What Happens When Dating Goes Online? Evidence from U.S. Marriage Markets and Health Outcomes

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Abstract

This paper studies how online dating platforms have impacted marital outcomes, assortative matching, and sexually transmitted disease (STD) rates in the United States. We construct county-level measures of online dating usage using data from website-based platforms (2002–2013) and mobile app-based platforms (2017–2023). Leveraging county-level variation and an instrumental variable strategy, we show in the desktop era, a 1% increase in online dating sessions raises divorce rates by 0.50%, while in the mobile era, a 1% increase in online dating activity lowers marriage and divorce rates by 0.40% and 0.33%, respectively. We also document shifts in assortative matching. Desktop sites reduce sorting along education and employment dimensions, whereas mobile sites reduce sorting by employment, but increase sorting by race. Across both eras, we find no evidence that greater online dating usage increases average STD rates. Average effects are negative or statistically insignificant, but are positive for some subpopulations. We develop a search and matching model where technological changes impact search costs, market size, and market noise can explain our empirical findings.

Keywords: Dating, apps, marriage, divorce, assortative matching, online platforms, sexually transmitted diseases

JEL codes: J1, M1, M2

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1 Introduction

Online dating platforms dramatically changed how people search for romantic partners. By 2013, meeting via online dating platforms had surpassed meeting through friends as the most common way for couples to meet (Rosenfeld et al., 2019), and the platforms themselves emerged as some of the largest and most profitable tech companies over the past two decades. Match Group, the parent company of popular dating websites and apps including Match.com, OKCupid, Tinder and Hinge, generates billions of dollars in annual revenue (Match Group, 2025a). Similarly, Bumble, another popular dating application (app), was valued at 13 billion USD during its 2021 IPO (Financial Times, 2021). Similar to other digital platform markets, online dating potentially improves the efficiency of finding romantic partners through algorithmic matching and through the availability of a larger pool of potential partners. However, several media outlets raised concerns that they also facilitate infidelity (Klein, 2022), increase sexually transmitted disease (STD) rates (NBC News, 2018), encourage sexual harassment (Anderson et al., 2020), and generally prevent successful long-term partnership formation (Stockel-Walker, 2019).

Despite the widespread adoption of online dating platforms, there is a lack of empirical research using field data to examine whether and how the digitization of dating has impacted relationship formation and health outcomes. This paper aims to estimate how the usage of online dating platforms in the United States impacts relationship outcomes (e.g., marriage and divorce rates, and assortative matching) as well as the prevalence of STDs. We focus on two distinct time periods, capturing two generations of platforms and technologies: (1) desktop website-based dating platform usage from 2002 to 2013 (using Comscore data), and (2) mobile app-based dating platform usage from 2017 to 2023 (using data from Tapestri and Dewey). The two generations of platforms had fundamentally different technologies, with desktop platforms focusing on extensive surveys and long form profiles, and mobile apps focusing on location-based matching and image-based "swiping."

We first develop a simple search-and-matching model, following Halaburda et al. (2018) and Fong (2024), to explain how technological changes can shape dating markets. Drawing on the digitization literature (Goldfarb and Tucker, 2019), key model parameters are (i) pool size (the number of users in the market), (ii) search/inspection costs, and (iii) the strength of the signal of match quality, which captures the information available in dating profiles. Simulations show that lowering search costs raises the expected value of participation but reduces match rates conditional on participating, as users continue searching. A larger pool size has non-monotonic effects on participation; moving from a small baseline, a larger pool of potential matches increases matching opportunities and incentives to participate in the market and search. However, larger pool sizes generate choice overload and greater competition, reducing participation. Match probabilities monotonically fall with additional users. Less noise lowers search value and also has negative effects on match rates. Relative to offline markets, desktop platforms increased pool size and reduced search costs and noise; relative to desktop platforms, mobile apps further expanded pool size and lowered search costs, but likely produced noisier match-quality signals. Overall, the model's predictions of the effects are ambiguous, but give us guidance for interpreting empirical findings.

We then turn to empirically estimating the effects of online dating platform usage on: (i) sexually transmitted disease prevalence, capturing some potentially negative aspects of online dating; (ii) marital relationship outcomes, i.e., marriage and divorce rates, capturing the effects of online dating on relationship stability; and (iii) measures of assortative matching, such as based on education and race (e.g., share of couples of the same race). Our outcome data are at the county-year level, so we aggregate our key usage variable — number of online dating sessions — to that level. Although we have individual × website or app -level data on platform usage, we aggregate all dating website and apps into one "online dating" category due to the extensive multi-homing across platforms present in both datasets.

A key challenge in identifying the causal effect of online dating on outcomes of interest is the endogeneity present in online dating platform use. A key source of this endogeneity is correlated unobservables. For example, a high proportion of single people in a county can contribute to both high online dating usage and low marriage rates. Online dating usage can also correlate with unobserved time-varying shocks (e.g., internet usage) that impact outcomes. To identify causal effects, we include county and year fixed effects, as well as controls such as internet and streaming usage and demographic characteristics (e.g., population size, female share of the population). More importantly, we adopt an instrumental variables approach to deal with the remaining unobserved time-varying shocks. We instrument online dating usage in a given county with *online dating usage in nearby counties* within a doughnut-shaped region – counties that are more than 20 km and less than 100 km away.[1] The two key identifying assumptions for this instrument are: (1) network effects — as more users join dating platforms in neighbouring areas, platform value increases, attracting additional users in the focal county. This is likely true since dating platforms allow users to view profiles within a radius of up to 160km (100 miles), and (2) the unobserved shocks influencing online dating usage and our outcomes propagate more slowly than the network effects of online dating; e.g., the spread of STDs across counties is likely slower than the diffusion of online dating. Put otherwise, there are no spillovers in outcomes across counties except through the dating platform usage channel. This is more likely as counties are farther apart, justifying our "doughnut" strategy. To verify that our estimates are driven by relevant instruments rather than spurious spatial correlation, we conduct a placebo test. Instead of using nearby counties to construct the instrument, we assign each county an instrument drawn from a randomly selected county, which should have no explanatory power. Consistent with this expectation, the placebo IVs are not relevant, and the IV estimates from the placebo test are not statistically significant.

Our IV estimates show substantial heterogeneity of effects between the desktop and mobile eras. For relationship outcomes, we find that higher levels of desktop usage lead to higher divorce rates in the subsequent year, and a null effect on new marriages. On average, a 1% increase in desktop dating sessions increases the number of divorces by 0.5%. By contrast, mobile app usage reduces both marriage and divorce rates. A 1% increase in mobile dating app sessions reduces the number of marriages and divorces by 0.40% and 0.33%, respectively. For STD outcomes, our analysis does not broadly support the commonly claimed link between online dating and STD transmission (e.g., Matthews-King, 2019). Our estimates suggest that in the average county, a 1% increase in desktop dating platform sessions reduced chlamydia, syphilis, and gonorrhea rates by 0.1%, 0.4% and 0.44%, respectively. In the mobile app period, we find a 1% increase in the dating app sessions in the average county reduces gonorrhea rates by 0.84%, with no significant changes in chlamydia

[1] We carry out robustness checks with different distances.

or syphilis rates.

We then explore effect heterogeneity based on the marketed 'intent' of the dating platform ("relationship minded" vs. "casual") as well as the sexual orientation of the users and their age. These dimensions capture how different types of dating platforms can generate different outcomes and how user groups can respond differentially to technological improvements in search and matching. For example, younger users may be quicker to adopt new dating platforms, or LGBTQ+ users may experience a greater reduction in search frictions. We show that the divorce effects in the desktop era are primarily driven by older users, while for younger users, dating site usage increases marriage rates without increasing divorce rates. In the mobile era, we find that increased usage of LGBTQ+ oriented apps increases marriage rates, but otherwise, dating app usage reduces marriages and divorces for all subgroups. For STD outcomes, we show that in the desktop era, only usage by older users increases STD rates, whereas in the mobile era, positive effects are driven by the usage of younger users and LGBTQ+ oriented platforms.

Through the lens of our model, in the desktop era, platforms expanded the participant pool while reducing search costs and noise, which drove users to become more selective (i.e., matching probabilities fall, but conditional on matching, expected match values rise). This mechanism can simultaneously explain stable marriage rates, higher divorce rates, and lower STD rates, as better screening reduced mismatches while the improved outside options encouraged some individuals, especially older users, to exit existing relationships. In contrast, the mobile era combines much lower search costs with substantially noisier signals, shifting the market toward high participation but low match rates and potentially additional "mis-matches." This combination could reduce the number of offline interactions, which could be why we observe lower STD rates, fewer marriages, and fewer divorces. The exceptions in the mobile era are younger users and LGBTQ+ platform usage; there, dating platform usage likely generated particularly large drops in search costs, which likely substantially increased participation, overwhelming the decrease in match probabilities, and driving additional offline interactions and STD rate increases.

We also study how dating platforms affect sorting and assortative matching outcomes. We find that the penetration of mobile dating apps increases the share of same-race couples. For the average county, a 1% increase in mobile dating app sessions increases the percent of couples who are of the same race by 0.064%. This contradicts previous work (Ortega and Hergovich, 2017) and dating app commissioned surveys (Tinder, 2018). We also find that in regions with higher platform use, marital sorting patterns defy the macro trends of increasing sorting by education and labor market participation (Greenwood et al., 2014; Eika et al., 2019). During the desktop period, the share of couples with similar education levels decline, with more couples where the wife is more educated than the husband. At the same time, in both periods, the share of dual-earner couples decline, driven by an increase in couples where the wife is more likely to stay out of the labor market. All in all, these results suggest that the rise of online platforms altered the composition of couples formed (and continued to remain married) but had limited impact on the traditional gender roles among couples.

Overall, our study makes several contributions to the literature on the effects of digital platforms and the literature on partnership formation. Several studies have examined the relationship between online dating and relationship and health outcomes. Cacioppo et al. (2013) found that couples who met online were more likely to have a higher level of marital satisfaction than those who met offline. Rosenfeld and Thomas (2012) found that individuals in thin markets (people who are gay, lesbian, or are middle-aged) are especially likely to meet their partners online. On the other hand, online dating use is associated with higher levels of anxiety and depression (Holtzhausen et al., 2020), unsafe sex (Choi et al., 2016), and STDs (Cabecinha et al., 2017).

The majority of the literature linking online dating to downstream outcomes is correlational in nature, with two notable exceptions. Using the staggered entry of Craigslist across cities in Florida, Greenwood and Agarwal (2016) found that the introduction of Craigslist increased HIV incidence, particularly among historically at-risk populations. As well, the closest paper to ours is that by Büyükeren et al. (2023), who examine the impact of Tinder on dating behavior, relationships, and the health of college students. By leveraging Tinder's early-stage promotional activity, which focused on Greek life on college campuses, the authors found that Tinder increased the rate of sexual activity, sexual assault, and STDs among students involved in Greek life. However, they found no evidence that Tinder impacted relationship quality.

The current study contributes to this line of research by examining the effect of online dating on various outcomes, including long-term relationships/marriage. Moreover, our two data sources cover two generations of online dating technologies over a period of nearly 20 years. Compared to Büyükeren et al. (2023), we focus on a wider set of online dating platforms rather than just Tinder and on a broader population than only college students. Tinder users may be younger than the users of other apps and have different motivations for using online dating apps compared to other population groups. As such, our paper provides a higher-level perspective on the evolution of the effects of online dating activity in the US. We find similar results to Büyükeren et al. (2023) for younger users on mobile platforms, but also contrasting effects for older users, and a more consistently negative effect for desktop-based platforms.

Our paper also relates to the literature in economics and marketing studying various aspects of online dating, including mate preferences and matching efficiency (Hitsch et al., 2010a,b), search (Bruch et al., 2016), how the number of potential partners can impact matching outcomes (Fong, 2024; Halaburda et al., 2018), and its impact on assortative matching (Lee, 2016). With the exception of Lee (2016), these papers typically focus on online dating activity. We contribute to this literature by studying how online dating impacts downstream outcomes. Unlike Lee (2016), we also examine the effect of online dating on relationship incidence and health outcomes, rather than the attributes of relationships that are formed.

More broadly, our paper contributes to the literature on evaluating the effectiveness of peer-to-peer platforms, and the role of platforms in disintermediating or transforming various economic and social activities. Researchers have extensively studied the effects of entry of ride-sharing apps such as Uber and Lyft, for example in Burtch et al. (2018), Chen et al. (2019) and Shin et al. (2023). The effects of AirBnB on the accommodations market has been evaluated in Farronato and Fradkin (2022). Cullen and Farronato (2021) studies the effectiveness of TaskRabbit in disintermediating the market for home services, and Farronato et al. (2023) study how peer-to-peer platform mergers affect matching efficiency in the dog-sitting market. To the best of our knowledge, no similar comprehensive studies exist on online dating platforms. Moreover, to the best of our understanding, there are no papers that compare the market effects of *two generations* of platforms (desktop and mobile) - in that sense, our paper has a uniquely long-term perspective on the effects of digitization.

While our empirical approach has several limitations - our IV approach relies on strong assumptions, we cannot pin down the exact channels through which online dating platform usage affects outcomes, and we cannot draw welfare implications from our findings - our paper is a first step in examining how online dating platforms have impacted relationship and health outcomes.

The rest of the paper is organized as follows. In Section 2, we provide a brief background on dating platforms. In Section 3, we develop a conceptual framework regarding the expected outcomes. Section 4 describes our empirical methodology and data sources, with Section 5 discussing the findings regarding marital and health outcomes along with the heterogeneity in these findings. We provide several robustness checks in Section 6. Finally, in Section 7, we conclude.

2 Background

While dating platforms that match singles have existed for a very long time, including newspaper classified ads, telephone message services, and video dating services, these earlier services were over time supplanted by online dating services. The first generation of online dating services are website-based platforms that emerged between the mid 1990s and the early 2000s. Early popular entrants include Match.com and eHarmony, and later entrants include Plenty of Fish and OKCupid. These services have different monetization strategies: Match.com is a subscription based service, requiring users to pay a monthly fee for contacting additional potential matches. Plenty of Fish and OKCupid are free and ad-supported.

Generally, the main value proposition of these services is their matching algorithms, which require a large amount of user data. The users of these services were often required to answer numerous survey questions about their characteristics and preferences. For example, eHarmony utilized a 258 question questionnaire to construct user profiles and suggest matches (Tugend 2009). OKCupid relied on users answering thousands of questions about their preferences and their ideal match (Slater 2013, p.61). Potential matches offered on the website were often derived from stated preferences, browsing behavior,[2] or a combination of the two.

In the 1990s and early 2000s, the usage of online dating platforms was accompanied by some social stigma, which declined over time. In 2005, 29% of Pew survey respondents thought that online daters are "desperate," but this number declined to 21% in 2012 (Madden and Lenhart, 2006; Smith and Duggan, 2013). In addition, popular concerns about online dating platforms included the threat of users accidentally or purposefully misrepresenting themselves. A Scientific American article from 2007 described online dating as "deception at light speed" (Epstein 2007). Nonetheless, relative to in-person dating, online dating platforms were praised by users as providing them with a large pool of daters (Madden and Lenhart, 2006) and a method for ex-ante filtering, producing higher quality potential matches, a "standard... higher than you would find in an average pub" (Gold, 2009).

Many of these dating websites focused on helping users find long term relationships. eHarmony was founded by a psychologist and Christian theologian, and eHarmony's promotional materials emphasized that their matching algorithm was "proven to predict the success of long-term relationships" (Slater, 2013). Match.com similarly advertises itself as a "serious dating site" for "serious singles" (Match Group 2025b).

[2] Users could also often search the websites' databases based on criteria (age, height, etc).

The second generation of online dating services are app-based platforms that emerged in the late 2000s and early 2010s. Examples include Grindr, Tinder, Hinge and Bumble. Usage costs and match frictions were substantially lower on this set of apps (Pierce 2016). Users could make profiles quickly without having to take long questionnaires about their preferences, and pictures played an important role. The primary method of choosing matches is "swiping," where a user sees one profile at a time, and they choose to swipe right to like the profile or swipe left. Swiping brings up another profile. Typically, conversations can only be started by a user who expresses interest in another.

The reduced frictions from this new mechanism facilitated an even larger set of potential matches and faster matching. However, a number of popular press articles in the mid 2010s criticized mobile dating apps, suggesting that they "ruined online dating" (Berger 2016). Critics suggested that the "instant gratification" coming from gamification and the focus on pictures rather than other profile features was facilitating short-term matches ("hookups") at the expense of longer-term stable relationships (Sales 2015). The focus on appearance on these apps was also suggested to be bad for mental health (Bearne 2018). However, mobile dating apps disputed these stories. According to Tinder, the majority of users on the app are looking for "meaningful connections" rather than "hookups" (Bonos 2015). Tinder subsequently redesigned the app interface to make user information such as their jobs or their schooling more visible on their profiles (Swales 2015). The popular mobile app Hinge markets itself as the "dating app designed to be deleted" - i.e., designed to facilitate long-term romantic relationships. Hinge's Chief Product Officer stated that "if you are not interested to actually find somebody, if you are wanting to stay on dating apps, then you're going to quickly learn that Hinge is not the best app for you" (Carman 2019).

Another difference between the two generations of dating platforms is user demographics, in part because app-based platforms require smartphones, their users tend to be younger.A 2023 survey by the Pew Research Center documented that the largest age groups for Tinder, Bumble, and Hinge is 18-24, while the largest age group for Match, OkCupid, and eharmony are 50-64, 30-49, and 65+, respectively (McClain and Gelles-Watnick, 2023). We find similar differences in user demographics in our two datasets, which we describe in Section 4.2.

3 Conceptual Framework and Mechanisms

We develop a stylized model of search and matching to help conceptualize the effects of online platforms on the dating market and provide guidance on interpreting our empirical findings. We describe the model in detail in Appendix B, and present an overview of the key forces and comparative statics in this section.

In the model, individuals engage in a sequential search process. An individual i inspects another individual j's profile and pays a search cost c^s, which represents the effort involved in observing j's attributes. Upon viewing j, i may decide he likes j, which yields an additional cost c^l. This cost represents the effort cost of sending j a message or a static way to present a limit on the number of likes that online dating users can send.[3] If individuals i and j both like one another, this forms a match.[4] The quality of this match

[3]Popular online dating apps, such as Tinder and Hinge, often have such limits.

[4]On platforms that do not have a "like" feature, the messaging system serves a comparable role.

depends on a random horizontal match value, which comes from a Gumbel distribution with variance σ. The horizontal match value is observed by i only after a match (e.g., after messaging). If i and j match, i can end their search session and receives the match value. Otherwise, i can continue searching. Individuals also have an outside option to not like anyone and stop the search. There is a total of N individuals on each side of the market.[5] Following Halaburda et al. (2018) and Fong (2024), we introduce a choice overload parameter that changes match values as a function of overall market size (i.e., the number of potential matches). A larger N also implies more competitors, which reduces the chances that a potential match sees i's profile.

The key outcomes of this model for the purpose of our empirical exercise are (i) *average match probability*, which corresponds to the likelihood that users i and j like one another on the platform, and (ii) *the expected value* users receive from searching (i.e., inspecting one profile), which roughly approximates the expected match value net of search costs.

As per anecdotal information about the platforms themselves, and as per the existing literature on digitization and online platforms (Goldfarb and Tucker, 2019), we consider that online dating platforms can have three effects on the dating market as parameterized by our model:

1. *Reduction in marginal search costs:* compared to the offline world, it is easier and faster to inspect a potential dating partner on an online platform than in the offline world. Moreover, dating platform designs evolved to further reduce these frictions, i.e., the swipe mechanism on mobile dating platforms.

2. *Increase in the number of potential matches:* as search costs fall and as platforms aggregate information about candidates (see analogously Brynjolfsson et al., 2003), the set of potential matches for an individual should be larger on online platforms than offline world, and larger on mobile platforms compared to desktop platforms.[6]

3. *Varying levels of noise in candidate inspection:* The signal strength (as measured by the signal-to-noise ratio) that individuals observe when inspecting potential matches should differ between online and offline search, and across desktop and mobile platforms. Desktop platforms were designed to aggregate information about candidates' personality, lifestyle, preferences and characteristics, accompanied by lengthy surveys (Piskorski et al., 2008) and filters to improve the screening process. We interpret this as an improvement in signal quality relative to offline dating. By comparison, mobile dating platforms generally provide more limited information compared to the desktop platforms. They are also not known to utilize lengthy surveys to enroll participants. In that sense, we conjecture that the quality of the signal is worse on mobile platforms relative to desktop-based platforms.

The model has several predictions about the potential effects of such changes. We present comparative statics related to key parameters capturing these features in the model in Table 1 below. Specifically, we present how changes in the number of users, in marginal search costs, and in the noise in candidate inspection impact the probability of making a match (i.e., user "a" liking user "b" and user "b" liking user "a"), as well

[5] This is an assumption we make for simplicity, unlike Fong (2024), which studies the effects of unequal changes on the two sides of the market.

[6] As discussed earlier, the share of individuals in the U.S. who mention having used an online dating platform has increased over time.

as changes in the expected value consumers receive from searching, or in other words, using the platform. For ease of exposition, we omit specific parameter values and focus on the main directional effects. Additional figures, with detailed explanation of parameter values used for simulations, are provided in Appendix B.

Table 1: Mechanisms and Expected Outcomes

	Effect on Value from Search	Effect on Match Rates
N Users (↑)	↑, then ↓	↓
Search cost (↓)	↑	↓
Noise (↓)	↓	↓

1. Increase in market size: An increase in the market size results in an increase and then decrease in the expected value of searching and a monotonic reduction in the probability of matching. This occurs because, holding everything else constant, a small increase in pool size increases the opportunities to match, making the platform more attractive. But as pool size continues to grow, users have to sort through more irrelevant profiles (choice overload). Also, since we assume the market is balanced, an increase in market size should also increase competition, meaning each user faces more rivals when pursuing any given potential match. As a result, their expected value from searching and liking drops with a large increase in the number of users, and an individual is less likely to match with another user.[7]

2. Reduction in marginal search costs: The effects of search costs in this model are straightforward. As search costs fall, the value of investing more in additional searches increases, and the probability of "liking" a given user falls. At the same time, when inspecting potential partners is cheaper, users overall receive higher expected value from using the platform. However, match rates fall — with lower search costs, users have higher reservation utilities, and a stronger incentive to continue searching.

3. Change in noise: In our model, changes in noise change users' expectations about their matches. With more noise, users may receive a better or worse match. Our simulations suggest that greater noise increases the expected value of searching on the platform and match probability because in noisy environments, users are more likely to take chances on liking potential candidates in the hope of drawing a high match value.

With these forces in mind, we consider two changes in matching technologies: the transition from an offline dating market to a desktop dating market, and the transition from a desktop dating market to a mobile dating market. We discuss these two transitions below.

The transition from an offline world (a high search cost, high noise, and low pool size setting) to a desktop online dating market should reduce search costs, reduce noise, and increase the number of potential partners (and competition).

[7] This is consistent with empirical evidence. Fong (2024) shows that online dating users are less likely to use the platform when informed of larger market sizes.

The increase in the pool size and reduction in noise both reduce the expected benefit from using the platform. With lower noise, there are fewer positive "surprises" that come from additional search as compared to the offline dating market. Moreover, increased pool size increases one's competition on the same side of the market and, if the growth in the user base is sufficient, reduces expected match rate and expected match values, and disincentivizes users from searching. However, the reduction in search costs pushes against that — as users incur lower costs from search, their value from searching will increase. This increase may overwhelm the other two effects and lead to additional searching. The increase in the number of users and reduction in search costs also reduce match probabilities. There are fewer users liking one another because of the higher option value of skipping to the next user. This occurs even as more people search.

In terms of offline outcomes, this technological change can either raise or lower marriage rates, depending on whether the improved matching or the improved option value (i.e., the pressure to continue searching and like fewer potential matches while holding out for a better option) dominates. Divorce rates can also decrease or increase correspondingly, depending on the extent to which low quality matches are screened out and whether users who were previously in committed relationships increase their dating market activity and search more. Finally, STD rates increase or decrease depending on whether the additional searching and lower noise filters out risky partners, as the lower search cost reduces the number of in-person encounters.

A transition from a desktop dating market to a mobile dating market should increase noise, further reduce search costs and increase market size. Holding all else constant, the latter two of these indicators point towards reducing match probabilities, and while an increase in noise would predict an increase in match probabilities as users may like other candidates in the hope of being positively surprised in a highly uncertain environment.

Despite the overall ambiguous predictions on offline outcomes, this model gives us some guidance as to which forces are likely driving the observed changes in outcomes that we present later.

4 Empirical Analysis

4.1 Data

4.1.1 Online Dating Usage Data

We gather data relating to the usage of dating platforms from three data sources that cover desktop and mobile dating usage: Comscore, Tapestri, and Dewey. We provide details below.

Desktop Data (Comscore) Comscore is a company that runs panels to gather online browsing data from households in the U.S. The data are accessed through Wharton Research Data Services and include information about the online desktop browsing activity of between 45,000-100,000 households each year (Petrova et al., 2021) from 2002 to 2021 (except the years 2003 and 2005). We can track which domains are visited, the date and timestamp of each visit, the number of pages viewed, organized in sequence of sessions for each household. There is limited demographic data for the sample, including age, race, and educational attainment of the head of household, whether a child is present and number of people in the household,

household income and whether the household has broadband access. Since demographic data provides only zip codes, we use crosswalks from the US Department of Housing and Urban Development to convert the data to county-year level. After merging with the crosswalk using the zip codes, we have data on 3,215 counties across all years, nearly all 3,234 U.S. counties. We drop county-years with less than 2 households. For the remainder of this paper, we use "households," "user," and "person" synonymously.

Mobile Data (Tapestri) Because mobile online dating app usage became popular in the 2010s, we also obtain mobile app usage data from the firm Tapestri for the years 2017-2022.[8] Tapestri offers individuals small financial incentives in exchange for joining their app and sharing their mobile app consumption data. The app data allows us to observe, conditional on an individual consenting to sharing their location and usage information, the incidences of opening an app, coordinates of the device, dates of opening an app, and for a subset of individuals in the data, their demographic characteristics—age range and gender. Therefore, the data set allows us to observe various locations and consumption incidences of individuals. Our processing of the data for location approximation is detailed in Appendix C.2.

There are a few limitations of this data set. First, some devices are observed only for a short amount of time, such as one day. Therefore, we keep only devices that are observed in the data for at least 30 days. This leaves us with data from over 23 million unique devices. Second, unlike the Comscore dataset, we cannot observe the times individuals spend and the number of pages they look at on the dating apps.[9] Third, these data may not be representative of the general population. As described above, individuals register with Tapestri to receive payment in exchange for sharing their data. This sample may be younger and may have a lower income relative to the general population.

A key limitation of this dataset is that mobile apps opt in to allowing Tapestri to observe app usage. Starting in 2019, several popular dating apps, such as Tinder and Bumble, are no longer observed in the Tapestri data. This greatly restricts our ability to observe online dating usage. Therefore, we only use Tapestri data from the years when the most popular apps are observed in the data and observed usage levels are consistent with external sources — 2017 and 2018. We supplement the mobile data with data from Dewey, described below.

