ABSTRACT

Title of Dissertation:	MARRIAGES MADE IN SILICO: ESSAYS ON SOCIAL NORMS, TECHNOLOGY ADOPTION, AND INSTITUTIONS IN ONLINE MATRIMONIAL MATCHING PLATFORMS
	Sabari Rajan Karmegam, Doctor of Philosophy, 2020
Dissertation directed by:	Prof.Anandasivam Gopal, Department of Operations & Information Systems

Online matrimonial platforms have emerged as a way to take the highly institutionalized process of arranged marriages online while preserving the offline social, cultural, and gender norms. While there is a rich body of empirical work on online dating, the corresponding literature on online matrimonial platforms is sparse. My dissertation seeks to fill this gap.

In my first essay, I look at mobile adoption's role in online matrimonial platforms' engagement and matching outcomes. The analysis shows that unlike the dating market where the market's transaction costs are eased by the ubiquity and personal nature of the mobile device for all users, here subgroups associated with strong endogamous preferences benefit with mobile adoption. My work extends the mobile ecosystem study to the societal context where institutional norms take precedence and influence mobile adoption outcomes.

In my second essay, I study how the search frictions, social norms, and disempowerment that results from the gender skew in online matching platforms can be mitigated by using appropriate market design. I use a quasi-experimental methodology by relying on two interventions designed by the platform to reduce women's cognitive load. The interventions improved the overall well-being of women on platforms. My work here aims to increase awareness on the role platforms needs to play to improve women's well-being while ensuring that online platforms do not unravel.

In my third essay, I look at whether the sanctity of institutional norms and traditional markers of status - involvement of multiple stakeholders through parental involvement and social norms related to endogamy and gender roles are retained in online matrimonial platforms. I find that "platformization" leads to institutional unbundling, with outcomes guided by more liberal ethos. This essay extends the platform literature on institutional contexts and shows that transition to online settings may not be seamless.

My dissertation thus contributes to the literature on Information Systems by highlighting the need to consider the societal, cultural, and gender norms to further our understanding of the market design and technology adoption in highly institutionalized contexts.

MARRIAGES MADE IN SILICO: ESSAYS ON SOCIAL NORMS, TECHNOLOGY ADOPTION, AND INSTITUTIONS IN ONLINE MATRIMONIAL MATCHING PLATFORMS

by

Sabari Rajan Karmegam

Dissertation submitted to the Faculty of the Graduate School of the University of Maryland, College Park, in partial fulfillment of the requirements for the degree of Doctor of Philosophy
2020

Advisory Committee:
Professor Anandasivam Gopal, *Chair*
Professor Siva Viswanathan
Professor David M. Waguespack
Professor Kunpeng Zhang
Professor Anna Alberini, *Dean's Representative*

Dedication

To my parents, Vijaya and Karmegam, who gave me wings to fly, and to this day, wish that I fly higher.

To my wife and best friend, Vaishali, for being my pillar of strength and the reason, I could live my dreams.

Finally, to my daughter, Ahaana, who brings out the smile on my face, every single day.

Acknowledgments

I always wished for a mentor, whom I could emulate throughout my life. I am grateful that I found one in Anand, but he is a tough act to follow. As they say, keep your friends close, I decided to keep my mentor closest, and took up a job in the area. Thanks, Anand, for always willing to give advice and pushing me to be a better researcher.

Siva was the first person I spoke to in UMD, and to this day, if I need validation or advice on something, I reach out to him. I am ever grateful for the innumerable hours he spent in the initial years of my PhD, shaping my ability to identify interesting research.

I wish I had taken Dave's course earlier; it was only after his class that I could better appreciate research methodologies and consciously focused on improving research design. I am thankful for his constructive and valuable feedback in the past three years.

I sincerely thank Jui, who is a wonderful collaborator and friend. A lot of the work I do derives inspiration from her body of work.

I sincerely thank Anna for keeping her doors open whenever I've reached out to her with an econometrics issue. I've always felt my spirits go up after a conversation with her. I still do wish that she had taught us AREC623.

I want to express my gratitude to KZ for always being there to share feedback. I have benefited immensely whenever I've gone to him seeking any technical help.

I also sincerely thank Kislaya and Il-Horn for all the guidance and help throughout my PhD journey.

I am also grateful to the guidance and support from many other faculty and staff at the University of Maryland. My sincere thanks to all the senior management team at the partner online matrimonial platform, especially the Product Head, and Data Science Lab Head.

A big thanks to PhD program buddies over the years - Yang, Dongwon, CheWei, Aishwarya, Deb, Lanfei, Weiguang, Mikhail, Abdullah, Jaehoon, Vidit, Lauren, Yifei, Sandeep, Rohan, and Ben. A special thanks to Raveesh, who is more like a family now. And finally, Justina, a big thanks for all the encouragement and for lifting our spirits whenever someone felt down. It means a lot to know that you are always there to lend an ear.

To all, I am thankful that I could take this journey.

Table of Contents

List of Tables

List of Figures

Chapter 1: Introduction

The process of arranging marriages in most Asian societies is heavily institutionalized, with procedures for identifying potential partners and vetting them based on traditions and norms that go back decades. Decisions about marriage in collectivist societies like India are made in multi-stakeholder contexts where family members and extended community members have a strong (Agrawal 2015; Kamble et al. 2014; Mathur 2007; Medora et al. 2002). In such contexts, marital preferences are significantly shaped by endogamy (Desai and Dubey 2012; Fuller and Narasimhan 2008b), i.e., preferences for staying within the community as defined through religion, community, kinship, or caste. There are also well-defined terms for acceptable behavior with respect to marriage based on gender norms. In recent years, there has been a systematic move towards transiting search and match process of marriages to *online matrimonial platforms*. These platforms have replaced, complemented, or even augmented the institutional process of arranged marriages, representing the advent of new technology into the complex social dynamics that support the institution by enabling efficient and systematic search across a vast pool of potential spouses (Seth 2011). As a precursor to online matrimonial matching platforms, dating platforms provide an interesting and valuable analog. However, while empirical work on dating platforms is relatively well-developed, the corresponding literature on matrimonial platforms is sparse. Online matrimonial platforms significantly differ from online dating platforms in terms of how institutional, social, cultural, and gender norms affect market design, technology adoption, and user behavior. This dissertation, and the three essays therein, represent an early attempt to fill this gap in the IS literature. In collaboration with a leading matrimonial platform in India, I present three essays that combine econometric analyses, network analyses, and quasi-experimental methods to answer specific questions within this context. Each of these essays is described in brief below, while subsequent chapters provide the complete essays.

In my first essay (chapter 2), I look at mobile adoption's role in online matrimonial platforms' engagement and matching outcomes. The combination of mobile app adoption and matching platforms has fundamentally transformed many spheres of economic activity, building on the mobile device's ubiquitous and personal nature. One such area that has been transformed is the dating platforms, where research shows that mobile adoption leads to greater engagement with the platforms as well as a greater number of matches made through the platform. However, little work has addressed the matrimonial matching market. In this essay, I study how mobile adoption affects matrimonial matching platforms' engagement and efficiency. The analysis shows that unlike the dating market, the mobile device's adoption does enhance engagement with the platform but does not necessarily lead to greater matches. While the transaction costs of the market are eased by the ubiquity and personal nature of the mobile device in terms of engagement, institutional factors still affect the resulting matches. A closer look at how this behavior varies across institutional factors reveals some interesting nuances for subgroups that are associated with strong endogamous preferences (Brahmins and Muslims). On average, I observe that these subgroups show a positive, significant increase in matching outcomes on adopting the mobile channel. This work extends the mobile ecosystem study to social activities that have hitherto been unexplored in the matching and dating literature. It shows that societal and institutional norms emerging from the offline context take precedence in mobile adoption outcomes in certain contexts.

In my second essay (chapter 3), I focus on gender norms and the worsening gender skew that manifests in most matching platforms online. The presence of this gender skew is particularly damaging in the context of dating and matrimonial matching platforms, since it affects the well-being and user experience of women participants. In this essay, I study how the resulting search frictions and disempowerment that results from a gender skew, and the associated congestion issues that women face, can be mitigated through the use of appropriate market design. I consider interventions based on social norms prevalent in the offline setting that may help reduce the effects of gender skew for women. Social norms prevalent in the Indian matrimonial setting dictate that women marry someone who is older in age, educationally more qualified, and earn more while imposing no such strong conditions for men. The relaxed social norms for men, and strong gender skew in online matrimonial platforms accentuates certain behaviors in men. Men tend to be a lot more active and send out more expressions of interest to women in a relatively indiscriminate manner. My data indicates that for every expression of interest that men receive in the platform, women, on average, receive 40 expressions of interest. This resulting congestion for women can cause significant cognitive effort to process while also leading to less-than-salubrious user experience for women in general. Reduction in congestion for women involves addressing the search frictions that tend to arise from market thickness. In this essay, I study how platform level intervention in reducing the congestion for women improves their well-being and user experience on the platform. In a related question, I also study if the subgroups of women who benefit from the platform's interventions choose to improve their well-being when given the ability to do so, rather than having the platform roll out these changes en masse. I use a quasi-experimental methodology to study these questions based on two interventions implemented by the platform. The first intervention – which I term *platform-level intervention* – restricted the visibility of women to counterparties (men, here) based on age, education, income, and marital status. The rationale here was that one way to reduce congestion for women was to restrict those who are able to view their profiles ex-ante, by only allowing those counterparties who are more likely to be acceptable to the focal person. The results suggest that this platform-level intervention had the desired effect – women in the treatment group received fewer unwanted requests for contacts, experienced more matches, and initiated more contacts themselves, representing a better user experience in summary. In the second intervention, women were given the ability to set these parameters themselves, thereby adding agency. The results showed that not all women were willing to make these changes upon registering on the platform, but older and more educated women chose to do so once they have observed behavior on the platform for a few days. My work here aims to increase awareness of improving women's well-being on online platforms, if online dating and matrimonial platforms have to survive, and flourish.

In my third essay (chapter 4), I look at whether the sanctity of institutional norms is maintained when transitioned to an online platform, in the context of arranged marriages. Online digital platforms have fundamentally transformed many of the economic activities which were traditionally managed offline. Early platform adopters focused on activities that were easily codifiable and modular. As "platformization" becomes more prevalent, activities from highly institutionalized contexts are likely to move online, raising questions about how seamless the transition is likely to be and whether it will capture the offline environment's full essence. We specifically investigate if the traditional markers of status - involvement of multiple stakeholders through parental involvement, and social norms related to endogamy and gender roles are retained in online matrimonial platforms. I introduce a novel measure of network-based group norms, based on endogamy, which uses the caste preferences for partner provided by the individual during signup. As part of this work, my analysis shows that move online, attenuate, and even remove traditional markers' impact, which is highly influential in offline settings. Profiles managed by parents have lower profile appeal, deviation from group norms that invites sanctions offline, and are viewed positively online. Thus, "platformization" leads to institutional unbundling, with outcomes guided by more liberal ethos. This essay extends the platform literature on institutional contexts and shows that transition to online settings may not be as seamless.

In summary, the three essays contribute to the literature in Information Systems in multiple ways. I bridge the gap of our understanding of online matrimonial platforms. My work highlights the need to consider the societal, cultural, and gender norms to further our understanding of the market design and technology adoption in highly institutionalized contexts. With more such institutions coming online, it is imperative to understand the effect of norms that guides these institutions. In the next chapter, I describe the first essay in detail.

Chapter 2: Close, But No Cigar? The Effect of Mobile Adoption on the Efficacy of Matrimonial Matching Platforms in India

Introduction

India is home to more than 1.2 billion people and over 1.18 billion mobile connections. Despite these high numbers, the low usage of mobile data per capita suggests that large segments of the market remain unconnected. The introduction of Reliance Jio, a service started by Reliance Industries in 2016, led to a radical increase in data consumption in India, from 256 MB per consumer to over 3.2 GB in the last three years, paving the way for a significant increase in the adoption and diffusion of mobile and app-based services across multiple sectors. One such sector that has seen a tremendous increase in mobile and app adoption within the country, while remaining unexplored in the extant literature, pertains to online *matrimonial matching platforms*.

Matrimonial matching platforms are relevant, mainstream, and highly popular, existing, and operating within the highly institutionalized context of matrimonial arrangements in India's traditional society. The size Indian wedding market is non-trivial: 11 to 13 million marriages happen every year, with a value of $40-50 billion (Dar 2017; Pandit 2017). As of 2016, 6% of the marriages in India were facilitated through the online matrimonial matching platforms, a number which is growing (Dar 2017). Our interest in matrimonial platforms lies in understanding how the growth of mobile adoption impacts the matrimonial matching process as this process is shifting online. That is, we analyze how adoption of the mobile channel by individuals utilizing online matrimonial platforms in India impacts the efficacy of the matching process. To do this, we build on existing literature in Information Systems that looks at online dating markets (Jung et al. 2019).

Recent work set in the online dating context has considered the effect of mobile adoption on how user behavior changes, given that the mobile channel allows the user to be more socially engaged. Jung et al. (2019) find that increased social engagement with the platform, as measured by key metrics like profile visits and messages sent, also leads to enhanced matching outcomes, i.e., more people find dating partners through the mobile channel. We draw from this work but argue that findings in the online dating context in North America may not generalize to other contexts where institutional factors like caste and religion are critical to the matching process and may be instrumental in impacting the efficacy of the matching platform. We argue that in contrast to online dating, while individuals looking for a matrimonial match may be more engaged on the platform thanks to enhanced ubiquity and the ease of access provided by mobile devices, the effect of mobile adoption on eventual matching outcomes on an online matrimonial platform in a context with highly endogamous preferences is likely more ambiguous. We contend that in the Indian context matching outcomes will continue to be guided by strong institutional norms and logics, the lower transaction costs engendered by the mobile channel notwithstanding.

Indian society has long been known for its system of ‘arranged marriages’ – marriages that are a product of careful negotiation and “matching” by elders in the family – that suggest a decision-making process driven by multiple stake-holders (Agrawal 2015; Annavarapu 2018). Offline matrimonial matching in this context has traditionally relied on existing gender roles and expectations, kinship and caste networks, marriage bureaus, and "word of mouth" (Titzmann 2013; Titzmann 2015). The influence of these factors is likely to be preserved even as the overall marital matching process has moved online in spite of the ubiquity and ease provided by mobile devices, as they are guided by long-standing, relatively inelastic social norms.

The literature on marriages in the Asian context, and specifically in India, has primarily focused on discussing sociological aspects of the marriage context and is based largely on ethnography. This research has sought to address questions regarding the disintermediation of community networks and the reduction of search costs (Seth 2011), propagation of conventional preferences (Agrawal 2015), and the role of caste and religion (Titzmann 2015). However, pursuant to the significant influx of mobile and online matching in this sector, it is striking that there is little systematic study of how technology adoption or mobile adoption has affected matrimonial matching outcomes.

We address the gap in the literature through this study by building on the existing literature in online dating as well as prior work that addresses the institutional factors of marriage within the Indian context. We pose the following research question: *1)* what is the impact of mobile adoption on user behavior on the matrimonial matching platforms? We consider two sets of outcomes here– *platform engagement*, i.e., the number of times the user logs in as well as the number of other individuals contacted, and *matches*, captured by the number of dyads actually formed on the platform. In addition, we are interested in how mobile adoption may impact behavior differently than in the North American online dating context. It is possible that given the presence of strong social norms within Indian society, preferences for matrimonial matching can show significant evidence of endogamy, i.e. desire to marry within the same community. These preferences vary across segments of society, representing institutional factors that can induce variations on how the adoption of mobile devices may be influential. Thus, we also examine the following research question: *2)* Beyond the effect of mobile adoption, how do institutional factors particular to the Indian matrimonial context moderate the impact of mobile adoption on user behavior on the matrimonial platform?

We rely on the literature studying Asian marriages to identify two critical institutional factors that may influence user behavior on the matrimonial platform, and thereby moderate the role of mobile adoption on platform efficacy - *religion and caste*. These two factors have been studied extensively in the literature on marriages in India (Seymour 1999), an institution that is still guided by cultural beliefs and rules that shape the cognition and the behaviors of the actors involved. In traditional Asian societies, the marriage process is shaped by endogamy perpetrated through religion, community, kinship or caste, the traditional roles of gender in the society, and role of the family in propagating the rituals related to marriage. Thus, in the matrimonial context, deep-rooted social and community norms become critical to understanding the process. In Asian societies even today, parents or family members often assume the primary role of selecting marriage partners for their children (Yeung et al. 2018). With increasing educational levels, there is clearly increasing involvement of the bride and groom in the matrimonial process, thereby making it a joint decision process (Allendorf and Pandian 2016). The presence of multiple stakeholders in the decision-making process implies that social and community norms will continue to influence how individuals respond when they adopt the mobile channel. We therefore consider two sources of deeply entrenched endogamous norms here – caste and religion.

We consider how caste and religion affect behavior using two groups that represent the most conservative communities in terms of social practices - members of the *Brahmin* caste and the people adhering to *Islam*. The Brahmin community, a group of castes spread across India, is generally associated with conservatism, higher education and incomes, greater social connections, and adherence to strict social norms when it comes to marriage, with a specific emphasis on endogamy (Desai and Dubey 2012). The Indian Muslim community is also spread across the country and is associated with strict norms for endogamy as well as an equal emphasis on conservatism (Mukherjee et al. 2007) although socioeconomically, this community differs significantly from the Brahmin community as well as from population averages in India. In considering these two similar yet distinct communities, we delve deeper into how mobile adoption may influence user behavior leading to platform engagement and matching.

We conduct our analysis of matrimonial matching on a unique dataset acquired from an Indian online matrimonial platform considered to be a market leader in this segment. The platform provided us with roughly nine months of data from 2016-2017 on new customers who signed on, including their login behavior, potential partners they reached out to as well as the responses they received from these counterparties; our analysis is based on this archival data. The platform is available through PC-based browsers as well as a mobile app accessed through mobile devices. Our primary objective is to understand how behavior on the platform differs across mobile and non-mobile customers, and how these differences are moderated by institutional factors. The ideal identification here would be a randomized experiment wherein the channel condition is assigned to different customers exogenously; unfortunately, this is unrealistic and infeasible in our context. Instead, we use a combination of coarsened exact matching and a difference-in-difference analysis as our identification strategy. In robustness tests, we consider alternative forms of matching, such as the look-ahead matching method between immediate mobile adopters. We also run a set of falsification tests to establish robustness, all of which support the broad set of results we obtain through our primary analysis.

Our results show that consumers who adopt the mobile channel do engage more with the platform, facilitated by the ubiquity of the mobile device, and consistent with prior work from the online dating context (Jung et al. 2019). However, our results deviate significantly from online dating literature when we look at the impact on matches. Specifically, the effect of mobile adoption on the actual number of matches made does *not* increase proportionally. A closer look at how this behavior varies across institutional factors reveals some interesting nuances for subgroups that are associated with strong endogamous preferences and strict social norms (Brahmins and Muslims). We see that these subgroups with endogamous preferences, on average, show a significant increase in matching outcomes on adopting the mobile channel. Mobile adoption within the matrimonial setting appears to work for those with strong endogamous preferences, in contrast to online dating where such institutional pressures and endogamous preferences have not been considered and may not exist in full measure.

Our work brings to the fore the role of institutional factors and endogamous preferences in determining how technology adoption, specifically mobile adoption, may lead to greater success on matching platforms. While increased engagement is no doubt desirable and can be achieved through the ubiquity of the mobile device, platform owners need to consider how the equally important outcome of actual matches may not follow from mobile adoption as seamlessly. Marriages in most societies involve long-term decision-making, with multiple stakeholders, and are associated with risk aversion as well as fears of the loss of reputational capital (Fuller and Narasimhan 2008b). In such settings, platform owners should rightfully consider the important role of local institutional norms and social mores, and their interactions with the adoption of technology, in forming expectations of outcomes on the platform. Our work here extends the study of mobile adoption to such an institutionalized setting where social norms and technologies interact in interesting and unpredictable ways, with many implications for theory and practice.

Theoretical Background

Arranged Marriages in Asian Societies

Arranged marriages, as an institution, remain relatively common in Indian society, in both preference and practice (Fuller and Narasimhan 2008b). The process by which such marriages are consummated is long, elaborate, and involves not only immediate family (parents and siblings), but also extended family, community members, and friends. The family of the prospective bride/groom initiates the marriage matching process at the appropriate time (anecdotally, early 20s for women, mid-20s for men (Seth 2011)) through a series of actions, which may also be performed in parallel. First, the family reaches out to extended kinship networks and friends to help locate potential alliances for the focal individual. In addition, it is also common to enlist the services of matrimonial agencies ("brokers") specializing in a specific caste or community. Finally, for initial leads, it is also acceptable to use newspaper advertisements, although this practice is waning due to the advent of online matrimonial services. From the initial candidate set of counter-party profiles generated in this manner, certain profiles are shortlisted for a more detailed screening process.

Different screening mechanisms are used in this context, most of which tend to be informal "background" checks of the potential partner and the extended family through common kinship networks and extended social contacts to assess the prospects of the counterparty. Unique to India, an acceptable form of screening occurs through the matching of horoscopes, based on elements of Hindu astrology that provides a measure of compatibility between any two individuals. Post these screening processes, families of the prospective partners initiate contact and maintain communication through multiple channels (phone, online chats/messages, face-to-face meetings) to further assess compatibility. Once there is agreement on all sides, across families as well as potential spouses, the "match" is viewed as confirmed, and all conversations with other potential partners cease. The search process culminates in the final wedding ceremony which can extend over several days, with active participation of family and the kinship network (Seth 2011).

Online matrimonial platforms have replaced, complemented, or even augmented the process described above, representing the advent of new technology into the complex social dynamics of arranged marriages (Seth 2011). These platforms descended from newspaper matrimonial columns and started as a profile listing service. Three major platforms – *shaadi.com*, *bharatmatrimony.com*, and *jeevansaathi.com*, were launched in the late 1990s, evolving beyond listings to providing algorithm-driven matchmaking services that remain popular even today. They serve by retaining some idiosyncratic elements of the Indian marriage process (horoscope matching, for instance) while also providing families with the benefits of digital platforms and online matching. Since these are similar to online dating platforms that have been studied in the literature, we study their contrasts below.

Matrimonial Platforms and the Pursuit of Endogamy

Dating platforms and those associated with matrimonial matching create value by reducing search costs in their respective markets (Agrawal 2015; Bapna et al. 2016a; Hitsch et al. 2010a; Titzmann 2013), enabling individuals to access profiles of counterparties that may not have been seen otherwise. Moreover, both types of platforms facilitate communication and interaction, allowing transaction costs to be further reduced (Agrawal 2015; Finkel et al. 2012). Users within both sets of platforms are likely to exhibit strong sorting patterns along attributes like age and education, in addition to physical traits such as looks, height, and weight (Hitsch et al. 2010a; Titzmann 2015). Both types of platforms arguably help increase diversity in matches by extending an individual's reach within the search space for partners (Jung et al. 2019).

There are also some important differences between dating and matrimonial matching that are worth noting. In terms of motivation, dating platforms consist of a mix of people looking for either a short term relationship or a long term relationship

(Hitsch et al. 2010b), while those on matrimonial platforms do so with the full knowledge that they are looking for a long-term marital alliance. Casual dating is discouraged and socially proscribed in such platforms. Further, the marriage market is guided not only by the individual's preferences but also by social norms relating to what is viewed as legitimate and suitable, which vary by individual communities in a diverse country like India. The preferences of larger family units as well as extended kinship networks are also partially reflected on such platforms (Seth 2011; Seymour 1999). As a result, a significant difference between dating platforms and matrimonial platforms pertains to how the latter involve community members that social and cultural customs, thereby becoming an instrument for the perpetuation of *endogamy*.

Endogamy refers to the practice of marriage within a group and is an indicator of group cohesion as well as a mechanism of social isolation from other groups (Gordon 1965; Rosenfeld 2008). Endogamous marriages perpetuate shared identities through the active involvement of families in the decision-making process. Kalmijn (1998) argues that marriage patterns are dictated by three social forces – first, the preferences expressed for certain characteristics in a spouse, which are influenced by the homogenous network of the individual and shares similar social characteristics. Second, the influence of other members of the social group, such as the extended kinship networks. "Mixed" marriages may disrupt internal unity and homogeneity within a group, thereby leading members of the group to regulate marriages either through sanctions or through instilling a strong sense of group identity. Finally, marriage patterns are influenced by the constraints of the local marriage market, such as skewed gender ratios (Poston and Glover 2005) and the supply of feasible partners

(Pierre-André Chiappori et al. 2002). Given the interplay of socioeconomic and cultural factors, matrimonial matching reflects strong endogamy, i.e., individuals prefer to marry someone with similar cultural backgrounds, enabling them to develop a familiar lifestyle that is likely to produce social confirmation and affection. In the Indian context in particular, there is a strong baseline preference for endogamy offline, which transfers to the online context. How does mobile adoption affect user behavior in the presence of this baseline endogamy? We address this question more specifically next.

The Effects of Mobile Adoption

A growing body of work has documented how the adoption of mobile devices has influenced user behavior. A primary theme within this literature pertains to establishing the differences in user behavior between the mobile and PC channels. Three significant factors have been implicated in this work: first, the smaller screen size on most mobile devices, relative to the PC, has implications for overall search costs, which influence how users interact with the technology (Ghose et al. 2013). Second, the smaller form factor of mobile devices accords significant portability, leading to ubiquity (Lee et al. 2016). Finally, by virtue of ubiquity, the mobile channel provides timely access to information (Ghose et al. 2013). When viewed through these factors, the mobile channel effectively complements the PC channel and increases the overall activity in multi-channel platforms (Einav et al. 2014; Xu et al. 2014). Mobile devices therefore offer access to information, anytime, anywhere (Balasubramanian et al. 2002; Watson et al. 2002), are universal, and help remove constraints related to time and space. Okazaki and Mendez (2013) conceptualize the ubiquity of mobile devices under multiple dimensions: offering continuity (always on), simultaneity (ability to multitask), immediacy (responding fast), and portability (providing time-place independence). These characteristics deliver increased searchability using contextual information (Pascoe 2000) while also making the mobile user easily reachable (Junglas and Watson 2006).

These benefits notwithstanding, the mobile channel also presents challenges to users and platforms alike. The smaller form factor and screen size increase the burden on users in terms of information gathering, leading to higher search costs, especially for complex searches (Ghose et al. 2013). Thus, when users are faced with choices involving complex decision making, or purchases involves idiosyncratic products which may require careful inspection, the mobile device may not be the preferred channel (Maity and Dass 2014). Indeed, research shows that mobile users tend to use the channel for the purchase of low-risk, habitual purchases rather than larger and more critical services (Chae and Kim 2003). However, in the retail sector where recommender systems may help mitigate search costs, the mobile channel appears to provide higher sales (Lee et al. 2016). Furthermore, prior research shows a pronounced ranking effect within mobile devices - most people start browsing from top of lists and therefore, products or services ranked higher receive significantly more attention from users (Ghose et al. 2013).

In our specific context, the search for a marital partner represents a complex and multi-stage decision-making process, where endogamous norms drive decisions, and therefore where the benefits and costs associated with mobile can play out in different ways. We provide these arguments next.

The Effect of Mobile Adoption on Engagement and Matching on Matrimonial Platforms

Our interest in this paper is understanding how mobile adoption impacts engagement and matching on matrimonial platforms. We define two forms of engagement here: first, the user's engagement with the platform could be *passive*, measured in terms of the number of logins. In contrast, *active* engagement is measured by the number of counterparties that are contacted (number of "interests" expressed) by the focal user, representing purposeful action on the platform. The ubiquity of the mobile channel, when added to the enhanced searchability offered by mobile devices and their personal nature suggests that mobile adoption by a focal user should be associated with increased engagement on the platform (Ghose et al. 2013; Jung et al. 2019). Thus, users that adopt mobile are more likely to log in more often and reach out to more counterparties, i.e. send out more "expressions of interest."

With respect to the actual matched formed, which remains the most important metric of performance in this context, we argue that prior work related to dating platforms may not apply equal measure here. Prior research in dating has argued that the mechanisms of ubiquity, impulsivity, and disinhibition lead to more matching outcomes as a result of mobile adoption (Jung et al. 2019), in addition to enhanced engagement. However, we contend here that within matrimonial matching, these dynamics are less likely to show up as a result of mobile adoption. It is first useful to establish what a matching outcome represents in the context of matrimonial platforms. A positive outcome, i.e., a matched dyad, can occur in two ways. First, it can occur through the action of the focal user sending an "expression of interest" (EI) which is accepted by the counterparty. Second, a dyad may form through a receipt of an EI from another person that is then accepted. We term the former effect the *direct* effect of mobile adoption, since the adopter generates the initial contact. The second path represents an *indirect* effect of mobile adoption, since the initial contact is largely independent of the focal person's mobile adoption decision.

In matrimonial contexts, the long-term nature of the sought alliances and higher levels of risk-aversion and reputational loss aversion that is associated with the institution is likely to reduce the actual formation of a dyad. When decisions are collective and made under a set of preferences that are reflective of strong social norms that dictate how and when matches may be made, the effects of disinhibition and impulsivity provided by the mobile device are less likely to affect outcomes. More to the point, responding to EIs instantly introduces multiple stakeholders into the process, where a clear record of interest that is observable by many others is established. As established earlier, marriage is a long-term decision with significant consequences. The formation of a dyad thus indicates the first serious step towards a formal offline process initiation, raising social costs for both parties as well as the risks of reputational loss if the process does not proceed positively (Banerjee et al. 2013). Thus, the value of mobile adoption may not manifest in more dyads being formed.

These dynamics can affect the possibility of dyads forming both directly and indirectly. In the case of direct matching outcomes, a focal user sending out an EI is likely to receive a response to his/her interest based on assessments of social acceptability and endogamous preferences, which are likely to be largely independent of whether the mobile device is adopted or not. Similarly, in the case of indirect matching outcomes, a focal user's response to an EI is again largely driven by collective decision-making, which again is unlikely to be influenced by the mobile channel and the associated mechanisms of impulsivity and disinhibition. The central role of collective decision-making and stable preferences counters the value that is otherwise provided by mobile adoption. Therefore, we expect mobile adoption to be associated with greater engagement but not necessarily greater matching outcomes, measured as the formation of dyads. However, the effect of mobile adoption on matching may be more visible in specific subcommunities where the search process may be structurally different. We explore these arguments below.

The Effects of Enhanced Endogamy

While the overall effects of mobile adoption in the population may not lead to a positive effect on matching outcomes, it is worth considering how these may be different for specific communities that display highly endogamous preferences. While the process of searching for a partner involves several factors - looks, education, occupation, and social compatibility, among others. In most contexts, search predicated on multiple factors is associated with substitutable preferences (Blair 1988; Kelso and Crawford 1982; Roth and Sotomayor 1990), i.e. one factor can substitute for another in terms of the utility for the person making decisions. However, in the case of highly endogamous preferences, there exist relatively rigid requirements about certain factors that drive endogamy. These rigid requirements cannot be substituted for in any way since any deviation from social norms established with the community is proscribed (Seth 2011). Thus, communities exhibiting enhanced endogamy display lexicographic preference structures. Search is driven by a well-defined process where the main factors of interest have to be matched successfully before the next set of factors can be gauged, with little scope for variance in terms of what constitutes an acceptable match.

In the Indian context, enhanced endogamy is often displayed along specific dimensions like religion, caste, or language, and thus may exhibit lexicographic preferences along these dimensions. The focal party has a sequence of criteria in their mind that helps them in assessing the choice set of counterparties. Priority order in the sequencing is assigned to factors governing endogamy, i.e., the first dimension that needs to be matched pertains to the factor determining endogamy, with little or no substitutability. Thus, we argue that preference substitutability is low for groups whose choice sets are strictly lexicographic, such that caste, religion, and subcommunity membership become non-negotiable search parameters.

The ease of use and ubiquity provided by the mobile device can help in cases with low preference substitutability, since search costs associated with a narrow and well-defined search process are more easily handled; prior research suggests that more well-specified and structured tasks are easily carried out on the mobile device (Ghose et al. 2013). Furthermore, in highly endogamous communities with lexicographic preferences, there is shared understanding of when incoming queries of interest from individuals within the same community are likely to be received positively, since the partner preferences on both sides of the dyad are similar. In such communities, both the sender and the receiver of EIs tend to have the same clearly defined preferences. Thus, we expect that in highly endogamous communities, the adoption of the mobile channel may be associated with greater matching outcomes. To illustrate this logic, we consider two communities that are typically associated with enhanced endogamous preferences, described below.

Enhanced Endogamous Preferences on Religion

Inter-religious marriages are rare in India, more so in case of arranged marriages where religion-based endogamy is very common. In some religious groups, marriage outside the religion is discouraged, to the point where an inter-religious marriage can only occur when one of the parties undergoes conversion, making the process particularly complex (Grover 2018). Group-based group sanctions are particularly high for inter-religion marriages, with the threat of being excommunicated from the group(Grover 2018; Jaiswal 2014). We focus attention on one religious group that has arguably the most clearly defined and strong endogamous preferences – the Indian Muslim community.

Indian Muslims, as a community, represent a highly conservative and religious subpopulation. As a minority community within the country, there is strong adherence to the basic Islamic principles across the country. Thus, while marriages within the broader Muslim community across the country are acceptable, marriages outside the faith run counter to this viewpoint. In effect, members of the Muslim community show preferences that are highly endogamous in nature, especially with respect to religion (Goli et al. 2013). If our conjecture is right, we expect to see the adoption of mobile devices in this community to be associated with more dyads formed, representing more matches on the platform, all else being equal.

