Information Transparency and Customer Churn: Evidence from the Insurance Industry

Abstract

Customer churn (not renewing their contracts) is a major issue in the services industry. In this study, we examine the role of a price/service comparison website for car insurance services in customer churn. Two competing theories on information transparency inform this relationship, price elasticity (which induces churn) and high product informedness (which reduces churn). To address this tension, we used a unique dataset from a major European car insurance company to show that customers who are acquired by a price/service comparison website are 3% less likely to churn than customers from traditional channels, implying that transparency on price and service information helps to reduce customer churn. We also propose a randomized field experiment with actual customers of the car insurance company to corroborate our preliminary results. These findings contribute to the IS and Marketing literature by linking acquisition channels, information transparency, and customer churn, offering implications to managers to allocate resources to high information transparent channels to reduce customer churn.

Keywords: price/product comparison websites, information transparency, customer churn, price elasticity, product informedness, randomized field experiment

Introduction

Customer "churn" (not renewing term contracts) has been a major problem for firms in service industries, such as financial services, utilities, health care, telecommunications, and insurance (e.g., Neslin et al. 2006). A high churn rate often takes place in industries where information is highly transparent. Especially, price/service/product comparison websites (Smith and Brynjolfsson 2001; Smith 2002) in these industries seem to lower customers’ switching cost (Chen and Hitt 2006) for changing services providers. For instance, a car driver can easily access insurance quote comparison websites such as www.thezebra.com to compare insurance policies of different car insurance providers and decide which one to purchase, renew an existing contract, or to churn. Such comparison websites raise concerns for car insurance companies because
information transparency allows consumers to learn about competitors’ price and service offerings and motivate them to churn if they find cheaper or more attractive options. On the contrary, another company, Progressive (www.progressive.com), seems to have embraced the concept of information transparency, and it has adopted an aggressive marketing strategy by also displaying insurance services and price information of their competitors (Granados et al. 2010). It seems to attract customers, but does it help to retain them? Our study is thus motivated by a fundamental research question with practical implications for managers, do comparison websites help companies to retain their customers, or encourage their customers to churn?

To address this research question, we develop a theory based on information transparency literature and customer churn studies. First, the IS literature on information transparency (e.g., Granados et al. 2010, 2012) mostly focused on transparency on some information elements (e.g., price, product), and the effects of the strategic use of these information elements by companies on market competition and customer outcomes. Among these studies, a few of them have examined the impact of information transparency on demand (Chevalier and Goolsbee 2003; Ellison and Ellison 2004; Granados et al. 2009 and 2012). Granados et al. (2012) suggested that price transparency increases price elasticity of demand, while product information (or informedness (Li et al. 2014)) mitigates this effect. Our study seeks to extend this line of research by investigating whether price/service comparison websites affect customer churn, and how information transparency helps to inform this effect. Second, customer churn studies have been mostly focused on after-sales factors, such as customer service experience (Gustafsson et al. 2003), firm’s service recovery efforts (Jamal & Bucklin 2006) or situational, relational and influential triggers (Roos et al. 2004). The effects of before-sales factors, for instance, customer acquisition channels, on the churn rate have seldom been studied. Our study extends the “churn” literature by incorporating acquisition channels, and price/product comparison websites in particular, as predictors of churn.

Integrating the literature, we offer two competing hypotheses. On the one hand, high level of information transparency enabled by price/service comparison websites increases price elasticity (Granados et al. 2012). Customers are sensitive to price changes in the market, and a competitive market with dynamic price changes make customer churn frequently. Thus, we propose H1a, comparison websites induce customer churn. On the other, high level of information transparency provided by comparison websites increases customer informedness (Ting et al. 2014). By comparison websites, customers are well-informed about the product they chose and other offerings in the market. The rich information they obtained before purchasing a product makes them confident about their choices and unwilling to assume additional search efforts to make a decision. Thus, we also propose H1b, a price/service comparison website reduces customer churn.