Mobile Data (Dewey) We use mobile app data from Dewey, which is collected from an opt-in consumer panel of Android smartphone users. We observe when and where a panelist opens a mobile app, which app they open, and the duration that the app is visible on the screen. For each panelist, we observe their gender, age, and ethnicity. These data include mobile app usage from January 2019 to December 2023. Participants were recruited for this panel via mobile ad campaigns and are paid monthly for their data. Therefore, this panel might suffer from similar limitations as Tapestri, in that it may not be representative of the general population. In addition, because some panelists drop out of the dataset, we retain only panelists who are observed in the data for at least seven days.[10] This leaves us with 405,604 unique panelists. Processing of

[8] 2017 was the earliest available year we could find mobile app data at the individual level.

[9] There is no clear analog to "Pages" for most mobile apps, and we also cannot observe when an individual closes the app.

[10] We use a different threshold from Tapestri because the Tapestri data has significantly more devices. Using a 30 day threshold for Tapestri is a more conservative approach, while allowing us to retain a large enough sample size.

the Dewey data are detailed in Appendix C.1.

In summary, for the mobile period, we combine two data sources, Tapestri and Dewey, so that we observe mobile dating app usage from 2017 until 2023.

Dating Platform Detection and Classification Although the most popular dating platforms are well known (e.g., Match.com, eHarmony, PlentyofFish, Tinder, Bumble), there are numerous other platforms that are less known but are popular enough to matter for the purpose of our exercise. For the Comscore data, there is no pre-defined classification of the domains into a "dating" category. As a result, we need to identify dating platforms. We do so using Crunchbase and Similarweb, which contain comprehensive lists of online dating websites, applications and start-ups. Additional details about this classification procedure is provided in Appendix C.3. In the Tapestri and Dewey data, dating apps are classified as such in the Apple and Google app stores.

Usage Measure Our data sources allow us to create a metric of penetration of online dating platforms to capture how widely an online dating service was used in a local market. Moreover, we aim to create a measure that not only captures the intensity of usage, but also is consistently meaningful and comparable across data sets.

For the desktop data, we quantify the average number of online sessions that include a visit to an online dating platform for each individual (household). We do so by calculating the number of sessions with at least one visit to a dating platform for each individual, and then taking the average over all individuals in our data in a county each year.

For mobile data, recall that we observe only when the individual opens the app. Therefore, our measure of usage intensity for the mobile data is the number of times that an individual opens a dating app each year, averaged over all individuals in the county.[11] This *mean sessions* dating penetration metric is derived for county c and year y. Other research has used similar metrics for usage. For example, Levy (2021) measures news consumption by the number of times an individual visits a news site.

We provide descriptive statistics and figures about this metric in Section 4.2, and in more detail in Appendix A.1 for the desktop data and A.2 for the mobile data. A notable difference between the Tapestri and Dewey data is that the Dewey data logs significantly more activity than Tapestri. For example, the mean dating app sessions range from 20 to 60 in the Tapestri data, while it ranges from 170 to 270 in the Dewey data (Tables A.3 and A.4 in the appendix). This may be due to differences in panel participants and data tracking technology, in addition to inherent population-wide trends in app usage. In our analysis, we address this with year fixed effects, which controls for average year (and dataset) level differences.

4.1.2 Marital Outcomes Data

Each state maintains their own vital records related to marriages and divorces. We manually collected county-level vital records from each state and collated them for county-level analysis. This dataset includes

[11] Recall that in the mobile data, individuals vary in terms of how many days we observe their mobile app usage. Therefore, we also weight by the number of days we have for each individual.

the number of marriages and divorces per county per year.[12]

4.1.3 STD Rates Data

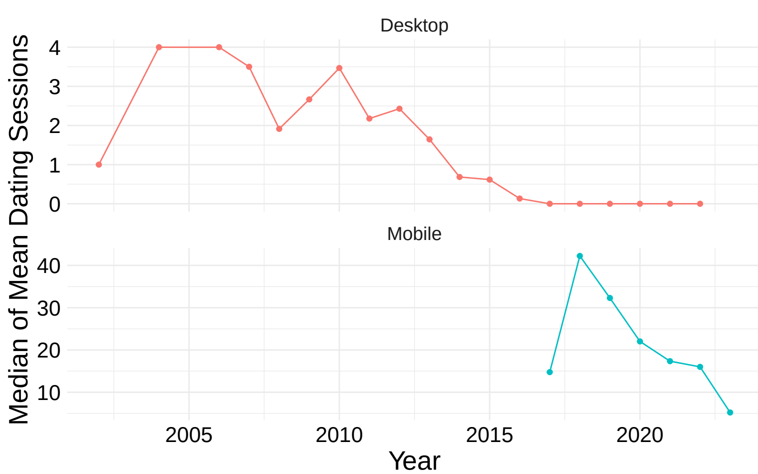
The National Center for HIV, Viral Hepatitis, STD, and TB Prevention at the Centers for Disease Control and Prevention maintain AtlasPlus, an online tool recording prevalence of sexually transmitted diseases at the county-level. Data is available for 3,234 counties. We obtained data at the county-year level from 2002-2024 on primary and secondary syphilis, chlamydia, and gonorrhea.

4.2 Descriptives

4.2.1 Online Dating Usage

In this section, we describe patterns in online dating usage. We report how online dating usage has changed over time in Figure 1 for both the desktop and mobile datasets. This figure yields two key takeaways. First, desktop online dating usage steeply declines after 2013. In fact, there are fewer visits to online dating websites in 2015 and onwards than in 2004, contradicting the upward trend in the popularity of online dating reported by other sources.[13] This decline in our data is likely attributed to the introduction of mobile dating apps, notably the launch of Tinder on iOS in 2012 and Android in 2013. Since Comscore data solely captures desktop usage, it fails to accurately measure online dating penetration beyond 2013. Consequently, our analysis using the desktop data focuses on data up to and including 2013.

Figure 1: Online Dating Site Penetration Over Time



Notes: This figure plots the median online dating sessions per county over years for the desktop and mobile datasets.

Second, mobile online dating differs from desktop online dating behavior. The mobile data show more

[12]We also have marital outcome data from the American Community Survey (ACS), which captures data from only the 574 more populated counties in the US. While the official ACS survey statistics provide us with some information regarding marital outcomes, these data are not sufficient as they only provide information for a select set of *more populated* counties. Therefore, we focus on the findings from the vital statistics data in the main paper.

[13]See Statista Research Department (2025).

online dating sessions than the desktop data. Mobile dating app usage peaks in 2019 and steadily declines. This is consistent with other sources reporting declining popularity in online dating apps.[14] This difference may be due to inherent differences in usage of mobile versus desktop online dating platforms, but it may also be due to differences in the desktop and mobile panels, or general differences in mobile versus desktop internet usage. Therefore, we conduct our analyses with the mobile and desktop data separately.

Table 2: Age Distribution of Online Dating Users: Mobile vs. Desktop

	Desktop		Mobile		
Age	Mean	SD	Mean	SD	Diff
18-20	0.02	0.13	0.07	0.26	0.054***
21-24	0.04	0.20	0.18	0.39	0.139***
25-29	0.07	0.25	0.27	0.44	0.198***
30-34	0.10	0.30	0.13	0.33	0.025***
35-39	0.10	0.30	0.10	0.30	0.004***
40-44	0.14	0.35	0.08	0.27	-0.063***
45-49	0.15	0.35	0.07	0.25	-0.080***
50-54	0.13	0.34	0.04	0.20	-0.087***
55-59	0.09	0.28	0.03	0.17	-0.058***
60-64	0.07	0.25	0.02	0.13	-0.048***
65+	0.10	0.30	0.02	0.13	-0.083***

Notes: ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Observations are at the individual-year level. The desktop data are from Comscore for the years 2002-2013 and the mobile data are from Tapestri for the years 2017-2018 and Dewey for the years 2019-2023. The number of observations in the desktop data is 651,880, and 5,190,698 in the mobile data.

In Table 2, we further explore the differences in usage between the mobile and desktop datasets. Namely, we observe differences in the ages of online dating users (i.e., individuals who have visited at least one online dating platform) between these two datasets. The table reports the difference in the proportion of online dating users in each age group between the desktop and mobile data. Consistent with surveys conducted by the Pew Research Center (Pew Research Center, 2013, 2016), those who use mobile dating apps tend to be younger than those who use desktop dating sites.

The types of mobile versus desktop online dating platforms may also differ in terms of who they are targeted towards. We consider two types of dating platforms: those that primarily cater to individuals seeking longer-term relationships (“relationship-minded”) and to LGBTQ+ users (“LGBTQ+”). We make these classifications using ChatGPT and manually verify a random portion of responses.[15] For instance, our procedure classifies sites like eHarmony and Coffee Meets Bagel to be relationship-minded, and Tinder and Bumble to not be relationship-minded (i.e., casual). Also, our method classifies Grindr as an LGBTQ+ platform, while Tinder is not classified as such, despite supporting LGBTQ+ matches.

Table 3 reports the usage intensity between the desktop and mobile panel for all dating platforms and by

[14]Examples include Battle (2024), and Roman (2025).

[15]Specifically, we asked ChatGPT for each dating site, “is [site] mainly targeted at people looking for serious relationships?”, “is [site] exclusively targeted at people looking for serious relationships?”, and “is [site] primarily targeted at people looking for serious relationships?”. If there are discrepancies across the responses, we manually classify the site ourselves. We take similar steps to define whether the site is targeted at those looking for LGBTQ+ partners. We describe the classificaiton steps in detail in Appendix C.3.

Table 3: Summary Statistics for Dating Platform Penetration in Desktop and Mobile Data

	Desktop		Mobile		
	Mean	SD	Mean	SD	Diff
Mean No. of Dating Sessions	7.24	25.32	75.65	214.09	69.221***
Mean No. of Relationship-Minded Sessions	2.77	11.37	49.87	149.44	47.500***
Mean No. of LGBTQ+ Sessions	2.31	9.36	0.44	8.58	-1.858***

Notes: ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Observations are at the county-year level. Fixed effects for county are included. The desktop data are from Comscore for the years 2002-2013 and the mobile data are from Tapestri for the years 2017 and 2018, and Dewey for the years 2019, 2022 and 2023. We exclude the years 2020 and 2021 from analysis to account for Covid-related disruptions. The desktop and mobile data have 27,533 and 14,604 observations, respectively.

dating platform type at the county-year level. Like in Figure 1, mobile dating usage is higher than desktop dating usage. The difference in dating penetration is more stark when looking at relationship-minded dating platform sessions; the proportion of relationship-minded dating sessions relative to overall dating sessions is higher for mobile compared to desktop. That is, relationship-minded platforms have greater proportionally usage in the mobile than the desktop periods. Conversely, exclusively LGBTQ+ dating platforms have lower usage in the mobile period. Again, we note that these differences in usage can also result from a combination of many factors, including the availability of dating platforms (i.e., a smaller proportion of dating platforms may be relationship-minded in later years), and differences in the individuals in the desktop and mobile panels. These differences should be kept in mind when interpreting our findings. Through the lens of our model from Section 3, the increased usage of mobile relative to desktop platforms is consistent with reduced search costs and increasing noise on those platforms relative to desktop platforms. As the costs of search falls and noise increases, there is a strong incentive by users to look through more profiles.[16]

Recall that in the Comscore data, we observe household income, age, education attainment, and race of the head of the household. Table A.9 in the appendix reports the demographic characteristics of the users, breaking down the usage also for relationship-minded and LGBTQ+ only platforms.[17] We see higher dating platform use for income groups under \$100K relative to those with income \$100K and above. We also see some small and partially significant differences between racial groups dating platform use, but we do not find significant differences in terms of education level. Similar patterns follow for the relationship-minded or LGBTQ+ dating sites. Male users are significantly more likely to use online dating apps than female users, as shown in Figure 2.[18]

4.2.2 Outcomes

In this section, we describe the data on marriages, divorces, and then STD rates. Figure 3 shows that the median marriage and divorce rates per county for the counties in our sample generally decline over time but increased in 2024.

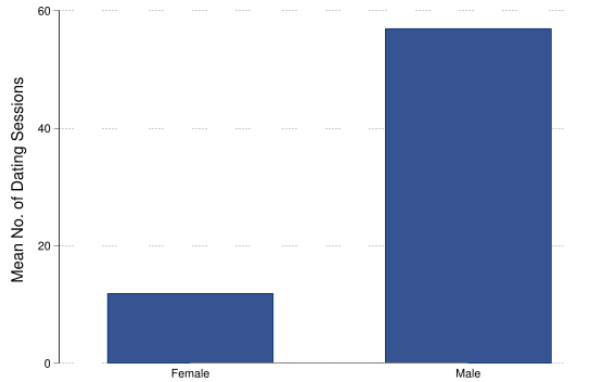
Figure 4 plots the median rates of the three diseases—chlamydia, syphilis and gonorrhea—per county over

[16]This is also consistent with the increase in activity on mobile dating platforms identified by Jung et al. (2019).

[17]For Comscore data, we focus on households with a size of one in calculating these demographics to ensure that the demographics reflect the person using the online dating platform.

[18]Recall that we only observe gender in the Tapestri data, so we cannot conduct the analogous analyses on demographics as in the desktop data.

Figure 2: Online Dating Usage by Gender (Mobile Data)



Notes: The source of the data is Tapestri for the years 2017 to 2018, and Dewey for the years 2019 to 2023.

time. All diseases have generally increased over time but exhibit different patterns. Chlamydia and gonorrhea rates have steadily increased until 2020, while syphilis has increased more consistently. Furthermore, syphilis has much lower case rates than the other two diseases. In addition to different time trends, the diseases can also affect different populations. For example, the age and sex distributions of chlamydia cases are different from that of gonorrhea due to differences in the prevalence of symptoms (National Academies of Sciences et al., 2021). Due to the differences in these diseases, we report the effects of online dating on each STD separately. We note that STD rates may not reflect the true prevalence of these diseases. The reported rates depend on disease surveillance, which was severely impacted during the COVID pandemic. The 2021 CDC STD surveillance report states "Disruptions in STI-related prevention and care services due to the COVID-19 pandemic likely continued in 2021, but the impact was most acute in 2020."[19] Furthermore, the pandemic in parts of the US substantially changed both online and offline interactions, potentially substantially affecting estimates for those years. Therefore, we exclude online dating data from years 2020 and 2021 from our analyses. In Appendix A.7, we present the results including these years and compare the estimates with the ones reported in the main text.

4.3 Empirical Specification

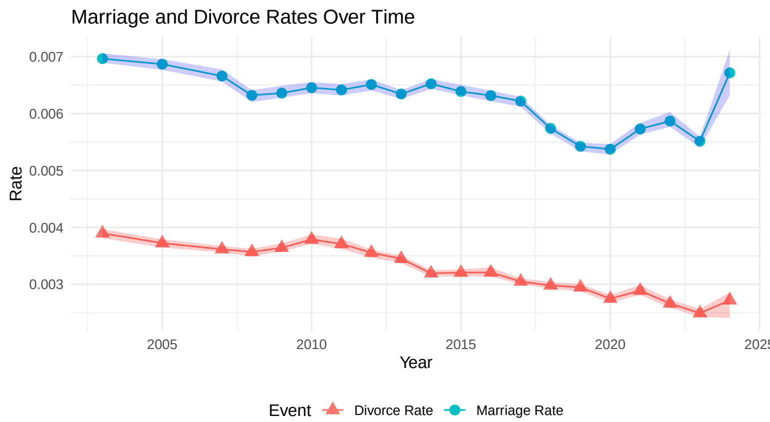
We are interested in estimating the impact of usage of online dating on marital and health outcomes. In particular, throughout the analysis, we will be running specifications similar to the following:

$$Y_{ct} = \beta MeanDatingSessions_{ct} + \gamma_c + \alpha_t + \mathbf{X_{ct}}\delta + \varepsilon_{ct}, \tag{1}$$

where Y_{ct} is the outcome of interest in county c in year t, $MeanDatingSessions_{ct}$ represents the online dating platform usage intensity. Recall that our data spans multiple time periods and datasets. In the

[19]See Centers for Disease Control and Prevention (2023)

Figure 3: Marriage and Divorce Rates



Notes: This figure plots the median marriage and divorce rates per county over time. Rates are calculated by the number of marriages and divorces divided by the county's population each year. Shaded regions represent 95% confidence intervals.

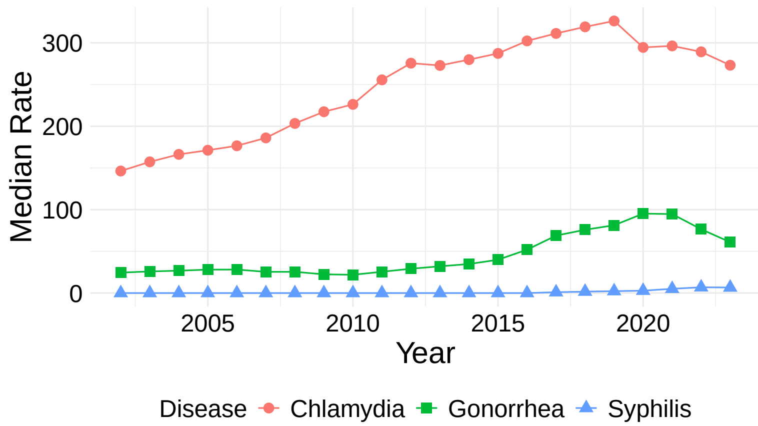
desktop (Comscore) data, the mean dating sessions is the average number of browsing sessions with a visit to an online dating platform in the county in year t. In the mobile data, mean dating sessions represents the number of times an online dating app was opened per individual in the county in year t. Because these measures capture different user behaviors and are not directly comparable in levels, we conduct all analyses for the desktop and mobile periods separately. Within the mobile period, we further pool two datasets that rely on distinct participant panels and data collection methodologies. This results in level differences as discussed in Section 4.1.1. Throughout our analyses, we include county and year fixed effects, γ_c and α_t, to account for the time-invariant characteristics of geographic locations as well as the trends in dating. The year fixed effects also absorb dataset-specific level differences. Consequently, identification comes from within-county variation over time rather than cross-sectional differences in measurement levels. In all specifications, we use the inverse hyperbolic sine (arcsinh) transformation for $MeanDatingSessions_{ct}$. In addition, we control for a number of county- and year-specific characteristics, denoted by the matrix $\mathbf{X_{cy}}$, which may correlate with both online dating and internet usage, including logged population, logged income, share of young (individuals between 18 and 24), share of female and share of streaming media and social media usage.[20] [21]

Outcomes. As discussed earlier, we focus on the effects on marital outcomes — including the number of marriages and divorces, and characteristics of relationships — and STD rates. For marital outcomes, we focus on the number of new marriage and divorces registered in each county per year, and for relationship characteristic outcomes, we focus on sorting along the following dimensions — education, employment,

[20] "Share of young" definition is changed to 20 to 24 for the years 2000-2010 and 2021-2022, consistent with the change in reclassification made by Census.

[21] We use the following streaming media websites to calculate usage of these sites: Netflix, Hulu, Peacock, Disney+, HBO, Sling and Fubo. Similarly, we use Facebook, Twitter, Instagram, TikTok, Reddit, Pinterest, Snapchat, WhatsApp, LinkedIn, Discord, Telegram and BeReal to account for the social media usage (i.e., the mean number of sessions with at least one visit to a social media site. These data are included in the Comscore, Dewey and Tapestri datasets.

Figure 4: STD Rates



Notes: This figure plots the median rates (cases per 100,000) of chlamydia, syphilis and gonorrhea over time over all counties in our dataset. The STD data comes from AtlasPlus.

income, and race. For both of these classes of outcomes, we measure the effect of online dating usage in year t on outcomes in year $t+1$. We lag the online dating usage measure because relationships that form through online dating may not lead to marriage in under one year. We chose a one year lag in dating usage because, according to a survey of 3,370 US residents conducted by Francis-Tan and Mialon (2015), the median time until marriage was one to two years. We also consider STD rates per county-year, separately for syphilis, chlamydia, and gonorrhea. For these outcomes, we measure the effect of online dating penetration in year t on STD rates in year t. We do not introduce a time lag here because these outcomes take less time to be realized, as the incubation time for chlamydia, primary syphilis, and gonorrhea ranges from 1–4 weeks.

Identification. Estimating the effects of online dating on marital and health outcomes is a challenging task due to the set of correlated unobservables that may jointly determine both the prevalence and use of dating platforms as well as the outcome variables of interest. For instance, economic factors such as joblessness may drive both the ability to pay, and thus the time spent on dating platforms, as well as marriage and divorce rates. Similar factors unobservable to the econometrician exist for health outcomes—for instance, changes to the number of bars and drinking establishments may alter participation in online spaces as it affects the outside options of meeting individuals offline, and may have an impact on one's health. Changes in local social behaviors and dating norms may also influence both the adoption of dating platforms and health and marriage outcomes. These correlated unobservables can bias the OLS estimates in either direction. For example, an increase in joblessness can increase online dating usage (e.g., individuals have more free time) but also decrease marriage rates, thus biasing the effect of online dating towards zero. Conversely, counties with more singles can have more online dating usage and also higher marriage rates simply because of more eligible partners, thus biasing the effect of online dating upwards. County and year fixed effects partially account for these trends but cannot fully address selection and omitted variable concerns.

Additionally, the OLS regression in Equation 1 likely suffers from attenuation bias for two reasons: (i) our main independent variable of interest, $MeanDatingSessions_{ct}$, is measured with an error based on a relatively small sample of users (we assume this error is independent of unobserved shocks that impact our outcomes of interest), and (ii) especially in the mobile dataset, we have a short panel where the presence of any serial correlation could generate an attenuation of the coefficient of interest towards zero.

To address these challenges, we use an instrumental variables (IV) identification strategy. Our IV is "nearby region" dating platform usage. We instrument the dating platform usage in county c in year y on the usage of dating platforms in counties that fall within the 20 to 100 kilometer radius surrounding county c, accounting for county-pair and year fixed effects.[22] The key assumption behind the validity of our instruments is that although each county has some independent shocks that influence its own online dating adoption rate, there is some geographic correlation in adoption due to changes in nearby user bases. To illustrate, suppose there are three counties, A, B and C. Counties A and B are neighbors, as are counties B and C. However, A and C are relatively distant from one another. An idiosyncratic shock that increases dating platform usage in county A means there is a more robust online dating market for platform users in neighboring county B. This should increase usage in county B, which in turn, increases online dating usage in county C. Since counties A and C are not neighbors, it is less likely that their unobservable idiosyncratic shocks to usage are correlated. In the example above, usage in county A would serve as an instrument for usage in county C. Moreover, assuming that measurement errors in penetration are random and are independent between counties A and C, this IV would help with the attenuation bias explained above.

An implicit assumption here is that idiosyncratic county shocks that drive online dating adoption or changes in our outcomes of interest propagate less than the effect of adoption itself. Returning to our previous example, we assume that any shocks that impact STD rates in county A would not directly impact STD rates in county C within the same year. Although STDs can spread from county to county, we assume that they do not do so in this relatively short time frame, unlike the spread of online dating adoption due to network effects. Law et al. (2004) supports the plausibility of this assumption, as they find that neighborhood spillover effects for chlamydia, gonorrhea, and syphilis are all confined to distances of less than 10 km, below our minimum distance threshold of 20 km. This assumption is more likely to hold the farther away counties A and C are from each other. One factor that works to our advantage in our identification strategy is that the outcomes we observe—marriage and divorce rates and health outcomes—are unlikely to change dramatically within short term periods due to changes in nearby counties.

To increase the predictive power of our instrument, we also include the nearby county's attributes, including its income, population, share of the population between ages 20–24, share of the population that is female, and the county's social media and streaming usage, as additional IVs. We assume that these attributes also fulfill the exclusion restriction, in that a nearby county's attributes do not directly impact STD and marital outcomes in the focal county. For the Comscore data, we have 54,122 county-pairs, for the Tapestri data, we have 59,358 county-pairs and for the Dewey data, we have 51,704 county-pairs. For the regression specifications, like in Yildirim et al. (2024), analysis is conducted at the county pair-year level with county-pair and year fixed effects. We cluster standard errors at the county-pair level.

[22] For reference, on popular dating apps like Tinder and Hinge, users can see potential matches up to a radius of 160 km (100 miles).

One might be concerned that nearby counties are not predictive of online dating penetration, or that these instruments produce spurious correlations. To address this, in Appendix A.9, we conduct a placebo test by replacing the set of nearby counties with a set of randomly selected counties, regardless of distance. For example, if county A has three nearby counties within the 20-100 km range, the placebo test instead selects three random counties to serve as the "nearby" counties. We then use these counties' characteristics as the instruments. In this placebo test, we expect that the measured effects on our outcomes of interest are statistically indistinguishable from zero. This is indeed what we find: using a random selection of counties leads to no first stage relationships, and null second stage effects.

Heterogeneity We consider several measures of user heterogeneity to decompose the effects, as well as find evidence for some of the mechanisms described in Section 3. We look at three key measures of heterogeneity: user age, the intent of dating platform usage, and the sexual orientation of users. Specifically, we estimate the following three sets of regressions:

$$Y_{ct} = \beta_1 CasualSessions_{ct} + \beta_2 RelationshipSessions_{ct} + \gamma_c + \alpha_t + X_{cy}\delta + \epsilon_{ct} \tag{2a}$$

$$Y_{ct} = \beta_1 NonLGBTQSessions_c t_{ct} + \beta_2 LGBTQSessions_{ct} + \gamma_c + \alpha_t + X_{cy}\delta + \epsilon_{ct} \tag{2b}$$

$$Y_{ct} = \beta_1 Under35Sessions_{ct} + \beta_2 Over35Sessions_{ct} + \gamma_c + \alpha_t + X_{cy}\delta + \epsilon_{ct}, \tag{2c}$$

where the outcomes and most explanatory variables are the same as in Equation 1, but where we break down usage into group-specific usage. Like in the main specification, different sub-group dating sessions may be correlated with unobservables that influence the outcomes. We address this endogeneity problem by instrumenting for each sub-group dating session value with the mean dating sessions for the same sub-group in nearby counties, along with the attributes of the nearby counties (as in the main specification).

In specification (2a), we test the effects of heterogeneity in outcomes by user intention. Dating platforms differentiate themselves to target different types of users. Casual platforms prioritize short-term interactions and relationships, while relationship-minded platforms have at least some focus on fostering long-term relationships. These distinctions should differentiate how their usage influences marital and health outcomes. For example, we might expect that online dating platforms targeted towards relationship-minded users may be more effective at changing marriage rates than those targeted towards casual daters. The variable $RelationshipSessions_{ct}$ denotes the online dating sessions with visits to a platform that we classify as relationship-focused, while $CasualSessions_{ct}$ refer to activity on all other dating platforms.

In specification (2b), we look at heterogeneity in outcomes with respect to the usage of dating platforms that are targeted primarily towards LGBTQ+ users. The breakdown is motivated by platforms like Grindr, which cater primarily to the LGBTQ+ community, being specifically implicated in discussions about rising STD rates (Kelsey, 2015). Moreover, one of our STD outcome measures, syphilis rates, is a disease whose testing is specifically recommended to men in same-sex relationships, with no explicit guidelines for heterosexually active men, or to women.[23] Finally, through the lens of our model in Section 3, LGBTQ+ users (and LGBTQ+ user targeting platforms) are located in different areas of the parameter space as compared

[23]Excepting pregnant women (see Centers for Disease Control and Prevention, 2024).

to heterosexual users, and the impact of desktop and mobile platforms on their outcomes may be different. There are relatively fewer LGBTQ+ daters in the population as compared to heterosexual daters,[24] so the baseline N is smaller. Moreover, in the offline world, LGBTQ+ individuals looking for partners would have to go to LGBTQ+ venues, which were relatively rare, primarily located in large urban areas, and potentially risky due to harassment (Gallant, 2019). This means that the decrease in search costs from online dating for LGBTQ+ users may have been greater than for heterosexual users.

