords: Bank Telemarketing, Causal Machine Learning, Communication Channels, Heterogeneous Treatment Effects, Explainable AI, Interpretable Causal ML, Decision Support
JEL Clasifications: M31, G21, C45, C21

1. Introduction

Bank telemarketing campaigns are a significant marketing tool widely used for promoting financial products and acquiring customers. With advancements in data analytics and machine learning, numerous studies have focused on improving campaign effectiveness, with a large portion adopting models that predict the likelihood of customers subscribing. These approaches have contributed to targeting processes by identifying customer groups with a high probability of response.

However, managerial decision-making processes in telemarketing campaigns are often not limited to the question of which customer will subscribe. The crucial question is how marketing interventions affect customer behavior. In this context, the choice of communication channel is not merely a descriptive variable but a strategic intervention. While predictive machine learning models offer high accuracy, their outputs often remain at a correlational level and fail to directly reveal the causal effects of marketing decisions. This limitation is

particularly pronounced in telemarketing applications where communication channels are not randomly assigned and observational data is used.

Recent causal machine learning approaches aim to overcome these limitations by combining flexible learning algorithms with causal inference principles. These methods allow for the estimation of the effects of interventions on the outcome variable, even under high-dimensional and nonlinear data structures. Furthermore, they enable the analysis not only of average effects but also of heterogeneous treatment effects at the customer level, allowing for more targeted design of marketing strategies.

This study examines the causal effect of communication channel selection on customer subscription decisions in bank telemarketing campaigns. Using an open-access bank marketing dataset, mobile and landline communication channels were modeled as alternative interventions. The analysis was conducted in three stages. In the first stage, the average causal effect of the communication channel was estimated using the Double Machine Learning method. In the second stage, conditional average treatment effects were calculated using the Causal Forest model to reveal customer-level heterogeneities. Finally, a SHAP-based interpretability analysis was applied to explain which variables shaped these heterogeneous effects.

In this context, the study offers three fundamental contributions to the bank telemarketing literature. First, it moves beyond approaches that treat communication channel choice as a predictive variable, modeling this choice as a causal intervention. Second, it reveals that campaign effectiveness exhibits significant heterogeneity depending on customer segments and the macroeconomic context. Third, by combining causal machine learning with explainable artificial intelligence methods, it proposes a more transparent and applicable analytical framework for marketing decision support processes.

2. Literature Review

2.1. Bank Marketing and Telemarketing Studies

Research aimed at improving the effectiveness of bank marketing campaigns has gained significant prominence in the financial literature, particularly with the proliferation of telemarketing applications. Studies focusing on predicting the success of bank telemarketing generally develop data-driven approaches to understand customer behavior and predict product subscription probability. One of the most widely used datasets in this field is the real-world bank marketing dataset containing telemarketing campaign data from Portuguese banks (Moro et al., 2014). This study demonstrates the performance of predictive models in telemarketing by comparatively evaluating logistic regression and other classical machine learning methods.

A large portion of these studies have focused on predicting customer responses to campaigns, and classification-based machine learning models have been widely used. Logistic regression, decision trees, support vector machines, and, more recently, ensemble methods have frequently been preferred to predict the probability of success of bank campaigns (Lessmann et al., 2015; Moro et al., 2014). Numerous comparative studies have shown that ensemble methods, in particular, offer higher prediction accuracy compared to traditional singular models.

A number of follow-up studies have used more sophisticated machine learning models to predict telemarketing success. For example, Xie et al. (2023) compared bank telemarketing prediction models with methods such as Random Subspace and Multi-Boosting, analyzing the prediction performance of different classification techniques. These studies demonstrate that

machine learning models can surpass classical statistical models in predicting bank telemarketing performance.

Dynamic ensemble selection methods are also attracting attention in the field of telemarketing prediction. The META-DES-AAP method proposed by Feng, Yin, Wang, and Dhamotharan (2022) has improved the success of predicting bank telemarketing sales using ensemble-based classifier selection strategies. This study presents a significant innovation in the telemarketing literature by attempting to optimize not only prediction accuracy but also economic benefit.

On the other hand, the literature on customer classification and interaction prediction in banking has demonstrated the applicability of deep learning and hybrid models. For example, hybrid neural network and ensemble models developed by Guo et al. (2023) have shown high performance in predicting telemarketing success. These studies show that the machine learning-based approach to predicting telemarketing strategies is becoming increasingly diverse and enriched.

A common feature of this literature is that variables such as communication channel, customer demographics, and campaign history are generally included as independent variables in prediction models. However, these prediction-oriented approaches are limited in directly revealing the causal contribution of intervention variables—for example, the value of a particular communication channel—to the outcome. Therefore, the current bank marketing literature focuses less on causal inference in terms of decision support processes and mostly produces correlation-based results. This situation does not provide marketing managers with sufficiently strong causal insights to determine which strategy should actually be preferred.

