The Causal Effects of Online Dating Apps: Evidence From U.S. Colleges *

Berkeren Büyükeren, Alexey Makarin, Heyu Xiong

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Abstract

Online dating apps have become a central part of the dating market over the past decade, yet their broader effects remain unclear. We analyze the impact of the popular dating app—Tinder—on dating behavior, relationships, and health of young adults. For identification, we rely on the fact that Tinder's initial marketing strategy centered on Greek organizations (fraternities and sororities) within college campuses. Using a comprehensive survey containing more than 1.1 million responses, we estimate a difference-in-differences model comparing student outcomes before and after Tinder's rise and across individuals with varying Greek organization membership. We show that the introduction of Tinder led to a sharp and persistent increase in the frequency of sexual activity with no corresponding impact on the likelihood of relationship formation. In terms of distributional implications, we find that male students predisposed to higher levels of sexual activity based on their observable characteristics experienced a more notable increase in dating success—a heterogeneity pattern not observed among female students. Finally, in terms of overall well-being, dating apps have downstream benefits through relative improvements to students' mental health, but also costs due to increased incidences of sexual assaults and sexually transmitted diseases.

*Büyükeren: EIEF and LUISS. Email: bbuyukeren@redphd.it. Makarin: MIT Sloan School of Management and CEPR. Email: makarin@mit.edu. Xiong: Case Western Reserve University. Email: heyu.xiong@case.edu. We are grateful to Daron Acemoglu, Luca Braghieri, Leonardo Bursztyn, Joe Doyle, Sarah Eichmeyer, Ruben Enikolopov, Daniel Ershov, Raymond Fisman, Matthew Gentzkow, Ro'ee Levy, Andrea Prat, Jesse Shapiro, Ekaterina Zhuravskaya, seminar participants at EIEF, MIT Sloan, and Tulane University, and conference participants at the CEPR Workshop on Media, Technology, Politics, and Society, the MEA, the Northeast Ohio Economics Workshop, the Quebec Political Economy Conference, and the WEAI Annual Conference for the helpful comments and feedback. We thank Pryce Davies for the superb research assistance. Alexey Makarin gratefully acknowledges financial support from the MIT Sloan Health Systems Initiative.

1 Introduction

The past two decades have seen a dramatic shift in how people form romantic relationships and, by extension, how the dating market operates. The share of U.S. heterosexual couples who met online has skyrocketed, growing fourfold since the early 2000s and reaching 39% by 2017. In fact, online dating has become the most popular mode of meeting romantic partners (see Figure 1).

The rapid growth of online dating in the past ten years coincided with the advent of smartphone-based dating apps. While online dating services have been around since the 1990s, the emergence of mobile-phone-based applications, headlined by the launch of Tinder, represented a structural change in what was previously a niche industry. By taking advantage of geolocational capabilities and offering an always-on-hand presence, Tinder and other apps that followed have redefined how people meet romantic partners and have popularized online dating to an unprecedented level.

Despite the growing popularity of dating apps, the broader implications of their mainstream adoption remain poorly understood. On one hand, economic theory would predict that the entry of a new matching technology, capable of reducing search costs and alleviating information asymmetries, could improve efficiency and allocations (Adachi, 2003; Hitsch, Hortaçsu, and Ariely, 2010a; Ellison and Ellison, 2018). On the other hand, the rise of dating apps has been accompanied by growing public concern—numerous popular press articles have linked dating apps to the rise of hookup culture,[1] declining mental health and sexual activity among young adults,[2,3] and a more skewed distribution of dating matches.[4]

This paper provides the first empirical analysis of the causal impact of online dating apps. We focus on Tinder, a pioneer in the dating-app space that remains a dominant market leader to date.[5] We center our attention on U.S. college students, who were the main target audience of Tinder at the outset and who belong to the age group most affected by the advent of dating apps.[6]

To identify the causal impact of Tinder, we exploit a key institutional feature of Tinder's launch

[1]Is romance really dead? CNN, June 19, 2022.

[2]A decade of fruitless searching': the toll of dating app burnout. *The New York Times*, August 31, 2022.

[3]A 'failure to launch': Why young people are having less sex. *Los Angeles Times*, August 3, 2023.

[4]How she ghosted me: the men being radicalised by Tinder data. *New Statesman,* January 10, 2020.

[5]According to a PEW Research Center Survey in July 2022, 79% of U.S. adults between the ages of 18 and 29 who have ever used online dating have used Tinder at least once (McClain and Gelles-Watnick, 2023).

[6]In the spring of 2013, only 10% of adults aged 18 to 24 reported using online dating services. This number grew to 27% by 2015, after the rollout of Tinder (Smith, 2016). For other age cohorts, the change between 2013 and 2015 was much smaller. See Figure A1 for more details.

strategy, which was to identify socially influential members of college communities and harness preexisting social networks in order to promote the app. In practice, this involved leveraging Greek organizations (fraternities and sororities) operating on college campuses.[7] Tinder relied heavily on Greek organization members to serve as brand ambassadors, and it used fraternity and sorority events as a means to popularize the app.[8] This strategy was widely documented and attested to contemporaneously by both outside observers and the founders of Tinder themselves.[9] As a consequence, the adoption and use of Tinder on college campuses was said to be significantly higher among students who participated in Greek life.

We first quantitatively confirm that Tinder usage was indeed tightly connected to Greek life on college campuses. Analyzing the universe of college-newspaper articles from 2013 through 2016 available on LexisNexis, we document that Tinder was consistently more likely to be discussed at colleges with a greater presence of Greek organizations. The articles also reveal personal anecdotes that corroborate the spread of Tinder through Greek systems. We also show that colleges with Greek life were more likely to be located in towns that exhibited higher Google search intensity for Tinder during the app's initial rollout. Finally, using data on app usage from over 13 million devices, we show that during the fall of 2017—the earliest period for which such data is available—Tinder use was significantly higher in colleges with a more pronounced Greek life presence.

Motivated by this pattern of early diffusion, we pursue a difference-in-differences research design that exploits the differential spread of Tinder between Greek and non-Greek students following its full-scale launch. To carry out our analysis, we utilize the National College Health Assessment (NCHA), which surveys college students on a semester-by-semester basis—approximately 1.1 million students at 500 colleges from 2008 through 2019—and provides detailed measures of students' sexual activity, relationships, and physical and mental health.

Applying the difference-in-differences strategy, we compare students before and after the full-scale launch of Tinder and across their Greek affiliation. College-by-survey-wave fixed effects allow us to account not only for variables whose impact on student behavior is constant across colleges and time, such as college selectivity or country-wide shocks, but also for any time-varying

[7] Fraternities and sororities are social organizations at American colleges and universities. They play a central role in the college experience of many American undergraduate students (Even and Smith, 2022).

[8] Here's one of the college kids helping Tinder take over campuses. *Huffington Post,* July 2, 2013.

[9] How Tinder used Greek life for more than just hookups. *Fortune,* August 9, 2016.

differences within colleges, such as idiosyncratic changes in campus culture. Rich individual-level controls, such as age, gender, race, and body mass index (BMI), further adjust for potential shifts in the composition of the survey respondents across colleges and over time. We confirm the absence of pretrends in our estimates, which supports the validity of the parallel-trends assumption.

First, we characterize the impact of online dating apps on the dating market equilibrium in terms of sexual activity and relationship formation. This empirical analysis is guided by theoretical predictions in Antler, Bird, and Fershtman (2022, 2023), namely, that reduced frictions in the dating market can lead to prolonged search and more frequent turnover in romantic couplings. Our results are consistent with these theoretical predictions.

We find that the introduction of Tinder led to a significant differential increase in the frequency of sexual activity and the number of sexual partners among students involved in Greek life, as compared to their peers at the same institutions in the same semester. In terms of magnitude, after the introduction of Tinder, Greek-affiliated students (hereafter, "Greek students"), on average, had 0.21 more sex partners and became 2.9 percentage points more likely to have had sex in the previous 12 months, equivalent to 0.06–0.07 standard deviations.[10] At the same time, we find no evidence that Tinder affected the share of students in a cohabiting relationship status. Taken together, these results suggest that online dating apps may induce greater experimentation and turnover in sexual relationships prior to the establishment of a stable romantic match.

Second, we examine the implications of dating apps for relationship quality. Matching on dating apps differs greatly from offline dating. On one hand, the former is associated with substantially lower search costs. Accordingly, one might speculate that the introduction of Tinder would possibly lead to higher relationship quality. On the other hand, matching in online dating apps relies on arguably more superficial informational cues which can lead to worse pairings. We measure relationship quality using three separate questions reporting instances of relationship problems and abuse. We find little evidence that Tinder affects the share of students experiencing relationship difficulties, suggesting that Tinder neither improves nor worsens match quality.

Next, we study the distributional consequences of Tinder in the dating market. Economists have long recognized that technologies facilitating an increase in market scale may exacerbate inequal-

[10]As a further point of reference, the former effect is about 34% of the difference in the number of sex partners between male students of short (below 25th percentile, or 167 cm) and tall (above 75th percentile, or 189 cm) height.

ity across the "talent" distribution (Rosen, 1981; Koenig, 2023). In the case of the dating market, online dating apps promote economies of scale by reducing search costs and allowing individuals to meet people well beyond the confines of their immediate social networks. In line with this logic, we show that, for male students, the positive effects on sexual activity and relationship formation are significantly larger for students predisposed to experiencing a higher baseline level of sexual activity, as predicted using LASSO (least absolute shrinkage and selection operator) based on students' observable characteristics. In other words, for males, the "gains" from online dating accrue disproportionately to those who were already likely successful in dating prior to the new matching technology. For females, this pattern of heterogeneity is completely absent and the impact of online dating apps is largely equalized across groups. These contrasting findings suggest that the distributional effects of Tinder vary significantly by gender and in the case of males, the introduction of online dating apps may facilitate the rise of "superstars" in the dating market.

Having shown the primary effects of Tinder on the dating market equilibrium, we explore the potential downstream ramifications of increased sexual activity on mental and physical well-being.

In terms of mental health, we find that Tinder has a positive average impact on the reported mental well-being of students involved in Greek life. The improvement is around 0.05 standard deviations in magnitude and is observed across all components of the index, including severe depression and reported instances of self-harm. The impact is larger and more pronounced for female students. These findings contradict the common view that dating apps may be causing disproportionate mental distress among young adults due to factors such as online harassment (Smith and Duggan, 2013). It also stands in contrast to the deleterious effects of other social networking platforms, such as Facebook (Allcott, Braghieri, Eichmeyer, and Gentzkow, 2020; Braghieri, Levy, and Makarin, 2022). We speculate that the effect could be consistent with an improvement in self-image as a result of students receiving more romantic attention after the introduction of dating apps (Jung, Bapna, Ramaprasad, and Umyarov, 2019). We find this explanation to be well-aligned with the narrative evidence from around the time of the introduction of dating apps.

