Does Premium Subscription Pay Off? Evidence from Online Dating Platform

Short Paper

Yinan Yu
McGill University
1001 Sherbrooke Street West
Montreal, QC, Canada
yinan.yu2@mail.mcgill.ca

Jui Ramaprasad
McGill University
1001 rue Sherbrooke Street West
Montreal, QC, Canada
jui.ramaprasad@mcgill.ca

Animesh Animesh
McGill University
1001 Sherbrooke Street West
Montreal, QC, Canada
animesh.animesh@mcgill.ca

Alain Pinsonneault
McGill University
1001 Sherbrooke Street West
Montreal, QC, Canada
alain.pinsonneault@mcgill.ca

Abstract

While freemium business model is gaining increasing popularity, we are still unclear about how the IT-enabled premium features affect users' behavior. We study this question in the context of an online dating platform. Drawing support from the framework of purchase funnel, we decompose individuals' online dating behavior into three stages, including consideration, evaluation, and matching. We construct a daily panel dataset consisting of users' premium subscription information, micro-level behavioral data, and demographic information. Using propensity score matching in combination with difference-in-differences estimator, we evaluate the causal impact of premium subscription on users' behavior during the whole dating process. We find that premium adoption leads to an increase in outcomes at each stage. Namely, after subscribing premium, users visit more profiles, approach more people through private messages, and achieve more matches. However, premium features do not appear to enhance the efficiency of finding a match. This study extends the literature on freemium business model and online dating by investigating how the IT-enabled targeted search and information collection influence people's online dating behavior.

Keywords: premium subscription, IT-enabled premium features, freemium, online dating, funnel stages

Introduction

The freemium model, wherein a *free* layer of service is provided to attract users and a *premium* is charged for an enhanced version supporting advanced features (Anderson 2009), has become a burgeoning monetization strategy for various online platform businesses, such as file hosting, music streaming, and online dating. According to Statista (2013), for example, freemium has become the most commonly used pricing strategy for apps on Apple. However, despite the increasing popularity and prosperity of the freemium model, the impact of premium subscription on consumers' behavior and its performance are still not well understood. Therefore, this study examines the effect of premium subscription on subscribers' behavior at different stages of their decision making process. Specifically, we examine the user engagement on the platform as well as the efficiency with which a user achieve an outcome.

Of particular interest is the online dating context as many of the online dating platforms employ the freemium model and these online dating platforms have witnessed rapid proliferation in recent years. Recent data suggests that approximately 30 percent of Internet users in the U.S. between age 18 and 29 are using dating websites or app (Statistia 2017). Further, the adoption of online dating has been increasing for nearly every age group (Murnane 2016). Thus, online dating provides an appropriate context for studying the effect of premium adoption on user behavior. To examine this research question, we collaborate with one of the largest dating sites in North America. This platform offers several premium features, such as advanced search filters (e.g., searching by attractiveness, personality, body type, etc.,) and richer information (e.g., revealing the people who "like" the focal user, providing acknowledgement that a message sent by the focal user was read by the recipient). Such IT-enabled features distinguish online matching process from its offline counterpart by refining the search scope and enabling collection of weak signals of interest, which reduces search frictions and may therefore help users achieve matches more efficiently. We get access to a large dataset containing 50,000 users' premium subscription information, micro-level behavioral data, and demographic information.

To tap into the effect of premium subscription, we describe users' online dating via the framework of purchase funnel, which models consumers' decision-making into three steps: consideration, evaluation, and purchase (e.g., Wiesel and Pauwels 2011). Analogously, the online matching process can be classified into multiple stages consisting of creating a consideration set by visiting profiles of potential dates, evaluating the users in the consideration (based on various criteria such as attractiveness, age, etc.,) to select users whom to contact, engaging in online conversation by sending/receiving messages to mutually decided whether the users match or not, and achieving the final match. Through breaking down the process into multiple sub-processes, we are able to disentangle the effect of premium subscription in different stages. We utilize propensity score matching in combination with difference-in-differences estimator to identify the causal effect of premium subscription on users' behavior. We find that premium adoption enhances users' engagement at each stage. Interestingly, however, we do not find evidence that premium features improve efficiency of finding a match.