Enhanced Endogamous Preferences on Caste

Caste in India is defined as a small and named group of persons, characterized by endogamy, with group membership based on hereditary rights, rituals and social norms shared by group members, and a common occupation (Béteille 1996). The word "*Caste*" encompasses two levels of an integrated system – *Varna* and *Jati*, the subdivisions within each *Varna*. Several studies show that assortative matching on the basis of caste in India is close to perfect (Bradford 1985; Deolalikar and Rao 1992; Dhar 2013). The *Varna* system consists of four social groups - Brahmins are identified as the learned; followed by Kshatriyas, the warriors; Vaishyas the traders; and the Shudras, involved in labor (Dhar 2013; Raina 2004).[1] However, in modern India, it is the *Jati* which is more visible and utilized in social engagements. Every *Jati* member knows its exact relative positioning compared to every other *Jati* within the caste hierarchy (Gupta 2000). Regardless of the relative vertical positioning, Banerjee et al. (2013 find that caste preferences for marriages are strictly "horizontal" rather than "vertical". There is little or no interest in "marrying up" the caste hierarchy. Online matrimonial platforms also reflect these societal norms related to caste and have sub-platforms or properties along caste and community line. The registration and search options within the platforms are also based on caste and community.

Within this system, one specific community is particularly noted for its strong preference for endogamy – the *Indian Brahmin* community. The Brahmin community is a collection of castes falling under the same *Varna*. While socioeconomically successful, this community also shows higher levels of educational attainment than the population (Desai and Dubey 2012; Ramesh Bairy 2010). Clearly, the engagement

[1] There are many communities that remain outside the orthodox Varna system. In Modern India, these are classified for administrative purposes as Scheduled Castes (SC) and Scheduled Tribes (ST).

levels of this community on the online matching platform would be high, as would be the effects from mobile adoption. However, this community is also associated with strict endogamy; while marriages within the Brahmin community are legitimate and common, there are relatively few instances of marriage outside the community (Fuller and Narasimhan 2008b). Such marriages outside the community are disapproved of and a source of embarrassment, even leading occasionally to censure (Ramesh Bairy 2010). Thus, strict endogamy is associated with the Brahmin marriage process, and is a common knowledge among other groups. Here again, we expect mobile adoption to be associated with better engagement and matching outcomes, given the presence of enhanced endogamous preferences.

Data and Methodology

Research Site - Online Matrimonial Platform

To conduct this research, we obtained data from one of the leading online matrimonial platforms in India. This platform serves users based out of India as well as members of the Indian diaspora. Users within the platform reflect the diversity of India, with a multitude of religion, language, region, caste, and sub-castes represented. The platform can be accessed through an online version from a web browser on a personal computer or a mobile browser on a smartphone, or through an iOS or Android mobile app. The platform operates on the freemium model, i.e., it operates a two-tier business model that offers free access to the basic set of features or content, while charging for premium features (Anderson 2008) The paid version of the platform comes with additional features, including the ability to view phone numbers and horoscopes of other users, send personalized messages & SMS, and instantly chat with prospective matches.

Platform users provide their profile information and partner preferences with respect to age, height, education, profession, location, caste and religion parameters. The platform has invested in proprietary matching algorithms that match users to suitable partners based on the user's expressed preferences. The platform also highlights the profiles of paid subscribers and provides them primacy in search results. The presence of single women on the platform could sometimes invite the attention of frivolous, non-serious users but the platform actively discourages non-serious users (Kaur and Dhanda 2014) ; the users undergo stringent verification process through online and offline mechanisms to weed out non-serious users to ensure the quality and integrity of the platform.

For our analysis, we identified new users who joined the platform over an eight-week period between October 2016 and November 2016. We subsequently track their activity on the platform for a period of at least three months, or as long as they are active on the platform. We collected demographic data for this set of users, and also had access to a daily panel of behavioral and transactional data on the platform for each user, including the logins made from various channels (PC or mobile), expressions of interest sent out and received, and the total number of matches made. We use this data to examine adoption behavior, i.e. when users start to use the mobile channel offered by the platform during the first eight weeks on the platform. The number of users on the mobile channel per week post-registration (Figure 1) shows that a majority of users adopt the mobile channel immediately upon joining the platform. Over subsequent weeks, additional users adopt the mobile channel in relatively smaller numbers. This pattern of mobile adoption allows us to separate users into three distinct categories.

First, we identify “immediate adopters”, i.e. those who adopt the mobile channel at the time of registration on the platform. Second, we see a set of “late adopters”, i.e. those who adopt the mobile channel at some point within the first 4-6 weeks. Finally, we also observe a set of “never adopters” who do not adopt the mobile channel even after six weeks on the platform. These discrete sets of users offer a set of counterfactuals, allowing us to estimate the effects of mobile adoption by comparing activities of “immediate adopters” to “never adopters.” We can also use tests of robustness to compare “immediate adopters” to “late adopters,” using a variation of the look-ahead matching procedure used by Jung et al. (2019). For the majority of users, the majority of activities on the platform tend to occur in the initial 2-3 weeks, unlike dating apps where users return frequently and linger for extended durations (Hitsch et al. 2010a; Hitsch et al. 2010b). Therefore, in studying the effects of mobile adoption on engagement and matching outcomes, we focus on first two weeks on the platform.

Empirical Approach and Identification

A randomized experiment would be the ideal strategy for identification of the causal effect of mobile adoption, wherein a population of users is randomly assigned to the mobile channel or the PC channel exogenously, and their subsequent behaviors recorded (Aral and Walker 2011; Bapna and Umyarov 2015). A variation of this design would include only those interested in the mobile channel, who would then be randomly assigned to either a mobile or PC channel. Since all users in this design would have expressed an interest in the mobile channel, any differences in their outcomes can be attributed to mobile adoption. Experiments such as these are not feasible, however, since no platform is likely to impose such restrictions on the users in the field (Jung et al. 2019). We, therefore, use a combination of matching and difference-in-difference analysis to create a pseudo-experimental design whereby we can account for channel selection and bias that this may induce in our analysis.

The purpose of using matching in our study design is to limit any ex-ante differences that may exist between those users who choose to adopt or not adopt the mobile channel immediately. To create a matched sample of such similar users, based on observable characteristics, we use Coarsened Exact Matching (CEM) (Blackwell et al. 2009). CEM provides some benefits in comparison with propensity score matching, which has remained popular in the literature. First, CEM relies on algorithms for creating coarsened strata that are largely independent of any influence that the researcher may be able to apply, even involuntarily (Blackwell et al. 2009). Second, CEM limits the degree of ex-ante heterogeneity between treatment and control groups, thereby increasing the strength of the causal claim (Overby and Forman 2015). Third, CEM is more flexible than propensity score matching as it considers both univariate and multivariate imbalances between treatment and control groups (Burtch et al. 2018). Finally, CEM takes into account heterogeneity between treatment and control groups, thus ensuring that the treatment indicators are independent of other covariates.

In our matching procedure, the treatment group refers to "immediate adopters," while the control group is the "never adopters." We use *k-to-k* matching to ensure that the number of treated and control units is the same in all strata, using the default Null method which performs random matching within each strata to reduce bias. We match on observable demographics - gender, age, caste, religion, language, profile operator, years of education, income, city tier, whether the user is a paid subscriber, and a dummy variable indicating whether the user holds a minimum undergraduate degree. Post matching, we assess the imbalance between matched and control groups using the L_1 statistic, the difference between the multidimensional histogram of all pretreatment covariates in treatment and control groups (Iacus et al. 2012). Perfect balance is indicated by $L_1 = 0$, while values over 0.8 indicate an imbalance, with the maximum being $L_1 = 1$. The multivariate L1 distance in our case is 0.21 showing balanced groups. As seen in Table 2, which provides summary statistics across treatment (mobile adopters) and control (non-adopters) groups, the matching provides consistent statistics across observable demographics. We describe the individual variables next.

Variable Definitions

Table 1 provides detailed information on the variables used for analysis. Summary statistics and the correlation matrix are available in Tables 2 and 3, respectively.

Dependent Variables

We use engagement and matching outcomes as dependent variables. *Passive* engagement is represented by *TotalLogin*, which is the aggregate of logins made by the focal user in the given time period (two weeks, unless specified). *Active* engagement is represented by *TotalEIs*, which is the sum of all expressions of interest (EI) sent by the focal user in given time period. With respect to an actual match, defining such an event in online settings is a challenge. In the dating context, Hitsch et al. (2010a) identified a successful match when users exchange phone numbers or email address on the platform. Bapna et al. (2016a) defined a match based on a sequence of at least four messages between any two users. In our context, we conceptualize a match using two scenarios. In the first scenario, a focal user A can initiate a match with user B by sending an EI. When user B accepts, a match is formed. In the second scenario, focal user A receives an EI from user B, which, when accepted, results in a match. Once these EIs are sent and accepted, ongoing conversations are usually taken offline, hence reflecting a “match.” [2]

In the first scenario, the match is achieved when the counter-party accepts the issued EI by the focal user A. The counterparty cannot see the whether the focal user has adopted mobile or not. Therefore, the effect of mobile adoption by user A is not clearly associated with the formation of a match. We refer to these as indirect matching outcomes. We measure indirect matching outcomes by the total number of positive responses to the EIs sent by the focal user to others on the platform in a given period of time, referred to as ***TotalEIAccept***.

In the second scenario, the match is achieved by focal user A since he or she exercises agency in accepting the received EI. We refer to these as direct matching outcomes since they are associated with the focal user’s mobile adoption decision. This variable is represented by ***TotalReceiveEIAccept***, which is the aggregate of all acceptances made by the focal user in response to the EIs received. The reduced search costs, ubiquity, and ease of use of mobile phones should allow the focal user to achieve more such matches on the platform (Jung et al. 2019). The activities within the platform are aggregated across all channels for the purposes of our analysis – mobile app, mobile browser and the PC browser.

---

[2] Alternative methods for measuring actual matches have been tried by the platform– when users become inactive on the platform or delete their profiles, efforts are made to contact them to ask if they have found a match. Unfortunately, the response rate is less than 10%, making it hard to use this information.

Independent Variables

The main variable of interest in our study is ***MobileAdoption,*** a dummy variable for which 1 represents the treatment group (*immediate adopters*), and 0 represents the control group (*non-adopters*). In robustness checks using the look-ahead matching, the treatment group remains the same (*immediate adopters*), but with *late adopters* as the control group. Immediate adopters may access the platform through multiple channels - mobile app, mobile browser, and the PC browser, while the non-adopters access the platform through the PC browser alone. Individual dummy variables represent groups with strong endogamous preferences –*Brahmin and Muslim,* for which 1 represents the corresponding group, and 0 otherwise.

Controls

We control for factors that may influence the outcomes of interest, including the variables used for the coarsened exact matching – gender, age, caste, religion, language, years of education, income, a dummy variable indicating whether the user holds a minimum undergraduate degree, and a dummy variable indicating paid subscriber status. We also control for the profile operator, which could be the focal person, family member, friend, or a relative. We include the controls for the city tier, where tier 1 refers to the major 6 metropolitan cities in India, tier 2 refers to mid-level cities, and tier 3 refers to large towns. We account for any systematic time effects by controlling for the week of joining the platform. These systematic time effects also help to account for the idiosyncratic beliefs and norms within specific communities that show up during different times of the year. For instance, for some communities, marriages are not arranged during a specific season (typically January) for religious reasons. These are captured through time effects. In the interest of statistical power and to estimate the marginal effects of individual-specific characteristics, we do not include user fixed effects in the baseline regression specification.

Estimation Procedure and Results

Our main estimation equation is as follows:

$$Outcome_i = \alpha_0 + \alpha_1(Mobile\ Adoption_i) + \alpha_2(\ Endogamous\ Groups_i) + \alpha_3(\ Mobile\ Adoption_i x\ Endogamous\ Groups_i) + \beta D_i + \gamma_t + \varepsilon_{it}$$

Where $Outcome_i$ refers to engagement or matching outcomes discussed above, and $Mobile\ Adoption_i$ is the treatment dummy variable. $Endogamous\ Groups_i$ refers to the endogamous groups that we argue may differentially influence the effect of mobile adoption on matching outcomes –namely, *Brahmin* and *Muslim*. The main effect of mobile adoption is provided by the coefficient α_1, which captures the treatment effect. The coefficient α_3 captures the hypothesized moderating effects of institutional factors. We cross-sectionalize the daily panel data on user behavior from the first two weeks of activity on the platform; thus, the unit of analysis is the focal user. In robustness tests, we estimate similar models for a four-week period, with fully consistent results. We control for D_i, demographic attributes of the user. We also control for the specific week within the 8-week period when the user signed up on the platform, to capture any external influences that may systematically influence all such users, represented byγ_t. In the regression analysis for active engagement, we control for total logins by the user, since more logins are likely to lead to further activity on the platform. Similarly, for the regression analysis of direct matches for the focal user, we control for total logins, total EIs received, and total EIs read. For the analysis of indirect matching outcomes, we control for number of logins, and number of EIs sent. The models are estimated using OLS, with robust standard errors. In robustness tests, we also used models for count data to estimate the treatment effects - negative binomial regression, Poisson and zero-inflated models – and obtained results that are largely consistent with those reported here in terms of the observed effects. These are available upon request.

Summary Statistics and Main Effects

Summary statistics for the sample are provided in Table 2. Our sample consists of 79% men; this gender skew is typical in matrimonial platforms, and is also similar to the gender ratios observed in online dating platforms (Hitsch et al. 2010b). Nearly one-third of the users come from the major metropolitan cities like Delhi, Mumbai, Bangalore, and Chennai (Tier 1 cities), with the representation of women from the Tier 1 cities comparatively higher than in the full sample. Men on the platform have lower educational levels on average, with 73% reporting 3-year college degrees compared to 91% in the case of women. Table 2 also provides summary statistics on engagement for the initial two weeks on the platform, measured by overall logins (*Total Login*) across multiple channels. Passive engagement, measured by logins, are higher for women (23.76) than for men (16.46). Active engagement, measured by EIs sent, is higher for men relative to women (10.38 versus 4.39). Women, in general, receive more interest compared to men at a ratio of 40:1, in spite of the 8:2 ratio in the full sample. In general, women achieve more matches (*TotalReceiveEIAccept* and *TotalEIAccept*), and see higher odds of their EIs accepted when they initiate the interaction (4.39 vs. 0.92) relative to men (0.1 against 10.38).

Table 4 reports the estimations for the main effects of mobile adoption for engagement and matching outcomes. Columns 1 and 2 provide the results for active and passive engagement, respectively, while columns 3 and 4 provide the results for direct and indirect matching outcomes. We find a positive and statistically significant relationship between mobile adoption and engagement outcomes in general across the full sample. For the initial two weeks in the platform, on average, mobile adopters login 26.26 more times and also send in 1.34 more EIs than non-adopters. We find that mobile adoption leads to an increase in the engagement outcomes relative to users that only use the PC channel, which is consistent with existing literature on online dating platforms. However, our findings diverge from existing work when we look at matching: these benefits in engagement notwithstanding, we do not see an associated effect on the number of matches (dyads) formed as a result of mobile adoption. Immediate mobile adopters are not statistically different from non-adopters on average when it comes to achieving matching outcomes on the platform. That is, mobile adoption does not lead to an identifiable increase in matching outcomes relative to users that only use the PC channel.

The Role of Mobile Adoption in Enhanced Endogamy

Recall that we argued that subgroups with enhanced endogamous preferences would actually benefit from mobile adoption even in matches achieved. In Tables 5 and 6, we show our analysis for the two highly endogamous sub-groups – *Brahmins* and *Muslims*. Columns 1 and 3 in Table 5 show that, on average, there is no direct effect on matching outcomes observable for Brahmin users, relative to the population of users on the platform. However, Columns 2 and 4 show significant interaction terms between mobile adoption and the *Brahmin* dummy variable, indicating that on average, immediate mobile adopters within the Brahmin community achieve better direct and indirect matching outcomes relative to others on the platform. For Muslim users, the direct matching outcomes are higher relative to the population of users on the platform, as seen in Column 1 of Table 6. However, the interaction term of mobile adoption and the *Muslim* dummy variable is significant in Column 2, showing that direct matching outcomes are enhanced for this endogamous group through mobile adoption. However, mobile adoption does not result in an increase in indirect outcomes for Muslims, as seen in Column 4 of Table 6. To summarize, we see overall positive matching outcomes for the highly endogamous groups, which supports our argument that mobile adoption has a positive effect on matching outcomes for groups that face a more structured search process. The twin mechanisms of enhanced endogamy and low preference substitutability that endogamy generates paradoxically render the mobile device more effective in improving outcomes associated with engagement as well as matching on the platform.

The Effect of Mobile Adoption on Non-endogamous groups

While we see how mobile adoption affects matching outcomes for highly endogamous groups, it is worth examining how mobile adoption may affect subgroups that display relatively weaker endogamous preferences. Would these users display systematically different matching outcomes, relative to the population? We identify a set of users on the platform who choose to not disclose their caste, do not provide any caste preferences for prospective partners, and specify explicitly that they do not wish to disclose their caste or community associations – we refer to these users as the DWS (*Do not Wish to Specify*) group. We use a dummy variable to identify users in this group, and repeat the analysis as before, shown in Table 7. As seen in Columns 2 and 4 of Table 7, this group receives no systematic benefit from adopting the mobile channel, in contrast to highly endogamous groups where the matching process is actually helped by mobile adoption. The interaction of the *DWS* variable and mobile adoption is insignificant across both matching outcomes, as would be expected. In fact, the DWS group shows a small and marginally significant negative coefficient in terms of matching outcomes overall, relative to the population, which is not surprising since caste-based endogamy is a strong norm in this context. Individuals who explicitly buck the social norm are likely to and do receive a small penalty in terms of matching outcomes. Thus, this analysis also provides some indirect evidence for how endogamy, in particular caste-based endogamy, is a prevailing norm within the marital matching context here.

Testing for Disinhibition and Impulsivity

Recall that prior research identified disinhibition and impulsivity as key mechanisms for the mobile effect within the dating context (Jung et al. 2019) – these mechanisms are unlikely to apply in the marital matching setting. In this section, we report on tests conducted to examine if disinhibition and impulsivity are indeed muted here.

Jung et al. (2019) refer to impulsivity as the extent to which the focal user performs due diligence before responding to an EI from a counter-party – the user would thus be acting impulsively if she/he responded to the EI without checking the profile of the sender. We measure impulsivity in our context as the difference between the count of profiles which were checked for counterparties by the focal user when an EI is received (*TotalReceiveEIRead)* and the direct matching measure (*TotalReceiveEIAccept).* Users who act impulsively by accepting EIs received without even checking the details of the sending party will show negative values – they tend to accept invitations without checking their antecedents. In contrast, those who perform due diligence before accepting a request to correspond further will either show values of zero (all EIs that are accepted are first checked for some fit) or positive values (EIs are read first but not accepted). Figure 4 provides the average of the *Impulsivity* measure for men and women across the treatment and control groups for the full sample. Across all groups, we find the mean value to be positive, showing that impulsivity of the nature addressed by Jung et al. (2019) is largely absent here. Indeed, mobile users appear to be even more selective than non-adopters. Even after normalizing by the number of total EIs received, we see similar trends in Figure 5, providing evidence for why impulsivity may not be at play even when the user moves to the mobile channel.

Unlike impulsivity, disinhibition in the dating context manifests in the significant relaxation of preferences that are typically exercised offline (Jung et al. 2019). For instance, women using online dating sites are more willing to interact with people of a different race, less education, and men who are shorter than them, all of which may not occur in equal measure offline. Jung et al. (2019) argue that mobile use enhances disinhibition on the part of individuals, which leads to greater matching outcomes. In the marriage context, given endogamy, we believe this is unlikely to occur. A full-scale test for disinhibition requires information on all counterparty users who send an EI to all other users - unfortunately we do not have access to this complete dataset. However, we can devise a more specific test by considering the DWS group discussed earlier. Recall that the DWS group explicitly choose to not provide any caste-based information in their profile. Arguably, these individuals should be attractive to most people on the platform since they are unconstrained by any caste-based preferences. Therefore, women receiving EIs from men in this group should, if disinhibition holds, be more likely to respond positively, regardless of their own caste. On the other hand, if disinhibition does not hold and caste-based endogamy continues to apply strongly, we should see DWS men receive fewer responses, all else being equal.

We operationalize this test using two outcome variables: *TotalReceiveEI*, which refers to the total EIs received by a user, and ***TotalEIAccept*.** We only consider men in this analysis, since we are interested in the extent to which they receive positive responses from women on the platform (there are no same-sex dyads in the sample). As before, we include dummy variables for mobile adoption, DWS membership, and an interaction term to account for disinhibition from mobile adoption, consistent with Jung et al. (2019). The results for the analysis are shown in Table 7. As is evident, DWS men received fewer EIs than the population, on average, and the interaction term with mobile adoption is insignificant. The effects on indirect matching outcomes, shown in Columns 3 and 4, show that DWS men are accepted less, on average, than the population even after mobile adoption. These results support the argument that disinhibition is less likely to manifest in this setting, and that endogamous norms are critical. We conducted the analysis separately for mobile adopters and non-adopters separately with similar results, available upon request. In summary, impulsivity and disinhibition are not likely to be influential in this setting as users move to the mobile channel, at least as far as caste-based endogamy is concerned.

Robustness Checks

We also conducted a set of robustness checks to complement the analysis reported above. First, we conducted the analysis by considering engagement and matching outcomes for the first week on the platform, as opposed to two weeks. The results for the one-week analysis are provided in Table 9 and are similar to those presented above qualitatively. We find an increase in overall engagement outcomes with mobile adoption as seen in the Column 1 (passive engagement) and Column 2 (active engagement); however, there are no changes in the results pertaining to direct matching (Column 3) and indirect matching (Column 4) outcomes. The matching outcomes for the mobile adopters and the non-adopters are almost indistinguishable.

We also use an alternative matching approach as a robustness test. We use the Look-Ahead propensity score matching (LA-PSM) approach used in Bapna et al. (2016b), which has been observed to outperform traditional PSM in dealing with time-invariant unobservable characteristics that strongly impact both the decision to adopt and the outcomes. Jung et al. (2019) used this approach to match existing mobile users to existing PC users who have the same propensity score and but adopted the mobile app in the later time period. In our case, the treatment and the matched control group ultimately adopt the mobile channel at different times; using the Look-Ahead method allows us to account not only for the observed characteristics via matching, but also for unobserved time-invariant characteristics linked to the user's intrinsic propensity to adopt the mobile channel. The only difference here is that we used CEM, in lieu of PSM, to match “immediate adopters” to “late adopters”, who adopt the mobile channel at a later time. Late adopters adopted the mobile channel after the initial two weeks on the platform, thereby allowing us to study their behaviour in the first two weeks. We used the same observable variables to conduct the Look-Ahead matching. Post matching, the imbalance L_1 statistic between the treatment and control groups was 0.36, showing balance, with 9681 observations each in the treatment and control groups. The analyses using this sample is shown in Table 10, and the results are largely consistent with those reported earlier. Engagement as measured by logins increases for the treatment group, but we do not see any increase in matching outcomes with the mobile adoption. The moderation tests using the endogamous groups also provide fully consistent results and are not shown in the interest of space but are available upon request from the authors.

As a final robustness test, we conducted falsification tests to rule out the possibility that we observe spurious correlations. First, we pooled the matched set of control and treatment groups and then randomly assigned the treatment (*mobile adoption*) to users in the sample in the same ratio (1:1), thereby creating a new sample where the treatment has now been randomly generated. We repeat this process 1000 times, thereby creating 1000 samples with replacement, with the same ratio of treated to untreated observations. For each of these samples, we run the baseline regressions for engagement and matching outcomes independently. We then conducted z-tests to compare the coefficients for the mobile adoption dummy variable across these samples with those estimated from the analysis on the original dataset reported in Table 4. The results from the z-tests show that the coefficients obtained in our main analysis are statistically different from those obtained through the placebo samples ($p<0.01$), suggesting that the probability of our results being generated by chance were very small. Going one step further, we use only the control group, and randomly assign the treatment dummy to half of this group, while leaving the other half untreated. We then run the same baseline regression on this sample to see if the analysis renders significant coefficients. We expect to see no such significant coefficients here. However, if the control group is truly different from the treated sample in some unobservable way, it is possible for this placebo test to provide significant results. We repeat this process 1000 times, and check the average of coefficients obtained in this manner. The results show that the obtained coefficients are not distinguishable from the null effect, based on a z-test ($p<0.01$), indicating that the results from the full sample are robust. The detailed results of these placebo tests are available from the authors upon request.

Discussion and Conclusion

Online and mobile platforms have received significant traction in India in recent years, thanks to the availability of cheap mobile data and a corresponding increase in the supply of platform-based business models for activities that were traditionally carried out offline. One such interesting yet understudied context that has made the leap online pertains to the matrimonial matching process. In this paper, we set out to explore how the frantic pace of mobile adoption across the nation influences the manner in which the heavily institutionalized process of finding marital alliances is carried out online and through the mobile channel. While internet-based matchmaking has been present in the Indian context for roughly two decades, it has mostly attempted to replicate the offline process, thereby preserving as many social norms as possible. Thus, the matching process remains a collective one where families are involved in every step. Social norms pertaining to caste-based kinship networks continue to matter, and endogamous preferences continue to dominate. Given these institutional factors, we set out to answer how the adoption of mobile devices, representing a personal, ubiquitous, and versatile channel, affects the efficacy of the matching process, thereby providing a contrast to the more familiar online dating context (Jung et al. 2019).

Working through a collaboration with a leading Indian online matrimonial matching platform, we used data on all new registrants on the platform for a period of 8 weeks to study how users are able to first, engage with others on the platform, and second, actually form matches (dyads). Conceptualized through the twin outcomes of engagement and matching, we studied how adopting the mobile channel affects engagement and matching outcomes for users on the platform. Moving to the mobile channel remains a strategic objective for the platform firm, since it is generally presumed to lead to better outcomes for all concerned (Ghose 2017). The ubiquitous and personal nature of the mobile channel should allow users to find matrimonial matches more expeditiously, while allowing the platform to provide more services through the mobile app while also converting more users to becoming paid subscribers. The benefits of mobile adoption have been studied in the literature on online dating and have been shown to enhance the benefits for both individuals and platform owner. However, we take the position that such benefits are more nuanced in formal settings like marital matching, where institutional factors are play and still affect how users operate when faced with technology.

Building on prior work that has addressed the role of endogamy, social norms, and institutional factors like caste, we show that while mobile adoption leads to greater engagement on the platform for the average user, mobile adoption may not help the average user find more matches per se. Rather, due to prevailing preferences for endogamy and the presence of a collective decision-making process, matching outcomes are unlikely to improve radically as a result of going mobile. By contrasting behavior across matched samples of mobile and PC-based users, using coarsened exact matching, we are able to show these nuances in the effects of mobile adoption. However, what happens when specific groups are known to be extremely endogamous? In such cases, intriguingly, the search process for a counterparty is more structured and arguably less complex, since the preference set is narrowly defined. We show that for such highly endogamous settings, mobile adoption works well by enhancing both engagement and matching outcomes. Indeed, as users move away from explicitly stated endogamous preferences, such as in the case of DWS users, the benefits from going mobile appear to wane. The mechanisms identified in prior work, such as impulsivity and disinhibition (Jung et al. 2019), appear to have less influence here while endogamy and social norms appear to hold sway even as users move mobile.

Our work thus shows that in certain contexts, societal and institutional norms emerging from the offline context take precedence, and this has implications for platform owners. In our conversations with senior management at the platform firm, we were repeatedly informed about the level of frustration experienced at the fact that while users were more engaged on the mobile app, they were not observing greater matches. Our analysis provides evidence that when catering to a large and diverse group of participants, it is important to acknowledge that the use of technology and resulting outcomes are not a simple function of channel adoption. The diverse groups the platform caters to are likely to have varying demands for preferences and adherence to social norms, leading to a more nuanced set of implications for the technology investments the platform must make to enable features that aid mobile transactions. Our findings have implications for other platforms as well that operate in contexts that are guided by strong social norms and have a basis in cultural or religious beliefs and any activities that propagate them. Our findings could be generalized across dating and matrimonial platforms where the focus is on matching users with highly endogamous preferences. For example, eHarmony has a sub-platform focusing on devout Christian singles and advertise it as a "relationship site" as against a dating site. Similarly, Jwed and JDate focus on marriage-minded Jewish singles; LoveHabibi prominently advertises and distinguishes different Islamic sects - Shias and Sunnis. Thus, our findings are not restricted to the Indian context but apply widely to settings involving endogamous populations, as well as where the diaspora has settled beyond their home country. In the final analysis, mobile technology may not represent an ideal choice for all areas of activity.

Our work here is subject to certain limitations. First, like most empirical work using archival, secondary data, there are several pieces of information that we do not possess in our dataset, which limits the extent to which we can clearly rule out some alternative mechanisms. Further, we cannot rule out the effects of unobservable variables in our analysis – we are able to control for observable attributes in our analysis, through the use of matching and as control variables. However, this limitation remains in our work. Second, we do not have information on all counterparties that correspond with the users in our primary dataset. This precludes our ability to control entirely for the characteristics of the formed dyads. A more complete dataset would allow us to augment our analysis and we hope to do so in future research. Third, while we argue that certain subgroups (Muslims and Brahmins) are more endogamous, we do not have a measure of endogamy with respect to the many dimensions on which endogamous preferences may be constructed (language, food habits, professions), We hope that such a measure will be developed in future research for online matrimonial matching platforms. Finally, while we account for channel selection through matching, we recognize that a randomized experiment would be the ideal methodology. This remains a limitation, and is consistent with the treatment of channel use in the literature (Jung et al. 2019).

In conclusion, our work studies the effect of mobile adoption on the efficacy of users on a matrimonial matching platform in India. Set within the institution of arranged marriages, which have been prevalent in traditional Asian societies for many generations, we study how the role of the mobile device interacts with social norms and institutional factors that are influential in this domain. We depart from existing research studying the adoption of mobile devices in matching markets, primarily in the dating context, by showing that endogamy is a critical feature that needs to be managed by managers of the research site. Effectively, endogamy sets out the boundaries of the search process for individuals, as they look for potential partners online. In highly endogamous groups, the mobile device assists the search process since the parameters of search are well defined. Mobile adoption changes user behavior on matrimonial platforms by initially boosting engagement. However, in other subgroups where endogamous preferences may not be as explicit and rigid, the benefits of mobile adoption on matches on the platform are not as compelling. Our work thus provides a cautionary note for the use of technology within heavy institutionalized settings, while also laying out where true value resides. As the mobile ecosystem becomes more mainstream, we believe more such work is needed for a fuller understanding of the business value of the mobile device.

Chapter 3: Profile Gating? Addressing Congestion to Improve Women's Well-Being on Online Matching Platforms

Introduction

Online dating and matrimonial platforms face an interesting variation of the problem of plenty - plenty of men, but very few women to match. Men outnumber women dramatically on dating and matrimonial apps. The typical ratio observed ranges from between 60:40 to 90:10 on these apps[3]. These platforms thus face the twin challenges of a worsening gender skew combined with the odds-based approach practiced by men. Gender skew in the platforms accentuates certain behaviors in men. Men tend to be a lot more active and send out more expressions of interest to women in a relatively indiscriminate manner. As reaching out to multiple counterparties is seen as relatively costless and riskless, and with many platforms encouraging such an odds-based approach, men are not as selective as women. These twin challenges have the unfortunate consequence of significant congestion on the platform, even when there are significant numbers of parties present. Past studies in matrimonial platforms show that for every expression of interest that men receive in the platform, women, on average, receive 40 expressions of interest (Karmegam et al. 2020), which can cause significant cognitive effort to process while also leading to a less-than-salubrious user experience for women in general. If the vicious cycle of worsening gender skew and increased usage of men's odds-based approach is left unchecked, fewer women are likely to join the platform, thereby reducing the attraction for men in turn, and therefore

[3] http://www.netimperative.com/2019/04/05/online-dating-trends-men-outnumber-women-on-tinder-by-9-to-1-while-grinder-wins-for-age-diversity/

leading to the platform unraveling. Amidst the question of congestion in platforms is the increasing realization that the well-being and equitable participation of women on the platform is paramount.

Beyond equity and the user experience, the rampant gender skew on such platforms can also give rise to behavior that smacks of online harassment (Rudder 2014; Slater 2013; Whitty and Gavin 2001; Whitty and Carr 2006). A 2016 Consumer's Research study found that 57% of women respondents reported being harassed on the dating apps they used.[4] Things do not seem to have improved over time. In a recent survey conducted by Pew Research Center in November 2019, over 60% of the women users in the age group 18-34 expressed frustration that someone on the platform continued to contact them, even after indicating their lack of interest.[5] Not surprisingly, more users (45%) have expressed frustration than hopefulness (28%) on dating platforms. The problems are not restricted to women - 43% of men have indicated that they have not received enough messages on the app, suggesting that not enough women are initiating matches or sending messages, thus leading to frustration at both ends of the market. However, there is no doubt that it is far more challenging for women than men. With increased technology adoption, women have become digitally vulnerable due to increased visibility, interconnectedness, and decreased cost of transactions for those with potential malintent. Women are subject to more technostress, cyberbullying, and cyberstalking compared to men. Studies suggest that online dating and matrimonial

[4] https://this.org/2018/09/27/online-dating-apps-have-a-major-problem-with-sexual-harassment-but-solutions-must-start-offline/

[5] https://www.pewresearch.org/fact-tank/2020/03/06/young-women-often-face-sexual-harassment-online-including-on-dating-sites-and-apps/

platforms have unshackled women and empowered them to take the first step (Bapna et al. 2016a; Hitsch et al. 2010b; Jung et al. 2019). However, increased search costs and online harassment are disempowering women in terms of making the first move. These observations raise an important question: if matching platforms are to thrive by ensuring equitable and engaged participation, what can platform owners do to improve the well-being of women users on the platform? This forms the core research question we address in this paper.