2.2. Machine Learning versus Causal Inference in Marketing

Machine learning methods are widely used in marketing literature, particularly for predicting customer behavior and forecasting campaign success. These classification and regression-based approaches have become important tools in decision support systems due to their high predictive accuracy. In recent years, especially with the increase in large-scale customer data, gradient boosting, random forest, and deep learning-based models have become standard tools in marketing analytics (Wedel and Kannan, 2016; Bertsimas & Kallus, 2020). However, the main limitation of these models is that they mostly address the relationships between variables at the correlational level and cannot clearly distinguish the causal aspect (Varian, 2016).

In marketing applications, the fundamental question for managers is often not "which customer will buy?" but rather "which intervention will change the outcome?". In this context, a model with high predictive accuracy may not always show whether a particular marketing action is truly effective. In banking and marketing applications, particularly those using observational data, classical machine learning models can be insufficient for causal inference because intervention variables are generally not assigned randomly (Athey & Imbens, 2016; Chernozhukov et al., 2018a).

This limitation has significantly increased interest in causal inference approaches in the marketing and applied economics literature in recent years. Causal analyses aim to evaluate the effect of a marketing intervention on an outcome variable by controlling for potential confounding factors. In this context, approaches such as Double Machine Learning (DML), which enable reliable inference under high-dimensional covariates, offer a strong alternative to classical econometric methods (Chernozhukov et al., 2018; Chernozhukov et al., 2018b).

Athey and Imbens (2019) systematically addressed how machine learning methods can be used in causal inference problems, clearly highlighting the difference between predictive approaches and causal analysis. This approach is increasingly being adopted not only in academic literature but also in marketing and business analytics applications. Indeed, recent studies show that causal machine learning methods provide more reliable policy recommendations in decision problems such as campaign design, targeting, and channel selection (Bertsimas & Kallus, 2020; Knaus et al., 2021).

Nevertheless, a significant portion of the applications in the marketing literature still considers prediction accuracy as the primary performance metric. Making decisions that involve direct intervention, such as communication channel selection, based on correlation-based results rather than causal effects carries significant strategic risks. This situation necessitates clearly defining the difference between machine learning-based prediction models and causal inference methods in marketing applications.

This study aims to go beyond the prediction-oriented approaches commonly used in banking telemarketing literature and address the impact of communication channels on customer behavior within a causal framework. Accordingly, by using methods that combine machine learning with causal inference, the aim is to reveal not only "what will happen" in marketing decisions, but also "what factors influence what will happen."

2.3. Heterogeneous Treatment Effects and Causal Machine Learning

In marketing and banking applications, the assumption that an intervention has the same effect on all individuals is often unrealistic. While the Average Treatment Effect (ATE) is useful for summarizing the overall impact of a marketing intervention, it can overlook customer-level differences. Especially in banking applications with heterogeneous customer profiles, evaluating ATE alone is insufficient to determine who the intervention is effective or ineffective for (Athey & Imbens, 2016).

This limitation has led to the development of the Heterogeneous Treatment Effects (HTE) approach in the literature. The heterogeneous treatment effects framework acknowledges that the effect of an intervention can vary depending on individual characteristics, contextual factors, or environmental conditions. This approach has the potential to answer the question of "which strategy is more effective for which customer?", particularly in areas such as marketing campaigns, customer targeting, and communication channel selection (Künzel et al., 2019).

In recent years, causal machine learning methods have come to the forefront in predicting heterogeneous treatment effects. These methods can offer flexible predictions in high-dimensional and complex data structures without being bound by the linear assumptions of classical econometric models. In this context, Causal Forest and its more general framework, Generalized Random Forests, adapt random forest algorithms to the causal inference problem, making it possible to estimate the Conditional Average Treatment Effect (CATE) for each observation (Wager & Athey, 2018; Athey, Tibshirani, & Wager, 2019).

The main advantage of the Causal Forest method is that it directly places heterogeneity at the center of the model by dividing the data space in a way that maximizes the treatment effect. This feature enables the capture of nonlinear relationships and complex interactions frequently encountered in the marketing literature. Recent studies show that such methods provide reliable CATE predictions not only in simulation environments but also in real-world applications (Nie & Wager, 2021; Chernozhukov et al., 2018b).

In the marketing analytics literature, heterogeneous treatment effects are associated with uplift modeling and personalized targeting approaches. These studies demonstrate that considering individual marginal effects instead of average effects to determine who a campaign should be applied to yields more efficient results (Gutierrez & Gérardy, 2017; Bertsimas & Kallus, 2020). However, many applications in the uplift and CATE literature are limited in explaining the causes of heterogeneity, and the interpretability of model outputs stands out as a significant problem.

