The Effect of Personal Selling on Customer Conversion under Partial Compliance

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The Effect of Personal Selling on Customer Conversion under Partial Compliance

Personal selling is crucial for business growth, prompting companies to invest significantly in their sales forces. However, measuring the effectiveness of personal selling poses significant challenges due to selection bias introduced by firms' strategic targeting. Moreover, the perception of personal selling as intrusive often leads majority of targeted customers to avoid engagement, resulting in further consumer-side selection bias. This study aims to evaluate the effectiveness of personal selling using observational data, controlling for both selection biases arising from firms' targeting policies and consumer partial compliance. We employ propensity score matching to construct comparable groups of targeted and non-targeted consumers. Subsequently, we apply an instrumental variable approach, with targeting status serving as the instrument for treatment, to infer the effects of personal selling. Focusing on the impact of phone calls from representatives, a form of personal selling, in the prescription delivery service market, we find that phone calls do encourage conversion. However, the effectiveness of personal selling is significantly underestimated when not correcting for selection bias due to partial compliance. Our findings suggest that personal selling should specifically target inexperienced consumers and that firms should prioritize strategies to enhance compliance among targeted individuals.

Keywords: personal selling, partial compliance, targeting prescription delivery
Track: Sales Management and Personal Selling

1. Introduction

Personal selling is a critical component of the marketing mix across industries like hospitality, insurance, telecommunications, and pharmaceuticals, with firms in the U.S. spending over $800 billion annually on sales teams—almost three times the amount spent on advertising. Despite this significant investment, measuring the effectiveness of personal selling is complex due to the use of multiple marketing channels and the challenges posed by targeting strategies. Companies typically target the most likely customers to convert, creating selection bias between targeted and non-targeted consumers. Additionally, consumer-side biases, such as partial compliance, further complicate evaluations. Partial compliance occurs when consumers ignore or refuse sales efforts, leading to systematic differences between those who engage and those who do not. This is especially problematic in personal selling, where noncompliance rates are high—over 80% of sales calls go unanswered.

Although partial compliance has been addressed in other fields like economics and biostatistics (Abadie et al., 2002; Angrist et al., 1996), it remains underexplored in marketing. This paper aims to fill this gap by using observational data to examine the true impact of personal selling, accounting for both firm-side and consumer-side biases and providing a more accurate assessment of its effectiveness and financial implications for firms.

2. Empirical Method

We present the econometric model to address the selection bias issue that arises from a firm's targeting policy and customer's partial compliance, within the broader context of the general marketing activities, rather than solely focusing on personal selling. Define I_i as the target status of individual i, which is equal to 1 if the individual is targeted by the marketing activity, and 0 otherwise. Further, define C_i as the compliance indicator of the individual, which is equal to 1 if the individual, conditional on being targeted, chooses to be exposed to the marketing activity, and 0 otherwise. The treatment status of the individual, T_i, can be written as $T_i = I_i \times C_i$,[1] meaning, the individual is treated only if they are targeted ($I_i = 1$) and choose to comply ($C_i = 1$). The

[1] The value of C_i does not matter if $I_i = 0$. For simplicity, we assume that $C_i = 0$ if i is not targeted.

outcome variable y_i represents the individual's response (e.g., conversion), which is specified as the following:

$$y_i = f(\alpha + \gamma \cdot T_i + \beta \cdot X_i + e_i) \tag{1}$$

where f is a general function, X_i a set of observed covariates (e.g., demographics and past purchase history), and e_i an error term capturing the unobserved factors that affect the individual's decision. The parameter of interest is γ, representing the treatment effect, that is, the impact of the marketing activity.