While our findings suggest that the introduction of Tinder has led to improved mental health among Greek students, we also discover that it has been associated with some negative consequences. Specifically, we observe a significant differential increase in the reported incidence of sexual assault reports; we also find a positive impact on the probability of being diagnosed with chlamydia and having tested for HIV. The effects are substantial in magnitude, with the probability of sexual assault and HIV tests both rising by 2 percentage points, and the probability of being diagnosed with STDs growing by 0.5 percentage points off the mean of 2%.[11]

Finally, we examine the effects on academic performance. They largely mirror our earlier findings. Specifically, we detect no differential change in the share of students claiming that their academic performance was hindered by relationship difficulties. Similarly, fewer Greek students report that mental health issues worsened their academic performance. However, alarmingly, we note a significant increase in the proportion of students who indicated that their academic performance suffered due to experiences of sexual assault.

We perform a series of tests to rule out competing explanations. First, to assuage the issue of selection into Greek organizations, we estimate a version of our specification that includes the interactions between the post-Tinder-introduction indicator and a set of student characteristics, including age, gender, race, height, and BMI. Our results remain unchanged. Next, to account for the possibility of complex interactions between control variables, we predict the number of sex partners using a LASSO procedure based on the set of control variables, their square terms, and first-order interactions, and then include the LASSO-predicted number of sex partners interacted with post-Tinder-introduction as a control variable. Our results remain invariant to this change as well. These robustness checks suggest that our results are unlikely to be driven by omitted differences between Greek members and other students.

Another potential concern is that our estimates could be biased by self-image-driven misreporting. This is unlikely for several reasons. First, the NCHA survey is anonymous and does not involve individually assigned enumerators. Second, the cause for misreporting would have to be convoluted, such that it accounts for both increases in the reported number of sexual partners and in reported STD diagnoses. Third, we observe no differential change in nonresponse rates for our outcomes. We also take steps to show that our results are not driven by differential smartphone adoption or by the administrative crackdown on Greek activity that occurred at select universities during our study period.

A remaining issue critical to our research design is the viability of the Stable Unit Treatment

[11] Naturally, we find that the mental health improvements are mainly observed among individuals not reporting having experienced sexual assault.

Values Assumption (SUTVA) in this setting. Because non-Greek students were not prohibited from using Tinder and because Greek and non-Greek students inhabit the same campuses (where they are free to associate and interact), spillovers between treated and nontreated units can occur. This may lead to complications with the veracity of our estimates and questions about whether these estimates may be somehow impacted by the possible effects of Tinder on non-Greek students.

To alleviate this concern, we employ a complementary research design that defines treatment at the college level based on the share of college students active in Greek life. The idea behind this approach is that, because of strong network effects in the utility of dating apps, the overall usage of Tinder is likely greater on campuses with a larger Greek presence. This is attested to by our college-newspaper findings and by Tinder's strategy of targeting Greek students. With this approach, we estimate the impact of Tinder on all students by comparing more-Greek versus less-Greek colleges. With the sole exception of mental health improvement, our individual-level results generalize to the overall student population. In particular, we find positive effects on sexual activity, no effect on cohabitation or mental health, and increases in reported sexual assaults and STDs. The effect sizes are somewhat larger than in the individual-level specification, suggesting that, if anything, spillovers attenuate the true effect of Tinder's introduction.

Overall, our findings suggest that the advent of Tinder has significantly reshaped the dating-market equilibrium in line with existing economic theories: prolonging the search, increasing turnover in romantic relationships, and skewing the distribution of dating activity toward a select group of highly active daters. These patterns imply that Tinder might have contributed to the rise of hookup culture on college campuses (Wade, 2017). At the same time, contrary to widespread concerns, our findings do not indicate that online dating apps have negatively impacted mental health or played a role in bringing down sexual activity among young adults (Twenge and Park, 2019; Twenge, Cooper, Joiner, Duffy, and Binau, 2019).

Related Literature This paper is the first to study the causal impact of mobile online dating technologies on individual outcomes. The vast majority of existing research relies on correlational exercises—see Bonilla-Zorita, Griffiths, and Kuss (2021) for the literature review. For instance, in a survey of 400 college students, Shapiro et al. (2017) find that Tinder use is positively associated with the number of sex partners and having experienced nonconsensual sex. Surveying college students in Hong Kong, Choi, Wong, and Fong (2018) find that dating-app users were more likely to report being sexually abused in the previous year relative to nonusers. Holtzhausen et al. (2020) find a negative association between the use of swipe-based dating apps and mental health. While these studies are informative about the potential issues associated with dating apps, causal evidence is lacking. The review article by Bonilla-Zorita et al. (2021) advises that "it is recommended for further study to [...] consider methodologies that can establish causality" (p. 2272).

The only study identifying a causal relationship between online dating and health is Greenwood and Agarwal (2016). Using the staggered introduction of Craigslist across cities in Florida from 2002 to 2006 for identification, the authors find that Craigslist entry is associated with significantly higher asymptomatic HIV counts, especially among Black patients. In contrast, we focus on Tinder, a platform used solely (and much more often than Craigslist) for online dating and study it during a time when online dating became normalized (Rosenfeld, Thomas, and Hausen, 2019). We also study a variety of additional outcomes, not only STDs, thus drawing a much more comprehensive picture of the overall effects of online dating technologies.[12]

This paper also relates to significant literature on marriage markets in economics, dating back to Becker's Theory of Marriage (Becker (1973); for a recent overview, see Chiappori (2020)). The dating market as a precursor to the marriage market has also received attention from economists. We add to this literature by documenting how online dating apps change the equilibrium dating patterns, empirically, in a particular community—in this case, colleges. Much of the work in this line of research has focused on using online interactions to identify mate preferences to better understand current marriage markets and to predict how online dating might shape these markets. This is exemplified by Hitsch et al. (2010a), who use the demographic, physical, and interaction data of 6,000 randomly selected online daters to estimate a model of mate-match preferences. The authors find that actual online matches closely resemble the ideal matches generated by the Gale-Shapley algorithm, suggesting that online dating markets are efficient and have uniquely low search costs, unlike real-world marriage markets.[13] Antler et al. (2022, 2023) study the dating market theoret-

[12] A few studies examine how online-dating-platform design causally shapes user behavior. Bapna, Ramaprasad, Shmueli, and Umyarov (2016) analyze the impact of an anonymous viewing feature on user behavior. Jung et al. (2019) study the impact of the mobile-app creation by online dating sites on users who initially use the online platform and then switch to the mobile platform. Using a differences-in-differences strategy, the authors find that mobile-app adoption caused users to view more profiles, log in throughout the day, and be more impulsive and uninhibited.

[13] Other studies estimating online partner preferences include Hitsch, Hortaçsu, and Ariely (2010b), who document the quantitative importance of racial preferences; Huber and Malhotra (2017), who find a preference for partners

ically, suggesting that, by lowering search costs, dating apps may lead to greater experimentation and prolonged search before marriage. Our estimates are in line with these predictions.

We also relate to the nascent literature on the causal effects of the internet and, more narrowly, social networking technologies on sexual activity, marriage, and individual well-being. Bhuller, Havnes, Leuven, and Mogstad (2013) find a positive impact of internet use on sex crime, possibly due to increased consumption of pornography (see also Ciacci and Sviatschi, 2022). Bellou (2015) finds that broadband internet has led to higher marriage rates by thickening the marriage market. Allcott et al. (2020), Mosquera et al. (2020), and Allcott, Gentzkow, and Song (2022) document the negative impact of social media on one's well-being broadly defined, although not considering outcome variables related to dating or sexual behavior. Braghieri et al. (2022) leverage the staggered introduction of Facebook across U.S. colleges to document its negative effects, specifically on mental health.[14] We contribute to this research agenda by examining the causal impact of a social networking technology—online dating apps—that has so far been overlooked, but that has arguably shifted the societal landscape just as much as social media.

2 Background

Tinder is a social networking and online dating application. It soft-launched on the Apple App Store in September 2012. In contrast to existing online dating platforms, Tinder was designed from the ground up to be a smartphone-based app. Its biggest innovation was the swipe feature (released in May 2013), which allowed the user to anonymously swipe right or left to indicate like or dislike for other users' profiles. Two users are matched and allowed to interact only if they both swiped right on each others' profiles. The Android version of Tinder launched in July 2013.

Simply put, Tinder has normalized and popularized online dating, especially among young

with similar political characteristics; Brech, Vandenbulcke, and Baert (2019) and Egebark, Ekström, Plug, and van Praag (2021), who reveal that women tend to prefer more highly educated partners, while men do not seem to have a preference for higher education, and that both men and women place a similar premium on physical attractiveness. Fisman, Iyengar, Kamenica, and Simonson (2006), Fisman, Iyengar, Kamenica, and Simonson (2008), and Bhargava and Fisman (2014) estimate mating preferences in the context of in-person speed-dating experiments. In the context of arranged marriages in India, Banerjee, Duflo, Ghatak, and Lafortune (2013) study marriage preferences by analyzing matrimonial newspaper advertisements and find a strong preference for within-caste marriage. Bursztyn, Fujiwara, and Pallais (2017) conduct a field experiment showing that single female MBA students reported lower desired salaries and willingness to travel when they expected their classmates to see their preferences.

[14]For a comprehensive overview of the literature on the economics and politics of social media, see Zhuravskaya, Petrova, and Enikolopov (2020) and Aridor, Jiménez Durán, Levy, and Song (2024).

adults. By 2020, Tinder had 75 million monthly active users, and by 2021, Tinder had recorded more than 65 billion matches worldwide (it is available in more than 190 countries). The popular press has credited it with effectively changing the dating culture among young adults in the United States and many other places in the world (Abolfathi and Santamaria, 2020). Many competitors have since launched, but Tinder remains the market leader. As of July 2022, 79% of adults aged 18–29 and 46% of all U.S. adults who have ever engaged in online dating have used Tinder at least once. This usage far surpasses that of any other online dating apps or websites (McClain and Gelles-Watnick, 2023).[15]

Tinder capitalizes on network effects, so gaining early traction was crucial to its success. To accomplish this, Tinder was heavily targeted toward college students in its initial launch. To grow its user base in the first year, the developers followed the college-by-college promotion strategy. Search data from Google Trends corroborate the fact that Tinder targeted the college student population. Table A1 presents the top 30 cities for the search term "Tinder" for 2013 and 2014. These data reveal that in the first two years that Tinder became available nationally, most of the top cities in terms of Google search intensity for Tinder were college towns, or at least contained a college whose student body was a significant part of the local population.

However, beyond just promoting the app first to college students, Tinder founders took a further step, focusing on the Greek system within college campuses. This strategy aimed to take advantage of the existing and already dense networks in order to spread the app. Because fraternities and sororities often hosted parties and organized other social events, they could function as the linchpin of social activity on college campuses. As such, they are socially influential sub-communities with an outsize influence on the overall student body.

Leveraging Greek organizations on college campuses became an important part of Tinder's initial launch strategy. As the app's co-founder Justin Mateen told Forbes.com in 2016: "We penetrated the Greek system. ... The most valuable lesson I learned is the power and influence that the Greek system has on a student body."[16] Mateen himself was a fraternity member at the University of Southern California, where he and his co-founders launched the app through the university's

[15]Note that 53% of individuals between the ages of 18 and 29 have reported ever using online dating apps or websites (McClain and Gelles-Watnick, 2023). As such, 42% of all young adults aged 18–29 in the United States have used Tinder at least once.