Therefore, in the current literature, not only estimating heterogeneous treatment effects but also explaining which variables drive this heterogeneity has become a critical research topic. Supporting causal machine learning models with interpretability increases the applicability of model outputs, especially in decision support-oriented fields such as marketing and banking. However, despite these methodological advances, empirical applications that analyze communication channel selection, heterogeneous treatment effects, and the macroeconomic context together in bank telemarketing remain limited.

This study examines the impact of communication channels in the context of banking telemarketing within the framework of CATE (Calculated Activity Efficiency Testing), revealing the existence of heterogeneous treatment effects using causal machine learning methods. In this respect, the study goes beyond the existing bank marketing literature, which focuses on average effects, and demonstrates how differentiated effects at the customer level can be integrated into decision support processes.

2.4. Role of Macroeconomic Context in Campaign Effectiveness

The effectiveness of marketing campaigns is not limited solely to customer characteristics and campaign design; the prevailing macroeconomic context directly influences individuals' financial expectations, risk perceptions, and consumption decisions. In recent years, the marketing literature has increasingly emphasized the role of macroeconomic indicators such as economic uncertainty, employment conditions, and interest rates on consumer behavior (Srinivasan and Hanssen, 2022; Kırmızıkaya, 2025).

Current studies reveal that macroeconomic conditions alter the marginal effects of marketing interventions. It has been shown that the additional contribution of marketing campaigns can be limited, particularly during periods of high economic confidence, while some marketing communication channels can produce relatively stronger effects during periods of uncertainty and economic contraction (Steenkamp and Fang, 2011; Lamey et al., 2012; Gharios and Abu Khalaf, 2024). These findings indicate that marketing strategies should be designed in a way that is sensitive to the economic context, not statically.

In the context of banking and financial services, macroeconomic indicators play an even more significant role in customer behavior. Employment levels and interest rates influence demand for deposit and investment products by shaping individuals' perceptions of income security and their savings tendencies. Recent empirical studies show that financial decisions are strongly correlated with macroeconomic expectations, and this relationship is reflected in the effectiveness of marketing campaigns (Gennaioli and Shleifer, 2018; Coibion et al., 2020).

Nevertheless, studies in the banking telemarketing literature that address the causal relationship between communication channel choice and macroeconomic conditions are quite limited. Most research includes macroeconomic variables only as control variables in the model, but does not examine in detail how these variables shape the effect of marketing interventions. This leads to the neglect of an important dimension of heterogeneity in campaign performance (Srinivasan and Hanssen, 2022).

This study examines how the effectiveness of the communication channel changes depending on economic conditions at the customer level by including employment level and financial environment indicators, which represent the macroeconomic context, in the causal analysis framework. In this respect, the study offers a current and original contribution to the banking marketing literature by addressing the relationship between macroeconomic conditions and operational marketing decisions from a heterogeneous treatment effects perspective.

3. Methodology

3.1. Research Framework

This study examines the impact of communication channel selection on customer subscription decisions in bank telemarketing campaigns within a causal machine learning framework. Unlike predictive machine learning models commonly used in the existing literature, this study defines the communication channel as a strategic intervention (treatment) variable and aims to causally predict the effect of this intervention on the outcome variable.

The analysis framework consists of three main stages. In the first stage, the average effect of the communication channel on the entire sample is estimated using the Double Machine Learning (DML) method. In the second stage, conditional mean treatment effects (CATE) are calculated through a Causal Forest model to reveal customer-level heterogeneities. Finally, SHAP-based interpretability analysis is applied to explain which variables shape the obtained CATE values.

3.2. Treatment, Outcome and Covariates

In the study, the choice of communication channel was defined as a binary intervention variable. Communication channels made via mobile phone were considered as the treatment group, and communication channels made via landline phone were considered as the control group. The outcome variable is a binary variable indicating whether the customer subscribes to the term deposit product or not.

To increase the validity of the causal inference, a high-dimensional set of covariates, including customer demographics, past campaign interactions, and macroeconomic indicators, was included in the model. These variables were considered as factors that could create potential confounder effects between the choice of communication channel and customer behavior. Considering that the communication channel is not randomly assigned and may be related to customer characteristics, campaign dynamics, and macroeconomic conditions, potential confounder variables that could affect both treatment assignment and outcome were included in the model. In this context;

- Demographic variables (e.g., age),
- Campaign dynamics (e.g., campaign, days since last contact),
- Previous campaign results (outcome of the previous campaign and related variables),
- Macroeconomic context indicators (employment level, short-term interest rate, consumer price index, employment variation rate, consumer confidence index)

were used as covariate sets. The duration variable in the dataset contains information generated after customer communication channel, therefore it carries a risk of information leakage in causal analysis. For this reason, this variable was excluded from the analysis and the models were built only on variables known before communication channel. Categorical

variables were digitized using the one-hot encoding method, and the final feature matrix was converted into a 60-dimensional representation.