Online matching platforms are decentralized two-sided marketplaces, where users search for matches, and the transaction is deemed complete when one of the users sends a request and the counterparty accepts it. The number of matches formed on online matching platforms is commonly assumed to be a fraction of the product of numbers of agents on each side (Rochet and Tirole 2006). A study on the cross and direct network effects on e-commerce platforms found that the growth in sellers primarily drives buyers' growth (Chu and Manchanda 2016). Roth (2018) argues that for a marketplace to work effectively, it needs to account for a few crucial factors - provide thickness, overcome congestion, and make it safe for all participants. By providing thickness, the marketplace can attract a sufficient proportion of potential market participants. By providing enough time or enough alternatives the marketplace can overcome congestion. The marketplace can make it safe for the participants by ensuring that participants find more value in participating within the marketplace, and do not engage in any strategic behavior, which brings down the overall marketplace welfare.

Applying these principles to the dating and matrimonial platform contexts, we argue that these platforms require more women to register and participate. Signing up more women or engage in strategies like "gender gating", where platforms incentivizes/disincentivizes users based on gender, could be a long-drawn process involving extensive advertising; hence, the focus should be on improving the well-being and user experience of women on the platform by reducing congestion, increasing the efficacy of matching for women, and empowering them to make the first step on the matching platform. Reduction in congestion involves addressing the search frictions that tend to arise from market thickness. Low-productivity users, in this case men, in a thick market could crowd out more appropriate matches for the focal woman user, thereby significantly increasing search costs (Shimer and Smith 2001). Prior work on market thickness suggests that increased market thickness reduces overall matching rates (Li and Netessine 2020). The matching rate could depend on the individual's belief about market thickness; individuals are likely to be more selective when they believe that there are possible matches available and tend to be more selective when they believe that there is more competition (Yu 2019). While the above studies have looked at the overall matching rates, we focus on women's well-being as an interim step that can eventually lead to a better overall matching rate.

Past research on the gender preferences on online dating and matrimonial platforms suggests that women prefer men within a specific age range - not too old, and not younger. Women also prefer someone with more or similar educational and occupational attainment. Platforms have focused on recommending the users based on the focal person's preferences; however, in most cases, it does not restrict the profile visibility if the counterparty has set the preferences in a way that includes the focal person. Such an intervention may ensure that women are not in the consideration set of *counterparties* who are unlikely to be considered seriously by the focal user. Thus, one such intervention that may help enhance the experience for women on such platforms reflects a specific research question we address: *given the gender skew in online matching platforms, can platforms improve the well-being of women by restricting the women's profile visibility*? Since this intervention may have differential effects on the subgroups on which it targets, we pose a related question: *Do the subgroups of women who benefit from platform-level intervention, make informed choices to restrict their profile visibility when given the option?*

We conduct our analysis in partnership with a leading online matrimonial platform. While there are fundamental differences between online dating and matrimonial platforms in terms of the motivation of the users, some of the challenges women face on both types of platforms are similar. These common challenges include: gender skew, congestion, high level of interests/messages that women receive, and odds-based riskless approach used by men. Our analysis is based on two interventions implemented by the platform in May 2019 and November 2019 in different sub-domains. The first intervention – which we term *platform-level intervention* – restricted the visibility of women to counterparties (men, here) based on age, education, income, and marital status. For example, a 25-year-old woman's profile was visible to only those men who fall in the age range 24-35. Our study's primary objective is to understand if interventions whereby profile visibility is reduced to the most likely set of counterparties contributes to the overall well-being of women participants. In operationalizing well-being, we look at three outcomes – the number of incoming requests that women see, the matching rate, and the extent to which women initiate contact with counterparties.

In the second intervention – which we term *individual-level intervention*— rather than the platform applying the intervention across the board, women were given the option to restrict these dimensions (age, income, education) selectively for themselves. Women users could thus exercise these choices on the day of registration, potentially without understanding the reason for why these measures may help or could make these changes at any point in time, thereby reflecting "learning" that may accrue on the platform itself. To enhance identification, we are able to compare subdomains on the platform where these interventions were implemented to others where no such interventions occurred, thereby allowing us to quasi-experimental matched samples to enhance causal inference. We also conduct a series of robustness checks, all of which support the broad set of results we obtain from our primary analysis.

Our results show that the platform level intervention had the desired effect on women's well being. We find that post-intervention, congestion reduced for women, which also led to an increase in the efficacy of matching for them. The increase in efficacy could be attributed to more appropriate counterparties getting in touch with the focal users. We also see that post-intervention, thanks to reduced congestion, women initiate more matches. We notice that the intervention has not made men worse off; on average, their activity and efficacy of matching remain the same. Closer inspection reveals that though congestion reduces for all age groups, women above the age of 25 seem to benefit more. Women with higher educational and occupational attainments also seem to benefit more. However, when we specifically look at individual-level interventions where women are able to selectively restrict profile visibility, we note that it is only women who are older that appear to be enforcing such restrictions, which raises interesting implications for platform design, especially in matrimonial and dating platforms where gender skew continues to be an issue.

Our work highlights the challenges that women face on online platforms because of existing social norms and platform design. Platform owners have to take a larger role in ensuring that women can exercise their choice and are not harassed online. While giving the women the option to exercise choice to reduce the congestion may seem like an attractive choice, however, our study shows that platform level interventions can actually be quite beneficial in reducing congestion and ensuring the well-being of women. The challenge remains that only a subgroup of women who are older seem to benefit more. The platforms may have to take additional measures for women, who are younger, and maybe digitally more vulnerable. Our work here is aimed at increasing the awareness of improving the well-being of women on online platforms, if online dating and matrimonial platforms have to survive, and flourish.

Theoretical Background

Our paper contributes to the literature on gender norms as applicable to three streams of prior research: market design of online matching platforms, online harassment and digital vulnerabilities, and finally, women's empowerment and well-being on online dating and matrimonial platforms.

Gender Differences in Online Matching Markets

There are significant gender differences in preferences on the online matching platforms such as dating and matrimonial platforms. In the specific case of matrimonial platforms, women register on them to find a marriage partner, unlike men who may be in for short-term relationships (Kaur and Dhanda 2014). Matrimonial platforms may discourage such behaviors, but they cannot entirely discount such behaviors by some users (Agrawal 2015; Seth 2011) . Women tend to value men's present and future earning potential, with preferences for someone with higher educational qualifications and income (Fisman et al. 2006; Hitsch et al. 2010b). Men also show stronger preferences for physical attractiveness than women. Men prefer to marry or date someone younger (Agrawal 2015; Fisman et al. 2006; Hitsch et al. 2010a). At present, the age for serious consideration for marriage ranges between 22-24 for women and 26-28 in the case of men.

Further, most online dating platforms face an asymmetry in the number of users on each side of the markets (Yu 2019). It is anecdotally evident that women are in the minority in all platforms – this is reflected across both dating and matrimonial platforms (Karmegam et al. 2020; Slater 2013). Given the gender skew in the platforms and the relative paucity of an appropriate consideration set for men across the few women that are present on the platform, men are likely to be relatively indiscriminate in how they reach out to women in order to initiate contact. The lowered transaction costs on the platform as well as the possibility for arms-length interactions at first, unfortunately, enhance the possibility of this form of indiscriminate behavior. Thus, men are likely to reach out to far younger women, relatively more qualified in terms of education, occupation, and earning levels, thereby bucking social norms that are more prevalent in offline matrimonial settings. Given the gender skew, it is also likely that men engage in an odds-based approach, whereby they send out more contact requests to women, regardless of inherent fit, with the view of increasing the odds of receiving a positive response (Yu 2019). Though the efficacy of this approach is suspect, it remains a strategy espoused by men on the platform and also has the unfortunate effect of setting off a vicious cycle of increasing the congestion on the platform, enhancing the search costs for women, and reducing their eventual participation as a result of the gender asymmetry on the platform.

Congestion Due to Market Thickness

In the platforms literature, market thickness refers to the scenario where the likelihood of finding a match depends on the availability of other users or agents on the platform (Li and Netessine 2020; Roth 2018; Yu 2019). Market thickness has been studied extensively in the context of matching in the labor markets. The technology, availability of users at both ends, the urgency to form a match, make this market thick. Thick markets come with challenges given the short time in which agents need to conduct due diligence on agents at the other end, send out interest to match, and finally complete the matching process. Thick markets suffer from congestion (Li and Netessine 2020). Congestion could occur due to multiple reasons - inefficiencies induced by technology-aided tools like recommendation systems, search frictions caused by process, and congestion externalities induced by the process.

Past research shows that recommendation systems promote diversity (Fleder and Hosanagar 2009), enable targeting, and help users discover an appropriate match. However, the recommendation systems in online dating and matrimonial platforms could exacerbate the situation arising from gender skew. The platforms promote new users and more attractive users, thereby increasing the congestion for the users who register afresh. Congestion could also occur due to search frictions. When there are too many alternatives, and information to consider, users may have to engage in multiple searches and more complex evaluations, leading to higher cognitive effort (Hagiu and Jullien 2011). When users are presented with many choices, it could lead to information overload and hinder the decision-making process (Ghose et al. 2014). Finally, congestion externality by low-productivity users could reduce contacts between other pairs of users who might be better-matched but could miss out on this match given the presence of other entities on the platform (Shimer and Smith 2001). The group of men using the odds-based approach could act as these “low-productivity” members on the market, effectively increasing the cost of congestion asymmetrically for women. Given the presence of this congestion, how are women on the platform affected? We address this question next.

Women's Well-being on Online Platforms

In a recent study on the gender pay gap in Uber, Cook et al. (2018) identify three reasons for the prevailing pay gap. First, men are willing to drive in areas with higher crime and drinking bars, unlike women who are likely to focus on safety. Second, men are far more experienced, and on average, spend more time driving than women. Third, men are likely to drive faster and hence clock more miles. The concerns that define women's well being in the offline settings manifest in the online settings, even when men and women are on the same side of the equation in gig platforms. Some of the concerns heighten in the online world, as women are far more vulnerable while using digital technologies compared to men. Ransbotham et al. (2016) identify the mechanisms that make a certain set of users more digitally vulnerable, which include increased visibility, interconnectedness, and decreased costs of transactions. Increased visibility on the online matching platforms comes with consequences; it provides information access to users, who are unlikely to be in the focal user's consideration set for initiating any transactions. The focal users would have preferred to keep the information hidden to such entities or users. Though interconnectedness offered by technology increases the scale of desirable social interactions, it also increases the vulnerabilities, including cyberbullying, cyberstalking, and technostress (Lowry et al. 2016; Tarafdar et al. 2013). Finally, online social transactions tend to lower costs for all participants, which leads to large sets of users indulging in apparently utility-maximizing behavior without considering the consequences, which appears particularly true for men on online dating and matrimonial platforms. The above factors have led to a scenario where women continue to be experience behavior similar to harassment on these platforms.

In a survey by Pew research online dating apps, 28% of the women reported having been contacted by someone in a 'harassing' manner.[6] It may not always be intentional nefarious action like cyberstalking or cyberbullying that harms women's well-being;

[6] https://www.pewresearch.org/fact-tank/2020/03/06/young-women-often-face-sexual-harassment-online-including-on-dating-sites-and-apps/

other externalities also tend to harm women's well-being in online platforms. There is a common concern about being lied to or deceived on online dating platforms compared to traditional dating (Couch et al. 2012). Due-diligence is paramount, and women put much premium in the due-diligence effort by trying to learn facts about a potential partner before initiating a conversation (Finkel et al. 2012; Shukla and Kapadia 2007). There is likely to be technostress for women on online dating platforms - stress that the user experiences due to their usage of apps of information systems (Ayyagari et al. 2011; Tarafdar et al. 2007). The literature on technostress argues that the form tends to be context-specific and can manifest in multiple ways (Tarafdar et al. 2013), with the consequences which may include - reduced overall efficacy and enhanced burnout by system usage. Online dating platforms have significantly reduced the disinhibition amongst the women in initiating the first step. However, given the high level of traffic for women, the situation of dual-task interference (DTI) manifests (Jenkins et al. 2016). DTI is a cognitive limitation that results in significant performance loss. In our context, the DTI occurs when women cannot initiate any match, as there is constant traffic of incoming requests. Thus, the overall market design, social norms, and gender norms put considerable stress on women's well-being on online platforms.

The onus is on platform designers to evolve market design elements and provide features, making women feel safe and helping them realize the benefits of online platforms, thus contributing immensely to the well being of women users. We highlight three such elements, which would improve women's well-being on online dating and matrimonial platforms: reduce congestion and thus reduce search frictions, improve the efficacy of matching, and empower women to initiate matches.

Congestion can be reduced in multiple ways. One of the options is by adopting gender gating (Yu 2019), where the platform either incentivizes more women in joining or disincentivizes the other side from joining. Platforms like Bumble allow only women to initiate a match, thus reducing the congestion for women. However, some of these options may not be feasible for all platforms, especially with matrimonial platforms where users may have narrow preferences along multiple dimensions - religion, language, caste, or sub-caste. We specifically look at an intervention that would restrict profile visibility based on generally accepted gender preferences, or widely followed social norms. For example, women prefer to marry someone who is not too old and has educational and occupational accomplishments similar to or better than theirs. As explained earlier, the reduction of congestion is likely to reduce the search friction and improve the overall efficacy of matches. Such market design elements would empower the women to take the first step, as they are not bogged down by the congestion, and see the platform as a safe space for finding matches.

To summarize, we consider if changes in the market design or features on online dating and matrimonial platforms improve the well-being on the platform by reducing congestion, improve efficacy, and empowering women to initiate matches. We argue that minimizing search frictions and easing the vulnerabilities by reducing harassment can benefit women on online platforms. In place of formal hypotheses, we allow the empirical analysis to provide us with guidance. In the next section, we outline the platforms' intervention, and the econometric analysis we did to test the arguments above.

<u>Intervention 1 – Platform Level Intervention</u>

Data and Methodology

To conduct this research, we partnered with a leading online matrimonial matching platform in India. Like most of the other platforms, our partner platform is also grappling with the challenges associated with the gender skew. While our partner platform is growing consistently and adding subscribers daily, the gender skew issue has persisted, even if it has not worsened over the years. The platform regularly conducts experiments by rolling out features or intervention in one of the sub-platforms it operates. For our analysis, we relied on a quasi-experimental intervention design on the platform. Figure 6 presents the quasi-experimental design. The platform rolled out the intervention in sub-domain B in May 2019. Sub-domain A is closely related to sub-domain B in terms of geographical proximity and cultural factors. It is a regular practice for the platform to use both the domains interchangeably to roll out features and compare outcomes.

The intervention restricted a specific set of users who could view the focal woman user's profile based on four conditions: age, education, income, and marital status. The terms for restrictions are provided in Table 12. For example, a 25-year-old woman's profile will not be shown to a man who is 35+. A man whose educational qualification is a high school degree or less will not be able to view the profiles of women who have better educational qualifications. A man who has been married before will not be able to see the profile of women who have never been married previously. Finally, a man will also not be able to view those profiles, where the woman earns $3500 Indian equivalent currency or more compared to the man.

In Aug 2019, the platform rolled out the intervention across all the sub-domains. Thus, the restrictions based on age, education, income, and marital status were applied across all users. In a subsequent intervention in subdomain C in Nov 2019, the platform provided women the choice to set parameters. The set up for this experiment is parallel to the platform-level intervention, where subdomain C served as the treatment group and subdomain D as the control. Women had the choice to set values different from the default values applicable for platform level intervention. Please refer to figure 8.

Empirical Approach and Identification

While a randomized experiment would be an ideal strategy for identifying such interventions' causal effect, we had to rely on a quasi-experimental set-up of coming up with the matched samples to reduce the bias in the estimates for the intervention. We kept the intervention day T, as the base, the pre-treatment group constituted all the users who joined the platform between days T-60 and T-45. The post-treatment group constituted all those users who joined the platform between days T+15 and T+30. We use the data for thirty days of activities post joining the platform. The choice of the time-period is to avoid any activity overlap between treatment groups. We construct the matched sample from the four groups to limit any ex-ante differences that may exist between the users in the control and treatment group before and after the intervention. We use Coarsened Exact Matching, which is increasingly becoming the de-facto method for creating matched samples in IS literature. We create the matched samples by not only matching the users from subdomains A and B but also match the users before and after the treatment. We match on observable demographics - gender, age, education, income, location tier, religion, caste category, profile operator, and paid subscription. We originally started with over 70,000 profiles, and finally, end up with 18,338 profiles. We describe the individual variables next.

Table 11 provides detailed information on the variables used for analysis. Summary statistics are available in Table 13.

Variable Definition

Dependent Variables

For indicators of women's well-being in platforms, we look at three factors - congestion, matching efficacy, and empowerment. The first factor, congestion, is represented by ***TotalEIReceived,*** which is the sum of all expressions of interest (EI) received by the focal user in the given time. A high number of EIs received increases the overall congestion and, thus, cognitive load for women in platforms. Any reduction in the EI received would indicate a reduction in the congestion for women. With the intervention, the focal user's profile is likely to be shown to a comparatively smaller subset of users, leading to a reduction in EIs received by the focal user. The reduction is likely to have cascading effects on the outcomes, including the variables representing matching efficacy and empowerment. The second factor, the matching efficacy, is represented by ***TotalIncomingMatch***. In this instance. We look specifically at the match, which is formed when the focal user A receives an EI from user B, which, when accepted, results in a match. An increase post-intervention in the TotalIncomingMatch would indicate an improvement in the overall matching efficacy. It would serve as an indicator that the interests received by the focal user are from a more appropriate consideration set. The final factor, empowerment, is represented by ***TotalEISent,*** which is the aggregate of all EIs sent by the focal person. Reducing congestion is likely to empower women users to take the first step and initiate matches.

Independent Variables

The two important variables for our study are ***Treatment*** and ***TimeTreatment.*** *Treatment* is a dummy variable for which 1 represents the treatment group- subdomain B, and 0 represents the control group - subdomain A. *TimeTreatment* is a dummy variable for which 0 represents the pre-intervention period, and 1 represents the post-intervention period. The interaction of *Treatment* and *TimeTreatment* is the main variable of interest, as it provides the intervention's effect on our dependent variables. For our analysis of woman subgroups of interest, we use dummy variables - *Age26AndAbove, EduHigher,* and *WithIncome*. *Age26AndAbove* is 1 for those users whose age is 26 and above; it is 0 for those users who are 25 and below. *EduHigher* is 1 for users who either have a Masters's degree or above or have undergraduate professional degrees with high potential, and it is 0 for other users. Users with earn income have *WithIncome* value as 1, and 0 otherwise.

Controls

We control factors that may influence the outcomes of interest, including the variables used for the coarsened exact matching – gender, age, caste, religion, language, years of education, income, and a dummy variable indicating paid subscribers status. We also control for the profile operator, which could be the focal person, family member, friend, or relative. We include the controls for the city tier, where tier 1 refers to the major 6 metropolitan cities in India, tier 2 refers to mid-level cities, and tier 3 refers to large towns. We account for any systematic time effects by controlling for the week of joining the platform.

Regression Analysis

Our main estimation equation is as follows.

$$WellBeingFactors_i = \alpha_0 + \alpha_1(Treatment_i) + \alpha_2(TimeTreatment_i) + \alpha_3(Treatment_i x\, TimeTreatment_i) + \beta D_i + \gamma_i + \varepsilon_i$$

Where *WellBeingFactors* refers to the three important factors discussed earlier - *TotalEIReceived*, *TotalIncomingMatch*, and *TotalEISent*. The intervention's main effect is provided by the coefficient α_3, which captures the effect of the profile restrictions on the treatment group. We cross-sectionalize the daily panel data on user behavior from the 30 days of activity on the platform; thus, the analysis unit is the focal user. For the analysis, we control for the demographic attributes of the user - D_i. We also control for the specific week when the user signed up on the platform, to capture any external influences that may systematically influence all such users, represented byγ_i . In the regression analysis for the *TotalEIReceived*, we control for the total days the user was active since more active days are likely to lead to further incoming activity as more active users are given primacy in the recommender systems. Similarly, for the regression analysis of *TotalIncomingMatch* and *TotalEISent* for the focal user, we control for total days active, and total EIs received. For all the models, we control the *ProfileViews*, a variable that indicates how many times the individual's profile has been viewed. The main models are estimated using OLS, with clustered standard errors. The clustering is based on the location. To a large extent, location determines other factors, including - education, occupation, income, and technology usage. In robustness tests, we also used models for count data to estimate the treatment effects and obtained results that are largely consistent with those reported here in terms of the observed effects.

Summary Statistics and Main Effects

Summary statistics for the matched sample for intervention 1 is provided in Table 13. Our sample consists of 20% women, exemplifying the gender skews we see in the matching platforms. The median age of women for our sample is 25; hence we consider the variable *Age26AndAbove* to further split the sample for women. On average, men have lower years of education, 14.78 years compared to 16.04 years for women. However, considering the variable *EduHigher,* over 25% of the men have a Masters's degree or above or have undergraduate professional degrees with high earning potential. 42% of the women in our sample and 87% of the men report their income. Women are more likely to have paid subscriptions in our sample - 11% compared to 4% in men's case. One important consideration in the matrimonial platforms is the focus on the caste preferences. In our sample, 15% of women have indicated that they are willing to look for partners outside their own caste, while 51% of women prefer to marry within their own caste. The corresponding percentages for men are 25% and 43% respectively.

Table 13 also provides summary statistics on the activities within the platform. On average, women receive 40 times more EIs compared to men; in our sample, women received 152.84 EIs compared to 3.76 received by men. The EIs received indicates a high level of congestion for women on these platforms. *TotalIncomingMatch* is 1.65 for women, which indicates that the matching efficacy for women is very low, around 1%. The matching efficacy for men is a respectable 13%. Women send out 15.44 EIs compared to 37.78 in case of men. Not surprisingly, the average profile views for women is 1498.68 compared to 128.64 for men. In the given 30-day period, men are likely to be more active in a purposeful way by sending out EIs or accepting EIs. In our sample, *DaysActive* for men is 5.64 compared to 4.59 for women.

Table 14 reports the estimation for the intervention's main effects, which restricts profiles of the focal person being shown to counterparties. Columns 1,2, and 3 provides results for congestion variable - *TotalEIReceived*. We are interested in the coefficient for the interaction terms - *Treatment* and *TimeTreatment*. We find that post-intervention, the *TotalEIReceived* reduces for the overall sample, as seen in column 1. A closer look indicates that all the reduction comes specifically for women, as seen in column 2. Women received 10.3 less EIs post-intervention. This roughly translated to a reduction of 6% of the congestion. We do not see any statistically significant relationship for men. The results suggest that there is a significant reduction in congestion for women.

How does the reduction in congestion translate to better outcomes for women, we look at other parameters - *TotalIncomingMatch* and *TotalEISent*. Columns 4,5, and 6 provide the results for *TotalIncomingMatch*. We find that women accept more EIs post-intervention, significantly improving their matching efficacy. As seen in column 5, women have 1.03 more matches, which roughly translates to over 62% improvement in women's matching efficacy. Thus, we find that the platform level intervention has improved the well-being in the platform by reducing the EI received. The lowering in EI received, reduces the overall search frictions for women, thus lowering the overall due-diligence costs. The profiles received by women are more appropriate and relevant, thus increasing the matching efficacy. We also notice that there is a decrease in the matching efficacy for men; it reduces by 0.141. An important question now is if the platform-level intervention leads to empowering women to send out more EIs. Results from columns 8, do suggest that women do send out 9.235 more EIs post-intervention; this suggests an almost 60% increase compared to the average values. There is no statistically significant change for men post-registration. Our findings suggest that the platform's intervention to reduce the overall congestion, and thus improve the overall well-being of women on online platforms, had the desired effect. The congestion reduced significantly, leading to increased matching efficacy for women and empowered them to send out more EIs. We now look specifically at those set of women who are likely to benefit, given that the intervention was along 3 critical dimensions - age, education, and income.

Split Sample Analysis - Who benefits by the intervention

Table 15a-c provides the split sample analysis for the three groups based on age, education, and income using the variables *Age26AndAbove, EduHigher*, and *WithIncome*. Table 15a provides the results for the *TotalEIReceived*. As seen in columns 1 and 2 of Table 15a, women who are below the age of the median age of 25, receive fewer EIs post-intervention. However, even those women above 25, the reduction in congestion is very close to the average reduction seen earlier in Table 14.

Columns 3 and 4 suggest that only those women, who have higher educational qualifications fare better with the intervention, the EI received by the group reduces by 11.52. Results from columns 5 and 6 suggest that the women who do not have income receive far fewer EIs (13.58 less) than those with income. Table 15b provides the result for *TotalIncomingMatch*. Columns 1 and 2 suggest that women who are 26 and above see their matching efficacy increase by 1.648, well above the average value of 1.033 seen earlier in Table 14. While the other women groups see an overall increase in matching efficacy, women with income (col 5) and higher educational qualifications (col 3) benefit more from the intervention. Table 15c provides the result for *TotalEISent*. Like *TotalIncomingMatch*, we find that women 26 and above (col 2), with higher educational qualifications, send more EIs post-intervention. In summary, the platform initiative to improve women's well-being tends to benefit certain subgroups more than others. Women who have clearer matching expectations, as evidenced by the age, those who have a higher level of educational qualification, and those with income, suggesting economic independence tend to benefit more.

Caste Considerations

While the focus of our paper is to highlight women's well-being in platforms, however, the context remains rooted in the matrimonial setting in India, where caste continues to play a significant role. We examine how the caste preferences of women determine outcomes for them. The results for caste preferences based on split-sample analysis are available in Table 16. Users with caste preference the same as theirs receive fewer EIs post-intervention (col 1). The results for users with open caste preferences are not significant (col 2). The matching efficacy also improves for both the groups, with users with no caste preferences having better efficacy than the average group values (col 3 and 4). We do not see any significant results for the EIs sent (col 5 and 6). The result for caste-based preferences is a mixed bag, with users having narrower caste preferences likely benefiting from the reduction in congestion and improvement in the matching efficacy. However, there is no empowering effect when it comes to users with particular caste-based preferences.

Robustness Checks

We also conducted a set of robustness checks to see if the results we obtained earlier hold up and complement our analysis. First, we conducted the analysis using various count models - Poisson regression, negative binomial regression, zero-inflated Poisson, and zero-inflated negative binomial regression models. Stata's "countfit" command suggests that zero-inflated negative binomial regression is the best count model for analysis specific to women. Given the higher values of zeros for men, the best count model for analysis is zero-inflated Poisson. We include the analysis for women in Table 20. The results are consistent with our main results. For women, *TotalEIReceived* reduces post-intervention (col 1), *TotalIncomingMatch* representing the matching efficacy improves post-intervention (col 2), so does the *TotalEISent* (col 3).

In our analysis, we also check if the parameters we identified - congestion, matching efficacy, and empowerment varies from time to time from the day of joining the platform. We ran the models for 3 days, 7 days, and 14 days, along with the 30 days model provided earlier. The results for the models are available in Table 21. The results are consistent with our main results, except for some interesting findings for the

TotalEIReceived. The maximum impact in terms of reduction in congestion is felt in the initial three days from joining for women (col 1). The results for the initial seven days and 14 days is not significant for the *TotalEIReceived*. We also see an immediate increase in matching efficacy (col 5) and the empowerment in sending EIs (col 9). The results suggest that there is an immediate effect as well as a long-term effect on the congestion. In the medium term, we do not find much impact as far as the congestion is concerned. Whereas the benefits for the matching efficacy and empowerment is consistent and keeps growing with time.

Intervention 2 - Choices Made by Women When Given an Option

A natural corollary for platform level interventions is to give users the option to make the choices to restrict counterparties from seeing the profile. However, as illustrated in the past studies, women may not adapt their online behavior to serve their needs best. It is widely accepted that women should focus on security and privacy on online apps. The social, cultural expectations and privacy concerns reflect in women showing different social behaviors on online platforms. Given the perceived risks related to privacy, security, and online harassment, women may not realize the full potential of online platforms. Bartel Sheehan (1999) observed that even though women appear more concerned about their privacy online, but do not adapt their online behavior to protect their privacy as men do.

Identification Strategy

In intervention 2, though, we have a quasi-experimental set up similar to intervention 1; there could be endogeneity in the choices at multiple levels - we provide the details for three such choices. First, women can choose an option that is different from the default values. Second, they could choose an option that is either narrower or broader compared to default values. Third, they can opt to choose while registering on the platform or choose after learning how the platform operates. Given that groups were not randomized, the best-case scenario would be if the platform rolled out intervention two concurrently in a different subdomain. We would have been able to assess the effect of individual choice compared to the baseline, as depicted in Figure 8. Given that the platform rolled out the intervention one to all the users, it would be hard to causally determine the effect of choices made. Hence for this work, we focus on the question as to whether those subgroups of women, who benefit from platform-level intervention, make a choice to restrict profile visibility when the option is made available by the platforms. For our analysis, we looked at two sub-groups of users - first, those who chose on the day of registration; second, those who chose between day two and day thirty. The understanding is that these users are different - the first group, have an inherent choice structure, and the second group, makes choices after "learning" or is responding based on outcomes. To create matched samples using CEM, we compare the above two groups with the control group, which constitutes women who do not make any choices even after 30 days in the platform.

Dependent, Independent, and Control Variables

For analysis about the choices made by the subgroups of women, we consider the following variables - *WomenChoiceOnReg*,*AgeChoiceOnReg*,*EduChoiceMadeOnReg*,*and* *AgeEduIncChoiceMadeOnReg*. For the dummy variable *WomenChoiceOnReg* value 1 refers to those women who choose to restrict other users on the day of registration; 0 refers to those who do not make any choice after 30 days. Similarly, for the dummies with value 1 in variables *AgeChoiceOnReg* refers to those users who make a choice along the age dimension; *EduChoiceMadeOnReg* refers to those users who make a choice along the education dimension*, and; AgeEduIncChoiceMadeOnReg* refers to those users who make a choice along all three dimensions - age, education, and income. In all three instances stated above, 0 refers to users who do not make any choice even after 30 days. We use *Age26AndAbove*, *EduHigher*, and *WithIncome* as independent variables, the subgroups of users who benefit from first intervention.

Econometric Specification

We use the following econometric specification to determine whether those subgroups that benefit from intervention 1 make a choice when provided the option.

$$\Pr(ChoiceFactors = 1) = \beta_0 + \beta_1(SubGroups_i) + \beta_2 D_i + \gamma_i + \varepsilon_i$$

Here ***ChoiceFactors*** refer to the four types of choices discussed earlier - *WomenChoiceOnReg*, *AgeChoiceOnReg*, *EduChoiceMadeOnReg*, and *AgeEduIncChoiceMadeOnReg*. ***SubGroups*** refer to *Age26AndAbove*, *EduHigher*, and *WithIncome*. We control for demographic factors, as well as the week of joining the platform. In the panel version of the model, we consider the *ChoiceFactors*, but with a variation. We consider the choices that were made in between for age, education, all factors combined. In the panel probit model, the dummy variable stays as 1 for the remaining period once the choice is made. We include user fixed effects and lag the activity variables by two days. The activity variables include - *TotalEISent*, *TotalEIReceived, ProfileViews,* and *TotalMatches*, the sum of the total incoming and outgoing matches. Outgoing matches refer to the scenario, where the counterparty accepts the EI sent by the focal person.

Summary and Results

The second set of research questions focuses on whether the subgroups of women who benefit from platform level interventions make choices to restrict the counterparties when given the option. As discussed earlier, we look at the effect on the treated group alone. The summary statistics for the treated group is available in Table 17. This group constitutes 55% of women in the age group of 26 and above, 91% with higher educational qualifications, and 39% with income. Our sample consists of 87% of women who never married before. 51% of users make a choice related to age, education, or income. Users retain the default value for the marital status in all instances - those who never married before, restrict their profile visibility to only those who never married before. It is similar for those who were separated, divorced, or were widowed. 16% of users make a choice related to age only on the day of registration, and 13% of the users make a choice related to age within day 30. 8% of users choose to restrict users based on education while registering, and 25% of the users choose between day 2 and day 30. Surprisingly, very few users choose to restrict users based on income alone; hence we do not consider that factor for our analysis. 3% of the users choose to restrict users from viewing their profile based on all three parameters - age, education, and income, while 10% of the users choose between day 2 and day 30.

The results from the probit model are available in Table 18. Recall we created a matched sample of users who chose to restrict profile visibility and compared them with users who do not choose even after 30 days. For example, for column 1, the matched sample was created by comparing users who made a choice on registration, with those who did not make any choice even after 30 days. The results from columns 1-4 suggest that women who are age 26 and above are more likely to choose to restrict profile visibility on registration and make choices related to education on registration. Women with income are unlikely to make choices either related to education or make choices on all parameters on the day of registration. Thus, the results suggest that women who benefit from the interventions are less likely to choose to restrict profile visibility while registering their profile.

Now we consider the scenario where users may make a choice between days 2 and 30 after registration. We opt for the panel probit model in Table 19 to see as to which groups make a choice. In this instance, users choose based on "learning" from their activities on the platform. Recall we created the matched sample by comparing users who made a choice in between to those who never made a choice even after 30 days. We specifically look at three choices - age, education, and all three, including income. As seen in columns 1-3 in Table 19, women aged 26 and above are likely to choose to restrict across all three parameters - age, education, and income. Women with income are likely to restrict counterparties along the dimension of education (col 2). Paradoxically, women with higher educational qualifications are unlikely to restrict users based on education. To summarize, only women aged 26 and above, a subgroup that benefits from platform-level intervention, are likely to make choices during registration. The same subgroup of women is also likely to benefit from learning on the platform and make choices that are likely to benefit them. The choices made by the subgroups could be attributed to certain imminence or urgency associated with the process for this age group. Women aged 26 and above are also quite certain about their preferences, quickly narrow down on the type of matches they would like to communicate on the platform. Income or the educational qualification of women, do not seem to be playing a role in women making choices for their own well-being on online matching platforms.