This study advances our knowledge for both freemium business model and the dating markets. Since we decompose users' online dating behavior into different stages, we are able to go beyond user engagement and investigate the effect of premium adoption in greater detail. Moreover, we also take the process efficiency into consideration, which provides managerial implications for premium feature design. We will extend the study by 1) exploring mechanisms behind the observed results, 2) examining whether and how the effect of premium subscription varies across different population groups, and 3) using alternative identification strategies to model the interrelationship between consecutive stages.

Related Literature

Our study draws upon two streams of literature: freemium online communities and dating markets. The freemium business model, which is particularly suitable for versioned products and tiered services, has been used in the software industry for decades. Analytical works have examined the adoption strategy and pricing strategy of freemium model for software (e.g., Niculescu and Wu 2014; Zhang et al. 2016). A more closely related context with our study is freemium online communities. Earlier studies examine the antecedents of premium adoption in online communities and document the significant impact of social engagement and peer influence. For instance, Oestreicher-Singer and Zalmanson (2013) find that users actively participating in the online music community show stronger willingness to pay for the premium services. Utilizing a randomized experiment, Bapna and Umyarov (2015) find that a friend adopting premium service significantly increases the odds of a user's own adoption. Subsequently, Bapna et al. (2017) study the consequence of premium subscription and find that users engage more with the platform after subscribing premium services. People attempt to extract value from their payment so that they are able to achieve balance between inputs and outputs to minimize cognitive dissonance. Our study belongs to the latter category. Additionally, we move beyond user engagement and examine how premium subscription alters users' online dating behavior, and how it affects the efficiency of achieving outcomes at different stages.

The second literature that our work builds on is the work on dating and marriage markets. This literature documents a sorting pattern that dating partners usually exhibit similar traits (e.g., Becker 1973; Kalmijn 1998; Tayor et al. 2011). In offline dating markets, it is difficult to differentiate whether such sorting pattern is caused by preferences or search frictions. However, since the search costs in online dating are significantly lower than in offline dating, Hitsch et al. (2010) tease out the impact of preferences for sorting process through analyzing observational data from online dating market. Further – and particularly relevant to this study – previous studies identify different stages involved in the dating process, for example, the underlying search process, contact initiation stage, and match stage (e.g., Bapna et al. 2016). Compared with standard online dating, IT-enabled premium services provide additional features that enable targeted search and provide richer information/signals, which may alter users' searching and sorting behavior at different stages. Our study aims to provide new insights into how IT-enabled premium features impact users' online dating behavior, by leveraging our ability to track users through these difference phases of their search process.

Research Framework

Marketing literature models consumer choice process in a shopping/consumption as various stages (Bettman 1979; Engel and Blackwell 1982; Kotler et al. 2006). We adopt a classification that consists of three stages: consideration, evaluation, and purchase stage (e.g., Wiesel and Pauwels 2011). On online dating platforms, users start collecting information by searching for other users and visiting their profiles. This process forms a consideration set. Next, they further evaluate each alternative in their consideration set and are also evaluated by others. The outcome of this evaluation stage is the decision to engage in online conversation, with a subset of the users in the consideration set, by sending/receiving messages. This process of sending/receiving messages ultimately leads to the final stage, matching. Figure 1 depicts the conceptual model of this study. We attempt to investigate the impact of premium subscription in different funnel stages. The underlying idea is that premium option provides features that facilitate targeted search and provide rich information signals[1], which may have different effects on users' behavior at different stages in the matching funnel.

One of the most important advantages of online dating compared to offline dating is that it significantly reduces the search friction for the matching process (Hitsch et al. 2010). While the free service offered by the platform allows users to search for potential partners based on basic demographics information (e.g., as age, height, ethnicity, religion, etc.), premium subscription provides additional search filters (e.g., search by attractiveness, body type, and personality) that are conducive to expressing users' own preferences and gathering more information. Thus, the further reduced search friction boosts the size of the consideration set. On the other hand, studies on targeting show that closely matched items substitute customer's information search beyond the targeted offers (Fong 2017). Premium subscribers are able to receive more signals than ordinary (non-premium, free) users because of advanced features such as knowing the identity of people who like you. Therefore, the size of the consideration set may be reduced due to more targeted options enabled by this feature, which shrinks the scope but improves the efficiency of the consideration process. Next, when subscribers move on to the evaluation stage, they may approach more people if the consideration set formed in the last step is enlarged. Then during conversations, premium options help users collect more signals through message read receipt. Hence, it is also likely that subscribers would only limit their evaluation within a small group of people from who they have obtained certain feedback to minimize uncertainty. The evaluation efficiency is improved as a result of reduced information asymmetry. Finally, the increased user engagement, expanded consideration set and evaluation set, and the improved efficiency in these two stages would lead to better matching outcomes.