Assuming that there is full compliance (i.e., $T_i = I_i$), equation (1) simplifies to:

$$y_i = f(\alpha + \gamma \cdot I_i + \beta \cdot X_i + e_i) \tag{2}$$

However, as the firm strategically selects customers for the marketing activity, selection bias emerges, such that $E[e_i|I_i = 1] \neq E[e_i|I_i = 0]$. One way to address the issue is matching: for each targeted individual i, find a non-targeted individual j with observed characteristics similar to those of i. That is, $Z_i \cong Z_j$ where Z_i and Z_j are the observed characteristics of i and j, respectively. After matching, the necessary condition is $E[e_i|I_i = 1, Z_i] = E\left[e_j|I_j = 0, Z_j\right]$, which ensures that Rosenbaum and Rubin's (1983) SITA condition is satisfied. This allows for an unbiased estimate of γ from equation (2). However, when Z_i involves high dimensions, direct matching based on Z_i may not be feasible, and PSM is often used. In PSM, the propensity score $s_i = g(Z_i)$ represents the probability of individual i being selected for targeting, where g is a general (e.g., logit) function. Matching is then performed based on the propensity score, and the identification assumption is $E[e_i|I_i = 1, s_i] = E\left[e_j|I_j = 0, s_j\right]$.

In case of partial compliance, where a substantial proportion of targeted individuals have $C_i = 0$, meaning that $T_i < I_i$, identifying the treatment effect γ becomes more complex. This is due to potential systematic differences between compliers (i.e., $C_i = 1$) and non-compliers (i.e., $C_i = 0$) among targeted individuals, even when the SITA condition holds. Thus, estimating equation (1) from a direct comparison of treated and non-treated individuals will give a biased estimate of γ.

To address this issue, we deploy a two-step method. In the first step, we apply PSM to match each targeted individual with a non-targeted individual based on observed characteristics Z_i that are relevant to how a firm chooses whom to target, as well as patient and claim characteristics. In the second step, we use the targeting assignment (I_i) as an instrumental variable for the treatment status, T_i, in the estimation of equation (1).

We argue that I_i is a valid instrument for T_i for two main reasons because it satisfies the relevance condition (i.e., T_i can only equal to 1 if I_i=1) and the exogeneity condition, assuming the SITA condition holds. However, in the empirical application, it is critical to ensure that the *exclusive restriction* condition holds—that is, the targeting status I_i should not directly affect the outcome variable y.[2] We will provide more details on this in Section 4.

Assuming the above conditions are satisfied, equation (1) can be estimated using the matched sample by the control function approach. We begin by estimating the first stage regression where T_i is regressed on I_i and other observed variables X_i in equation (1) using a linear probability model:

$$T_i = \lambda_0 + \lambda_1 I_i + \lambda_2 X_i + \zeta_i \tag{3}$$

In the second stage, using the control function method, we plug the estimated residual $\hat{\zeta}_i$ from the first-stage regression into a logit probability function to account for the potential correlation between T_i and the error term e_i in equation (1).

The IV method eliminates the need for additional matching between compliers and non-compliers, which would require identifying characteristics affecting compliance and estimating a separate propensity score. This additional matching can be challenging, as it demands extra data and must satisfy a further SITA condition, potentially reducing the sample size and precision of the treatment effect estimate (γ). The proposed two-step approach, combining Propensity Score Matching (PSM) with instrumental variables, provides a more efficient and feasible solution for estimating the true treatment effect in complex marketing contexts.

3. Empirical Application

3.1. Personal Selling and Other Communications

This study examines the effectiveness of personal selling via phone calls, to encourage patients to switch from pharmacy pick-up to home delivery for medications, employed by one of the largest Pharmacy Benefit Managers (PBMs) in the U.S., which offers home delivery services for medications. The company facilitates home delivery services by leveraging its access to comprehensive health records via employer contracts. These records include prescription, insurance, and medical

[2] For example, suppose we re-specify as $y_i = f(\alpha + \gamma \cdot T_i + \beta \cdot X_i + \rho \cdot I_i + e_i)$. The coefficient ρ is equal to zero.

information, enabling the company to track patients' medication regimens and calculate the expected incremental profit (i.e., profit score) from converting a patient to home delivery. This score guides the targeting of communication campaigns, tailored to different patient segments.

