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RESEARCH ARTICLE

LOVE UNSHACKLED: IDENTIFYING THE EFFECT OF MOBILE APP ADOPTION IN ONLINE DATING[1]

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The proliferation of smartphones and other mobile devices has led to numerous companies investing significant resources in developing mobile applications, in every imaginable domain. As apps proliferate, understanding the impact of app adoption on key outcomes of interest and linking this understanding to the underlying mechanisms that drive these results is imperative. In this paper, we explore the changes in user behavior induced by adoption of a mobile application, in terms of engagement and matching outcomes in the online dating context. We also identify three mechanisms that are somewhat unique to the mobile environment, but are hitherto unestablished in the literature, that drive this shift in behavior: ubiquity, impulsivity, and disinhibition. Our main identification strategy uses propensity score matching combined with difference-in-differences, coupled with a rigorous falsification test to confirm the validity of our identification strategy. Our results demonstrate that mobile app adoption induces users to become more socially engaged as measured by key engagement metrics such as visiting significantly more profiles, sending significantly more messages, and importantly, achieving more matches. We also discover various mechanisms facilitating this increased engagement: ubiquity of mobile use—users log in more, and login across a wider range of hours in the day. We find that men act more impulsively, in that they are less likely to check the profile of a user who messaged them before replying to them. This effect is not visible for women who continue to be deliberate in their checking before replying even after adoption of the mobile app. Finally, we find that both men and women exhibit disinhibition, in that users initiate actions to a more diverse set of potential partners than they did before on dimensions of race, education, and height.

Keywords: Mobile applications, online dating, social engagement, adoption, ubiquity, implusiveness, disinhibition

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Introduction and Background

The proliferation of smartphones and other mobile devices has led to numerous companies investing significant resources in developing mobile alternatives for consumers, with apps emerging in every imaginable domain. Ericsson (2015) reports that based on the rising number of smartphone subscriptions and increasing data consumption per subscriber, mobile data traffic will grow nine times between 2014 to 2020. The same report mentions that the growth in data traffic between 2019 and 2020 will be greater than the total sum of all mobile data traffic up to the end of 2013. These industry reports suggest that companies are willing to allocate significant resources for the development and maintenance of mobile applications. Yet, similar to prior questions about returns to IT investments (Brynjolfsson and Hitt 1996), the long-term viability of the mobile ecosystem hinges on a detailed understanding of the linkage between the channel shift from web to mobile and outcomes to end-users and firms that are investing in this channel shift. While our focus is answering this question in the context of online dating platforms, our work generalizes beyond the context of dating to the plethora of firms that are investing in the channel shift from the web to mobile. This generality stems from our identification of the underlying mechanisms that lead to change in behavior as users increasingly adopt mobile apps. We see the mechanisms of ubiquity, implusiveness, and disinhibition as applying to digital channel shifts (web to mobile) that are happening across the board—ranging from our context of dating to online education, online shopping, and music streaming. Companies are investing substantial amounts of money in creating mobile applications and experiences, and they need theoretical and practical guidance on the business value of such investments. Our paper addresses this need and gap in the literature.

Understanding of the drivers of this growth comes from examining whether users perceive mobile platforms, which typically provide access to similar resources and repositories as the traditional web-based Internet, to be different. Early research looking at differences in user behavior across the mobile and traditional (personal computer-based) Internet has shown that mobile Internet tends to differ substantially. Ghose et al. (2012) find that, in contrast to the conventional wisdom associated with the web, in the mobile domain, using the Internet has higher search costs and geography matters more to users. They conclude that this makes the mobile Internet less "Internet-like." With regard to higher search costs, they see that higher ranked search results get even more attention in the mobile domain than they do in the PC world. This emphasizes the notion that the primacy effect of being first in a sequence (Carney and Banaji 2012; Miller and Krosnick 1998) is more salient in the mobile domain and that users feel an increased search burden due to the smaller screen size of the mobile devices. Ghose et al. (2012) also find that, following Tobler's (1970) first law of geography, stores located in close proximity to a user's home are much more likely to be clicked on mobile phones relative to PCs. This reaffirms the prior literature that has established the role of geography on the Internet (Blum and Goldfarb 2006; Hampton and Wellman 2003), and yet highlights the fact that the local effect on the mobile Internet is further enhanced by location-based features that are now core to smartphone technology.

More recent advances in smartphone technology, including voice recognition, biometric identification, high resolution imaging, and advanced GPS that allows location accuracy within five meters has further fueled the evolution of the app ecosystem. As of January 2017, Apple's App Store surpassed more than two million apps, an increase from 1.5 million in June 2015 (Statista 2017), and this trend is expected to accelerate. A key evolving thesis that underlies this projected growth is the belief that the next generation of context-aware apps engage their users in a way that traditional enterprise systems and web-based applications cannot. E-commerce apps on a smartphone that is "worn" by a consumer can use GPS and location data to tailor recommendations that are specific to the user's context. Those include cookbook recommendations that match the characteristics and cuisine of a particular cafe that the user has checked into, or a concierge feature from a travel app that automatically shows up after a user checks into her hotel (using the app) and enters her room. These apps fulfill real-time needs that consumers have in their daily patterns of activity, both at work and in their leisure time. Thus, we see the shift to the smartphone-enabled mobile ecosystem as a major channel shift, similar in potential impact to the move from the offline channel to the online channel (Brynjolfsson et al. 2003; Cachon et al. 2008). This channel shift from offline to online to mobile is accelerating the ongoing digitization of social processes ranging from cooking a meal and traveling, as described above, to consuming media, interacting with our friends, and dating—the context of this study. While finding a partner historically has been a purely offline endeavor, online platforms that enable interactions combined with recent advances in the advent of big data and algorithmic matchmaking (Slater 2013) have shifted this search for a mate online. Indeed, 46% of the single population in the United States uses online dating to initiate and engage in the process of selecting a partner.[2] Bapna et al. (2016) show, in the context of dating markets, that the Internet not only replicates the physical world pro-

[2] "About 49 million singles in the U.S. have tried online dating, according to Statistic Brain Research Institute" (https://www.statisticbrain.com/online-dating-statistics).

cesses of human interaction, but also extends and impacts these processes and outcomes through a variety of technology-enabled features.

Now, with the increased industry attention to mobile applications, the search for a partner has also now "gone mobile." Several online dating sites have entered the mobile channel by creating apps for their users (e.g., Match.com, eHarmony). In addition, we also see a variety of stand-alone mobile-only dating apps in the market (e.g., Tinder, Skout, and Grindr). Following Bapna et al. (2018), we focus on social engagement as a key metric for the long-term sustainability and profitability of online dating platforms. These platforms generate revenues through advertising, which increases with social engagement, and premium subscriptions. As users become more socially engaged, they interact with other users more frequently and are more likely to pay for premium subscriptions (Oestreicher-Singer and Zalmanson 2013). In particular, in online dating, social engagement entails visiting profiles and, critically, engaging in conversations with others. These activities lead to more eyeballs and attention that is monetized via advertising revenue, and from the users' perspective they increase the likelihood of achieving a match. Thus, social engagement benefits both the site and the user.

The interesting aspect of social engagement in the online dating context is that while each particular user may exit a dating site after achieving a successful match, this successful user's departure is a highly desirable outcome for the website.[3] As our conversations with senior executives in the online dating industry indicate, successful matching outcomes are key drivers of positive word-of-mouth recommendations: the success stories of existing users draw in fresh new users to the site.

Our particular interest is to empirically identify changes in user engagement and outcomes as one moves from the personal computer-based environment to the mobile app environment on smartphones, and establishing a robust methodology to do this. Prior literature has examined the foundations of content generation and usage and their linkage to geography and social network ties (Ghose and Han 2011), as well as the differences in browsing behavior between mobile and personal computer users (Ghose et al. 2012). Thus, while the differences between mobile and personal computer users have been examined, neither the effect of a user's adoption of mobile application on social engagement nor the mechanisms via which this effect manifests have been studied in the literature.

Thus, in this paper, we focus on identifying the effect of the adoption of a mobile application on user behavior in the context of an online dating platform, which provides objective measures of social engagement as well as outcome measures. In doing this, we seek to understand the mechanisms that facilitate the link between mobile application adoption and engagement, focusing on (1) ubiquity, where a user's presence on the dating site is spread over different hours of the day, (2) impulsivity, where users react spontaneously and without deliberation to "stimuli" from other users, and (3) disinhibition, where users are less inhibited and reduce the constraints in their engagement with a more diverse set of users on the dimensions of race, height, and education levels. In summary, we ask the following research questions:

- What is the impact of mobile application adoption on social engagement, as measured by profile viewing, and messaging?

- What is the impact of mobile application adoption on matching outcomes?

- What are the mechanisms that facilitate the relationship between mobile application adoption and change in user behavior? In particular, does mobile application adoption impact ubiquity of access and usage, disinhibition, or impulsivivity in users' engagement behaviors?

An underlying challenge in identifying these effects is the possible endogeneity issues in drawing causal inference regarding the impact of mobile app adoption. While it is natural to envision a randomized experiment where a mobile app is randomly assigned to all new users of the website, this is not an ideal identification strategy in our context since our goal is to study the causal behavioral changes in naturally occurring adopters.

Instead, the ideal experiment would be the one that observes a set of users who naturally choose to adopt the mobile app on their own and then randomly intentionally delays adoption for some of them (say, by throwing a fake installation error). This would allow us to observe experimentally what would have happened to the users who otherwise wanted to adopt the mobile app but were not able to versus the users who wanted to adopt and succeeded. In other words, statistically speaking, for our research question we are interested in the average treatment effect on the treated (ATET). Unfortunately, this type of randomized experiment is unethical and is not in the best interest of our partner company. Hence, we

[3] This phenomenon is not completely unique to online dating. For example, search engines also consider it a success if a user finds what they were looking for faster rather than slower despite potential short-term ad revenue loss for the engine. We are not aware of any major search engine that deliberately shows users bad search results in the hopes of keeping them longer on the search engine. Such a myopic strategy does not seem sustainable in the long run.

are limited to working with observational data[4] and utilize the combination of propensity score matching technique and difference-in-differences analysis, along with a rigorous falsification test, to identify our effect. A key methodological advance is the addition of the falsification procedure to the propensity score matching with the difference-in-difference estimator to identify the effects of interest. The falsification step is an important safeguard that prevents the researcher from incorrectly detecting a statistically significant effect, when none exists, due to overly wide matching calipers, poor predictive performance of a propensity score model, and other parameters in the matching stage. We demonstrate, later in the paper, that traditional choices of caliper sizes from the literature can get tricked into mistakenly detecting significant results in our context even when treatment effects cannot possibly exist (say, the significant treatment "effect" is detected even before the treatment has occurred).