Regarding the second intervention, we ran the panel probit model with no lag, 2 days lag in Table 22, and get results consistent with the results we obtained in our analyses in Table 19.

Discussion and Conclusion

Online matrimonial platforms are built on the expectation that men and women will be able to navigate the complex yet necessary social processes that lead to a successful marital match but through reduced transaction costs online. Yet, the reality is that these platforms, similar to dating platforms, have vastly higher numbers of men relative to women, representing a significant gender skew. How does this gender skew affect the well-being and user experience of women on the platform, especially when they are at the receiving end of significant attention? Does the gender skew increase the cognitive costs women face, thereby preventing them from receiving the same level of benefits that men may receive? We address these questions in this paper but through the lens of platform market design.

The approach we take is to reduce the negative effects of congestion and market thickness that women face by changing the choice structure made available to users. Prior work in online dating has used this approach by controlling the choice sets presented to users on the basis of age, location, and the number of profiles available per day (Jung et al. 2020; Yu 2019). In our case, we use market design that reduces the visibility of a focal profile belonging to a woman, based on age, education, and income, thereby affecting choice structure with a view to relieving the effects of congestion. We contend that choice structure should just be based not only on partner preferences but also on reducing the choice set by ex-ante eliminating those users that are likely to fall outside socially acceptable norms for an acceptable match. Partnering with a leading matrimonial platform in India, we designed our interventions based on this approach, thereby raising questions on whether an appropriately modified choice structure does indeed provide much-needed relief to women on the platform. Beyond market design per se, we theorized that these modifications to the platform will help reduce the effects of unwanted attention that women tend to face on matrimonial platforms and thus minimize the extent to which they may experience vulnerability, while also enhancing their engagement and matching outcomes on the platform. To the extent that empowering women on such platforms serves both economic and social goals, our interventions can be termed successful if they do show significant benefits.

Our results show that women do benefit significantly from the platform's intervention – once the congestion faced by women who have newly joined the platform reduces, the overall efficacy of matching improves, and women feel empowered to initiate matches. In terms of differential effects, the beneficial impact of the intervention is greater for women who are arguably in the most attractive segment of the market – educated women above the age of 26 who earn more than the median income on the platform. While younger women do see a far higher reduction in congestion, they do not benefit as much in terms of the follow-up action related to an increase in efficacy, or the initiation of new matches. Thus, a mere reduction in congestion is not enough for certain subgroups to see improved matching or greater engagement with the platform – this brings up interesting opportunities for the platform in terms of how it can specifically enhance the value proposition for women across multiple age groups and demographics. Interestingly, when women are provided agency in terms of allowing them to manipulate these parameters, we find that education and income do not appear to correlate with a decision to increase the restrictions on who can view their profiles. However, older women appear to be more inclined to make further changes on these dimensions, either on the day of registration or later.

To the extent that the new baseline, implemented through the platform-level intervention, is able to meet the requirements for most women, we infer that market design has helped in addressing a pressing issue faced by managers in the firm. Our conversations with the platform operator reveal a sense of urgency amongst the senior management in addressing the gender skew problem. In the recent past, the platform had run aggressive advertisement campaigns focusing on messages about women empowerment and their safety, with the objective of getting more women to register on the platform. However, these advertisements have to be matched with an appropriate set of market design parameters that help reduce the social costs that women face – while the platform model continues to supplant traditional offline match-making activities that have existed in Indian society for many years, there is an increased recognition that simply porting the process online is not enough. Factors that affect the well-being and user experience of women on such platforms, thanks to the easing of transaction and search costs as well as the scale that technology allows, have to also be concurrently managed through appropriate platform design.

Our findings in this paper thus have both theoretical and practical implications. First, our results show that the platform needs to reduce the congestion in a thick market to enhance the wellbeing of women participants on the platform. However, mere reduction of congestion may not be a sufficient condition; some users with age and experience may benefit more. Platforms may have to follow up with other interventions to empower women. Our work can be extended to challenges faced by women in other platforms as well. Online platforms may intervene by redirecting the flow of work by giving priority to women, thus empowering them. For example, ride-hailing platforms could prioritize allocating women drivers in areas with specific requirements in terms of safety, traffic, and opportunities – whether women will avail of these opportunities when provided agency remains an open question.

Our work here is subject to limitations. First, although we have a quasi-experimental set up with matched samples across platform subdomains that are separate, the ideal option would have been to conduct a randomized experiment. However, such randomized experiments in settings such as ours with enhanced sensitivity and cultural implications are difficult to operationalize. Therefore, to the extent possible, using matching, controls, and econometric analysis, we believe we have provided results that have reduced the possibility of bias emerging from selection issues. That said, we acknowledge that we cannot fully rule out the influence of unobserved variables. Second, at this stage, we do not have the counterparty information. Having that information will help us understand if the intervention has shifted the demographics of incoming requests and matches. Unfortunately, this additional data remains unavailable at this time. Third, we acknowledge the endogeneity issues in our analysis on the individual intervention; we are working with the platform to implement a variant of an intervention that would address these issues.

In conclusion, our work addresses an important theoretical question on the effects of reducing congestion for women to facilitate their overall well-being on online platforms. This remains a problem with important practical implications for online matching platforms grappling with gender skew issues, especially in socially sensitive areas like matrimonial matchmaking and dating. Our study suggests that such interventions do work, but do not equally benefit all sections of women. Online platforms must have a comprehensive strategy to address the effects of gender skew. If left unchecked, it will lead to the exodus of women and lead to the platforms' unraveling.

Chapter 4: Status (dis)Advantage: Effect of Stakeholder Diversity and Deviation in Group Norms in Online Matrimonial Platforms

Introduction

In the last few decades, a large number of economic activities that were traditionally managed offline have moved online, typically through the medium of Internet-based digital platforms. Within these activities that have been transferred online, those that are easily codifiable and modular are more easily "platformatized". In contrast, activities that exist in heavily institutionalized offline settings have not made this transition to a platform-based model with as much ease. Furthermore, when they do make the transition, it is not clear that all the salient aspects of the original offline activity also transfer online or play the same role. Effectively, as the platform-based model gains traction and more activities move online, a clearer understanding of how this transition affects the underlying dynamics of the original setting is needed, so as to better manage both the newly online process as well as to aid the transition process. Examining these transitions in some detail is necessary especially in heavily institutionalized contexts since many institutional norms may not transfer online. Factors that are influential offline, like status, social norms, and quality signals, may behave in very different ways when moved to an online platform-based setting. In this paper, we study the transition of one such heavily institutionalized context and specifically investigate how traditional markers of status and social norms operate online. To the extent that status, social norms, and gender play a very different role online, our work helps inform theory in online platforms on how institutional norms may change when moved from a purely offline model to a platform-based one. In this paper, we study these transitions in a relatively under-explored institutional setting within contemporary IS research – matrimonial matching for arranged marriages in India.

Matrimonial matching remains popular in Indian society, and operates within the broader institution of arranged marriages. In the last two decades, online matrimonial matching platforms have emerged as a way to take the offline process online. These platforms share some features with online dating platforms that have been examined in the IS literature (Karmegam and Gopal 2019). They are highly prevalent in Indian society and increasingly have become mainstream. The process of arranging marriages in most Asian societies is heavily institutionalized, with several widely accepted norms that guide how such matches are made. These norms have been discussed in the popular press but include, the central role played by the parents of grooms and brides in decision-making, the presence of strongly endogamous preferences to marry within the same community, and clearly defined roles and expectations from women (Agrawal 2015; Allendorf and Thornton 2015; Desai and Dubey 2012; Seth 2011; Titzmann 2015). These norms are particularly relevant in the Indian context, where the existing offline matching process reinforces them across most communities in the sub-continent. Given their primacy, matrimonial matching platforms have mimicked these offline aspects, by highlighting factors like religion, caste, and community online. However, whether these institutional norms continue to hold remains an open question within the platforms literature as well as in online matching (Agrawal 2015; Seth 2011).

In this paper, we address this broad question of the relevance of offline social norms in the online world, but focus on three specific factors that have been implicated in prior work studying Indian marriages within the sociology literature (Allendorf and Pandian 2016; Desai and Andrist 2010; Seth 2011; Yeung et al. 2018). First, decisions about marriage in collectivist societies like India are made in multi-stakeholder contexts where family members have equal influence. In particular, *parents* occupy an exalted position, such that a matching process managed by a parent is viewed as being more legitimate, and therefore of higher status, all else being equal (Agrawal 2015; Kamble et al. 2014; Mathur 2007; Medora et al. 2002; Zaidi and Shuraydi 2002). Others in the community respond positively when considering a potential match through parents or family members, while self-managed matrimonial arrangements are viewed with less legitimacy. However, does this status extend online? In matrimonial platforms, the system allows each individual profile to designate an operator of the profile during registration, where it is possible to denote parents as the operator. In contrast to dating apps, matrimonial platforms allow family members or parents to operate the profile and manage online interactions. Thus, the first research question we address is: *do profiles managed by parents on the platform experience the same high status that is seen offline, in terms of markers for better profile appeal including the overall matches achieved?*

Marital preferences in India are significantly shaped by endogamy (Desai and Dubey 2012; Fuller and Narasimhan 2008b), i.e., preferences for staying within the community as defined through religion, community, kinship, or caste. Within these, caste-based endogamy retains particular influence. Any deviation from caste norms can disrupt internal unity and homogeneity within a group, thereby leading members of the group to regulate marriages either through sanctions or through instilling a strong sense of group identity (Ahlawat 2015; Kalmijn 1998). In offline settings, therefore, deviations from caste norms in the case of marriage are frowned upon and typically met with rigid disapproval. However, prior research in dating shows that when moved online, people tend to relax social norms more easily (Bapna et al. 2016a; Hitsch et al. 2010b). The access to a diverse set of individuals, as well as the reduction in transaction and search costs online, help relax norms that are otherwise prevalent offline. We study if these dynamics are true in the case of matrimonial matching as well but on the critical dimension of caste. Thus, the second research question we address is: *does deviation from caste-based group social norms in the context of online matrimonial matching lead to lower/higher profile appeal? If not, is the negative effect of this deviation from social norms mitigated by the presence of high-status profile operators, such as the parent?*

Finally, we consider the important issue of gender. It is accepted that, like other Asian societies, Indian society is patrilineal and patriarchal (Seymour 1999). In the specific case of marriage, men typically have greater agency and leeway in terms of the choices they can make, while women, on the other hand, have lesser agency in terms of identifying potential partners, and deviations from social norms are less acceptable in general. During the matrimonial matching process, there are more clearly defined norms for communication, coordination, and preferences in the case of women, relative to men. When this process moves online, do these gender-based norm differences carry over as well? This remains an open question in the literature. On the one hand, technology can induce greater parity in terms of how men and women interact, thereby reducing the extent to which typical offline gender-based differences manifest when online. On the other hand, if institutional norms associated with gender and marriage are resilient, these differences will exist online as well. We examine this issue through our third research question: *is there a difference between men and women in how deviation from social norms and profile operator status (parental control) leads to higher/lower profile appeal in online matrimonial platforms?*

We conduct our analysis on data gathered in collaboration with a leading Indian online matrimonial platform. The platform provided us with data for all those users who registered on the platform between October 2016 and January 2017. The dataset included profile information, partner preferences, number of potential matches that were contacted by each individual, the responses received from others on the platform, as well as the total matches (*realized dyads*) formed. Our econometric analysis, conducted on this extensive dataset, is aimed at understanding the effects of the profile operator, deviations from caste-based group norms, and gender on matching outcomes, i.e., dyads formed where two individual profiles are mutually linked.

One of the challenges in our work here is to establish a caste-based group norm, which is necessary to measure the extent to which an individual deviates from it. We, therefore, introduce a novel measure of group norms, based on caste-based endogamy, which uses the partner preferences each individual provides to the platform when they register. We use these partner preferences set at the time of registration to create a preference vector over all other castes within the platform at the group (caste) level. We then measure the similarity of an individual's preference vector to the group preference vector to calculate the deviation from group norms. This gives us the ability to measure the effects of deviation for an individual from the group norms, and thus indirectly the strength of each individual's endogamous preferences on the platform.

Further, we also face the issue of endogenous selection in the case of profile operator, i.e., the person that is selected to manage the profile is collectively determined by the family. Therefore, the effect of this decision on the realized matches on the platform is likely biased. The ideal option here would be to assign the profile operator to a profile exogenously but clearly, this is unrealistic and infeasible (Jung et al. 2019). Therefore to address this issue, we use two different types of matching methodologies – coarsened exact matching (Blackwell et al. 2009) and twin analysis using exact matching – wherein observable factors like age, religion, caste, education, and occupation are same except for the profile operator status (Jaffe et al. 1993). This allows us to create a sample with two equivalent subsamples of profiles that are mostly identical, except for the profile operator variable that is different, allowing us to reduce the potential bias from selection.

The results of our analysis show that there are indeed significant differences in terms of how these norms influence the effectiveness with which new matches are made on the platform. We observe that unlike the offline context, profiles managed by family members or parents are less likely to achieve matches on the platform. Furthermore, deviations from caste-based group norms, in general, leads to more matches or higher profile appeal, again providing some evidence for how offline norms may not apply in full measure online. However, the interactive effect of deviation from group norms and a family member operating the profile reduces the efficacy of the profile, showing the limits to how much offline norms can be disregarded within the marital matching process. Interestingly, we see these effects accentuated in the case of women – the negative effect of parental operation of the profile is particularly negative for women, relative to men. Deviations from group noms by women is also viewed positively by others on the platform. In general, we see that many institutional norms that are applied rigorously offline are not as influential online, showing that as institutional settings transfer online, a new set of norms are likely to emerge that are nevertheless hybrids of existing offline norms. Our work furthers a deeper understanding of how these changes occur from platformization, especially in the context of social practices that have deep roots in tradition, social norms, and institutional order.

Our work here contributes to the extant literature on digital platforms, but by taking a different perspective – we consider how aspects of a social process with strong traditions and norms are changed when moved to an online platform model. To the extent that technology and platforms can contribute to significant changes in social and economic processes, our work shows how new dominant logics may emerge online even in very institutionalized domains like marital matching in India. There are several other such institutionally dense settings that are being transferred to platform models, such as the process of raising venture capital funding, the acquisition of MBA degrees online, and the process of providing therapies for chronic diseases on platforms (Ahlers et al. 2015; Arbaugh et al. 2009; Talboom-Kamp et al. 2016). In all of these cases, it is possible that the traditional sources of status, quality, and influence may change when moved online, which has implications for individuals who join the platform as well as the platform providers themselves. While matching platforms thus far have focused on relatively straight-forward contexts, we believe that the next wave of platforms is likely to tackle increasingly complex and institutionally dense contexts. Our work here is aimed at furthering our understanding of these complex transitions, from an institutional and platform perspective.

Theoretical Background

Platforms, Institutions, and the Arranged Marriage Process

In the past decade, there has been an exponential increase in the development of digital platforms to support diverse economic and social activities (Constantinides et al. 2018). Our focus here is on online matching platforms, also referred to as multi-sided markets, which facilitate transactions between individuals or organizations that otherwise would have difficulty finding each other (Rochet and Tirole 2003). Matching platforms rely on network effects (Parker and Alstyne 2005) and reduce market frictions by lowering search and transaction costs. Successful matching platforms have thus far focused on contexts where transactional complexity is reasonably straight forward, and market frictions can be clearly reduced. Over time, more complex settings have started to move to a platforms model, such as the use of platforms for dating (match.com) and for receiving quick advice from physicians online (healthtap.com). However, as the underlying activity becomes institutionally dense and socially complex, the appeal of the online platforms model has to be balanced against the feasibility of transferring much of the relevant set of institutional and social norms online. Consider, for instance, the process of acquiring venture capital (VC) investments for startups – clearly, the VC literature shows that the process of investing in a startup is complex, and embedded in a social process that involves networks, syndicate partners, domain experts, and still carries significant risk (Gompers and Lerner 2001). Many institutional norms operate in this environment that make the process of acquiring venture capital particularly complex and time-consuming (Guler 2007). While some platforms have emerged in this area to help reduce market frictions (crunchbase.com, for instance), the overall process remains largely offline. Alternative models like equity crowd-funding platforms also exist (Ahlers et al. 2015), but many institutional elements that define the VC-entrepreneur relationship are typically lost. In general, institutionally dense contexts are not easily ported to a platforms model, and when they are, it is likely that many of the salient features of the original offline activity are significantly modified. Given this background, we look at a setting that remains highly institutionalized, with well-established social norms – Indian arranged marriages.

It is worth first defining what we mean by highly institutionalized contexts here. Social scientists have characterized institutions as an enduring or recurrent feature of social life (Mohr and White 2008). Institutions thus can refer to specific types of conventions or practices that have been put in place to manage social interactions and have acquired legitimacy over time. These include the set of activities, values, norms, social structure, and role systems that define a functional area, field, or activity (Greenwood et al. 2002). Institutions thus are a fundamental and pervasive feature of social existence. The institution of arranged marriages, a widely accepted mode of matchmaking in many parts of the world (Hamon and Ingoldsby 2003), fits well within this broader definition of an institutionalized activity (Gupta 1976; Mohr and White 2008). In the Indian context, in particular, the system of arranging marriages remains highly institutionalized, with a clearly defined set of operating principles, structures, and social norms that confer legitimacy on those using the institution to find suitable matches for themselves or close family members (Ang and Cummings 1997; DiMaggio 1988; Dimaggio and Powell 1983; Meyer and Rowan 1977). While there may be some variations in terms of how specific communities use the institutional process to find matches, there is considerable homogeneity in the baseline processes across the country that reflect adherence to a common set of institutional beliefs and norms. We briefly describe the main steps of the traditional, offline process of match-making, as practiced in India below.

The Arranged Marriage Process – Offline Form

The process of finding a match is typically initiated when individuals reach marriageable age, i.e. 26-28 years for men and 22-24 years for women (Desai and Andrist 2010; Seth 2011). Once the process is initiated, the informal network consisting of immediate family members, friends, and community members is activated and involved in the search process. Information about the individual and their appropriate partner preferences are conveyed orally or through a detailed bio. The process of selecting a suitable match usually involves multiple criteria that includes personal compatibility, looks, education, occupation, and other economic factors, as well as factors like religion, language, caste, and sub-caste. Endogamy along the line of religion and caste is pervasive and is used as the primary filtering criterion before other factors are considered (Agrawal 2015; Fuller and Narasimhan 2008b; Seth 2011; Titzmann 2013). In some instances, families may choose to widen the search by approaching marriage brokers or offline matrimonial agencies, placing a matrimonial ad in the newspapers, or by creating a profile in online matrimonial platforms (Kaur and Dhanda 2014). Once a profile meets the specified criteria, initial contact with the counterparty family is established. Background checks are performed in parallel to assess the personal character of the counter-party and, most importantly, to verify family background and reputation (Kaur and Dhanda 2014; Seth 2011).

Once the pre-screening process is completed, a formal visit is arranged whereby the two families meet each other while the prospective partners are allowed to interact to assess mutual compatibilities. If all goes well, the process converges here either in terms of proceeding to the next stage or choosing to stop any further interactions. At this stage, the process is close to finalization. If the families decide to move ahead with the alliance, a new and complex process of negotiation commences about logistics relating to the actual marriage ceremony. In Indian weddings, the costs of the ceremonies are typically borne by the families and not the individuals per se. An engagement ceremony is conducted to formalize the arrangement. The entire matrimonial matching process culminates in the marriage ceremonies and rituals that last for a couple of days to several days, depending upon the community. Across the match-making process, there are two important institutional factors that differentiate the method from alternative modes by which marriages are contracted in other parts of the world – the presence of parents or family members as active decision makers and the presence of strong endogamous preferences along caste. In addition, there are clearly demarcated social norms based on gender that are prevalent in Indian society that influence the matrimonial matching process as well. We briefly discuss these institutional norms, and their role in the offline process described thus far, below.

Parents and Family Members as Stakeholders

In collectivist societies like India, even today, parents or family members often assume the primary or co-equal role of selecting marriage partners for their children (Yeung et al. 2018), so as to ensure close identification with the family and to discourage focus on the autonomous self (Allendorf and Pandian 2016; Seth 2011). The interest of the family is given primacy and going against the wishes of family is considered anathema in decisions involving career and marriage. Marriages arranged thus are considered a union of families, not merely individuals, with implications for the entire family (Mathur 2007). As discussed above, parents are involved in every aspect of the marriage process and parental judgment carries significant weight, even though in more recent years, there is greater collaboration between parents and their children during the matching process (Agrawal 2015; Fuller et al. 2008; Mathur 2007). As an institutional mechanism, parents also play a significant role in the enforcement of the normative and coercive conformance to societal norms related to marriage (Meyer and Rowan 1977). They ensure that the symbols and rituals related to marriages for their community are strictly followed, thereby providing strong legitimacy within the extended kin network for both the marriage as well as new entrants into the family.

The notion that parental involvement provides for legitimacy and consequently, higher status, is well accepted in traditional and collectivist societies like India. Status in such systems is acquired by individual actors or groups by virtue of accumulated acts of deference, and their position in the social hierarchy (Sauder et al. 2012). Parental figures and family "elders" thus acquire this high status in social engagements, and in particular in the domain of marital matching. Prior research in status argues that status serves as the signal for quality (Podolny 1993; Podolny 1994) and helps differentiate between entities when there is a high degree of uncertainty (Podolny 1994). Parental involvement in the search for a marital partner is typically associated with higher status. Given the high levels of uncertainty and the sensitive nature of the social process, there is great value given to parental involvement since these potential alliances come with higher assurances of familial acceptance, greater probability of an eventual positive outcome, and the ostensible weight of experienced judgment brought to the process. In other words, alliances where parents or families are viewed as being co-equal decision-makers are associated with higher status (Jensen 2008), and are considered less risky (Benjamin and Podolny 1999), and more attractive, all else being equal.

Endogamy with Respect to Caste and Religion

Arranged marriages in India are characterized by endogamy, which refers to the practice of marriage within a group and is an indicator of group cohesion as well as a mechanism of social isolation from other groups (Gordon 1964; Rosenfeld 2008). Kalmijn (1998) argues that marriage patterns are determined by two major social forces. First, the preferences expressed for certain characteristics in a spouse, which are influenced by the homogenous network of the individual. Second, the influence of other members of the social group, such as the extended kinship networks. “Mixed” marriages may disrupt internal unity and homogeneity within a group, thereby leading members of the group to regulate marriages either through sanctions or through a strong sense of group identity. In India, endogamy primarily tends to perpetuate through caste and religion, with language and sub-caste being secondary factors. Caste is determined by birth and transitions from one caste to another are not allowed by definition (Hutton 1963). Caste-based norms can extend to restrictions on eating and drinking with members of other castes, an implicit hierarchy of castes (with Brahmins being viewed as the highest caste group), preferred professions or occupations within a caste, and finally, a strong preference for marrying within the caste, i.e. caste-based endogamy(Hutton 1963).

While some of these norms based on caste have been loosened in modern times, such as those associated with professions and eating, other conventions continue to survive, including those associated with marriage (Bradford 1985; Deolalikar and Rao 1992; Dhar 2013; Gupta 2000). In particular, Banerjee et al. (2013) found that caste preferences continue to guide the choice of a spouse in modern India. Individuals conform to caste norms to blend in with others and avoid sanction associated with violations of group norms, i.e. deviation from expectations of marrying within the set of acceptable castes. These expectations are reinforced through coercive and normative means by members of the extended institutional environment, including the extended family network, friends, and co-workers (Ahlawat 2015; Ahuja and Ostermann 2016). Thus, endogamy based on caste persists since deviations for endogamous norms are difficult even for the educated and modern professional (Banerjee et al. 2013).

Gender-Based Norms

In Indian society, women typically are dependent on men in specific social and cultural spheres. The patrilineal and patriarchal nature of society (Seymour 1999) drives the process by which families and social groups find a marital match for women, relative to men. Women are identified as custodians of family and caste status (Desai and Andrist 2010; Srinivas 1978) and thus are more likely to be expected to conform to caste norms. The reputational losses associated with unsuccessful matches or deviations from caste-based norms are perceived to be higher and more impactful for women; these extend even to affluent and educated women with significant professional achievement (Fuller and Narasimhan 2008a). In essence, from a risk aversion perspective as well as a viewpoint that reinforces their traditional status as dependents on their male relatives, women are treated differently when it comes to marriage. The role of parental involvement is more pronounced for women, while deviations from group norms are less observed. Indeed, recent evidence from a nationally representative sample shows that 95% of women surveyed in India were married within their caste(Desai and Dubey 2012), significantly higher than men.

In summary, gender-based variations are commonly observed in the Indian marriage market, in particular within the offline match-making context. Furthermore, the primary role of parents and the presence of caste-based endogamy is prevalent in the offline setting. In taking the matrimonial matching process online, service providers have found several ways to replicate these institutional aspects. We describe these platforms in the next section, before we provide arguments for why the online context may change the institutional set-up significantly.

Online Matrimonial Platforms – Moving the Search Process Online

Online matrimonial platforms started purely as a listing service, following the model of newspaper matrimonial columns (Agrawal 2015). Over time, the form and functionality of these online services have evolved into the familiar matching platform format. There are several firms in the marketplace that offer forms of matching platforms for specific communities, accounting for approximately 6% of the marriages conducted in India (Baruah 2018; Garg and Narasimhan 2013). Three firms -

Shaadi.com, Bharatmatrimony, and Jeevansathi, command over 90% of the market (Garg and Narasimhan 2013). Consistent with the matching platform model in other domains, the features on these platforms adhere to the "search, matching, and interaction" (*SMI*) framework (Ahuvia and Adelman (1992), suitably adapted for the matrimonial search task. Search aids provide for information gathering by allowing users to provide information about themselves on their profile pages. The matching process aids decision making through the use of a proprietary algorithm that recommends prospective partners. In addition, the platforms provide features that enable users to conduct custom searches by specifying additional criteria. Finally, there are options for enhancing interaction with others through the use of built-in chat features or by the sharing of phone numbers and email addresses. Thus, these platforms share many features with similar contexts like dating platforms, with some notable exceptions associated with the institutional factors that are unique to the matrimonial setting, which we describe briefly next.

Capturing the Role of Parents and Family

One of the most striking aspects of online matrimonial platforms is the embedding of the family in the overall matching process. Unlike dating apps, the registration process here can be initiated by the individual as well as the family member with no restrictions, thus closely mirroring the offline setting. The platform allows, indeed requires, each profile to be associated with an "operator" who could be the parent, family member, or sibling of the individual seeking a match, instead of the individual per se. Similar to dating apps, users provide detailed personal information about age, height, weight, eating habits, drinking and smoking habits. Users also specify information related to education, occupation, and income, which may be verified in certain cases using national ID data. Additionally, users are also asked to provide information about their families, such as the type of family ("orthodox," "traditional," "moderate, "liberal"), affluence ("middle class," "upper-middle class," "rich", "affluent"), and structure ("nuclear," "joint family"). In addition, the platform provides an “about me” section where open-ended text on other relevant information can be provided. Past research suggests that when a family member manages the profile, the information provided on the profile emphasizes the family rather than the individual (Agrawal 2015; Kaur and Dhanda 2014), which is consistent with the offline norm where parental involvement is considered desirable. To further the sense that parents are involved, the platform allows the option of specifying the parents’ contact details as the primary means to initiate further interaction. Of course, individuals can choose to manage their profile independently, which is reflected in the profile information and represents a deviation from what is observed in the offline context.

Capturing Caste-Based Endogamy

Caste remains one of the crucial deciding factors in finding a match and therefore, there is considerable functionality devoted to capturing these nuances. There is a separate section for religious background in profile descriptions, where the user specifies the religion, caste, and sub-caste details. Religion is a required field, but caste and subcaste remain optional. The platform provides a list of the most visible and populous castes in the form of a drop-down menu. In addition to the main caste, the user can also choose one of the sub-castes nested within the main caste. Users can also specify partner preferences based on similar parameters pertaining to caste – these preferences are used to generate a set of recommended partners for every profile. The platform does not place any restrictions on partner preferences set by the user. Thus, the user can deviate from the group norms by not conforming to the caste-based preferences provided by his or her immediate caste or community. Conformance or deviation here is not binary and may involve nuances. For instance, the user could specify a set of "acceptable" castes from which responses will be entertained or elicited. Further, users could set up their preferences such that only members of their own caste are selected by the recommendation system, thereby allowing for strict endogamy. At the other extreme, the user could completely deviate from prevalent norms by specifying "caste no bar" as the caste preference option. Thus, the platform provides the ability to not only be completely endogamous in preferences but also express no endogamous preferences.

Reinforcing Norms for Women on the Platform

Online matrimonial platforms are sensitive about perceptions of customers with respect to gender and are therefore careful to not include any particular design elements or features that reinforce offline norms for women. Consistent with other online platforms, the policy to remain gender-neutral is espoused on the platform. That said, however, offline norms pertaining to gender do manifest in two ways. First, women appear to have lower levels of agency on the platform, relative to men, consistent with norms that are observed in offline settings. This lower levels of agency manifest empirically in less engagement in the matching and interaction phases on the platform (Seth 2011; Titzmann 2013), as well as a reluctance to be the first party to reach out to counter-parties (Karmegam and Gopal 2019). Second, profiles of women show clear trends in terms of self-presentation on the platform that de-emphasize themselves and accentuate family values (Titzmann 2015). For instance, in the “about me” sections, women tend to use terms like “family-oriented individualism”, in an effort to reconcile “modern” and “traditional” elements during the matrimonial matching process. Profiles of men rarely present these hybrid descriptions and tend to focus mostly on what they expect from spouses. Thus, we see that offline norms about gender continue to persist. Whether they lead to better outcomes for women online remains an open empirical question.

The Incomplete Transfer of Institutional Norms Online

The three institutional aspects of the offline matrimonial matching process outlined above clearly differentiate these from other contexts like dating, but it is unclear if they seamlessly transfer to the online context. Alternatively, it is possible that the openness afforded by technology platforms as well as newer dominant logics that exist online changes the underlying process. We theorize about these effects next.

In an offline arranged marriage, the existing patriarchal structure working through active parental involvement is never questioned or doubted, even in the presence of professional or economic achievement (Abraham 2010; Mathur 2007; Titzmann 2015). However, prior work in institutional bundling, observed in the context of online education, suggests that parental involvement online may not be as effective (Macfarlane 2011; Wellen 2013). Specifically, institutional bundling suggests that when traditional tasks move to new channels or models, it is possible for the underlying task to be “unbundled” so that different institutional and social norms become relevant not for the whole activity but for specific tasks. In the case of online education, academic control over teaching and research has remained while the role of administration and student management has often been institutionally unbundled and handed over to platform operators or for-profit entities (Gehrke and Kezar 2015). If handled well, this unbundling may not affect the student experience but changes the institutional role played by academic administrators (Marginson 2013). The higher status enjoyed by faculty remains in place but is limited to teaching and research.

Analogously, matrimonial platforms engender a process of institutional unbundling of the marital search process into separate tasks. The first task of identifying a candidate set of counterparties can be unbundled from the subsequent processes of due diligence and deeper conversations about compatibilities. The task of creating a candidate set, performed on the platform, may be better handled by individuals rather than parents or families; the high status that parental involvement engenders is then deployed subsequently after some initial matching has been carried out by the individuals. Extending this argument, parental involvement even in the early stages of the search process could actually be detrimental, since counterparties may choose to interact during this stage of the process with the actual individual directly. Thus, even though parental involvement does represent high status, the process of unbundling has shifted the value of parental involvement away from the early stages of the marital search online, diminishing the effect of this factor.

We argue that a similar dynamic could lead to a reduction in caste-based endogamy online as well, for three reasons. First, broader societal changes in Indian society, aided by modernization, could lead to a reduction in the normative value of endogamy per se, which manifests more visibly online (Ahuja and Ostermann 2016; Allendorf and Pandian 2016; Allendorf and Thornton 2015). Developmental idealism

(DI) theory suggests that as societies move along the trajectory from traditional to modern, there is an associated increase in individualism, autonomy, and regard for women's autonomy and rights (Allendorf and Thornton 2015; Thornton et al. 2015). Viewed collectively, these social forces could show up in online matrimonial platforms as systematic deviations from group caste-based endogamy, i.e., those deviating from group norms are not sanctioned but appear more attractive, all else being equal.

In addition to societal changes, at the individual level, online platforms afford greater privacy and security, relative to the offline process. Thus, users are less constrained by group norms; prior work in dating shows that online users tend to be more disinhibited and exhibit preferences and actions that go against accepted social and institutional norms (Bapna et al. 2016a; Jung et al. 2019). Thus, on average, deviations from group norms may simply be more acceptable online, compared to the traditional offline process where there is greater social visibility and a greater threat of sanctions. Finally, the entry of online dating apps in India has helped shape user behavior and change the dominant logic operating in the country with matters relating to romance and marriage (Das 2019). Indeed, many Indians consider dating apps as a precursor to and possible form of matrimonial matchmaking (Baruah 2018). Dating platforms have an obviously more liberal ethos and institutional logic, compared to matrimonial platforms, and individuals may carry the same ethos to the matrimonial platform. Thus, while deviation from group norms may be disapproved in the offline settings, in online platforms, the spillover from dating apps is likely to push towards less endogamy. While we cannot clearly differentiate between these alternative mechanisms, we argue that less endogamous preferences with respect to caste online will lead to greater effectiveness on the platform in terms of finding matches.