3.3. Estimation of Average Treatment Effects: Double Machine Learning

The mean treatment effect of the communication channel was estimated using the Double Machine Learning (DML) method. The DML approach is a semi-parametric method that aims to consistently obtain causal effect estimates even under high-dimensional covariate sets. In this approach, separate machine learning models are established for outcome and intervention variables, and the biases estimated through these models are eliminated.

The DML method, developed by Chernozhukov et al. (2018b), combines the predictive power provided by flexible machine learning models with econometric causal inference principles. In this way, model misidentification problems encountered in classical regression-based approaches are significantly reduced. In this study, the DML method was used to reliably estimate the mean effect of the communication channel.

3.4. Estimation of Heterogeneous Effects: Causal Forest

To analyze customer-level heterogeneities by going beyond average effect estimates, the Causal Forest model was used. Causal Forest is a version of the random forest algorithm adapted to causal inference, aiming to reveal how treatment effects vary for different customer groups.

Developed by Wager and Athey (2018), this method allows for the estimation of conditional average treatment effects for each observation by dividing the sample space in a way that maximizes the differences in treatment effects. This approach is particularly important in marketing applications for answering the question of "which customers are more effectively treated". In this study, customer-level CATE values of the communication channel were calculated using the Causal Forest model.

3.5. Explaining Treatment Effect Heterogeneity: SHAP Analysis

To improve the interpretability of CATE values obtained with the Causal Forest model, SHAP (SHapley Additive exPlanations) based explanation analysis was applied. The SHAP method is a game theory-based approach that calculates the marginal contribution of each variable to the model output.

Developed by Lundberg and Lee (2017), the SHAP framework allows for the transparent interpretation of complex machine learning models. In this study, a surrogate model representing CATE predictions with high accuracy was trained, and the customer characteristics and macroeconomic factors shaping the effectiveness of the communication channel were analyzed through SHAP values. This approach aims to reveal not only the existence but also the causes of causal effect heterogeneity.

In the final stage of the study, the SHAP method was used to explain the sources of CATE heterogeneity beyond classical prediction explanation. Accordingly, CATE values obtained with the Causal Forest model were taken as target variables, and a surrogate model that relearns these values with high accuracy was established. The performance of the surrogate model trained using the Random Forest Regressor was obtained as $R^2 = 0.993$ and MAE = 0.0029. This high accuracy indicates that the explanations obtained via SHAP reflect the true heterogeneity of the structure.

3.6. Methodological Contribution

This methodological framework goes beyond the predictive approaches commonly used in bank telemarketing literature by considering both the average and customer-level causal effects of the communication channel. Furthermore, the integrated use of causal machine learning and interpretable artificial intelligence methods provides a more transparent and applicable analytical infrastructure for marketing decision support processes.

4. Results

4.1. Average Treatment Effect Results

The Average Treatment Effect (ATE), estimated using Double Machine Learning (DML), shows the average effect of mobile phone (cellular) communication channel on the probability of customer subscription across the entire sample. The ATE value was calculated as -0.0068. This value suggests that mobile phone communication channel may be associated with a rather limited effect of approximately -0.68 percentage points on the probability of subscription.

However, the inclusion of zero in the 95% confidence interval (95% CI: [-0.0460, 0.0323]) limits the ability to make clear claims about the direction and magnitude of the average effect. Furthermore, a warning was received in the model output indicating that the covariance matrix could not be fully determined, suggesting that standard error-based inferences and confidence interval interpretations should be approached with caution. Therefore, the ATE result obtained with DML does not provide convincing evidence that the communication channel has a strong and homogeneous effect on the entire customer base.

This finding suggests that the effect of the communication channel may be heterogeneous at the customer level. Indeed, when evaluated together with the results revealed by the Causal Forest analysis, it is seen that mobile phone communication channel had a negative impact in a significant portion of the observations (14.5%). The concentration of positive and negative effects in different customer segments leads to the average effect remaining relatively small and uncertain. This situation shows that ATE alone is not a sufficient indicator for policy or operational decisions; however, conditional mean treatment effects (CATE) and segment-based heterogeneity are much more informative in terms of decision support.

4.2. CATE Distribution and Heterogeneity

The Conditional Average Treatment Effects (CATE) estimated by the Causal Forest model reveal that the effect of the communication channel differs significantly depending on customer profiles and contextual conditions. The CATE distribution presented in Figure 1 shows that although the treatment effects are concentrated just above zero, they exhibit a wide spread in both directions. This finding clearly demonstrates that the effect of the communication channel is not homogeneous and has a strong heterogeneity structure at the customer level.