[16]How Tinder used Greek life for more than just hookups. *Fortune,* August 9, 2016.

Greek system. He said, "We knew that if it were to resonate with college kids who were already in a very socially charged environment, that other people would find value in the product as well."[17]

To promote the app during the early days, the whole Tinder team would "drive by every fraternity and sorority in Los Angeles, then San Diego, then Orange County, and every school we could cover," according to co-founder Sean Rad. The strategy paid dividends: every time they visited a sorority or fraternity to discuss Tinder, they would see sign-ups immediately after.[18]

Tinder also sent its vice president of marketing at the time, Whitney Wolfe Herd, on a cross-country trip to pitch the app to fraternity and sorority members. Wolfe Herd herself was a sorority member at Southern Methodist University and would go on to found the rival dating app Bumble. According to Joe Munoz, who developed Tinder's technical backend, Wolfe would go to sorority chapters, "do her presentation, and have all the girls at the meetings install the app. Then she'd go to the corresponding brother fraternity—they'd open the app and see all these cute girls they knew." Tinder had fewer than 5,000 users before Wolfe's trip; when she returned, there were some 15,000 (Moazed and Johnson, 2016).[19]

Invigorated by the success of this college-based marketing campaign, Tinder creators doubled down on this strategy by hiring on-campus representatives across the United States through a campus ambassador program, mostly recruiting them from Greek organizations.[20] For instance, Nick Aull, who served as a brand representative for Tinder at Tufts University in 2013, was a member of the Theta Delta Chi fraternity. Aull organized Tinder-themed fraternity parties where to enter, partygoers had to download the Tinder app on their smartphones. Aull also partnered with fraternity and sorority chapters at nearby schools such as Boston University and Harvard University to organize events there.[21]

To further investigate the prevalence of Greek students among Tinder representatives, in Octo-

[17] Inside Tinder: meet the guys who turned dating into an addiction. *Time,* February 6, 2014.

[18] Founder of $3 billion Tinder reveals the clever marketing tricks. *Business Insider,* February 15, 2017.

[19] It is also important to note that despite the fact that Tinder's advertising strategy targeted and emphasized select schools, it is infeasible to use these patterns for a staggered rollout identification. The detailed information on which colleges Tinder was first promoted at and when proved to be inaccessible. Furthermore, unlike platforms like Facebook which had a phased school-by-school launch, Tinder's release strategy was different. Once Tinder was made available on the App Store, it became instantly accessible to everyone, irrespective of their college. Therefore, it is more logical and feasible to base the identification strategy on the timing of Tinder's full launch in the summer of 2013 and its decision to target a certain subset of the student body within colleges, rather than attempting to trace the differences in advertisement timing across schools.

[20] How Tinder acquired 50 million users. *Hackernoon,* July 1, 2021.

[21] Here's one of the college kids helping Tinder take over campuses. *Huffington Post,* July 2, 2013.

ber 2022, we conducted a thorough search for "Tinder Campus Ambassador" on the professional social networking website LinkedIn. We identified 47 such ambassadors, most of whom served in the position during 2018 to 2020. Importantly, 33 of these 47 individuals indicated on their profiles that they were involved in Greek life during college, many in leadership positions.

Because of these strategies, fraternity and sorority members became the earliest adopters of Tinder on college campuses. In 2013, Aull estimated that only 40% of undergraduate students at Tufts had downloaded the Tinder app, but 80% of the school's Greek population used the service. In a 2016 interview, Rad stated that the fraternity and sorority demographic group remained one of Tinder's most active user cohorts at the time.[22]

Fraternities and sororities continued to be important for Tinder long past the initial launch. For instance, in 2019, it came to light that Tinder has been signing exclusive partnerships with Greek organizations to prevent them from partnering with competitors—most notably, Bumble.[23] In October 2022, 33 of the 47 Tinder college ambassadors we found on LinkedIn listed fraternity or sorority membership in their profiles.

We also note that the early expansion of Bumble—the second most popular online dating app among young adults: 51% of 18-29 year-olds who have engaged in online dating have used the app (McClain and Gelles-Watnick, 2023)—bore striking similarities to that of Tinder, with a heavy reliance on sororities and fraternities. Early on, in 2015, Bumble's founder and the former Tinder employee, Whitney Wolfe Herd, spent weekends "traveling to Texas campuses, bringing free yellow Hanky Panky underwear to the sororities and free beer to the fraternities, telling the fraternity brothers that all the girls were looking for their next formal dates on Bumble."[24] Similarly, in 2021, Bumble employed 420 brand ambassadors across more than 100 college campuses.[25]

Following the release of Tinder, online dating became a much more common and pronounced feature of college social life. This is evident both anecdotally and also in survey data. Specifically, we examine several waves of surveys conducted by the Pew Research Center (PEW) and the Online

[22] How this college junior scored a scholarship ... from Tinder. *Refinery 29,* April 18, 2016.

[23] Frats are signing "exclusive contracts" to use Tinder or Bumble. *Futurism,* August 14, 2019.

[24] How Whitney Wolfe Herd turned a vision of a better internet into a billion-dollar brand. *Time,* March 19, 2021.

[25] In our search of college newspapers on LexisNexis mentioning Bumble, we found only three articles in 2015 and ten articles in 2016. Out of these 13 articles, 11 were published in schools with Greek life on campus, indicating a tight relationship between Bumble and Greek life, similar to that of Tinder. These numbers also show that Bumble does not appear to be a significant topic in our college newspaper data before the end of 2016. Despite this, it's important to note that our findings after 2016 could reflect the combined influence of both Bumble and Tinder on college campuses.

College Social Life Survey series that asked questions regarding online dating and dating apps. Table A3 shows that the number of college-age respondents who indicated they used online dating services ranged from 0% to 10% from 2005 through 2013, depending on the survey source and the specific question asked. However, after Tinder became widely adopted, the number jumped to 29% in 2015 and 50% in 2019, underscoring the remarkable normalization of online dating for this demographic group within a relatively short period of time. Figure A1 illustrates similar trends for the young adults more broadly, without restricting the sample to college students and using data from two surveys conducted by PEW in April–May 2013 and June–July 2015, just before and soon after Tinder became a dominant player in the market. The data shows that in the spring of 2013, young adults were much less inclined to use online dating websites or apps compared to other age cohorts. However, two years after Tinder was introduced, the percentage of young adults utilizing online dating websites and apps increased dramatically, from 10% to 27%, whereas usage among other age groups did not experience such a significant change.

3 Data

Throughout the majority of our study, we use two primary sources of data: the National College Health Assessment (NCHA) survey and the LexisNexis data on college newspapers.

3.1 National College Health Assessment Survey Data

The main dependent and independent variables in our empirical analysis are derived from the NCHA survey. The NCHA was launched in 1998 to gather detailed data on the physical and mental health of college students.

The survey is conducted each semester across a large number of colleges. From 2008 through 2019, the survey data contains close to 1.3 million individual student responses. To ensure more consistent comparisons, we restrict our attention only to full-time undergraduate students, reducing our sample to approximately 1.1 million student responses. Since the survey employs a rotating panel of colleges, the resulting dataset is an unbalanced panel, meaning that some of the colleges included in one semester may not be present in another.

The rich nature of the NCHA survey allows us to conduct a comprehensive, multi-faceted analysis of the impact of dating apps, specifically Tinder, on the behavior and health of young adults. The survey contains information about sexual activity, relationship outcomes, potential negative consequences of sexual activity, mental health questions, and academic performance.

For sex-related outcomes, we use measures of recent sexual activity (i.e., the number of sex partners a student had in the previous year and whether a student had sex in the previous 30 days), relationship status (i.e., whether a student was in a romantic relationship at the time of the survey), and cohabitation status (i.e., whether a student was in a romantic relationship with cohabitation at the time of the survey). We also examine questions related to relationship quality, such as whether a student had been in an abusive relationship, been in a difficult relationship, or experienced relationship problems in the previous year. To explore negative outcomes associated with sexual activity, we examine whether a student had experienced sexual assault, had been diagnosed or treated with chlamydia in the previous year, or had ever tested for HIV.

To examine mental health outcomes, we use a comprehensive set of questions that assesses whether a student felt hopeless, overwhelmed, exhausted (not physically), very lonely, very sad, severely depressed, experienced overwhelming anxiety or overwhelming anger, engaged in intentional self-harm, or even considered suicide. Respective outcomes were defined based on experiencing these mental health issues over the period of the preceding 12 months. In order to aggregate the responses and reduce data dimensionality, we follow Braghieri et al. (2022) and construct an index of poor mental health by standardizing all the variables based on the questions mentioned above to have a mean of zero and a standard deviation of one, summing the resulting variables, then standardizing the sum to also have a mean of zero and a standard deviation of one.

In addition to the previously mentioned variables, our analysis also uses students' membership status at fraternities and sororities on campus. This information is crucial to our empirical strategy: it allows us to compare students who had been specifically targeted by Tinder to encourage app adoption with students who were less likely to have faced such pressure. Furthermore, we calculate the proportion of Greek students in each college to use in an alternative college-level specification.

For a detailed description of variable definitions with the precise question formulations and coding, see Table A2.

3.1.1 Descriptive Statistics and Trends in Sexual Activity

Table 1 presents descriptive statistics for individual students and colleges included in the survey. Panel A of Table 1 indicates that the majority of survey respondents are White (70%), while Black and Asian students comprise 6% and 12% of the sample, respectively. About 10% of surveyed students are a part of Greek life. The median full-time undergraduate college student who responded to the survey was a sophomore, as indicated by the college grade variable, and was 20 years old.

The remaining panels of the table provide insight into survey respondents' sexual behavior, relationship information, health, and experiences with sexual assault. Panel B shows that the average number of sexual partners in the survey sample was 1.5, while 47% and 11% of the students were in a romantic relationship and cohabiting, respectively. Panel C reveals that the percentage of students who experienced abusive relationships in the previous year was relatively low (11%), but a high percentage reported having been in a difficult relationship or experiencing relationship problems (32% and 31%, respectively). Panel D reveals that a non-negligible portion of students reported negative consequences related to sexual activity, with 9% reporting having experienced sexual assault and 2% reporting being diagnosed with or treated for chlamydia. Additionally, about 26% reported having ever been tested for HIV. Finally, Panel E indicates that a striking number of students reported experiencing mental health issues, with 35% having felt so depressed that it was difficult to function at least once in the previous 12 months.

Because our study explores the impact of a dating app on college students, we pay special attention to the overall trend in sexual activity amongst individuals in our sample. This is particularly pertinent given the numerous studies indicating that the percentage of young adults who engage in sexual intercourse has been declining in recent years (Twenge et al., 2019). We investigate whether this is evident in our data as such trends may lead to mechanical and spurious relationships.