Our results demonstrate that when users adopt the mobile app, they become more socially engaged in that they visit significantly more profiles, send significantly more messages, and, importantly, achieve more matches. We show that this increased engagement is facilitated by each of the following: first, ubiquity—users log in more often, and log in during more diverse hours of the day. Further, we find that men act more impulsively, in that they are less likely to check the profile of a user who messages them before replying. This effect is not visible for women who continue to be more deliberate in their checking before replying behavior. Finally, we find that both men and women exhibit disinhibition, in that users engage with a more diverse set of potential partners than they did before on dimensions of height, education, and race. This includes engaging (both initiating contact or replying to communication) with users of shorter height, or users with fewer years of formal education, or users from a race that is different from theirs, than they otherwise would.

The remainder of the paper is organized as follows. The next section provides a brief literature review focusing on the mechanisms that we expect to see facilitating the relationship between mobile application adoption and social engagement. We then describe the institutional details of our online dating context, the data, and provide some empirical regularities specific to our context, followed by an explanation of our identification approach as well as our novel falsification test. We report the results of our analysis, and present various additional robustness checks. Finally, we present our conclusions and discuss our contributions and managerial implications.

[4]We acknowledge and attempt to account for limitations of using observational data for causal inference by using rigorous falsification testing.

Theoretical Background and Mechanisms

One of the main goals of this study is to understand the drivers of the relationship between mobile application adoption and social engagement. While prior literature has investigated some aspects of the impact of mobile use on behavior (e.g., the impact of smaller screen size; Adipat et al. 2011; Ghose et al. 2012; Overby and Lee 2006), we do not have a clear understanding of the specific mechanisms that underlie the relationships between mobile application adoption and user behavior. We suggest, and empirically demonstrate, that ubiquitous access, impulsivity, and disinhibition are key driving factors in this relationship.

Ubiquity

Two unique aspects of the mobile environment are *ubiquitous* access (access anywhere) and universal access (the ability to stay connected), which allow users to access information at any time and at any place (Watson et al. 2002). Balasubramanian et al. (2002) argue that mobile adoption will relate to ubiquitous usage as time is a precious resource that is limited for most people, and the mobile Internet has fewer of the constraints related to time and space. Okazaki and Mendez (2013) contend that several capabilities of mobile devices enable users' ubiquitous usage, such as continuity and simultaneity (e.g., being "always on"), immediacy (e.g., quickness of an action), portability (e.g., easy to carry), and searchability (e.g., capability to examine). Increase in ubiquitous access can also stem from the personal nature of mobile devices (Chae and Kim 2003). This increases the likelihood that people use their mobile devices in more environments. Further, Shankar et al. (2010) allude to the mobile device as a cultural object, making it a part of everyday traditions and practices.

Given this, we may expect that due to flexible and ubiquitous access to information, mobile adopters will access information more often and engage with the app and related website more frequently. However, while past studies have focused on the conceptualizations of ubiquity (see, for instance, Barnes 2002; Junglas and Watson 2006; Okazaki et al. 2009), prior research has not empirically validated the ubiquitous usage behaviors that happen with a channel shift to mobile, (i.e., when an online desktop user adopts the mobile application). In this paper, we ask not only about whether user access is more ubiquitous, but also whether ubiquity is a mechanism that facilitates a change in the user's engagement after the adoption of the mobile app.

Prior literature has suggested that value of a mobile device to individuals arises from the ability to meet spontaneous needs (Anckar and D'Incau 2002). As an example, Bauer et al. (2007) argue that being able to perform a ticket purchase anywhere and anytime adds to a user's desire for freedom and spontaneity. We posit that spontaneity includes impulsivity and disinhibition. From the perspective of our classification, we claim that spontaneous interactions should be further classified by how much due diligence is done prior to acting and with whom one interacts. This allows us to operationalize and separate impulsivity from disinhibition. In the following sections, we look at these two additional mechanisms that allow us to understand whether spontaneity plays a role in the relationship between mobile app adoption and engagement and matching outcomes: impulsivity, wherein users act without due diligence, and disinhibitive actions and reactions. We start by discussing impulsivity.

Impulsivity

We conceptualize and define *impulsivity* to capture the extent of diligence (or lack thereof) the focal user exhibits when she is messaged by another user. We believe that such a change in user behavior (i.e., the diligence they conduct) after mobile adoption could arise from the reduction in contextual frictions that apps enable. Prior research has found evidence that the portability and accessibility that mobile phones enable facilitate more impulse purchasing (Ghose et al. 2012; Schwartz 2011). Liu et al. (2013) study, from a consumer perception perspective, the role of website attributes such as visual appeal, ease-of-use, frames, graphics, and one-click check-out on impulse purchasing. Their work suggests that different features within a web shopping environment play a role in encouraging impulsive behavior. Brasel and Gips (2014) suggest that the touch interfaces on mobile devices increase the intention of impulsive behavior. In the same vein, Billieux et al. (2007) have shown the linkage between use and dependence on the mobile phone and urgency.

Our work focuses on the impact of a channel shift, which goes beyond the impact of individual features, on impulsivity in engagement. We consider an action impulsive if it happens without much diligence (i.e., the focal user replies to a message without checking the profile of the sending user). We call the measure *GetNoCheckReply* to count how often they reply without checking in an impulsive manner. To be clear, when conceptualizing impulsivity we conjecture that while on a PC, they may take the time to study user profiles in more detail before making a decision, while when on a mobile they are likely to be more spontaneous in their reaction (i.e., they may react "in-the-moment" without doing the due diligence).

Disinhibition

Broadly speaking, with regard to *disinhibition* we build on the foundational work of Goffman (1956, 1959), which claims that social interactions are performances in which individuals act to project a desired image of themselves. Specifically, if a focal person engages—this could be initiating views or replying to messages (i.e., both action and reaction)—with a wider (than the baseline) set of users on dimensions such as race, education, and height, we refer to that as disinhibition. We rely on prior work that demonstrates that Internet-based channels have been shown to decrease disinhibited actions in a variety of contexts. Kling et al. (1999) review social behavior on the Web and state that "people say or write things under the cloak of anonymity that they might not otherwise say or write" (p. 82). This disinhibition has been observed in online settings ranging from adult films and books (Holmes et al. 1998) to pizza orders (McDevitt 2012). In our online dating context, it is well known that for heterosexual users (the subjects of our research), social inhibitions play multiple, and often gender-asymmetric, roles in mate-seeking and matching (see Bapna et al. 2016). Across genders, social norms inhibit the expression of latent or inherent preferences such as interracial (Harris and Kalbfleisch 2000) or same-sex (Pachankis and Goldfried 2006) preferences. Consistent with this prior literature, we expect that mobile application adoption will facilitate disinhibited actions in mate-seeking activity. In particular, we suggest that we will observe behavior that will go against the baseline norms established in the literature (Fisman et al. 2006). As users shift from the web to the mobile channel, we believe the personal nature of mobile devices (e.g., users rarely share their mobile phones, users use mobile phones in more private places) provides a higher level of anonymity to users compared to the PC (Chae and Kim 2003). Shankar et al. (2010) argue that the personal characteristic of mobile devices protects users' security and privacy and facilitates personal and social experiences. Therefore, the increase of anonymity due to mobile adoption will lead to more disinhibited action and reaction.

Impact on Engagement and Matching Outcomes

While we suggest in the sections above that the ubiquity of smartphone usage, disinhibition, and impulsivity associated with smartphone usage could increase social engagement, prior literature has also documented that mobile environments are resource constrained (Ghose et al. 2012). Relative to PCs, smartphones have smaller screens and lower computational power, which have been linked to higher search costs in applications that require information search (Ghose et al. 2012).

Search costs are particularly relevant in the dating context, as finding a partner is often considered to be a search-intensive process. Therefore, when looking at the impact of mobile adoption on social engagement and matching outcomes, we expect higher search costs associated with a mobile device could lead to a reduction in social engagement. This is in contrast to the expected increase in social engagement as a result of increased access and ubiquity and spontaneity. Thus, understanding the impact and direction of the causal link between mobile app adoption and social engagement is an empirical question, which we address in this paper.

Data

Institutional Details

In order to conduct this study, we partnered with one of the world's largest online dating websites, which we call monCherie.com (name disguised). MonCherie.com is offered to users in both the standard online version, accessed through personal computers, and as a mobile application, accessed through users' mobile devices. Both of these offer the following functionality to all of their users:

- Users may set up their own online profiles where they describe themselves as well as reveal characteristics sought in a desired partner. Users may also put a set of their pictures into their profiles.

- Users may search for profiles of other users using an advanced search engine that allows filtering by age, location, religion, and a large number of other demographic variables. Users may also discover partners using a proprietary recommendation engine that is provided by the website.

- Users may view profiles of all other users without limitations.

- Users may send private messages to any other user without limitations.

- Users may secretly rate other users by choosing two actions: "like" or "dislike".[5] These ratings are not known to the rated users (unless some premium features are purchased separately). We refer to this action as a *vote*.

[5]The official and more polite term for dislike is a "pass" but the meaning of that action is much closer to dislike than to "pass for now and return later," since the disliked users will not be shown again to the focal user.

The mobile application is available for free to all monCherie users without any limitations and supports the two dominant mobile platforms: Android and iOS. While being limited to the smaller screen of mobile devices, mobile users are able to accomplish the same tasks as personal computer users. Our data was collected for approximately three months during 2016.