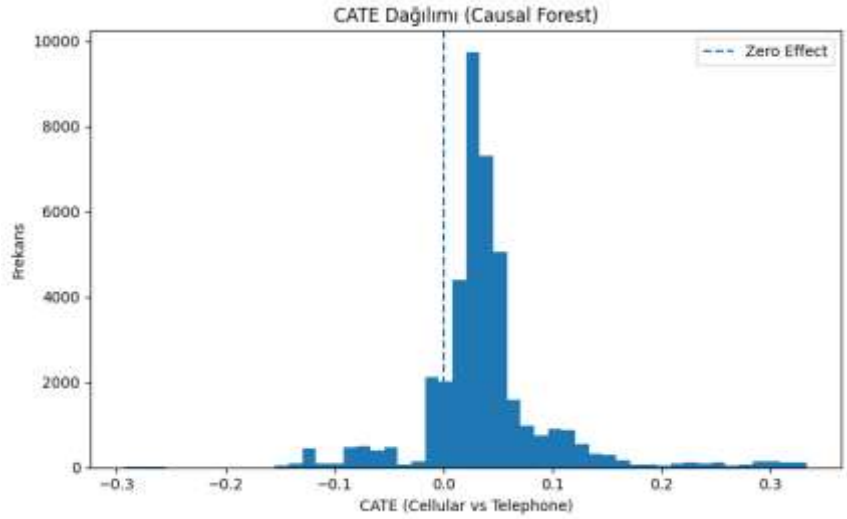

Figure 1. Distribution of conditional mean treatment effects (CATE) estimated using the Causal Forest model.

The mean of the CATE distribution was calculated as 0.0375. This value indicates that mobile phone communication channel can produce an effect of approximately +3.75 percentage points on average, being stronger in some customer segments. However, when the percentages of the distribution are examined, it is seen that the treatment effects vary over a fairly wide range. In the lower 5%, the CATE value drops to approximately -0.060; this shows that under certain customer and period conditions, mobile phone communication channel can reduce the probability of subscription by approximately 6 percentage points. The median CATE value is approximately 0.032, indicating that the effect is positive but moderate for most customers. In the top 95%, the CATE value reaches approximately 0.131, showing that in some segments, mobile phone communication channel can increase the probability of subscription by up to 13 percentage points.

A more detailed examination of the CATE distribution reveals that the treatment effect is heterogeneous not only in magnitude but also in sign. According to the analysis results, the CATE value is negative in approximately 14.5% of the observations. In this negative effect group, the average CATE value was calculated as approximately -0.044. In other words, in this customer segment, mobile phone communication channel reduces the probability of term deposit subscription by an average of 4–5 percentage points compared to landline communication channel. This result shows that the communication channel can have not only a weak but also a negative effect under certain conditions.

When these findings are considered together, it becomes clear that summarizing the effect of the communication channel with a single average value is significantly limited. Even if the average treatment effect appears small or indistinct, the CATE distribution reveals that channel selection can be quite beneficial in some customer segments and clearly detrimental in others. Therefore, instead of implementing a "uniform" communication channel strategy in telemarketing campaigns, a segment-based channel planning approach that is sensitive to customer profiles and contextual conditions is considered far more suitable for decision support.

4.3. Macroeconomic Context and CATE

Figure 2 shows the average CATE values at different levels of the employment level variable, representing the macroeconomic context. The graph clearly reveals that changes in

employment levels play a systematic role in the causal effect of the mobile phone communication channel channel.

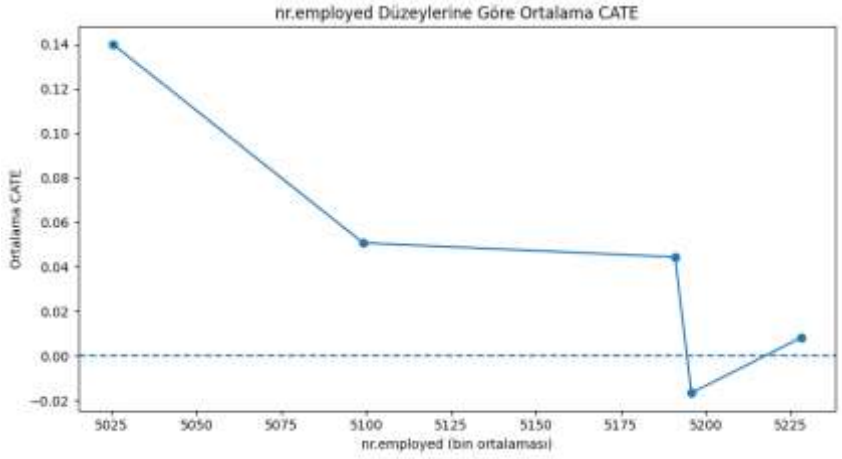

Figure 2. Average CATE values at different levels of the employment level variable.