In this paper, we examine the extent to which a comparison website affects the likelihood of customer churn in the auto insurance industry. Insurance companies acquire customers using both traditional channels (e.g., call centers, agents) and also digital channels (e.g., own websites, third-party price comparison sites). The degree of information transparency for both types of channels provides us the source of variation to understand how information transparency affects customer churn. Insurance products/service offerings in this industry are relative homogeneous across acquisition channels and companies, providing us a strong identification strategy with fewer potential confounding factors. Specifically, we used individual level dataset from a major European auto insurance company with 84,842 observations spanning 2008-2015. This dataset provides rich information about where customers come from (i.e., the acquisition channel), when they terminate their contract (churn), customer characteristics, car characteristics, and detailed information about their contracts.

To test the competing hypotheses, we initially adopted an identification strategy with the strict assumption that customers are as good as randomly assigned to acquisition channels, conditional on the characteristics of themselves, their cars, and their contracts. Under this assumption we used a linear probability model (Angrist and Pischke 2009) as our baseline specification. Then we challenged our assumption of exogeneity step by step. Since the assumption may be violated if there are systematic difference in those characteristics across customers, we used matching techniques (Rubin 1977, Heckman et al. 1998) to attenuate the potential self-selection bias. Moreover, to account for unobserved heterogeneity, we also conducted an Instrumental Variable (IV) analysis (Wooldridge 2010).

Using these econometrics methods, we found hypotheses 1b to be supported. The finding shows that customers who visit a price/service comparison website are more likely to be retained, by at least 3% compared to other channels. We found relative consistent results in terms of effect size and significance across different methods, however, to our surprise, our IV analysis shows a much larger effects of

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comparison websites, about 18.4% (more likely to retain customer). We were therefore very conservative to make a strong conclusion with these econometric results, and we seriously considered this source of unobserved bias and sought to find a remedy. It is plausible that endogenous issue could bias our results. For example, the dynamics of price competition in the insurance market and after-sales service quality for individual customers are not included in our analysis due to data availability, but these omitted variables may be correlated with both the churn likelihood and the idiosyncrasy of comparison websites. To address these potential concerns, in this research-in-progress, we propose a design of an ongoing randomized field experiment to uncover the causal effects of price/product comparison websites on customer churn.

Our initial findings have theoretical contributions and managerial implications. First, to our knowledge, this is the first study to investigate and quantify the relationship between price/service comparison websites and customer churn, providing evidence that such comparison websites may help to retain customers, thus extending the IS literature on acquisition channels, information transparency, and customer churn. Also, this study provides tangible guidance to managers on how to utilize transparency strategy, such as acquiring more customers from price/service comparison websites. In addition, since firms always face the question of which channel to invest and how much they should allocate their resources to different channels, our findings imply that firms should invest in information transparent channels, such as price/service comparison website, due to their effectiveness in retaining customers and reducing customer churn.

Related Literature

Customer Churn and Customer Retention

Our study is related to the literature on customer churn (e.g., Jamal & Bucklin 2006, Ahn et al. 2006) and customer retention (e.g., Bolton 1998, Gustafsson et al. 2005) in the marketing and IS literatures. These literatures aim to understand what drives customers to churn, and their main finding is that customer satisfaction (Gustafsson et al. 2003) is the dominant reason for retention. And situational, reactional and influential triggers (Roos et al. 2004), service quality and price (Granados et al. 2012) have significant effects on customers’ decision to churn or not. Among these studies, one stream uses statistical learning (e.g., Lemmens & Croux 2006) and data mining tools (Berry & Linoff 2004) to predict customer churn, while the other attempts to construct cognitive and behavior models to analyze customer retention or churn. Our study intends to theoretically expand and empirically test the prediction models of customer churn by incorporating acquisition channels and methodologically enrich these studies by combining econometrics analysis and experimental design to establish a link between comparison websites on customer churn.