Finally, in specification (2c), we consider the heterogeneity in outcomes with respect to usage by different age groups - those under 35 and over 35. Conceptually, there are two potential differences between the two groups: their search costs, and the relative increase in their market sizes due to the introduction of online dating. Search costs for younger users are likely lower, as they have a lower opportunity cost of spending more time browsing the platforms and talking to potential matches. We expect that going from the offline to desktop dating platforms, the older population experiences a larger increase in market size, relative to the younger population, as these dating sites were more popular among the older population.

5 Results

We start with the analysis of relationship outcomes, focusing on the annual rates of marriage and divorce. We then look at effects on STD rates and then assortative matching. Since the outcome variable is arcsinh transformed, we rely on Bellemare and Wichman (2020) to interpret the magnitudes at the average values of the dependent and the independent variables.

5.1 Marital Outcomes

Table 4 shows how the number of new marriages and new divorces in year $t+1$ change in response to changes in the usage of online dating platforms in the previous year t. The table reports both the OLS estimates (columns (1) and (3)) and the IV estimates (columns (2) and (4)). Panels A and B report the findings for desktop and mobile data, respectively.

Before getting into specific results, the strength of the IVs warrants discussion. We report the first stage outcomes of the 2SLS specifications in Appendix A.4, which show that the nearby county's mean dating sessions significantly correlates with the focal county's dating sessions. Additionally, the first stage regressions have high explanatory power on the endogenous variable, as demonstrated by the large first stage F statistics. These high F stats are not solely due to the fixed effects and other controls. In an alternative specification where we regress the endogeneous variable only on the instruments (excluding exogenous regressors), the F stats for the desktop and mobile periods are 868.28 and 2,979.6. We also report the Anderson-Rubin (AR) F statistic and its p-value in each specification with a single endogenous regressor (Anderson and Rubin, 1949).[25] A large AR F-stat, or a corresponding small p-value, rejects the null hypothesis that the coefficient of interest, mean dating sessions, is equal to zero. However, in several specifications, the KP Wald F stats are small, suggesting that the instruments have weak explanatory power on the endogenous variable, the

[24] For example, in San Francisco in 2005, the LBGTQ+ share of the population was 15% (Gates, 2006).
[25] Lal, Lockhart, Xu, and Zu (Lal et al.) provides examples of its use.

mean dating sessions. To test whether our results are driven by irrelevant instruments, we conduct a placebo test with random counties serving as instruments, as previously mentioned, which gives us more confidence that our instruments are relevant. Finally, recall that we consider nearby counties to be those within 20–100 km. In a robustness check, we tested several other distances, including 50–100 km, 50–150 km, and 100–200 km. These distances yielded higher KP Wald F-statistics and yielded estimates in a consistent direction as the main results discussed below (Appendix A.6). Taken together, these methods suggest that our results are directionally robust to weak instruments, though this caveat should be kept in mind when interpreting the findings.

One might also be concerned about spatial correlation. We estimated our regressions with Conley standard errors to account for spatial correlation and find that all key results remain identical with similar magnitudes.[26]

In both Panels A and B of Table 4, OLS estimates are not statistically significant. However, IV estimates in Panel A strongly suggest that higher utilization of desktop-based dating platforms results in significantly more divorces, with the coefficient positive and statistically significant (0.887). This implies that a 1% increase in desktop dating platform sessions in the average county increases divorces by 0.50%. Looking at Panel B with the mobile data shows a different pattern. Here, we find a negative and statistically significant effect of higher use of dating apps on both new marriages and new divorces, with respective coefficients -0.636 and -0.529. An increase of 1% in dating app sessions in the average county decreases marriages 0.40% and divorces by 0.33%. These elasticities appear to be large, but they do not necessarily represent drastic changes in divorce rates in real terms. For example, a 1% increase in divorces in the 2002-2013 period represents 1.6 divorces per year for the mean county. For the later period, a 1% increase represents one additional divorce per year.

Discussion of Average Outcomes In summary, the average effects suggest that higher usage intensity of early online dating platforms resulted in higher divorce rates, while higher usage intensity of mobile dating apps had the opposite effects, driving a decline in marriage and divorce rates.

For the desktop results, the increase in divorces can be consistent with worsening or improving relationships formed through dating platforms. More divorces can come from worsening relationships if expected platform match values fall, or if desktop platforms reduce match quality, resulting in more divorces. More divorces can also be the result of improving relationships by increasing the expected platform match values, raising the value of the outside option (i.e., online dating) for individuals already in existing relationships. That is, online dating increases the outside option value of their current relationship. Existing surveys find mixed evidence on match satisfaction.[27]

In the desktop era, we do not find a decrease in marriage rates, suggesting it is unlikely that match values fell. Our model in Section 3 can also generate consistent predictions: the transition from offline to

[26]These tables can be obtained from the authors.

[27]Sharabi and Dorrance-Hall (2024) find evidence that online daters find marriage less satisfying than offline daters, while Cacioppo et al. (2013) shows the opposite — that marriages from online dating are less likely to end in divorce. Potarca (2020) finds no difference in reported match quality online and offline.

Table 4: Use of Dating Websites & Apps and Marriage and Divorce Outcomes

	Arcsinh # New Marriages		Arcsinh # New Divorces	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Panel A: Desktop Data				
Mean Dating Sessions (Arcsinh)	0.001	0.005	0.009	0.887***
	(0.003)	(0.140)	(0.006)	(0.270)
Dep. Var Mean	6.453	6.450	5.743	5.774
Ind. Var Mean	0.641	0.646	0.636	0.642
First Stage F-Stat	.	295.444	.	234.041
AR F-Stat	.	3.059	.	25.570
AR F-Stat p-value	.	0.003	.	0.000
KP Wald F-Stat	.	2.509	.	3.118
Obs	16136	258305	14692	229653
No. of Counties	2188	2188	1921	1921
Panel B: Mobile Data				
Mean Dating Sessions (Arcsinh)	-0.014	-0.636***	-0.025	-0.529**
	(0.011)	(0.207)	(0.025)	(0.260)
Dep. Var Mean	6.166	6.168	5.435	5.312
Ind. Var Mean	0.745	0.733	0.744	0.730
First Stage F-Stat	.	135.358	.	114.860
AR F-Stat	.	10.286	.	5.600
AR F-Stat p-value	.	0.000	.	0.000
KP Wald F-Stat	.	2.563	.	2.238
Obs	7024	108337	5461	85925
No. of Counties	2115	1933	1671	1516
FE	Year, County	Year, County-Pair	Year, County	Year, County-Pair
Controls	Yes	Yes	Yes	Yes

Notes: ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Standard errors are clustered at the county level in columns (1) and (3) and at the county-pair level in columns (2) and (4). Nearby counties are counties within a 20-100 km radius of the focal county. Controls included are focal county streaming and social media penetration, log population, share young, share female and log income. Instruments are nearby county dating, social media and streaming penetration values as well as nearby county population, income, share young, share female. The desktop data comes from Comscore for the years 2002-2013 and the mobile data comes from a combination of Tapestri for the years 2017 and 2018, and Dewey for the years 2019, 2022 and 2023. Mobile data focused only on common counties for Tapestri and Dewey. Years 2020 and 2021 are excluded due to COVID-19 disruptions. Data on marriage and divorce outcomes are from the Vital Statistics of states. We study the effect of dating app penetration in year *t* on outcomes in year *t+1*. OLS estimates are presented in Appendix A.8.

desktop increased the participant pool and reduced search costs and noise. Our simulations show that thicker markets with cheap search and less noise reduces the probability that any given encounter becomes a match, but improves sorting and screening out mismatches, and improving the option of "going back to the market" for those already in relationships. This perspective is consistent with the contemporaneous views of dating platform executives, who in 2013 described online dating as having produced "better relationships, but more divorce" (Slater, 2013).

Mobile effects look different from the desktop results and are likely driven by a different combination of primitive factor changes through the lens of our model in Section 3. The transition to an increasingly larger participant pool, with even bigger decreases in search costs due to swiping and an increase in noise

Table 5: Effects of Relationship-Minded, LGBTQ+, and Age Mean Dating Sessions on Marriage and Divorce Outcomes

	Marriages			Divorces		
	Relationship	LGBTQ+	Age	Relationship	LGBTQ+	Age
Panel A: Desktop Data	(1)	(2)	(3)	(4)	(5)	(6)
Mean Casual Sessions (Arcsinh)	0.112			4.024**		
	(0.254)			(1.747)		
Mean Relationship Sessions (Arcsinh)	-0.023			-1.207		
	(0.106)			(0.839)		
Mean Not LGBTQ+ Sessions (Arcsinh)		-0.047			1.720***	
		(0.174)			(0.493)	
Mean LGBTQ+ Sessions (Arcsinh)		0.100			-1.138**	
		(0.138)			(0.498)	
Mean Dating Sessions 18-34 (Arcsin)			0.436**			-0.168
			(0.170)			(0.240)
Mean Dating Sessions 35+ (Arcsin)			-0.141			0.784***
			(0.105)			(0.134)
Dep. Var. Mean	6.450	6.450	7.136	5.774	5.774	6.457
Ind. Var. Mean	0.562	0.584	0.600	0.554	0.575	0.591
Het. Var. Mean	0.628	0.607	0.694	0.633	0.613	0.683
KP Wald F-Stat	0.843	1.569	1.48	0.719	1.780	1.47
Observations	258305	258305	108383	229653	229653	96091
No. of Counties	2321	2321	1427	2043	2043	1262
Panel B: Mobile Data	(1)	(2)	(3)	(4)	(5)	(6)
Mean Casual Sessions (Arcsinh)	-0.268***			-0.145		
	(0.071)			(0.107)		
Mean Relationship Sessions (Arcsinh)	-0.301**			-0.560***		
	(0.132)			(0.204)		
Mean Not LGBTQ+ Sessions (Arcsinh)		-0.580***			-0.550**	
		(0.201)			(0.262)	
Mean LGBTQ+ Sessions (Arcsinh)		0.038**			0.007	
		(0.017)			(0.025)	
Mean Dating Sessions 18-34 (Arcsin)			-0.428***			-0.263**
			(0.147)			(0.110)
Mean Dating Sessions 35+ (Arcsin)			-0.446**			-0.112
			(0.190)			(0.145)
Dep. Var. Mean	6.168	6.168	6.400	5.312	5.312	5.581
Ind. Var. Mean	0.700	0.732	0.771	0.689	0.730	0.766
Het. Var. Mean	0.694	0.240	0.721	0.695	0.250	0.710
KP Wald F-Stat	3.953	2.103	1.51	3.090	1.987	2.07
Observations	108337	108337	84681	85925	85925	67990
No. of Counties	2296	2296	1526	1868	1868	1198
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Standard errors are clustered at the county-pair level in all columns. Nearby counties are counties within a 20-100 km radius of the focal county. Controls included are focal county streaming and social media penetration, log population, share young, share female and log income. Instruments are nearby county dating, social media and streaming penetration values as well as nearby county population, income, share young, share female. The desktop data comes from Comscore for the years 2002-2013 and the mobile data comes from a combination of Tapestri for the years 2017 and 2018, and Dewey for the years 2019, 2022 and 2023. Mobile data focused only on common counties for Tapestri and Dewey. We exclude the year 2020 and 2021 from analysis to account for Covid-related disruptions. Data on marriage and divorce outcomes are from the Vital Statistics reports of the states. We study the effect of dating website/app penetration in year t on outcomes in year $t+1$.

from less informative profiles, can push the market to high participation and thus high expected returns of continuing to search. The increase in pool size and decrease in search costs predict that each user evaluates more profiles, but each interaction is less likely to turn into a match and a relationship since the option value of continuing to swipe is high. As a result, there is lower conversion, leading to fewer serious stable matches. Although an increase in noise predicts a rise in match rates (because individuals are more likely to like others), the other two forces plausibly dominate this effect. Moreover, even if the increase in noise dominates, the additional matches would have high variance, which would create additional "mis-matches" that would be less likely to reach marriage.

Increased penetration of mobile dating apps can reduce divorce rates for two reasons: (i) a reduction in marriages should mechanically reduce divorces, and (ii) if the effects coming from more users and reduced search costs dominate the noise effects, then the matches made on mobile platforms are likely of higher quality, since they were chosen despite the availability of a large set of alternatives.

Table 5 shows the 2SLS heterogeneity analysis, with Panel A showing results for desktop platforms, while Panel B shows results for mobile platforms. Columns (1) and (4) in each panel reflect the casual / relationship-minded usage heterogeneity, columns (2) and (5) show the heterosexual / LGBTQ+ heterogeneity, and then columns (3) and (6) show the age-group heterogeneity. We discuss these results next, as they help provide us with additional evidence that can help interpret the average findings discussed above.

Desktop Heterogeneity Estimates from the heterogeneity results in Table 5 present additional evidence consistent with the model-driven explanation above. Although we do not find heterogeneity in marriage rate effects by the type of desktop platform used (columns 1 and 2), we identify a positive statistically significant relationship between the intensity of usage by young users and marriage rates: a 1% increase in mean under-35 sessions increases marriage rates by 0.23% (column 3).

For divorces (columns 4-6), we also find interesting heterogeneity when breaking down usage by platform type and user age-group. The increase in divorce is primarily driven by older users and heterosexual platform usage, which is what we would expect considering that older users are more likely to be already married at the time of their adoption of the platform, and that heterosexual platform users are driving the main effects given their prevalence in the data. Specifically, an increase of 1% in the number of mean sessions by users over 35 is associated with an increase of 0.47% in the divorce rate (column 6). An increase of 1% in desktop non-LGBTQ+ platform usage increases divorce rates by 0.89%. A possible mechanism for this increase in divorces for this age group is that going from offline to the desktop dating era, the market size significantly increases for the older population, as these sites were more popular for this age group. At the same time, desktop dating sites reduce noise. Both of these changes make dating site usage more attractive, and can increase the outside option to the marriage (i.e., finding another partner), which precipitates divorces.

In our model, the heterogeneity could come about because of underlying differences between the older and the younger user populations. While they both experience decreases in search costs moving from the offline dating to the desktop era, older users are more likely to already be or had been married. This may suggest the changes in marriage rates in response to matches formed through dating sites may be more statistically detectable for younger populations.[28]

In addition to the heterogeneity effects discussed above, we also find, in column (4), that the increase

[28] Individuals who were previously married are less likely to get married again, than those who were never married (Schweizer, Schweizer).

in divorces was primarily driven by the increase of casual, rather than relationship-focused platform usage. This is consistent with previous surveys looking at samples of dating platform users who were married or in relationships an report many users looking for uncommitted sex partners (Vera Cruz et al., 2023).

Increases in LGBTQ+ platform usage reduce average divorce rates, which is difficult to square with the other findings (e.g., the overall positive effect on online dating platforms on divorces, as well as the non LGBTQ+ effects). Because most states did not legalize same-sex marriage until after 2010, marriage rates for LGBTQ+ individuals during this period do not necessarily reliably reflect changes in relationship formation. As a result, the divorce result for LGBTQ+ platform usage is difficult to interpret.

Mobile App Heterogeneity The average effect of online dating on marriage in the mobile era is negative, suggesting a decrease in either average match values or match probabilities. Heterogeneity estimates from Table 5 suggest this as well, with usage by nearly all groups decreasing marriage rates. In column (1), we show that both the usage of casual and relationship-minded apps are associated with decreasing marriage rates. An increase of 1% in casual sessions decreases marriage rates by 0.16%, and an increase of 1% in relationship-minded app sessions decreases marriage rates by 0.18%. We find a similar negative effect for non LGBTQ+ sessions (column 2). Finally, usage by both young and older users decreases marriage rates (column 3). A 1% increase in mobile dating platform usage reduces marriage rates by 0.28% for both under-35 and 35+ users.

The exception is LGBTQ+ app sessions (column 2), which are associated with an increase in marriage rates. The estimated coefficient of 0.038 implies that a 1% increase in LGBTQ+ app usage raises marriage rates by approximately 0.009%. The magnitude of the coefficient is smaller than for heterosexual (non-LGBTQ+) app usage but is still meaningful. This reflects that while they constitute a smaller population overall, LGBTQ+ individuals likely use mobile apps more intensively given the thin offline, and even desktop, markets. In fact, our results are consistent with the findings of Rosenfeld et al. (2019), whereby over 60% of ç couples in long term relationships have met online. Moreover, with the 2015 legalization of LGBTQ+ marriage across the US, LGBTQ+ matches can have an impact on marriage rates. Through the lens of our model from Section 3, LGBTQ+ users likely experienced a proportionally larger shock to market size than heterosexual users, though from a very low baseline. At the same time, a pronounced decline in search costs allows individuals to search more extensively, increasing the likelihood of encountering high-value matches and thereby promoting the formation of long-term relationships and marriage.[29]

Alongside the negative marriage effects, the mobile sample shows negative effects on divorces. Less divorce may indicate stronger long-term relationships and marriages. However, divorces should also fall when marriages fall, since it is impossible to get divorced without first getting married. The combination of negative divorce and marriage effects is consistent with the second story. The negative divorce effects are driven by relationship-minded app usage (column 4) — a 1% increase in these sessions reduces the divorce rate by 0.33%. Notably, this coefficient statistically overlaps with the marriage rate effect coefficient from column (1). Similarly, the aggregate negative effect is also concentrated through heterosexual mobile app

[29] For example, Albo (2016) discusses the difficulty, and potential danger, associated with searching for LGBTQ+ partners in the pre-internet era.

usage (column 5) — a 1% increase in the usage of non-LGBTQ+ oriented apps reduces the divorce rates by 0.34%. Again, this is a similar effect to the decrease in marriages in column (2).

Altogether, these results are not necessarily inconsistent with mobile platforms' stated goals of facilitating long term relationships or marriage, since conditional on making a match, match values might be higher on mobile platforms than matches made offline or on desktop platforms. We cannot rule this out as we do not observe the quality of the marriages formed, only the quantity. That said, on average, there is a decrease in the number of marriages, consistent with the congested, noisy and low-search-cost environment.

5.2 Sexually Transmitted Diseases (STDs)

Table 6 reports the effects of online dating on the county STD rates reported in that year. We focus on the three most commonly reported STDs, chlamydia, syphilis, and gonorrhea. In both the desktop data and mobile data, the OLS estimates do not reveal any significant correlation between online dating usage intensity and STD rates. However, the IV estimates show a statistically significant negative effect of online dating for all three STD rates in desktop data (Panel A). A 1% increase in the mean dating sessions for the desktop data is associated with a 0.1% decrease in chlamydia rates, 0.4% decrease in syphilis rates, and a 0.44% decrease in gonorrhea rates.

For mobile dating app sessions (Panel B), IV estimates again indicate a negative and significant effect on gonorrhea rates (-1.442, in column (6)). A 1% increase in mean dating app sessions is associated with a 0.84% decrease in gonorrhea rates. Effects on chlamydia and syphilis are statistically insignificant.

Discussion of Average Outcomes There are oft-voiced public health concerns regarding increasing dating app use leading to increases in STD transmissions. Focusing on individuals from Los Angeles county, Beymer et al. (2014) reports greater likelihood of testing positive for gonorrhea and chlamydia for those who meet potential partners on dating apps, relative to those who meet partners in offline or other internet settings. These findings report correlational outcomes that suggest negative health concerns stemming from the use of dating platforms and apps. Similarly, earlier studies point to the internet as a contributing factor to the upward trend of STDs (Chan and Ghose, 2014). However, our findings from Panels A and B suggest the opposite — four of the six outcomes reported in Table 6 have a negative sign for the estimated coefficients which are statistically significant at the 95% level.

Recall that our proposed explanation for the marriage and divorce results for desktop platforms, based on our model in Section 3, is that improvements in screening, reductions in search costs and the increase in market size are driving the dating market to a more selective and better matched equilibrium relative to offline dating. In particular, our model shows that as search costs fall, there is an increase in expected value from searching and a decrease in match probabilities, driving users to be more selective. This is consistent with the decrease in STD rates across the board — there are fewer mismatched meetings, and users can potentially screen out the seriousness of their potential partners. Desktop dating sites could allow users to better to screen out high risk individuals, as their profiles tend to be detailed, enabling users to better assess partner characteristics and risks before meeting.

Table 6: Effect of Mean Number of Sessions (Inverse Hyperbolic) on Dating Websites/Apps on STD Outcomes

	Chlamydia Rate (Arcsinh)		Syphilis Rate (Arcsinh)		Gonorrhea Rate (Arcsinh)	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Desktop Data						
Mean Dating Sessions (Arcsinh)	0.001	-0.177**	-0.009	-0.445**	0.013	-0.713***
	(0.004)	(0.088)	(0.007)	(0.177)	(0.009)	(0.198)
Dep. Var Mean	6.104	6.085	0.637	0.646	4.032	4.141
Ind. Var Mean	0.640	0.642	0.640	0.642	0.640	0.642
First Stage F-Stat	.	447.164	.	447.189	.	447.164
AR F-Stat	.	13.026	.	3.688	.	16.835
AR F-Stat p-value	.	0.000	.	0.001	.	0.000
KP Wald F-Stat	.	8.232	.	8.221	.	8.232
Obs	23070	384538	23077	384546	23070	384538
No. of Counties	2795	2795	2795	2795	2795	2795
Panel B: Mobile Data						
Mean Dating Sessions (Arcsinh)	-0.000	-0.030	-0.011	0.179	-0.012	-1.442***
	(0.005)	(0.109)	(0.020)	(0.406)	(0.012)	(0.390)
Dep. Var Mean	6.488	6.491	1.836	1.809	5.005	5.066
Ind. Var Mean	0.676	0.670	0.676	0.670	0.676	0.670
First Stage F-Stat	.	297.804	.	297.804	.	297.804
AR F-Stat	.	12.628	.	26.604	.	12.676
AR F-Stat p-value	.	0.000	.	0.000	.	0.000
KP Wald F-Stat	.	3.034	.	3.034	.	3.034
Obs	12664	219455	12664	219455	12664	219455
No. of Counties	2729	2728	2729	2728	2729	2728
FE	Year, County	Year, County-Pair	Year, County	Year, County-Pair	Year, County	Year, County-Pair
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Standard errors are clustered at the county level in columns (1), (3) and (5) and at county-pair level in columns (2), (4) and (6). Nearby counties are counties within a 20-100 km radius of the focal county. Controls included are focal county streaming and social media penetration, log population, share young, share female and log income. Instruments are nearby county dating, social media and streaming penetration values as well as nearby county population, income, share young, share female. The desktop data comes from Comscore for the years 2002-2013 and the mobile data comes from a combination of Tapestri for the years 2017 and 2018, and Dewey for the years 2019, 2022 and 2023. Mobile data focused only on common counties for Tapestri and Dewey. Years 2020 and 2021 are excluded due to COVID19 disruptions. STD data are from CDC Atlas and rate refers to incidence of the diseases among 100,000 people. We study the effect of dating app penetration in year t on outcomes in year t.

Panel B shows that the decline is STD rates due to mobile dating platforms more modest, relative to desktop dating sites. Recall that moving from desktop to mobile platforms increases the pool size and further decreases search costs, which work to decrease match rates. However, this change also increases noise, as mobile dating profiles are less informative than desktop profiles, which pushes match rates and participation up, working against the other two changes. This may explain why the decrease in STD rates is more modest when dating activity shifts from desktop to mobile, relative to the offline-to-desktop transition.

Also, the more modest decrease in STDs in the mobile period relative to the desktop period, together with our marriage and divorce results from the previous section, suggest that a different mechanism is behind the decline in STD rates with mobile app usage. We provide additional discussion of these contrasts between the two time periods, as well as a general discussion of plausible mechanisms by examining heterogeneity in the effects. Table 7 shows the 2SLS heterogeneity analysis, with Panel A showing results for desktop platforms, and Panel B showing results for mobile platforms. Columns (1), (4) and (7) in each panel reflect the casual/relationship-minded usage heterogeneity, columns (2), (5) and (8) show heterogeneity by LGBTQ+ and heterosexual orientation of dating platform usage, and columns (3), (6) and (9) show age-group heterogeneity, comparing usage by those under and over 35.

Desktop Heterogeneity As discussed above, our proposed explanation for the average findings is that desktop platforms, via reduced noise, lower search costs, and a greater pool size, reduced mis-matching in the dating market, although they also increased selectivity and decreased the rate of matching. We provide some supporting evidence for this in Table 7. In columns (1), (4) and (7), we show that the effects on all three STD outcomes are primarily driven by relationship-focused desktop site usage, as opposed to casual site usage. For example, an increase of 1% in relationship-minded sessions decreases chlamydia rates by 0.15%. Similarly, we find that the average negative effects were driven by non-LGBTQ+ platform sessions. In columns (5) and (8), we observe statistically significant and negative effects for non-LGBTQ+ platform usage and syphilis and gonorrhea. A 1% increase in non-LGBTQ+ platform usage decreases gonorrhea rates in the county by 0.46%. Together with the null effects of the same sessions on marriage rates, this evidence is consistent with the notion that the average quality of meetings that took place increased, but the number of meetings fell.

These results are consistent with criticisms of desktop dating platforms from contemporary observers and dating executives, which are the problems of (i) "distance" (online matches realizing they live too far away), and (ii) "funnel time" or "asynchronicity," which is the length of time between an online conversation and an offline meeting (Slater, 2013). Both of these issues sum up to desktop dating platforms having effective filtering mechanisms that ensure users see others with characteristics they wanted, but not the right mechanism or incentive scheme to ensure that users were meeting offline. These concerns were what precipitated the evolution of the next generation of mobile dating apps, which emphasized location, gamification, and quick interactions.[30]

Notably, the only demographic with a positive effect of online dating usage on STDs is for older users (column 6). When sessions by these users increase by 1%, syphilis rates increase by 0.34%. This is also the main demographic where we saw an increase in the number of divorces in Table 5. Together, this is consistent with the story explained in the previous section: desktop platforms increased outside options for already married older users, precipitating their re-entry into the market and leading to more offline encounters and a corresponding increase in STD rates.

Mobile Heterogeneity In the aggregate estimates from Table 6, the effects of mobile platform usage on STD outcomes are more similar to the desktop results as compared to the marriage and divorce results. However, the heterogeneity estimates in Panel B of Table 7 highlight some key differences which point to the different effects of online dating platforms in the two time periods.

In columns (1), (4) and (7), we do not find that the effects of mobile sessions on STD rates are clearly driven by either casual or relationship-minded platforms. In column (1), neither of the coefficients is statistically significant, in column (4), the casual coefficient is significant and negative but the relationship-minded one is not, and in column (7) the situation is reversed.

We do, however, find generally contrasting effects between the LGBTQ+ and heterosexual platforms.

[30]The CEO of an early GPS-based mobile dating app stated that their goal was for users to think "This person is real, they're near me, and I may actually be able to encounter them in the real world." (Foster (2012)). A co-founder of Tinder stated that they "always saw Tinder, the interface, as a game" (Stampler (2014)).