Empirical Regularities

For this study, we acquired rich information about approximately 100,000 monCherie.com users who joined the platform at approximately the same time, during a particular week in March 2016, a time period separated by a dashed line in Figure 1. The aforementioned figure demonstrates the distribution of times of the first adoption of the mobile application for the subset of users that do adopt the mobile app in our data. As is evident from Figure 1, the vast majority of mobile users are "immediate adopters" who tend to adopt the mobile app almost immediately upon registering on the website. Interestingly, however, Figure 1 also demonstrates that once the initial spike in adoption recedes, the rate of new adoptions quickly becomes relatively flat, showing little difference between "late adopters" and "very late adopters," this observation will help motivate our identification strategy as in this study we will only focus on these late adopters. While the decision to restrict our attention to late adopters is driven primarily by identification strategy, from a practical point of view it is also arguably a segment of the user base that is more likely than, say, the immediate adopters to be consciously making the adoption decision rather than just doing it automatically. Hence, quantifying such benefits of adoption to this subpopulation has practical value for the sustenance of the app diffusion. From the identification point of view, this approach gives us two advantages in our matching procedure: (1) when we match mobile adopters to similar non-adopters, excluding immediate adopters allows us to get overall better matching as late adopters have more similar observable and unobservable characteristics to non-adopters than immediate adopters, and (2) we can match adopters to other adopters rather than to non-adopters based on a look-ahead procedure we describe later in the paper, using behavioral data observed prior to adoption (clearly, such a procedure is not possible for immediate adopters by definition, as no behavioral data is observed before mobile adoption for them).

For each of the users in our sample, we have data on a set of demographic variables: gender (gender = 1 for men, 0 otherwise), age, race, education, height, and self-reported body type (whether the person reported themselves as being over-

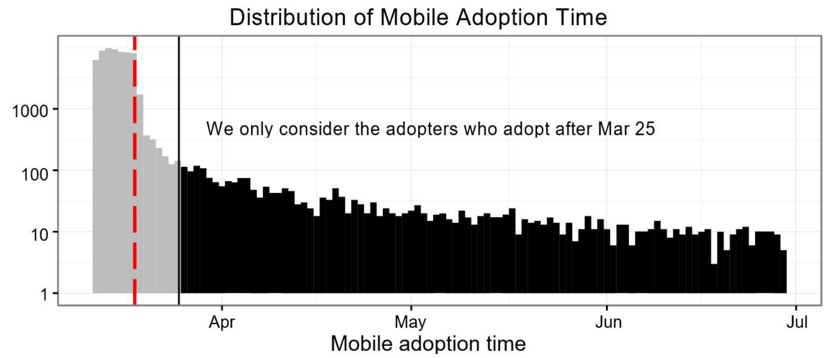

Figure 1. Distribution of User Mobile Adoption

Table 1. Summary Statistics of Adopter Demographic Characteristics

Gender	Variable	Mean	St. Dev.	Minimum	Median	Maximum
Female	Age	36.10	12.61	18.09	32.84	74.17
Male	Age	33.22	11.49	18.01	29.72	76.34
Female	Asian	0.11	0.32	0.00	0.00	1.00
Male	Asian	0.09	0.29	0.00	0.00	1.00
Female	Black	0.11	0.32	0.00	0.00	1.00
Male	Black	0.08	0.27	0.00	0.00	1.00
Female	Edu Years	3.87	1.65	0.00	4.00	6.00
Male	Edu Years	3.76	1.72	0.00	4.00	6.00
Female	Full Figured	0.32	0.47	0.00	0.00	1.00
Male	Full Figured	0.10	0.30	0.00	0.00	1.00
Female	Height In	64.90	2.92	57.87	64.96	74.02
Male	Height In	70.51	2.85	59.84	70.87	77.95
Female	Latin	0.09	0.29	0.00	0.00	1.00
Male	Latin	0.08	0.27	0.00	0.00	1.00
Female	White	0.67	0.47	0.00	1.00	1.00
Male	White	0.73	0.44	0.00	1.00	1.00

weight). Table 1 outlines the key descriptive statistics of user demographics for both men and women for mobile adopters that we study in this paper. As is evident from Table 1, men and women appear to be different in every demographic attribute.

In addition to the demographics, we also have micro-level behavioral data about our users that allows us to operationalize our site-specific social engagement and success outcome constructs, namely, profile viewing, messaging, and matching. Because we only concentrate on the late adopters, we will be able to control for the user's behavior prior to mobile adoption.[6]

As social engagement relates to actions taken by the user to initiate interaction with other users, here, we measure profile

[6]As we described, these behavioral variables are impossible to compute for immediate adopters as there is no well-defined website behavior for them prior to their mobile app adoption, making it impossible to use these variables for matching. Therefore, immediate adopters were not suitable for purposes of identification.

viewing and messaging activity for the users in our sample. Specifically, for every user in our sample we have time-stamped data of every profile the focal user visited (the action that we call *ViewSent*) as well as all the timestamped profile visits that the focal user received from other users (we call that action *ViewRcvd*). For each of these visits we know the time of the visit and whether the visits were made using a mobile device or a PC. Also, for every user in our sample we know the number of private messages that the focal user has sent to other users (*MsgSent*) as well as the number of messages received from other users (*MsgRcvd*). While the content of messages is not shared with us, we are aware of the time and of the length of the message as measured in characters. In addition, we also know the number of votes that the focal user sent to others and received from others (*VoteSent* and *VoteRcvd*).

Table 2 outlines the statistics of user activity for mobile adopters in the first two weeks. As is evident from Table 2, women, on average, send far fewer votes (23.99 versus 30.97 for men) and more than two times fewer views (8.49 for women versus 20.54 for men). In addition, note that women are far less likely to initiate explicit contact via sending a message (1.87 unique conversations initiated by women versus 4.7 conversations by men). On the received side as per Table 3, women receive four times the number of votes than men (131.56 versus 33.65), four times the number of views (30.59 versus 7.41), and almost five times the number of messages (6.9 versus 1.28). Given these extreme gender asymmetries in user behavior, we report all the subsequent statistics and results separately for the two genders.

In addition to the social engagement variables above, one of the key outcome variables for users is a successful match. It is a challenge to define a perfect and all-encompassing measure of success in the context of dating. One such measure could be two users setting up a first date as used by Hitsch et al. (2010). They consider it a match when two users exchange phone numbers or email addresses in their messages on an online dating website.[7] However, it can be easily seen that this measure of a match is not perfect as many first dates turn out to be unsuccessful and do not result in a relationship.

The main difficulty with defining a perfect success measure arises from the fact that any relationship is an ongoing process. It is impossible to know whether any match was ultimately "successful" until one observes it for its entire duration, as relationships can fail at any stage. Thus, we refrain from any attempts to create a perfect measure and instead define *success* in online dating as successful online communication. Without this initial and critical step of successful online communication, the relationship cannot proceed to a successful offline date, a successful relationship, or to a successful marriage.

Therefore, we adopt the definition of a match as per Bapna et al. (2016) who define the communication of user A and user B as a success, that is, it results in a match if user A messaged user B, user B responded, and then user A messaged user B again and user B responded again (with user A possibly responding to that and so on), therefore forming a sequence of at least *four* messages[8] between user A and user B. In this scenario, since user A initiated the match, we refer to this match as *MatchSent* for user A and *MatchRcvd* for user B. For more details about the robustness of the match definition the reader is referred to Bapna et al. (2016).

Given the above definition of a match, one of our outcome variables, the one that matters to the users of the dating platform, is the total number of matches achieved by a focal user. This choice reflects the dating context of mate seeking that we study. Dating is defined as a prolonged period of polygamous learning that eventually leads to a long-term relationship such as marriage. In that spirit, we posit that there is positive expected utility in each additional match. Referring back to Tables 2 and 3, the descriptive statistics show that women achieve a significantly higher number of matches than men,[9] and that more than 75% of these matches for women are received matches (that is, matches when the man sends the first message and the woman simply responds, thus supporting the conversation and leading to a match that she did not initiate). More than 75% of matches for men are "matches sent," that is, matches initiated by the man, while less than 25% of matches for women are "matches sent." Again, this supports that our further analysis is conducted separately for women and men.

In the next section, we describe the methodology we use for understanding the relationship between mobile app adoption, social engagement, and the number of matches.

[7]For reasons of privacy and sensitivity to the user base, our research partner could not provide us access to the actual content of the messages.

[8]Note that four messages are only the low side of the threshold. Many of conversations that we will label as matches are much longer than four messages.

[9]This is mathematically possible since there are fewer women on this website than men.

Table 2. Summary Statistics of Adopter Activity During Pretreatment Period

Gender	Variable	Mean	St. Dev.	Minimum	Median	Maximum
Female	Vote Sent	23.99	246.18	0	0	6,063
Male	Vote Sent	30.97	146.58	0	0	3,101
Female	View Sent	8.49	24.98	0	0	355
Male	View Sent	20.54	60.49	0	0	755
Female	Msg Sent	1.87	6.84	0	0	106
Male	Msg Sent	4.70	23.60	0	0	429
Female	Match Sent	0.20	1.15	0	0	23
Male	Match Sent	0.52	2.55	0	0	40

Table 3. Summary Statistics of Incoming Activity for Adopters During Pretreatment Period

Gender	Variable	Mean	St. Dev.	Minimum	Median	Maximum
Female	Vote Rcvd	131.56	274.24	0	0	2,629
Male	Vote Rcvd	33.65	64.62	0	5	961
Female	View Rcvd	30.59	64.57	0	1	604
Male	View Rcvd	7.41	17.83	0	1	285
Female	Msg Rcvd	6.90	15.84	0	0	183
Male	Msg Rcvd	1.28	4.71	0	0	91
Female	Match Rcvd	0.83	3.27	0	0	60
Male	Match Rcvd	0.10	0.49	0	0	9

Empirical Approach and Identification

The gold standard method to understand causal relationships is through running randomized trials (Aral and Walker 2011), which has been gaining popularity in the information systems literature (Andrews et al. 2015; Bapna et al. 2016; Bapna and Umyarov 2015). We describe the ideal experiment for our context below, and then discuss the practical infeasibility of running it in our context. We use a standard empirical strategy for observational data that is based on a combination of propensity score matching (to account for treatment selection bias) combined with difference-in-difference analysis. While this identification strategy is familiar in the literature (Goh et al. 2013; Rishika et al. 2013; Xu et al. 2016), we go beyond by adding an important falsification test, detailed later in this section.