Finally, we consider how the role of endogamy and parental involvement may differentially affect women on the platform. On the one hand, it is well established that women in Indian society are likely to be viewed as needing more protection, are not expected to initiate conversations with unknown men about marriage and are viewed as representative of family honor. As a result, there is greater risk-aversion displayed on average with respect to women, in particular with matters relating to marriage. Indeed, some of these dynamics extend to women in general, as seen in the context of dating apps where men are expected to "make the first move" (Filipovic 2013). Thus, if these norms perpetuate online, we would expect profiles for women operated by the individual herself to be less attractive to others, since these represent deviation from the norm and thereby, greater uncertainty about how the rest of the matching process will unfold. Similarly, deviations from caste-based preferences are likely to be less appreciated in the case of women, relative to men.

On the other hand, it could be argued that online platforms have created a level playing field where such gender-based norms do not apply as strictly. Even in online dating, it is far more acceptable for women to initiate the first move, thereby breaking with social stereotypes (Filipovic 2013; Hitsch et al. 2010b). Gender-based differences are prevalent but are reducing in other platform contexts, such as with Uber drivers (Cook et al. 2018) where there is no differential pay across genders. Thus, it is possible that in matrimonial matching platforms, there is no discernible difference between men and women in terms of how deviation from the norm is either rewarded or sanctioned, even though such variations continue to exist offline.

In summary, we consider how three institutional norms that are prevalent in the offline matrimonial matching process in India are able to transfer to the online platforms context. We argue that there are likely to be significant differences in how these institutional factors operate online. In lieu of formal hypotheses, we allow the empirical analysis to provide us with guidance. In the next section, we outline the dataset that was assembled to test these arguments in some detail.

Data and Methodology

Research Site - Online Matrimonial Platform

To address our research questions, we partnered with one of the leading online matrimonial platforms in India. The platform has been active for the last two decades and caters to users based within India as well as members of the Indian diaspora. In terms of coverage, it represents most religions, castes, and regions and thus typifies the diversity in India. Users can access the platform from PC or mobile browsers, and also through mobile apps. Users can register themselves on the platform without paying any fee and can perform basic search and match functions. The paid version of the platform provides additional features, including the ability to view phone numbers and horoscopes of other users, send personalized messages & SMS, and instantly chat with prospective matches. During registration, users provide their profile information and partner preferences, as described above. The platform uses proprietary matching algorithms to recommend profiles based on the user's expressed preferences. The platform users also undergo stringent verification process through online and offline mechanisms to weed out non-serious users to ensure the quality and integrity of the platform.

For our analysis, we identified new users who joined the platform in the four months between October 1st, 2016 and 31st, January 2017. We were able to collect demographic data for this set of users, and also had access to a daily panel of behavioral and transactional data on the platform for each user. We describe the details of some of these variables in the following section. For the majority of users, most of the activities on the platform tend to occur in the initial 3-4 weeks, which is consistent with evidence from matrimonial platforms (Karmegam and Gopal 2019) while also clearly differentiating this context from online dating, where the activity on the platform lasts much longer since there is no clear and final objective (Jung et al. 2019). This difference in activity levels and timelines is not trivial but informs much of our analyses, as we focus our attention on the first 30 days when most users are active and engaged.

Variable Definitions

Table 23 provides detailed information on the variables used for analysis. We first describe the dependent variables used in our analysis.

Dependent Variables

We use three measures as the dependent variable - ***TotalProfileView, TotalReceiveEI, and TotalEIAccept***. Each of these three variables represent, in varying degrees, the extent to which a specific profile is found to be appealing by counterparties on the platform, allowing us to capture the extent to which institutional norms and deviation play a role. *TotalProfileView* represents the total number of times other users view the focal person's profile on the platform. This measure is arguably the weakest, and the most passive, representation of profile appeal. Profile views may not lead to further action from the counterparties, even though they are viewed by interested counterparties; hence, we use this variable in a specific form of robustness described later.

As our primary dependent variables, we consider the other two constructs. *TotalReceiveEI* represents the count of *expression of interests* (EI) received by the focal user in the platform in the given period. An EI represents purposeful action in that it is the first step in initiating a match with another user on the platform, through the generation of an internal platform-based message (similar to the messages that are generated on platforms like LinkedIn). *TotalReceiveEI* denotes the first stage of the eventual matching process, when the focal user A receives an EI from counter-party user B. Since it relates to an actual and visible expression of interest, it represents a stronger measure of the extent to which the profile of focal user A is found to be appealing.

Beyond the initial EI received by the focal user, we also consider *TotalEIAccept*, which represents an actual matched dyad within the platform. Defining a match in the online setting is a challenge, more so in the search and match process that online dating and matrimonial platforms enable, since the eventual outcome is rarely visible, i.e. the actual start of the dating relationship or marriage is not observed. Multiple match formulations have been used in the past - in the dating context, (Hitsch et al. 2010b) identified a successful match when users exchange phone numbers or email addresses on the platform. Bapna et al. (2016a) defined a match based on a sequence of at least four messages between any two users. In our context, we use the match parameter as defined by Karmegam and Gopal (2019). The match could occur in two ways. In the first scenario, focal user A receives an EI from user B, which, when accepted, results in a match. In the second scenario, a focal user A can initiate a match with user B by sending an EI. When user B accepts, a match is formed. Since we are interested in the extent to which the focal profile is appealing, we use the process as defined in the second scenario described above. We measure the total number of positive responses to the EIs sent by the focal user to others on the platform in a given period, referred to as *TotalEIAccept*, which represents the formation of a dyad on the platform and is completed by the counter-party's decision to accept the issued EI. Hence, *TotalEIAccept* is the strongest measure of the profile appeal of the focal user in matrimonial platform.

Independent Variables

We focus on three variables as part of our study - profile operator, group norm deviation, and gender. The profile operator or ***PO*** is a dummy variable where 1 represents profiles where the individual's parents are listed as the profile operator, and 0 when the individual operates the profile. With respect to gender, we classify the profiles based on the gender of the individual and use sub-sample analyses as described later. The third central variable pertains to measuring group norm deviation, i.e. the extent to an individual chooses to deviate from endogamy. In order to measure this deviation, we require a measure of endogamy, representing group norms. There is no clear measure available in the literature, and hence we developed a novel measure of endogamy. We discuss this measure in some detail in the next section.

Measure for Caste-based Endogamy and Deviation from Group Norms

During the registration process, new users provide their caste information as well as express partner preferences along the dimension of caste. Users have the option of choosing multiple castes whose members are acceptable to them as potential matrimonial partners. Each user therefore uses a set of options provided in a drop-down menu to select the set of castes suitably. We aggregate these preferences for each user upto the caste, thereby constructing a network where each node is the caste, and the edges are the total number of members of that caste who have identified members of another caste (node) as acceptable partners. This network thus captures, at the level of the castes, the aggregate preferences expressed by members of that caste, which represents the group norms. Endogamy can thus be measured as the baseline preferences expressed in this network by individual castes on the platform. In Figure 9, we provide a partial caste network to describe the construction of this network, based on five castes chosen as exemplars - Agarwal, Kashyap, Arora, Khatri, and Bhatia. The aggregate caste preferences are directed edges from one caste node to another. In this instance, 7051 members from the Agarwal caste have expressed preferences for matches from their own caste. Additionally, some members of this caste have indicated that members of other castes are acceptable, including 42 for Khatri, 24 for Kashyap, 62 for Arora, and 13 for Bhatia. With a full caste network, we can thus create a caste preference vector for each caste over all other castes.

To measure any single individual's deviation from group norms, we can simply calculate the nominal distance from that individual's preferences for partners to the group's preferences. We do this using the cosine similarity metric, which provides a measure of the concordance between the individual's and group's preference vectors.

We refer to this as the individual's *Similarity index*. The value of the *Similarity Index* lies between 0 and 1: a person showing conformance to group norms will have the smallest distance from the caste preference vector, with values closer to 1. In contrast, a person deviating from group norms will have a value closer to 0. While this measure approximates the deviation from group norms, we need to normalize the deviation across castes, since members of a caste can vary on how endogamous they are on average. For example, a specific *Similarity Index* in caste A may not necessarily be comparable to the Similarity Index in Caste B, as members of caste A could be more inherently liberal, while those in caste B could be more conservative. Thus, to normalize, we calculate the mean and standard deviation for each caste's Similarity Index and identify those individual profiles that are one standard deviation away from group means. These users who deviate from the group norms are presumed to be less endogamous compared to others within their caste. We use a dummy ***GNDev*** and set it to 1 for those falling outside one standard deviation and set it as 0 for others. In summary, the combination of the *Similarity Index* and *GNDev* gives us an objective measure of endogamy as well as the deviation from group norms exhibited by the specific individual.

Controls

We control for factors that may influence the outcomes of interest like – individual information (age, gender, photo availability in profile, paid subscriber, location tiers), educational background, occupation details, and family background (religion, caste, subcaste). We also account for any systematic time effects by controlling for the week in which the user joins the platform. The choice of joining on a specific week or month is sometimes based on idiosyncratic beliefs and norms within specific communities that show up during different times of the year. For instance, specific communities avoid making any decisions related to marriages during certain weeks in a year, based on the moon calendar (Polome 1997).

Regression Analysis

Empirical Approach and Identification

In our analysis, we look at three important institutional markers - group norms, gender, and profile operator. The group norms or the caste preferences can be safely assumed to be mostly exogenous, since they are determined at the level of the caste and not by any individual. In the platform, neither men nor women observe what other men and women have specified in their caste preferences, thereby making any strategic choices of partner castes unlikely unless directly associated with a desire to be more appealing, which is the underlying mechanism we test for. Furthermore, as explained below, we use matching methods to create a set of counterfactual profiles for each individual – this matching approach helps to account for any bias that may result from the strategic setting of preferences. With respect to gender, since we perform subsample analysis, we explicitly account for any differences that may exist across how men and women operate on the platform. Therefore, while there is selection in that these users have opted to join the platform (which remains a limitation in most research on matching platforms), the effects of gender can be estimated largely without bias.

The more immediate threat to causal inferences in our analysis is the choice of profile operator, since this is chosen specifically to enhance the odds of generating appropriate matches on the platform. An ideal strategy to identify the causal effect of the profile operator on outcomes would be to conduct a randomized experiment, whereby users joining the platform are randomly assigned the profile operator status (Aral and Walker 2011; Bapna and Umyarov 2015). Given the social milieu in India and considering that such decisions are a personal choice, random assignments are not feasible nor is any platform likely to impose such restrictions on their users (Jung et al. 2019; Karmegam and Gopal 2019). We, therefore, use matching methodologies to create a pseudo-experimental design so as to reduce the bias from profile operator choice. Specifically, we match profiles operated by parents to those that are identical but operated by individuals, thereby limiting any ex-ante differences that may exist between the profiles which can affect outcomes.

For our analysis, we use two different types of matching methods - coarsened exact matching (CEM) and twins matching, a form of exact matching. CEM helps to create a matched sample of similar users, based on observable characteristics (Blackwell et al. 2009). CEM is a Monotonic Imbalance Bounding (MIB) matching method, which implies that we can ex-ante choose the balance between the treated and control groups. CEM approximates a fully blocked experimental design as it comes with adjustable parameters that can ensure zero imbalance (Iacus et al. 2012). A fully blocked randomized experimental design has lower model dependence, higher power, more efficiency, more robustness, and less imbalance (King and Nielsen 2019). CEM has been widely adopted in the IS literature for matching (Greenwood and Wattal 2017; Mitra and Ransbotham 2015), and provides significant advantages over the propensity scoring method (King and Nielsen 2019), as it can be computationally fast even with large data sets.

In our CEM matching procedure, we match the treated “parent” profile to the control “individual” profile. We use *k-to-k* matching with the default null method, which performs random matching within each stratum to reduce bias. We match on important observable demographic factors related to education, occupation, and family background, which are captured as part of the profile information. Post matching, we assess the imbalance using the L1 statistic, the difference between the multidimensional histogram of all pretreatment covariates in treatment and control groups (Iacus et al. 2012). The multivariate L1 distance in our case is 0.61, showing fairly balanced groups.

As an alternative matching procedure, we follow the principles as applied to identical twins in Ashenfelter and Krueger (1994), which has been used in contexts like patent citations (Jaffe et al. 1993), business establishment locations (Kalnins and Lafontaine 2013), and crime controls (Nagin 1999). Twin matching is a form of exact or precision matching wherein the values of all the key covariates are matched except for the treatment. Those observations which do not have a match are pruned from the analysis. In general, twin or precision matching is considered to be the most restrictive and conservative; Nagin (1999) describes twin matching as "surest way of accounting for a variable that may somehow be biasing the results,", thus being the next best thing to random assignment. For our analysis, we identified all the critical parameters including age, gender, occupation, education, religion, caste, location, and income, that are relevant to decisions pertaining to marriage in the Indian context, and found an equivalent twin, triplet, or quadruplet. The twins are almost similar in all respect except for the profile operator. We used the CEM command in STATA, which allows for twin/precision matching with zero imbalance (Blackwell et al. 2009). The L1 statistic with twin matching is zero. The treatment and the control groups are unbalanced since, for an individual, there could be an equivalent twin, triplet, or a quadruplet counterfactual profile. We describe the main estimation equation next.

Estimation Procedure

Our main estimation equation is as follows:

$$Y_i = \alpha_0 + \alpha_1(PO_i) + \alpha_2(GNDev_i) + \alpha_3(PO_i x\, GNDev_i) + \beta D_i + \gamma_t + Tw_i + \varepsilon_{it}$$

Where Y_i refers to dependent variables (matched dyads and incoming EIs), PO_i is a dummy equal to 1 if parents operate the profile, 0 otherwise. $GNDev_i$ is a dummy equal to 1 if the user is one standard deviation away from the average group norms. Tw_i are twin fixed effects and γ_t are time fixed effects and D_i, demographic control variables. Time fixed effects account for systematic changes over time. To simplify the analysis, we collapsed the 30-day panel of observations into a cross-sectional dataset, while allowing for time fixed effects based on when the user signed onto the platform. This approach allows us to examine the effect of the institutional norms as well as deviations on the cumulative appeal of the profile within the critical 30-day period.

In the regression analysis for incoming EIs, we control for total logins by the user, since more logins are likely to lead to further activity on the platform, which can lead the focal user to show up higher in the recommendation system for other users. Similarly, for the regression analysis of relationship dyads for the focal user, we control for total logins and the total EIs sent, since both these are likely to increase the responses from other users. The baseline models are estimated using OLS, with robust standard errors. In robustness tests, we also used models for count data to estimate the treatment effects - negative binomial regression, and zero-inflated models – and obtained results that are consistent with those reported here. These results are available upon request from the authors.

Summary Statistics and Main Results

Summary statistics shown in Table 24 includes information on all the users in our sample, numbering roughly 835,000 profiles that were registered on the platform between Oct 1st, 2016, and Jan 31st, 2017. We refer to this dataset as the master sample. From this master sample, the matched samples based on CEM and twins matching were selected. The summary statistics for these two subsamples are also shown in Table 24. As is evident, the gender ratio on the platform is relatively skewed, with 74% male profiles, which is typical of matrimonial platforms and is also similar to the gender ratios observed in online dating platforms (Jung et al. 2019). In contrast, the gender ratio is maintained at parity in the CEM sample, while the ratio varies in the twins matched sample. The sample shows differences pertain to other parameters as well, which include age, location tiers, paid subscription status, and mobile adoption behavior. In terms of profile operator, in the master sample, parents manage 28% of profiles, individuals manage 65% of profiles, while friends or other family members manage the rest 7%. Parents manage a higher proportion of profiles in the case of women at 53%, compared to men at 20%, indicating a higher level of agency for men. Beyond gender, in most other cases, there is concordance between the master sample and the matched samples. As expected, on the platform, men send more EIs relative to women, and have fewer EIs accepted by the counterparty. Women also receive more profile views relative to men, while there is a small difference in the extent to which profiles of either gender appear to deviate significantly from their relative group norms.

Switching to the regression analyses, we start by first presenting the analyses on two outcome measures - the total number of matched dyads (*TotalEIAccept*) and the total EIs received (*TotalReceiveEI*). The results from the OLS regressions on *TotalEIAccept* are shown in Tables 25 and 26, across both the CEM and twin matching samples. Similarly, the results for *TotalReceiveEI* are shown in Tables 27 and 28. We first discuss results for the profile operator, and subsequently those for deviation from group norms.

As shown in Table 25, columns 1-6, the profile operator variable has a significant impact on the number of matched dyads that are formed by counterparties responding positively to an EI. Profiles where parents are listed as profile operators are associated with fewer matched dyads, providing evidence that an offline norm does not lead to the same expected result online. There is also a lowering of interest in the incoming requests, as seen in Table 27, columns 1- 6. In the CEM sample, parent-managed profiles receive fewer incoming EIs (roughly 2.5) compared to profiles managed by individuals. The higher status accorded to parents and families in this milieu notwithstanding, as the process moves online, we see evidence of institutional unbundling in that individuals managing their profiles are viewed as being more appealing, all else being equal.

We examine if these effects are different across gender, by splitting the sample into men and women in and estimating separate equations, provided in Tables 26 and 28. As seen in Table 26, columns 1-8, having parents manage the profile leads to lower matched dyads across the board for both men and women. The outcomes, however, vary when it comes to the incoming EIs for men. In Table 28, columns 1-4, we find that for men, having parents as the profile operator leads to a positive and significant outcome – these profiles receive more incoming requests compared to the similar profiles managed by individuals. In contrast, women receive fewer EIs when parents manage the profile, as seen in Table 28, columns 5-8. To summarize, we find that for the most part, the high status enjoyed by parents in the matrimonial matching setting does not seem influential in online platforms. On average, across most conditions, parent-operated profiles lead to worse outcomes for both men and women. The only positive effect seen is for men who receive more EIs when parents manage the profile. Thus, we see evidence of institutional unbundling in that individuals managing their profiles are viewed as being more appealing, all else being equal.

We now turn to the influence of deviation from group norms on outcomes. Recall that we differentiate here between those users whose preferences are consistent with their group norms and those who significant deviate from them (GNDev = 1). The results in Table 25, columns 2,3,5 and 6 provide the coefficients when the dependent variable is the number of matched dyads formed. The results interestingly show that when the focal profile deviates from group norms, there is a systematic increase in counter-party responses that lead to a matched dyad. Furthermore, profiles for women see a higher marginal effect when they deviate from group norms, as seen in Table 26, columns 5-8. With respect to incoming EIs, we see similar results – deviation from group norms leads to more incoming EIs, as seen in Table 27 columns 2,3,5, and 6. Women receive roughly 9.197 more EIs when they deviate from group norms compared to than those who do not deviate from the group norms (Table 28, column 5). Similarly, men also benefit when they deviate from group norms, as seen in Table 28, columns 1-4. To summarize, deviating from group norms leads to better results, across all treatments, demonstrating that unlike the offline setting, where deviating from group norms invites sanctions or disapproval, deviating from group norms leads to a better outcome in online platforms.

While we have focused on the direct effects of profile operator and deviation from group norms, it is worth examining what their interaction effects may be. On the one hand, profiles that are managed by parents and do not deviate from group norms are likely to be the most appealing, since this directly reflects the offline institutional norms. On the other hand, if a profile deviates from offline norms on both dimensions, does the profile receive additional attention on the platform? We examine these by studying the interaction effects across both dependent variables. Across all regressions we estimate, the coefficients of the interaction terms are negative, indicating that the cumulative effect of the profile being run by parents and deviation from group norms ends up lowering the extent to which the focal profile receives EIs from others as well as is able to gather matched dyads. Interestingly, the coefficients from the CEM sample render significant coefficients while those from the twin-matched samples show insignificant coefficients. Since the twin-matched samples also include twin fixed effects, it is possible that the insignificant coefficients are a result of lower power. However, it is worth noting that while individual-run profiles and deviation from group norms appear to generate largely positive responses on the platforms, the combination of both factors may be a step too far, when compared to the traditional offline process.

Robustness Checks

As stated earlier, for ease of interpretation, we used OLS for our main models. However, the dependent variables we study are essentially count variables. Therefore, to establish robustness of the models discussed above, we also fit the following count models to our data - negative binomial regression model, zero-inflated negative binomial (ZINB) model, and zero-inflated Poisson (ZIP) model. The Akaike information criteria (AIC) and Bayesian information criterion (BIC) statistics across these models suggest that the negative binomial model has the best fit amongst these count models. We therefore provide the results from this model in Table 29, across men and women, consistent with the results shown above. The results from the other count models are largely similar and are available from the authors on request. The overall results are qualitatively consistent with those discussed before. When parents manage the profile for men, there are fewer dyads formed in the first 30 days on the platform, while deviation from group norms helps the profile form more completed dyads. A similar result is obtained from women, as seen in Table 29, column 3. These results are mirrored with respect to the number of EIs received from others on the platform, across men and women. Finally, the interaction coefficients are not statistically significant for the most part, showing consistency with the OLS results.

Profile Switch

Our identification strategy has relied on matching across individuals so as to reduce bias. An alternative, and arguably more robust way, approach to examine the effect of profile operator on outcomes, given deviation from group norms, is consider cases where the profile operator is changed by the family during the first 30 days on the platform. This change occurs relatively rarely and could occur in both direction - individuals could take over from parents or vice versa. This information is reflected on the profile, thereby being exogenous to others on the platform. However, the small number of cases where profile operator changes precludes a full regression analyses. Instead, in the spirit of exploratory data analysis, we use line charts to examine how the change in profile operator may influence the extent to which the profile is found to be more or less appealing.

As discussed earlier, most activities on the platform take place in the initial 3-4 weeks. Therefore, we used the following process to come up with the control and treatment groups. First, we shortlisted those profiles that switched operators from the family to the individual. Since we are interested in examining pre- and post-trends from the change, we consider all those profiles that switched operators between day 8 and day 21 on the platform, thereby allowing us to observe their activities for seven days pre-switch and seven days post-switch. The switching profiles are designated as the "treatment" group. For this group, we compiled pre-status change outcomes such as total logins, total EIs sent and received, total profile views, and the total number of relationship dyads formed. Subsequently, we use CEM to find a "control" group of profiles that are similar to these profiles but that do not change operators. Unlike the matching process described earlier, in this case we match not only based on observable demographics but also on the profile-level *observed activities* before the switch. This procedure provides a set of "treated" profiles where operators change, and an identical control group where no such change occurs. This process is replicated for those profiles that switch from self to family as well. Having assembled these datasets, we then plot the daily outcomes associated with the profiles centered around the switching event, similar to the relative time model used in prior research (Greenwood and Wattal 2017). We focus on the following outcomes - EIs received, relationship dyads formed, and daily profile views. The sample for these graphs is shown in Table 30.

Figures 10-15 provide the pre/post trends for the profile switch analysis. Each graph includes two treatment groups, and their corresponding control groups. Figures 10 and 11 show profile-level outcomes for incoming EIs for women and men, respectively. We observe that for profiles that switch from family to self, there is a significant increase in incoming EIs, more so for women. This trend corroborates our earlier finding - that self-managed profiles have better outcomes compared to those managed by family. Figures 12 and 13 depict trends for the average daily dyads formed. With this outcome, a response from the counterparty may not appear on the same day but could be delayed, since dyad formation is asynchronous. Thus, there is no clear trend for this outcome associated with the profile switch. Figures 14 and 15 show pre/post trends for daily profile views, and we see a clear increase in profile views for both men and women when the profile operator switches from the family to the individual, corroborating our earlier results. To summarize, the profile switch analysis corroborates the results we saw earlier with CEM, twin matching, and the robustness checks done with count models.

Discussion and Conclusion

What happens to highly institutionalized contexts when they are transferred to online platforms? This question largely motivated our work in this paper. Certain fields, like banking and financial services, have long been associated with strong institutional norms as well as institutional players that help apply normative and coercive pressures on those within the industry (Ang and Cummings 1997). However, firms in this industry have also been early movers to the online world, though the more institutionalized elements of their businesses tend to remain largely offline. As the process of "platformization" becomes more common across multiple social and economic activities, more activities from institutionalized contexts are likely to move online, raising questions about the extent to which the online platform is able to capture the full essence of the offline environment. Indeed, in contexts like venture capital, for instance, although equity crowdfunding may have replicated specific elements of the venturing process, the traditional VC model has continued to persist (Ahlers et al. 2015)In this paper, we thus address the broader question – do institutional norms and markers of status that are influential in the offline setting have the same efficacy online?

We study this question through the prism of a highly institutionalized setting - Indian arranged marriages. Consistent with practices in South-east Asia, East Asia, and the Middle East, the institution of the arranged marriage has deep-rooted social norms and is typically governed by well-specified social regulations, which may vary across countries and cultures but exist in some form across Asian societies (Yeung et al. 2018). The literature on Indian marriages, in particular, shows that marital preferences and outcomes in offline settings continue to be guided by institutional norms. The entry of online matrimonial platforms in the Indian market has enabled the move of the search process, at least in the early stages, to the online environment, where traditional offline norms have been embraced without tweaking the institutional processes. The traditional markers of social norms and regulations - the primacy of the family in the search process as well as the ability to practice endogamy along religious and caste lines- have been preserved and even actively propagated. We thus theorize about whether these offline norms are still influential in the platform setting, arguing that the move online may actually attenuate, and even remove, their impact.

Our results show that this is indeed the case – to a large extent, these traditional norms lead to less positive outcomes on the platform, in contrast to the offline setting. Using data collected through a collaboration with a leading Indian online matrimonial platform, we show that the counter-party responses to a profile operated by the parents or family is viewed as being less appealing. Similarly, sticking to group norms, in terms of endogamy, is also viewed less favorably. Interestingly, these effects are more pronounced for women on the platform, indicating further how online norms appear to deviate systematically from the more traditional offline setting. Some of this may be attributed to the entry of dating apps into the Indian market, given the similar demographic segment that both types of platforms tend to target. However, it is worth noting that even in India, the online dating ethos is clearly more liberal (Baruah 2018) while the matrimonial market remains more traditional. Indeed, the Indian government released an advisory to matrimonial platforms in 2017, to ensure that users signed a declaration stating that the purpose of their presence on the platform was for matrimonial purposes, and not for other reasons like dating (Doshi 2016). Thus, it is particularly noteworthy that despite these trends, user behavior on these platforms is distinctly different from the offline setting.

Our conversations with the platform operator firm indicate that while parental influence and participation in the search process is still very much present, there is a growing sense that their role is not as central as it would be offline. Recent research from sociology also suggests that parents are seen to be increasingly ceding space to individuals in the decision-making process, more so in standing behind the individual in decisions related to deviation from endogamous norms (Kaur and Dhanda 2014). The most striking advantage of online platforms might well be the ability to connect with other users that are unlikely to be matched to the focal user in the normal course of action offline; indeed, this shows up clearly in the dating context (Jung et al. 2019) . In the matrimonial context, this could lead to users deviating from their group norms in attempting to, or responding to overtures from, people from other social groups or castes. To the extent that platforms reduce the impact of location and transaction costs, as well as provide the benefits of relative anonymity and privacy, the relaxation of institutional norms online appears reasonable and even desirable. The institutional unbundling of the search process, potentially into early-stage and late-stage search, allows for these norms to be relaxed even if the later stages of the marriage planning show returns to strong institutional norms. Unfortunately, we are not privy to the remainder of the marriage process once the users leave the platform, which remains a topic for future research.

One of the contributions of our work here is the development of a network-based measure of endogamy, using the partner preferences over castes provided by the new users on the platform. This measure also helps us identify those users who deviate from group norms. In our analysis, we find that with deviation, users have better matching outcomes, more so in the case of women. Thus, instead of inviting social sanctions, users benefit from deviation as they are now in the consideration set of more users. We also looked at the effect of deviating from group norms when parents operate the profile. This interaction is possibly the only instance in our analysis where we observe some of the deep-rooted traditions manifest themselves. Both men and women had lower matching outcomes, and women also had lower incoming EIs with the arrangement. In general, we find that "platformization" of this highly institutionalized context leads to more "democratization." with traditional institutional markers playing a diminished role online. This trend has been noted within the industry as well, as captured by this quote from a CEO of an online matrimonial platform in 2015 - "*82 percent of male profiles are posted by the prospective grooms rather than by their parents, up from 60 percent five years ago. Among women, the share of self-postings is at 56 percent, up from 30 percent five years ago*" (Harris 2015).

Our work here is subject to limitations. First, like most empirical work using observational data, there could be several missing pieces of information, which limits the extent to which we can rule out alternative mechanisms or explanations. We have controlled for most relevant variables that are provided in the user profile page, but we cannot rule out the effects of unobserved variables. Second, we do not have the information on the counterparties who accepted the EI requests or who sent in the expression of interests to the focal users. The counterparty information would have given us a complete picture of the demographics of users who responded positively/negatively to the profile operator status and deviation from group norms. Third, while we implicitly compare online behavior to offline norms, we do not observe these offline norms. We base our descriptions of the offline process on the extensive literature on arranged marriages and endogamy within the social sciences literature.

Detailed data on the offline process is typically hard to locate at scale and represents an avenue for future research. Fourth, while we choose the number of matched dyads or number of incoming EIs as a measure of profile appeal, we cannot speak to the extent to which these matches are of "high quality"; indeed, in much of this research, the final outcome of an actual marriage is extremely hard to observe since the process largely moves offline. We recognize this as a limitation which exists even in prior work in dating platforms (Bapna et al. 2016a; Jung et al. 2019). Finally, while we account for profile operators through matching methods, by going as far as doing the stringent twins matching, we recognize that a randomized experiment would be the ideal methodology. Given the constraints involved for the platform owners, this is rarely ever feasible in the field, especially in institutionalized fields such as these (Jung et al. 2019).

In conclusion, our work addresses an important question on the transition of offline norms with "Platformization" in the case of highly institutionalized contexts. Set within the institution of arranged marriages, which have been prevalent in traditional Asian societies, we studied whether the factors that are influential offline, like status, group norms, and gender norms, continue to be influential in the online setting. Our study suggests that offline norms do not translate as seamlessly. Users are guided by a liberal ethos as experienced in other online platforms, and the traditional signals do not carry the same weight as it does in the offline world. Profiles managed by parents do not have the same appeal as the one managed by individuals. User profile appeal improved with deviation from group norms. In the case of women, the profile appeal increased when they have higher agency, or when they deviate from group norms, a scenario which is likely to invite sanctions in the offline settings. Our work thus provides a reality check to platforms operating in or planning to enter highly institutionalized settings. While the platforms may try to replicate all the offline norms in online settings, user's online behavior may discount if not entirely dismiss the traditional norms. As the platform models pervade all economic activities, including those areas with strong institutional norms, we believe more such work is needed to come up with mechanism design, which would improve the overall user experience and outcomes in online platforms.