Specifically, we find that the effects of LGBTQ+ platform usage are substantially more positive compared to heterosexual platform usage. For two of the three STDs, the LGBTQ+ coefficients are positive, suggesting that LGBTQ+ platform usage increases STD rates. A 1% increase in LGBTQ+ platform usage increases chlamydia rates by 0.01% (column 2), and increases syphilis rates by 0.07% (column 5). The large syphilis effect is particularly notable, given that this is the primary STD which has a strong incidence among men who are gay and bisexual (Centers for Disease Control and Prevention 2025). For gonorrhea, the LGBTQ+ coefficient in column (8) is negative, but it is an order of magnitude lower than the coefficient for heterosexual platform sessions.

As suggested by our marriage and divorce results, these results point to mobile dating having a potentially different effect on different sub-populations. While mobile dating pushes heterosexual users into markets that are (on average) overly competitive, LGBTQ+ users move into a region of the parameter space that encourages more activity and matching. The substantial increase in market size (from a very low baseline), together with the increasing noise and decreasing search costs, means that LGBTQ+ users may search more and thus get more matches (despite lower match rates), but some of those matches may be lower quality or carry greater risk. However, at the same time, the effects are not uniformly negative, as some LGBTQ+ users are forming long-term stable high quality matches (see LGBTQ+ marriage effects in Table 5). This interpretation is also consistent with the larger proportion of LGBTQ+ dating app users who claim that they had a positive experience with online dating in recent surveys, as compared to heterosexual users (McClain and Gelles-Watnick, 2023).

Finally, increasing usage by younger users increases some STD rates. In column (3), we show that increasing usage by users under 35 by 1% increases chlamydia rates by 0.11%. As for LGBTQ+ platform users, the effects for younger users are typically less negative than the effects for older users. This is consistent with the findings of Büyükeren et al. (2023), which showed that the introduction of Tinder on college campuses increased student sexual activity and STD rates.

In the context of our framework, a possible reason we observe younger users driving STD rates is because of the heterogeneity in search cost and in market size changes across age groups. Younger users, who were more likely to adopt mobile technology, and who experienced the largest decline in search costs due to their lower cost of time, were likely pushed into an area of the parameter space where participation increased the most. As a result, mobile dating platform participation for younger users may have increased to such an extent that it generated additional encounters. Due to the increased noise, these additional encounters may be riskier. With these additional encounters, there might be more "mis-matches" for this user group, leading to higher STD rates. For older users, whose search costs plausibly did not fall to the same level of younger users, the congested mobile environment likely pushes participation (and plausibly match rates) down, leading to older users staying in their existing, more stable arrangements and reducing their risk of contracting STDs.

Overall, the evidence suggests that mobile dating platforms did not increase match rates, or improve match quality conditional on matching, for at least some segments of the user population. This is consistent with recent complaints about mobile platforms resulting in worse choices. Repeated surveys suggest that users are not happy with the operation of mobile dating platforms, and that these apps do not facilitate additional relationships or dating opportunities (Prendergast, 2025). According to Hinge, a popular dating app, only 1 in 500 swipes results in phone numbers being exchanged (The Dating Apocalypse, 2016). There has also been a recent decrease in the number of users on these platforms (Morris, 2025).

Table 7: Effects of Relationship-Minded, LGBTQ+, and Age Mean Dating Sessions on STD Outcomes

	Chlamydia			Syphilis			Gonorrhea		
	Relationship	LGBTQ+	Age	Relationship	LGBTQ+	Age	Relationship	LGBTQ+	Age
Panel A: Desktop Data	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Mean Casual Sessions (Arcsinh)	0.028			-0.056			-0.006		
	(0.134)			(0.279)			(0.326)		
Mean Relationship Sessions (Arcsinh)	-0.262**			-0.465*			-0.951***		
	(0.113)			(0.242)			(0.291)		
Mean Not LGBTQ+ Sessions (Arcsinh)		-0.146			-0.513**			-0.881***	
		(0.098)			(0.201)			(0.219)	
Mean LGBTQ+ Sessions (Arcsinh)		-0.135			0.096			0.236	
		(0.143)			(0.305)			(0.348)	
Mean Sessions 18-34 (Arcsinh)			-0.064			-0.149			-0.894***
			(0.088)			(0.216)			(0.243)
Mean Sessions 35+ (Arcsinh)			-0.090			0.399***			-0.198
			(0.057)			(0.150)			(0.151)
Dep. Var. Mean	6.085	6.085	6.205	0.646	0.646	0.883	4.141	4.141	4.530
Ind. Var. Mean	0.549	0.572	0.600	0.549	0.572	0.600	0.549	0.572	0.600
Het. Var. Mean	0.636	0.617	0.692	0.636	0.617	0.692	0.636	0.617	0.692
KP Wald F-Stat	2.557	2.539	2.14	2.549	2.536	2.15	2.557	2.539	2.14
Observations	384538	384538	156303	384546	384546	156309	384538	384538	156303
No. of Counties	2795	2795	1875	2795	2795	1875	2795	2795	1875
Panel B: Mobile Data	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Mean Casual Sessions (Arcsinh)	-0.082			-0.989***			0.066		
	(0.051)			(0.223)			(0.146)		
Mean Relationship Sessions (Arcsinh)	0.020			0.159			-0.868***		
	(0.066)			(0.282)			(0.181)		
Mean Not LGBTQ+ Sessions (Arcsinh)		-0.208			-0.874*			-1.295***	
		(0.129)			(0.494)			(0.404)	
Mean LGBTQ+ Sessions (Arcsinh)		0.056***			0.320***			-0.124***	
		(0.012)			(0.050)			(0.040)	
Mean Sessions 18-34 (Arcsinh)			0.180**			-0.055			-0.294**
			(0.089)			(0.295)			(0.126)
Mean Sessions 35+ (Arcsinh)			-0.460***			-1.176***			-0.302*
			(0.114)			(0.376)			(0.161)
Dep. Var. Mean	6.491	6.491	6.555	1.809	1.809	1.855	5.066	5.066	5.168
Ind. Var. Mean	0.595	0.669	0.708	0.595	0.669	0.708	0.595	0.669	0.708
Het. Var. Mean	0.647	0.208	0.663	0.647	0.208	0.663	0.647	0.208	0.663
KP Wald F-Stat	5.281	2.178	2.36	5.281	2.178	2.36	5.281	2.178	2.36
Observations	219455	219455	164552	219455	219455	164552	219455	219455	164552
No. of Counties	2728	2728	2227	2728	2728	2227	2728	2728	2227
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Standard errors are clustered at the county-pair level in all columns. Nearby counties are counties within a 20-100 km radius of the focal county. Controls included are focal county streaming and social media penetration, log population, share young, share female and log income. Instruments are nearby county dating, social media and streaming penetration values as well as nearby county population, income, share young, share female. The desktop data comes from Comscore for the years 2002-2013 and the mobile data comes from a combination of Tapestri for the years 2017 and 2018, and Dewey for the years 2019, 2022 and 2023. Mobile data focused only on common counties for Tapestri and Dewey. We exclude the year 2020 and 2021 from analysis to account for Covid-related disruptions. STD data are from CDC Atlas and rate refers to incidence of the diseases among 100,000 people. We study the effect of dating app penetration in year t on outcomes in year t. OLS estimates are presented in Appendix A.8.

5.3 Online Dating and Implications for Assortative Matching

Evidence of assortative matching in the U.S. is well-documented, with studies reporting increasing levels of marital sorting along dimensions of race (Qian and Lichter, 2007), education (Mare, 1991; Schwartz and Mare, 2005; Hirschl et al., 2024), and income (Greenwood et al., 2014; Eika et al., 2019). Observed sorting patterns are not determined by the homogamous preferences of individuals alone, but also by the frequency with which individuals from differing backgrounds may interact. Offline environments are segregated along the aforementioned dimensions: schools and workplaces tend to be sorted along education and income; neighborhoods tend to be sorted along race and income (Goni, 2022). Thus, couples formed through offline encounters may exhibit homogamy even in the absence of individual preference for homogamy.

Online meeting technologies have the potential to alter these observed sorting trends. Following the mechanisms explained in Section 3, first, online meeting technologies expand one's pool and may thus increase the diversity of individuals one interacts with. If the greater degrees of mixing result in more heterogamous couples, this can reduce sorting. Second, online dating technologies can reduce the cost of searching for and courting potential partners along the preferred dimensions, contributing to greater degrees of sorting. This finding would be in line with Goni (2022), who reports lowering search costs in marital matching increases sorting. Dating platforms offer individuals the ability to 'filter' candidates based on characteristics such as education, race, and religion, reducing the cost of search particularly along the filtered dimensions. Dating apps such as Bumble make candidates' education and employment characteristics salient, displaying them alongside one's image and name as the first information on a candidate, which can further contribute to screening on these dimensions. Finally, algorithms may contribute to providing recommendations along the shared dimensions to improve the likelihood of a match.

We test the effects of online dating platform penetration on sorting outcomes in the US using data from the IPUMS American Community Surveys, which provides annual survey data on individuals and households.[31] The data include 8.1 million married individuals for years 2005 to 2024. For each individual, we observe their county of residence, demographics, in addition to that of their spouse. Using the same identification framework described in Section 4.3, we look at sorting outcomes related to race, education, employment, and income.[32]

Table 8 reports the effects of online dating penetration on the percent of couples in the county who share the same race, same education level, and employment status, as well as the wife's average income relative to the husband's income. Across the outcomes, OLS point estimates are small and imprecise, while the IV uncovers economically meaningful effects that are generally in the same direction as the OLS effects.

[31] For more information on how the data is collected, see IPUMS USA (2025).

[32] We also look at the number of times the husband and wife (in heterosexual relationships) have been previously married (Table A.15). We do not find statistically significant effects on this outcome.

Table 8: Effect of Mean Number of Sessions (Inverse Hyperbolic) on Dating Websites/Apps on Sorting Outcomes

	Pct. Couples with Same Race		Pct. Couples with Same Edu.		Pct. Both Employed		Pct. Wife Greater Income than Husband	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Desktop Data								
Mean Dating Sessions (Arcsin)	0.007	0.011	-0.115	-4.155***	-0.077	-3.796***	0.018	0.926
	(0.048)	(0.546)	(0.099)	(1.417)	(0.105)	(1.321)	(0.087)	(0.962)
Dep. Var Mean	93.338	93.871	44.093	44.281	49.879	51.140	24.633	24.980
Ind. Var Mean	0.958	0.968	0.958	0.968	0.958	0.968	0.958	0.968
First Stage F-Stat	.	17.529	.	17.529	.	17.529	.	17.529
AR F-Stat	.	3.241	.	6.367	.	12.003	.	5.528
AR F-Stat p-value	.	0.002	.	0.000	.	0.000	.	0.000
KP Wald F-Stat	.	3.195	.	3.195	.	3.195	.	3.195
Obs	3452	55058	3452	55058	3452	55058	3452	55058
No. of Counties	465	465	465	465	465	465	465	465
Panel B: Mobile Data								
Mean Dating Sessions (Arcsin)	0.191	7.744***	-0.005	0.475	0.032	-5.253**	-0.066	2.512
	(0.146)	(2.442)	(0.171)	(1.762)	(0.195)	(2.230)	(0.175)	(1.731)
Dep. Var Mean	88.026	88.761	43.323	43.493	51.468	52.811	27.224	27.456
Ind. Var Mean	0.948	0.951	0.948	0.951	0.948	0.951	0.948	0.951
First Stage F-Stat	.	44.598	.	44.598	.	44.598	.	44.598
AR F-Stat	.	8.265	.	3.797	.	3.399	.	2.312
AR F-Stat p-value	.	0.000	.	0.000	.	0.001	.	0.024
KP Wald F-Stat	.	2.049	.	2.049	.	2.049	.	2.049
Obs	2092	34967	2092	34967	2092	34967	2092	34967
No. of Counties	460	412	460	412	460	412	460	412
FE	Year, County	Year, County-Pair	Year, County	Year, County-Pair	Year, County	Year, County-Pair	Year, County	Year, County-Pair
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Standard errors are clustered at the county level in columns (1), (3) and (5) and at county-pair level in columns (2), (4) and (6). Nearby counties are counties within a 20-100 km radius of the focal county. Controls included are focal county streaming and social media penetration, log population, share young, share female and log income. Instruments are nearby county dating, social media and streaming penetration values as well as nearby county population, income, share young, share female. The desktop data comes from Comscore for the years 2002-2013 and the mobile data comes from a combination of Tapestri for the years 2017 and 2018, and Dewey for the years 2019, 2022 and 2023. Mobile data focused only on common counties for Tapestri and Dewey. We exclude the year 2020 and 2021 from analysis to account for Covid-related disruptions. Outcome variables are from the 1-Year American Community Survey. We study the effect of dating app penetration in year t on outcomes in year $t+1$.

Columns (1) and (2) report that during the desktop period, both the OLS and IV effects on the share of same-race couples are near zero and insignificant. In contrast, in the mobile era, the IV coefficient is positive and large (7.744). Homophilous racial preferences are documented in Hitsch et al. (2010a). Our findings suggest that increases in mobile dating intensity contribute to higher racial homogamy, consistent with a prediction that reducing search costs can contribute to greater degrees of sorting along one's preferred dimensions. Findings also align with surveys that find interracial couples being equally likely to be formed via online and offline meetings (Rosenfeld and Thomas, 2012). Looking at the racial groups more closely (Table A.14 in the online appendix), we find that racial sorting intensified among both white and black couples (columns 4 and 6, Panel B). Thus, even when one's potential pool is larger, mobile meeting technologies may still push individuals to more in-group matches.

When we look at couples' sorting on education in columns (3) and (4), we see that in the desktop data, the IV coefficient on same-education couples is negative and precisely estimated (-4.155), while OLS coefficient is not statistically significant. In the mobile era, the IV point estimate is insignificant. Table A.16 in the online appendix further demonstrates for this early era a significant increase in the share of couples where the wife is more educated than the husband (column 4, Panel A). So, the decline in educational sorting with online dating is primarily due to women marrying men that are less educated than themselves. These results suggest that the earliest wave of online dating reduced educational homogamy—consistent with a meeting technology that expanded search across schooling lines, partially offsetting strong homophilous preferences observed within platforms (Hitsch et al., 2010a). This finding is in contrast with the long term trend of increasing assortative matching in education that is often linked to household income inequality (Greenwood et al., 2014). Our findings suggest that couples formed via online dating platforms may go against the reported macro trends.

In columns (5) and (6) of Table 8, we see that the share of dual-earner couples declined with increasing online dating usage. The IV estimate is negative and significant in both desktop (-3.796) and mobile periods (-5.253). The direction of this result is consistent with the education result: if online dating technology weakened positive sorting on schooling or labor market participation dimensions, it can generate fewer dual-earner couples. The decline in dual-earners may also reflect the participation of the younger individuals in online dating. Matches facilitated by online dating may involve disproportionately more individuals from younger cohorts, who tend to have lower levels of schooling and lower likelihoods of dual earning. Appendix Table A.17 shows that, the decline in dual earners is due to a higher share of couples where the wife is out of labor force, in both the desktop and mobile periods. Combining with earlier findings, with increasing levels of dating technologies, couples who get (or remain) married increasingly consist of those where wives are more educated than husbands, or are coupled with a working husband.

Finally, columns (7) and (8) in Table 8 indicate that the share of couples where the wife is the primary breadwinner does not change with online dating. While the IV coefficients are positive, neither in the desktop nor in the mobile period we observe a precise effect. The null finding suggests persistence of norms around lower marriage propensities when the wife would out earn the husband. Changing meeting technologies do not seem to have overturned this marital pattern. Appendix Table A.17 also indicates no change in the share of couples where the husband is the main breadwinner.

6 Robustness Checks

Results Including the COVID-19 Period (Including 2020 and 2021) The main body of our analysis intentionally leaves out 2020 and 2021 due to the COVID-19 pandemic, which affected not only the modality of personal interactions but also STD surveillance. The pandemic years were a period of undertesting for STDs, and likely due to the lack of detection and follow-up treatment, the STD transmission increased (Rogers et al., 2021). These changes might have generated behaviors that cannot be generalized to other years.

Regardless, we conduct a robustness test that repeats our analysis but includes these two years (Appendix A.7). Including 2020 and 2021 leaves more results consistent with our key findings. For marriage and divorce outcomes, Table A.18 indicates negative and significant effects on marriage and divorce in the mobile era, consistent with the results reported in Table 4. Similarly, when we look at the STD outcomes in Table A.19, coefficients for the desktop years and chlamydia and gonorrhea results for the mobile years remain consistent with those in Table 6. The only change is the insignificant effect on syphilis becomes positive and significant in Table A.18 with the COVID period. The change in the direction and the magnitude of the syphilis coefficient are consistent with the medical studies reporting an increase in syphilis rates during the pandemic period, particularly for younger populations (Stanford et al., 2021). Overall, estimated effects for STDs remain largely consistent.

Robustness of the Instrument to Alternative Ranges Throughout the benchmark analysis, we use the online dating usage of nearby counties, defined as those between 20 and 100 from the center of the focal county as instruments. These instruments were selected because they are close enough to the focal county so that the online dating usage of the nearby county can impact the online dating usage of the focal county (relevance), but are far enough where it does not directly impact outcomes in the focal county in the short-term (exclusion restriction). One worry is that 20 km is too close, such that the exclusion restriction might be violated. Therefore, we test how our results change as we shift the range for the instrument description. We focus on the following ranges: 50–100 km, 50-150 km, and 100-200 km. These ranges are sufficiently close such that the nearby regions' online dating usage is expected to influence the usage of the focal county, but also increase the distance to reduce the concerns for violation of the exclusion restriction.

We report these findings in Appendix A.6. The exercise shows that our benchmark 20-100 km range yields more conservative lower bound estimates. The estimates for marriage (Figure A.6a) and divorce (Figure A.6b) with these alternative ranges bolsters the differences between the desktop and the mobile periods. The sign of the estimates for new marriages are consistently positive for all distance ranges during the desktop period, while they are consistently negative during the mobile period. Similarly, the estimates for divorce in the desktop period are significant and positive for all km ranges, while negative for the mobile period.

The estimates for STDs in Figure A.7 indicate that, as we move beyond the 100km range, for both desktop and mobile periods, all estimates are negative and significant at 95% level. This analysis shows that our results are robust to alternative definitions of "nearby" counties. If anything, our estimates become generally more precise and the KP Wald F-stats increase as the minimum distance increases, increasing our confidence in the presence of an effect.

Alternative Instruments In Appendix A.9, we use a set of "placebo" instruments to test the validity of some of the main assumptions related to our IV approach. Specifically, we choose a set of random counties (keeping the number of peer counties similar to our benchmark 20-100 distance setting) and then assign these random counties to each focal county as the peers. Like in our main specification, we use the average online dating platform and internet use characteristics and their demographics as instruments. If our 2SLS estimates are generated by the correlated trends in either the outcomes of interest or dating site penetration among the US counties, we would expect a random-county based IV to generate a decent first stage and similar results as well.

However, what we find is that the "placebo" IV generates null effects, implying that the instruments are not relevant when a random set of peer counties are used. In addition, in the first stage, the mean dating sessions of the random peer counties do not correlate with that of the focal county, unlike with our nearby counties. This suggests that our distance-based instruments have explanatory power on a county's online dating usage, and our estimates are driven by meaningful spatial spillovers.

7 Conclusion

In this paper, we study how the rise in online dating has impacted marital and health outcomes. Dating platforms started out as websites, but after 2013, mobile dating apps have gained popularity. Due to this shift in types of dating sites, we use two data sources from two different time periods to measure online dating usage: desktop dating site usage from 2002 to 2013, and mobile dating app usage from 2017 to 2023. We then relate online dating usage in each US county to the county's marriage and divorce rates, and gonorrhea, chlamydia, and syphilis rates. The geographic variation in online dating usage plays a large role in our identification strategy.

We use an instrumental variables identification strategy, with online dating usage in nearby (but not adjacent) counties as the instrument, to identify the impact of online dating usage. Due to the presence of network effects in online dating, we expect that a higher level of online dating usage in one county increases online dating usage in nearby counties. The key assumption is that shocks that impact our outcomes of interest do not propagate to nearby counties faster than shocks that impact online dating usage. To strengthen the explanatory power of the instrument, we also consider additional factors such as income, population demographics, and social media usage as instruments, assuming these do not cause short-term changes in marriage, divorce, and STD rates of the focal county other than through the instrumented variable.

The analysis offers three key findings. First, the impact of online dating on marital outcomes differs between the early desktop and later mobile technologies. In the desktop period, higher dating site usage is linked to an increase in divorces. In the mobile period, higher dating app usage is associated with declines in both marriages and divorces on average, with a larger magnitude for marriage than divorce. These findings are consistent with a mechanism where the mobile technologies reduce search frictions and change meeting dynamics in ways that may lower marriage formation overall, but do not uniformly weaken the expected value obtained from the formed relationships, as suggested by lower divorce rates.

Second, despite widespread anecdotal concerns, we do not find evidence that online dating is associated with higher STD incidence on average. In the desktop era, we find negative average effects on chlamydia, syphilis, and gonorrhea, consistent with improved matching or better screening lowering risky encounters, net of any increase in the potential number of partners. In the mobile era, we continue to find negative average effects for gonorrhea, but effects for chlamydia and syphilis remain small and insignificant. However, these average effects mask heterogeneity: syphilis and chlamydia rates are higher in areas with greater use of LGBTQ+ dating platforms, and chlamydia rates are higher where usage is more concentrated among younger users.

Third, online dating appears to have shifted marital sorting trends. The early desktop era is associated with less sorting on education, while both periods see a lower share of dual-earner couples. In the mobile era, we see evidence of increased racial homogamy. These findings align with the idea that new meeting technologies expand one's pool, but also reduce search costs along the salient or preferred dimensions of search, which can contribute to additional sorting.

Our study has some limitations, which also point to additional potential areas for future work. First, our data limits us to specific subsamples of the overall U.S. population, such as those who join the Comscore, Tapestri, and Dewey panels. While fairly large, these samples may not be representative of the entire population, and in some counties, there are few users, so our measure of online dating penetration may be noisy. It may be useful for future research to compare outcomes across different subsets of the population. Second, our instrument requires a set of assumptions, such as that the use of online dating activities in nearby counties (within 20-100km range) do not directly impact the outcomes of a focal county other than through online dating platform use. Our robustness checks with alternative distances alleviate this concern to some degree. Also, some indicators suggest that our instruments are weak, potentially biasing our 2SLS estimates. We attempt to address this with the placebo test with irrelevant instruments (in which we find no effect, as expected), use the Anderson-Rubin F test, and explore alternative distances which improve instrument relevance. However, the potential for weak instruments should be kept in mind when interpreting our results. Finally, due to lack of data, we are unable to dive in depth into the nuances of effects, such as whether the married couples who met through online dating report higher quality matches, or whether the increase in divorce rates comes from the marriages formed through online dating or because online dating presents a better "outside" option. The aggregated data also leave us unable to definitively test for why mobile and desktop dating platforms have different effects because so many aspects of online dating usage differ between these two periods (e.g., different types of sites, changes in the population using online dating, etc.). However, to our knowledge, this is the first paper to study the broad effects of online dating platforms on relationship and health outcomes using field data. We hope that future research can further address our study's limitations and better advance our understanding of the impact of online dating platforms on society.

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Index of Appendices

A Appendix: Descriptive Statistics and Additional Regressions

A.1 Comscore Data

Table A.1: Summary Statistics for Desktop Data - (Comscore, All Years and Counties)

	Mean	SD	Min	Max	25th	Median	75th	99th	N
Number of People in County	23.68	68.81	1.00	2,614.00	3.00	7.00	18.00	279.00	27,533
Number of People Ever Visiting Dating Website	6.54	20.36	0.00	810.00	1.00	2.00	5.00	84.00	27,533
Mean Number of Online Browsing Sessions	3,008.42	2,108.31	1.00	72,057.67	1,765.67	2,746.50	3,768.92	10,268.18	27,533
Mean Number of Dating Website Browsing Sessions	7.24	25.32	0.00	1,593.50	0.20	2.00	6.55	82.40	27,533
Percentage of Dating Website Browsing Sessions	0.23	0.65	0.00	23.29	0.01	0.07	0.21	2.69	27,533
Mean Pages Visited on All Websites	22,165.95	19,339.35	1.00	553,083.00	10,832.48	19,626.01	28,245.50	87,532.00	27,533
Mean Pages Visited on Dating Websites	146.41	1,096.15	0.00	126,141.67	0.25	12.77	84.94	2,082.40	27,533
Percentage Pages Visited on Dating Websites	0.59	2.13	0.00	88.42	0.00	0.07	0.41	8.94	27,533
Mean Time Spent (hours) on All Websites	500.02	560.91	0.00	58,873.93	248.77	426.93	629.18	1,992.30	27,533
Mean Time Spent (hours) on Dating Websites	1.63	10.05	0.00	895.37	0.00	0.18	1.02	22.35	27,533
Percentage Time Spent on Dating Websites	0.32	1.26	0.00	61.50	0.00	0.04	0.21	4.55	27,533
Mean Days Visiting Dating Website	4.61	11.86	0.00	404.00	0.18	1.76	5.00	46.00	27,533

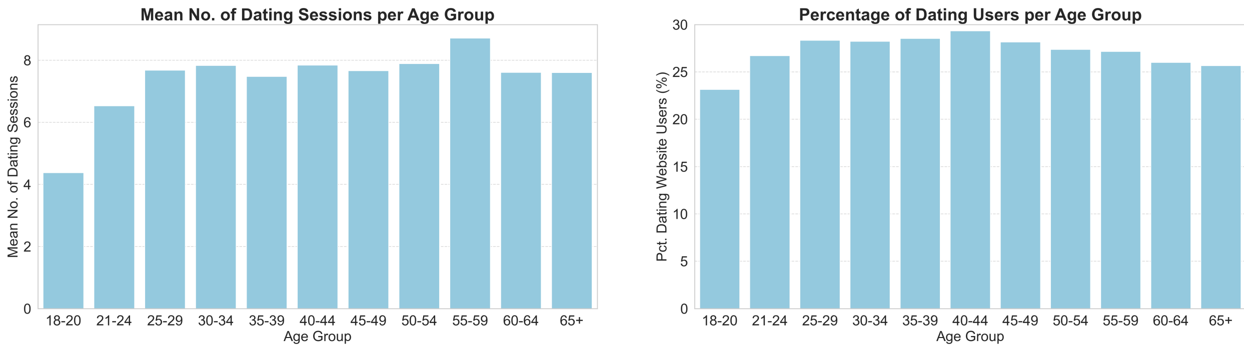
Notes. Data is from Comscore for the years 2002-2013 (excluding 2003 and 2005). Observations are at the county-year level. Values are aggregated across all days in a year. Statistics related to online activity are the person-level means for each county.