The ideal experiment, which we feel describes our causal question the best, is as follows: (1) take the population of users who decided to adopt a mobile app on their own, (2) randomly split these users into two groups: one group will be allowed to successfully adopt the app (treatment group) while the other group (control group) will be prevented from adopting it, for instance, by giving an installation error, (3) watch the differences between the treatment group and control group after the treatment. Since both the treatment and the control groups expressed the desire to adopt the app but only the treatment group could (randomly) succeed with the adoption, the differences in future outcomes cannot be explained by preexisting differences and must be attributed to the effect of the actual mobile app adoption. In other words, the studied population of inference in our study is the self-selected population of users who expressed the desire to adopt the app. However, randomly blocking mobile app adoptions is practically infeasible in our field context.

Difference-in-Difference Technique with Propensity Score Matching and Falsification

In lieu of a randomized experiment, we employ a three-step empirical approach: (1) propensity score matching to create the treatment and control groups of similar users, (2) difference-in-difference to estimate the changes in trends between the groups, and (3) falsification test to confirm that this procedure is falsifiable (meaning, it also detects no significant effect when it is known that there is no treatment effect). This technique is designed to exploit the natural cases when otherwise similar users happened to adopt or not adopt the app by pure chance, and thus, serves as an approximation to randomization (recognizing all the inherent assumptions and limitations).

Standard propensity score matching (PSM) is a two-step approach where first a treatment predictive model is built to predict the likelihood of being self-selected into treatment based on observable characteristics and behaviors (Heckman et al. 1998; Rosenbaum and Rubin 1983). Then, the observed self-selected treated users are matched to control users having the same propensity scores. This methodology aims to create matched pairs of treated and non-treated group subjects with similar covariate values and similar propensity to be treated. A well-known limitation of PSM is that it can only account for observed covariates (Pearl 2009; Shadish et al. 2002) as matches are constructed only using observed variables.

To mitigate this issue in our context, we employ the difference-in-difference (DID) technique to the matched sample that results from PSM. DID compares the change in outcomes of the treated units before and after the treatment to the change in the untreated units over the same period of time. As the PSM approach makes the comparison group for the DID estimation similar to the treatment group in terms of observed characteristics, integrating PSM with DID analysis helps account for the influence of unobserved characteristics, enhancing the inference related to DID analysis and improving the consistency of the estimates (Stewart and Swaffield 2008). For these reasons, this method is becoming increasingly popular among empirical researchers in IS (Goh et al. 2013; Rishika et al. 2013; Xu et al. 2016).

In our main matching procedure, we use one-to-one static PSM matching without replacement. To calculate the propensity scores, we rely both on the demographic variables (such as age, height, education level, and so on) as well as the behavioral covariates (such as the number of views sent in the pretreatment period[10]).

The following is our propensity score equation:

$$\log\left(\frac{\Pr\left(Treatment_i = 1\right)}{\Pr\left(Treatment_i = 0\right)}\right) = \alpha + \beta \bullet D_i + \gamma \bullet A_{i0} + \varepsilon_t$$

where the Pr($Treatment_i$ = 1) is the propensity to be treated (i.e., adopt the mobile app), D_i are demographic attributes of user i as summarized in Table 1 and A_{i0} are behavioral attributes of user i during the pretreatment period as summarized in Table 2. Since this is a propensity score model, we use the estimated coefficients of this model for predictive purposes in order to predict the propensity score of each user and to match users with similar propensity scores.

To evaluate whether our PSM procedure was successful in matching the treatment group to a similar control group, we first compare the differences in user demographics between the treatment and control groups in Table 4. Another critical assumption of the DID approach is the common trend assumption that the average change in the variables of interest has been the same for both the treatment and control groups prior to the treatment. Therefore, we also plot the micro-level user behavior of these two groups in Figure 2. Figure 2 demonstrates that there is no statistical difference in the trends of user behavior prior to the treatment. We further check this assumption using a relative time model specification as reported later in the "Robustness" section. As demonstrated by both Table 4 and Figure 2 no significant differences are observed in either the user demographics or user behavior in the pretreatment period.

With the matched sample, we employ the DID approach to identify the effect of mobile app adoption on user behavior. We utilize a classic DID approach with two observations per user (before/after) and utilize it as a user-week-level panel.[11] Our main estimation equation using the DID model for user i in week t is

$$\begin{aligned}\log\left(1 + Activity_{it}\right) = \alpha_0 + \alpha_i \times MobileAdopter_i \\ + \alpha_2 \times AfterMobileAdoption_{it} + \alpha_3 \\ \times \left(MobileAdopter_i \times AfterMobileAdoption_{it}\right) \\ + \beta \bullet D_i + \gamma \bullet A_{i0} + \tau_t + \varepsilon_{it}\end{aligned}$$

where $Activity_{it}$ is the dependent variable of interest (e.g., $ViewSent_{it}$, $MsgSent_{it}$, $MatchSent_{it}$). $MobileAdopter_i$ is a treatment dummy variable (denoted with "1" if a user is assigned to the treatment group and "0" otherwise). $AfterMobileAdoption_{it}$ is a dummy variable which takes the value "0" for the week immediately prior to adoption and "1" for the week immediately after adoption, for each treated user

[10]The full set of variables used in the matching stage of the PSM procedure are listed and summarized in Tables 1 and 2. We refer to the period prior to March 25 as the pretreatment period. The pretreatment period is separated by a solid black line in Figure 1.

[11]Weekly level data is required for our ubiquity analysis since the Gini coefficient cannot be computed on a daily level. We decided to use the same unit of analysis for all our results so that they are comparable. We also estimated models using user-day-level observations for the dependent variables that are well defined on the daily level and the results are qualitatively identical to the results presented here.

Table 4. Comparison Between Two Groups Prior to Treatment

N	Gender	Variable	Mean(Treat)	Mean(Ctrl)	Percent Diff.	t-value	p-value
132	Female	Age	36.47	35.82	1.82	-0.29	0.78
162	Male	Age	31.12	31.57	-1.42	0.26	0.80
132	Female	Asian	0.12	0.08	60.00	-0.87	0.38
162	Male	Asian	0.05	0.04	33.33	-0.38	0.70
132	Female	Black	0.08	0.09	-16.67	0.31	0.76
162	Male	Black	0.07	0.07	0.00	0.00	1.00
132	Female	Edu Years	4.00	3.79	5.60	-0.72	0.47
162	Male	Edu Years	3.63	3.63	0.00	0.00	1.00
132	Female	Full Figured	0.29	0.29	0.00	0.00	1.00
162	Male	Full Figured	0.10	0.14	-27.27	0.73	0.47
132	Female	Height In	65.64	65.16	0.74	-1.05	0.30
162	Male	Height In	70.53	70.75	-0.32	0.54	0.59
132	Female	Latin	0.05	0.03	50.00	-0.45	0.65
162	Male	Latin	0.09	0.06	40.00	-0.60	0.55
132	Female	White	0.73	0.79	-7.69	0.81	0.42
162	Male	White	0.73	0.79	-7.81	0.92	0.36

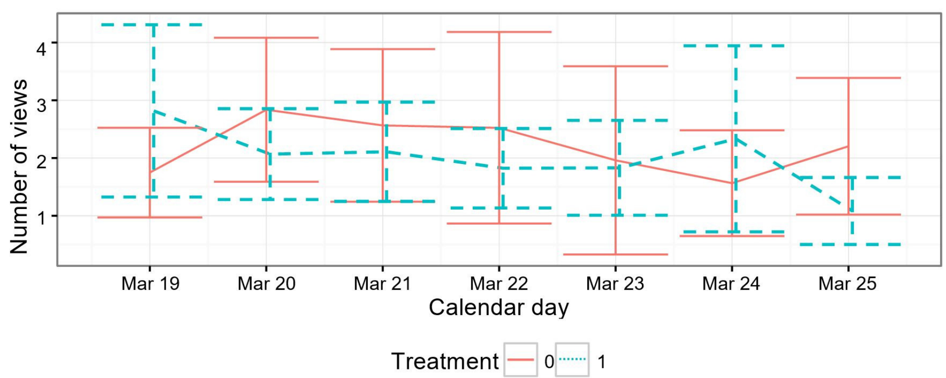

Figure 2. Pre-adoption Viewing Behaviors of Matched Users

and her matched pair. The main coefficient of interest in this model is α_3, the difference-in-difference estimator, which captures how user behavior in the treatment group changes after mobile adoption compared to that of control group over the same period.

In our main model, we also control for demographic attributes D_i of user i as summarized in Table 1 as well as behavioral attributes A_{i0} of user i during pretreatment period as summarized in Table 2. Finally, we include the time fixed effects τ_t to control for common systematic changes over time across all users.

In addition to the combination of PSM and DID, we next describe the falsification test we used in order to ensure that these results are not sensitive to the choice of matching parameters: the exact regressors used in the propensity score equation, the randomization seed, the size of the caliper, and so on.

Falsification Test

The idea of our novel falsification test relies on reestimating the exact same DID model with all the same data, model parameters, functional form, constraints, propensity score matching equation, and caliper size but with only one small change: we shift *AfterMobileAdoption*$_{it}$ one time period earlier. That is, the *AfterMobileAdoption*$_{it}$ variable (described in our DID model) will be equal to "1" the week that precedes the actual mobile adoption, not after. Naturally due to the time shift, *AfterMobileAdoption*$_{it}$ will be equal to "0" two weeks before the actual mobile adoption, not one week.

Since the shifted *AfterMobileAdoption*$_{it}$ points to the week before the actual adoption, not after, the users have not yet actually adopted the mobile yet and, therefore, the same model that we just used to prove the main effect must now produce the lack of significant coefficients because no treatment effect is possible before the treatment has actually occurred.