Tables

Table 1**: **Chp2- Variable Definitions

Variable Name	Definition
MobileAdopters	1- Immediate Adopters/0- Non Adopters or Late Adopters
Dependent Variables	
Engagement Outcomes	
TotalLogin (Passive)	Total Logins by the user
TotalEI (Active)	Total expression of interest (EI) sent by user
TotalReceiveEI (Engagement-Incoming)	Total EIs received by user
Matching Outcomes	
TotalReceiveEIAccept (Direct)	Total EIs accepted by the focal user from the EIs received. Leads to formation of dyad
TotalEIAccept (Indirect)	Total EIs accepted by the counter parties from the EIs sent by the focal user. Leads to formation of dyad
Endogamous Groups	
Brahmin	1-Brahmin/0-Non-Brahmin
Muslim	1-Muslim/0-Non-Muslim
DWS	1- If the user does not wish to specify the caste, or parents had inter-caste or inter-religion marriage/0-Otherwise
User Controls	
Self	If the profile is maintained by the focal user
Family	If the profile is maintained by family
EduBachDummy	1- If user has a minimum undergraduate degree/0-Otherwise
T1,T2,T3	Represents city tiers with T1 referring to tier 1 city like Mumbai
Other Demographic Controls	Age, education, occupation, paid subscription, annual income, religion, profile photo availability,
Other Controls	
TotalEIRead	Total EIs read by the counter party from the one sent by focal user
TotalViewProfile	Total views for the focal user's profile page

**The activities represent cross-sectional 2 weeks data, unless specified*

Table 2: ***Chp2- Summary Statistics (Matched Samples)***

	Overall		**Men**		**Women**		**Mobile Adopters**		**Non-Adopters**		**Brahmin**		**Muslim**		**DWS**	
	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
Men	0.79	0.41	-	-	-	-	0.79	0.41	0.79	0.41	0.74	0.44	0.85	0.35	0.80	0.40
EduBachDummy	0.77	0.42	0.73	0.44	0.91	0.29	0.77	0.42	0.77	0.42	0.89	0.31	0.70	0.46	0.72	0.45
Age	27.52	4.69	27.91	4.72	26.06	4.29	27.52	4.68	27.52	4.70	28.38	5.24	26.24	4.31	27.41	4.72
Yrsofedu	15.29	1.64	15.15	1.67	15.84	1.42	15.29	1.64	15.29	1.64	15.74	1.49	14.85	1.69	14.93	1.75
Self	0.67	0.47	0.75	0.44	0.39	0.49	0.72	0.45	0.62	0.49	0.59	0.49	0.74	0.44	0.74	0.44
Family	0.26	0.44	0.19	0.39	0.53	0.50	0.22	0.41	0.30	0.46	0.34	0.47	0.19	0.40	0.19	0.39
Muslim	0.07	0.26	0.08	0.27	0.05	0.22	0.07	0.26	0.07	0.26	-	-	-	-	0.14	0.34
Brahmin	0.08	0.27	0.07	0.26	0.10	0.29	0.07	0.26	0.08	0.27	-	-	-	-	-	-
Paid	0.03	0.18	0.02	0.15	0.08	0.26	0.03	0.18	0.03	0.18	0.06	0.24	0.01	0.10	0.02	0.13
T1	0.33	0.47	0.32	0.47	0.37	0.48	0.33	0.47	0.33	0.47	0.40	0.49	0.37	0.48	0.33	0.47
T2	0.23	0.42	0.23	0.42	0.23	0.42	0.23	0.42	0.23	0.42	0.26	0.44	0.19	0.39	0.26	0.44
T3	0.43	0.50	0.45	0.50	0.39	0.49	0.43	0.50	0.43	0.50	0.34	0.47	0.44	0.50	0.41	0.49
TotalLogin	17.98	43.15	16.46	39.24	23.76	55.19	32.92	56.35	3.04	10.06	20.06	45.23	12.53	30.25	12.19	30.56
TotalEI	9.14	72.19	10.38	79.74	4.39	28.41	14.63	86.45	3.64	53.74	11.11	81.05	6.18	55.72	8.02	86.75
TotalEIAccept	0.27	1.67	0.10	0.63	0.92	3.37	0.43	2.14	0.11	0.98	0.39	1.97	0.20	1.57	0.19	1.34
TotalReceiveEI	8.07	30.42	0.66	2.70	36.34	58.48	11.20	37.90	4.94	19.87	11.16	34.78	3.33	13.94	5.20	20.60
TotalViewProfile	112.69	372.52	33.76	110.03	413.84	712.48	157.79	463.11	67.59	242.93	149.46	381.38	36.96	140.09	55.49	206.55
TotalReceiveEIAccept	0.32	2.86	0.24	2.75	0.59	3.25	0.48	3.02	0.15	2.68	0.48	3.81	0.32	5.06	0.24	3.30
Observations	126706		100394		26312		63353		63353		9780		8999		7249	

Table 3*: *Chp2- Correlation Table

	MobileAdopters	TotalLogin	TotalEI	TotalEIAccept	TotalReceiveEI	TotalReceiveEIAccept	Women	Brahmin	Muslim	DWS	Self	Family	EduBachDummy	TotalEIRead	TotalViewProfile
MobileAdopters	1														
TotalLogin	0.35	1													
TotalEI	0.08	0.18	1												
TotalEIAccept	0.09	0.25	0.09	1											
TotalReceiveEI	0.1	0.27	0.01	0.41	1										
TotalReceiveEIAccept	0.06	0.16	0.58	0.25	0.12	1									
Women	0	0.07	-0.03	0.2	0.48	0.05	1								
Brahmin	-0.01	0.01	0.01	0.02	0.03	0.02	0.03	1							
Muslim	0	-0.03	-0.01	-0.01	-0.04	0	-0.04	-0.08	1						
DWS	-0.04	-0.03	0	-0.01	-0.02	-0.01	-0.01	-0.07	0.06	1					
Self	0.11	0	0.02	-0.04	-0.15	-0.02	-0.3	-0.05	0.04	0.04	1				
Family	-0.09	0.03	-0.02	0.05	0.17	0.02	0.31	0.06	-0.04	-0.04	-0.84	1			
EduBachDummy	0	0.05	0.02	0.06	0.11	0.04	0.17	0.08	-0.05	-0.03	-0.07	0.08	1		
TotalEIRead	0.07	0.2	0.95	0.14	0.04	0.68	-0.01	0.01	-0.01	0	0.01	-0.01	0.03	1	
TotalViewProfile	0.12	0.36	0.15	0.41	0.89	0.24	0.41	0.03	-0.06	-0.04	-0.17	0.19	0.12	0.2	1

Table 4*: *Chp2- Main Results – Mobile Adoption

	Dependent Variable			
	Engagement Outcomes		**Matching Outcomes**	
	Passive	**Active**	**Direct**	**Indirect**
	(1)	(2)	(3)	(4)
MobileAdopters	26.26***	1.344***	0.0114	0.0146
	(0.216)	(0.425)	(0.0125)	(0.00908)
Women	-5.794***	-17.11***	0.181***	0.408***
	(0.382)	(0.713)	(0.0218)	(0.0153)
TotalLogin		0.222***	-0.00102***	0.00466***
		(0.00524)	(0.000156)	(0.000113)
TotalReceiveEI			-0.00682***	
			(0.000465)	
TotalEIRead			0.0604***	
			(0.000205)	
TotalEI				0.000365***
				(6.01e-05)
Constant	-45.16***	-21.60	-0.676	-0.372
	(14.31)	(26.67)	(0.787)	(0.570)
User Controls	Y	Y	Y	Y
User Fixed Effects	N	N	N	N
Time Fixed Effects	Y	Y	Y	Y
Observations	126,706	126,706	126,706	126,706
R-squared	0.238	0.055	0.477	0.192

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

Table 5*: *Chp2- Moderating Role of Caste (Brahmin)

	Dependent Variable			
	Matching Outcomes			
	Direct		**Indirect**	
	(1)	(2)	(3)	(4)
MobileAdopters	0.0115	0.00195	0.0146	0.00675
	(0.0125)	(0.0130)	(0.00908)	(0.00939)
Brahmin	0.0310	-0.0300	-0.00461	-0.0543**
	(0.0227)	(0.0310)	(0.0165)	(0.0225)
MobileAdopters x Brahmin		0.126***		0.103***
		(0.0437)		(0.0317)
Women	0.181***	0.181***	0.408***	0.408***
	(0.0218)	(0.0218)	(0.0153)	(0.0153)
TotalLogin	-0.00102***	-0.00103***	0.00467***	0.00466***
	(0.000156)	(0.000156)	(0.000113)	(0.000113)
TotalReceiveEI	-0.00681***	-0.00681***		
	(0.000465)	(0.000465)		
TotalEIRead	0.0604***	0.0604***		
	(0.000205)	(0.000205)		
TotalEI			0.000365***	0.000365***
			(6.01e-05)	(6.01e-05)
Constant	-0.682	-0.688	-0.371	-0.376
	(0.787)	(0.787)	(0.570)	(0.570)
User Controls	Y	Y	Y	Y
User Fixed Effects	N	N	N	N
Time Fixed Effects	Y	Y	Y	Y
Observations	126,706	126,706	126,706	126,706
R-squared	0.477	0.477	0.192	0.192

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

Table 6*: *Chp2- Moderating Role of Religion (Muslim)

	Dependent Variable			
	Matching Outcomes			
	Direct		Indirect	
	(1)	(2)	(3)	(4)
MobileAdopters	0.0113	0.00399	0.0146	0.0126
	(0.0125)	(0.0130)	(0.00908)	(0.00941)
Muslim	0.0795**	0.0300	-0.0122	-0.0259
	(0.0334)	(0.0405)	(0.0242)	(0.0294)
MobileAdopters x Muslim		0.0984**		0.0272
		(0.0453)		(0.0329)
Women	0.183***	0.182***	0.407***	0.407***
	(0.0218)	(0.0218)	(0.0153)	(0.0153)
TotalLogin	-0.00102***	-0.00101***	0.00466***	0.00467***
	(0.000156)	(0.000156)	(0.000113)	(0.000113)
TotalReceiveEI	-0.00680***	-0.00680***		
	(0.000465)	(0.000465)		
TotalEIRead	0.0604***	0.0604***		
	(0.000205)	(0.000205)		
TotalEI			0.000365***	0.000365***
			(6.01e-05)	(6.01e-05)
Constant	-0.719	-0.715	-0.365	-0.364
	(0.787)	(0.787)	(0.571)	(0.571)
User Controls	Y	Y	Y	Y
User Fixed Effects	N	N	N	N
Time Fixed Effects	Y	Y	Y	Y
Observations	126,706	126,706	126,706	126,706
R-squared	0.477	0.477	0.192	0.192

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

Table 7*: *Chp2- Profiles with No Caste/Community Stated (DWS)

	Dependent Variable			
	Matching Outcomes			
	Direct		**Indirect**	
	(1)	(2)	(3)	(4)
MobileAdopters	0.0105	0.0151	0.0141	0.0110
	(0.0125)	(0.0129)	(0.00909)	(0.00933)
DWS	-0.0441*	-0.0103	-0.0221	-0.0449*
	(0.0255)	(0.0330)	(0.0185)	(0.0240)
MobileAdopters x DWS		-0.0818		0.0553
		(0.0509)		(0.0369)
Women	0.182***	0.182***	0.408***	0.408***
	(0.0218)	(0.0218)	(0.0153)	(0.0153)
TotalLogin	-0.00102***	-0.00102***	0.00466***	0.00467***
	(0.000156)	(0.000156)	(0.000113)	(0.000113)
TotalReceiveEI	-0.00682***	-0.00681***		
	(0.000465)	(0.000465)		
TotalEIRead	0.0604***	0.0604***		
	(0.000205)	(0.000205)		
TotalEI			0.000365***	0.000365***
			(6.01e-05)	(6.01e-05)
Constant	-0.663	-0.659	-0.365	-0.368
	(0.787)	(0.787)	(0.570)	(0.570)
User Controls	Y	Y	Y	Y
User Fixed Effects	N	N	N	N
Time Fixed Effects	Y	Y	Y	Y
Observations	126,706	126,706	126,706	126,706
R-squared	0.477	0.477	0.192	0.192

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

***Table 8**: Chp2- Testing for Disinhibition in online matrimonial platforms*

	Dependent Variable			
	Engagement - Incoming Request		**Matching - Indirect**	
	(1)	(2)	(3)	(4)
DWS	-0.107***	-0.128***	-0.0267***	-0.0128
	(0.0238)	(0.0308)	(0.00756)	(0.00976)
MobileAdopters	-0.00109	-0.00408	-0.00226	-0.000300
	(0.0119)	(0.0122)	(0.00376)	(0.00386)
MobileAdopters x DWS		0.0522		-0.0342**
		(0.0479)		(0.0152)
TotalEI	-0.0132***	-0.0132***	-0.000815***	-0.000814***
	(8.16e-05)	(8.16e-05)	(2.59e-05)	(2.59e-05)
TotalLogin	0.00254***	0.00254***	0.00139***	0.00139***
	(0.000167)	(0.000167)	(5.31e-05)	(5.31e-05)
Constant	-1.660**	-1.664**	-0.165	-0.162
	(0.781)	(0.781)	(0.248)	(0.248)
User Controls	Y	Y	Y	Y
User Fixed Effects	N	N	N	N
Time Fixed Effects	Y	Y	Y	Y
Observations	100,394	100,394	100,394	100,394
R-squared	0.585	0.585	0.244	0.244

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

Table 9*: *Chp2- Robustness Checks - Main Effects with 1 Week Data

	Dependent Variable			
	Engagement Outcomes		**Matching Outcomes**	
	Passive	**Active**	**Direct**	**Indirect**
	(1)	(2)	(3)	(4)
MobileAdopters	34.17***	0.756	0.00495	0.0253
	(0.700)	(1.216)	(0.0383)	(0.0261)
TotalLogin		0.139***	-0.000894**	0.00297***
		(0.0118)	(0.000375)	(0.000254)
TotalReceiveEI			0.00162	
			(0.00118)	
TotalEIRead			0.0697***	
			(0.000531)	
TotalEI				0.000118
				(0.000154)
Constant	-38.17	142.0*	10.32***	3.117*
	(48.19)	(78.99)	(2.486)	(1.694)
User Controls	Y	Y	Y	Y
User Fixed Effects	N	N	N	N
Time Fixed Effects	Y	Y	Y	Y
Observations	19,342	19,342	19,342	19,342
R-squared	0.236	0.051	0.525	0.216

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

Table 10*: *Chp2- Robustness Tests: Main Effects with Look-Ahead Matching

	Dependent Variable			
	Engagement Outcomes		**Matching Outcomes**	
	Passive	**Active**	**Direct**	**Indirect**
	(1)	(2)	(3)	(4)
MobileAdopters	18.54***	1.505***	-0.000513	0.00625
	(0.133)	(0.264)	(0.00830)	(0.00718)
TotalLogin		0.271***	-0.00105***	0.00534***
		(0.00522)	(0.000165)	(0.000143)
TotalReceiveEI			-0.00233***	
			(0.000375)	
TotalEIRead			0.0671***	
			(0.000219)	
TotalEI				0.000851***
				(7.63e-05)
Constant	-26.46***	-18.00	-0.341	-0.242
	(8.804)	(16.35)	(0.513)	(0.444)
User Controls	Y	Y	Y	Y
User Fixed Effects	N	N	N	N
Time Fixed Effects	Y	Y	Y	Y
Observations	126,706	126,706	126,706	126,706
R-squared	0.242	0.053	0.480	0.159

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

Table 11*: *Chp3- Variable Definition

Variable Name	Definition
Dependent Variables	
TotalEIReceived	Total number of expression of interest (EI) received by the focal user
TotalIncomingMatch	Total EIs accepted by the focal user from the ones received
TotalEISent	Total number of EIs sent by the focal user
Intervention 2 (Choices could be made on day of registration (suffix with OnReg) or anytime from day 2-30 (suffix with InBetween).	
WomenChoiceOnReg	Equal to 1 if women make choice on the day of registration, 0 otherwise
AgeChoiceMadeOnReg/AgeChoiceMadeInBetween	Equal to 1 if women make age choice, 0 otherwise.
EduChoiceMadeOnReg/ EduChoiceMadeInBetween	Equal to 1 if women make education choice, 0 otherwise.
AgeEduIncChoiceMadeOnReg/AgeEduIncChoiceMadeInBetween	Equal to 1 if women all three choices- age, education and income, 0 otherwise.
Independent Variables	
Treatment	Equal to 1 for treatment group, 0 for control group
TimeTreatment	Equal to 1 for pre-intervention registrations, 0 for post-intervention registrations
Age26OrAbove	Equal to 1 if user's age is 26 or above, 0 otherwise
EduHigher	Equal to 1 if user has professional degree or higher, 0 otherwise
WithIncome	Equal to 1 if user works and has income, 0 otherwise
User Activities Controls	
DaysActive	Total number of days where user initiated purposeful action
ProfileViews	Total number of times, the focal user's profile was viewed
Other Demographic Controls	Age, marital status, location, religion, caste, subcaste, profile photo availability and Language spoken

Table 12: ***Chp3- Intervention Design***

Intervention Dimension	Personal Information for Men	Women whose profile is visible
Education	High School education or under	High School education, Undergraduate degrees
Marital Status	Unmarried	Unmarried
	Widowed/Divorced/Awaiting Divorce	Widowed/Divorced/Awaiting Divorce
Age	20-29	10 years younger to 1 year older
	30-39	10 years younger to 2 years older
	40-49	10 years younger to 3 years older
	50-59	15 years younger to 4 years older
	>=60	15 years younger to 4 years older
Annual Income	Any Value	Upto 0.2M local currency higher
	Example – 1M	Less than or equal to 1.2M

Table 13*: *Chp3- Summary Statistics

Variables	Overall		Women		Men	
	mean	**sd**	**mean**	**sd**	**mean**	**sd**
Age	28.95	4.43	26.11	3.73	29.66	4.31
Age25AndBelow	0.21	0.41	0.51	0.50	0.13	0.34
Age26AndAbove	0.79	0.41	0.49	0.50	0.87	0.34
Women	0.20	0.40	1.00	0.00	0.00	0.00
Paid	0.05	0.22	0.11	0.31	0.04	0.19
Yrsofedu	15.03	1.68	16.04	1.35	14.78	1.66
EduHigher	0.76	0.43	0.79	0.40	0.75	0.43
WithIncome	0.78	0.41	0.42	0.49	0.87	0.33
SameCastePref	0.45	0.50	0.51	0.50	0.43	0.50
CasteNoBar	0.23	0.42	0.15	0.36	0.25	0.43
PartnerPrefSet	0.87	0.34	0.90	0.31	0.86	0.34
LocationIndia	0.95	0.23	0.98	0.13	0.94	0.24
MaritalStatusSingle	0.96	0.19	0.96	0.20	0.96	0.19
Treatment	0.53	0.50	0.54	0.50	0.53	0.50
TimeTreatment	0.62	0.48	0.59	0.49	0.63	0.48
TotalMatches	1.78	5.96	4.65	10.47	1.07	3.80
TotalEISent	33.31	180.02	15.44	61.05	37.78	198.69
TotalEIReceived	33.57	100.66	152.84	179.76	3.76	12.21
TotalIncomingMatch	0.73	3.02	1.65	5.33	0.49	2.01
TotalOutgoingMatch	1.06	3.74	3.00	6.74	0.57	2.23
DaysActive	5.43	5.62	4.59	5.35	5.64	5.67
ProfileViews	386.75	880.71	1419.73	1498.68	128.64	274.10
Shortlist	5.72	25.81	6.16	20.18	5.61	27.03
Observations	18338		3666		14672	

Table 14*: *Chp3- Main Effects

	Dependent Variables								
	TotalEIReceived			TotalIncomingMatch			TotalEISent		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Overall	Women	Men	Overall	Women	Men	Overall	Women	Men
Treatment	-2.545	5.701	0.426	-0.0596	-1.044***	0.0579	-18.88***	-7.526**	-35.58***
	(1.792)	(7.149)	(0.505)	(0.149)	(0.321)	(0.107)	(7.152)	(3.275)	(9.240)
TimeTreatment	-7.294***	-27.54***	-0.745***	-0.685***	-1.518***	-0.469***	0.0743	-2.877	-7.967**
	(1.143)	(4.552)	(0.179)	(0.101)	(0.255)	(0.0719)	(3.612)	(2.543)	(3.466)
Treatment x TimeTreatment	-2.439***	-10.30***	-0.0787	0.0646	1.033***	-0.141***	-3.888	9.235***	-3.375
	(0.868)	(3.804)	(0.185)	(0.121)	(0.347)	(0.0503)	(4.892)	(3.285)	(4.445)
TotalEIReceived				-0.0122***	-0.00542	-0.0300***	-0.909***	-0.123**	-12.37***
				(0.00316)	(0.00358)	(0.00790)	(0.316)	(0.0489)	(2.692)
DaysActive	-2.341***	-5.886***	-0.292***	0.136***	0.456***	0.0681***	8.351***	4.364***	2.522
	(0.120)	(0.444)	(0.0449)	(0.00947)	(0.0330)	(0.00637)	(0.485)	(0.292)	(1.618)
ProfileViews	0.110***	0.120***	0.0370***	0.00225***	0.000748	0.00411***	0.107***	0.0143**	0.737***
	(0.00211)	(0.00243)	(0.00266)	(0.000406)	(0.000461)	(0.000545)	(0.0396)	(0.00615)	(0.167)
Constant	63.16***	177.0***	2.388	0.871**	4.723***	2.462***	91.75***	27.74***	267.5***
	(6.083)	(13.30)	(2.164)	(0.356)	(0.766)	(0.224)	(32.67)	(9.615)	(57.90)
User Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Dummies for Registration Week	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	18,338	3,666	14,672	18,338	3,666	14,672	18,338	3,666	14,672
R-squared	0.858	0.833	0.695	0.249	0.273	0.338	0.200	0.231	0.440

Robust standard errors in parentheses, clustered on location
*** p<0.01, ** p<0.05, * p<0.1

Table 15*: *Chp3- Split Sample Analysis

Table 15a: Split – Sample Analysis (Important subgroups) - TotalEIReceived

	Dependent Variable - TotalEIReceived					
	(1)	(2)	(3)	(4)	(5)	(6)
	Age25AndBelow	Age26AndAbove	EduHigher=1	EduHigher=0	WithIncome=1	WithIncome=0
Treatment x TimeTreatment	-15.16***	-10.55**	-11.52***	-6.606	-6.042	-13.58**
	(4.937)	(5.218)	(4.305)	(10.68)	(5.771)	(5.978)
Constant	91.68***	170.4***	166.9***	175.4***	93.66***	189.7***
	(21.49)	(23.41)	(14.04)	(25.05)	(28.16)	(14.82)
User Controls	Y	Y	Y	Y	Y	Y
Dummies for Registration Week	Y	Y	Y	Y	Y	Y
Observations	1,870	1,796	2,910	756	1,540	2,126
R-squared	0.849	0.843	0.828	0.865	0.828	0.841

Table 15b: Split – Sample Analysis (Important subgroups) - TotalIncomingMatch

	Dependent Variable - TotalIncomingMatch					
	(1)	(2)	(3)	(4)	(5)	(6)
	Age25AndBelow	Age26AndAbove	EduHigher=1	EduHigher=0	WithIncome=1	WithIncome=0
Treatment x TimeTreatment	0.423	1.648***	1.069**	0.916**	1.404**	0.973***
	(0.285)	(0.553)	(0.427)	(0.434)	(0.642)	(0.308)
Constant	2.802***	3.768***	4.677***	3.868***	4.528***	5.612***
	(1.034)	(1.094)	(0.831)	(0.841)	(1.028)	(1.279)
User Controls	Y	Y	Y	Y	Y	Y
Dummies for Registration Week	Y	Y	Y	Y	Y	Y
Observations	1,870	1,796	2,910	756	1,540	2,126
R-squared	0.332	0.243	0.277	0.366	0.279	0.277

Robust standard errors in parentheses, clustered on location
*** p<0.01, ** p<0.05, * p<0.1

Table 15c: Split – Sample Analysis (Important subgroups) - TotalEISent

	Dependent Variable - TotalEISent				
	(1)	(2)	(3)	(4)	(5)
	Age25AndBelow	Age26AndAbove	EduHigher	WithIncome	Paid
Treatment x TimeTreatment	2.079	17.66**	10.86***	15.93*	13.93**
	(2.204)	(7.354)	(3.489)	(8.638)	(5.283)
Constant	14.32	21.92*	26.47***	14.76	13.97
	(9.473)	(12.74)	(7.406)	(13.34)	(16.78)
User Controls	Y	Y	Y	Y	Y
Dummies for Registration Week	Y	Y	Y	Y	Y
Observations	1,870	1,796	2,910	1,540	405
R-squared	0.361	0.215	0.242	0.225	0.471

Robust standard errors in parentheses, clustered on location
*** p<0.01, ** p<0.05, * p<0.1

***Table 16**: Chp3- Caste Choices and its Effect on Outcomes*

	TotalEIReceived		TotalIncomingMatch		TotalEISent	
	(1)	(2)	(3)	(4)	(5)	(6)
	SameCastePref	CasteNoBar	SameCastePref	CasteNoBar	SameCastePref	CasteNoBar
Treatment x TimeTreatment	-13.10**	-18.30	0.659*	2.473*	4.093	17.75
	(5.593)	(14.47)	(0.338)	(1.406)	(2.770)	(13.67)
Constant	248.1***	54.49	2.992**	7.221**	19.18*	60.15***
	(29.25)	(41.22)	(1.346)	(3.161)	(11.08)	(18.80)
User Controls	Y	Y	Y	Y	Y	Y
Dummies for Registration Week	Y	Y	Y	Y	Y	Y
Observations	1,879	558	1,879	558	1,879	558
R-squared	0.827	0.860	0.310	0.282	0.318	0.265

Robust standard errors in parentheses, clustered on location
*** p<0.01, ** p<0.05, * p<0.1

Table 17*: *Chp3- Summary Statistics for Intervention II

Variables	Overall	
	mean	**sd**
WomenChoiceOnReg	0.51	0.50
AgeChoiceMadeOnReg	0.16	0.37
EduChoiceMadeOnReg	0.08	0.28
AgeEduIncChoiceMadeOnReg	0.03	0.17
AgeChoiceMadeInBetween	0.13	0.34
EduChoiceMadeInBetween	0.25	0.43
AgeEduIncChoiceMadeInBetween	0.10	0.30
Age	26.84	5.73
Age26AndAbove	0.55	0.50
Paid	0.09	0.28
Yrsofedu	15.48	1.66
EduHigher	0.91	0.29
WithIncome	0.39	0.49
MaritalStatusSingle	0.87	0.34
Observations	3992	

Table 18*: *Chp3- Probit Model – Choices made on the day of registration

	Dependent Variables - Choices Made			
	(1)	(2)	(3)	(4)
	WomenChoiceOnReg	AgeChoiceMadeOnReg	EduChoiceMadeOnReg	AgeEduIncChoiceMadeOnReg
Age26AndAbove	0.161*	0.0268	0.346*	0.238
	(0.0862)	(0.118)	(0.198)	(0.256)
EduHigher	0.0797	-0.173	0.0327	-0.284
	(0.230)	(0.325)	(0.439)	(0.524)
WithIncome	-0.151	-0.170	-0.439**	-0.596**
	(0.0933)	(0.129)	(0.204)	(0.297)
Constant	-1.852***	-2.106***	-14.03***	-10.78***
	(0.465)	(0.605)	(1.639)	(1.689)
User Controls	Y	Y	Y	Y
Dummies for Registration Week	Y	Y	Y	Y
Observations	1382	666	411	321
Pseudo-R:	0.169	0.166	0.499	0.442

Robust standard errors in parentheses, clustered on location
*** p<0.01, ** p<0.05, * p<0.1

Table 19*: *Chp3- Panel Probit Model – Women Making Choices from Day 2

	Dependent Variables - Choices made from day 2 onwards		
	(1)	(2)	(3)
	AgeChoiceMadeInBetween	EduChoiceMadeInBetween	AgeEduIncChoiceMadeInBetween
Age26AndAbove	0.873***	0.291***	0.534***
	(0.130)	(0.0994)	(0.139)
EduHigher	-0.00565	-0.624***	-0.0953
	(0.177)	(0.162)	(0.189)
WithIncome	-0.0626	0.253***	-0.0911
	(0.121)	(0.0972)	(0.128)
TotalEISent_lag	0.00447***	-0.00130	0.00299*
	(0.00156)	(0.00143)	(0.00161)
TotalEIReceived_lag	0.000870	0.00101	0.00133
	(0.00106)	(0.000958)	(0.00113)
TotalMatches_lag	-0.0130**	-0.00183	-0.0105*
	(0.00557)	(0.00534)	(0.00633)
ProfileViews_lag	-7.64e-05	0.000195	-0.000191
	(0.000184)	(0.000171)	(0.000199)
lnsig2u	3.223***	1.884***	3.254***
	(0.0500)	(0.0500)	(0.0498)
Constant	-6.391***	-1.835***	-6.829***
	(0.207)	(0.176)	(0.222)
User Controls	Y	Y	Y
Dummies for Registration Week	Y	Y	Y
Observations	60,884	60,884	60,884
Number of mid	1,964	1,964	1,964

Robust standard errors in parentheses, clustered on location
*** p<0.01, ** p<0.05, * p<0.1

Robustness Checks

Table 20*: *Chp3- Count Model for Main Effects

	(1)	(2)	(3)
	TotalEIReceived	TotalIncomingMatch	TotalEISent
Treatment	0.0527***	-0.439***	-0.290***
	(0.000118)	(0.00783)	(0.0336)
TimeTreatment	-0.175***	-0.798***	-0.405***
	(0.000672)	(0.0111)	(0.0226)
Treatment x TimeTreatment	-0.0331***	0.662***	0.673***
	(0.000436)	(0.00631)	(0.0648)
TotalEIReceived		-0.000619***	-0.00267**
		(0.000182)	(0.00120)
DaysActive	-0.00646***	0.144***	0.147***
	(0.00110)	(0.0122)	(0.0164)
ProfileViews	0.000362***	9.89e-05**	0.000220*
	(8.85e-07)	(4.46e-05)	(0.000128)
Constant	4.422***	-0.0473	1.892***
	(0.00525)	(0.0970)	(0.151)
User Controls	Y	Y	Y
Dummies for Registration Week	Y	Y	Y
Observations	3,666	3,666	3,666

Robust standard errors in parentheses, clustered on location
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 21*: *Chp3- Model based on days (3 days, 7 days, and 14 days) for Women

	TotalEIReceived				TotalIncomingMatch				TotalEISent			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	3 days	7 days	14 days	30 days	3 days	7 days	14 days	30 days	3 days	7 days	14 days	30 days
Treatment	1.537	1.681	1.520	5.701	-0.308	-0.576**	-0.654***	-1.044*	-1.586	-3.011***	-4.055*	-7.526**
	(3.659)	(5.818)	(8.527)	(12.75)	(0.0653)	(0.0235)	(0.00522)	(0.111)	(0.585)	(0.0326)	(0.333)	(0.517)
TimeTreatment	-11.92*	-17.32**	-22.84**	-27.54***	-0.308	-0.609	-0.874	-1.518	-1.087	-1.985	-1.306	-2.877
	(1.466)	(1.235)	(1.205)	(0.254)	(0.125)	(0.230)	(0.321)	(0.632)	(0.531)	(0.683)	(0.525)	(2.841)
Treatment x TimeTreatment	-3.897*	-3.629	-3.464	-10.30*	0.314*	0.541***	0.594***	1.033**	1.658*	3.009**	4.644**	9.235*
	(0.392)	(0.602)	(0.767)	(1.114)	(0.0265)	(0.00555)	(0.000427)	(0.0162)	(0.179)	(0.0875)	(0.205)	(0.821)
TotalEIReceived					-0.00399	-0.00394	-0.00437	-0.00542	-0.0560	-0.0675	-0.0852	-0.123
					(0.00404)	(0.00214)	(0.000860)	(0.00150)	(0.0229)	(0.0121)	(0.0225)	(0.0593)
DaysActive	-3.856*	-5.176*	-5.620**	-5.886***	0.508**	0.534**	0.494**	0.456*	4.229*	4.423**	4.375**	4.364***
	(0.539)	(0.417)	(0.156)	(0.0566)	(0.0149)	(0.0238)	(0.0292)	(0.0416)	(0.365)	(0.240)	(0.283)	(0.0492)
ProfileViews	0.142**	0.135**	0.128***	0.120***	0.000788	0.000718	0.000708	0.000748	0.00934	0.00974	0.0110	0.0143
	(0.00503)	(0.00273)	(0.00169)	(0.000440)	(0.000707)	(0.000356)	(0.000170)	(0.000263)	(0.00381)	(0.00158)	(0.00291)	(0.00806)
Constant	82.91*	103.8*	132.2*	177.0*	1.892*	2.364**	2.895***	4.723**	1.509	2.942	4.557	27.74
	(10.84)	(16.04)	(18.65)	(23.29)	(0.212)	(0.105)	(0.00297)	(0.242)	(0.720)	(2.092)	(2.117)	(7.472)
User Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Dummies for Registration Week	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	3,666	3,666	3,666	3,666	3,666	3,666	3,666	3,666	3,666	3,666	3,666	3,666
R-squared	0.836	0.842	0.839	0.833	0.128	0.171	0.210	0.273	0.186	0.203	0.199	0.231

Robust standard errors in parentheses, clustered on location
*** p<0.01, ** p<0.05, * p<0.1

***Table 22**: Chp3- Panel Probit Models with No Lag and Two Days Lag*

	AgeChoiceMadeInBetween		EduChoiceMadeInBetween		AgeEduIncChoiceMadeInBetween	
	(1)	(2)	(3)	(4)	(5)	(6)
	No Lag	2 days lag	No Lag	2 days lag	No Lag	2 days lag
Age26AndAbove	0.518***	0.715***	0.268***	0.288***	0.521***	0.564***
	(0.112)	(0.144)	(0.0965)	(0.112)	(0.125)	(0.152)
EduHigher	-0.0149	-0.0293	-0.573***	-0.760***	-0.0959	-0.120
	(0.158)	(0.200)	(0.154)	(0.272)	(0.170)	(0.204)
WithIncome	-0.0237	-0.0745	0.232**	0.259**	-0.0915	-0.104
	(0.105)	(0.135)	(0.0943)	(0.112)	(0.116)	(0.138)
Paid	0.310*	0.651***	-0.156	-0.136	0.473**	0.602***
	(0.176)	(0.224)	(0.167)	(0.225)	(0.187)	(0.221)
TotalEISent	0.00211	0.00639***	-0.00108	-0.00156	0.00295*	0.00319*
	(0.00142)	(0.00168)	(0.00137)	(0.00208)	(0.00153)	(0.00176)
TotalEIReceived	0.000357	0.000968	0.000996	0.00119	0.00134	0.00156
	(0.000951)	(0.00126)	(0.000924)	(0.00120)	(0.00104)	(0.00122)
TotalMatches	-0.00681	-0.0147**	-0.00291	0.000693	-0.0104*	-0.0115
	(0.00498)	(0.00607)	(0.00468)	(0.0104)	(0.00595)	(0.00701)
ProfileViews	-1.28e-05	-7.04e-05	0.000183	0.000200	-0.000195	-0.000252
	(0.000165)	(0.000221)	(0.000163)	(0.000208)	(0.000183)	(0.000216)
lnsig2u	2.842***	3.475***	1.722***	2.071***	3.011***	3.564***
	(0.0489)	(0.0513)	(0.0493)	(0.0519)	(0.0489)	(0.0503)
Constant	-5.375***	-6.805***	-1.773***	-1.871***	-6.308***	-7.690***
	(0.181)	(0.232)	(0.169)	(0.278)	(0.197)	(0.242)
User Controls	Y	Y	Y	Y	Y	Y
Dummies for Registration Week	Y	Y	Y	Y	Y	Y
Observations	62,848	58,920	62,848	58,920	62,848	58,920
Number of mid	1,964	1,964	1,964	1,964	1,964	1,964

Robust standard errors in parentheses, clustered on location
*** p<0.01, ** p<0.05, * p<0.1