In Figure 2, we plot the average number of sex partners for individual students over time separately for Greek and non-Greek students. We distinguish between the two groups of students given the rationale of our identification strategy. Reassuringly, we observe that the frequency of sexual activity for non-Greek students is fairly stable and shows no discernible trend, but for seasonal fluctuations, throughout the entire sample period. By contrast, for Greek students, there appears to be a dramatic rise in sexual activity that coincides with the rise of Tinder. These twin sets of observations form the foundation of our empirical strategy and we explore these patterns more systematically in the following sections.[26]

3.2 LexisNexis Newspaper Data

Our secondary source of data is the universe of college newspaper articles available on the LexisNexis platform during the 2013–2016 period. At the time of our search, this resulted in a total of 796,612 articles from 600 newspapers across 574 college campuses.

We analyzed the headlines and full-text of these articles—searching for the keyword *Tinder*—to ascertain the use and popularity of the app on individual college campuses. We calculated the number of articles pertaining to Tinder written by students at each college, which serves as a proxy for the college-specific popularity of Tinder during its initial expansion period.

Additionally, to examine whether reporting and coverage of Tinder varied between college campuses with and without Greek activity, we further supplement the newspaper data with additional college-level characteristics. For each college present in the LexisNexis database, we collect information from the college's Common Data Set (CDS) on whether that college has fraternity or sorority housing, and the percentage of undergraduate students participating in Greek life. For each college, we attempt to find this information for the 2012–2013 academic year, which is the year just prior to the public release of Tinder. For the colleges where the 2012–2013 CDS data are not available, we use information from the earliest available year. Ultimately, we are able to collect Greek-life information for 540 colleges from the LexisNexis sample.

3.3 App Use Data

To further validate our first stage using the actual app use data, we use data from Complementics, a data exchange platform that consolidates device-level information regarding the location and timing of mobile app usage. We obtain this data for the earliest time period available, from September 21 to December 31, 2017. For each day within this period, we have two datasets: a location and

[26]It may be surprising that we do not observe a (smaller) uptick in sexual activity among non-Greek students given the potential spillover effects and given that those students could also use Tinder. This suggest that, on average, the use of Tinder among non Greek students is not substantial enough to generate an observable increase in sexual activity. However this need not be true on campuses with large Greek presence where spillover from Greek to non Greek students might be more significant. This dynamic aligns closely with the initial launch strategy of Tinder, aimed at leveraging social networks to expand its user base. We conduct a more detailed examination of these potential spillover effects and their implications for our empirical strategy in Section 7.2.

an app usage dataset. The location dataset captures the zip code of a series of "pings" from 13.2 million devices in the United States, each identified by a 64-digit device hash. The app use dataset documents the app name and device id for each unique app use session in each day. We exclusively retain data related to Tinder app usage. For each day, we determined the primary zip code of a device by calculating the modal location of its "pings," enabling us to count the number of unique devices within a zip code. We then merge this device-level location data with the app use dataset using the device hash. We measure the average penetration of Tinder within a zip code during the Fall 2017 semester by dividing the total daily number of devices using Tinder by the total daily number of unique devices. We then merge these data with the Greek life indicators from the Common Data Set introduced above.

4 Empirical Strategy

To identify the impact of Tinder on student dating behavior and health, we employ a difference-in-differences strategy that exploits the fact that students involved in Greek life were more likely to adopt and use the app. That is, we compare student outcomes before and after the full-scale launch of Tinder between Greek and non-Greek students.

This approach is summarized in the following regression specification:

$$y_{ict} = \alpha_{ct} + \beta \times Greek_i \times Post_t + \gamma X_i + \varepsilon_{it} \quad (1)$$

where y_{ict} is the outcome of student i attending college c surveyed during semester t; $Greek_i$ equals one if a student i is a member of a Greek organization (fraternity or sorority) and zero otherwise; $Post_t$ refers to the period after the full-scale launch of Tinder in Spring 2013, a timing choice that we discuss in detail below; α_{ct} represent a set of college-semester fixed effects; and X_i is a vector of individual-level student characteristics (including standalone $Greek_i$).

While Tinder soft-launched in the Apple App Store in September 2012, in terms of timing, we consider Spring 2013 as the last academic semester prior to treatment. We do so for four reasons. First, Tinder did not develop its innovative swipe feature until May 2013. Second, Tinder did not launch on the Android platform until July 2013. With Android accounting for 51.5% of the U.S.

smartphone market share in 2013, Tinder was effectively unavailable to half of the mobile-phone-using population until the fall 2013 semester.[27] Third, using a panel of millions of American mobile phone users, Abolfathi and Santamaria (2020) show that Tinder downloads did not start taking off until in July 2013 (see Figure A2). Fourth, as displayed below in Section 5, consistent discussion of Tinder in college newspapers did not start until the fall of 2013. As such, throughout the paper, we use the summer of 2013 as the time of the full-scale launch of Tinder.

The coefficient of interest in Equation (1), β, identifies the average treatment effect on the treated (ATT) of Tinder under the assumption that the sexual or health outcomes of Greek-life students would have evolved along similar trends as their non-Greek peers within the same college in the absence of Tinder. We assess the viability of this assumption by estimating a fully dynamic version of Equation (1) that allows us to check for pretrends and visualize the evolution of the outcome variable prior to the release of Tinder.

We utilize a rich set of fixed effects to address competing explanations. Specifically, college-semester fixed effects account for any time-invariant differences across colleges (e.g., certain colleges may have a reputation as "party schools"), any shocks that affect students across all colleges at the same time (e.g., one could expect greater dating activity after the spring break), and, most rigorously, any college-semester-specific shocks, addressing all alternative interpretations that have to do with college-specific shocks, such as fluctuations in college-specific norms surrounding romantic and sexual activity. To reduce the possibility of our estimates being driven by the survey compositonal changes, in non-dynamic specifications, we control for a rich set of student-level controls such as age, gender, race, international student status, height, and BMI.

It is worth noting that because we do not utilize variation in treatment timing, our research design approximates the canonical 2×2 difference-in-differences framework and eludes some of the potential limitations with two-way fixed-effects models that have been raised in recent econometrics literature (Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021). As a result, we estimate Equation (1) using OLS, with the standard errors clustered at the college level.

[27] See the press release by Comscore at https://bit.ly/3HbtVQr.

4.1 Selection Into Greek Organizations

Because our analysis involves repeated cross-sectional data, a possible concern we face is that the treatment group is changing over time. Specifically, if the composition of Greek students was trending in ways that deviate from the rest of the student population, this may bias our difference-in-differences estimates, especially if those changes coincide with the timing of Tinder's release.

To address this, we perform two exercises. First, we show in Figure A3 that the share of undergraduate students active in Greek organizations remains fairly static before and after the introduction of Tinder. This is reassuring, as it demonstrates that the popularity of Greek life did not systematically change after the full-scale release of Tinder.

Second, we show that while Greek students have always been different from the overall student population on average, those differences did not widen following the availability of Tinder. As shown in Table A4, the difference between Greek and non-Greek students across a wide array of characteristics was fairly balanced between the pre- and post-Tinder periods. With the notable exception that Greek students became less international relative to the rest of the student population, none of the other changes are statistically significant.

These patterns suggest that differential selection into Greek organizations is unlikely to drive any potential findings. Nevertheless, to further assuage this concern, we will include the aforementioned student-level controls in most of our analysis and will present robustness checks for interacting these characteristics with the post-full-scale-launch indicator.

5 First-Stage Relationship

A key assumption that underlies our research design is that fraternity and sorority members were more likely to adopt and use Tinder. While anecdotal evidence in Section 2 does point to the importance of Greek organizations for the early penetration and diffusion of the Tinder dating app on college campuses, in this section, we provide some quantitative evidence in support of this idea.

Our main challenge is that we lack exact data on Tinder usage across individuals within colleges. To overcome this limitation, we utilize information from college newspapers and Google Trends around the time of Tinder's full-scale launch. We then complement these sources with the zip-code-level data on relative Tinder use during the fall of 2017.

5.1 Evidence From College Newspapers

First, we use LexisNexis to collect all articles containing the word *Tinder* that appeared in college newspapers around the time of Tinder's launch (2013–2016).

We consider the discussion of Tinder in news articles a proxy for the popularity of the dating app on college campuses. This presumption is reasonable because these newspaper articles are written by students and reflect trends or development pertinent to student life on campus.

With this data, we test whether colleges with greater fraternity and sorority presence had more articles written about Tinder following the app's introduction. These results are visually summarized in Figure A4. Prior to 2013, no articles regarding Tinder were published in college newspapers. However, from Fall 2013 onward, colleges with Greek life became disproportionately likely to publish articles related to Tinder—the share of colleges with Greek life or greater Greek presence that published Tinder-related articles far exceeded that of their non-Greek/less-Greek counterparts. Figure A5 displays the corresponding dynamic difference-in-differences estimates, confirming that the disparities in the frequency of Tinder-related articles between colleges with varying levels of Greek life are indeed statistically significant for most of the study period.

To ensure that this result is not driven by a differential propensity for news production between Greek and non-Greek colleges, we regress the incidence and number of college newspaper articles published about Tinder between 2013–2016 on measures of Greek life participation, controlling for the total number of articles published. These results are presented in Table A5. Our analysis reveals a strong positive correlation between Greek life at a college and Tinder coverage. Specifically, colleges with Greek life had a 14.5-percentage-point higher likelihood of publishing at least one article about Tinder in their newspapers from 2013 to 2016, and, on average, published one more Tinder-related article during that period compared to colleges without Greek life. The extent of news coverage is also increasing in the share of students involved in Greek life.

Because college newspapers often feature interviews or commentary from current students, we investigate the content of the articles for additional context. In the text of these articles, we find numerous direct references to the influence of Greek organizations on the early diffusion of Tinder.

For instance, in fall semester of 2013, when Tinder started gaining traction, a sophomore student at the University of Nebraska-Lincoln told the *Daily Nebraskan* that "he had heard of Tinder from his fraternity brothers."[28] Similarly, the *Daily Emerald* of the University of Oregon published a story that included accounts from two sorority students who described meeting their boyfriends on Tinder.[29] During the same semester, a second-year student at UC Davis said she created a Tinder profile after one of her sorority sisters recommended the app.[30]

We also discovered similar anecdotes in articles published by newspapers at UCLA, Arizona State University, and Yale University in the fall of 2013. Altogether, from 2013 through 2016, 105 Tinder-related articles were published by newspapers at colleges with Greek life that included specific references to fraternities or sororities or featured interviews with fraternity or sorority members. This textual evidence further substantiates the intricate link between Greek organizations and Tinder in the early days of its launch.

5.2 Evidence From Google Search Intensity

We conduct an additional test of the first-stage relationship in the early diffusion of Tinder using data from Google Trends. Specifically, we focus on the 540 colleges sourced from LexisNexis and examine whether the cities or towns of those colleges rank among the top 100 cities in the United States in terms of Google search intensity for *Tinder* during the period from 2013 through 2014. We explore how the likelihood of ranking higher in Google search intensity varies as a function of participation in Greek life at those colleges. We adopt the same metrics of Greek life activity as employed in the newspaper exercise, namely, the presence of Greek organizations at a college and the indicators for whether the proportion of undergraduate students involved in fraternities or sororities was greater than the median in our sample.