In sum, the technology-enabled premium features would exert different impacts on users' behavior at different stages. The aim of this study is to empirically test these effects.

---

[1] Although the premium features examined in this study are specific to the focal platform, targeted search and provision of richer information signals are commonly available across online dating platforms.

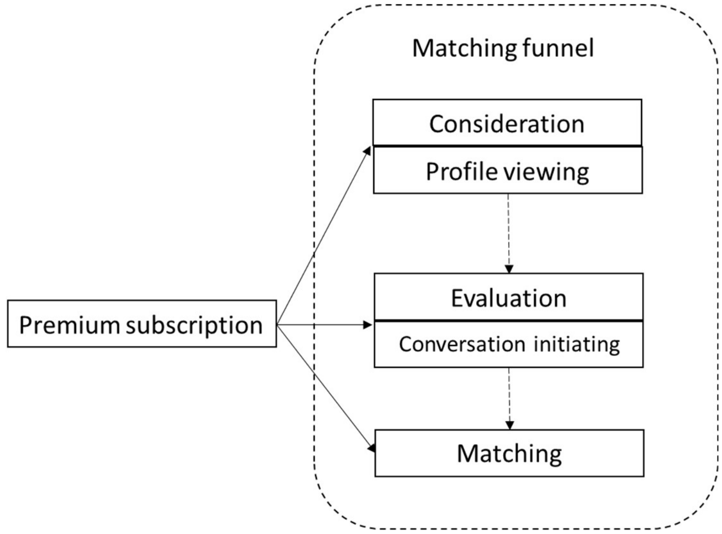

Figure 1. Conceptual Framework

Data and Empirical Strategy

Empirical Context and Data

To investigate our research questions, we leverage a dataset from a large online dating platform in North America. This platform employs the freemium business model. Every registered user can access a free version of service wherein users can set up their profiles, search for other users by basic demographic information, browse others' profiles, rate other users' overall attractiveness by voting "like" or "pass", and send private messages to any other user. A premium is charged for enhanced features including advanced search filters, knowing the identity of the people who have "liked" you, message read receipts, and ad-free experience.

We use a large dataset including 50,000 randomly selected users who joined the platform during a week in early March 2016 (i.e., March 11, 2016 to March 17, 2016), whose behavior was then tracked in the following three months. We collect the data on users' premium subscription status. Totally, there are 1,630 users (i.e., 3.26 percent of users) adopting premium in our sample. Figure 2 demonstrates the number of users who subscribed to the premium service in each day during our study period. The period located before the dashed line indicates the joining period of the users in our sample. It shows that most of the premium subscribers adopted the service immediately after they joined the platform.

We also collect timestamped data for three types of micro-level behavior. Specifically, we count the number of unique profiles visited by the focal user (i.e., *ViewSent*) as a measure of users' information searching behavior, or the size of his/her consideration set. We measure the evaluation process using the number of likes the focal user voted (i.e., *VoteSent*) and the number of unique users s/he approaches through private messages (i.e., *MsgInit*). Aligned with Bapna et al. (2016), we define a match between two users as there are at least three sequential messages exchanged between them. Namely, if user A initiated a message to user B, user B responded and user A messaged user B again, there is a successful match between them (i.e., *MatchSent* for user A). Symmetrically, we also calculate the number of times the focal user's profile visited by others (i.e., *ViewRcvd*), the number of votes that s/he obtained (i.e., *VoteRcvd*), and the number of unique users who approach him/her (i.e., *MsgRcvd*). Finally, we also collect users' demographic information (e.g., age, ethnicity, and education level). Table 1 presents the summary statistics of demographic information and user activity for premium subscribers in the pre-subscription period.