Table 23: Chp4- Variable Definitions

Variable Name	Definition
Dependent Variables	
TotalEIAccept	Total number of expression of interest (EI) accepted by counter parties from the EIs sent by the focal user
TotalReceiveEI	Total EIs received by focal user
TotalProfileView	Total number of times the profile of the focal user is viewed by others in the platform
Independent Variables	
PO (Profile Operator)	Equal to 1 if the profile is managed by parents, 0 is managed by the individual
GNDev(Group Norm Deviation)	Equal to 1 if the user is one standard deviation away from the average group norms, 0 otherwise. Refer to the endogamy definition section on how the group norms are calculated
User Activities Controls	
TotalLogin	Total number of login sessions for the focal user
TotalEI	Total number of EIs sent by the focal user
User Controls	
Mobile Adopters	If the users has adopted the mobile channel from day one of the registration
EduBachDummy	1- If user has a minimum undergraduate degree/0-Otherwise
Paid	1 If the user is a paid subscriber, 0 otherwise
T1,T2,T3	Represents city tiers with T1 referring to tier 1 city like Mumbai
Other Demographic Controls	Age, education, occupation, annual income, religion, caste, subcaste, profile photo availability and Language spoken

Table 24: Chp4- Summary Statistics

	Overall Sample						CEM - Sample Main						Twins - Sample Main					
	Overall		Women		Men		Overall		Women		Men		Overall		Women		Men	
Variables	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
TotalEIAccept	0.65	2.90	1.80	5.23	0.25	1.12	0.83	3.49	1.79	5.59	0.33	1.26	1.26	4.59	1.9	5.74	0.28	1.15
TotalReceiveEI	15.87	48.49	57.77	82.22	1.47	5.07	20.89	54.83	57.03	82.16	2.18	6.45	42.62	86.34	69.03	102.73	2.45	8.01
TotalViewProfile	203.27	573.89	606.05	978.27	64.86	196.84	260.21	621.52	580.72	928.28	94.22	243.53	575.77	1128.76	867.58	1347.41	131.92	352.45
PO = 1 (Parents)	0.28	0.45	0.53	0.50	0.20	0.40	0.5	0.5	0.5	0.5	0.5	0.5	0.47	0.5	0.51	0.5	0.41	0.49
PO = 0 (Self)	0.65	0.48	0.40	0.49	0.74	0.44	0.5	0.5	0.5	0.5	0.5	0.5	0.53	0.5	0.49	0.5	0.59	0.49
GNDev	0.08	0.27	0.08	0.28	0.07	0.26	0.07	0.26	0.08	0.26	0.07	0.26	0.06	0.23	0.05	0.22	0.07	0.25
Gender (Men)	0.74	0.44	-	-	-	-	0.66	-	-	-	-	-	0.4	-	-	-	-	-
EduBachDummy	0.78	0.41	0.90	0.30	0.74	0.44	0.82	0.38	0.91	0.28	0.78	0.42	0.85	0.36	0.94	0.24	0.71	0.45
Age	27.45	4.89	26.20	4.63	27.87	4.91	27.48	4	25.58	3.71	28.46	3.78	24.65	3.13	23.2	2.41	26.86	2.79
Yrsofedu	15.40	1.62	15.87	1.44	15.24	1.65	15.54	1.56	15.82	1.34	15.39	1.65	15.63	1.42	15.89	1.08	15.23	1.74
MobileAdopters	0.68	0.47	0.71	0.45	0.67	0.47	0.68	0.47	0.73	0.44	0.65	0.48	0.68	0.47	0.72	0.45	0.61	0.49
Paid	0.09	0.29	0.14	0.35	0.08	0.26	0.09	0.28	0.06	0.24	0.1	0.3	0.06	0.23	0.06	0.24	0.05	0.21
T1	0.33	0.47	0.36	0.48	0.32	0.47	0.34	0.47	0.32	0.47	0.35	0.48	0.25	0.43	0.22	0.41	0.3	0.46
T2	0.24	0.43	0.25	0.43	0.23	0.42	0.24	0.43	0.25	0.44	0.23	0.42	0.14	0.35	0.15	0.35	0.13	0.34
T3	0.43	0.50	0.39	0.49	0.44	0.50	0.42	0.49	0.42	0.49	0.42	0.49	0.61	0.49	0.63	0.48	0.57	0.5
TotalLogin	25.75	52.71	32.98	57.71	23.26	50.64	28.51	56.41	28.82	50.05	28.35	59.44	32.24	62.3	35.45	63.87	27.37	59.52
TotalEI	14.78	113.31	7.08	42.67	17.43	128.83	14.26	103.59	7.09	47.13	17.97	122.87	9.2	50.2	6.86	36.22	12.75	65.86
Observations	834927		213537		621390		302284		103138		199146		14879		8977		5902	

Table 25: Chp4- Main Effect – Matched Dyads (All users)

	Dependent Variable - Expression of Interest Acceptance (Matched Dyad)					
	Coarsened Exact Matching			Twins Matching		
	All			All		
	1	2	3	4	5	6
PO	-0.252***	-0.250***	-0.239***	-0.141*	-0.133*	-0.120*
	(0.0116)	(0.0116)	(0.0120)	(0.0740)	(0.0740)	(0.0768)
GNDev		0.190***	0.260***		0.940***	1.030***
		(0.0220)	(0.0300)		(0.190)	(0.242)
PO x GNDev			-0.148***			-0.220
			(0.0432)			(0.365)
Total Login	0.00714***		0.00710***	0.0117***	0.0117***	0.0117***
	(0.000112)		(0.000112)	(0.000845)	(0.000844)	(0.000844)
Expression Sent	0.000430***		0.000409***	0.0134***	0.0133***	0.0133***
	(5.57e-05)		(5.57e-05)	(0.000935)	(0.000934)	(0.000934)
Constant	0.756***		0.746***	0.0574	0.0470	0.0232
	(0.256)		(0.256)	(2.402)	(2.400)	(2.400)
User Controls	Y	Y	Y			
Time Fixed Effects	Y	Y	Y	Y	Y	Y
Caste Fixed Effects	Y	Y	Y			
Twin Fixed Effects				Y	Y	Y
Observations	302,284	302,284	302,284	14,879	14,879	14,879
R-squared	0.208	0.21	0.21	0.446	0.447	0.447

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

Note : Chow test confirms that the intercept and slope terms are different for the profile operator groups

Table 26: Chp4- Main Effect – Matched Dyads (Split Samples)

	Dependent Variable - Expression of Interest Acceptance (Matched Dyad)							
	Men				Women			
	CEM		Twins Matching		CEM		Twins Matching	
	1	2	3	4	5	6	7	8
PO	-0.0944***	-0.0878***	-0.0505*	-0.0440	-0.521***	-0.494***	-0.257**	-0.224*
	(0.00492)	(0.00511)	(0.0265)	(0.0277)	(0.0317)	(0.0330)	(0.117)	(0.121)
GNDev	0.128***	0.169***	0.127*	0.161**	0.283***	0.453***	1.422***	1.714***
	(0.00933)	(0.0127)	(0.0655)	(0.0779)	(0.0600)	(0.0820)	(0.309)	(0.417)
PO x GNDev		-0.0882***		-0.102		-0.361***		-0.624
		(0.0183)		(0.127)		(0.118)		(0.596)
Total Login	0.00314***	0.00314***	0.00372***	0.00372***	0.0210***	0.0210***	0.0160***	0.0160***
	(4.94e-05)	(4.94e-05)	(0.000353)	(0.000353)	(0.000371)	(0.000371)	(0.00128)	(0.00128)
Expression Sent	-0.000430***	-0.000432***	0.000917***	0.000917***	0.0167***	0.0167***	0.0335***	0.0335***
	(2.16e-05)	(2.17e-05)	(0.000278)	(0.000279)	(0.000338)	(0.000338)	(0.00181)	(0.00181)
Constant	-0.0991	-0.101	0.123	0.114	2.596***	2.594***	0.328	0.261
	(0.111)	(0.111)	(1.151)	(1.151)	(0.678)	(0.678)	(3.328)	(3.329)
User Controls	Y	Y			Y	Y		
Time Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Caste Fixed Effects	Y	Y			Y	Y		
Twin Fixed Effects			Y	Y			Y	Y
Observations	199,146	199,146	5,902	5,902	103,138	103,138	8,977	8,977
R-squared	0.280	0.280	0.585	0.585	0.214	0.214	0.450	0.450

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

Note : Chow test confirms that the intercept and slope terms are different for the profile operator groups

Table 27: Chp4- Alternate Outcome – Incoming Requests (All Users)

	Dependent Variable - Incoming Expressions of Interest					
	All					
	Coarsened Exact Matching			Twins Matching		
	1	2	3	4	5	6
PO	-2.519***	-2.501***	-2.465***	-4.010***	-3.932***	-3.907***
	-0.0951	(0.0951)	(0.0987)	-0.546	(0.545)	(0.566)
GNDev		2.232***	2.457***		8.876***	9.059***
		(0.180)	(0.246)		(1.402)	(1.782)
PO x GNDev			-0.478			-0.447
			(0.355)			(2.691)
Total Login	-0.0876***	-0.0882***	-0.0882***	-0.0706***	-0.0707***	-0.0707***
	-0.000915	(0.000916)	(0.000916)	-0.00619	(0.00618)	(0.00618)
Constant	12.74***	12.64***	12.63***	-6.903	-7.003	-7.051
	-2.102	(2.102)	(2.102)	-17.71	(17.67)	(17.68)
User Controls	Y	Y	Y			
Time Fixed Effects	Y	Y	Y	Y	Y	Y
Caste Fixed Effects	Y	Y	Y			
Twin Fixed Effects				Y	Y	Y
Observations	302284	302284	302284	14,879	14,879	14,879
R-squared	0.783	0.784	0.784	0.915	0.915	0.915

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

Note : Chow test confirms that the intercept and slope terms are different for the profile operator groups

Table 28: Chp4- Alternate Outcome – Incoming Requests (Men and Women)

	Dependent Variable - Expression of Interest Received							
	Men				Women			
	CEM		Twins Matching		CEM		Twins Matching	
	1	2	3	4	5	6	7	8
PO	0.226***	0.202***	0.171*	0.199**	-6.433***	-6.125***	-6.193***	-5.947***
	(0.0194)	(0.0201)	(0.0945)	(0.0988)	(0.227)	(0.236)	(0.848)	(0.878)
GNDev	0.471***	0.318***	0.669***	0.816***	9.197***	11.14***	14.06***	16.27***
	(0.0368)	(0.0501)	(0.233)	(0.278)	(0.429)	(0.587)	(2.248)	(3.027)
PO x GNDev		0.325***		-0.442		-4.096***		-4.727
		(0.0722)		(0.455)		(0.846)		(4.331)
Total Login	0.00830***	0.00829***	0.000354	0.000375	0.0194***	0.0194***	-0.0472***	-0.0472***
	(0.000194)	(0.000194)	(0.00126)	(0.00126)	(0.00266)	(0.00266)	(0.00925)	(0.00925)
Constant	-2.604***	-2.596***	-0.256	-0.294	21.73***	21.70***	-5.669	-6.176
	(0.436)	(0.436)	(4.103)	(4.103)	(4.849)	(4.849)	(24.19)	(24.19)
User Controls	Y	Y			Y	Y		
Time Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Caste Fixed Effects	Y	Y			Y	Y		
Twin Fixed Effects			Y	Y			Y	Y
Observations	199146	199146	5,902	5,902	103,138	103,138	8,977	8,977
R-squared	0.576	0.576	0.890	0.890	0.814	0.814	0.909	0.909

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

Note: Chow test confirms that the intercept and slope terms are different for the profile operator groups

Table 29: Chp4- Robustness Check – Count Models

	Count Model -Negative Binomial Regression			
	Men		Women	
	TotalEIAccept	TotalReceiveEI	TotalEIAccept	TotalReceiveEI
	1	2	3	4
PO	-0.180***	0.177***	-0.236***	-0.0199***
	(0.0145)	(0.00909)	(0.0141)	(0.00667)
GNDev	0.511***	0.575***	0.386***	0.380***
	(0.0307)	(0.0217)	(0.0333)	(0.0166)
PO x GNDev	-0.0346	-0.0935***	-0.00162	0.00438
	(0.0463)	(0.0315)	(0.0489)	(0.0241)
TotalLogin	0.0163***	0.0185***	0.0201***	0.0131***
	(0.000161)	(0.000125)	(0.000234)	(0.000101)
TotalEI	0.00429***		0.0257***	
	(0.000123)		(0.000521)	
Constant	-2.422***	-0.507***	-0.994***	3.193***
	(0.0164)	(0.00968)	(0.0174)	(0.00757)
/lnalpha	1.365***	1.068***	1.243***	0.0206***
	(0.0102)	(0.00521)	(0.00782)	(0.00408)
User Controls	Y	Y	Y	Y
Time Fixed Effects	Y	Y	Y	Y
Observations	199146	199146	103138	103138

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

Table 30: Chp4- Profile Switch

Gender	Deviation	Control Self to Self	Treatment Self to Family
Men	0	318	322
	1	25	21
Women	0	211	210
	1	20	21

Gender	Deviation	Control Family to Family	Treatment Family to Self
Men	0	112	112
	1	20	18
Women	0	82	82
	1	14	11

Figures

Figure 1– Chp2- Mobile adoption across 8 weeks

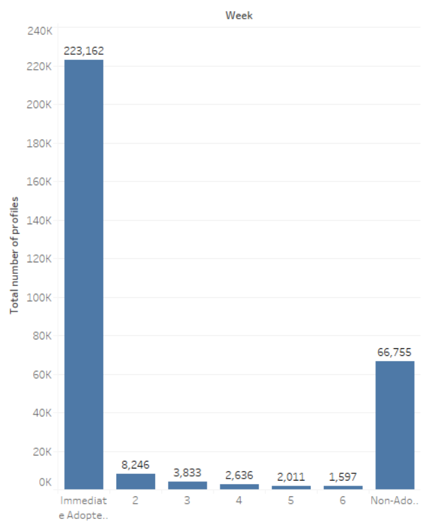


Figure 2– Chp2- Adopters grouping – immediate, late and never adopters

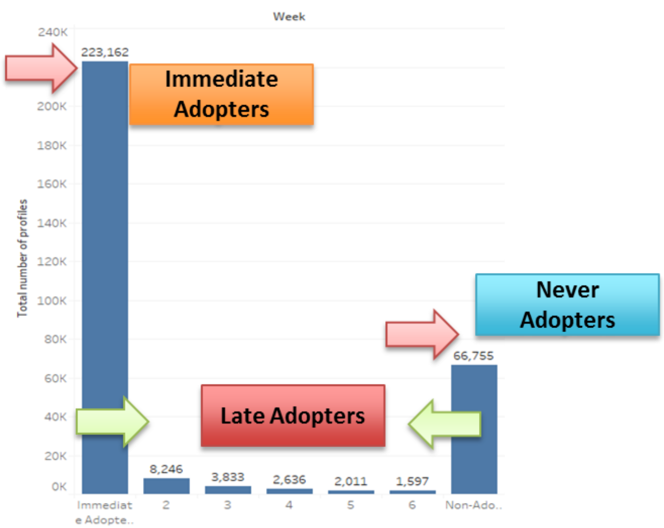


Figure 3 - Chp2- Profile signup across the 8 week time period

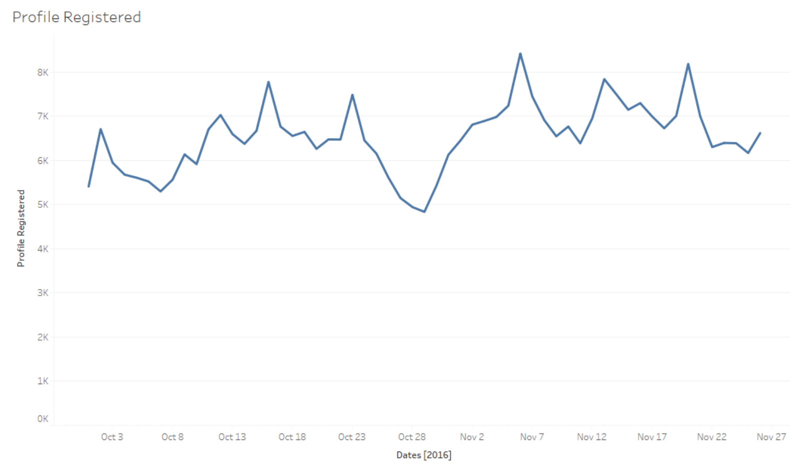


Figure 4– Chp2- Impulsivity/Non-Impulsivity

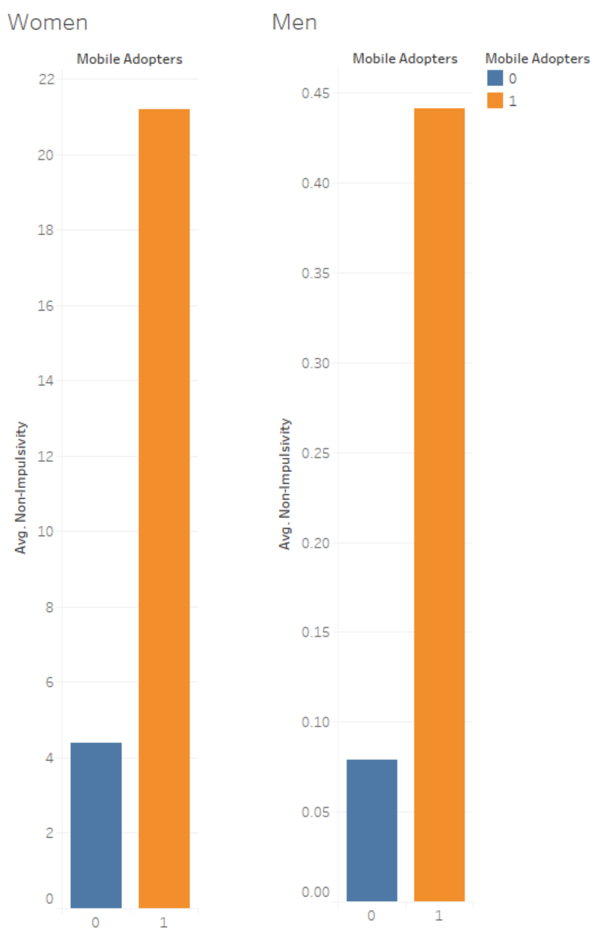


Figure 5 – Chp2- Impulsivity/Non-Impulsivity (normalized)

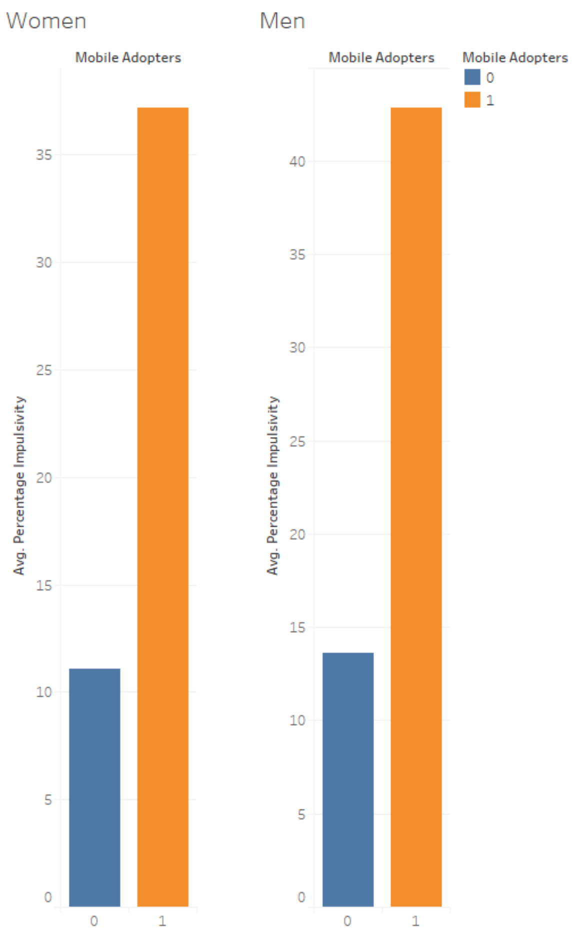


Figure 6 – Chp3- Treatment Groups (Platform Level Intervention)

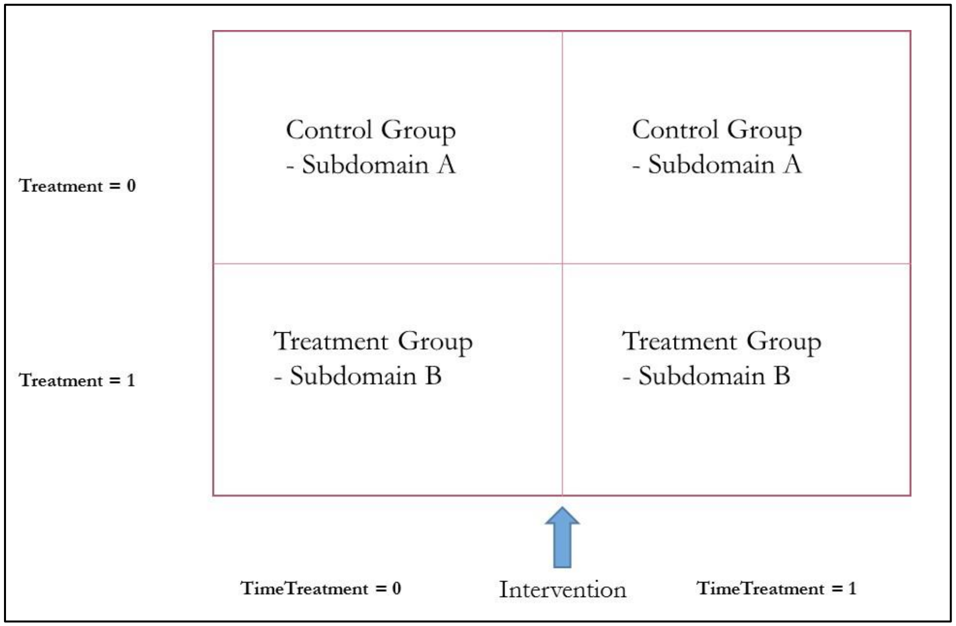


Figure 7 - Chp3- Matched Samples (Platform Level – Intervention)

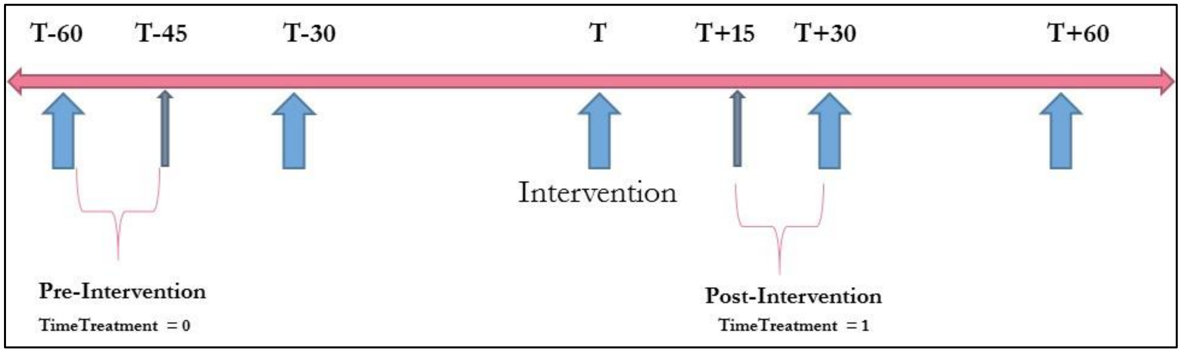


Figure 8 - Chp3- Intervention II – Choices Presented to Individual

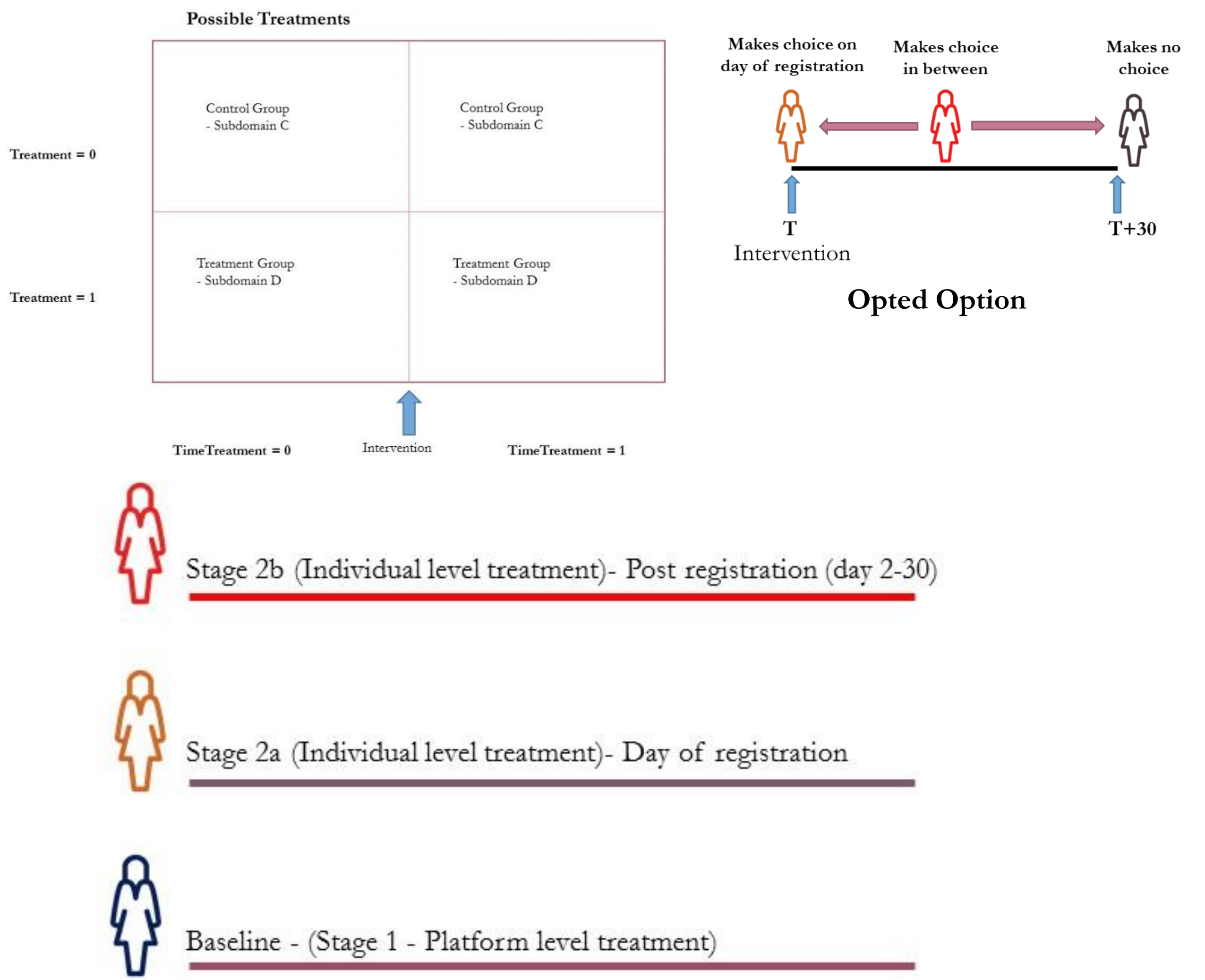


Figure 9 – Chp4- Partial Caste Network

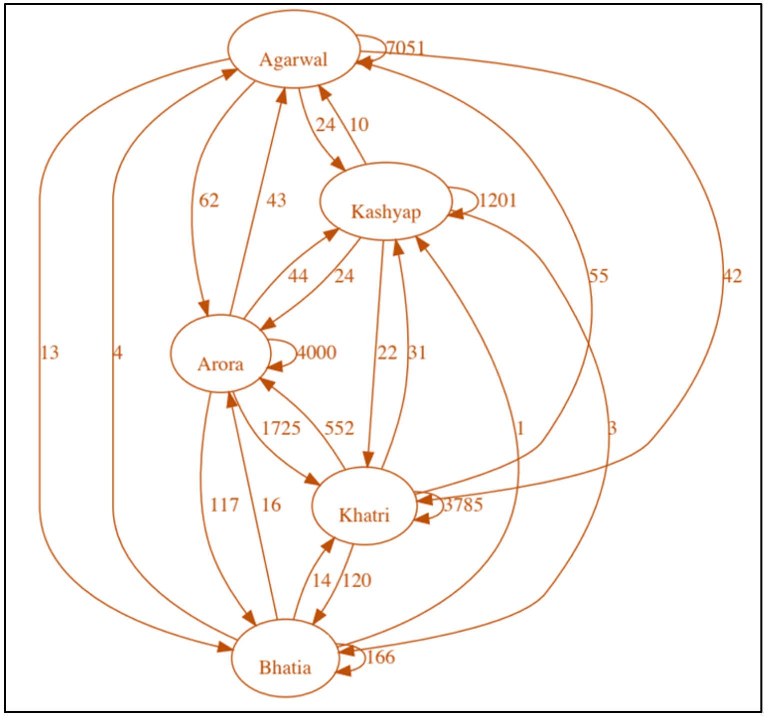


Figure 10 - Chp4- Profile Switch (Women – Incoming EI)

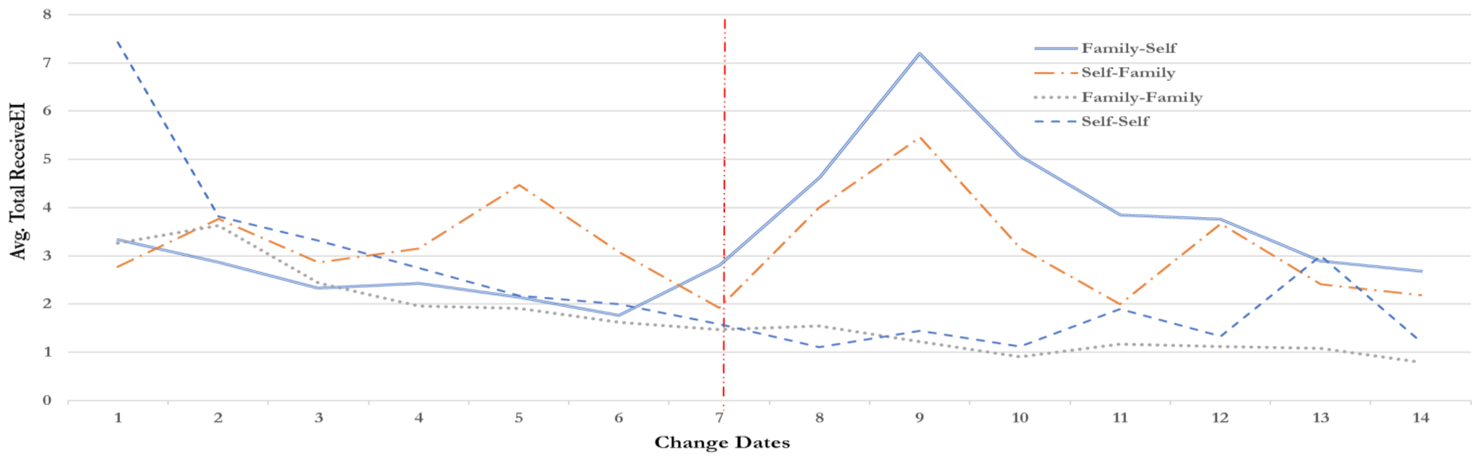


Figure 11 – Chp4- Profile Switch (Men – Incoming EI)

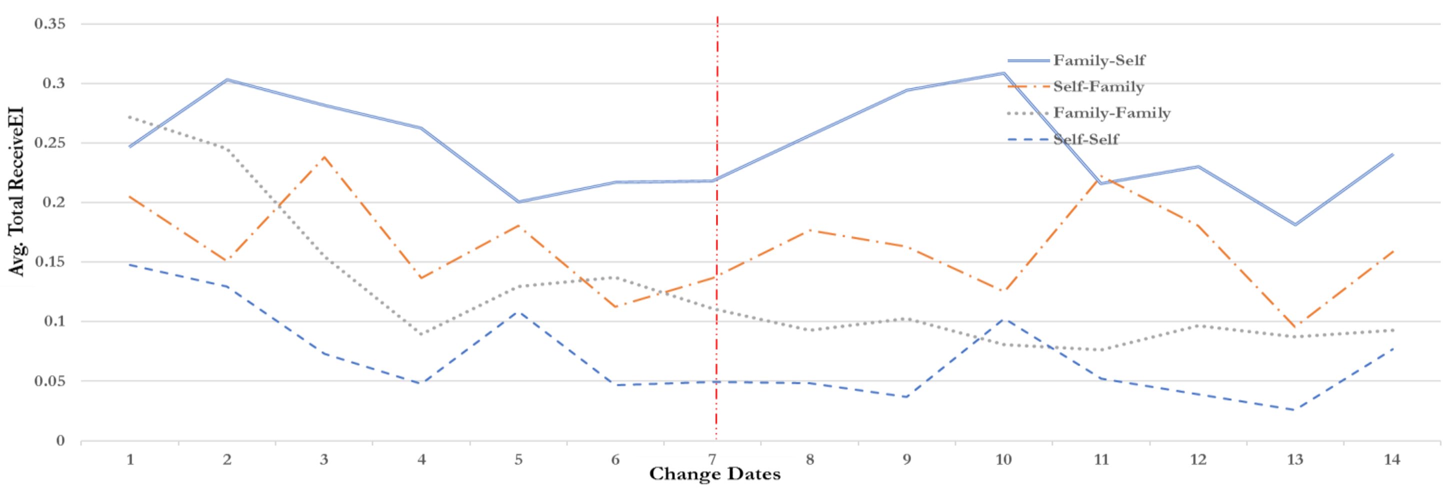


Figure 12 – Chp4- Profile Switch (Women – Relationship Dyad)