At low and medium levels of employment level, the average CATE values of mobile phone communication channel are positive and relatively high. This suggests that customers may be more responsive to direct and personal communication channels during periods of lower employment. Conversely, it is observed that the average CATE approaches zero or falls into negative values in certain intervals where the employment level value increases.

This finding shows that the effectiveness of mobile phone communication channel depends not only on individual customer characteristics but also on macroeconomic conditions. In particular, during periods of high employment levels, the marginal contribution of mobile phone communication channel weakens and can have a negative effect in some cases. Therefore, it is concluded that the choice of communication channel should be designed in a way that is sensitive to the macroeconomic context, rather than as a fixed strategy.

4.4. Explaining CATE Heterogeneity via SHAP

Figure 3, a summary graph of the global SHAP, shows that defining the communication channel in a 'uniform' manner can limit campaign effectiveness. Even if the average effect appears small or unclear, the fact that mobile phone communication channel negatively impacts approximately one in seven customers reveals that channel selection should be optimized in a way that is sensitive to customer profile, campaign history, and macroeconomic conditions.

Figure 3 shows the summary graph of the global SHAP calculated through the surrogate model, which takes the CATE values obtained with the Causal Forest model as the target variable. The graph reveals that the main variables explaining the heterogeneity in the effect of the communication channel (mobile phone vs. landline phone) are mainly macroeconomic context indicators and campaign dynamics. Among the variables with the highest SHAP significance are employment level, consumer price index, and short-term (euribor3m) interest rate. This finding shows that the effectiveness of the communication channel is strongly sensitive not only to customer demographics but also to the economic conditions of the period in which the campaign is conducted.

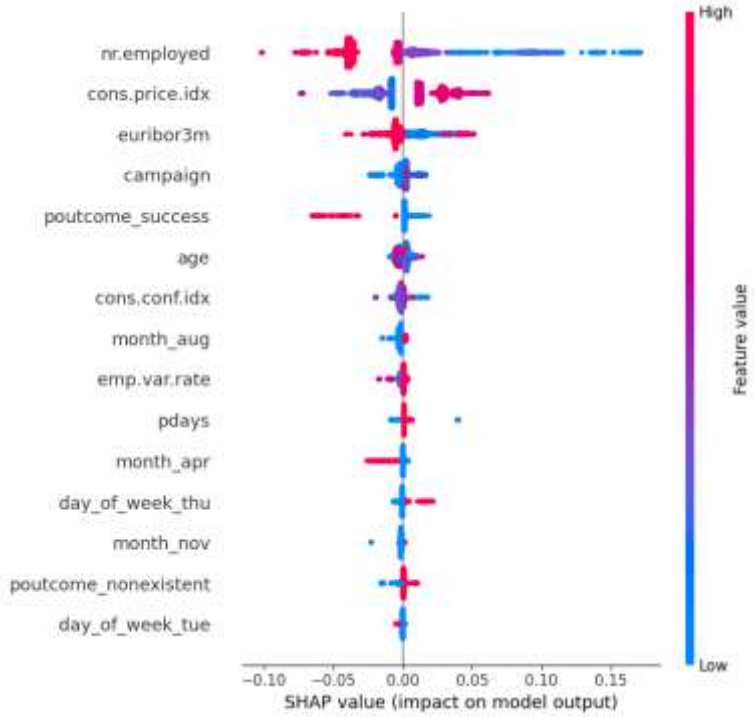

Figure 3. Summary graph of the global SHAP (Conditional Mean Treatment Effect) calculated for the entire sample, showing the variables explaining the conditional mean treatment effect (CATE).

Considering the color scale, it is seen that high values of some macroeconomic variables have a reducing effect on CATE, while low values have an increasing effect. In addition, variables representing campaign history, such as number of contacts in the current campaign, output Fsuccess, and days since last contact, also make significant contributions to CATE. These results reveal that the impact of the communication channel exhibits a multidimensional structure and is shaped by both the economic context and customer-campaign interactions.

Figure 4 shows the SHAP results for the customer segment located in the upper tier of the CATE distribution, where mobile phone communication channel generated the highest positive impact on the probability of term deposit subscriptions. In this segment, the SHAP values of the variables employment level, consumer price index, and short-term (euribor3m) interest rate show a significant divergence. The findings indicate that the effect of mobile phone communication channel is significantly strengthened under specific macroeconomic conditions.