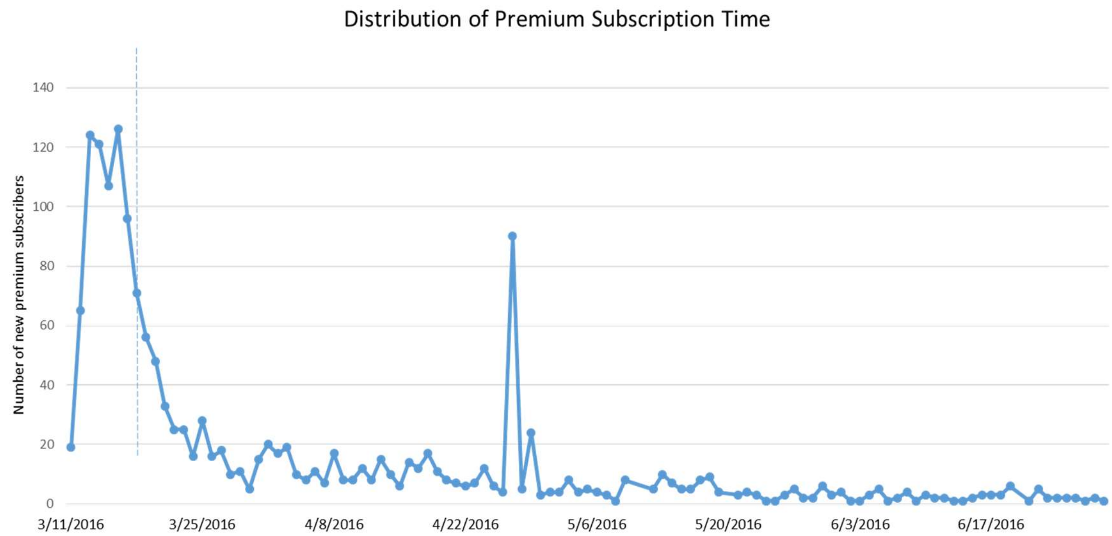

Figure 2. Distribution of Premium Subscription

Table 1. Summary Statistics for Premium Subscriber during Pre-subscription Period

Variable	Mean	Std.Dev	Min	Median	Max
Activity					
ViewSent	7.67	20.6	0	0	418
VoteSent	12.31	57.07	0	0	1,041
MsgInit	2.67	13.14	0	0	390
MatchSent	0.10	0.48	0	0	10
ViewRcvd	3.86	11.47	0	1	218
VoteRcvd	10.24	24.25	0	4	637
MsgRcvd	2.28	10.37	0	0	258
Demographic					
Age	32.21	10.78	18	30	67
Asian	0.04	0.21	0	0	1
Black	0.08	0.27	0	0	1
Latin	0.09	0.29	0	0	1
White	0.62	0.49	0	1	1
Education Level	3.57	1.73	0	4	6

Identification Strategy

Although as we described above, many premium subscribers adopted the service right after they joined the platform, we restrict our analyses to late adopters due to the following reasons. First, compared to immediate subscribers who may adopt the premium service automatically, late adopters made the subscription decision more consciously. Therefore, it is more valuable to examine the effect of premium subscription on behavior of this subgroup. Second, since we will match premium subscribers with non-subscribers, it is hard to obtain the pre-subscription observable characteristics for immediate adopters, which jeopardizes the matching performance. Therefore, we select users who adopted premium service one week after the joining period (i.e., from March 25, 2016 to Jun 14, 2016).

Drawing inferences about the effect of premium subscription merely based on subscribers' behavior before and after the adoption may be prone to identification issues, since other factors such as platform promotions may influence their behavior as well. To address these issues, we adopt a commonly used empirical strategy for observational data that combines propensity score matching (PSM) and difference-in-differences (DID) analysis to infer the causal impact of premium subscription on user dating behavior. The DID estimation is a widely used in information systems (IS) literature to address the identification issues mentioned above (e.g., Chan and Ghose 2014; Rishika et al. 2013). It measures the effect of the treatment by capturing the differences in pre- and post-treatment outcomes between the treatment and the control group. In our context, by comparing the change in subscribers' behavior across time relative to that of non-subscribers, we are able to estimate the causal effect of premium adoption.

Propensity score matching

Since the behavior of premium subscribers may be different from standard users even before premium adoption, we employ PSM to select a group of non-subscribers who are very similar to subscribers in terms of a set of observable pre-subscription characteristics (Caliendo and Kopeinig 2008; Dehejia and Wahba 2002; Rosenbaum and Rubin 1983). PSM calculate the propensity of each user adopting premium on this high-dimensional characteristics. We use both user activities (*ViewSent, VoteSent, MsgInit, MatchSent, ViewRcvd, VoteRcvd,* and *MsgRcvd,*) and demographic characteristics (e.g., age, ethnicity, and education level) to compute the propensity score.