The trick for a valid, robust falsification test is that the exact same model (same caliper size, randomization seed, matching procedure, etc.) and the exact same data except for the time shift are used to establish both the main results and the falsification results. However, for the main results, the model must find a strongly significant result while for the shifted time the same model must report lack of any significant results.

While other pretreatment tests are available and known in the literature, they frequently use one model to estimate the main effect and a *different* model to demonstrate the lack of pretreatment differences. The latter strategy can potentially be abused by picking an overly optimistic model for the main results and an overly conservative type of a model for showing the lack of pretreatment differences. Our falsification test is immune to that since the model and all model estimation parameters are identical for both of these estimations.

In other words, the expected behavior for our model with the falsification test is as follows:

1. When the *AfterMobileAdoption*$_{it}$ indicator is not shifted and is equal to "1" during the true week of user's adoption, the model should detect significant differences between the treatment and control groups.

2. However, once the *AfterMobileAdoption*$_{it}$ indicator is shifted by one time period and is equal to "1" right before the actual adoption, the model results should change immediately and the same model should report that no significant differences are observed.

If the second item in the list fails the test and the model still reports a significant result even when the *AfterMobileAdoption*$_{it}$ indicator points before the actual adoption, then it is clear that the main results should not be trusted. This test allows us to discover the following potential issues if they are present to a sufficient degree:

1. *Inappropriate matching*. This may happen due to overly broad caliper sizes, bad propensity score model predictive model, a code bug, and so on. When matching is poor and dissimilar users are matched together, it is very easy to discover the main significant results and even pass some of the pretreatment tests from the literature as discussed below. However, the falsification test will also demonstrate significant differences before the treatment when there should be none since the exact same model is used.

2. *Inappropriate main model*. This may happen when matching is done correctly but a statistically inappropriate or overly sensitive model is used for the main outcome variable. Say, the researcher forgot to use a heteroscedasticity consistent estimator, account for autocorrelation, etc., and the model tends to report even random noise as a significant effect. Once again, in such a case it would be easy to find the main significant results. However, the falsification test will also show significant results when there should be none since the same model is used in both cases and in both cases it relies on inappropriate statistical assumptions and misinterprets noise as a useful signal.

3. *The presence of true nonremovable pretreatment differences*. This may happen when true unobserved pretreatment differences are present between the treatment and control group that cannot be removed by a matching procedure. In such a case, the groups would be balanced in terms of observed covariates but remain unbalanced in terms of unobserved but important covariates. The falsification test will be able to detect that otherwise well-balanced groups (in terms of known covariates) seem to produce significant treatment effect estimates even before the treatment has occurred, suggesting the presence of unaccounted but impactful covariates.

To summarize, if our analysis is done properly, our main results should show strong significance as treatment effect should be seen after the treatment while at the same time our falsification test should produce statistically insignificant results using the exact same model as no treatment effect is possible before the treatment has occurred.

In the next section, we report the results of estimating our main model and our falsification test as described above.

Results and Analysis

Main Results

Table 5 reports the results of DID estimations for the three main outcomes of interest: ViewSent, MsgSent, and TotalMatch. In each specification, we find a positive and statistically significant relationship between the mobile app adoption and change in the corresponding user behavior.

The results of our main model show that the number of views sent by the treatment users increases by 179% per week for females as compared to the control group and by 234% per week for males. We find that the number of messages sent increases by 71.3% per week for females in our treatment group as compared to the control group and by 61% per week for males.

Finally, we find that total matches increase by 21.2% per week for males and by 64% per week for females. This suggests that there are significant differences in engagement through viewing, messaging, and matching outcomes that are induced by adopting the mobile app, even when controlling for both observed and some unobserved characteristics.

Falsification Test

As described in the previous section, if our analysis is done properly, our main results should show strong significance as treatment effect should be seen after the treatment while at the same time our falsification test should produce statistically insignificant results using the exact same model as no treatment effect is possible before the treatment has actually occurred. Table 6 reruns our main results for viewing, messaging, and matching using a fake treatment date and finds no significant effect, as expected. As mentioned earlier, the idea behind this test is to ensure against spurious results that could arise from the sensitivity of matching based models to parameter choices, such as the size of the caliper, at the model building stage. To drive home this point, observe that in Table A1 and Table A2 (see the Appendix), when we use the standard caliper size (0.2 times standard deviation of the distribution of the propensity score; Austin 2011) the falsification test fails and we observe significant results even when we use a fake adoption time. We believe that adding the falsification test is an important methodological contribution to researchers using the combination of PSM plus DID in setting the correct matching parameters.

Mechanisms

Ubiquity

To examine whether adopting the mobile app causes ubiquitous usage of the website, we first investigate whether mobile adoption has increased the frequency of accessing the website. We examine this by counting the number of hours that each user showed up on the website in the week as measured by a variable called *AllLogin*. For example, if a focal user, let's call her user A, only logged in at 1 p.m. on Monday, 1 p.m. on Tuesday, 1 p.m. on Friday and 5 p.m. on Saturday in the first week of April, *AllLogin* for that user would be equal to four, since the user showed up at four different hours in that week. Therefore, we calculate the *AllLogin* variable for each user based on the day of adoption and we rerun the main equation with *AllLogin* as the outcome variable. As is demonstrated in Table 7, we find that once the users adopt the mobile app, login activity increases by 192% per week for females and by 175% per week for males.

To further understand whether the adoption of a mobile channel substitutes or complements the website use on PC channel, we repeat the analysis using logins only from the PC channel. The *DesktopLogin* column in Table 7 shows that mobile app adoption does not have a significant effect on the frequency of accessing the website through the PC channel.

In addition, we examine the ubiquity of the platform usage by estimating the change in diversity of login hours for the treatment group as compared to the control group. We calculate the *Gini* coefficient to measure of the diversity of login hours at the weekly level.[12]

If we were to take the previous example of user A's activity in the first week of April, user A logged in at 1 p.m. three times in the week, logged in at 5 p.m. once, and was never seen logging in at any other hour of the day in that week. Therefore, the most popular login hour for user A is 1 p.m. and that hour accounts for 75% of all user A's logins in the week, 5 p.m. is the second most popular hour for user A and accounts for the balance of user A's logins in the week. User A was not seen at 9 p.m. (or any other hour) at all, so these hours account for 0% of user's logins. This distribution allows us to calculate the Gini coefficient for user A of 0.9375 and thus demonstrates the diversity of different login hours of the day for user A. This represents the ubiquity of the user's access of the online dating platform. As another example, if

[12]This is one of the reasons why we select the weekly panel. The Gini coefficient, as we measure it, cannot be estimated on a daily level.

Table 5. Main Results

	Dependent Variable					
	View Sent	Msg Sent	Total Match	View Sent	Msg Sent	Total Match
	Female			Male		
Treatment	0.7696***	0.5569***	0.3616***	0.3867*	0.2580*	0.0848
	(0.2089)	(0.1594)	(0.1305)	(0.2125)	(0.1437)	(0.0661)
After	0.2462	0.2330	0.0367	−0.1068	0.0031	−0.0019
	(0.2040)	(0.1556)	(0.1274)	(0.2042)	(0.1381)	(0.0636)
Treatment After	1.0265***	0.5384***	0.4947***	1.2046***	0.4760**	0.1925**
	(0.2885)	(0.2202)	(0.1802)	(0.2887)	(0.1953)	(0.0899)
User controls	Y	Y	Y	Y	Y	Y
User fixed effects	N	N	N	N	N	N
Time fixed effects	Y	Y	Y	Y	Y	Y
Observations	256	256	256	306	306	306
R^2	0.4403	0.3633	0.3288	0.3838	0.3796	0.2055

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

Table 6. Falsification: Main Results

	Dependent Variable					
	View Sent	Msg Sent	Total Match	View Sent	Msg Sent	Total Match
	Female			Male		
Treatment	0.1397	0.1925	0.1587	−0.0583	−0.0573	−0.0905
	(0.2505)	(0.1768)	(0.1307)	(0.2343)	(0.1378)	(0.0642)
After	−0.1631	−0.1039	0.0458	−0.0568	−0.0481	−0.0630
	(0.2296)	(0.1621)	(0.1198)	(0.2199)	(0.1293)	(0.0602)
Treatment After	0.6370*	0.3657	0.2140	0.4157	0.2970	0.1662*
	(0.3241)	(0.2288)	(0.1692)	(0.3106)	(0.1827)	(0.0851)
User controls	Y	Y	Y	Y	Y	Y
User fixed effects	N	N	N	N	N	N
Time fixed effects	Y	Y	Y	Y	Y	Y
Observations	210	210	210	262	262	262
R^2	0.3422	0.2593	0.2539	0.3048	0.3807	0.2706

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

Table 7. Ubiquity

	Dependent Variable					
	GIni	All Login	Desktop Login	Gini	All Login	Desktop Login
	Female			Male		
Treatment	−0.0585**	0.4706***	0.4828	−0.0193	0.2632*	0.2351
	(0.0252)	(0.1769)	(0.1820)	(0.0164)	(0.1555)	(0.1583)
After	−0.0056	0.2117	0.2059	0.0043	−0.0506	−0.0512
	(0.0237)	(0.1727)	(0.1778)	(0.0158)	(0.1494)	(0.1522)
Treatment After	−0.0465	1.0701***	−0.1152	−0.0476**	1.0126***	0.2232
	(0.0311)	(0.2443)	(0.2515)	(0.0209)	(0.2113)	(0.2152)
User controls	Y	Y	Y	Y	Y	Y
User fixed effects	N	N	N	N	N	N
Time fixed effects	Y	Y	Y	Y	Y	Y
Observations	169	256	256	208	306	306
R^2	0.2663	0.4468	0.2885	0.3940	0.4222	0.3331