Table A.2: Summary Statistics for Desktop Data by Year (Comscore)

	Number of Counties	Number of People	Number of People Ever Visiting Dating Website	Mean Days Dating Website Visited	Mean Number of Online Browsing Sessions	Mean Number of Dating Website Browsing Sessions	Percentage of Dating Website Browsing Sessions
2002	3,002.00	93,167.00	20,670.00	0.88	1,810.65	1.31	0.07
2004	2,830.00	50,529.00	15,399.00	0.96	4,024.57	2.52	0.06
2006	2,896.00	84,183.00	22,231.00	1.28	2,400.84	2.01	0.07
2007	2,889.00	88,337.00	20,292.00	0.83	3,154.33	2.78	0.09
2008	2,748.00	57,076.00	17,299.00	0.97	2,693.53	2.97	0.12
2009	2,686.00	55,992.00	19,766.00	1.30	2,836.09	5.06	0.15
2010	2,648.00	54,209.00	28,653.00	3.06	3,118.73	12.29	0.36
2011	2,722.00	63,428.00	26,772.00	2.30	2,429.52	8.41	0.28
2012	2,646.00	55,315.00	23,950.00	2.46	3,268.25	9.97	0.27
2013	2,459.00	46,780.00	20,748.00	3.09	2,761.66	12.68	0.46

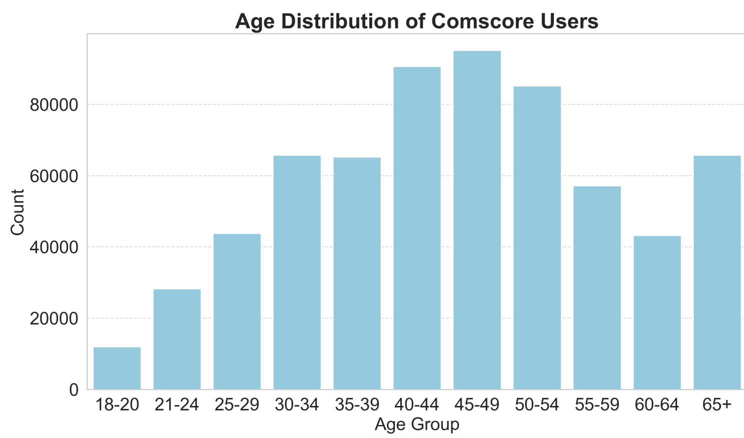
Notes. Data is from Comscore for the years 2002-2013 (excluding 2003 and 2005). Observations are at the county-year level. Values are aggregated across all days in a year. Statistics related to online activity are the person-level means for each county.

Figure A.1: Desktop Data – Online Dating Platform Penetration by Age of Head of Household (Comscore)



Notes. The figures show the mean dating sessions of dating websites by age group and the percentage of users who have positive dating sessions. Panelists from 2002 to 2013 are included.

Figure A.2: Desktop Data – Age Distribution of Desktop Dating Platform Users (Comscore)



Note: The figure shows the age distribution of the Comscore panelists from 2002 to 2013.

A.2 Tapestri and Dewey Data

In this section, we provide summary statistics for the mobile browsing data from Tapestri (see details on Table C.2) and Dewey Data (see details on Table C.1).

A.2.1 Individual-Level Summary Statistics

Table A.3: Mobile Dating App Session Summary Statistics, by Year (Tapestri)

	Mean	SD	Min	Max	25th	Median	75th	99th	N
2017	20.39	80.48	0	5,284	0.00	0.00	8.00	385.00	6,321,242
2018	65.67	172.82	0	6,860	0.00	6.00	44.00	871.00	5,728,147

Notes. Data is from Tapestri and for the years 2017-2018. Observations are at the individual-level. A dating app session refers to a visit to a dating app by the user. Only users present in the data for at least 30 days are included.

Table A.4: Mobile Dating App Session Summary Statistics, by Year (Dewey)

	Mean	SD	Min	Max	25th	Median	75th	99th	N
2019	270.82	2,722.89	0	239,081	0	0	0	6,347	195,545
2020	180.19	1,921.77	0	182,628	0	0	0	4,249	195,565
2021	200.61	2,367.12	0	262,021	0	0	0	4,373	160,457
2022	210.21	2,462.38	0	191,112	0	0	0	4,523	157,023
2023	171.66	2,074.43	0	244,889	0	0	0	3,600	108,096

Notes. Data is from Dewey and for the years 2019-2023. Observations are at the individual-level. Values are aggregated to the year level. A dating app session refers to a visit to a dating app by the user.

Table A.5: All Mobile App Sessions Summary Statistics, by Year (Tapestri)

	Mean	SD	Min	Max	25th	Median	75th	99th	N
2017	753.57	960.35	30	1,139,052	207.00	450.00	972.00	4,074.00	6,321,242
2018	808.73	2,458.13	30	5,413,104	275.00	521.00	991.00	4,547.00	5,728,147

Notes. Data is from Tapestri for the years 2017-2018. Observations are at the individual-level. Only users present in the data for at least 30 days are included.

Table A.6: All Mobile App Sessions Summary Statistics, by Year (Dewey)

	Mean	SD	Min	Max	25th	Median	75th	99th	N
2019	15,576.45	28,046.54	1	719,886	599	3,667	18,203	131,663	195,545
2020	16,074.61	27,975.92	1	668,071	699	4,507	19,236	132,261	195,565
2021	21,610.07	37,496.39	1	1,043,113	717	5,854	25,915	176,281	160,457
2022	23,585.71	39,837.49	1	696,416	648	6,216	29,110	184,891	157,023
2023	23,572.90	39,510.18	1	647,128	691	5,878	29,393	179,935	108,096

Notes. Data is from Dewey for the years 2019-2023. Observations are at the individual-level. Values are aggregated to the year level.

Figure A.3: App Usage Session Comparison: Data from Tapestri and Dewey

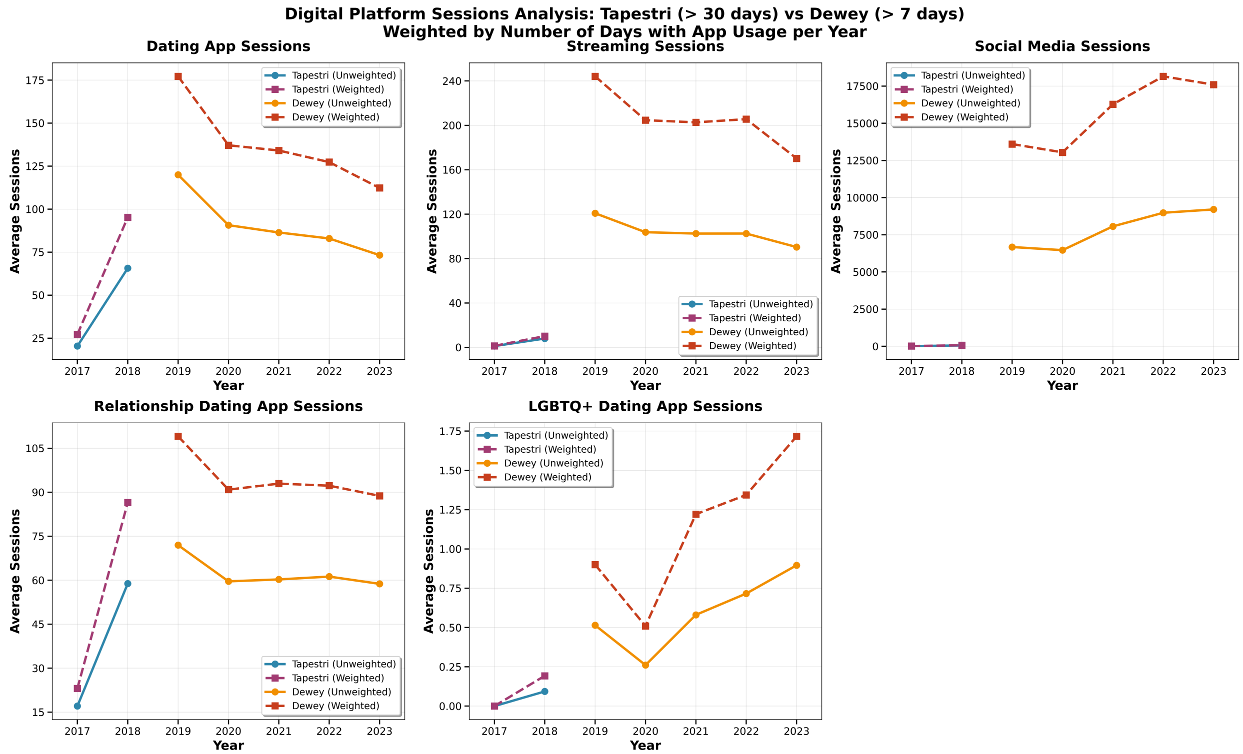
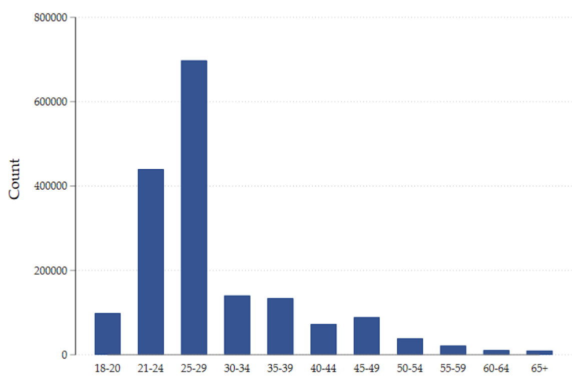
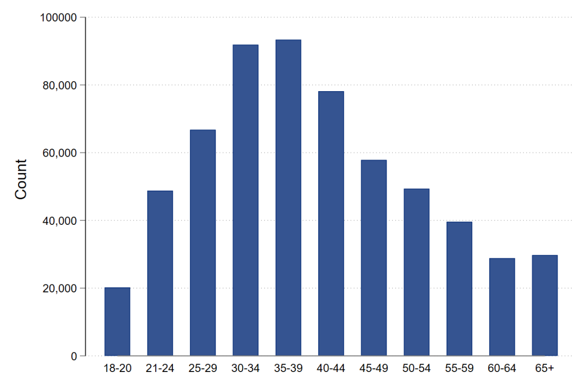


Figure A.4: Age Distribution of Users, Mobile Data Sources



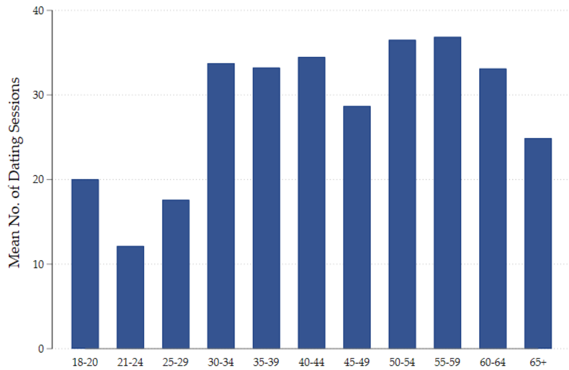
(a) Age Distribution (Tapestri)



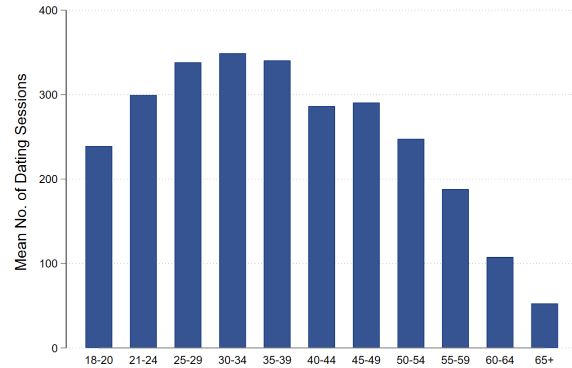
(b) Age Distribution (Dewey)

Notes. We observe age for all Dewey panelists, but observe age only for approximately 20% of Tapestri panelists. Tapestri figure includes years 2017 and 2018, while Dewey's includes 2018 to 2023.

Figure A.5: Online Dating Penetration by Age (Mobile Data)



(a) Online Dating Penetration by Age (Tapestri)



(b) Online Dating Penetration by Age (Dewey)

Notes. We observe age for all Dewey panelists, but observe age only for approximately 20% of Tapestri panelists. Tapestri figure includes years 2017 and 2018, while Dewey's includes 2018 to 2023.

A.2.2 County-Level Summary Statistics

Table A.7: Mean No. of Dating App Sessions (Tapestri)

	Mean	SD	Min	Max	25th	Median	75th	99th	N
2017	15.53	8.52	0	229	11	15	19	39	3,162
2018	43.31	16.03	0	250	34	42	50	99	3,216

Notes. Data is from Tapestri for the years 2017-2018. Observations are at the county-level. Values are aggregated to the year level. A dating app session refers to a visit to a dating app by the user. Only counties with more than one person are included. Only users present in the data for at least 30 days are included. Observations are weighted based on the number of days we observe each individual.

Table A.8: Mean No. of Dating App Sessions (Dewey)

	Mean	SD	Min	Max	25th	Median	75th	99th	N
2019	138.32	254.24	0	2,878	0	33	185	1,293	2,522
2020	116.07	277.16	0	4,816	0	23	135	1,143	2,559
2021	114.28	279.69	0	5,045	0	18	130	1,240	2,499
2022	108.44	249.61	0	3,893	0	17	123	1,197	2,543
2023	93.44	229.76	0	3,180	0	6	97	1,217	2,418

Notes. Data is from Dewey for the years 2019-2023. Observations are at the county-level. Values are aggregated to the year level. A dating app session refers to a visit to a dating app by the user. Only counties with more than one person are included. Only users present in the data for at least 7 days are included. Observations are weighted based on the number of days we observe each individual.

A.3 Demographic Characteristics of Desktop and Mobile Data Samples

Table A.9: Demographic Characteristics and Dating Websites Use (Desktop Data)

	All Dating Websites (1)	Relationship-Minded Websites (2)	LGBTQ+ Dating Websites (3)
Panel A: Household Income			
<15k	0.228***	0.110***	0.101***
	(0.025)	(0.013)	(0.011)
15-25k	0.176***	0.085***	0.075***
	(0.025)	(0.009)	(0.009)
25-35k	0.142***	0.077***	0.071***
	(0.016)	(0.006)	(0.005)
35-50k	0.081***	0.041***	0.039***
	(0.010)	(0.008)	(0.008)
50-75k	0.065***	0.035***	0.032***
	(0.009)	(0.006)	(0.006)
75-99k	0.039***	0.018**	0.019***
	(0.009)	(0.006)	(0.004)
Dep. Var Mean	0.756	0.449	0.389
Obs	651,935	651,935	651,935
R-squared	0.027	0.027	0.021
Panel B: Educational Attainment by Head of Household			
Less than HS	0.052	-0.014	0.007
	(0.064)	(0.030)	(0.035)
High School	0.016	-0.013	-0.008
	(0.034)	(0.014)	(0.018)
Some College	0.023	0.004	-0.001
	(0.038)	(0.020)	(0.027)
Associate Degree	0.021	0.002	0.009
	(0.049)	(0.033)	(0.033)
Bachelor Degree	-0.010	-0.000	-0.006
	(0.047)	(0.027)	(0.033)
Dep. Var Mean	0.682	0.432	0.403
Obs	163,271	163,271	163,271
R-squared	0.055	0.043	0.034
Panel C: Race of Head of Household			
White	0.057	0.058*	0.051*
	(0.052)	(0.029)	(0.025)
Black	0.085*	0.027	0.011
	(0.044)	(0.024)	(0.020)
Asian	0.138	0.039	0.132*
	(0.088)	(0.041)	(0.067)
Dep. Var Mean	0.756	0.449	0.389
Obs	651,935	651,935	651,935
R-squared	0.025	0.026	0.020
Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes

***, **, * indicate significance at the 1%, 5%, and 10% level respectively. This table reports the differences in arcsinh-transformed dating sessions relative to the income level of 100k+ (Panel A), Graduate Degree (Panel B), and Other Races (Panel C). Standard errors are clustered at the year level. Year and county fixed effects are included. Observations are at the individual-year level. The data are desktop data from Comscore for the years 2002-2013.

A.4 First Stage IV Results

A.4.1 Desktop Data, Relationship-Minded Heterogeneity

Table A.10: First-Stage: Mean Number of Sessions (Inverse Hyperbolic) on Dating Websites (Desktop)

First-Stage Outcome	Mean Dating Sessions (Arcsinh)	Mean Casual Sessions (Arcsinh)	Mean Relationship Sessions (Arcsinh)
	(1)	(2)	(3)
Nearby Mean Dating Sessions (Arcsin)	0.003*		
	(0.002)		
Nearby Mean Casual Sessions (Arcsinh)		0.001	-0.000
		(0.002)	(0.002)
Nearby Mean Relationship Sessions (Arcsin)		0.001	0.005***
		(0.002)	(0.002)
Nearby Mean Streaming Sessions (Arcsin)	0.002	0.004	-0.001
	(0.002)	(0.003)	(0.002)
Nearby Mean Social Sessions (Arcsin)	-0.007**	-0.004	-0.010***
	(0.003)	(0.003)	(0.002)
Nearby Log Population	-0.028	-0.034	-0.000
	(0.031)	(0.032)	(0.001)
Nearby Per Capita Income (Log)	-0.081***	-0.078***	-0.005
	(0.026)	(0.027)	(0.003)
Nearby Share Young	2.284***	2.094***	0.036***
	(0.377)	(0.390)	(0.011)
Nearby Share Female	0.923***	1.209***	0.008
	(0.341)	(0.353)	(0.022)
Dep. Var Mean	0.642	0.549	0.635
Obs	384546	384546	386287
R^2	0.246	0.259	0.253
F-Stat	447.189	412.383	215.689
No. of County-Pairs	52588	52588	52588
No. of Years	10	10	10
Year FE	Yes	Yes	Yes
County-Pair FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes

***, **, * indicates significance at the 1%, 5%, and 10% level respectively. Standard errors are clustered at the county-pair level. The table reports the first stage results for IV regression specifications using nearby county dating website penetration as instruments. Mean dating sessions are arcsinh-transformed. Nearby counties are counties within a 20-100 km radius of the focal county. Controls included are focal county streaming and social media penetration, log population, share young, share female and log income. Instruments are nearby county dating, social media and streaming penetration values as well as nearby county population, income, share young, share female. The online activity data are from desktop data available through Comscore for the years 2002-2013.

A.4.2 Desktop Data, Interaction with LGBTQ+

Table A.11: First Stage: Mean Number of Sessions (Inverse Hyperbolic) on Dating Websites (Desktop)

First-Stage Outcome	Mean Dating Sessions (Arcsinh)	Mean Not LGBTQ+ Sessions (Arcsinh)	Mean LGBTQ+ Sessions (Arcsinh)
	(1)	(2)	(3)
Nearby Mean Dating Sessions (Arcsin)	0.003*		
	(0.002)		
Nearby Mean Not LGBTQ+ Sessions (Arcsinh)		0.004*	-0.001
		(0.002)	(0.002)
Nearby Mean LGBTQ+ Sessions (Arcsin)		0.000	0.003**
		(0.002)	(0.002)
Nearby Mean Streaming Sessions (Arcsin)	0.002	0.001	0.002
	(0.002)	(0.003)	(0.002)
Nearby Mean Social Sessions (Arcsin)	-0.007**	-0.006*	-0.008***
	(0.003)	(0.003)	(0.002)
Nearby Log Population	-0.028	0.000	-0.000
	(0.031)	(0.031)	(0.001)
Nearby Per Capita Income (Log)	-0.081***	-0.086***	-0.001
	(0.026)	(0.026)	(0.003)
Nearby Share Young	2.284***	2.551***	0.020*
	(0.377)	(0.380)	(0.011)
Nearby Share Female	0.923***	1.416***	-0.009
	(0.341)	(0.342)	(0.023)
Dep. Var Mean	0.642	0.572	0.615
Obs	384546	384546	386287
R^2	0.246	0.266	0.245
F-Stat	447.189	458.420	177.650
No. of County-Pairs	52588	52588	52588
No. of Years	10	10	10
Year FE	Yes	Yes	Yes
County-Pair FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes

***, **, * indicates significance at the 1%, 5%, and 10% level respectively. Standard errors are clustered at the county-pair level. The table reports the first stage results for IV regression specifications using nearby county dating website penetration as instruments. Mean dating sessions are arcsinh-transformed. Nearby counties are counties within a 20-100 km radius of the focal county. Controls included are focal county streaming and social media penetration, log population, share young, share female and log income. Instruments are nearby county dating, social media and streaming penetration values as well as nearby county population, income, share young, share female. The online activity data are from desktop data available through Comscore for the years 2002-2013.

A.4.3 Mobile Data, Interaction with Relationship-Minded

Table A.12: First Stage: Mean Number of Sessions (Inverse Hyperbolic) on Dating Websites (Mobile)

First-Stage Outcome	Mean Dating Sessions	Mean Casual Sessions (Arcsinh)	Mean Relationship Sessions (Arcsinh)
	(1)	(2)	(3)
Nearby Mean Dating Sessions (Arcsin)	0.009***		
	(0.003)		
Nearby Mean Casual Sessions (Arcsinh)		0.008***	-0.002
		(0.003)	(0.002)
Nearby Mean Relationship Sessions (Arcsin)		-0.000	0.013***
		(0.003)	(0.002)
Nearby Mean Streaming Sessions (Arcsin)	0.002	0.015***	-0.000
	(0.003)	(0.004)	(0.003)
Nearby Mean Social Sessions (Arcsin)	0.002	0.024***	-0.005
	(0.005)	(0.005)	(0.004)
Nearby Log Population	-0.019	-0.018	-0.002***
	(0.045)	(0.045)	(0.001)
Nearby Per Capita Income (Log)	0.083*	0.091*	0.005**
	(0.048)	(0.048)	(0.003)
Nearby Share Young	0.059	-0.050	-0.013
	(0.636)	(0.658)	(0.013)
Nearby Share Female	-1.023**	0.969**	-0.072***
	(0.430)	(0.453)	(0.020)
Dep. Var Mean	0.693	0.592	0.676
Obs	226073	226073	226122
R^2	0.462	0.423	0.464
F-Stat	302.365	195.795	251.999
No. of County-Pairs	58623	58623	58623
No. of Years	5	5	5
Year FE	Yes	Yes	Yes
County-Pair FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes

***, **, * indicates significance at the 1%, 5%, and 10% level respectively. Standard errors are clustered at the county-pair level. The table reports the first stage results for IV regression specifications using nearby county dating app penetration as instruments. Mean dating sessions are arcsinh-transformed. Nearby counties are counties within a 20-100 km radius of the focal county. Controls included are focal county streaming and social media penetration, log population, share young, share female and log income. Instruments are nearby county dating, social media and streaming penetration values as well as nearby county population, income, share young, share female. The online activity data are from mobile data available through Tapestri for the years 2017 and 2018, and Dewey for the years 2019, 2022 and 2023. Data from the years 2020 and 2021 are omitted due to Covid-related disruptions.

A.4.4 Mobile Data, Interaction with LGBTQ+

Table A.13: First Stage: Mean Number of Sessions (Inverse Hyperbolic) on Dating Websites (Mobile)

First-Stage Outcome	Mean Dating Sessions	Mean Not LGBTQ+ Sessions (Arcsinh)	Mean LGBTQ+ Sessions (Arcsinh)
	(1)	(2)	(3)
Nearby Mean Dating Sessions (Arcsin)	0.009***		
	(0.003)		
Nearby Mean Not LGBTQ+ Sessions (Arcsinh)		0.008***	0.000
		(0.003)	(0.002)
Nearby Mean LGBTQ+ Sessions (Arcsin)		0.005***	0.072***
		(0.002)	(0.003)
Nearby Mean Streaming Sessions (Arcsin)	0.002	0.003	-0.008***
	(0.003)	(0.003)	(0.002)
Nearby Mean Social Sessions (Arcsin)	0.002	0.002	-0.012***
	(0.005)	(0.005)	(0.003)
Nearby Log Population	-0.019	-0.017	-0.010***
	(0.045)	(0.045)	(0.001)
Nearby Per Capita Income (Log)	0.083*	0.061	0.002
	(0.048)	(0.048)	(0.003)
Nearby Share Young	0.059	-0.033	0.020
	(0.636)	(0.635)	(0.013)
Nearby Share Female	-1.023**	-0.978**	-0.071***
	(0.430)	(0.428)	(0.021)
Dep. Var Mean	0.693	0.692	0.200
Obs	226073	226073	226122
R^2	0.462	0.462	0.362
F-Stat	302.365	272.784	82.627
No. of County-Pairs	58623	58623	58623
No. of Years	5	5	5
Year FE	Yes	Yes	Yes
County-Pair FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes

***, **, * indicates significance at the 1%, 5%, and 10% level respectively. Standard errors are clustered at the county-pair level. The table reports the first stage results for IV regression specifications using nearby county dating app penetration as instruments. Mean dating sessions are arcsinh-transformed. Nearby counties are counties within a 20-100 km radius of the focal county. Controls included are focal county streaming and social media penetration, log population, share young, share female and log income. Instruments are nearby county dating, social media and streaming penetration values as well as nearby county population, income, share young, share female. The online activity data are from mobile data available through Tapestri for the years 2017 and 2018, and Dewey for the years 2019, 2022 and 2023. Data from the years 2020 and 2021 are omitted due to Covid-related disruptions.

A.5 Additional Sorting Results

Table A.14: Effect of Mean Number of Sessions (Inverse Hyperbolic) on Dating Websites/Apps on Sorting Outcomes (1)

	Pct. Couples with Same Race		Pct. Couples Both White		Pct. Couples Both Black	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Desktop Data						
Mean Dating Sessions (Arcsin)	0.007	0.011	0.128*	1.209	-0.089**	-0.668
	(0.048)	(0.546)	(0.070)	(1.040)	(0.043)	(0.676)
Dep. Var Mean	93.338	93.871	79.227	78.568	7.416	9.054
Ind. Var Mean	0.958	0.968	0.958	0.968	0.958	0.968
First Stage F-Stat	.	17.529	.	17.529	.	17.529
AR F-Stat	.	3.241	.	6.704	.	1.758
AR F-Stat p-value	.	0.002	.	0.000	.	0.091
KP Wald F-Stat	.	3.195	.	3.195	.	3.195
Obs	3452	55058	3452	55058	3452	55058
No. of Counties	465	465	465	465	465	465
Panel B: Mobile Data						
Mean Dating Sessions (Arcsin)	0.191	7.744***	0.542	19.816***	0.128	4.430***
	(0.146)	(2.442)	(0.435)	(6.258)	(0.091)	(1.521)
Dep. Var Mean	88.026	88.761	69.650	70.131	7.165	8.714
Ind. Var Mean	0.948	0.951	0.948	0.951	0.948	0.951
First Stage F-Stat	.	44.598	.	44.598	.	44.598
AR F-Stat	.	8.265	.	7.672	.	8.919
AR F-Stat p-value	.	0.000	.	0.000	.	0.000
KP Wald F-Stat	.	2.049	.	2.049	.	2.049
Obs	2092	34967	2092	34967	2092	34967
No. of Counties	460	412	460	412	460	412
FE	Year, County	Year, County-Pair	Year, County	Year, County-Pair	Year, County	Year, County-Pair
Controls	Yes	Yes	Yes	Yes	Yes	Yes

***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Standard errors are clustered at the county level in columns (1), (3) and (5) and at county-pair level in columns (2), (4) and (6). Nearby counties are counties within a 20-100 km radius of the focal county. Controls included are focal county streaming and social media penetration, log population, share young, share female and log income. Instruments are nearby county dating, social media and streaming penetration values as well as nearby county population, income, share young, share female. The desktop data comes from Comscore for the years 2002-2013 and the mobile data comes from a combination of Tapestri for the years 2017 and 2018, and Dewey for the years 2019, 2022 and 2023. Mobile data focused only on common counties for Tapestri and Dewey. We exclude the year 2020 and 2021 from analysis to account for Covid-related disruptions. Outcome variables are from the 1-Year American Community Survey. We study the effect of dating app penetration in year t on outcomes in year $t+1$.