Information Transparency and Online Channels

This study also relates to the IS literature on information transparency (e.g., Granados et al. 2010; Li et al. 2014). The information transparency literature (Granados et al. 2010) discusses how customer, sellers and market react to information transparency with different types (e.g., price/product/service transparency), and how sellers and intermediaries utilize transparency strategies to shape market competition and influence customer behavior. Moreover, some studies (e.g., Granados et al. 2012) looked at advanced applications in electronic markets that entail information transparency, especially for price transparency, which makes customer smarter (Granados et al. 2010). In addition, Li et al. (2014) argued that product informedness assists customers to purchase suitable products that better fit their needs so that the impact of price on customers’ purchase decision attenuates. These studies explain the effect of acquisition channels on customer behavior by using information transparency theory, and they extend the theory to understand how price/service comparison websites affect customers’ decision to churn.

Hypotheses Development

Drawing upon and integrating the literatures on customer churn and information transparency, we offer two set of justifiable explanations for the mechanisms that drives the effect of price/service comparison websites on customer churn, leading to two competing hypotheses. On the one hand, high level of information transparency provided by price/service comparison websites increases price elasticity (e.g., Granados et al. 2012). In a high transparent environment, customers behave strategically towards supply changes in the market. To maximize their utility, customers are sensitive to price changes in pursuit of a better price. A competitive market with dynamic price changes makes customers to change their decision
more frequently, thus increasing their likelihood to churn. In our setting of the car insurance industry, compared to other channels (e.g., call centers, agents), a price/service comparison website is arguably more transparent in terms of both price and service since it provides these information of other companies as a reference. This high transparent environment increases customers’ likelihood to seek for a better price, thus increasing their likelihood to churn. Accordingly, we propose:

**H1a:** Customers acquired from a price/service comparison website are more likely to churn.

On the other hand, high level of information transparency provided by comparison websites increases customer informedness (Ting et al. 2014). In a high transparent environment, customers are more informed about price and product offerings, and they can easily search, compare, and find cheaper or better options. After choosing their product or service, customers are more confidence in and satisfied with their decision, and they will be less motivated to take additional efforts to search for similar products or service, which reduce their likelihood to churn. In our setting, customers acquired from a price/service comparison websites are well-informed about the price and service in the market, can make an informed decision, and thus may be unwilling to make additional decisions. Hence, we have:

**H1b:** Customers acquired from a price/service comparison website are less likely to churn.

It is noteworthy that these two hypotheses are not mutually exclusive. To the degree that some customers may be more motivated by dynamic price differentials, and others are less willing to compare prices after purchasing since they were well-informed about price and service information, it is plausible that both hypotheses could hold for different customers. However, the goal of this study is to determine which mechanism prevails (i.e., has a larger explanatory power on the effects of comparisons website on churn.)

### Data and Methods

To empirically examine the effect of a price/service comparison website on customer churn, we utilized a unique dataset from a major European auto insurance company. This rich dataset gave us information on customer characteristics, their cars and their contracts, contract duration, and from which channel (comparison website, the company’s own website, search engine, display advertisement, call center (inbound or outbound), or affiliate marketing channel) these customers purchased car insurance. The dataset comprises of 84,842 observations spanning 8 years from 2008 to 2015. Each observation gives the most recent information of each individual customer, no matter whether or when they churned (or not). For the independent variable, we constructed a dummy variable, Comparison, (=1 if the customer purchased insurance through a comparison website, and 0 otherwise). Our dependent variable is Churn, indicating whether the customer terminated their contract (1=yes, 0=otherwise). To account for confounding effects, we incorporated a set of covariates (X) about customer, their car, and their contract.

To avoid multicollinearity issues, we used machine learning techniques to extract the most important covariates that affect customer churn, covariates that are also correlated with acquisition channels. First, we calculated the pairwise correlations among all 83 variables in the dataset, and removed redundant ones (we tried different thresholds for correlation coefficients, e.g., 0.80, 0.85, 0.90). Then, we used the other variables to predict both the likelihood to choose a comparison website to purchase insurance previously, and the likelihood to churn. By using multiple machine learning algorithms (e.g., k-nearest neighbor, support vector machine, random forest), we found a consistent set of covariates that help to obtain at least 80% accuracy in the prediction models. Finally, we added these covariates as observed confounding factors into our main empirical analyses. The measures, description, summary statistics, and correlation matrix for the main variables can be found in Table 1 and Figure 1.