One particular challenge in our context is that premium users started the service at different dates, so that there is no unified premium start time for control users, making it hard to calculate pre-premium values of covariates to conduct PSM. To address this issue, we adopt a two-stage PSM approach (e.g., Qiao et al. 2017). The basic idea is as follow: in the first stage, we utilize all data across our study period to identify non-subscribers who are similar to subscribers in terms of overall behavior. For each matched pair, we assign the premium start time of the subscriber to his/her corresponding non-subscriber. After all non-subscribers have been assigned their premium start time respectively, we are able to conduct the second stage PSM, wherein only pre-premium data are used to do the matching and obtain the final matched sample. In each stage, we specify a Probit model and use the single nearest neighbor matching method without replacement to obtain a one-to-one matched non-subscriber for each of the subscribers. We require common support so that observations lying outside of the common support are discarded (Caliendo and Kopeinig 2008). We obtain 448 users in our final sample, with 224 users in each group.

Table 2. Balance Tests on Covariates after PSM

Variables	Mean (Subscriber)	Mean (Non-subscriber)	p-value
Activity			
ViewSent	7.67	6.54	0.067
VoteSent	12.31	13.8	0.355
MsgInit	2.67	2.79	0.741
MatchSent	0.10	0.11	0.803
ViewRcvd	3.86	4.43	0.278
VoteRcvd	10.24	11.83	0.055
MsgRcvd	2.28	2.58	0.267
Demographic			
Age	32.21	32.38	0.863
Asian	0.04	0.06	0.402
Black	0.08	0.06	0.464
Latin	0.09	0.09	0.998
White	0.62	0.66	0.378
Education Level	3.57	3.58	0.989

We conduct t-test analysis on primary variables between subscribers and non-subscribers to assess whether our matching is successful. The results presented in Table 2 suggest that all variables are not significantly different between the two groups at the 10% significance level. Namely, the pre-subscription observational covariates are balanced and the non-subscribers are comparable to the subscribers before premium adoption.

Difference-in-Differences Analyses

We set up our data as a daily panel dataset spanning from 14 days before to 14 days after premium subscription. Next we conduct our analyses under the panel DID framework to evaluate the effect of premium subscription on users' online dating behavior. In the current stage, we examine the effect of premium adoption on the outcomes of three funnel stages respectively. We propose the following model specification:

$$DV_{it} = \beta_0 + \beta_1 \, Premium_i \times After_t + \beta_2 Tenure_{it} + \alpha_i + \delta_t + \varepsilon_{it} \qquad (1)$$

DV_{it} denotes the dependent variables (i.e., measures of outcomes at each stage: *ViewSent, MsgInit*, and *MatchSent*; and measures of efficiency: *MsgInit/ViewSent*, average number of messages sent to each user, and *MatchSent/MsgInit*). The interaction term $Premium_i \times After_t$ is the main variable of interest, whose coefficient β_1 captures the average effect of premium adoption on subscribers' behavior. $Tenure_{it}$ is included to control for the decreasing trend of users' participation intensity on the platform. Since dependent variables are skewed, we apply the natural logarithm transformation on them to improve model fit. Additionally, we include a vector of user fixed effects α_i to account for time-invariant differences across users, and a vector of day fixed effects δ_t to control for common shocks over time. ε_{it} represents the error term. Notably, the variable $Premium_i$, which does not vary over time, and variable $After_t$, which does not vary across users, are absorbed in the variables that capture fix effects. Lastly, we cluster the standard errors at the individual level to account for heteroskedasticity in the data (Bertrand et al. 2004).

Preliminary Results

Table 3 shows the regression results of the effect of premium subscription on user dating behavior. Three columns correspondent to the three funnel stages, namely, consideration, evaluation, and final matching. The coefficients of the interaction term $Premium_i \times After_t$ are all positively significant at the 1% significant level. In other words, after adopting premium service, users visited more profiles, approached more people, and achieved more matches. The coefficient of the effect of premium subscription on profile visiting is 0.414, indicating that premium adoption leads to an increase of 41.4% in profile viewings in the two weeks afterwards. The negative coefficients of $Tenure_{it}$ indicates the decreasing trend of user behavior on the platform over time. These results are aligned with previous study showing that premium adoption positively influences users' engagement in online platform (e.g., Bapna et al 2017).