Table A6 presents the results. College towns with colleges that have Greek organizations are 5.2 percentage points more likely to rank among the top 100 cities in terms of Google search intensity for *Tinder* from 2013 through 2014, compared to college towns where colleges have no Greek organizations. The likelihood of appearing in this top 100 list is also significantly higher for colleges with a larger share of students involved in fraternities or sororities.

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[28] Dating app Tinder connects users through Facebook proximity. *Daily Nebraskan,* October 3, 2013.
[29] Wanna hook up? There's an app for that! *The Daily Emerald,* October 15, 2013.
[30] Tinder sweeps through UC Davis. *The California Aggie,* October 17, 2013.

5.3 Evidence from App Usage Data

To further confirm the heightened adoption of Tinder among college students in Greek life, we analyze the data on actual Tinder app usage from Complementics, covering the period from September 21 to December 31, 2017. We calculate the average daily penetration of Tinder within the main zipcode of each college and merge it with the Common Data Set based on the LexisNexis sample of colleges for greater comparibility of the first stage results. We then repeat the same correlational exercise that checks whether the usage of Tinder was higher in the zipcodes of colleges with a more substantial Greek life presence.

The results, shown in Table A7, reveal that colleges with Greek organizations had a 0.3 percentage point higher Tinder usage during the Fall 2017 semester, from a baseline of 1.7%, equating to a magnitude of 0.14 standard deviations. Furthermore, there is a positive association between the fraternity and sorority membership and Tinder use.[31] Overall, these results confirm that the patterns observed in the newspaper and Google Trends data are mirrored in the actual app usage statistics and that Tinder remained consistently more popular in colleges with greater Greek life presence four years after its full-scale launch.

Taken together, these first stage results confirm the presence of an intricate link between Greek students and online dating apps adoption and promotion.

6 Main Results

Encouraged by the first-stage evidence in Section 5, we estimate the impact of Tinder using the difference-in-differences strategy introduced in Section 4. To start, we investigate how Tinder altered the dating market equilibrium on college campuses by focusing on variables related to sexual activity, relationship formation, and relationship quality. Then we consider the distributional consequences of Tinder in terms of its differential effects across the student population. Finally, we explore the downstream impact of Tinder on a wider array of outcomes that may be related to romantic encounters such as sexually transmitted diseases, mental health, and physical well-being.

[31] The results are similar, albeit slightly noisier, when data is aggregated across multiple zipcodes per college and when we consider alternative ways of calculating Tinder penetration.

6.1 Impact of Tinder on Dating Market

Theoretical Predictions We start by characterizing the impact of Tinder on dating market behavior and outcomes among college-age students. Our analysis is guided by theoretical predictions from Antler et al. (2022, 2023) who develop matching models of the dating and marriage markets with search and learning frictions. In their models, advances in search technologies that facilitate meeting potential partners, such as the emergence of dating applications, are predicted to reduce the amount of time individuals spend dating each partner and increase the number of partners whom they date prior to marriage. We empirically test this hypothesis by examining the effect of Tinder on sexual activity and relationship formation.

Baseline Results We analyze the impact of Tinder on two questions related to sex activities from the NCHA survey: reported number of sexual partners within the previous 12 months and whether a respondent had sex within the previous 30 days. These two variables are informative of a student's frequency of sexual activity, which is indicative of search duration or turnover in the dating market.

First, we estimate an event-study version of equation (1) for these two outcomes, which would help us assess the plausibility of the common-trends assumption and, consequently, the viability of our difference-in-differences design. Specifically, we estimate the following specification:

$$Y_{ict} = \alpha_{ct} + \sum_{t=2008F}^{2018F} \beta_t \times Greek_i + \gamma \times Greek_i + \varepsilon_{ict} \tag{2}$$

where Y_{ict} measures behavior of student i in college c at semester t; $Greek_i$ takes the value of 1 if the student i is a fraternity or sorority member; and α_{ct} and β_t are the college-semester and semester fixed effects, respectively. Standard errors are clustered at the college level. We visualize the estimates by plotting the β_t coefficients over time, with the spring of 2013 as an omitted category.

Figure 3 presents the results. Through the lens of our difference-in-differences model, Figure 3 shows that the introduction of Tinder led to a significant increase in sexual activity. Specifically, in comparison to non-Greek students, students belonging to Greek organizations (fraternities or sororities) specifically targeted by the app increased the average number of sexual partners and the share of students who had sex in the previous thirty days. For both outcomes, the figures display an absence of pretrends and an upward trend-break following the full-scale launch of Tinder in the summer of 2013. These patterns support the identifying assumption that the sexual activity of Greek-affiliated and non-Greek-affiliated students would have evolved along parallel trends in the absence of Tinder's launch.

Next, to better assess the effects' magnitudes, we present the baseline estimates in a table format. Specifically, we estimate Equation (1) using a model with only the college-semester fixed effects, then enriching the model by including a set of controls, such as age, gender, race, grade, height, BMI, and an international student indicator. To explore the dating activity shifts in greater detail, we break down the changes in the number of sexual partners in the previous year into changes in the share of students having sex in the previous year (extensive margin) and the number of sexual partners conditional on having engaged in sexual activity in the previous year (intensive margin).

Table 2 presents the results. Compared to non-Greek students, students belonging to Greek organizations increased the average number of sexual partners they had in the previous year by 0.21. This effect amounts to a magnitude of 0.07 standard deviations in the outcome variable. Greek students also became 3 to 4 percentage points more likely to have engaged in sexual activity in the previous thirty days and in the previous year. Finally, we find significant changes along the intensive margin, as Greek students start to have 0.13–0.15 more sexual partners even conditional on having engaged in sexual activity in the past year (columns 3–4).

Effect Persistence Another takeaway from the event-study plots in Figure 3 is that the impact on Greek students does not dissipate more than four years after the launch of Tinder. This nonconvergence is perhaps surprising at the outset because one may expect the differences in Tinder use between Greek and non-Greek students to diminish over time as the app becomes more widespread.

However, we argue that such nonconvergence is plausible for two reasons. First, as we discuss in Section 2, Tinder's focus on college Greek organizations was not limited to the initial launch but persisted well after. Section 5 further shows that the differences in Tinder popularity between colleges with and without Greek life are still present even in 2017. Second, our data is a repeated cross-section rather than a longitudinal panel. Therefore, our dynamic estimates do not follow the same cohort over time; rather, they represent different cohorts of individuals while they are in college. Because the minimum age to use Tinder is 18, our college-student sample is comprised of individuals with their first opportunity to use the app. As a result, if there is a difference in the initial take-up of Tinder between Greek and non-Greek students when they first enter college or simply a difference in the speed of adoption—which is plausible given Tinder's continual attention to fraternities and sororities—then our estimates would reflect that, even if the discrepancy in Tinder usage disappears as these students age out of our sample.

6.1.1 Relationship Formation and Assortative Matching

The substantial gains in sexual activity are consistent with the notion that the reduction in search costs and alleviation of information asymmetries associated with technologies such as Tinder lead to greater experimentation in the dating market. However, the implications of such increased search frequency for the formation of stable relationships are less straightforward. While Tinder may make it easier to find the "right" partner, it also reduces the cost of continued searching, potentially undercutting the need to invest in any given relationship (Antler et al., 2022, 2023). Similarly, the resulting impact on relationship quality could also be theoretically ambiguous.

Because marriage is a very rare occurrence amongst individuals in our study population, we focus on whether students are in a cohabiting relationship with their partner as an instance of a stable match, as cohabitation is often a precursor to marriage and long-term partnership.

To measure relationship quality, we construct variables based on three separate NCHA questions. Specifically, we examine whether a student had been in an emotionally or physically abusive relationship within the previous 12 months; whether a student had found intimate relationships traumatic or very difficult within the previous 12 months; and whether they had experienced relationship difficulties within the previous year.

Table 3 displays the difference-in-differences estimates for these four outcomes. We find that the introduction of Tinder does not appear to be associated with significant changes in the likelihood that students are cohabiting with their relationship partners. We also do not observe consistent change in reports of relationship problems, either in a sample of all respondents or in a subsample of students currently in a (cohabiting) relationship.

Overall, the results indicate that the introduction of Tinder has led to a sizeable increase in sexual activity among students in fraternities and sororities—the communities specifically targeted by Tinder—compared to other students on campus. In contrast, the effect on relationship formation is small. Despite Tinder's innovative matching system reducing the costs of finding a partner, we also find little evidence that the app has any significant impact on relationship quality. These effects are consistent with the general perception[32] as well as with student experiences found in college newspapers[33,34] that the introduction of Tinder has widened the pool of potential partners, resulting in commitment problems, greater turnover, and possibly contributed to the rise of hookup culture.

6.2 Distributional Consequences

In a seminal article, Rosen (1981) argues that technical change facilitating an increase in market scale may amplify inequality across the talent distribution (Koenig, 2023). Because online dating apps allow individuals to more efficiently search for romantic partners well beyond the confines of their immediate social networks, they allow them to capitalize on economies of scale and match with large numbers of potential partners. As such, the introduction of online dating apps could have induced distributional changes in dating activity across the user population.

In this section, we explore whether Tinder contributes to the rise of "superstars" in the dating market. We examine whether the increase in sexual activity is equalized across all students or concentrated among certain sub-populations. To approximate "ability" in this particular market, we consider students' level of activity in the dating market as predicted by observable characteristics.

Specifically, we employ a LASSO procedure to predict an individual's propensity for sexual activity based on their characteristics. Specifically, we leverage the individual-level controls, their second-order polynomials, and all two-way interactions between these attributes to train a LASSO model on the pre-Tinder data, and then we use the resulting model to predict each student's number of sexual partners in the previous 12 months as a function of these complex interactions.[35] This predicted sexual activity variable is intended to reflect both individuals' preference for dating as well as their suitability or "attractiveness" in the dating market.

We then explore the heterogeneous impact of Tinder along this dimension separately across gender groups. To this end, we define quartiles based on values of the LASSO-predicted sexual activity variable for each gender and examine how our estimates vary across these quartiles separately

[32] You up? College in the Age of Tinder. *The New York Times,* February 14, 2018.

[33] Looking for love: Tulane students cope with new dating culture. *The Tulane Hullabaloo,* February 16, 2017.

[34] Online dating app Tinder gains popularity among college students. *The Daily Bruin,* February 15, 2014.

[35] To make LASSO feasible, we use a subset of our usual controls: age, gender, race, and BMI categories. However, our results remain similar if we include other variables and exclude some of the ones mentioned above.

for male and female students.

The total effects for each quartile are displayed in Figure A6. While the estimates are positive and statistically significant for both genders for all quartiles, we observe a noticeable jump in effect size for male students belonging to the top quartile of predicted sex activity. For female students, on the other hand, there is no discernible difference across quartiles. These patterns are confirmed in columns (1) and (2) of Table 4 which show that, for male students, the difference in effect on the number of sex partners between the upper and lower quartiles of LASSO-predicted sexual activity is statistically significant. While for female students, the point estimates across quartiles are virtually identical.