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

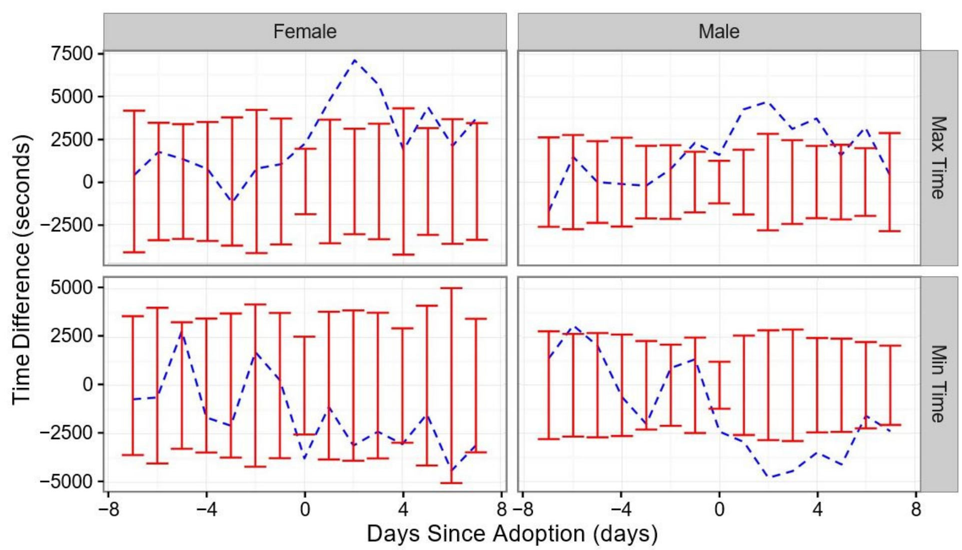

Figure 3. Minimum/Maximum Time Before and After Adoption

user A was always online at 1 p.m. in that week and never visited the website at any other time, her Gini coefficient would be approximately[13] equal to 1.0, demonstrating the lack of ubiquity as measured by the hour of the day access. As a third example, if user A was consistently coming back to the website every hour of the day, her Gini coefficient would be equal to 0 demonstrating the perfect 24/7 ubiquity. Introducing this measure allows us to compare the ubiquity of access induced by mobile app adoption between the treatment and control group. As shown in Table 7, we find a significant increase in ubiquity (decrease in Gini coefficient) for men, and an increase, although not stastistically significant, for women after the adoption of the mobile application. The

[13]The actual answer is 0.9583 due to the discrete nature of only having 24 hours in a day.

insignificant result for women is potentially attributable to the substantially lower sample size after the propensity score matching procedure and accounting for the fact that Gini coefficient cannot be estimated if a user never logged in at all. This argument is further examined by Figure 3, which compares the range of times users appear on the online dating platform immediately before and immediately after mobile adoption.

In Figure 3, a value of zero on the x-axis indicates the day of mobile app adoption and other values on the x-axis represent the distance from the mobile app adoption day (measured in days). The two graphs in the left column represent results for females and the two graphs in the right column represent results for males. The two graphs in the top row examine the latest time that the user showed up on the website in that day (*MaxTime*). The two graphs in the bottom row represent the earliest time that the user showed up on the website in that day (*MinTime*).

The confidence interval bars represent corresponding time distributions with respect to regular website visits, and the dashed line tracks the times with respect to mobile adoption times. It is clear that the range of times (i.e., the dashed lines) diverge immediately after mobile adoption. As users adopt the mobile application, they seem to show up much earlier on the website in the morning (*MinTime* analysis) and also show up much later in the evenings (*MaxTime* analysis) as compared to their regular browsing day, staying around an hour or even more later than usual for both males and females in the days immediately after adoption. It is also notable that the expanded range of activities only show up on and after mobile adoption (for nonnegative x on the x-axis) and seems to be within normal range before mobile adoption (for negative x on the x-axis) as expected if the analysis was done correctly and there were no pre-adoption trends.

Impulsivity

We operationalize *impulsivity* to capture the extent of diligence (or lack of) the focal user exhibits when she is messaged by another user (see Table 8). We consider an action impulsive if it happens without much diligence (i.e., the focal user replies to a message without checking the profile of the sending user). We call the measure *GetNoCheckReply* to count how often a focal user replies in an impulsive manner without checking the profile. We expect that users, armed with a smartphone, may start responding to incoming messages in the moment and be less inclined to wait to conduct their due diligence, that is, do a complete evaluation of someone who contacted them by checking out their profile.

We find that there is a significant increase in impulsivity for men, but the same is not the case for women, who continue to be diligent in responding to users who target them. This is consistent with other empirical regularities observed for men in online dating markets. In general, the quantity of messages men send to women is orders of magnitudes greater than the number of messages women send to men. It appears that the mobile environment makes men even less deliberate than their usually low baseline level. Note that we investigated whether there was evidence of targeted impulsivity (i.e., were men or women more impulsive with a subgroup of users, such as those of another race, or of shorter height, or of lower education), but found no support for a more granular implusivity effect, either for men or for women. Next, we investigate whether the set of users who are targeted or engaged with is altered as a result of mobile adoption (i.e., whether users are more disinhibited in their behavior after mobile app adoption).

Disinhibition

As discussed earlier, we posit that the increase in engagement relating to mobile app adoption could be through enabling disinhibited behavior (i.e., departure from existing social norms and preference structures for heterosexual dating; Fisman et al. 2006). We operationalize multiple constructs that allow us to examine evidence that supports this idea. It is well known that for heterosexual users (the subjects of our research), social inhibitions play multiple, and often gender-asymmetric, roles in mate-seeking and matching (see, e.g., Bapna et al. 2016). Across genders, social norms inhibit the expression of latent or inherent preferences such as interracial (Harris and Kalbfleisch 2000) or same-sex (Pachankis and Goldfried 2006) preferences. We operationalize disinhibited action as the likelihood of a focal user viewing or replying to other users (1) of a race other than their own, (2) of a short stature, as defined by a height that is at or lower than the 25th percentile as reported by the CDC for adults in the United States (McDowell et al. 2008), and (3) whose highest formal education level is high school or lower. We focus on profile viewing and replying to a message (i.e., action and reaction) to capture disinhibition broadly (see Table 9). Profile viewing is the initial explicit action that starts the communication process for matching and demonstrates a certain level of interest in the prospective date. Again, what we expect is that mobile application adoption will facilitate disinhibited behavior that is somewhat divergent from the baseline norms established in the literature (Fisman et al. 2006). We find a significant lowering of the preference barriers for the propensity to view users of a race different than their own, as well as viewing users of shorter stature and users with less years of formal education, upon the adoption of the mobile channel for both

Table 8. Impulsivity Measure: Reply Without Checking		
	Dependent Variable	
	Get No Check Reply Female	**Get No Check Reply Male**
Treatment	0.1250*	0.0016
	(0.0635)	(0.0130)
After	0.0599	−0.00001
	(0.0620)	(0.0125)
Treatment After	0.1361	0.0350**
	(0.0877)	(0.0177)
User controls	Y	Y
User fixed effects	N	N
Time fixed effects	Y	Y
Observations	256	306
R^2	0.2723	0.0856

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

Table 9. Disinhibition Measure: View Profile						
	Dependent Variable					
	View OtherRace	**View ShortHeight**	**View Highschool**	**View OtherRace**	**View ShortHeight**	**View Highschool**
	Female			**Male**		
Treatment	0.4583***	0.2969***	0.6443***	0.1367	0.2562*	0.2304
	(0.1446)	(0.1072)	(0.1692)	(0.1627)	(0.1362)	(0.1788)
After	0.1080	0.0467	0.1502	−0.1033	−0.0822	−0.1019
	(0.1412)	(0.1047)	(0.1652)	(0.1563)	(0.1309)	(0.1719)
Treatment After	0.6166***	0.4556***	0.7969***	0.8191***	0.7958***	1.0426***
	(0.1997)	(0.1481)	(0.2337)	(0.2211)	(0.1851)	(0.2431)
User controls	Y	Y	Y	Y	Y	Y
User fixed effects	N	N	N	N	N	N
Time fixed effects	Y	Y	Y	Y	Y	Y
Observations	256	256	256	306	306	306
R^2	0.4204	0.3773	0.4355	0.3924	0.3774	0.3671

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

men and women. In particular, the number of times the focal user viewed a profile of a user of a different race *(ViewOtherRaceSent)* increased by 85.3% per week for females and by 127% per week for males. Further, the number of times the focal user viewed a profile of a user of shorter stature *(ViewShortHeightSent)* increased by 57.7% per week for females and by 122% per week for males. Finally, the number of times the focal user viewed a profile of a user whose highest formal education level is that of high school or lower *(ViewHighschoolSent)* increased by 122% per week for females and by 184% per week for males. These results point to the importance of the disinhibited actions as an underlying mechanism linked to increased engagement from mobile.

With respect to disinhibited reaction, the main finding here is that women become more likely to reply to men of shorter stature and men with less years of formal education (see Table 10). Specifically, the results show that the number of times the focal user replied to a user of short stature *(MsgShortHeightReply)* increased by 20.4% per week for females with no significant changes in corresponding response patterns for males. Also, we find that the number of

Table 10. Disinhibition Measure: Message Reply

	Dependent Variable					
	OtherRace Reply	ShortHeight Reply	Highschool Reply	OtherRace Reply	ShortHeight Reply Male	Highschool Reply
	Female			Male		
Treatment	0.2225**	0.0116	0.2819***	−0.0062	−0.0106	−0.0047
	(0.0884)	(0.0575)	(0.0993)	(0.0198)	(0.0092)	(0.0286)
After	0.1084	0.0255	0.0934	−0.0186	−0.0092	−0.0342
	(0.0863)	(0.0562)	(0.0970)	(0.0190)	(0.0088)	(0.0275)
Treatment After	0.1658	0.1854**	0.3070**	0.0521*	0.0184	0.0680*
	(0.1221)	(0.0795)	(0.1371)	(0.0269)	(0.0125)	(0.0389)
User controls	Y	Y	Y	Y	Y	Y
User fixed effects	N	N	N	N	N	N
Time fixed effects	Y	Y	Y	Y	Y	Y
Observations	256	256	256	306	306	306
R^2	0.3349	0.2143	0.3044	0.1406	0.0986	0.0931

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

times the focal user replied to a user with less formal education *(MsgHighschoolReply)* increased by 35.9% per week for females with no significant changes in the corresponding response patterns of males.