Table 3. Effect of Premium Subscription on Online Dating Behavior

VARIABLES	(1) *ViewSent*	(2) *MsgInit*	(3) *MatchSent*
$Premium_i \times After_t$	0.414***	0.108***	0.046***
	(0.063)	(0.024)	(0.011)
$Tenure_{it}$	-0.009***	-0.002**	-0.001*
	(0.002)	(0.001)	(0.001)
User Fixed Effects	Yes	Yes	Yes
Day Fixed Effects	Yes	Yes	Yes
Constant	1.060***	0.216***	0.071***
	(0.100)	(0.045)	(0.022)
Observations	12,544	12,544	12,544
R-squared	0.043	0.023	0.014

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 4 presents the results on the impact of premium subscription on process efficiency. The first column correspondents to the ratio of the number of unique users the focal user approaches to the number of unique profiles s/he visits. This ratio indicates whether premium service improves the consideration efficiency. If it does, subscribers would initiate more conversations given the consideration set, meaning this ratio would increase after premium adoption. Second, we calculate the average number of messages sent by the focal user to the correspondents s/he approaches, which measures the evaluation depth. Third, we compute the ratio of the number of successful matches to the number of users the focal user approaches. Interestingly, we find premium adoption does not seem to have a significant effect on all three efficiency measures. Our results are robust to alternative matching method (e.g., exact coarsened matching) and count data model (e.g., negative binomial model). Due to the space limit, we do not include these results in the paper.

Table 4. Efficiency of Premium Subscription on Online Dating Behavior			
VARIABLES	(1) *MsgInit/ViewSent*	(2) Average Number of Message sent to Each User	(3) *MatchSent/MsgInit*
$Premium_i \times After_t$	0.004	0.071	-0.003
	(0.006)	(0.105)	(0.025)
$Tenure_{it}$	-0.0004	-0.0002	-0.003
	(0.0004)	(0.006)	(0.003)
User Fixed Effects	Yes	Yes	Yes
Day Fixed Effects	Yes	Yes	Yes
Constant	0.071***	1.422***	0.276***
	(0.017)	(0.255)	(0.071)
Observations	6,052	1,786	1,786
R-squared	0.008	0.027	0.017

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Conclusion and Future Directions

This study examines how premium subscription affects the outcomes and process efficiency of users' online dating behavior. We find that premium adoption increases users' engagement in all three stages of online dating process, namely, consideration, evaluation, and the final matching stage. However, it does not have significant impact on the measures of process efficiency. In other words, IT-enabled premium features boost the quantity of information processing during online dating through reducing search frictions, refining search scope, and facilitating signal of interest collections, but do not seem to improve the information quality systematically. This paper contributes previous literature on the impact of premium subscription and online dating by breaking down the decision making process according to the funnel framework and taking the process efficiency into consideration, such that the mechanism of how premium functions is investigated in more detail. Our results also provide important managerial implications. Premium users are shown to be substantially more engaged with the platform, which has significant chain effect. When premium users actively communicate with others, they increase the vitality and engagement of other users. Previous studies have established that user engagement leads to higher likelihood to subscribe premium service, such that the platforms are able to monetize their users.

Given these results, we will further pursue the following directions. First, since we observe that premium subscription does not appear to enhance the process efficiency of each stage, our future work will investigate the mechanism behind this phenomenon. For instance, one potential reason is that premium subscription improves the quantity of consideration set and evaluation set but not the quality. Second, since previous studies document significant gender asymmetry in dating behavior (e.g., Bapna et al. 2016; Fisman et al. 2006), we will explore how premium subscription affects male and female users differently. Finally, we currently investigate the effect of premium adoption at each stage separately. However, the earlier stages in the process are likely to influence the later ones as people may process iteratively. We will use alternative estimation approaches, such as simultaneous equations, to capture the dynamic nature of this process.

References

Anderson, C. 2009. Free: The Future of a Radical Price. Hyperion.

Bapna, R., Ramaprasad, J., and Umyarov, A. 2017. "Completing the Virtuous Cycle between Payment and Social Engagement in Freemium Social Communities," (Accepted, *MIS Quarterly*).

Bapna, R., Ramaprasad, J., Shmueli, G., and Umyarov, A. 2016. "One-Way Mirrors in Online Dating: A Randomized Field Experiment," *Management Science* (62:11), pp. 3100–3122.