Motivated by these patterns, we also re-examine the impact on cohabitation status by gender across the same distribution. Since cohabitation is a more rare outcome in our sample, we divide students into above and below median predicted sex activity by gender in order to maximize statistical power. Figure A6 shows similar skewed effects for cohabitation. Namely, for male students who are above the median in terms of predicted sex activity, there is a positive and significant effect on cohabitation rates. On the other hand, for below-median male students, the confidence intervals are centered around zero. For female students, this pattern is absent and the effects are approximately equal for students belonging to those two groups.

Altogether, our results suggest that, for male students, Tinder may lead to a greater concentration of dating activity at the top of the "attractiveness" distribution. For female students, the gains from Tinder were equalized across the same distribution. These contrasting patterns of heterogeneity suggest that the distributional impact of Tinder may be different across gender groups and, in particular, Tinder may facilitate the emergence of "superstar" effects for males in the dating market.

6.3 Downstream Effects

Having shown that Tinder affects sexual and romantic behavior among college students, we now turn to examine the potential downstream implications of increased sexual activity associated with the app's introduction on a broader set of outcomes related to the physical and mental well-being as well as academic performance.

6.3.1 Physical Well-Being

First, we explore the downstream effects of increased sexual activity on possible risks associated with increased sexual activity. To this end, we construct three variables based on the NCHA survey questions related to sexual violence and STDs: whether a student had been subject to sexual abuse within the previous 12 months; whether a student had been diagnosed or treated by any professional for chlamydia; and whether a student had ever been tested for HIV infection.

Table 5 reports the difference-in-differences estimates for these outcomes. Following the full-scale launch of Tinder, the incidence of sexual assault among Greek students increased by 1.9 percentage points, which is substantial given that the average incidence of sexual assault in our sample is 8.7%. The effect's magnitude corresponds to 0.07 standard deviations. Columns (3) through (6) also show a statistically significant increase in the incidence of chlamydia and HIV tests among Greek students, by 0.6 and 1.5 percentage points, respectively. The magnitudes are also of meaningful size when compared to the sample averages; they correspond to 0.04 standard deviations.[36] To further visualize the findings, we present event-study plots for these three outcomes in Figure 4. The figures display no pretrends and a clear trend break in the outcomes' evolution following the full-scale launch of Tinder in the summer of 2013.

Overall, these results suggest that by increasing sexual activity among college students, Tinder also had possible negative consequences in terms of the risks associated with increased sexual activity, such as increased reports of sexual assault and STDs.

6.3.2 Mental Health

Next, motivated by the discussions in the popular press about the potential harmful effects of online dating apps for mental health[37] as well as existing correlational evidence (Holtzhausen et al., 2020), we investigate whether the availability of Tinder had an impact on student's mental well-being.

Conveniently, the NCHA survey contains a wealth of questions covering a wide spectrum of mental-health-related issues: feeling hopeless, feeling overwhelmed, feeling exhausted (not physi-

[36] One caveat to a straightforward interpretation of the results on chlamydia, however, is that they could also reflect an increase in testing, as individuals engaging in casual or unprotected sex may take precautionary steps in seeking out tests for sexually transmitted diseases. Therefore our estimates may reflect an actual increase in chlamydia incidence as well as a behavioral response to the increased risk associated with casual sex activity.

[37] A decade of fruitless searching': the toll of dating app burnout. *The New York Times*, August 31, 2022.

cally), feeling very lonely, feeling very sad, feeling so depressed it was difficult to function, feeling overwhelming anxiety, feeling overwhelming anger, intentionally injuring oneself, and even seriously considering suicide. We define respective outcomes based on the incidence of these mental health issues in the previous 12 months. To reduce dimensionality and assuage the concern of multiple hypothesis testing, we follow Braghieri et al. (2022) and create an index for experiencing poor mental health within the last 12 months; specifically, we first sum up the standardized versions of the individual mental health variables, then we standardize the resulting variable.

The results are shown in Table 6. In contrast to both the press and the existing correlational studies, we find that Greek students, who were disproportionately targeted by Tinder, reported better mental health conditions in the semesters following Tinder's release. This pattern of relative improvement is present across all mental health conditions. On average, Greek students saw a 0.044-standard-deviation improvement in their mental health index.

When separated by gender, the results in Table 6 display a stronger improvement in reported mental health for female students. For male students, the effect appears to oscillate depending on the specific mental health issue. Whereas, for female students, the effect is consistently significant throughout all reported mental health problems. Figure 5 illustrates the sharp nature of this effect by presenting an event-study plot for the mental health index among female students. While the pre-Tinder coefficients are mostly nearing zero, the point estimates after the full launch of Tinder are consistently negative and statistically significant.

Given the results from the previous section showing an increase in sexual assault, the improvement in average mental health could be surprising. Because sexual assault is relatively rare in our sample, we hypothesize that the improvement in mental health is driven by individuals other than those who experienced sexual assault. Table A8 corroborates this hypothesis by showing that the positive effects become stronger when we exclude the victims of sexual assault from the sample.

We further examine the channels behind these effects on mental health by investigating whether they are driven directly by the increase in sexual activity. To do so, we add the number of sex partners in the previous year and sex incidence in the previous 30 days as additional controls. The results, displayed in Table A9, show that the effects on mental health remain unchanged after controlling for sexual activity and, if anything, the point estimates become larger in magnitude. This suggests that the chief channel through which Tinder is improving mental health may not be through increased sexual activity. Instead, we speculate that the relative gains in mental health could be, in part, a result of improved self-image or morale due to more sexual/romantic attention received after Tinder's introduction (Jung et al., 2019). For instance, a student from Elon College said the following about her experience using Tinder in 2014: "It is a huge ego boost. You get complimented a lot. You get matched a lot. I have a lot of matches and that's really fun."[38] Another possibility is that Tinder may induce substitution away from other more harmful online activities.

In summary, our findings indicate that the introduction of Tinder had a positive impact on the mental health of Greek-affiliated students, in comparison to their non-Greek peers within the same college and semester. The estimates appear to be more robust for female students as compared to male students. The estimates also suggest that this effect is not driven by increased sexual activity and instead aligns more with the possibility of Tinder enhancing students' self-image.

6.3.3 Academic Performance

Next, we examine the potential downstream effects of Tinder on academic performance through the outcomes we have studied so far. Specifically, based on a remarkably suitable NCHA question, we construct a series of indicator variables for whether a student reported that their academic performance was negatively affected by relationship difficulties, sexual assault, STDs, depression, anxiety, stress, ADHD, or an eating disorder. We then use these variables as outcomes in our individual-level difference-in-differences model in order to investigate Tinder's potential downstream impact on human-capital accumulation.

The results presented in Table 7 largely corroborate our earlier findings. For instance, consistent with the absence of an impact from Tinder on relationship formation or problems, we do not detect any differential change in the share of students claiming that their academic performance was affected negatively by relationship difficulties following Tinder's release. Similarly, consistent with our findings on mental health, fewer Greek students reported that health issues such as depression, anxiety, stress, or eating disorder had an adverse effect on their academic performance. Nevertheless, column 2 shows a significant increase in the proportion of students indicating that their academic performance suffered due to experiences of sexual assault. Overall, these results suggest that, through its impact on mental health and the incidence of sexual assault, Tinder has a

[38] See: jpetrocchi.wordpress.com/2014/04/09/the-growing-popularity-of-tinder-on-college-campuses/

meaningful, although potentially offsetting, downstream impact on student academic performance.

7 Robustness and College-Level Results

We now present a battery of exercises that probe the robustness of our baseline results. Specifically, we first address concerns related to (i) selection into the Greek system; (ii) issues of misreporting; (iii) differential smartphone adoption; and (iii) any crackdowns on Greek organizations occurring around the release of Tinder. Following that, we present estimates derived from an alternative college-level specification, which serves to tackle the concerns of within-college spillovers and the potential non-representativeness of Greek students compared to the overall student population.

7.1 Robustness Checks

7.1.1 Selection

Our identification strategy relies on comparing Greek and non-Greek students, which raises the concern that our results could be driven by certain characteristics or traits of Greek students that lead to increased sexual activity in the post-Tinder environment, rather than by their differential usage of Tinder. To address this concern, we conduct two sets of robustness tests.

First, we control for interaction terms between all our baseline student-level controls and a post-Tinder-introduction indicator. This allows for the possibility that the influence of individual student characteristics on sexual activity might change following the release of the app. Table A10 replicates our main results with these additional controls, suggesting that the varying importance of students' personal attributes does not explain our findings.

However, although the above exercise uses a rich set of individual characteristics, one may still be worried that a non-linear combination of these factors could jointly affect sexual behavior and contaminate our estimates. To assuage these concerns, we use the LASSO procedure introduced earlier in Section 6.2 to predict an individual's propensity for sexual activity based on their characteristics and then control for the interaction between the post-Tinder indicator and the LASSO-predicted sexual activity instead. As shown in Table A11, our baseline estimates remain robust to controlling for the resulting LASSO-predicted number of sex partners interacted with the post-

Tinder indicator. In fact, our estimates remain remarkably consistent in magnitude as compared to our baseline specification.[39]

Collectively, these two checks alleviate the concern that the differential outcomes of Greek and non-Greek students to Tinder could be driven by their differences in observable characteristics.

7.1.2 Misreporting

Misreporting is a critical issue shared by studies that rely on self-reported survey data. For instance, in our case, one may be concerned that respondents may lie about having a greater frequency of sex in order to improve their self-image. However, we argue that reporting bias is unlikely to drive the results in this paper, for several reasons.

First, the NCHA survey is administered anonymously, considerably reducing any incentive for respondents to lie due to concerns of stigma or reprisal. There were no individually assigned enumerators, and students typically completed the survey in a large classroom or on their own (ACHA, 2019). Moreover, because we use student-level variation in treatment, any changes in campus culture related to the willingness to discuss certain topics at a specific college during a specific semester would be absorbed by the college-semester fixed effects and would need to affect Greek students disproportionately in order to impact our estimates.

Second, our results are cross-validated between distinct sets of questions. For instance, if the Greek students start to differentially inflate their responses regarding sexual activity, it is unlikely that the same group of respondents would also suddenly start to wrongfully claim to have had STDs or experienced sexual assault if self-image were the cause of misreporting. The conjunction of the positive results on sexual activity as well as the increase in negative consequences associated with sex suggest that the relationship is genuine.

Finally, we also show that nonresponse rates on questions related to our outcomes remain qualitatively unchanged following the rollout of Tinder. Specifically, Table A12 presents the difference-in-differences estimates using nonresponse rates as outcomes. We observe that point estimates are nearing zero and, while two of the coefficients are statistically significant, the effect sizes are minus-

[39]This result may be surprising if we thought Tinder penetration would be wider among non-Greek students with higher LASSO predictions relative to non-Greek students with lower LASSO predicted values. The estimates' stability suggests that the LASSO-predicted number of sex partners does not seem to serve as a good proxy for Tinder use. One possibility is that highly "attractive" students had less incentive to use Tinder because they already had a satisfactory romantic life. In other words, it is Greek students that used the app more, and not "attractive" students more broadly.

cule and cannot explain our main findings. The coefficient signs also point in different directions, contradicting the narrative of an overall shift in levels of stigma.