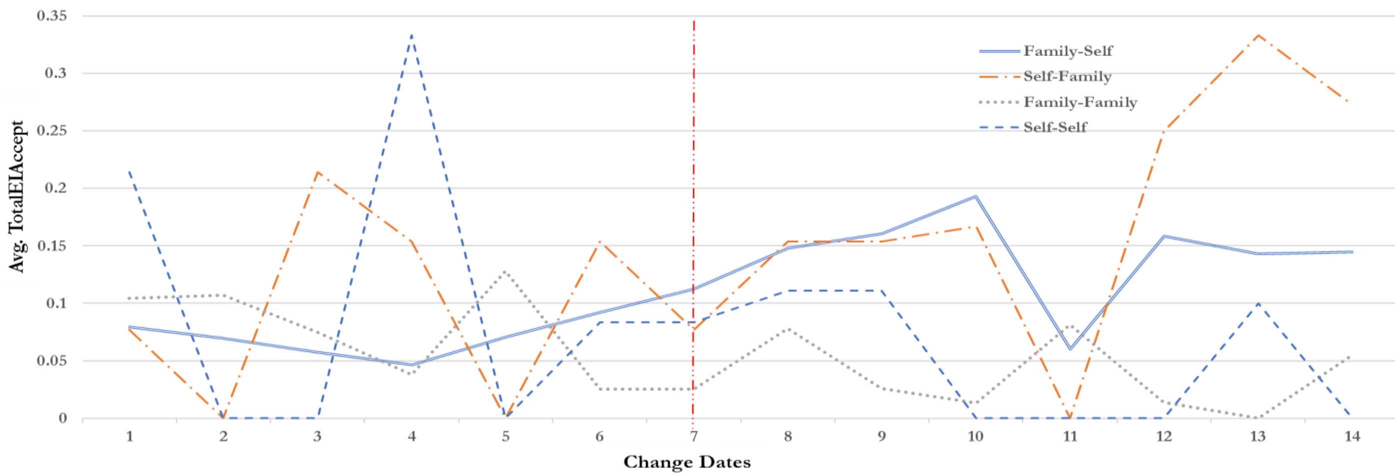


Figure 13 – Chp4- Profile Switch (Men – Relationship Dyad)

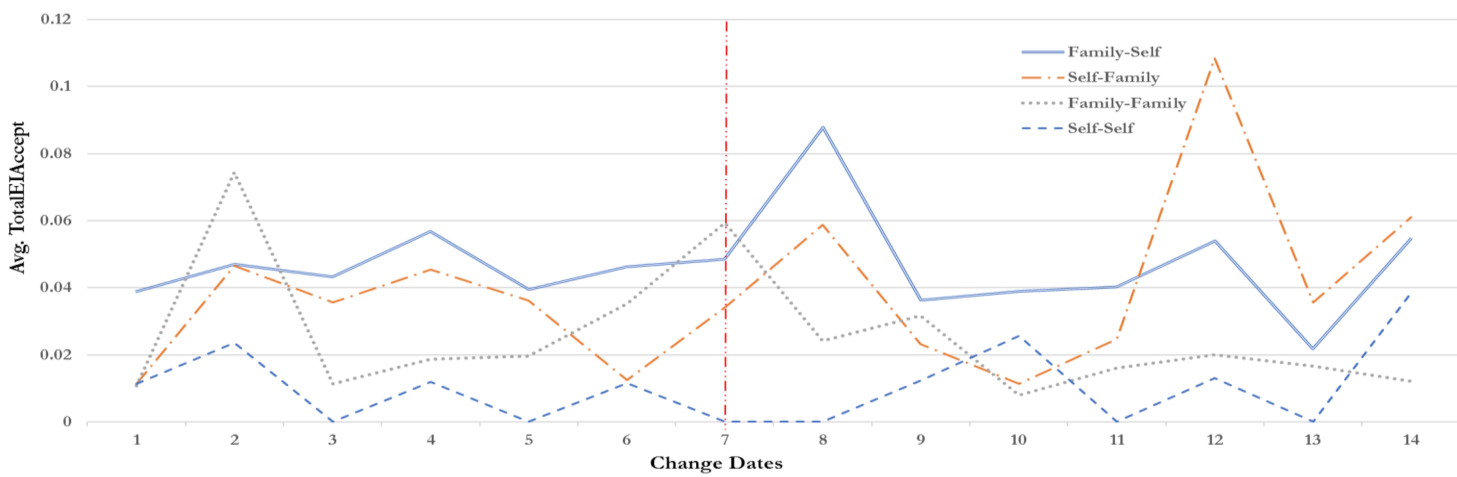


Figure 14 – Chp4- Profile Switch (Women – ProfileView)

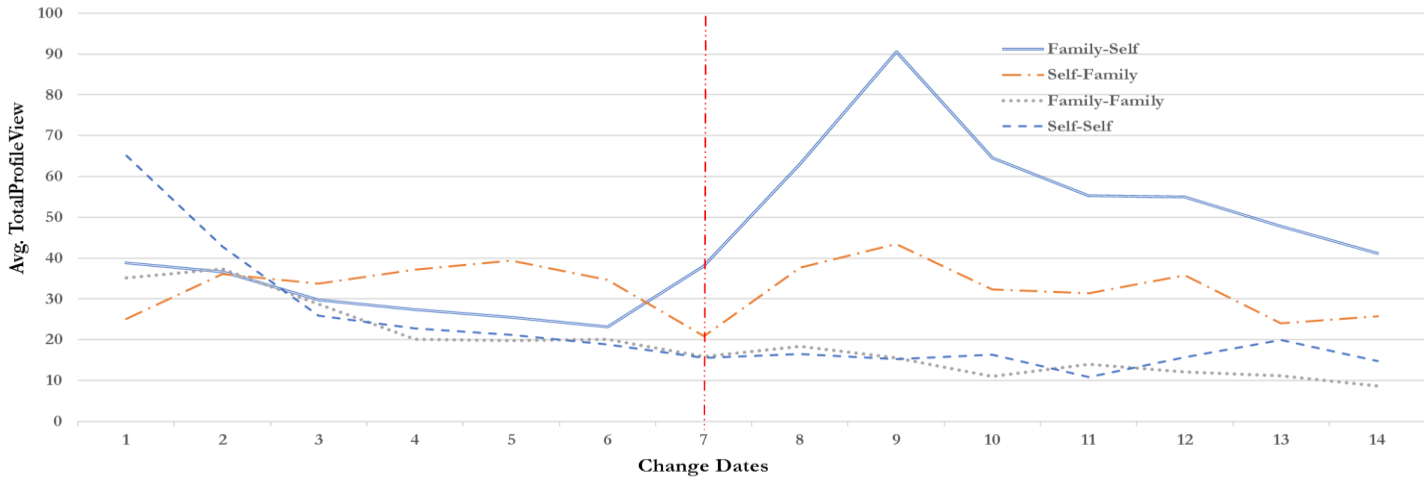
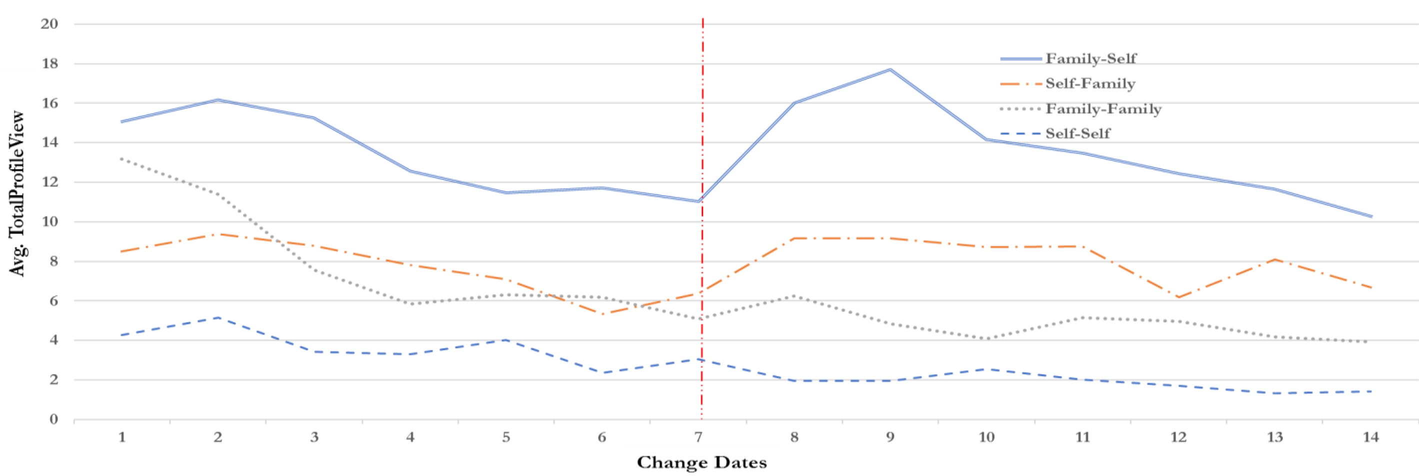


Figure 15 – Chp4- Profile Switch (Men – ProfileView)



Bibliography

Abraham, J. 2010. "Veiling and the Production of Gender and Space in a Town in North India:A Critique of the Public/Private Dichotomy," *Indian Journal of Gender Studies* (17:2), pp. 191-222.

Agrawal, A. 2015. "Cyber-Matchmaking among Indians: Re-Arranging Marriage and Doing 'Kin Work'," *South Asian Popular Culture* (13:1), pp. 15-30.

Ahlawat, N. 2015. "Marriage Norms, Personal Choices, and Social Sanctions in Haryana," *Sociological Bulletin* (64:1), pp. 91-103.

Ahlers, G. K., Cumming, D., Günther, C., and Schweizer, D. 2015. "Signaling in Equity Crowdfunding," *Entrepreneurship theory and practice* (39:4), pp. 955-980.

Ahuja, A., and Ostermann, S. L. 2016. "Crossing Caste Boundaries in the Modern Indian Marriage Market," *Studies in Comparative International Development* (51:3), pp. 365-387.

Ahuvia, A. C., and Adelman, M. B. 1992. "Formal Intermediaries in the Marriage Market: A Typology and Review," *Journal of Marriage and Family* (54:2), pp. 452-463.

Allendorf, K., and Pandian, R. K. 2016. "The Decline of Arranged Marriage? Marital Change and Continuity in India," *Population and Development Review* (42:3), pp. 435-464.

Allendorf, K., and Thornton, A. 2015. "Caste and Choice: The Influence of Developmental Idealism on Marriage Behavior," *American Journal of Sociology* (121:1), pp. 243-287.

Anderson, C. 2008. *The Long Tail : Why the Future of Business Is Selling Less of More*, (Rev. and updated ed.). New York: Hyperion.

Ang, S., and Cummings, L. L. 1997. "Strategic Response to Institutional Influences on Information Systems Outsourcing," *Organization Science* (8:3), pp. 235-256.

Annavarapu, S. 2018. "“We Match Better”–an Analysis of Online Matchmaking Ads in Contemporary India," in: *SocArXiv Papers*.

Aral, S., and Walker, D. 2011. "Creating Social Contagion through Viral Product Design: A Randomized Trial of Peer Influence in Networks," *Management Science* (57:9), pp. 1623-1639.

Arbaugh, J. B., Godfrey, M. R., Johnson, M., Pollack, B. L., Niendorf, B., and Wresch, W. 2009. "Research in Online and Blended Learning in the Business Disciplines: Key Findings and Possible Future Directions," *The Internet and Higher Education* (12:2), pp. 71-87.

Ashenfelter, O., and Krueger, A. 1994. "Estimates of the Economic Return to Schooling from a New Sample of Twins," *American Economic Review* (84:5), pp. 1157-1173.

Ayyagari, R., Grover, V., and Purvis, R. 2011. "Technostress: Technological Antecedents and Implications," *MIS Quarterly* (35:4), pp. 831-858.

Balasubramanian, S., Peterson, R. A., and Jarvenpaa, S. L. 2002. "Exploring the Implications of M-Commerce for Markets and Marketing," *Journal of the Academy of Marketing Science* (30:4), pp. 348-361.

Banerjee, A., Duflo, E., Ghatak, M., and Lafortune, J. 2013. "Marry for What? Caste and Mate Selection in Modern India," *American Economic Journal-Microeconomics* (5:2), pp. 33-72.

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

Bapna, R., Ramaprasad, J., and Umyarov, A. 2016b. "Monetizing Freemium Communities: Does Paying for Premium Increase Social Engagement?,").

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

Bartel Sheehan, K. 1999. "An Investigation of Gender Differences in on-Line Privacy Concerns and Resultant Behaviors," *Journal of Interactive Marketing* (13:4), pp. 24-38.

Baruah, J. 2018. "Indians Are Considering Online Dating as a Possible Form of Matchmaking," in: *The Economic Times*. Mumbai, India.

Benjamin, B. A., and Podolny, J. M. 1999. "Status, Quality, and Social Order in the California Wine Industry," *Administrative Science Quarterly* (44:3), pp. 563-589.

Béteille, A. 1996. *Caste, Class, and Power : Changing Patterns of Stratification in a Tanjore Village*, (2nd ed. ed.). Delhi ;: Oxford University Press.

Blackwell, M., Iacus, S., King, G., and Porro, G. 2009. "Cem: Coarsened Exact Matching in Stata," *The Stata Journal* (9:4), pp. 524-546.

Blair, C. 1988. "The Lattice Structure of the Set of Stable Matchings with Multiple Partners," *Mathematics of Operations Research* (13:4), pp. 619-628.

Bradford, N. J. 1985. "From Bridewealth to Groom-Fee: Transformed Marriage Customs and Socio-Economic Polarisation Amongst Lingayats," *Contributions to Indian Sociology* (19:2), pp. 269-302.

Burtch, G., Carnahan, S., and Greenwood, B. N. 2018. "Can You Gig It? An Empirical Examination of the Gig Economy and Entrepreneurial Activity," *Management Science* (64:12), pp. 5497-5520.

Chae, M., and Kim, J. 2003. "What's So Different About the Mobile Internet?," *Communications of the ACM* (46:12), pp. 240-247.

Chu, J., and Manchanda, P. 2016. "Quantifying Cross and Direct Network Effects in Online Consumer-to-Consumer Platforms," *Marketing Science* (35:6), pp. 870-893.

Constantinides, P., Henfridsson, O., and Parker, G. G. 2018. "Platforms and Infrastructures in the Digital Age," *Information Systems Research* (29:2), pp. 381-400.

Cook, C., Diamond, R., Hall, J., List, J. A., and Oyer, P. 2018. "The Gender Earnings Gap in the Gig Economy: Evidence from over a Million Rideshare Drivers," National Bureau of Economic Research.

Couch, D., Liamputtong, P., and Pitts, M. 2012. "What Are the Real and Perceived Risks and Dangers of Online Dating? Perspectives from Online Daters," *Health, Risk & Society* (14:7-8), pp. 697-714.
Dar, V. 2017. "E-Matchmaking Industry Is Still in Nascent Stage and Accounts for Approx 6% of Marriages in India," in: *Business World*.
Das, V. 2019. "Dating Applications, Intimacy, and Cosmopolitan Desire in India," *Global Digital Cultures: Perspectives from South Asia*), p. 125.
Deolalikar, A. B., and Rao, V. 1992. "The Demand for Dowries and Bride Characteristics in Marriage: Empirical Estimates for Rural South-Central India," [Unpublished] 1992. Presented at the Annual Meeting of the Population ….
Desai, S., and Andrist, L. 2010. "Gender Scripts and Age at Marriage in India," *Demography* (47:3), pp. 667-687.
Desai, S., and Dubey, A. 2012. "Caste in 21st Century India: Competing Narratives," *Economic and political weekly* (46:11), pp. 40-49.
Dhar, R. L. 2013. "Intercaste Marriage: A Study from the Indian Context," *Marriage & Family Review* (49:1), pp. 1-25.
DiMaggio, P. 1988. "Interest and Agency in Institutional Theory," *Institutional patterns and organizations culture and environment*), pp. 3-21.
Dimaggio, P. J., and Powell, W. W. 1983. "The Iron Cage Revisited - Institutional Isomorphism and Collective Rationality in Organizational Fields," *American Sociological Review* (48:2), pp. 147-160.
Doshi, V. 2016. "Date, Kiss or Marry,How Tinder Is Rewriting India’s Rules of Engagement," in: *The Guardian*.
Einav, L., Levin, J., Popov, I., and Sundaresan, N. 2014. "Growth, Adoption, and Use of Mobile E-Commerce," *American Economic Review* (104:5), pp. 489-494.
Filipovic, J. 2013. "Online Dating Levels the Romantic Playing Field for Women," in: *The Guardian*.
Finkel, E. J., Eastwick, P. W., Karney, B. R., Reis, H. T., and Sprecher, S. 2012. "Online Dating:A Critical Analysis from the Perspective of Psychological Science," *Psychological Science in the Public Interest* (13:1), pp. 3-66.
Fisman, R., Iyengar, S. S., Kamenica, E., and Simonson, I. 2006. "Gender Differences in Mate Selection: Evidence from a Speed Dating Experiment," *Quarterly Journal of Economics* (121:2), pp. 673-697.
Fleder, D., and Hosanagar, K. 2009. "Blockbuster Culture's Next Rise or Fall: The Impact of Recommender Systems on Sales Diversity," *Management Science* (55:5), pp. 697-712.
Fuller, C., and Narasimhan, H. 2008a. "Empowerment and Constraint: Women, Work and the Family in Chennai's Software Industry," *In an Outpost of the Global Economy–Work and Workers in India's Information Technology Industry*).
Fuller, C. J., and Narasimhan, H. 2008b. "Companionate Marriage in India: The Changing Marriage System in a Middle-Class Brahman Subcaste," *Journal of the Royal Anthropological Institute* (14:4), pp. 736-754.
Fuller, J., Narasimhan, H., Upadhya, C., and Vasavi, A. R. 2008. *In an Outpost of the Global Economy: Work and Workers in India's Information Technology Industry*.

Garg, S., and Narasimhan, T. E. 2013. "Booming Biz of Online Marriages," in: *Business Standard*. Kolkota, India: Business Standard.

Ghose, A. 2017. *Tap : Unlocking the Mobile Economy*. Cambridge, MA: MIT Press.

Ghose, A., Goldfarb, A., and Han, S. P. 2013. "How Is the Mobile Internet Different? Search Costs and Local Activities," *Information Systems Research* (24:3), pp. 613-631.

Ghose, A., Ipeirotis, P. G., and Li, B. 2014. "Examining the Impact of Ranking on Consumer Behavior and Search Engine Revenue," *Management Science* (60:7), pp. 1632-1654.

Goli, S., Singh, D., and Sekher, T. V. 2013. "Exploring the Myth of Mixed Marriages in India: Evidence from a Nation-Wide Survey," *Journal of Comparative Family Studies* (44:2), pp. 193-206.

Gompers, P., and Lerner, J. 2001. "The Venture Capital Revolution," *Journal of Economic Perspectives* (15:2), pp. 145-168.

Gordon, A. I. 1965. "Assimilation in American-Life - Gordon,Mm," *Review of Religious Research* (6:2), pp. 120-121.

Gordon, M. M. 1964. *Assimilation in American Life: The Role of Race, Religion, and National Origins*. New York,: Oxford University Press.

Greenwood, B. N., and Wattal, S. 2017. "Show Me the Way to Go Home: An Empirical Investigation of Ride-Sharing and Alcohol Related Motor Vehicle Fatalities," *Mis Quarterly* (41:1), pp. 163-187.

Greenwood, R., Suddaby, R., and Hinings, C. R. 2002. "Theorizing Change: The Role of Professional Associations in the Transformation of Institutionalized Fields," *Academy of Management Journal* (45:1), pp. 58-80.

Grover, S. 2018. "Marriage, Love, Caste, and Kinship Support : Lived Experiences of the Urban Poor in India." Abingdon, Oxon: Routledge.

Guler, I. 2007. "Throwing Good Money after Bad? Political and Institutional Influences on Sequential Decision Making in the Venture Capital Industry," *Administrative Science Quarterly* (52:2), pp. 248-285.

Gupta, D. 2000. *Interrogating Caste : Understanding Hierarchy and Difference in Indian Society*. New Delhi ;: Penguin Books.

Gupta, G. R. 1976. "Love, Arranged Marriage, and the Indian Social Structure," *Journal of Comparative Family Studies* (7:1), pp. 75-85.

Hagiu, A., and Jullien, B. 2011. "Why Do Intermediaries Divert Search?," *The RAND Journal of Economics* (42:2), pp. 337-362.

Hamon, R. R., and Ingoldsby, B. B. 2003. *Mate Selection across Cultures*. Thousand Oaks: Sage Publications.

Harris, G. 2015. "Websites in India Put a Bit of Choice into Arranged Marriages," in: *The New York Times*.

Hitsch, G. J., Hortacsu, A., and Ariely, D. 2010a. "Matching and Sorting in Online Dating," *American Economic Review* (100:1), pp. 130-163.

Hitsch, G. J., Hortaçsu, A., and Ariely, D. 2010b. "What Makes You Click?—Mate Preferences in Online Dating," *Quantitative Marketing and Economics* (8:4), pp. 393-427.

Hutton, J. H. 1963. *Caste in India, Its Nature, Function and Origins*, (4th ed.). Bombay: Indian Branch, Oxford University Press.

Iacus, S. M., King, G., and Porro, G. 2012. "Causal Inference without Balance Checking: Coarsened Exact Matching," *Political Analysis* (20:1), pp. 1-24.
Jaffe, A. B., Trajtenberg, M., and Henderson, R. 1993. "Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations*," *The Quarterly Journal of Economics* (108:3), pp. 577-598.
Jaiswal, T. 2014. "Indian Arranged Marriages : A Social Psychological Perspective." Hoboken: Taylor and Francis.
Jenkins, J. L., Anderson, B. B., Vance, A., Kirwan, C. B., and Eargle, D. 2016. "More Harm Than Good? How Messages That Interrupt Can Make Us Vulnerable," *Information Systems Research* (27:4), pp. 880-896.
Jensen, M. 2008. "The Use of Relational Discrimination to Manage Market Entry: When Do Social Status and Structural Holes Work against You?," *Academy of Management Journal* (51:4), pp. 723-743.
Jung, J., Bapna, R., Ramaprasad, J., and Umyarov, A. 2019. "Love Unshackled: Identifying the Effect of Mobile App Adoption in Online Dating," *MIS Quarterly* (43:1), pp. 47-72.
Jung, J., Lim, H., Lee, D., and Kim, C. 2020. "The Secret to Finding Love: A Field Experiment of Choice Structure in Online Dating Platform," *Available at SSRN*).
Junglas, I., and Watson, R. T. 2006. "The U-Constructs: Four Information Drives," *Communications of the Association for Information systems* (17:1), p. 26.
Kalmijn, M. 1998. "Intermarriage and Homogamy: Causes, Patterns, Trends," *Annual Review of Sociology* (24:1), pp. 395-421.
Kalnins, A., and Lafontaine, F. 2013. "Too Far Away? The Effect of Distance to Headquarters on Business Establishment Performance," *American Economic Journal: Microeconomics* (5:3), pp. 157-179.
Kamble, S., Shackelford, T. K., Pham, M., and Buss, D. M. 2014. "Indian Mate Preferences: Continuity, Sex Differences, and Cultural Change across a Quarter of a Century," *Personality and Individual Differences* (70), pp. 150-155.
Karmegam, S. R., and Gopal, A. 2019. "Close, but No Cigar? The Effect of Mobile Adoption on the Efficacy of Matrimonial Matching Platforms in India."
Karmegam, S. R., Gopal, A., and Ramaprasad, J. 2020. "Close, but No Cigar? The Effect of Mobile Adoption on the Efficacy of Matrimonial Matching Platforms in India."
Kaur, R., and Dhanda, P. 2014. "Surfing for Spouses: Marriage Websites and the 'New'indian Marriage," *Marrying in South Asia: Shifting Concepts, Changing Practices in a Globalising World*), pp. 271-292.
Kelso, A. S., and Crawford, V. P. 1982. "Job Matching, Coalition-Formation, and Gross Substitutes," *Econometrica* (50:6), pp. 1483-1504.
King, G., and Nielsen, R. 2019. "Why Propensity Scores Should Not Be Used for Matching," *Political Analysis* (27:4), pp. 435-454.
Lee, D., Gopal, A., and Park, S.-H. 2016. "Mobile & Me: An Experiment of Individual Heterogeneity and Channel Use in Recommendation Systems," *Academy of Management Proceedings* (2016:1), p. 11719.

Li, J., and Netessine, S. 2020. "Higher Market Thickness Reduces Matching Rate in Online Platforms: Evidence from a Quasiexperiment," *Management Science* (66:1), pp. 271-289.

Lowry, P. B., Zhang, J., Wang, C., and Siponen, M. 2016. "Why Do Adults Engage in Cyberbullying on Social Media? An Integration of Online Disinhibition and Deindividuation Effects with the Social Structure and Social Learning Model," *Information Systems Research* (27:4), pp. 962-986.

Macfarlane, B. 2011. "The Morphing of Academic Practice: Unbundling and the Rise of the Para-Academic," *Higher Education Quarterly* (65:1), pp. 59-73.

Maity, M., and Dass, M. 2014. "Consumer Decision-Making across Modern and Traditional Channels: E-Commerce, M-Commerce, in-Store," *Decision Support Systems* (61), pp. 34-46.

Marginson, S. 2013. "The Impossibility of Capitalist Markets in Higher Education," *Journal of Education Policy* (28:3), pp. 353-370.

Mathur, D. 2007. "What's Love Got to Do with It? Parental Involvement and Spouse Choice in Urban India," *Parental Involvement and Spouse Choice in Urban India (November 7, 2007)*).

Medora, N. P., Larson, J. H., Hortacsu, N., and Dave, P. 2002. "Perceived Attitudes Towards Romanticism; a Cross-Cultural Study of American, Asian-Indian, and Turkish Young Adults," *Journal of Comparative Family Studies* (33:2), pp. 155-+.

Meyer, J. W., and Rowan, B. 1977. "Institutionalized Organizations - Formal-Structure as Myth and Ceremony," *American Journal of Sociology* (83:2), pp. 340-363.

Mitra, S., and Ransbotham, S. 2015. "Information Disclosure and the Diffusion of Information Security Attacks," *Information Systems Research* (26:3), pp. 565-584.

Mohr, J. W., and White, H. C. 2008. "How to Model an Institution," *Theory and Society* (37:5), pp. 485-512.

Mukherjee, D. P., Das, S., and Banik, S. D. 2007. "Trends of Consanguineous Marriages in a Sunni Muslim Population of West Bengal, India," *Anthropologischer Anzeiger* (65:3), pp. 253-262.

Nagin, D. S. 1999. "Analyzing Developmental Trajectories: A Semiparametric, Group-Based Approach," *Psychological Methods* (4:2), pp. 139-157.

Okazaki, S., and Mendez, F. 2013. "Perceived Ubiquity in Mobile Services," *Journal of Interactive Marketing* (27:2), pp. 98-111.

Overby, E., and Forman, C. 2015. "The Effect of Electronic Commerce on Geographic Purchasing Patterns and Price Dispersion," *Management Science* (61:2), pp. 431-453.

Pandit, V. 2017. "Big Fat Indian Wedding Market Has Foreign 'Suitor' Zankyou Lining Up," in: *Business Line*. Ahmedabad: The Hindu.

Parker, G. G., and Alstyne, M. W. V. 2005. "Two-Sided Network Effects: A Theory of Information Product Design," *Management Science* (51:10), pp. 1494-1504.

Pascoe, J. 2000. "Using While Moving: Hci Issues in Fieldwork Environments," *ACM Transactions on Computer-Human Interaction* (7:3), p. 417.

Pierre-André Chiappori, Bernard Fortin, and Guy Lacroix. 2002. "Marriage Market, Divorce Legislation, and Household Labor Supply," *Journal of Political Economy* (110:1), pp. 37-72.
Podolny, J. M. 1993. "A Status-Based Model of Market Competition," *American Journal of Sociology* (98:4), pp. 829-872.
Podolny, J. M. 1994. "Market Uncertainty and the Social Character of Economic Exchange," *Administrative Science Quarterly* (39:3), pp. 458-483.
Polome, E. C. 1997. "From the Margins of the Hindu Marriage - Harlan,L, Coutright,Pb," *Journal of Indo-European Studies* (25:1-2), pp. 228-228.
Poston, D. L., and Glover, K. S. 2005. "Too Many Males: Marriage Market Implications of Gender Imbalances in China," *Genus* (61:2), pp. 119-140.
Raina, V. 2004. "Political Diversity, Common Purpose: Social Movements in India," *Inter-Asia Cultural Studies* (5:2), pp. 320-327.
Ramesh Bairy, T. S. 2010. *Being Brahmin, Being Modern : Exploring the Lives of Caste Today*. New Delhi: Routledge.
Ransbotham, S., Fichman, R. G., Gopal, R., and Gupta, A. 2016. "Special Section Introduction-Ubiquitous It and Digital Vulnerabilities," *Information Systems Research* (27:4), pp. 834-847.
Rochet, J.-C., and Tirole, J. 2003. "Platform Competition in Two-Sided Markets," *Journal of the European Economic Association* (1:4), pp. 990-1029.
Rochet, J.-C., and Tirole, J. 2006. "Two-Sided Markets: A Progress Report," *The RAND Journal of Economics* (37:3), pp. 645-667.
Rosenfeld, M. J. 2008. "Racial, Educational and Religious Endogamy in the United States: A Comparative Historical Perspective," *Social Forces* (87:1), pp. 1-31.
Roth, A. E. 2018. "Marketplaces, Markets, and Market Design," *American Economic Review* (108:7), pp. 1609-1658.
Roth, A. E., and Sotomayor, M. A. O. 1990. *Two-Sided Matching : A Study in Game-Theoretic Modeling and Analysis*. Cambridge [England] ; New York: Cambridge University Press.
Rudder, C. 2014. *Dataclysm: Love, Sex, Race, and Identity--What Our Online Lives Tell Us About Our Offline Selves*. Crown.
Sauder, M., Lynn, F., and Podolny, J. M. 2012. "Status: Insights from Organizational Sociology," *Annual Review of Sociology* (38:1), pp. 267-283.
Seth, N. 2011. "Online Matrimonial Sites and the Transformation of Arranged Marriage in India," in *Virtual Communities: Concepts, Methodologies, Tools and Applications*. IGI Global, pp. 951-974.
Seymour, S. C. 1999. *Women, Family, and Child Care in India : A World in Transition*. Cambridge, UK ; New York, NY, USA: Cambridge University Press.
Shimer, R., and Smith, L. 2001. "Matching, Search, and Heterogeneity," *The BE Journal of Macroeconomics* (1:1).
Shukla, S., and Kapadia, S. 2007. "Transition in Marriage Partner Selection Process:Are Matrimonial Advertisements an Indication?," *Psychology and Developing Societies* (19:1), pp. 37-54.
Slater, D. 2013. *Love in the Time of Algorithms : What Technology Does to Meeting and Mating*. New York: Current.

Srinivas, M. N. 1978. *The Changing Position of Indian Women*. Delhi: Oxford University Press.

Talboom-Kamp, E. P., Verdijk, N. A., Harmans, L. M., Numans, M. E., and Chavannes, N. H. 2016. "An Ehealth Platform to Manage Chronic Disease in Primary Care: An Innovative Approach," *Interactive journal of medical research* (5:1), pp. e5-e5.

Tarafdar, M., Gupta, A., and Turel, O. 2013. "The Dark Side of Information Technology Use," *Information Systems Journal* (23:3), pp. 269-275.

Tarafdar, M., Tu, Q., Ragu-Nathan, B. S., and Ragu-Nathan, T. S. 2007. "The Impact of Technostress on Role Stress and Productivity," *Journal of Management Information Systems* (24:1), pp. 301-328.

Thornton, A., Dorius, S. F., and Swindle, J. 2015. "Developmental Idealism: The Cultural Foundations of World Development Programs," *Sociology of development (Oakland, Calif.)* (1:2), pp. 277-320.

Titzmann, F.-M. 2013. "Changing Patterns of Matchmaking: The Indian Online Matrimonial Market," *Asian Journal of Women's Studies* (19:4), pp. 64-94.

Titzmann, F.-M. 2015. "Matchmaking 2.0. The Representation of Women and Female Agency in the Indian Online Matrimonial Market," *Internationales Asienforum* (42:3-4), pp. 239-256.

Watson, R. T., Pitt, L. F., Berthon, P., and Zinkhan, G. M. 2002. "U-Commerce: Expanding the Universe of Marketing," *Journal of the Academy of Marketing Science* (30:4), pp. 333-347.

Wellen, R. 2013. "Open Access, Megajournals, and Moocs:On the Political Economy of Academic Unbundling," *SAGE Open* (3:4), p. 2158244013507271.

Whitty, M., and Gavin, J. 2001. "Age/Sex/Location: Uncovering the Social Cues in the Development of Online Relationships," *CyberPsychology & Behavior* (4:5), pp. 623-630.

Whitty, M. T., and Carr, A. 2006. *Cyberspace Romance : The Psychology of Online Relationships*. Basingstoke [England] ; New York: Palgrave Macmillan.

Xu, J., Forman, C., Kim, J. B., and Van Ittersum, K. 2014. "News Media Channels: Complements or Substitutes? Evidence from Mobile Phone Usage," *Journal of Marketing* (78:4), pp. 97-112.

Yeung, W.-J. J., Sonalde Desai, and Jones, G. W. 2018. "Families in Southeast and South Asia," *Annual Review of Sociology* (44:1), pp. 469-495.

Yu, J. 2019. "Essays in Quantitative Marketing." Stanford University.

Zaidi, A. U., and Shuraydi, M. 2002. "Perceptions of Arranged Marriages by Young Pakistani Muslim Women Living in a Western Society," *Journal of Comparative Family Studies* (33:4), pp. 495-514.