The communication campaign employs tailored messaging for different patient segments. For *low-cost savers* (i.e., who can save less than a certain amount in a quarter[3]), the company highlights the nonmonetary benefits of home delivery, including avoiding trips to the local pharmacy, the quality of the service, and 24/7 pharmacist consultations. In contrast, for *high-cost savers* (who can save more than the low-cost savers in a quarter), the monetary benefit receives greater emphasis. A mix of communication channels, including emails, letters, and phone calls, is used, with the channel choice primarily dependent on the patient's profit score. Patients with positive profit scores typically receive emails, while those in the most profitable group receive both letters and emails. Phone calls are reserved for patients who meet two criteria: their profit score must exceed a specific threshold, and they must be eligible for calls based on patient and claim characteristics, including prior communications and potential savings.

Phone calls are considered highly effective in converting patients due to their personal nature, but they are expensive in terms of time and resources. Therefore, the company employs a prioritization strategy. Patients are contacted first based on how long they have been on the call list, then by their profit score. The company attempts to reach out to patients within two months, and if no contact is made within this window, patients are removed from the call list. However, the prioritization strategy does not account for the likelihood of a patient converting, due to the lack of detailed predictive models. Furthermore, because the number of available representatives fluctuates based on call volume, the actual targeting process may vary, leading to discrepancies between the planned and actual groups contacted. This institutional detail is important for our PSM to work. We view these fluctuations in the representative availability as exogenous shocks. When two patients have identical profit score and similar claim and patient characteristics but are targeted differently, this discrepancy can be attributed to these exogenous shocks. By matching such pair in our analysis, we ensure that the necessary SITA condition for PSM will hold.

We focus on personal selling as a key method for promoting home delivery services, leveraging phone call data to differentiate between patients who respond (compliers) and those who do not (non-compliers). The primary goal is to assess the effect of partial compliance. The study identifies two communication strategies involving personal selling: (1) email + phone call and (2) email + letter + phone call. Patients are considered targeted if they receive personal

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[3] To maintain data confidentiality, numbers that are sensitive to the company are not disclosed.

selling, and treated if they answer the phone call. To measure the marginal effect of personal selling, the email-only group serves as the control for the email + phone call group, and the email + letter group is the control for the email + letter + phone call group.

Although the communication timing varies, patients generally receive an email first, followed by a letter within a few days after the patient picks up the first medication from a local pharmacy. However, the timing of the phone calls depends on the availability of representatives. Since the patients typically receive the phone calls after the emails and letters, the effects of personal selling examined in this study should be viewed as marginal effects.

3.2. Data and Matching

Patients are considered converted if they switch from pharmacy pick-up to home delivery for at least one of their prescribed drugs within three months of being targeted by marketing communications. For each patient, we collect data on the communications used for targeting and whether or not the patient is converted. To match the targeted (those in the email + phone call or email + letter + phone call groups) and the non-targeted (those in the email only or email + letter groups), we use several key variables. The primary variable is the profit score (*Profit Score*) calculated by the company for each patient, which is a crucial factor in targeting decision. In addition , we collect demographics, the previous communications, claims history, and potential savings.

A logistic regression model is employed to predict propensity scores based on these variables. The matching process uses 1:1 nearest neighbor matching, ensuring a small difference in propensity scores (less than 0.001) between targeted and non-targeted patients. This method controls for covariates, allowing any remaining discrepancy in targeting to be attributed to exogenous shocks, like fluctuations in call center availability.

After matching, the full sample consists of 78,409 patients who were approached as part of at least one of the company's marketing campaigns from July 2019 to June 2020.[4] After matching, the sample used for the analysis consists of 843 pairs of patients in the email only and email +

[4] To separate the effect from the previous marketing communications, we exclude patients who received any communication from the company within six months before the sample period started. We also exclude those who have used the home delivery service for the same drug in the past.

phone call groups and 760 pairs in the email + letter and email + letter + phone call groups. In the matched sample, compliance with phone calls is relatively low, ranging from 15% to17%, suggesting that noncompliance could significantly impact the observed effectiveness of personal selling.