7.1.3 Smartphone Adoption and Socioeconomic Status

Unobserved heterogeneity in overall smartphone usage across college students might pose a problem for our analysis. For instance, if Greek students were more likely to possess smartphones than non-Greek students and if they started purchasing those around the launch of Tinder, then it is feasible that our results could be driven by other smartphone features rather than dating apps.

We argue that this is unlikely for three reasons. First, by the time period we study, smartphone adoption was already exceedingly high among the college-age population, with 79% of 18 to 24-year-old adults using smartphones by the fall of 2013.[40] Second, this explanation fails to explain the effects' persistence, as smartphone use would likely quickly equalize across demographic groups.

Finally, we take this possibility into account quantitatively by incorporating additional controls that are informative about the students' socioeconomic status. Because smartphones are more expensive than other phone types, financial backgrounds of students serves as a reasonable proxy for smartphone adoption. Following this logic, we include variables related to feelings of financial stress and hours worked for paid as well as volunteer work. When added to the regression, the coefficients in Table A13 are similar to the previous specifications, showing that differences in socioeconomic status between Greek and non-Greek students do not drive our results. In turn, this result may be indicative of a lack of significant differences due to smartphone adoption or usage.

7.1.4 Crackdown on Greek Organizations

Another concern could be that, in the latter half of our sample, certain colleges started a process of cracking down on Greek life, including suspending some Greek organizations altogether.[41] To the extent that these actions altered the share and composition of fraternity and sorority membership, they could have separately affected Greek members' dating activity and romantic endeavors. While we do not find evidence of an aggregate shift in the share of Greek-affiliated students or changes in their demographic composition (see Figure A3 and Table A4), we conduct an additional check

[40] Majority of mobile users now use smartphones, blame those pesky teens Engadget, October 30, 2013.
[41] Fraternity crackdown: universities are clamping down hard, but do bans work? NBC News, March 10, 2015.

to assuage this concern. Specifically, we calculate the average share of Greeks in each college before and after Tinder's rollout, then calculate the difference between the two measures, and then estimate our baseline results for colleges that did not experience a large drop in Greek share (below 2.8 percentage points, or the 5th percentile of the change distribution) or did not experience *any* reduction in Greek share. The results, presented in Table A14, stay robust in both cases, indicating that crackdowns on Greek life are unlikely to drive our estimates.

7.2 Spillovers and College-Level Results

Our difference-in-differences strategy allows us to estimate the average treatment effect on the treated (ATT) of Tinder on fraternity and sorority students. However, to the extent that Greek students may differ from other students in ways that are observable and unobservable to the econometrician, it remains an open question whether our estimates generalize to the overall student population. In other words, the ATT that we estimate may systematically differ from the average treatment effect (ATE) in this case.

Moreover, the identification of causal estimates in the difference-in-differences framework requires the Stable Unit Treatment Value Assumption (SUTVA), which precludes spillovers. This assumption can be violated in our setting if Tinder had meaningful effects on non-Greek students on college campuses. If these spillovers align with our main estimates, it merely suggests that our calculations provide a lower bound for Tinder's impact. However, if the spillovers go in the opposite direction, this could seriously confound our estimates.

To overcome these empirical challenges and better approximate what may be the true treatment effect for the general student population, we devise a secondary research design. Specifically, we utilize a college-level treatment based on the share of undergraduate students involved in Greek life. The logic is that because of the strong network effects of Tinder adoption, the greater the share of students active on the app, the greater the incentive for other students to join. This is consistent with the rationale behind Tinder's launch strategy described in Section 2, which was to take advantage of possible spillover effects from socially influential Greek students onto the rest of the student body, as well as with our first stage results in Section 5.

Formally, we estimate the following equation:

$$y_{ct} = \beta \times Post_t \times Greek\ Share_c + \gamma X_{ct} + \alpha_c + \delta_t + \varepsilon_{ct} \quad (3)$$

where α_c and δ_t represent the college and survey-wave (semester) fixed effects, respectively, and $Greek\ Share_c$ is the share of undergraduate students at college c who participated in Greek life across all survey waves in the NCHA. Here, we organize our analysis at the college-semester level and, thus, consider the college-level analogs of the student-level outcomes. Specifically, for each college and survey-wave pair, we compute the average number of sex partners per student and the share of students engaged in sexual activity, then we similarly aggregate all other main outcomes. We also include a vector of college-semester level controls, X_{ct}, which is again constructed based on aggregated student-level characteristics.

The coefficient of interest, β, captures the difference in average student outcomes before and after the release of Tinder and across colleges with high and low Greek life participation. To the extent that students at colleges with greater Greek life activity gain more exposure to Tinder due to Tinder's targeted marketing toward Greek students, and to the extent that their outcomes would have evolved along parallel trends otherwise, β reflects the causal effect of Tinder on U.S. colleges. Since many American colleges are located in remote and isolated college towns, spillovers between units in this specification should be negligible.

The results, presented in Table 8, demonstrate that, with the exception of mental health, all of our findings generalize to the overall student population. Columns 1 and 2 report a differential increase in sexual activity in colleges with a greater Greek presence following the full-scale launch of Tinder. Column 3 corroborates the absence of a significant impact on cohabitation incidence. Columns 5–7 show that the effects of Tinder on the incidence of sexual assault and chlamydia also hold at the college level. However, column 4 shows that the relative decline in mental health issues is absent for the overall student body. This suggests that the mental health benefits of Tinder might be specific to Greek students and could be offset by the app's adverse impact on other students.

To put the college-level results in perspective, increasing the share of Greek students at a college by one standard deviation implies a 0.1-standard-deviation larger increase in the average number of sex partners following the introduction of Tinder, as well as a 0.07-standard-deviation rise in the share of students engaged in sexual activity within the previous 30 days. These estimates, if anything, appear larger than the individual-level estimates presented in Section 6.1, consistent with the spillovers being positive and our baseline effects serving as a lower bound for the true impact.

Overall, the college-level results appear similar to our individual-level estimates, alleviating the concern that spillovers are driving those findings.

8 Conclusion

Choosing the right partner is one of the most consequential decisions an individual can make in their life. Since Becker (1973), economists have long held an interest in the workings and operations of the marriage market. Dating, as the precursor to marriage, is a fundamental step along this process. The sweeping changes to the landscape of dating brought about by the growing popularity of online dating, and of dating apps in particular, raise important theoretical and empirical questions.

In recent years, the possible sociological and psychological effects associated with the mass adoption of dating apps and their mainstream use have been heavily speculated upon in the popular press.[42] Yet, despite the substantial attention paid to this topic, credible evidence on the causal impact of dating apps remains scarce.

In this paper, we study the causal effects of the world's most popular mobile dating app, Tinder, on college students.[43] We focus on this particular age group for two primary reasons. First, because of Tinder's unique launch strategy—targeting students involved in Greek life—we can devise a credible identification strategy that allows us to estimate the impact of Tinder on this population. Second, college-age adults more broadly were the demographic directly targeted by Tinder, and we show that, based on survey evidence, Tinder can indeed be credited for normalizing online dating specifically for this age group.

Our identification strategy exploits a well-documented and critical key feature of Tinder's

[42] *Tinder and the Dawn of the "Dating Apocalypse"* (Vanity Fair, 08-06-2015)
How online dating has changed the way we fall in love (The Guardian, 02-13-2022)

[43] One potential limitation of our study is that we study only Tinder, rather than the universe of all dating apps. However, according to any measure, Tinder has been the dominant leader in this market. Also, Tinder's closest competitor, Bumble, pursued a strategy similar to Tinder's vis-a-vis Greek students; therefore our estimate may be capturing the combined impact of both apps post-2015. Finally, to the extent that all dating apps reduce search costs and alleviate information frictions and to the extent that these core features are what's driving our estimates, our results are likely to generalize to other dating apps.

launch campaign which involved targeting college campuses. However, Tinder also took advantage of dense social networks on college campuses and marketed its app to influential members of those networks, which, in practice, translated into targeting fraternity or sorority members. We provide both anecdotal and quantitative evidence to verify the fact that Tinder was more commonly used by Greek students and in colleges with high Greek-life participation. These twin sets of facts motivate the empirical strategy we pursue, which is a difference-in-differences design that considers Greek students and colleges with large Greek presence as treated units.

We find that the introduction of Tinder meaningfully changed the dating market equilibrium on college campuses. The use of Tinder increased the frequency of sexual activity but without any corresponding increase in the formation of long-term relationships. These results are consistent with Tinder facilitating the rise of hookup culture on college campuses. We show the distributional consequences of Tinder vary significantly by gender. For male students, the gains in sexual activity are largest among students who based on observable characteristics are most likely to engage in sexual activity. This pattern is completely absent for female students, for whom the impact of Tinder is equalized along the same dimension.

We characterize the downstream impact of these changes in terms of students' mental and physical health. Intriguingly, we find that increased sexual activity associated with dating apps also improved the average reported mental health status of its users. However, these effects also come at the cost of certain negative outcomes associated with sexual activity, such as increased prevalence of sexual assault and sexually transmitted diseases.

An important caveat to the conclusions we draw is that our results speak to the short-term effects of Tinder on a particular population—college-age students—following the initial release of the app. Understanding the longer-run impact of Tinder across the entire age distribution represents a promising direction for future research.

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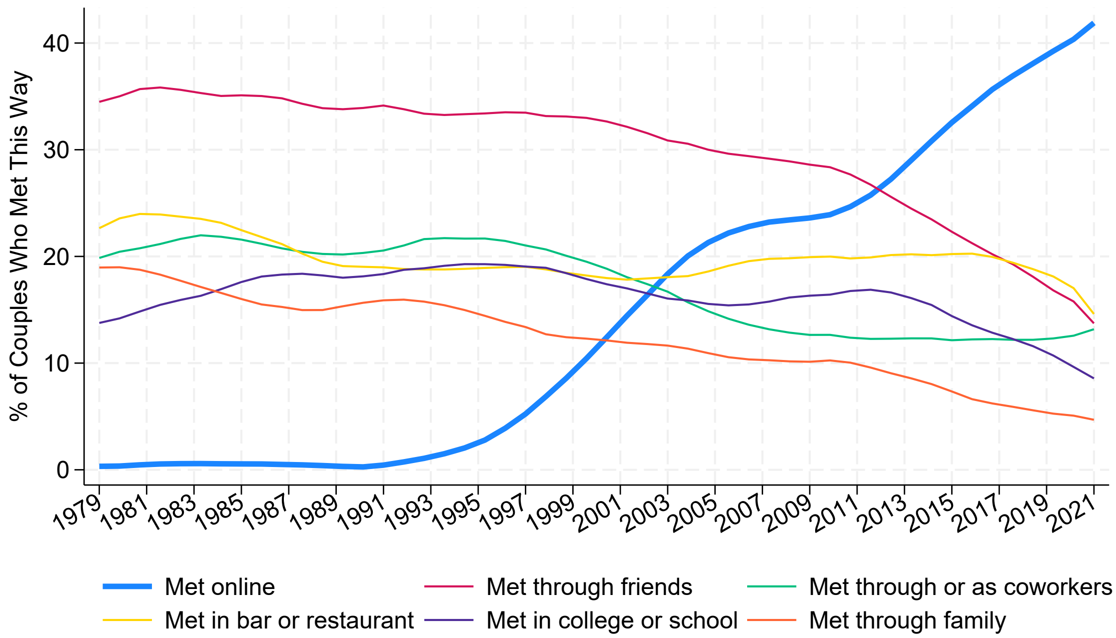
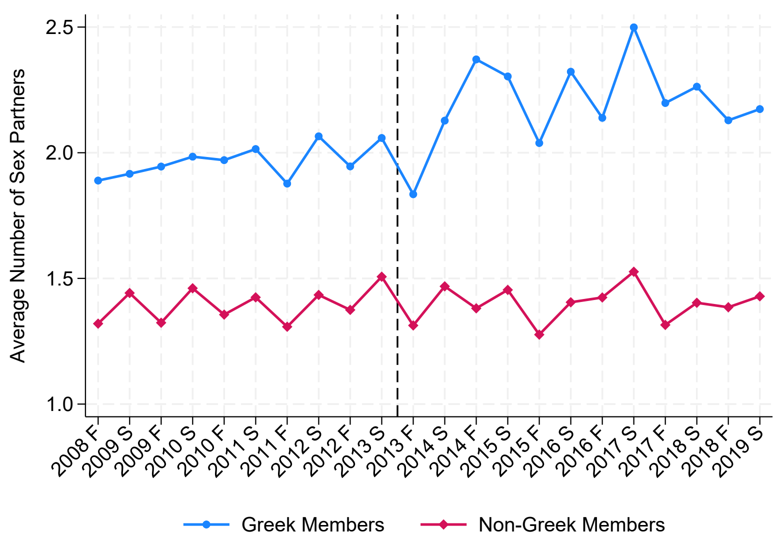
Figure 1: Share of Couples by When and How They Met