Furthermore, the upward influence of variables such as outcome of the previous campaign success and campaign on CATE in this segment suggests that mobile phone communication channel is more effective with customers who have previously responded positively to campaigns and have been exposed to specific campaign intensities. These results demonstrate that the success of a communication channel depends not only on customer characteristics but also on past interaction and contextual information.

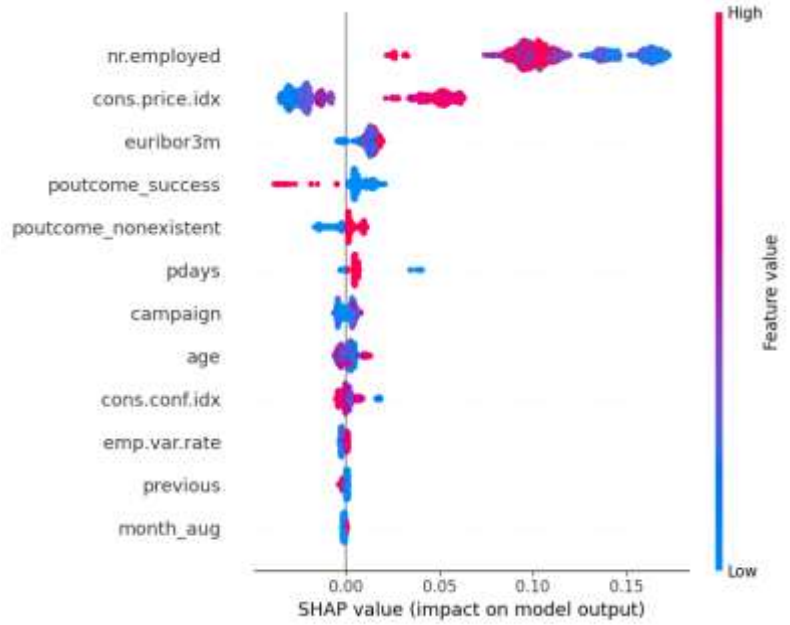

Figure 4. SHAP summary graph for the customer segment with high CATE values.

Figure 5 presents the SHAP results for the customer segment where the impact of mobile phone communication channel is weak or negative. The direction and intensity of SHAP effects in this segment differ significantly from the high-impact group presented in Figure 5. In particular, some macroeconomic variables and campaign dynamics appear to be concentrated in a direction that pulls CATE down.

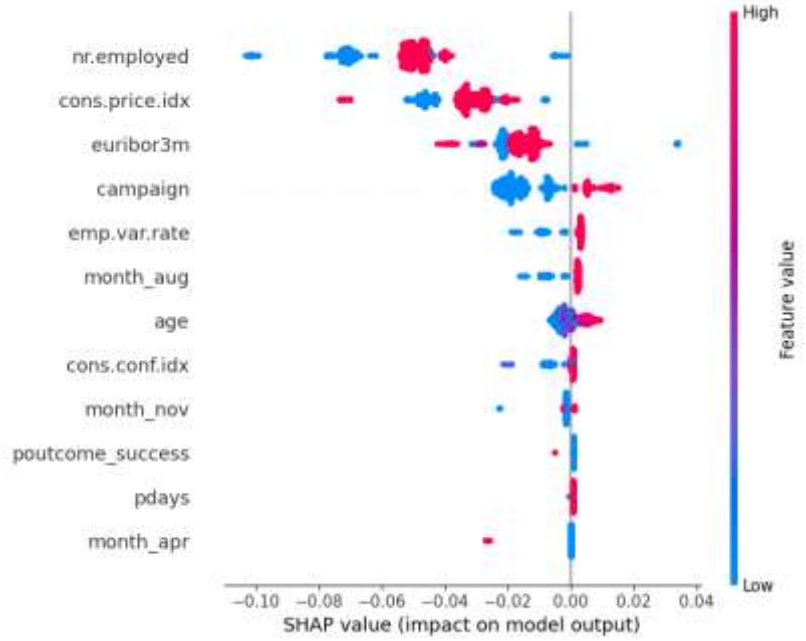

Figure 5. SHAP summary graph for the customer segment with low and negative CATE values.

These findings are consistent with CATE results showing that for approximately 14.5% of customers, mobile phone communication channel reduces the probability of subscription by an average of 4–5 percentage points compared to landline communication channel. Therefore, the impact of the communication channel is not only weakened but can also work in the opposite

direction under certain conditions. This clearly demonstrates that channel selection should be optimized on a segment-by-segment basis, considering customer profile, campaign history, and economic context, rather than a uniform policy.