Table A.15: Effect of Mean Number of Sessions (Inverse Hyperbolic) on Dating Websites/Apps on Sorting Outcomes (2)

	Times Husband Prev. Married (Arcsin)		Times Wife Prev. Married (Arcsin)		Year's Married (Arcsin)	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Desktop Data						
Mean Dating Sessions (Arcsin)	0.000	0.014	0.000	0.006	-0.000	0.017
	(0.001)	(0.009)	(0.001)	(0.009)	(0.001)	(0.015)
Dep. Var Mean	1.025	1.022	1.018	1.014	3.761	3.755
Ind. Var Mean	0.952	0.964	0.952	0.964	0.952	0.964
First Stage F-Stat	.	15.716	.	15.716	.	15.716
AR F-Stat	.	2.535	.	2.792	.	2.080
AR F-Stat p-value	.	0.013	.	0.007	.	0.042
KP Wald F-Stat	.	2.293	.	2.293	.	2.293
Obs	2719	43336	2719	43336	2719	43336
No. of Counties	465	465	465	465	465	465
Panel B: Mobile Data						
Mean Dating Sessions (Arcsin)	0.001	0.022	0.001	0.045**	-0.007**	0.003
	(0.002)	(0.016)	(0.002)	(0.020)	(0.003)	(0.026)
Dep. Var Mean	1.005	1.003	0.997	0.994	3.802	3.795
Ind. Var Mean	0.948	0.951	0.948	0.951	0.948	0.951
First Stage F-Stat	.	44.598	.	44.598	.	44.598
AR F-Stat	.	2.588	.	8.598	.	4.307
AR F-Stat p-value	.	0.012	.	0.000	.	0.000
KP Wald F-Stat	.	2.049	.	2.049	.	2.049
Obs	2092	34967	2092	34967	2092	34967
No. of Counties	460	412	460	412	460	412
FE	Year, County	Year, County-Pair	Year, County	Year, County-Pair	Year, County	Year, County-Pair
Controls	Yes	Yes	Yes	Yes	Yes	Yes

***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Standard errors are clustered at the county level in columns (1), (3) and (5) and at county-pair level in columns (2), (4) and (6). Nearby counties are counties within a 20-100 km radius of the focal county. Controls included are focal county streaming and social media penetration, log population, share young, share female and log income. Instruments are nearby county dating, social media and streaming penetration values as well as nearby county population, income, share young, share female. Outcomes include the number of previous marriages for the husband and wife and years married, calculated as the time since the last marriage; in cases of discrepancy between spouses, the shorter duration is used. The desktop data comes from Comscore for the years 2002-2013 and the mobile data comes from a combination of Tapestri for the years 2017 and 2018, and Dewey for the years 2019, 2022 and 2023. Mobile data focused only on common counties for Tapestri and Dewey. We exclude the year 2020 and 2021 from analysis to account for Covid-related disruptions. Outcome variables are from the 1-Year American Community Survey. We study the effect of dating app penetration in year t on outcomes in year $t+1$.

Table A.16: Effect of Mean Number of Sessions (Inverse Hyperbolic) on Dating Websites/Apps on Sorting Outcomes (3)

	Pct. Couples with Same Edu.		Pct. Couples with Wife More Educated	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Panel A: Desktop Data				
Mean Dating Sessions (Arcsin)	-0.115	-4.155***	0.012	3.236**
	(0.099)	(1.417)	(0.092)	(1.258)
Dep. Var Mean	44.093	44.281	28.301	28.373
Ind. Var Mean	0.958	0.968	0.958	0.968
First Stage F-Stat	.	17.529	.	17.529
AR F-Stat	.	6.367	.	10.198
AR F-Stat p-value	.	0.000	.	0.000
KP Wald F-Stat	.	3.195	.	3.195
Obs	3452	55058	3452	55058
No. of Counties	465	465	465	465
Panel B: Mobile Data				
Mean Dating Sessions (Arcsin)	-0.005	0.475	0.020	1.054
	(0.171)	(1.762)	(0.160)	(1.637)
Dep. Var Mean	43.323	43.493	30.919	31.004
Ind. Var Mean	0.948	0.951	0.948	0.951
First Stage F-Stat	.	44.598	.	44.598
AR F-Stat	.	3.797	.	1.946
AR F-Stat p-value	.	0.000	.	0.059
KP Wald F-Stat	.	2.049	.	2.049
Obs	2092	34967	2092	34967
No. of Counties	460	412	460	412
FE	Year, County	Year, County-Pair	Year, County	Year, County-Pair
Controls	Yes	Yes	Yes	Yes

***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Standard errors are clustered at the county level in columns (1), and (3) and at county-pair level in columns (2), and (4). Nearby counties are counties within a 20-100 km radius of the focal county. Controls included are focal county streaming and social media penetration, log population, share young, share female and log income. Instruments are nearby county dating, social media and streaming penetration values as well as nearby county population, income, share young, share female. The desktop data comes from Comscore for the years 2002-2013 and the mobile data comes from a combination of Tapestri for the years 2017 and 2018, and Dewey for the years 2019, 2022 and 2023. Mobile data focused only on common counties for Tapestri and Dewey. We exclude the year 2020 and 2021 from analysis to account for Covid-related disruptions. Outcome variables are from the 1-Year American Community Survey. We study the effect of dating app penetration in year t on outcomes in year $t+1$.

Table A.17: Effect of Mean Number of Sessions (Inverse Hyperbolic) on Dating Websites/Apps on Sorting Outcomes (4)

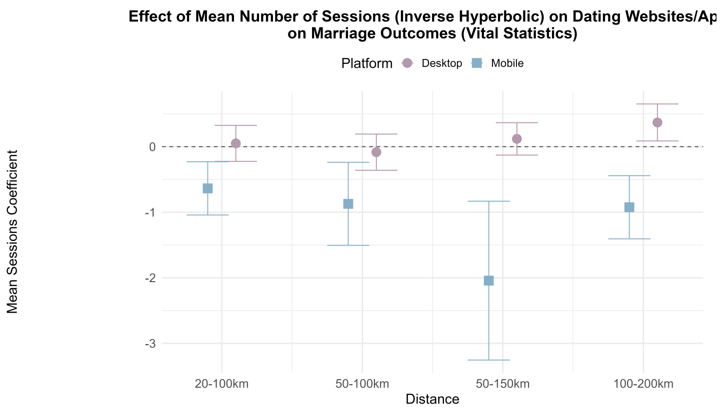
	Pct. Both Employed		Pct. Wife Not in Labor Force		Wife's Income as Pct. of Husband's Income		Pct. Wife Greater Income than Husband	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Desktop Data								
Mean Dating Sessions (Arcsin)	-0.077	-3.796***	0.000	8.471***	-0.191	5.843	0.018	0.926
	(0.105)	(1.321)	(0.095)	(2.004)	(0.349)	(4.110)	(0.087)	(0.962)
Dep. Var Mean	49.879	51.140	37.040	35.861	92.943	93.678	24.633	24.980
Ind. Var Mean	0.958	0.968	0.958	0.968	0.958	0.968	0.958	0.968
First Stage F-Stat	.	17.529	.	17.529	.	17.529	.	17.529
AR F-Stat	.	12.003	.	12.443	.	5.272	.	5.528
AR F-Stat p-value	.	0.000	.	0.000	.	0.000	.	0.000
KP Wald F-Stat	.	3.195	.	3.195	.	3.195	.	3.195
Obs	3452	55058	3452	55058	3452	55058	3452	55058
No. of Counties	465	465	465	465	465	465	465	465
Panel B: Mobile Data								
Mean Dating Sessions (Arcsin)	0.032	-5.253**	-0.206	6.009**	-0.594	5.038	-0.066	2.512
	(0.195)	(2.230)	(0.208)	(2.441)	(0.787)	(7.573)	(0.175)	(1.731)
Dep. Var Mean	51.468	52.811	37.659	36.477	103.171	103.444	27.224	27.456
Ind. Var Mean	0.948	0.951	0.948	0.951	0.948	0.951	0.948	0.951
First Stage F-Stat	.	44.598	.	44.598	.	44.598	.	44.598
AR F-Stat	.	3.399	.	5.361	.	1.102	.	2.312
AR F-Stat p-value	.	0.001	.	0.000	.	0.359	.	0.024
KP Wald F-Stat	.	2.049	.	2.049	.	2.049	.	2.049
Obs	2092	34967	2092	34967	2092	34967	2092	34967
No. of Counties	460	412	460	412	460	412	460	412
FE	Year, County	Year, County-Pair	Year, County	Year, County-Pair	Year, County	Year, County-Pair	Year, County	Year, County-Pair
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Standard errors are clustered at the county level in columns (1), (3), (5), and (7) and at county-pair level in columns (2), (4), (6), and (8). Nearby counties are counties within a 20-100 km radius of the focal county. Controls included are focal county streaming and social media penetration, log population, share young, share female and log income. Instruments are nearby county dating, social media and streaming penetration values as well as nearby county population, income, share young, share female. The desktop data comes from Comscore for the years 2002-2013 and the mobile data comes from a combination of Tapestri for the years 2017 and 2018, and Dewey for the years 2019, 2022 and 2023. Mobile data focused only on common counties for Tapestri and Dewey. We exclude the year 2020 and 2021 from analysis to account for Covid-related disruptions. Outcome variables are from the 1-Year American Community Survey. We study the effect of dating app penetration in year t on outcomes in year $t+1$.

A.6 Distance Robustness

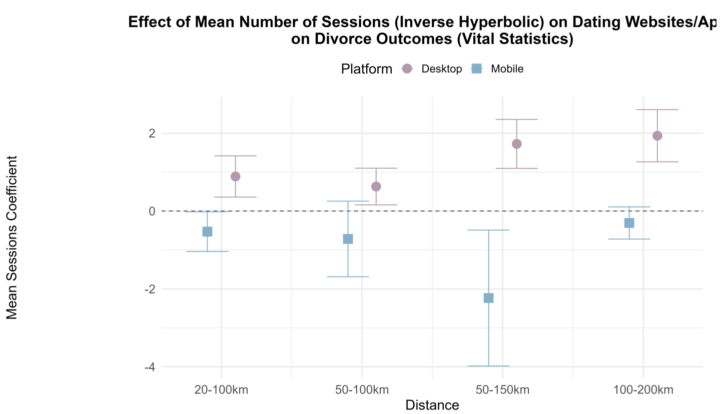
In this section, we test the robustness of our results to different ranges for the instrument. In the main paper, the instruments are the online dating usage of counties with 20–100 kilometers from the focal county. In the robustness checks, we check alternative distance ranges, including 50–100 km, 50–150 km, and 100–200 km. In the figures below, we plot the coefficient estimate and its 95% confidence interval for online dating usage on marriage, divorce, and STD rates for each distance range, starting with the 20-100km benchmark. We also report the Anderson Rubin and KP Wald F statistics for each range.

Figure A.6: Effect of Online Dating on Marriage Outcomes: Robustness by Distance Specification



	20-100km	50-100km	50-150km	100-200km
KP Wald F-Stat (Mobile)	2.563	1.648	1.717	3.109
KP Wald F-Stat (Desktop)	2.509	2.669	3.938	3.668
AR F-Stat (Mobile)	10.286	8.279	17.327	14.84
AR F-Stat (Desktop)	3.059	2.435	1.372	2.71

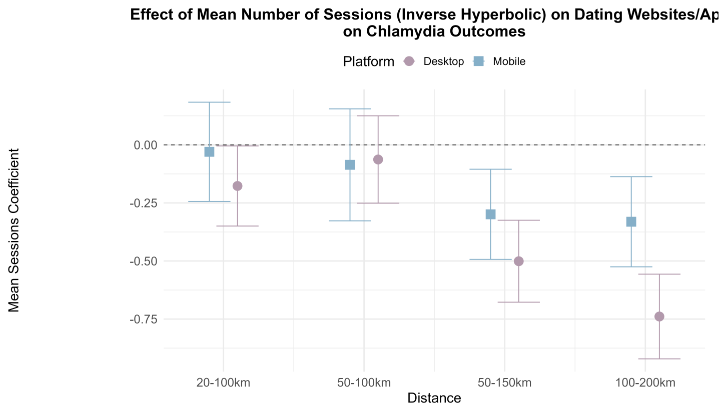
(a) Marriage



	20-100km	50-100km	50-150km	100-200km
KP Wald F-Stat (Mobile)	2.238	0.754	1.052	2.874
KP Wald F-Stat (Desktop)	3.118	2.988	5.446	5.835
AR F-Stat (Mobile)	5.6	3.88	8.523	11.467
AR F-Stat (Desktop)	25.57	19.873	60.217	84.824

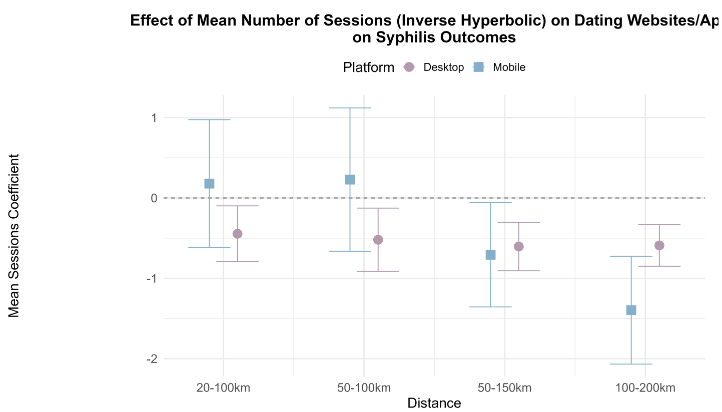
(b) Divorce

Figure A.7: Effect of Online Dating on STD Outcomes: Distance Robustness



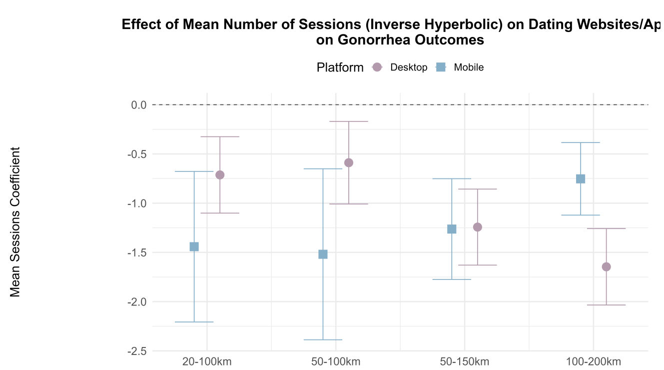
	20-100km	50-100km	50-150km	100-200km
KP Wald F-Stat (Mobile)	3.034	2.489	5.843	7.645
KP Wald F-Stat (Desktop)	8.232	6.559	12.404	16.756
AR F-Stat (Mobile)	12.628	10.726	19.209	17.762
AR F-Stat (Desktop)	13.026	8.562	25.75	45.524

(a) Chlamydia



	20-100km	50-100km	50-150km	100-200km
KP Wald F-Stat (Mobile)	3.034	2.489	5.843	7.645
KP Wald F-Stat (Desktop)	8.221	6.545	12.399	16.793
AR F-Stat (Mobile)	26.604	17.29	35.04	31.018
AR F-Stat (Desktop)	3.688	4.332	9.982	7.549

(b) Syphilis



	20-100km	50-100km	50-150km	100-200km
KP Wald F-Stat (Mobile)	3.034	2.489	5.843	7.645
KP Wald F-Stat (Desktop)	8.232	6.559	12.404	16.756
AR F-Stat (Mobile)	12.676	10.54	27.445	38.301
AR F-Stat (Desktop)	16.835	12.927	37.017	60.111

(c) Gonorrhea

A.7 Results for All Years (Including 2020 and 2021)

As noted in the main text, due to the concerns of COVID-19 confounds, we excluded years 2020 and 2021 from our analyses presented in the main text. In this section, we report the main estimates for the mobile data using all years.

Table A.18: Effect of Mean Number of Sessions on Dating Websites/Apps on Marriage Outcomes (Vital Statistics)

	Arcsinh # New Marriages		Arcsinh # New Divorces	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Panel A: Desktop Data				
Mean Dating Sessions (Arcsinh)	0.001	0.005	0.009	0.887***
	(0.003)	(0.140)	(0.006)	(0.270)
Dep. Var Mean	6.453	6.450	5.743	5.774
Ind. Var Mean	0.641	0.646	0.636	0.642
AR F-Stat	.	3.059	.	25.570
AR F-Stat p-value	.	0.003	.	0.000
KP Wald F-Stat	.	2.509	.	3.118
Obs	16136	258305	14692	229653
No. of Counties	2188	2188	1921	1921
Panel B: Mobile Data				
Mean Dating Sessions (Arcsinh)	-0.014**	-0.511***	-0.011	-0.394**
	(0.007)	(0.177)	(0.014)	(0.185)
Dep. Var Mean	6.204	6.210	5.252	5.208
Ind. Var Mean	0.705	0.702	0.700	0.696
AR F-Stat	.	13.697	.	6.305
AR F-Stat p-value	.	0.000	.	0.000
KP Wald F-Stat	.	2.704	.	3.175
Obs	9649	144394	7809	119716
No. of Counties	2116	1934	1778	1516
FE	Year, County	Year, County-Pair	Year, County	Year, County-Pair
Controls	Yes	Yes	Yes	Yes

Notes: ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Standard errors are clustered at the county level in columns (1) and (3) and at county-pair level in columns (2) and (4). Nearby counties are counties within a 20-100 km radius of the focal county. Controls included are focal county streaming and social media penetration, log population, share young, share female and log income. Instruments are nearby county dating, social media and streaming penetration values as well as nearby county population, income, share young, share female. The desktop data comes from Comscore for the years 2002-2013 and the mobile data comes from a combination of Tapestri for the years 2017 and 2018, and Dewey for the years 2019, 2020, 2021, 2022 and 2023. Mobile data focused only on common counties for Tapestri and Dewey. Data on marriage and divorce outcomes are from the Vital Statistics of states. We study the effect of dating app penetration in year t on outcomes in year $t+1$.

Table A.19: Effect of Mean Number of Sessions (Inverse Hyperbolic) on Dating Websites/Apps on STD Outcomes

	Chlamydia Rate (Arcsinh)		Syphilis Rate (Arcsinh)		Gonorrhea Rate (Arcsinh)	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Desktop Data						
Mean Dating Sessions (Arcsinh)	0.001	-0.177**	-0.009	-0.445**	0.013	-0.713***
	(0.004)	(0.088)	(0.007)	(0.177)	(0.009)	(0.198)
Dep. Var Mean	6.104	6.085	0.637	0.646	4.032	4.141
Ind. Var Mean	0.640	0.642	0.640	0.642	0.640	0.642
AR F-Stat	.	13.026	.	3.688	.	16.835
AR F-Stat p-value	.	0.000	.	0.001	.	0.000
KP Wald F-Stat	.	8.232	.	8.221	.	8.232
Obs	23070	384538	23077	384546	23070	384538
No. of Counties	2795	2795	2795	2795	2795	2795
Panel B: Mobile Data						
Mean Dating Sessions (Arcsinh)	-0.003	0.144	-0.001	1.658***	-0.016*	-1.491***
	(0.004)	(0.107)	(0.015)	(0.532)	(0.008)	(0.389)
Dep. Var Mean	6.488	6.494	1.879	1.857	5.086	5.149
Ind. Var Mean	0.647	0.639	0.647	0.639	0.647	0.639
AR F-Stat	.	16.500	.	25.394	.	11.988
AR F-Stat p-value	.	0.000	.	0.000	.	0.000
KP Wald F-Stat	.	3.060	.	3.060	.	3.060
Obs	17517	301464	17517	301464	17517	301464
No. of Counties	2729	2728	2729	2728	2729	2728
FE	Year, County	Year, County-Pair	Year, County	Year, County-Pair	Year, County	Year, County-Pair
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Standard errors are clustered at the county level in columns (1), (3) and (5) and at county-pair level in columns (2), (4) and (6). Nearby counties are counties within a 20-100 km radius of the focal county. Controls included are focal county streaming and social media penetration, log population, share young, share female and log income. Instruments are nearby county dating, social media and streaming penetration values as well as nearby county population, income, share young, share female. The desktop data comes from Comscore for the years 2002-2013 and the mobile data comes from a combination of Tapestri for the years 2017 and 2018, and Dewey for the years 2019, 2020, 2021, 2022 and 2023. Mobile data focused only on common counties for Tapestri and Dewey. STD data are from CDC Atlas and rate refers to incidence of the diseases among 100,000 people. We study the effect of dating app penetration in year t on outcomes in year t.

A.8 Individual Heterogeneity Tables

Table A.20: Effect of Mean Number of Sessions (Inverse Hyperbolic) on Relationship-Minded Dating Websites/Apps on Marriage Outcomes (Vital Statistics)

	Arcsinh # New Marriages		Arcsinh # New Divorces	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Panel A: Desktop Data				
Mean Casual Sessions (Arcsinh)	0.005	0.112	0.005	4.024**
	(0.005)	(0.254)	(0.006)	(1.747)
Mean Relationship Sessions (Arcsinh)	-0.006	-0.023	0.006	-1.207
	(0.005)	(0.106)	(0.005)	(0.839)
Dep. Var Mean	6.453	6.450	5.743	5.774
Ind. Var Mean	0.555	0.562	0.544	0.554
Het. Var Mean	0.629	0.628	0.633	0.633
KP Wald F-Stat	.	0.843	.	0.719
KP Wald p-value	.	0.453	.	0.565
Obs	16136	258305	14692	229653
No. of Counties	2188	2321	1921	2043
Panel B: Mobile Data				
Mean Casual Sessions (Arcsinh)	-0.024**	-0.268***	-0.006	-0.145
	(0.011)	(0.071)	(0.020)	(0.107)
Mean Relationship Sessions (Arcsinh)	-0.003	-0.301**	-0.031	-0.560***
	(0.012)	(0.132)	(0.025)	(0.204)
Dep. Var Mean	6.166	6.168	5.435	5.312
Ind. Var Mean	0.707	0.700	0.706	0.689
Het. Var Mean	0.705	0.694	0.707	0.695
KP Wald F-Stat	.	3.953	.	3.090
KP Wald p-value	.	0.000	.	0.001
Obs	7024	108337	5461	85925
No. of Counties	2115	2296	1671	1868
FE	Year, County	Year, County-Pair	Year, County	Year, County-Pair
Controls	Yes	Yes	Yes	Yes

Notes: ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Standard errors are clustered at the county level in columns (1) and (3) and at county-pair level in columns (2) and (4). Nearby counties are counties within a 20-100 km radius of the focal county. Controls included are focal county streaming and social media penetration, log population, share young, share female and log income. Instruments are nearby county dating, social media and streaming penetration values as well as nearby county population, income, share young, share female. The desktop data comes from Comscore for the years 2002-2013 and the mobile data comes from a combination of Tapestri for the years 2017 and 2018, and Dewey for the years 2019, 2022 and 2023. Mobile data focused only on common counties for Tapestri and Dewey. We exclude the year 2020 and 2021 from analysis to account for Covid-related disruptions. Data on marriage and divorce outcomes are from Vital Statistics of individual states. We study the effect of dating website/app penetration in year t on outcomes in year $t+1$.

Table A.21: Effect of Mean Number of Sessions (Inverse Hyperbolic) on Relationship-Minded Dating Websites/Apps on STD Outcomes

	Chlamydia Rate (Arcsinh)		Syphilis Rate (Arcsinh)		Gonorrhea Rate (Arcsinh)	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Desktop Data						
Mean Casual Sessions (Arcsinh)	-0.002	0.028	-0.005	-0.056	0.011	-0.006
	(0.004)	(0.134)	(0.008)	(0.279)	(0.009)	(0.326)
Mean Relationship-minded Sessions (Arcsinh)	0.003	-0.262**	-0.005	-0.465*	0.001	-0.951***
	(0.004)	(0.113)	(0.007)	(0.242)	(0.009)	(0.291)
Dep. Var Mean	6.104	6.085	0.637	0.646	4.032	4.141
Ind. Var Mean	0.544	0.549	0.544	0.549	0.544	0.549
Het. Var Mean	0.641	0.636	0.641	0.636	0.641	0.636
KP Wald F-Stat	.	2.557	.	2.549	.	2.557
KP Wald p-value	.	0.005	.	0.005	.	0.005
Obs	23070	384538	23077	384546	23070	384538
No. of Counties	2795	2795	2795	2795	2795	2795
Panel B: Mobile Data						
Mean Casual Sessions (Arcsinh)	0.006	-0.082	-0.007	-0.989***	0.001	0.066
	(0.006)	(0.051)	(0.019)	(0.223)	(0.011)	(0.146)
Mean Relationship-minded Sessions (Arcsinh)	-0.002	0.020	-0.013	0.159	-0.011	-0.868***
	(0.006)	(0.066)	(0.019)	(0.282)	(0.012)	(0.181)
Dep. Var Mean	6.488	6.491	1.836	1.809	5.005	5.066
Ind. Var Mean	0.595	0.595	0.595	0.595	0.595	0.595
Het. Var Mean	0.655	0.647	0.655	0.647	0.655	0.647
KP Wald F-Stat	.	5.281	.	5.281	.	5.281
KP Wald p-value	.	0.000	.	0.000	.	0.000
Obs	12664	219455	12664	219455	12664	219455
No. of Counties	2729	2728	2729	2728	2729	2728
FE	Year, County	Year, County-Pair	Year, County	Year, County-Pair	Year, County	Year, County-Pair
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Standard errors are clustered at the county level in columns (1), (3) and (5) and at county-pair level in columns (2), (4) and (6). Nearby counties are counties within a 20-100 km radius of the focal county. Controls included are focal county streaming and social media penetration, log population, share young, share female and log income. Instruments are nearby county dating, social media and streaming penetration values as well as nearby county population, income, share young, share female. The desktop data comes from Comscore for the years 2002-2013 and the mobile data comes from a combination of Tapestri for the years 2017 and 2018, and Dewey for the years 2019, 2022 and 2023. Mobile data focused only on common counties for Tapestri and Dewey. We exclude the year 2020 and 2021 from analysis to account for Covid-related disruptions. STD data are from CDC Atlas and rate refers to incidence of the diseases among 100,000 people. We study the effect of dating app penetration in year t on outcomes in year t.