Bapna, R. and Umyarov, A. 2015. "Do your Online Friends Make You Pay? A Randomized Field Experiment on Peer Influence in Online Social Networks," *Management Science* (61:8), pp.1902–1920.

Becker, G.S. 1973. "A Theory of Marriage: Part I.," *Journal of Political Economy* (81:4), pp. 813–846.

Bertrand, M., Duflo, E., and Mullainathan, S. 2004. "How Much Should We Trust Differences-in-Differences Estimates?" *The Quarterly Journal of Economics* (119:1), pp. 249-275.
Bettman, James R., Mary Frances Luce, and John W. Payne. 1998. "Constructive Consumer Choice Processes," *Journal of Consumer Research* (25:3), pp. 187–217.
Caliendo, M., and Kopeinig, S. 2008. "Some Practical Guidance for the Implementation of Propensity Score Matching," *Journal of Economic Surveys* (22:1), pp. 31-72.
Chan, J., and Ghose, A. 2014. "Internet's Dirty Secret: Assessing the Impact of Online Intermediaries on HIV Transmission," *MIS Quarterly* (38:4), pp. 955-976.
Dehejia, R. H., and Wahba, S. 2002. "Propensity Score-Matching Methods for Nonexperimental Causal Studies," *Review of Economics and Statistics* (84:1), pp. 151-161.
Engel, James F. and Roger D. Blackwell (1982), Consumer Behavior. Chicago: Dryden.
Fisman R, Iyengar S.S., Kamenica E, Simonson I. 2006. "Gender Differences in Mate Selection: Evidence from a Speed Dating Experiment," *The Quarterly Journal of Economics* (121:2), pp. 673–697.
Fong, N.M. 2017. "How Targeting Affects Customer Search: A Field Experiment," *Management Science* (63:7), pp. 2353–2364.
Hitsch, G.J., Hortacsu, A., and Ariely, D. 2010. "Matching and Sorting in Online Dating," *The American Economic Review* (100:1), pp. 130-163.
Kalmijn, M. 1998. "Intermarriage and Homogamy: Causes, Patterns, Trends," *Annual Review of Sociology* (24), pp. 395–421.
Kotler, Philip, Neil Rackham, and Suj Krishnaswamy. 2006. "Ending the War Between Sales and Marketing," *Harvard Business Review* (84:7/8), pp. 68–78.
Murnane, K. 2016. "Report Shows More People of All Ages Are Dating Online," Forbes, https://www.forbes.com/sites/kevinmurnane/2016/03/02/pew-report-who-uses-mobile-dating-apps-and-online-dating-sites/#286a179666e3
Niculescu, M.F. and Wu, D.J. 2014. "Economics of Free Under Perpetual Licensing: Implications for the Software Industry," *Information Systems Research* (25:1), pp. 173-199.
Oestreicher-Singer G, Zalmanson, L. 2013. "Content or Community? A Digital Business Strategy for Content Providers in the Social Age," *MIS Quarterly* (37:2), pp. 591–616.
Qiao, D., Lee, S.-Y., Whinston, A., and Wei, Q. 2017. "Incentive Provision and Pro-Social Behaviors," *Proceedings of the 50th Hawaii International Conference on System Sciences*.
Rishika, R., Kumar, A., Janakiraman, R., and Bezawada, R. 2013. "The Effect of Customers' Social Media Participation on Customer Visit Frequency and Profitability: An Empirical Investigation," *Information Systems Research* (24:1), pp. 108-127.
Rosenbaum, P. R., and Rubin, D. B. 1983. "The Central Role of the Propensity Score in Observational Studies for Causal Effects," *Biometrika* (70:1), pp. 41–55.
Statista. 2013. "Freemium is the No.1 Pricing Strategy in Most App Categories," https://www.statista.com/chart/1733/app-monetization-strategies/
Statista. 2017. "Online dating - Statistics & Facts," https://www.statista.com/topics/2158/online-dating/
Taylor LS, Fiore AT, Mendelsohn G, Cheshire C. 2011. "Out of My League: A Real-World Test of the Matching Hypothesis," *Personality and Social Psychology Bulletin* (37:7), pp. 942–954.
Zhang, Z., Nan, GF., Li, MQ., and Tan, Y. 2016. "Duopoly Pricing Strategy for Information Products with Premium Service: Free Product or Bundling?" *Journal of Management Information Systems* (33:1), pp. 260-295.