### Empirical Specifications

**Linear Probability Model (LPM).** In our setting, customers from a price/service comparison website and those from other channels can buy identical insurance products and identical services from the insurance company. In other words, there seems to be no systematic difference for the later customer relationship experience after both groups of customers have been acquired. If we classify the factors that affect customers’ churn decisions into before-sales factors (e.g., customer characteristics) and after-sales factors (e.g., service quality), it is reasonable to think that the before-sales factors may correlate with both churn decision and channels that customers chose before, while the after-sales does not seem to be
correlated with the channels. Therefore, whether to purchase insurance from a price/service comparison website is assumed to be as good as randomly assigning customers (Angrist and Pischke 2009), conditional on before-sales factors.

<table>
<thead>
<tr>
<th>Table 1. Measure, Description and Summary Statistics (N=84,842)</th>
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<tbody>
<tr>
<td><strong>Variable</strong></td>
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<tr>
<td><strong>Dependent Variable</strong></td>
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<td><strong>Independent Variable</strong></td>
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<td><strong>Customer Characteristics</strong></td>
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<td><strong>Contract Characteristics</strong></td>
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<tr>
<td><strong>Other Insurance (from the focal company)</strong></td>
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Figure 1. Correlation Plot
With this notion, our baseline LPM model is then:

\[ Churn_i = C_0 + \rho_1 \text{Comparison}_i + B_0 X_i + \epsilon_i \]  

(1)

For this linear probability model, \( X_i \) is the set of covariates (Table 1), while \( \epsilon_i \) is an error term. We assumed that \( E[\epsilon_i \mid \text{Comparison}_i, X_i] = 0 \) as we argued that \( \text{Comparison}_i \) is exogenous conditional on \( X_i \). In this setup, we could use the OLS estimator \( (\rho_1) \) to uncover the causal relationships between the comparison website and customer churn. The primary reasons we employed LPM instead of logistic regression are the following: On the one hand, we expect to make the interpretation of our results more straightforward since LPM yields results in terms of probability changes and allows for the coefficients to be comparable across models (Angrist and Pischke 2009). On the other hand, LPM renders unbiased consistent estimates of average marginal effect of a variable (Mood 2010; Wooldridge 2010).

**Propensity Score Matching (PSM).** However, the key assumption of Equation 1 that differences between treatments (purchasing from a price/service comparison website) and control (other channels) groups would have remained constant in the absence of the treatment does not always hold in practice (Angrist and Pischke 2009). Thus, we used additional estimation methods to corroborate our findings. Matching estimators allow us to reliably estimate the average treatment effect (Rubin 1997; Heckman et al. 1998; Austin 2011), even if the customers’ selection to purchase from a comparison website had not been completely random. In essence, the approach attempts to remove the selection bias by generating balanced covariate-specific treatment-control groups. The matching estimator \( (\rho_2) \) is as follows:

\[
\rho_2 = \frac{1}{n_1} \sum_{i \in \{\text{Comparison}_i = 1\}} \left[ Churn_{1,i} - \sum_j w(i, j) Churn_{0,j} \right] 
\]

(2)

Where the weights \( w \) are provided by the nearest matching via a greedy algorithm in our study, \( n_1 \) is the number of observation in the treatment group, \( Churn_{1,i} \) and \( Churn_{0,i} \) represent the churn status for treatment and control group respectively. \( \rho_2 \) could be more reliable than OLS estimator \( \rho_2 \) in the conditions that covariates across groups are not balanced and thus not comparable.

**Instrumental Variables (IV) Analysis.** Matching is still an observable strategy that can be controlled (Angrist and Pischke 2009), but it may suffer confounding effects from unobservable factors. To address concerns for potential unobserved heterogeneity that may bias our estimates \( (\rho_1 \text{ and } \rho_2) \), we employed an IV estimator \( (\rho_3) \). The IV analysis in our setting is to introduce a variable \( (Z_i) \) that is highly correlated with the treatment variable \( (\text{Comparison}_i) \) but not correlated with unobserved factors \( (\epsilon_i) \) that affect the dependent variable \( (\text{Churn}_i) \). The IV estimation \( (\rho_3) \) can be derived with 2 steps (Wooldridge 2010):

\[
\text{Comparison}_i = C_i + \pi_i Z_i + B_i X_i + \mu_i 
\]