Table A.22: Effect of Mean Number of Sessions (Inverse Hyperbolic) on LGBTQ+ Dating Websites/Apps on Marriage Outcomes (Vital Statistics)

	Arcsinh # New Marriages		Arcsinh # New Divorces	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Panel A: Desktop Data				
Mean Not LGBTQ+ Sessions (Arcsinh)	0.006	-0.047	0.001	1.720***
	(0.004)	(0.174)	(0.006)	(0.493)
Mean LGBTQ+ Sessions (Arcsinh)	-0.006	0.100	0.010*	-1.138**
	(0.005)	(0.138)	(0.006)	(0.498)
Dep. Var Mean	6.453	6.450	5.743	5.774
Ind. Var Mean	0.577	0.584	0.567	0.575
Het. Var Mean	0.608	0.607	0.613	0.613
KP Wald F-Stat	.	1.569	.	1.780
KP Wald p-value	.	0.083	.	0.047
Obs	16136	258305	14692	229653
No. of Counties	2188	2321	1921	2043
Panel B: Mobile Data				
Mean Not LGBTQ+ Sessions (Arcsinh)	-0.014	-0.580***	-0.024	-0.550**
	(0.011)	(0.201)	(0.025)	(0.262)
Mean LGBTQ+ Sessions (Arcsinh)	0.012	0.038**	-0.011	0.007
	(0.008)	(0.017)	(0.010)	(0.025)
Dep. Var Mean	6.166	6.168	5.435	5.312
Ind. Var Mean	0.744	0.732	0.744	0.730
Het. Var Mean	0.239	0.240	0.243	0.250
KP Wald F-Stat	.	2.103	.	1.987
KP Wald p-value	.	0.018	.	0.026
Obs	7024	108337	5461	85925
No. of Counties	2115	2296	1671	1868
FE	Year, County	Year, County-Pair	Year, County	Year, County-Pair
Controls	Yes	Yes	Yes	Yes

Notes: ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Standard errors are clustered at the county level in columns (1) and (3) and at county-pair level in columns (2) and (4). Nearby counties are counties within a 20-100 km radius of the focal county. Controls included are focal county streaming and social media penetration, log population, share young, share female and log income. Instruments are nearby county dating, social media and streaming penetration values as well as nearby county population, income, share young, share female. The desktop data comes from Comscore for the years 2002-2013 and the mobile data comes from a combination of Tapestri for the years 2017 and 2018, and Dewey for the years 2019, 2022 and 2023. Mobile data focused only on common counties for Tapestri and Dewey. We exclude the year 2020 and 2021 from analysis to account for Covid-related disruptions. Data on marriage and divorce outcomes are from the Vital Statistics reports of individuals states. We study the effect of dating website/app penetration in year t on outcomes in year $t+1$.

Table A.23: Effect of Mean Number of Sessions (Inverse Hyperbolic) on LGBTQ+ Dating Websites/Apps on STD Outcomes

	Chlamydia Rate (Arcsinh)		Syphilis Rate (Arcsinh)		Gonorrhea Rate (Arcsinh)	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Desktop Data						
Mean Not LGBTQ+ Sessions (Arcsinh)	-0.001	-0.146	0.004	-0.513**	0.005	-0.881***
	(0.004)	(0.098)	(0.008)	(0.201)	(0.009)	(0.219)
Mean LGBTQ+ Sessions (Arcsinh)	0.002	-0.135	-0.016**	0.096	0.008	0.236
	(0.004)	(0.143)	(0.007)	(0.305)	(0.009)	(0.348)
Dep. Var Mean	6.104	6.085	0.637	0.646	4.032	4.141
Ind. Var Mean	0.568	0.572	0.568	0.572	0.568	0.572
Het. Var Mean	0.623	0.617	0.623	0.617	0.623	0.617
KP Wald F-Stat	.	2.539	.	2.536	.	2.539
KP Wald p-value	.	0.005	.	0.005	.	0.005
Obs	23070	384538	23077	384546	23070	384538
No. of Counties	2795	2795	2795	2795	2795	2795
Panel B: Mobile Data						
Mean Not LGBTQ+ Sessions (Arcsinh)	-0.000	-0.208	-0.017	-0.874*	-0.011	-1.295***
	(0.005)	(0.129)	(0.020)	(0.494)	(0.012)	(0.404)
Mean LGBTQ+ Sessions (Arcsinh)	0.002	0.056***	0.041***	0.320***	-0.019***	-0.124***
	(0.003)	(0.012)	(0.013)	(0.050)	(0.007)	(0.040)
Dep. Var Mean	6.488	6.491	1.836	1.809	5.005	5.066
Ind. Var Mean	0.675	0.669	0.675	0.669	0.675	0.669
Het. Var Mean	0.206	0.208	0.206	0.208	0.206	0.208
KP Wald F-Stat	.	2.178	.	2.178	.	2.178
KP Wald p-value	.	0.015	.	0.015	.	0.015
Obs	12664	219455	12664	219455	12664	219455
No. of Counties	2729	2728	2729	2728	2729	2728
FE	Year, County	Year, County-Pair	Year, County	Year, County-Pair	Year, County	Year, County-Pair
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Standard errors are clustered at the county level in columns (1) and (3) and at county-pair level in columns (2) and (4). Nearby counties are counties within a 20-100 km radius of the focal county. Controls included are focal county streaming and social media penetration, log population, share young, share female and log income. Instruments are nearby county dating, social media and streaming penetration values as well as nearby county population, income, share young, share female. The desktop data comes from Comscore for the years 2002-2013 and the mobile data comes from a combination of Tapestri for the years 2017 and 2018, and Dewey for the years 2019, 2022 and 2023. Mobile data focused only on common counties for Tapestri and Dewey. We exclude the year 2020 and 2021 from analysis to account for Covid-related disruptions. STD data are from CDC Atlas and rate refers to incidence of the diseases among 100,000 people. We study the effect of dating app penetration in year t on outcomes in year t..

Table A.25: Effect of Mean Number of Sessions (Inverse Hyperbolic) on Dating Websites/Apps by Age Group on STD Outcomes

	Chlamydia		Syphilis		Gonorrhea	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Desktop Data						
Mean Dating Sessions 18-34 (Arcsin)	0.003	-0.064	-0.011	-0.149	-0.004	-0.894***
	(0.004)	(0.088)	(0.009)	(0.216)	(0.007)	(0.243)
Mean Dating Sessions 35+ (Arcsin)	0.004	-0.090	0.004	0.399***	0.008	-0.198
	(0.005)	(0.057)	(0.011)	(0.150)	(0.010)	(0.151)
Dep. Var. Mean	6.277	6.205	0.888	0.883	4.497	4.530
Ind. Var. Mean	0.602	0.600	0.602	0.600	0.602	0.600
Het. Var Mean	0.693	0.692	0.692	0.692	0.693	0.692
KP Wald F-Stat	.	2.14	.	2.15	.	2.14
KP Wald p-value	.	0.011	.	0.011	.	0.011
Observations	12077	156303	12083	156309	12077	156303
No. of Counties	1857	1875	1857	1875	1857	1875
FE	Year, County	Year, County-Pair	Year, County	Year, County-Pair	Year, County	Year, County-Pair
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Mobile Data						
Mean Dating Sessions 18-34 (Arcsin)	0.005	0.180**	-0.011	-0.055	-0.012	-0.294**
	(0.004)	(0.089)	(0.019)	(0.295)	(0.010)	(0.126)
Mean Dating Sessions 35+ (Arcsin)	0.002	-0.460***	-0.019	-1.176***	-0.008	-0.302*
	(0.004)	(0.114)	(0.017)	(0.376)	(0.009)	(0.161)
Dep. Var. Mean	6.564	6.555	1.942	1.855	5.146	5.168
Ind. Var. Mean	0.698	0.708	0.698	0.708	0.698	0.708
Het. Var Mean	0.664	0.663	0.664	0.663	0.664	0.663
KP Wald F-Stat	.	2.36	.	2.36	.	2.36
KP Wald p-value	.	0.005	.	0.005	.	0.005
Observations	10012	164552	10012	164552	10012	164552
No. of Counties	2455	2227	2455	2227	2455	2227
FE	Year, County	Year, County-Pair	Year, County	Year, County-Pair	Year, County	Year, County-Pair
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Standard errors are clustered at the county level in columns (1), (3) and (5) and at county-pair level in columns (2), (4) and (6). Nearby counties are counties within a 20-100 km radius of the focal county. Controls included are focal county streaming and social media penetration (for ages 18-34), log population, share young, share female and log income. Instruments are nearby county dating, social media and streaming penetration (for ages 18-34) values as well as nearby county population, income, share young, share female. The desktop data comes from Comscore for the years 2002-2013 and the mobile data comes from a combination of Tapestri for the years 2017 and 2018, and Dewey for the years 2019, 2022 and 2023. Mobile data focused only on common counties for Tapestri and Dewey. We exclude the year 2020 and 2021 from analysis to account for Covid-related disruptions. STD data are from CDC Atlas and rate refers to incidence of the diseases among 100,000 people. We study the effect of dating app penetration in year t on outcomes in year t.

A.9 Placebo: Random Nearby Counties

We follow the main specification from Tables 4 and 6 but with a placebo instrument where each county has a random set of nearby counties. The number of placebo random counties is equal to the real number of counties within a 20-100 km radius of the focal county.

Table A.26: Effect of Mean Number of Sessions (Inverse Hyperbolic) on Dating Websites/Apps on Marriage Outcomes (Vital Statistics) (Placebo)

	Arcsinh # New Marriages		Arcsinh # New Divorces	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Panel A: Desktop Data				
Mean Dating Sessions (Arcsinh)	0.001	-0.107	0.009	0.403
	(0.003)	(0.550)	(0.006)	(1.054)
Dep. Var Mean	6.445	6.408	5.741	5.729
Ind. Var Mean	0.640	0.633	0.636	0.630
AR F-Stat	.	0.402	.	5.508
AR F-Stat p-value	.	0.902	.	0.000
KP Wald F-Stat	.	0.169	.	0.119
Obs	15970	235688	14559	210247
No. of Counties	2163	2163	1907	1907
Panel B: Mobile Data				
Mean Dating Sessions (Arcsinh)	-0.010	-0.505	-0.026	0.500
	(0.010)	(0.575)	(0.025)	(0.757)
Dep. Var Mean	6.146	6.149	5.430	5.291
Ind. Var Mean	0.746	0.732	0.745	0.729
AR F-Stat	.	1.879	.	0.466
AR F-Stat p-value	.	0.069	.	0.860
KP Wald F-Stat	.	0.308	.	0.282
Obs	6903	96853	5375	77225
No. of Counties	2090	1910	1651	1498
FE	Year, County	Year, County-Pair	Year, County	Year, County-Pair
Controls	Yes	Yes	Yes	Yes

Notes: ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Standard errors are clustered at the county level in columns (1) and (3) and at county-pair level in columns (2) and (4). Placebo nearby counties are sets of random counties across the country. The number of placebo nearby counties is the same as the real number of counties within a 20-100 km radius of the focal county. Controls included are focal county streaming and social media penetration, log population, share young, share female and log income. Instruments are nearby county dating, social media and streaming penetration values as well as nearby county population, income, share young, share female. The desktop data comes from Comscore for the years 2002-2013 and the mobile data comes from a combination of Tapestri for the years 2017 and 2018, and Dewey for the years 2019, 2022 and 2023. Mobile data focused only on common counties for Tapestri and Dewey. Years 2020 and 2021 are excluded due to COVID19 disruptions. Data on marriage and divorce outcomes are from the Vital Statistics of states. We study the effect of dating app penetration in year t on outcomes in year $t+1$.

Table A.27: Effect of Mean Number of Sessions (Inverse Hyperbolic) on Dating Websites/Apps on STD Outcomes (Placebo)

	Chlamydia Rate (Arcsinh)		Syphilis Rate (Arcsinh)		Gonorrhea Rate (Arcsinh)	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Desktop Data						
Mean Dating Sessions (Arcsinh)	0.001	1.095	-0.010	0.230	0.015	0.691
	(0.004)	(1.025)	(0.007)	(0.964)	(0.009)	(1.121)
Dep. Var Mean	6.102	6.076	0.633	0.633	4.042	4.133
Ind. Var Mean	0.639	0.632	0.639	0.632	0.639	0.632
AR F-Stat	.	1.616	.	0.490	.	0.878
AR F-Stat p-value	.	0.125	.	0.843	.	0.523
KP Wald F-Stat	.	0.213	.	0.213	.	0.213
Obs	22711	353763	22712	353764	22711	353763
No. of Counties	2758	2758	2758	2758	2758	2758
Panel B: Mobile Data						
Mean Dating Sessions (Arcsinh)	0.000	-0.627	-0.013	0.716	-0.015	-0.445
	(0.005)	(0.427)	(0.020)	(1.102)	(0.012)	(0.612)
Dep. Var Mean	6.486	6.490	1.829	1.799	5.006	5.060
Ind. Var Mean	0.678	0.671	0.678	0.671	0.678	0.671
AR F-Stat	.	1.881	.	0.517	.	0.396
AR F-Stat p-value	.	0.068	.	0.822	.	0.905
KP Wald F-Stat	.	0.526	.	0.526	.	0.526
Obs	12488	202142	12488	202142	12488	202142
No. of Counties	2695	2694	2695	2694	2695	2694
FE	Year, County	Year, County-Pair	Year, County	Year, County-Pair	Year, County	Year, County-Pair
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Standard errors are clustered at the county level in columns (1), (3) and (5) and at county-pair level in columns (2), (4) and (6). Nearby counties are counties within a 20-100 km radius of the focal county. Controls included are focal county streaming and social media penetration, log population, share young, share female and log income. Instruments are nearby county dating, social media and streaming penetration values as well as nearby county population, income, share young, share female. The desktop data comes from Comscore for the years 2002-2013 and the mobile data comes from a combination of Tapestri for the years 2017 and 2018, and Dewey for the years 2019, 2022 and 2023. Mobile data focused only on common counties for Tapestri and Dewey. Years 2020 and 2021 are excluded due to COVID19 disruptions. STD data are from CDC Atlas and rate refers to incidence of the diseases among 100,000 people. We study the effect of dating app penetration in year t on outcomes in year t.

Table A.28: First Stage (Placebo)

	Desktop (1)	Mobile (2)
Nearby Mean Dating Sessions (Arcsin)	0.000	-0.001
	(0.002)	(0.004)
Nearby Mean Streaming Sessions (Arcsin)	-0.003	0.000
	(0.003)	(0.004)
Nearby Mean Social Sessions (Arcsin)	-0.000	0.000
	(0.003)	(0.004)
Nearby Log Population	-0.002	-0.073
	(0.036)	(0.046)
Nearby Per Capita Income (Log)	0.002	-0.082*
	(0.020)	(0.044)
Nearby Share Young	-0.340	-0.341
	(0.371)	(0.731)
Nearby Share Female	0.252	-0.929
	(0.503)	(0.806)
Dep. Var Mean	0.632	0.636
Obs	353764	209914
R^2	0.250	0.513
F-stat	409.028	243.421
No. of County-Pairs	50301	55628
No. of Years	10	5
Year FE	Yes	Yes
County-Pair FE	Yes	Yes
Controls	Yes	Yes

Notes: ***, **, * indicates significance at the 1%, 5%, and 10% level respectively. Standard errors are clustered at the county-pair level. The table reports the first stage results for IV regression specifications using placebo random nearby county dating app penetration as instruments. Placebo nearby counties are sets of random counties across the country. The number of placebo nearby counties is the same as the real number of counties within a 20-100 km radius of the focal county. Controls included are focal county streaming and social media penetration, log population, share young, share female and log income. Instruments are nearby county dating, social media and streaming penetration values as well as nearby county population, income, share young, share female. The online activity data are from desktop and mobile data available through Comscore for the years 2002-2013, Tapestri for the years 2017 and 2018, and Dewey for the years 2019, 2022, and 2023. Data from the years 2020 and 2021 are omitted due to Covid-related disruptions.

B Appendix: Theoretical Framework: A Model of Search

This section presents a stylized search model for online dating technologies. The purpose of this model is to illustrate how the pool size, noise in information, and search costs can act as potential mechanisms to explain the outcomes we observe in empirical analysis. The model is based on the underlying model for Fong (2024) and relates to the model in Halaburda et al. (2018).

While our results relate to both heterosexual and LGBTQ+ dating markets, for illustration purposes we will write the model based on a heterosexual market, and refer to each side of the dating platform as the men and the women side.

Consider a single search session for an individual i on an online dating platform with m men and w women. From the perspective of a heterosexual male user i, his market size ms_i is the number of women in his market, and his competition size cs_i is the number of men in his market. For tractability, we will assume that the participation on both the male and the female sides of the market are symmetric: $ms_i = cs_i = N$, and refer to N as the pool size.

We will assume that user i views profiles sequentially and decides whether to `like` or not to `like` each profile. Two individuals, i and j, match only if they both `like` each other. Before deciding whether to `like` another user j's profile, i does not know whether j has already `liked` his profile. i can view j's profile only once.

Although i can form multiple matches during a single search session, for simplicity, we assume that i's objective for his search session is to find one individual to go on a date with; at the end of the search session, i can choose to go on a date with another user that he has matched with during the session or select the outside option z. Individual i receives the following utility from going on a date with j:

$$\theta_{ij} = \delta + \nu_{ij}. \tag{3}$$

Here, θ_{ij} is the "match value", which is composed of a constant δ and an idiosyncratic horizontal match value (ν_{ij}).[33] We assume that $\nu_{ij} \sim \text{Gumbel}(0, \sigma)$.

To align with reality, search behavior is modeled as a finite-horizon sequential search model. In each time period t, user i views one profile, so the maximum number of time periods (i.e., total profiles he can search) is i's pool size. The following actions occur at the beginning of a search session. User i observes (or has rational beliefs about) his pool size. i then decides whether to participate in the market. If i does not participate, she receives a utility from the outside option z_{i0} and ends her session without viewing any profiles. If i participates, then the following sequence of events occurs.

1. i views j's profile, incurs a search cost c^s — which represents the effort and attention costs of evaluating a profile — and observes j's profile and expected match value $E[\theta_{ij}]$.
2. Given $E[\theta_{ij}]$, i `likes` j or does not `like` j.
   (a) If i `likes` j, then i incurs a cost c^l. [34]
      i. If j had already `liked` i, i and j match and then observes the realized match value θ_{ij}. If $\theta_{ij} > z_{it}$ (where z_{it} is the outside option), then $z_{i,t+1} = \theta_{ij}$.
   (b) If i and j do not match, or if i does not `like` j, then $z_{i,t+1} = z_{it}$.

[33] We assume a constant δ for simplicity, but one can extend this by allowing the match value to vary based on j's attributes.

[34] c^l can represent the disutility from additional effort and time to message a user or a static way to represent a limit on the number of `likes` or messages a user can send. Popular dating apps often use such limits. For example, the free version of Tinder has a limit on the number of likes sent.

The equations below formalize this sequence of events. For ease of exposition, we omit the $i$subscripts.

The value functions for not searching (ns), searching (s) and not `liking` (nl) profile j viewed at time t, given outside option z are as follows:

$$V_t^{ns}(z) = z + \epsilon_t^{ns} \tag{4}$$
$$V_t^{s}(z) = \max\{E_j[V_t^l(j,z)], V_t^{nl}(z)\} - c^s + \epsilon_t^s \tag{5}$$
$$V_t^{nl}(z) = \max\{V_{t+1}^{ns}(z), V_{t+1}^{s}(z)\} + \epsilon_t^{nl} \tag{6}$$

The ϵ values denote the utility that is observed by i, but not by the econometrician. $V_t^l(j,z)$ denotes the value function for `liking` the profile j viewed at t.

Let π denote the average probability that another user `likes` i. The value function for `liking` a profile j, given outside option z, is

$$V_t^l(j,z) = \pi \times \Bigg(\overbrace{\Pr\left(\theta_j > z\right) \times \max\{V_{t+1}^{ns}(\theta_j), V_{t+1}^{s}(\theta_j)\}}^{A} + \overbrace{\Pr(\theta_j \le z) \times \max\{V_{t+1}^{ns}(z), V_{t+1}^{s}(z)\}}^{B} \Bigg) + (1-\pi) \times \underbrace{\Bigg(\max\{V_{t+1}^{ns}(z), V_{t+1}^{s}(z)\} \Bigg)}_{C} - c^l + \epsilon_t^l. \tag{7}$$

The term denoted by A represents the expected next-period value function, conditional on i and j matching, and whether the realized match value of j is *greater* than the outside option. In this case, his outside option in the next period updates to θ_j. B denotes the expected next-period value function if i and j match and the realized match value of j is *not greater* than the outside option, in which case the outside option at $t+1$ does not update. C denotes i's value function if he does not match with j.

The pool size enters the model through the following mechanisms. First, a larger choice set (i.e., market size) can lead to choice overload, in which more choices are overwhelming and result in a reduction in the motivation to choose. For example, Chernev et al. (2015) suggest that having more choices can increase the complexity of the decision-making process, making it more difficult to evaluate each option (e.g., evaluating one option against another is less difficult than comparing it against ten others). In this paper's setting, an increase in the difficulty of the decision can be thought of as an increase in the cost to evaluate each profile as market size increases. We parameterize this mechanism with the following specification:

$$c_t^s = c^s + \alpha \log(ms_t), \tag{8}$$

where choice overload exists if $\alpha > 0$.

Second, a larger pool size can also lead to more competition. More competition (e.g., more men) reduces the likelihood that another user (e.g., another female user) sees user i's profile, thereby decreasing the probability that the other user `likes` his profile. This mechanism is expressed by rewriting the probability that a user j `likes` i, π_{ji}, as a function of competition size cs.

$$\pi_{ji}(cs) = \Pr(j \texttt{ likes } i | j \text{ sees } i) \times \Pr(j \text{ sees } i | cs) \tag{9}$$

The first probability on the right-hand side is the probability that j `likes` i conditional on j seeing i's profile, and the second probability is the probability that j sees i's profile. We parameterize $\Pr(j \text{ sees } i|cs)$

as the following.

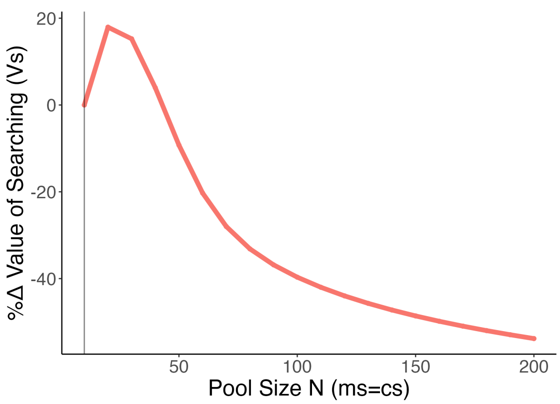
$$\Pr(j \text{ sees } i|cs) = \frac{S}{cs}, \tag{10}$$

where S is a constant. Thus, Equation 10 is the probability that j draws i's profile in S draws, assuming that j has an equal probability of seeing each profile in his market.

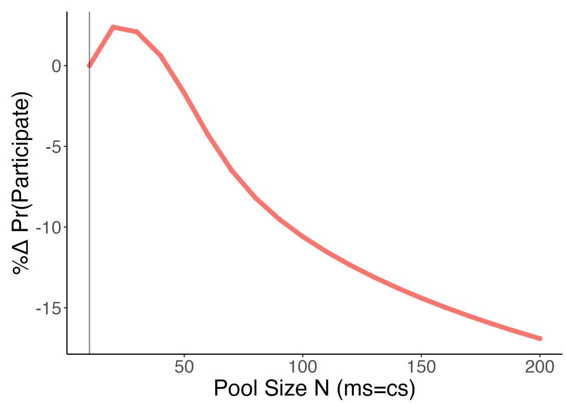
Simulations We show several simulations for the theoretical model outlined above. The simulations are partial equilibrium outcomes due to tractability purposes. For examples, $\Pr(j \texttt{ likes } i|j \text{ sees } i)$ is an equilibrium outcome, but for the purposes of this simulation, we hold this fixed. All results are compared in relative terms with respect to a baseline specification with the parameters: $S = 1$, $c^s = 1$,$c^l = 2$, $\sigma = 1$, $\alpha = 0.1$, $N = 10$, $\Pr(j \texttt{ likes } i|j \text{ sees } i) = 0.25$, and $\delta = 5$.

First, we show simulations of an increase in the pool size (N) in Figure B.1. The simulations suggest a clear monotonic decrease in the probability of matching with another given user j as the pool size increases. This occurs because users become more selective, as they have more opportunities to match. The expected value of search and in the probability of participation on the platform increases and then decreases as the size of the pool increases. A small pool size results in fewer opportunities to match, so users benefit from additional potential matches. But as the pool sizes increases further, the value of searching and participation rates go down because users have to sort through additional irrelevant choices and would also encounter more competition for any given user that they like.

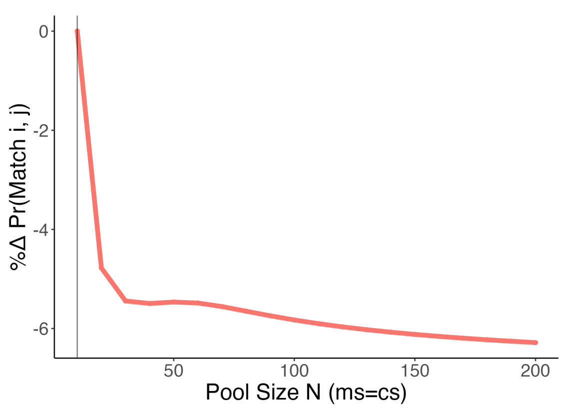
Figure B.1: Effects of Changes in N Users



(a) Value of Searching



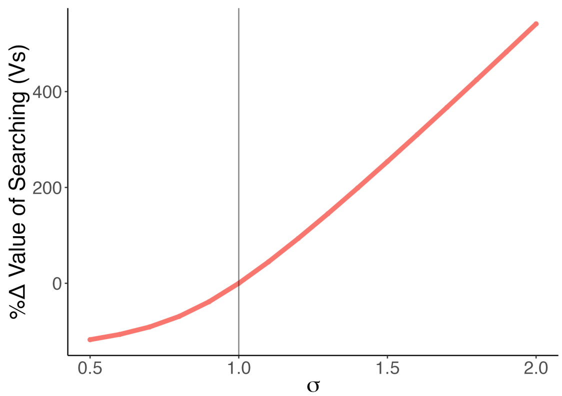
(b) Pr(Participate)



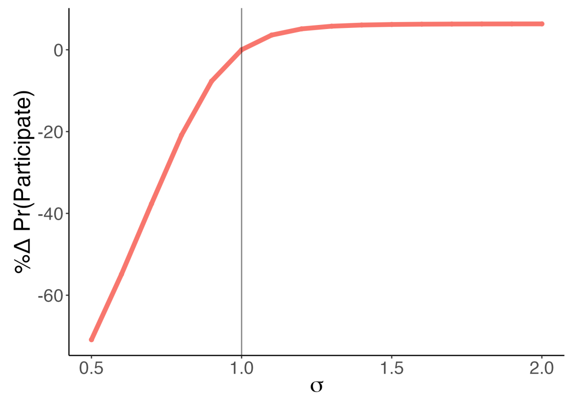
(c) Pr(Match)

Next, we show simulations of changes in the noise (σ) in the market in Figure B.2. Holding all else constant, increasing noise in the matching market results in increases in the expected value from searching and an increase in participation. Additional noise also increases the probability that users like a candidate and match rates. The reason is that additional noise in the market increases the variance of match valuations around the expected value, making users more likely to take a chance by participating and liking potential matches in the hope of drawing a high match value.