5. Discussion

This study goes beyond the predictive approaches commonly used in the banking telemarketing literature by examining the impact of communication channels on customer behavior within a causal and heterogeneous framework. The findings show that the impact of communication channels varies significantly depending on customer profiles and the macroeconomic context, and that this heterogeneity cannot be understood by looking only at average effects.

The analysis results reveal that the mean treatment effect (ATE) indicates a limited and, in some cases, weak effect, while conditional mean treatment effects (CATE) exhibit significant differences at the customer level. This finding supports the idea that uniform campaign strategies, frequently used in the marketing literature, are not equally effective for every customer segment. In particular, the fact that the impact of the communication channel is negative or negligible in some customer groups reveals that making intervention decisions based on average effects carries strategic risks.

The CATE distributions obtained with the Causal Forest model show that the impact of the communication channel is concentrated in certain segments and that this concentration exhibits a heterogeneous structure. These results are consistent with the current causal machine learning literature focusing on heterogeneous treatment effects. As highlighted in the literature, the success of marketing interventions often depends on the question of "to whom they are applied," and the findings of this study empirically support this approach in the context of banking telemarketing.

When examining the impact of the macroeconomic context, it is observed that indicators such as employment levels significantly shape the marginal effect of the communication channel. It was found that the CATE values of the communication channel were relatively low, particularly during periods of high employment levels; conversely, the effect strengthened in some customer segments during more uncertain or weak economic conditions. This finding demonstrates that marketing interventions cannot be considered independently of the economic conjuncture and that campaign strategies should be contextually adapted.

The results question the approach in the banking marketing literature that generally treats macroeconomic variables as control variables. This study reveals that macroeconomic conditions should be considered not only as fixed effects but also as conditioning factors shaping the effectiveness of the communication channel. In this respect, the findings support calls for marketing decisions to be considered within a contextually sensitive and dynamic framework.

One of the significant contributions of this study is demonstrating the applicability of causal machine learning methods in the context of banking telemarketing. This study clearly shows that the results offered by models with high predictive accuracy may be limited in terms of decision support unless supported by causal interpretability. CATE-based analyses provide marketing managers with a more meaningful decision-making framework, showing not only which customers will respond, but also which customers the intervention is truly effective for.

Finally, these findings challenge the common practice of treating communication channels as neutral predictors rather than strategic interventions, and offer important managerial implications for banking applications. Instead of applying the same communication channel to

all customers, developing targeted strategies that consider customer profiles and the economic context can increase campaign effectiveness and resource utilization efficiency. In this context, causal and heterogeneous effect analyses can contribute to the creation of more sustainable and effective decision-making mechanisms in banking marketing.

6. Conclusion

This study goes beyond the predictive approaches commonly used in banking telemarketing literature by examining the impact of communication channels on customer behavior within a causal and heterogeneous framework. Analyses conducted using open-access bank marketing data revealed that the impact of communication channels is not homogeneous for all customers; rather, it varies significantly depending on customer characteristics and the macroeconomic context. These findings suggest that assessments based solely on average effects can be limited and potentially misleading for marketing decisions.

Results obtained using causal machine learning methods revealed that while the average treatment effect (ATE) of the communication channel is relatively weak, conditional average treatment effects (CATE) are significantly concentrated in certain customer segments. This indicates that campaign strategies should be designed in a segment and context-sensitive manner, rather than with a "one-size-fits-all" approach. The fact that the impact of communication channels is negative or negligible in some customer groups suggests that implementing marketing interventions without proper targeting can lead to resource waste.

The study also identified macroeconomic context as a significant factor shaping the effectiveness of communication channels. Macroeconomic indicators such as employment levels influence customers' financial expectations and risk perceptions, thereby altering the marginal impact of marketing communication channels. The findings show that the effectiveness of communication channels can weaken during periods of favorable economic conditions; conversely, in more uncertain economic environments, the effect can strengthen in certain customer segments. These results highlight that banking marketing strategies cannot be considered independently of economic conditions and that campaign design must be context-sensitive.

In this context, the study offers important implications for banking practices. Instead of basing marketing decisions solely on models with high predictive accuracy, using analyses that focus on causal effects and consider customer-level heterogeneity can contribute to the development of more effective and efficient campaign strategies. Determining which customer segments and under which economic conditions a communication channel is truly effective can both increase campaign success and allow for more rational use of marketing budgets. In this respect, causal machine learning approaches offer a powerful tool for decision support processes in banking marketing.

The study also has some limitations. Since the analyses are based on an observational dataset, causal inferences should be evaluated within the framework of the assumptions of the methods used. Furthermore, the dataset is limited to a specific country and period; studies with datasets encompassing different economic conditions, countries, or communication channels could increase the generalizability of the findings. Further studies that address the time dimension in more detail, examine multiple intervention scenarios, and compare different marketing channels will contribute to further developing the framework presented in this study.

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