Altogether, our results indicate a significant increase in engagement driven by the mechanisms of ubiquity, implusivity and disinhibitions that are unique to the capabilities afforded by the mobile app ecosystem. Importantly, for users and online dating platforms this also results in an increase in matches obtained. In the next section, we demonstrate that these results are robust to alternative matching methods and to a longer time period of analysis, and are not biased by pretreatment trends.

Robustness

In this section we report a variety of robustness checks that lead to findings that are similar to our main findings reported in the previous section. First, we show the long-term effect of mobile channel adoption by examining the impact over the three month period. Second, we conducted the DID analysis with an alternative matching algorithm, LA-PSM. Subsequently, we rule out that there are correlated pre-adoption behavior changes that drive our results.

Long-Term Effect

Recall that in our main results, reported in Table 5, each user is represented using two data points: data capturing their activity in aggregate for the week prior to adoption and for the week post-adoption in the DID model. We now show that our results are robust to a longer window of analysis and a different unit of analysis. Specifically, we revise our DID data and create a full panel of daily observations per user over an approximately 90-day time span. We use the following panel data model:

$$\log\left(1 + Activity_{it}\right) = \alpha_{(i)} + \alpha_2 \times AfterMobileAdoption_{it}$$
$$+\alpha_3 \times \left(MobileAdopter_i \times AfterMobileAdoption_{it}\right)$$
$$+\tau_t + \varepsilon_{it}$$

where $Activity_{it}$ is the dependent variable of interest (e.g., $ViewSent_{it}$, *MsgSentit*, $MatchSent_{it}$). $AfterMobileAdoption_{it}$ is a dummy variable that takes the value "0" for all days prior to mobile adoption and "1" for all days including and after mobile adoption for each treated user and her matched pair. Here $\alpha_{(i)}$ is a user-level fixed effect and τ_t is a calendar day-level fixed effect. The main coefficient of interest in this model is α_3, the long-term effect difference-in-difference estimator, which captures the long-term changes in user behavior after mobile adoption.

The coefficient of interest α_3 captures the long-term average treatment effect over 2 to 3 months, during which time each user will have adopted the mobile application. The results in Table 11 demonstrate that our main results remain consistent even when examined over a longer time window. Note that the individual-level data used in this analysis allows us to include user-level fixed effects along with time fixed effects,

Table 11. Main Analysis: Long-Term Effect

	Dependent Variable					
	View Sent	Msg Sent	Total Match	View Sent	Msg Sent	Total Match
	Female			Male		
After	0.0846***	0.0553***	0.0268***	0.0376	0.0314**	0.0056
	(0.0242)	(0.0145)	(0.0100)	(0.0246)	(0.0134)	(0.0047)
Treatment After	0.3205***	0.1191***	0.0711***	0.2812***	0.0938***	0.0184***
	(0.0288)	(0.0173)	(0.0120)	(0.0300)	(0.0163)	(0.0057)
User controls	N	N	N	N	N	N
User fixed effects	Y	Y	Y	Y	Y	Y
Time fixed effects	Y	Y	Y	Y	Y	Y
Observations	12,672	12,672	12,672	15,552	15,552	15,552
R^2	0.3169	0.1918	0.1783	0.2517	0.2343	0.0873

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

as reflected in Table 11, but requires us to remove the $MobileAdopter_i$ variable as it is captured by the user's fixed effect now. In the main analysis reported above, we used the traditional difference-in-difference estimator with two time periods (before and after) and an extensive set of demographic and behavioral control variables at the individual level as well as time fixed effects.

Note also that it is not possible to do our main falsification test described in the section on the empirical approach for this type of a model since there are more than two observations per user and the time cannot be just shifted by one time period to achieve falsification. Therefore, we elected to use this type of a model as a robustness check rather than a main model.

Matching with LA-PSM

As mentioned previously, we verify the robustness of our results by attempting an alternative matching method that relies on somewhat different underlying principles. In this section, we report the results using look-ahead PSM (LA-PSM) matching (Bapna et al. 2018). Unlike traditional matching procedures, LA-PSM matches the existing mobile users to the existing PC users who have the same propensity score *and who also will adopt the mobile app in some later time period*. Since both sets of users do eventually adopt the mobile application, this methodology accounts not just for the observed characteristics, but also for unobserved time-invariant characteristics that cause users to eventually adopt a mobile app. For example, even if there is some unobserved but time-invariant characteristic (such as, say, "being a geek") in the mobile users, then the users in the treatment group would be equivalent to the matched users in the control group in that attribute since both the treatment and control group eventually adopted the mobile app. Bapna et al. (2018) perform an extensive simulation analysis highlighting the properties of this approach as compared to traditional PSM and randomized experiments. As demonstrated in Table 12, the results reveal significant positive effects of mobile app adoption on user behavior consistent with other results. It should be noted that estimates of two models reported in Table 5 and in Table 12 are different as they are measuring the effect of mobile app adoption in two different time periods and using different time granularity (weekly versus daily). We would also like to report that LA-PSM also passes the falsification test that we described above and that is reported in Table A1.

Ruling out Pre-adoption Trends

An alternative explanation for our results is that the adoption of the mobile application is correlated with a user's pre-adoption increase in intention and intensity to seek dates, and thus that our results could be attributed to this behavior and not the adoption of the mobile application itself. Our falsification test is the main tool that we use to rule out pre-treatment trends as well as a large number of other possible issues that may have caused the results by mistake.

To add extra evidence in addition to our falsification test, we examine the pre-adoption viewing, messaging, and matching activity and show that users' behavior just prior to the adoption of the mobile application is not different from other non-mobile users' behavior. In doing so, we deploy a class of models known as relative time models of trajectory based models for causal inference (Haviland and Nagin 2005). Our

Table 12. LA-PSM Results

	Dependent Variable					
	View Sent	Msg Sent	Total Match	View Sent	Msg Sent	Total Match
	Female			Male		
Treatment	-0.0530	-0.1522	-0.0593	0.2879	0.3344**	0.0566
	(0.2956)	(0.2210)	(0.1668)	(0.2158)	(0.1559)	(0.0805)
After	0.0388	-0.1748	-0.1385	0.2163	0.0044	-0.0503
	(0.2879)	(0.2153)	(0.1624)	(0.2091)	(0.1511)	(0.0780)
Treatment After	1.1995***	1.0285***	0.7649***	0.8476***	0.4286**	0.2127*
	(0.4070)	(0.3043)	(0.2297)	(0.2958)	(0.2137)	(0.1103)
User controls	Y	Y	Y	Y	Y	Y
User fixed effects	N	N	N	N	N	N
Time fixed effects	Y	Y	Y	Y	Y	Y
Observations	138	138	138	388	388	388
R^2	0.4207	0.3787	0.3218	0.2150	0.2009	0.1529

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

particular implementation of this model is similar to that of Greenwood and Agarwal (2015), who combined the use of absolute time controls and relative time controls interacted with the occurrence of the treatment. Overall, we estimate the existence of the unusual pre-adoption behavior by using the following two-way fixed effects model, including a dummy variable for the relative time period before and after adoption:

$$\log\left(1 + Activity_{it}\right) = \alpha_{(i)} + \tau_t + \beta \bullet T_{(n,i,t)} + \varepsilon_{i,t}$$

where $Activity_{it}$ is viewing, messaging, and matching behavior at time t, by user i. In the model, $\alpha_{(i)}$ are user fixed effects, τ_t are time fixed effects, and $T_{(n,i,t)}$ are series of dummies that indicate the chronological distance between the observation and the actual adoption of the mobile channel. Here, n ranges from minus four to three, representing the periods from four days before to three days after the mobile adoption. In addition, to avoid a dummy variable trap, following Burtch et al. (2016), we choose one day before mobile adoption as the baseline and omit the dummy variable for that day.

In the interest of space, we report only the results of our coefficient of interest, β, which indicates whether or not there is a significant increase in activity in the four days before and three days after adoption, in Table 13. In the table, a lack of significance in the $t - 4$, $t - 3$, and $t - 2$ periods shows pretreatment homogeneity between the mobile adopters and their counterparts in the control group.[14]

[14]We also confirmed that choosing a different pre-adoption day as baseline provides identical results.

Discussion and Conclusion

The widespread global penetration of smartphones, the deployment of various high-speed mobile infrastructures, and the rapid growth of the iOS and the Android app ecosystem has created a perfect storm for mobile to become an important channel for firms to connect with their consumers. Various industry reports suggest that the shift toward mobile as a channel is potentially as significant as the prior e-commerce revolution that legitimized the online channel as an alternative to the physical channel. For companies, the mobile platforms offer the potential to be the connector between their online and offline assets. Using complementary investments in cloud computing, big data, and predictive analytics, companies can deploy mobile apps to engage with their consumers in the context of their day-to-day life patterns. A key distinguishing feature of the growing deployments of mobile apps is that it affords users with an unprecedented level of ubiquitous access to the existing IT investments made by firms deploying such apps. Users, in the flow of their day-to-day work and life, can use these apps to connect with firms' back-end engines for product discovery, participate in m-commerce, and engage and interact with others through social networking platforms. As apps proliferate, understanding the impact of app adoption on key outcomes of interest and linking this understanding to the underlying mechanisms that drive these results is imperative. As with all technologies, the long-term viability of their diffusion hinges on rigorous estimates of returns to investments made in such technologies, which is the focus of this paper. In doing so, we follow a long line of IS literature that strives to estimate returns from early IT investments in enterprise systems and subsequent investments in e-commerce channels (e.g., Brynjolfsson and Hitt 1996).