(3a)

\[
\text{Churn}_i = C_2 + \rho_2 \text{Comparison}_i + B_2 X_i + \epsilon_i 
\]

(3b)

In essence, we assumed that \( \text{Corr} (Z_i, \text{Comparison}_i) \neq 0 \) and \( \text{Corr} (Z_i, \epsilon_i) = 0 \). In our dataset, we found that the duration of period between contracts signed date and executed date, termed as Period, could satisfy the conditions for a valid IV. First, Period is highly correlated with acquisition channels (e.g., Period for customers from a comparison website is 3.37 days in average, much faster than that for customers from other channels with 12.39 days). Second, there seems no ex ante reason that Period is correlated with after-sales factors (e.g., dynamic price differentials) that predict customer churn. Arguably, it is nearly a random decision by a customer to choose the contract executed date given the contract signed date, and this is barely correlated with the decision whether to churn one year later (normally the contract term is one year). Thus, we incorporated Period \( (Z_i) \) as an instrumental variable to uncover the causal effect of the price/service comparison websites on the likelihood of customer churn.

**Results**

Table 2 presents the results from a series of econometrics specifications. Using the LPM (column [1]-[5]) with covariates, we found relative consistent and statistically significant evidence suggesting that customers acquired from comparison websites are less likely to churn than those from other channels by 2.9\% (p<0.01) to 5.4\% (p<0.01) in average, supporting H1b.

The results from propensity score matching (column [7]) show a similar finding that customers from comparison websites are 3.8\% (p<0.01) less likely to churn. As shown in Figure 3 in the Appendix, there is
a substantial overlap in the range of the propensity score densities after PSM, indicating that matching is able to find counterfactual observations (Robin 1997). Furthermore, we further assessed the quality of matching by evaluating the balance of the observed covariates. Specifically, following Austin (2011), we estimated the standardized differences in means for each observed covariate between treatment (Comparison, =1) and control (Comparison, =0) groups. As shown in Figure 4 in the Appendix matching has balanced the covariates since the standardized differences are all close to zero.

Last, the estimated effect (column [6]) from instrumental variable analysis shows the same direction and significance with others, but surprisingly, the effect size is much larger (-18.4%, p<0.01). We tested the existence of the first stage for the 2SLS estimation. The F statistic (970.585, p<0.01) shows Period is not a weak IV (Woodridge 2010). Taken together, our finding shows the customers acquired from price/service comparison websites are less likely to churn hereafter, implying that product informedness enabled by comparison websites helps to retain customers.

### Table 2. The Effects of Purchasing through Comparison Website on Customer Churn

<table>
<thead>
<tr>
<th>Variables</th>
<th>Panel A: Linear Models</th>
<th>Panel B: Nonlinear Models</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Linear Probability Model</td>
<td>IV Analysis</td>
</tr>
<tr>
<td>Comparison</td>
<td>-0.040*** (0.003)</td>
<td>-0.054*** (0.006)</td>
</tr>
<tr>
<td>Customer</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>Car</td>
<td>√</td>
<td>√</td>
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<tr>
<td>Contract</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>Other Insurances</td>
<td></td>
<td>√</td>
</tr>
<tr>
<td>R²</td>
<td>0.027</td>
<td>0.046</td>
</tr>
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</table>

Notes: The No. of observations is 84842. All control variables, including customer, car, contract and other insurances, are included in nonlinear models in Panel B. All coefficients show estimated average marginal effects. Standard errors (clustered by Zip codes) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

### Robustness Checks

To further check the robustness of our results, we used different specifications. First, to consider that our dependent variable is a 0-1 dummy, we ran a logistic regression, and the resultant average marginal effect (reported in column [8]) shows similar findings but with a larger effect (7% less likely to churn).

Second, to consider the truncated nature of our data (we cannot track every customer until they churn away in the time window of our sample) and the nonlinear dependence of customer life time on churn likelihood, we conducted survival analysis (Wooldridge 2010) by using a Cox proportional hazard model. The result (Column [9]) (-3.6%) is consistent with those from the linear probability model (-3.8%) and propensity score matching (-4.1%), corroborating our main results.