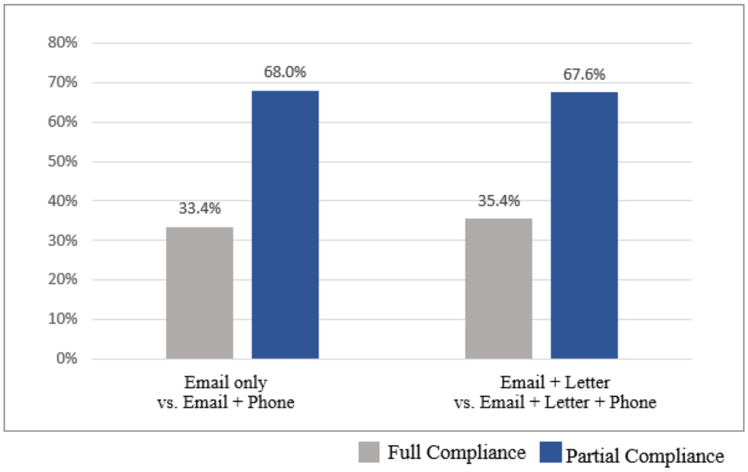
4. Results of the Estimations

4.1. Full compliance and partial compliance

After constructing the matched sample, we estimate the treatment effect of phone calls, considering that the effectiveness of phone calls may vary depending on the other communication channels used. To capture this variation, we conduct two separate comparisons: (1) the email-only group versus the email + phone call group, and (2) the email + letter group versus the email + letter + phone call group. Furthermore, to address the impact of partial compliance on personal selling, we estimate two different model specifications: (1) a logit model under the full compliance assumption (i.e., $T_i = I_i$), consistent with the standard practices that often overlook the noncompliance issue in evaluating marketing activities, and (2) the proposed method, which accounts for partial compliance and uses targeting status as an instrumental variable.

In our proposed model specification, a key concern is whether fluctuations in call center representative availability, such as seasonality or health shocks, might be correlated with conversion propensity, violating the necessary conditions for valid matching. To address this, the study includes fixed effects for year and month to control for seasonal effects. It also argues that time-varying health shocks are unlikely to affect patients with chronic diseases. Additionally, the study ensures that targeting status does not directly influence conversion outcomes, as the phone calls are automated and do not leave messages, mitigating potential bias and validating the use of targeting status as an instrumental variable. Figure 1 illustrates the percentage changes in the conversion rates of treated patients relative to those of the non-treated patients, based on the two mode estimation results. The “Full Compliance” model shows that personal selling increases the predicted conversion rate by about 33%–35%. However, after correcting for selection bias, the predicted increases go up to 68% (67.6%) for the email only group (email + letter group)—representing an increase of about 100%. This highlights that considering partial compliance is critical to measuring the true effectiveness of personal selling.

Figure 1. Percentage Increase in Conversion Rates from Personal Selling



4.2. The impact of noncompliance on the effectiveness of personal selling

In this subsection, we investigate how customer noncompliance affects the effectiveness of personal selling. Using the estimates from our proposed method, we calculate the changes in conversion rates and net profits if all patients comply, relative to when there are no phone calls. To address the impact of phone call on firms' profit, we follow the method adopted by the company to measure the profit. Revenue is calculated using the average margin from one home delivery ($Avg\ Margin$) and the number of future deliveries expected if a patient is converted ($Future\ Orders$). Based on company's practice, we assume that $Future\ Orders$ does not vary across various communication channels. The cost includes two components: (1) the fixed fulfillment cost ($Cost_{ful}$) for initiating each phone call, and (2) the cost of communication ($Cost_{comm}$). If the phone call is not answered, only the fulfillment cost ($Cost_{ful}$) applies. However, if non-treated patients are converted, additional inbound call costs ($Cost_{Inbound}$) apply when they contact the call center to initiate home delivery.

Net profit conditional on conversion is calculated as follows:

$$Net\ Profit = Avg\ Margin \times (1 + Future\ Orders) - Cost^{5} \tag{5}$$

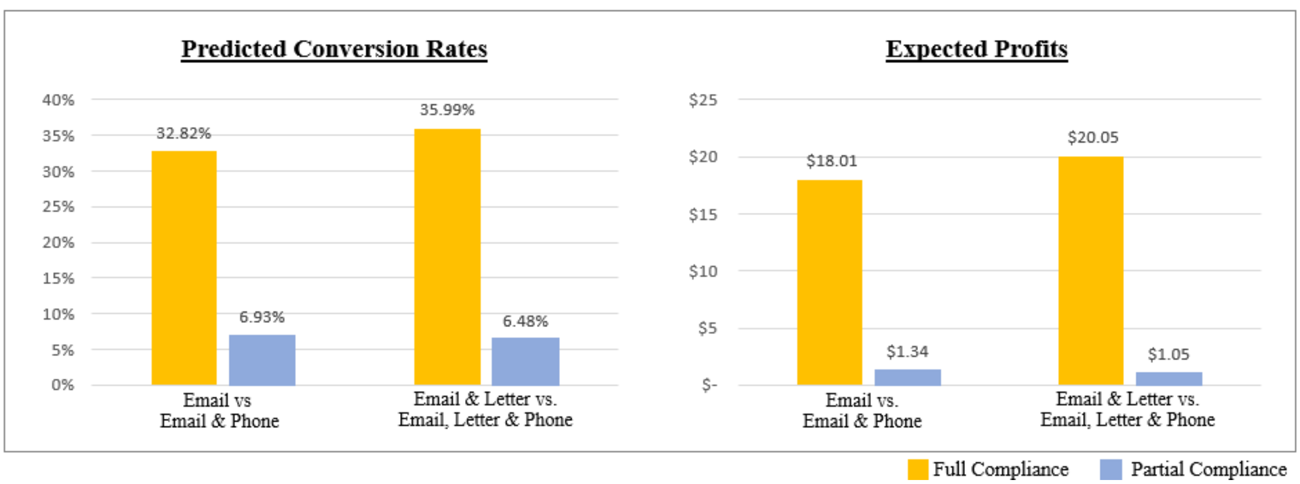
where $Cost$ is the sum of $Cost_{ful}$ and $Cost_{comm}$ for the treated patients, and the sum of $Cost_{ful}$ and $Cost_{Inbound}$ for the non-treated patients.

[5] To preserve data confidentially, we cannot reveal these numbers in this paper.

We compare the effects of phone calls under the full and partial compliance, illustrated in Figure 2. Given the 15%–17% compliance rate, phone calls increase conversion rate by 6.93% and 6.48% relative to the email only group and email + letter group, respectively. If there is full compliance, the company can expect about 4.7 times (i.e., 32.82%/6.93%) and 5.6 times (i.e., 35.99%/6.48%) more conversions. Full compliance also results in a more substantial increases in net profits. For example, while partial compliance leads to an increase in net profit of $1.34 ($1.05) in the email + phone group (email + letter + phone group), full compliance would result in a net profit increase of $18 ($20). This suggests that about 93%–95% of the potential net profit gains are lost due to noncompliance.

Our results highlight that the company should focus on encouraging customer compliance to improve the effectiveness of personal selling. To boost compliance, the company could consider strategies such as offering coupons or gifts to incentivize targeted patients to engages with representatives. To make sure targeted patients are aware of the incentives, the company can highlight such incentives in the emails and/or letters that are sent to the patients before initiating phone contact.

Figure 2. Effects of Phone Calls When Compliance is Full or Partial



5. Conclusion

This paper explores how to measure the effectiveness of personal selling in the prescription delivery service market, addressing challenges like selection bias from firms' targeting policies and partial compliance among consumers. The methodology involves two key steps: (1) using propensity score matching (PSM) to create comparable groups of targeted and non-targeted consumers, and (2) employing an instrumental variable (IV) approach, with targeting status as the instrument, to infer causal effects.

The study finds that personal selling via phone calls encourages patients to switch from pharmacy pick-up to home delivery. However, the impact is reduced due to partial compliance, as many patients avoid answering calls. The results also show that the effectiveness of personal selling is underestimated if partial compliance is not corrected for.

The paper contributes to the personal selling literature by emphasizing the importance of addressing customer noncompliance, which is often overlooked but critical for assessing personal selling effectiveness. It also highlights the need for firms to prioritize engaging with consumers unfamiliar with the service for better outcomes. The study has limitations, including data constraints on partial compliance, and suggests that future research should explore noncompliance in other marketing activities and how to encourage compliance. Further exploration of timing and other factors in personal selling is also encouraged.

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