Table 13. Relative Time Model

	Dependent Variable					
	View Sent	Msg Sent	Total Match	View Sent	Msg Sent	Total Match
	Female			Male		
T - 4	−0.0835	−0.0344	−0.0345	0.1309*	0.0459	0.0125
	(0.0742)	(0.0480)	(0.0367)	(0.0748)	(0.0442)	(0.0168)
T - 3	−0.0516	−0.0286	−0.0182	0.0406	0.0057	−0.0031
	(0.0730)	(0.0472)	(0.0361)	(0.0726)	(0.0430)	(0.0163)
T - 2	−0.0070	−0.0534	−0.0600*	0.0090	0.0221	−0.0064
	(0.0723)	(0.0467)	(0.0357)	(0.0715)	(0.0423)	(0.0161)
T + 0	0.6274***	0.3519***	0.2025***	0.5890***	0.2329***	0.0463***
	(0.0707)	(0.0457)	(0.0350)	(0.0700)	(0.0414)	(0.0157)
T + 1	0.2721***	0.2654***	0.1408***	0.1737**	0.0302	−0.0092
	(0.0706)	(0.0457)	(0.0349)	(0.0700)	(0.0414)	(0.0157)
T + 2	0.1169	0.1143	0.0415	0.1076	0.0302	−0.0052
	(0.0715)	(0.0463)	(0.0354)	(0.0709)	(0.0419)	(0.0159)
T + 3	0.1019	0.0716	0.0066	0.0905	0.0569	0.0173
	(0.0725)	(0.0469)	(0.0359)	(0.0716)	(0.0423)	(0.0161)
User controls	N	N	N	N	N	N
User fixed effects	Y	Y	Y	Y	Y	Y
Time fixed effects	Y	Y	Y	Y	Y	Y
Observations	1,702	1,702	1,702	2,094	2,094	2,094
R^2	0.4403	0.3792	0.3654	0.4399	0.3651	0.2213

Notes: $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. Robust standard errors in parentheses.

In this paper, we examine and quantify the changes in user behavior induced by adoption of a mobile application, in terms of engagement and matching outcomes, in the online dating context. Online dating platforms enable a very fundamental human activity, and are doing so at a scale that is unprecedented. Some facts can help shed light on the importance of studying these platforms. More than one third of those married between 2005 and 2012 in the United States met online (Cacioppo et al. 2013). Usage of online dating by 18- to-24-year-olds has increased nearly threefold since 2013, while usage by 55- to 64-year-olds has doubled (Pew Research 2016). Like many other social processes that make up our day-to-day lives, many salient aspects of dating have been duly digitized. Finding a romantic partner has moved from being a purely physical world activity to an activity conducted on the web, and now increasingly to an activity conducted on the mobile channel. We worked in partnership with one of the major online dating sites, which was interested in examining what happens to users' social engagement with the platform and the users' matching outcomes once they adopted the site's mobile app. We measure users' profile viewing and messaging intensity as measures of social engagement; we also looked at matching as an outcome variable. Our conversations with the senior executives of the dating platform revealed that increasing such engagement is a key driver for continued monetization and growth of the site. More active users provide more eyeballs for monetization through advertising and increased activity also links to the higher likelihood of getting matched through the site. An interesting nuance of the dating platforms, different from other social networking and gaming sites, where satisfied users continue to return and use the site, a satisfied user on an online dating platform is often one who finds a match and therefore leaves. To the casual observer, this churn may be linked to an inability to monetize users over the long-term. However, in the online dating context, successfully matched users (who may leave the site) are key for spreading positive word-of-mouth regarding the likelihood of getting a date or finding a partner, which influences other new users to join. Thus, the dating platform considers successful matching as a win-win outcome for itself and the users.

A key element of fully developing the potential of such rapidly spreading technologies is understanding the detailed mechanisms that are associated with changes in outcomes of interest. In this paper, one of our primary contributions is the identification of the mechanisms that are somewhat unique to the mobile environment, but were hitherto unestablished in the literature, that drive this shift in behavior: ubiquity, impulsivity, and disinhibition. Our main identification strategy uses propensity score matching combined with difference-in-differences, coupled with a rigorous falsification test to confirm the validity of our identification strategy.

Our results demonstrate that mobile app adoption induces users to become more socially engaged as measured by key engagement metrics such as visiting significantly more profiles, sending significantly more messages, and, importantly, achieving more matches. We also show that the mechanisms mentioned above facilitate this increased engagement: ubiquity of mobile use (users login more, and login across a wider range of hours in the day), disinhibited actions (users initiate actions to a more diverse set of potential partners) and reactions (users engage more often with certain categories of people on mobile which they otherwise tend to ignore on a PC). We also find that men, in particular, become even less deliberate and more impulsive when they start using the mobile channel.

While we study the impact of the channel shift from web to mobile in the context of online dating, our work generalizes to a broader set of firms that are engaged in this channel shift. We see the mechanisms of ubiquity and spontaneity (disinhibition and impulsivity) being generally applicable to a wide range of contexts. While industry reports and anecdotal evidence have pointed toward these mechanisms in a wide variety of mobile apps, we provide robust empirical evidence identifying the mechanisms underlying increased engagement from this channel shift. This has implications across the board as firms increasingly invest in creating value from mobile applications.

Our work has its share of limitations that are typical of studies using observational data. Even though we control for observable attributes in our treatment and control groups, it could be the case that there exist some lurking time-variant, unobservable differences for which our current method does not account. Further, in order to be conservative with our estimates of the impact of mobile app adoption, we excluded immediate adopters from our analysis, and created our treatment and control groups over a period where the adoption rate of the mobile app was in steady-state. This not only reduces the sample size, but also precludes us from analyzing the causal behavioral changes, if any, of the immediate adopters of such apps. Our main concern in using the immediate adopters is that we do not observe a control group that we could theoretically claim is equivalent to immediate adopters in unobserved attributes given the nature of our data. Instead, we match late adopters to non-adopters in the case of the regular PSM method (or to slightly later adopters in the case of the LA-PSM method) in order to answer identification questions. Future research may look to use natural experiments and instrumental variable techniques to draw inferences for that group of people.

Our work can be extended in multiple ways. The advent of mobile as a channel is only now reaching critical mass and future research should look at the mechanisms through which online and mobile social engagement translate to offline word-of-mouth. This is especially critical for dating platforms where successful matching for the user results in a customer who, at least for a period of time, is unlikely to visit the site again. Future research with larger sample sizes should also look at heterogeneous treatment effects, that is, whether the effect of mobile interventions varies across different subpopulations in different contexts. For instance, Andrews et al. (2015) use a randomized field experiment to show that consumers in crowded subway cars are more likely to respond to a mobile promotion. In the realm of dating and social networking, it would be interesting to see what contexts induce users be more socially engaged and obtain more matches.

In conclusion, our paper explores and empirically establishes how, and through which mechanisms, the mobile channel, by virtue of reducing contextual friction and being embedded in the daily work and life patterns of individuals, impacts social engagement and matching outcomes in the context of dating. As increasing IT investments are made in deploying context-rich mobile apps and in rolling out high-bandwidth mobile infrastructures, studies such as ours, that show the causal societal level gains from the adoption of mobile, are critical to justify such investments.

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Appendix

Table A1. Falsification: LA PSM Results

	Dependent Variable					
	View Sent	Msg Sent	Total Match	View Sent	Msg Sent	Total Match
	Female			Male		
Treatment	−0.7841**	−0.4059	−0.2665	−0.1945	−0.0518	−0.0825
	(0.3792)	(0.2597)	(0.1941)	(0.2388)	(0.1685)	(0.0852)
After	−0.1339	0.0214	−0.0187	−0.0195	−0.0277	0.0396
	(0.3232)	(0.2213)	(0.1654)	(0.2159)	(0.1523)	(0.0771)
Treatment * After	0.6824	0.2502	0.1902	0.5075*	0.3826*	0.1369
	(0.4561)	(0.3124)	(0.2334)	(0.3053)	(0.2154)	(0.1090)
User controls	Y	Y	Y	Y	Y	Y
User fixed effects	N	N	N	N	N	N
Time fixed effects	Y	Y	Y	Y	Y	Y
Observations	102	102	102	306	306	306
R^2	0.5426	0.5398	0.4348	0.2843	0.2327	0.1677

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

Table A2. PSM with Typical Caliper Results (0.2 times SD)

	Dependent Variable					
	View Sent	Msg Sent	Total Match	View Sent	Msg Sent	Total Match
	Female			Male		
Treatment	0.6906***	0.5317***	0.3981***	0.7017***	0.3386***	0.1488***
	(0.1675)	(0.1265)	(0.1002)	(0.1016)	(0.0758)	(0.0383)
After	0.1415	0.2049*	0.0769	0.1286	0.0834	0.0189
	(0.1637)	(0.1236)	(0.0979)	(0.0995)	(0.0742)	(0.0375)
Treatment * After	1.0415***	0.4933***	0.3901***	0.9639***	0.4082***	0.1606***
	(0.2314)	(0.1748)	(0.1385)	(0.1408)	(0.1050)	(0.0531)
User controls	Y	Y	Y	Y	Y	Y
User fixed effects	N	N	N	N	N	N
Time fixed effects	Y	Y	Y	Y	Y	Y
Observations	456	456	456	1,436	1,436	1,436
R^2	0.3859	0.2897	0.2509	0.3214	0.2144	0.1367

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

Table A3. Falsification: PSM with Typical Caliper Results (0.2 times SD)						
	Dependent Variable					
	View Sent	Msg Sent	Total Match	View Sent	Msg Sent	Total Match
	Female			Male		
Treatment	0.1046	0.1927	0.1570	0.1805	0.0489	−0.0327
	(0.2023)	(0.1318)	(0.0999)	(0.1135)	(0.0753)	(0.0382)
After	−0.1045	−0.0693	0.0225	−0.0278	0.0098	−0.0258
	(0.1866)	(0.1216)	(0.0921)	(0.1060)	(0.0704)	(0.0357)
Treatment * After	0.5817***	0.3280*	0.2276*	0.5148***	0.2889***	0.1849***
	(0.2637)	(0.1719)	(0.1302)	(0.1500)	(0.0995)	(0.0504)
User controls	Y	Y	Y	Y	Y	Y
User fixed effects	N	N	N	N	N	N
Time fixed effects	Y	Y	Y	Y	Y	Y
Observations	378	378	378	1,212	1,212	1,212
R^2	0.2821	0.2036	0.1667	0.2252	0.1909	0.1103

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