Taken in sum, the relative consistent results support hypothesis H1b that customers from price/service comparison websites are more likely to continue their contracts and not churn. But the result from the IV analysis reveals that there may exist endogeneity issues in our specifications. Though IV analysis provides consistent estimations, whether the identified IV is exogenous is not testable. In other words, we cannot test whether unobserved factors that are correlated with churn likelihood are also correlated with our IV.
Experimental Design

It is possible that customers are self-selected to purchase insurance through different channels based on their preferences. Propensity score matching mimics a randomized experiment to model their preference (or more specifically, their idiosyncratic propensities to decide through which channel to purchase). However, matching uses observable factors to model the “preferences”, may not capture the unobserved heterogeneity that may actually predict churn. Whereas, the issues for our IV analysis is that we are conservative about the validity of our instrument variable. But at the same time, based on the available data, we cannot reject that our IV is not valid. To remove the confounding effects from so called “preferences”, the best approach is to conduct a randomized field experiment.

Currently, we are running a randomized field experiment with our partner company. We will describe the experiment design here and will present the findings at the conference.

Participants in the field experiment include customers whose car insurance will expire within one month. The subsampled group consists of 9,436 customers at the point of their annual insurance policy renewal. The experiments will run over a course of two months and will be conducted separately for each month. Second, for each round of experiment, we randomly and evenly split those customers into group A (treatment) and group B (control). Both groups receive notices of their contract expiration by email. The notice sent to group A includes a recommendation message with link to a comparison website to check the quotes from available car insurance companies, whereas the notice sent to group B excludes such a message. We will compare the customer churn rate between group A and group B. The difference in customer churn rate across acquisition channels will only be due to the customers’ decision to use the comparison website. In addition, in order to avoid the non-response bias, we will also consider one-sided non-compliance (Gerber and Green 2012) cases that customers in treatment group do not click the link. The Figure 2 illustrates the experiment design.

Discussion and Conclusion

In this study, we investigated and quantified the effect of price/service comparison websites on the likelihood of customer churn. Utilizing a unique large dataset with over 80K customer-level observations, we conducted a series of econometrics analyses using linear probability model, logistic model, survival analysis, propensity score matching, and instrumental variable analysis. The consistent results from multiple models suggest that comparison websites help to retain customers and prevents churn. However, we maintain a conservative view toward our preliminary findings, and seek to further validate our results by running a randomized field experiment.

Our research-in-progress has some limitations. First, the empirical results from observational data may suffer from potential endogenous issues. Thus, we are conducting a series of randomized field experiments.
to address them. Moreover, the potential mechanism argued in the hypotheses section could not be corroborated without additional efforts on providing adequate evidence. For example, did customer feel well-informed when they purchased their insurance in price/service comparison websites, and did they check comparison websites less than before after purchasing? What is the effect of dynamic price differentials provided by comparison websites on customers’ decision making process about whether to churn? To answer these questions, we are planning to send survey questionnaires directly to customers, no matter whether they churn or not, to collect data after conducting our experiments.

Notwithstanding these limitations, this work represents initial efforts to theorize and empirically examine the complex relationship between price/service comparison websites and customer churn, thus extending the IS and marketing literatures on customer churn, acquisition channels, and information transparency. This study also provides insightful implication to managers on how to utilize transparency strategy, such as acquire more customers from highly transparent channels, to reduce customer churn to gain benefits. Giving the nature of research-in-progress, this ongoing study will identify and accumulate more knowledge to related fields on acquisition channels, information transparency and customer relationship.

Appendix

![Figure 3. Checking Balance before and after PSM](image1)

*Note:* there exists more overlap in the range of propensity score densities between treated (comparison =1) and control (comparison =0) group after PSM than before PSM, indicating the advantage of matching balance covariates.

![Figure 4. Covariate Balance Summary](image2)

*Note:* the standardized differences are all close to zero, indicating the good quality of the PSM estimates.
References