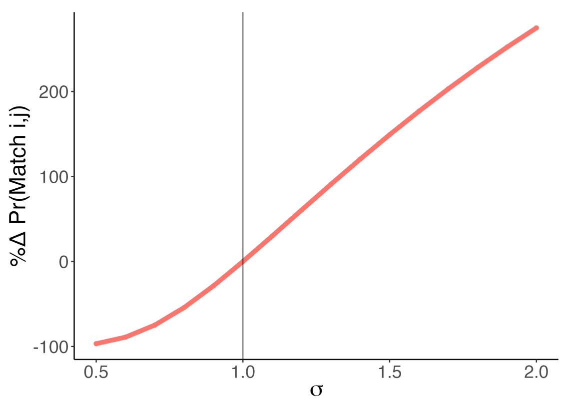
Figure B.2: Effects of Changes in Noise (σ)



(a) Value of Searching



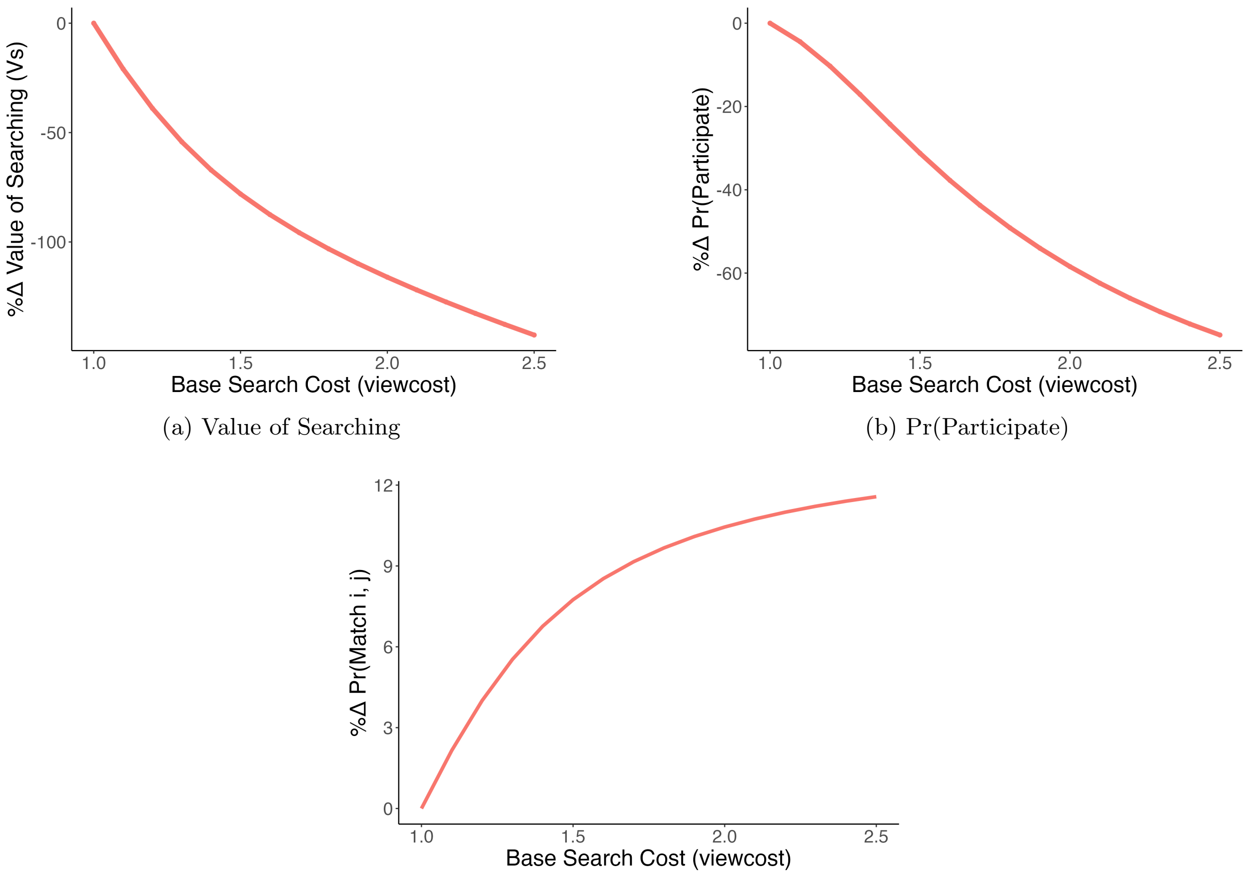
(b) Pr(Participate)



(c) Pr(Match)

Finally, we present simulations of the effects of changes in search costs (c_s) in Figure B.3. We find that increases in search costs decrease the expected value from searching, and therefore, participation on the platform. This is intuitive — as searching becomes cheaper, more users are willing to search. We also find that increases in search costs increase match probability. Again, as it becomes costlier to inspect an additional potential partner, users are more likely to "settle" for a given choice they're facing.

Figure B.3: Effects of Changes in Search Costs (c_s)



(a) Value of Searching

(b) Pr(Participate)

(c) Pr(Match)

C Appendix: Data Construction

C.1 Dewey Data Processing

We obtain app engagement usage collected from Android smartphones whenever and wherever these devices are used. Specifically, we use the anonymized, opt-in consumer panel from Global Wireless Solution's Magnify obtained through Dewey's platform[35]. The processing goes as follows: first, we download sessions, panelist, and devices datasets using Magnify's API. Then, we use Android App IDs to classify app usage in dating, social media and streaming apps, and assign the most repeated county in the panelists geolocated pings as the home county for each panelist. We are able to identify when an app is open in the foreground or in the main screen. We count as a session any opening of an app where the app is visualized on the main screen. We exclude users with less than 7 days of recorded usage in a given year. We use Android app ID codes to classify apps in dating, social media, and streaming apps.

C.2 Tapestri Location Data

The data from Tapestri also include datasets with location pings of users. However, the data do not identify their home location by zip code. We convert the recorded time of each ping from UTC to the time zone of the zip code the user was located in at the time of the ping. Thereafter, we compute the total pings for each zip code a user is tagged in between 10 PM and 6 AM. Our reasoning is that a user is most likely to be at home during these time periods. The zip code with the maximum number of recorded pings is marked as the user's home zip code.

C.3 List of Dating Websites and Apps

We use two data sources to construct a comprehensive list of dating websites and applications. Firstly, we search for companies whose descriptions include the term "dating" from Crunchbase. Crunchbase maintains a database of public and private companies. This list is used to identify websites related to dating from all websites visited in the desktop data. We search for unique websites in total. Table C.1 lists the websites obtained from Crunchbase.

We supplement the list of dating websites from Crunchbase with the most popular dating apps from Similarweb, a data aggregation firm focusing on website traffic for the mobile data. We use the top 50 most popular mobile apps as on August 31, 2023. These additional names help us identify apps which may not have their own website and thus, may be missing from Crunchbase data. The list of app obtained from Similarweb are in Table C.2.

Finally, for the heterogeneity analysis, we classify the list of dating websites and apps based on whether they cater to individuals looking for more serious relationships, relationship-minded, and if they are primarily designed for LGBTQ+ users (e.g. Grindr). We follow the steps below:

- We extract the list of dating websites and apps that are present in the desktop and mobile data respectively.
- We pose three prompts to the OpenAI ChatGPT3.5+. For each platform, they are:
    - Is [platform] mainly targeted at people looking for serious relationships? If so, respond with 'Yes'. If not, respond with 'No'.

[35] For details, see Dewey (2025)

  - Is [platform] exclusively targeted at people looking for serious relationships? If so, respond with 'Yes'. If not, respond with 'No'.
  - Is [platform] primarily targeted at people looking for serious relationships? If so, respond with 'Yes'. If not, respond with 'No'.

  Similarly, for each platform, the prompts are:

  - Is site marketed as a mainly LGBTQ+ dating platform? If so, respond with 'Yes'. If not, respond with 'No'.
  - Is [platform] marketed as an exclusively LGBTQ+ dating platform? If so, respond with 'Yes'. If not, respond with 'No'.
  - Is [platform] marketed as a primarily LGBTQ+ dating platform? If so, respond with 'Yes'. If not, respond with 'No'.

- We take the modal answer for each category for the classification and manually verify the responses using human research assistants. After this confirmatory step, some false positives are dropped. For smaller or defunct platforms, ChatGPT classification can be inaccurate.

We compared the ChatGPT classification with human classifications. Two human coders were asked to view each dating site or mobile app and determine whether the platform primarily caters to those looking for serious relationships. One additional coder was asked whether the platform primarily caters to LGBTQ+ users. For the serious-relationship classification, ChatGPT's assessments matched those of the two human coders for 79% and 73% of observations, respectively.

C.4 Independent Variables and Instruments

Nearby Counties We use TIGER/Line shapefiles from the U.S. Census Bureau's Master Address File / Topologically Integrated Geographic Encoding and Referencing (MAF/TIGER) Database (MTDB) for the year 2021 using the `R` package `tigris`. Centroids are calculated using the `sf` package in `R`. We compute geodetic distances between all county pairs using `geonear` in `Stata` and all county pairs within 200 km distance of each other is categorized as a nearby county pairs. Then, each pair is assigned to distance ranges of size 10 km. Depending on the specification, we limit the dataset to nearby county pairs falling within the given distance ranges.

Vital Statistics Data Collection The data on marriage and divorce rates are constructed searching Vital Statistics Records of all states via Freedom of Information requests and collated data from the 37 states for which data was publicly available. These data provided us with the number of new marriages and divorces registered in the state each year. In total, we collected data for 2,917 counties across 26 years. The data were combined with county population data.

Table C.1: List of Dating Websites (Crunchbase)

open	12like	2Lips	2RedBeans	3DegreesNation
3rdDegree App	420 Singles	50plus Treff	52 Le	6dgrs
7 Star Entertainment	7pm anywhere	8:00 PM	8dates Dating	A Little Nudge
A World Alike	ADUPS Technology	Abodva	About Last Night	About Love
Abricot	Accentudate	Acquaintable	Adam and Eva Matchmaking agency	Adopt
AdoptAGuy	AdopteUnMec	AdvanDate	Affinitas	Affmy
AfriDate	Afro Romance	AfroYamo	AiMatchMaker	AimerApp
Aisle	Align	Alike	Alikewise	Alone.Today
Amanda	Amando	Amare	American Singles	Amesinlove
Amolatina	Amāre	Anastasia Date	Anastasia Dating	Answerology
AntiLand	Anywr	Appetence	Approach Dating	Apps with love
AseeksB	Ashley Madison	Asiame	Asian Single Solution	Asian Singles Connect
Astrodita - Astrology Dating App	Atrinsic	Attractionfirst.com	Attractive World	Aura Transformation
Avalable	Avanta	Averdate	BARE: Dating Less Serious	BBPeopleMeet
BBW DateFinder	BBW Personals Plus	BEARWWW	BEHAPPY	BIU
BS Chat	BabyDating	Badoo	Baihe	BeCouply
Beatmatch	Beautiful Christian Soulmates	BeautifulPeople	Berkeley International	Besedo
Bestsugarbabysites.com	Betr Technologies, Inc.	Betterhalf	Beverly (formerly BEVscore)	Biem
Billionaire Dating Website	Birdy	Blaber	Blabroom	Black Book Singles
BlackPeopleMeet.com	BlackSingles	Blazr App	Bliinder	Blind Cupid
Blind8	Blinded	Blink Date	Bloom	Bloveit
BlueCity	Blued	Bone Fish	Boo	Boompi
Boop	Bounce	Boyfriend Pillow	Bracket Dating	Breeze
Brezaa	Bridal	Bridesandlovers.com	Bristlr	BuckleUp
Bumble	Bumpy	Butterflies Dating & Socials	Byte Factory	C-Date
COPILOT Japan	CRAZY KRUSH	CROSSPATHS	Cadie	Calgary Speed Dating
Candid	Cannection	CaramelClub	Careerflo	Carita
CarpeDM	Casual Hookups	Catholic Connect	Catholic Match	Catholic Mingle
Catholic Singles	ChaDate	Chai Meets Biscuit	Challengr	Chappy
CharmDate	CharmLive	Chat&Yamo	Chekmate	Chemistry.com
Cherry Blossoms	Chicago First Dates	Chirpme	Christian Connection	Christian Filipina
Christian Mingle	ChristianCafe.com	Cinema Dating	Cinemeet	Cingle
Cintaku	Circoo	Citrus	Claris	Clarity
Click2Asia	ClickDate	Clinx.io	CoDot	Cobble
Coffee Meets Bagel	Coffeepass - Friends & Matches	Colondee	Color Dating	Companion
Completely Free Dating	Connect	Cool Monkeys	Coopl	Cougar Life
Couple	Courtesan Ellie	Courtland Brooks	Cruiser	Crush Roulette
Crushh	Cubacitas	CupidLinked	Cupido	Curius Inc.
CurvesConnect	Cut to the Chase	DATEnhance	DBNA	DNA Romance LTD
DOWN	DaBoo App	DablTech	DanceKard	Dandy
DarniPora	Dashing Date	Date Jasmin	Date to Door	Date.ca
DateBox	DateME Kenya	DateMyFamily.com	DateNight	DatePlay
DateSalad	DateUp	Dated	Datedicted (bemydate)	Datefit
Dateind	Dateline	Datemakers	Dateolicious	Datepad
Datersearch.com	Dating Cafe	Dating Central Europe	Dating Group	Dating Ring
Dating Safety Tips	Dating Tech Group Ltd.	Dating Tips N Topics	DatingAdvice.com	DatingBullet.com
DatingDirect	DatingNews.com	DatingReviewsUK	DatingSauce	DatingSphere
Datingsite Kiezen	Davao Women	Deacon Group SARL	Deeper App	Delight
Delightful	Denga Love	Depixs	Derma Cupid	DesiCrush.com
Desti	Dig	Digital Reviews	Dil Mil	Dinner for Six
Disinibiti	Ditto	DivorceBond	DivorceForce	Divorceo
DominicanCupid	DontDateHimGirl	Doppl	Dot Dating App	Doubble
DoubleSquad	Doudou	Dovey	DownToEarth	DraftMate
Dream Singles	Duet	Duety	Duolop	EME Hive
ESHQ	EVE	EZ.Dating	EasyAffair	Eat With Me
Eatgether	Echu	Eddie Hernandez Photography	Edmonton Speed Dating	Elena's Models
Elite Connections International	Elite Introductions Reviews	Elite Matchmaking	Elite Personal Search	ElitePartner
Elitesingles	Enamorados	Engage	Et3arraf	Eteract.com
Eurodate	Evolve App	FDBK	FFA Connections	FM Connections
FRNZ labs	FUSE	FaceQuare	Fantasy Match	FarmersOnly
Fast-Forward (FFWD) Dating	FateDate	FeaturedDate	Feels	Feierabend Online Dienste
Fenpei Duixiang	FestUp	Fiix Applications	Fika	Filteroff

Find-Bride	FindDate	FindRentSell	FindandSmile	Findmate
Finya	First	FirstMet	Fitafy	Flamme - The Couples App
Flash	FlatMateMe.com	Flex	Flip	Flirt-Fever.de
Flirt.com	Flirtar	Flirtic.com	Flokkr	FlowMingle
Flutter Connect	Founder2be	FoundingBase	Fourplay Social	Franco-American
Free Dating	Free Hookup App	Free MnF	Friend of a Friend	FriendFinder Networks
FriendMatch	FriendScout24	Friendite	Friends4Friends	Friends4You
Fruitz	Funny Planet	Furmanski Group	GEL	GaiGai
GamerDating	Gather	Gatsby	Gayquation	General Dating Industry Support Services
GetLusty.com	GetTwoToTango	Giloon.com	Girls Funding	Gisuco
Gladpark	Glancee	Glaries	Glii - LGBTQ+ Dating App	Global Personals
Glukose	GoGaga	GoSporty	GoldSpoon	Goneby
GoodOnes	Goodnight	Goottah	Gossyp	Grazer
Grindr	GroupeeLove	Groupspeak	GujjuWeds	H Society
HANG5	HAPPII	HER	HOT or NOT	HUD app
Handsome Media	Hangoo	Happily	Happly	Happn
Happy Couple	HappyGo	Harmonica	Hater	HePays Sugardaddy Site
HeTexted Inc	Heart to Heart	Heart to Heart Dating Service	Heartbooker	Heartbroker
Heartstring	Hello Dating	HelloRelish	HereWeDate	Hi Hello
HiZup	Hicky	HighFliers	Hily Dating App	Himoon
Hinge	Hobbiespot	Holler Date	Hongsaox	HotChik
Huggle App	Hum Marriage	Huohua Qingsu	HurryDate	Hutch
Hyntt Interactive	Hype Dating	Hyperity	I-UM SOCIUS	ICIRED
ICrushiFlush	IRL	IThanks	Icebrkr	Iktoos
ImpressMe	Inner Circle	InterMatch	Interns Meet	Intersections Match
Introductions	Isodate	It's Just Lunch	JRMEX	JSCNetworks
JSwipe	Jabburr	Jaumo	Jdate	Jewave
Jewish FriendFinder	Jiayuan	Jigsaw	Jingle	Johnny Cassell
Join Me Tonight	Joompa	Journify	Joyride	Julie Ferman Associates
Jumpdates	June Dating	KYWRD	Kama	Karma
Karma the Game of Destiny	Keeper	Kekkonjoho Center	Kelleher Los Angeles	Keys
Khadijah Elite	KiKi	Kickoff	Kiev Personals	Kindra Connect
Kinkstr	Kippo	Kippy	Kismet Dating and Relationship	Kito link
Klip	KokTailz	Kwaan	LDSPlanet	LDSsingles
LGBTQutie.com	LUMA Luxury Matchmaking	Lada Labs	Launch Social Inc.	Lelala UG
LemonSwan	Lemur	LesPark	Let's	Let's Date
Let's Wait	Levoma	Lex	Ligalos Network	Lime Inc. Ltd
LimeMeet	Linda	Line Tree	Loggerbros	Lolly
Lolo	Loly Labs Inc.	Love The Network	LoveAndSeek	LoveLab.com
LoveMaker.cc	LoveRoom	Lovebuddies	Loveflutter	Loveopolis
Lovestruck.com	Lovetropolis.com	Lovfinity	Lovoo	Lua
Lumen	Luna	Lunch Actually Group	Lunchable	Lupper
Luv Talk	Luv.D	LuvFree.com - dating site	LuvHut	Luvango
Luvdoo	Luvguru	M8	MANHUNT	MFR Dating
MM	MONO	MPWH	Magick.Love	Mai Tai Group
Maly	Mamba	Maple	Marry in a Week	MarryU
Match Group	MatchMakers of Chicago	MatchMde	MatchMeHappy.co.uk	Matchbox Matrimonial
Matches That Matter	Matchmakers In The City	Mateable.com	Matter	Mattr.Social
MaybeMike	Mayze	Me So Far	Me Tang	Meaningful Connections
Meet Kinksters	Meet Market Adventures	Meet Positives	Meet & Right	Meet5
MeetCute	MeetMindful	MeetPlayLive	Meetch	Meetic
Meeting Place in Norden AB	Meetro	Meetual	Meetville	Meetwo
Merrydate	Mesh Labs Inc	Mi Media Manzana	Michi	Milian Technology
Military Singles Connection	Miliyo	Millionaire Match	Millionaire dating sites	Mingle Around
Mingout Social Technologies Pvt Ltd	Minu	Miss Date Doctor	Mitch	Mix Amore
Mixtable	Modamily	Molten Broom	Moment	More to Love
Motto	MouseMingle	Mrk & Co (Dine)	Muddy Matches	Muslim Zawaj
Mutual	MuzMuz	Muzz	My Cheeky Date	My Little Black Book
My Transgender Date	MyCircles	MyDiaspora	Müslüman Kalpler	NERVY
NICE PEOPLE	Nambii	NamoroOnline	NearGroup	NepaliVivah
Neqtr	Nerve.com	Neu.De	Nibble	Nico
Nine	Noa Systems	Noonswoon	NovaLova Dating	Nuhook
Number One	O-net	OMGPOP	OTP London Ltd	Obushu
Official	Offleash'd	Offline Society	Ohlala	OkCupid

OliveWoo	On for Friday	Ona	Once	OneGoodCrush.com
Online Personals Watch	OnlineBootyCall	Optdin, Inc.	OurTime	OutPersonals
PING	Paiq	Paired	Paktor	Parship
Parship Group	Pastroptard.com	Pay For A Date	PayCute	Pear.Me
Pearable Inc.	Peard	Peekaboo	Pembe Panjur	PenPal
People Media	Perfect 12	Perfect Match Jakarta	PerfectMatch	Perppl
Personal Dating Assistants	Pheramor	Photos For Tinder	Photoverified	Phresh
Piaoliu Pingzi	Pixedate	Piña Colada SF	Pleb	Plenty of Fish
Plus1.dating	Plutolife	Pof	Pool	Positivesingles
Posse Global	Premier Introductions Inc.	Press Play	Prime Singles	Prime-Date
Princess Date Agency	PromSocial	Promenad	Prompt - AR Dating & Video App	Proposal (Previously Muzproposal)
Pulsee	Pumpkin App	Pune Girls	Pure App	Pure Moderation
PurpleLord	Qinaqin Shipin Hunlian	Qingchifan	QuackQuack.in	Qualify LLC
Queerfeed Media	QuestChat	Quivr	RAVIEW Dating	RSVP
Ravore	ReRe	Real Social Dynamics	RealBlackLove Inc.	Realm
Rebound	Reco	Reddi	Relate	Relatieplanet Nederland
Relationship Hero	Relationship.AI	Relationships.com	RendezVous353	Rendezvous Software
Rentabiliweb Belgique	Resally	Resocious	Reveal	Revolution Dating
Rocketech	RocknRollDating	Royals App	Rudicaf	Run2meet
S DATING GAME	SCRUFF	SEI Club - Reviews	SEO Leverage	SETIPE
SHAKN Dating APP	SKWSH	SKYLOVE	SYNBOOK	Safer Date
SaleMill	Sandbox	Sapio	Sasha7	SayAllo
Scamalytics	Sdxpay	SecretBenefits	SeekingArrangement	Select Date Society
Selective Search	SeniorPeopleMeet	Seniormatch	Serendipity	Serndip
SetForMarriage	Setup	ShadiMatrimonies	She said' App	Siesta
Signal ground3	SilverSingles	Single Atlanta	Single Darlings	Single Muslim
Single Parents Mingle	Single Seniors Meet	Single Tavern	Single and Mature — Over 40's dating	SingleParentMeet
Singledk	Singles Warehouse	Sircle Advertising	Sister Wives	Sixians Technologies
Skiibo	Sliding-Doors	Slow Dating	Smile	Smitten
Snack App	So Syncd	SoWink	Socialwalk	Solian
Something More Austin	SongFlame	SoulSwipe	Spark Networks SE	Spark.com
SparkStarter	Sparkology	SpeedDate	Spheery	SpinTheCam
Spontana	Spontime	SpoonLuv	Spottle	Spouslr
Spowse	Spring.me	Stealth	Streameet	Strike
Struck	SuccessfulMatch	Sugarbook	Sugardaddie	Suments Data
Sunnyloft	Super-Smash Inc.	Swan	Sweet Pea	Swizzle
SwoonXO	Sylly	Symbios Group	TICKLE	TRUmatch
Tabler	Taffy Media Inc.	TagDates	Taimi	Taiwan Friend
TaiwanFriendFinder	TalkNow	Tangbei	Tangible Teleportation Co.	Tantan
Tastebuds	Tchatche	TeamKraft	Teamo.ru	Teleport
Teligence	Temptr	Tenfingers	TeraryumApp	Thai Cupid
Thai Love Date	The Bro App (BRO) - BroTech LLC	The Dating Awards	The Dating Lounge	The Eros App
The Flock - online dating with friends	The League	The List	The Love Group	The One
The Pitch Place	The Power Of Music (POM)	The Profile Laundry	The Round	The Sauce
The Wilson-Bey Group Multifaceted LLC	The hookup	TheGeminiWeb	ThisCouldBeHUGE!	Three Day Rule
ThreesomeDateWebsites	Thumdate	Thursday	Thurst	Timoo
Tinder	Tinder Para Casados	Todayte	Tonight (Dating App)	Touchgram Pty Ltd
Toyboy Warehouse	Trailr	Traição Agora	Traumoo	Travpart
Triangulate	Tripflingo	True.com	TrueYou	Trulymadly.com
TruuBlue	Tryst	Trystana	Tutton	Twinkle Apps
UK Singles Connection	UaDreams	Ukin	Ukrainian Fiancee Marriage Agency (UFMA)	Umatch
Unavine	United Young	Unmiss - Fast Dating App	UpDog Dates	UpForItNetworks
Ur My Type	Urban Swan	Utxtud8	VEARTH	VOX studios
Vacationship	Vanilla Bridge	Veganific	Venntro Media Company	Venus
Venus & Mars	Veridigm	Verified Millionaire Dating Sites	Vibes	VidChatting
Video Chatting Co.	Virtual Dating Assistants	Vizziy	Voxle	WE LOVE DATENIGHT
WILDEC	Waiter.love	Wandure Inc.	Waves	Weaver
Weesh	Wekaw Advisors	Weopia	Western Match	WhatsYourPrice.com
Whirl	WhiteMobi	Wishiz.me	WithCoffee	WizzLuck
Woo	WooDate	WooMe	Wovo	Wuiper
XOXO app	Xcbill Pay	Xiaoenai	Xoxo Tours	YESTODATE.COM
Yaass	Yakukon	Yalwa - The Local Internet Company	YesOrNow	You Qingqu
YouViaMe	Your Future Dating	Youyuan	Yue Baobao	Yvonne Allen & Associates
ZMC Coders LLC	Zang	Zappel	Zero G Software	Zhenai

Zhenih i Nevesta	Zhi Ji	Ziinkle	Zirby	Zodier
Zonacitas.com	Zoosk	ZotaPay	apnakoi	believr
blunder.one	buddystumbler	coopz	csajokespasik	datehookup.online
datenight	datepack GmbH	eCRUSH.com	eDarling	eDate
eDating For Free	eHarmony	eureka, Inc.	everythingIsTheBest	eÇift
facelovefinder	flikdate	fondhope	gay.com	gloxy
heybaby	humhum	iDateAsia.com	iSeeYa	iUV
ilios	inMessage	invme	iris Dating	itechbook
iwillfindyou.love	makromusic	meetnlunch	mint.me	myDoggySocial
myLovelyParent	myTamilDate	noii	oLive: Video Dating App	onSwingers
oomlato	ruby	seekBromance.com	sndbx	sozila
sumtu	tataUFO	vSocial		

Table C.2: List of Dating Apps (Similarweb)

3Fun: Threesome Couples Dating	Ashley Madison	BLK Dating: Meet Black Singles
Badoo: Dating. Chat. Meet.	Black People Meet Singles Date	Boo: Dating. Friends. Chat.
Bumble: Dating App & Friends	CatholicMatch Dating App	Chispa: Dating App for Latinos
Coffee Meets Bagel Dating App	DateMyAge Mature & Senior Date	Dating and Chat - Evermatch
Dating and Chat - SweetMeet	Dating and chat - Likerro	Dating and chat - Maybe You
Dating with singles - iHappy	Dating.com™: Chat, Meet People	Dil Mil: South Asian dating
FWB Hookup & NSA Dating Xfun	Feeld: Meet Couples & Singles	FlirtMe – Flirt & Chat App
Hily: Dating app. Meet People.	Hinge Dating App: Meet People	Kink D - BDSM, Fetish Dating
Loop: The Set Up Network	Match Dating: Chat, Date, Meet	Mingle2: Dating, Chat & Meet
Mutual - LDS Dating	Muzz: Muslim Dating & Marriage	OkCupid: Date and Find Love
Once: Perfect Match Dating App	Ourtime Date, Meet 50+ Singles	PURE: Anonymous Dating & Chat
Positive Singles Herpes Dating	RandoChat - Chat roulette	SALT - Christian Dating App
Seeking	SilverSingles: Dating Over 50	Stir - Single Parent Dating
The League: Intelligent Dating	Tinder Dating app. Meet People	Turn Up - Match through music!
Upward: Christian Dating App	Veggly – Vegan Dating App	Whatsflirt – Chat and Flirt
Wild: Hook up, Meet, Dating Me	WooPlus - Dating App for Curvy	Zoosk - Social Dating App