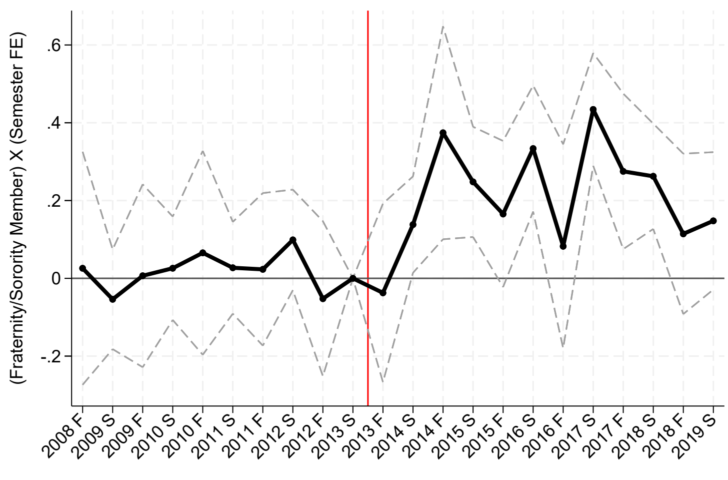
Notes: The figure is based on data from the How Couples Meet and Stay Together (HCMST) project, which surveys couples on when and how they met each other (Rosenfeld et al., 2019). We combine the datasets from the two main surveys (2009 and 2017–2022) and transform them to represent each relationship as a unique observation. A variable indicating meeting through a friend (or family) is assigned a value of 1 if the couple met through a friend (or family member) of either the respondent or their partner. The ways of meeting each other are not exclusive and, thus, need not add up to 100%.

Figure 2: The Average Number of Sex Partners between Greek and Non-Greek Members

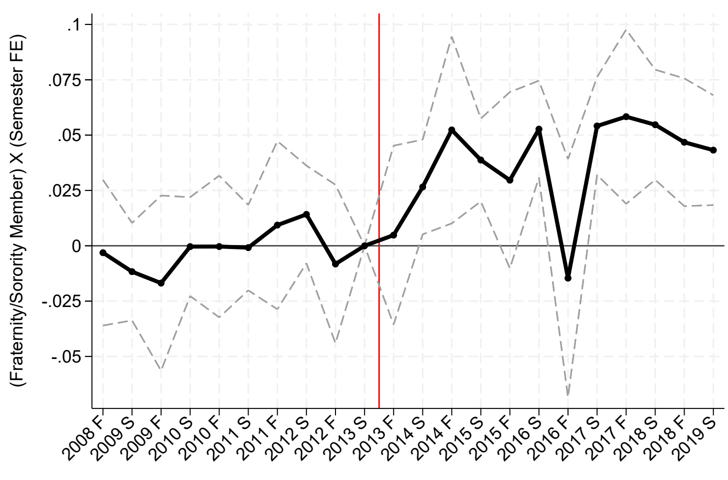


Notes: This figure presents the evolution of the average number of sexual partners for Greek and non-Greek members across semesters.

Figure 3: Effect of Tinder's Introduction on Student Sexual Activity



(a) Number of sex partners in the previous year

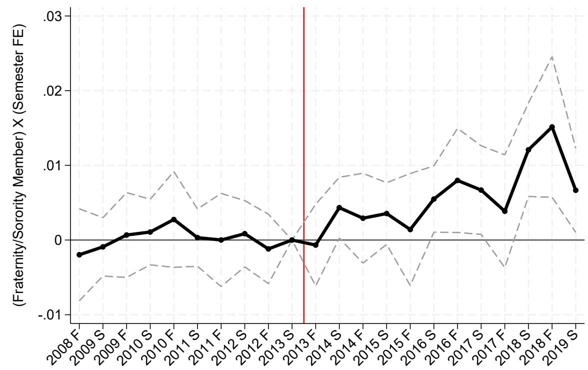


(b) Had sex in the previous month

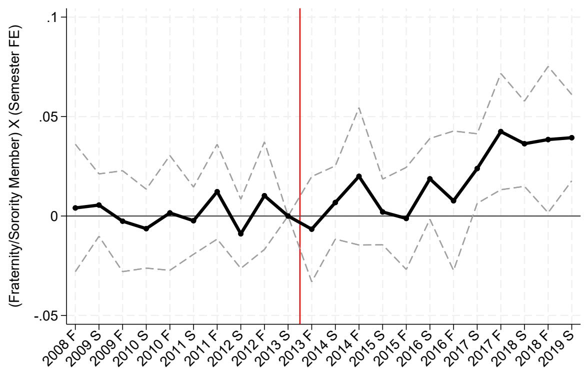
Notes: These event-study figures plot the coefficients for Greek membership interacted with semester indicators estimated using Equation (2). They illustrate the evolution of sexual activity for Greek life members relative to their peers within the same school and semester. The outcomes are: (a) the number of sex partners a student had within the previous 12 months, (b) the number of sex partners a student had within the last 12 months conditional on having sex with at least one partner, (c) an indicator for whether a student had sex within the previous 12 months, and (d) an indicator for whether a student had sex in the previous 30 days. The event-study regressions do not contain any controls. For detailed constructions of the outcome, treatment, and control variables, see Appendix Table A2. The upper and lower lines represent 95% confidence intervals. Standard errors are clustered at the college level.

Figure 4: Effect of Tinder's Introduction on Negative Consequences of Sexual Activity

(a) Sexual assault



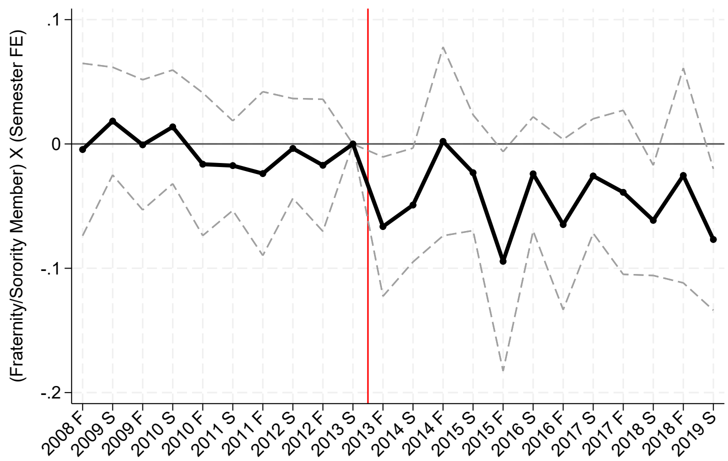
(b) Chlamydia



(c) HIV test

Notes: These event-study figures plot the coefficients for Greek membership interacted with semester indicators estimated using Equation (2). They illustrate the evolution of negative consequences of sexual activity for Greek life members relative to their peers within the same school and semester. The outcomes are (a) an indicator for whether a student reported being sexually abused within the previous 12 months, (b) an indicator for whether a student was diagnosed or treated with chlamydia within the previous 12 months, and (c) an indicator for a student ever having tested for HIV. The event-study regressions do not contain any controls. For details on constructions of the outcome, treatment, and control variables, see Appendix Table A2. The upper and lower lines represent 95% confidence intervals. Standard errors are clustered at the college level.

Figure 5: Effect of Tinder's Introduction on the Index of Poor Mental Health for Female Students



Notes: These event-study figures plot the coefficients for Greek membership interacted with semester indicators estimated using Equation (2). It illustrates the evolution of mental health issues for female Greek life members relative to their female peers within the same school and semester. The outcome variable is the overall index of poor mental health, which is constructed by adding up all the variables related to having experienced various mental health issues within the last 30 days—available in the NCHA; described in Appendix Table A2—and standardizing the obtained variable to have a mean of zero and a standard deviation of one in the pre-period. The event-study regression does not contain any controls. The upper and lower lines represent 95% confidence intervals. Standard errors are clustered at the college level.

Table 1: NCHA Summary Statistics

	Mean	Std. Dev.	25th Percentile	Median	75th Percentile	# of Obs
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Student Characteristics						
White	0.70	0.46	0	1	1	1,097,961
Black	0.06	0.24	0	0	0	1,096,858
Asian	0.12	0.32	0	0	0	1,096,645
Male	0.33	0.47	0	0	1	1,076,700
Greek involvement	0.11	0.31	0	0	0	1,072,732
Fraternity (Greek and male)	0.03	0.18	0	0	0	1,065,776
Sorority (Greek and female)	0.07	0.26	0	0	0	1,065,776
College grade	2.52	1.25	1	2	4	1,071,284
Age	21.27	4.93	19	20	22	1,073,659
BMI	24.48	5.45	20.98	23.18	26.57	1,061,744
Height	66.72	4.08	64	66	70	1,069,588
Panel B: Sexual Characteristics						
Number of sex partners (previous 12 months)	1.50	3.03	0	1	2	1,076,006
Sex previous 12 months	0.67	0.47	0	1	1	1,076,006
Sex previous 30 days	0.52	0.50	0	1	1	1,082,882
In relationship	0.47	0.50	0	0	1	1,076,544
Cohabiting	0.11	0.32	0	0	0	1,076,544
Panel C: Relationship Quality						
Abusive relationship	0.11	0.31	0	0	0	1,092,342
Difficult relationship	0.32	0.47	0	0	1	1,081,307
Relationship problems	0.31	0.46	0	0	1	1,069,588
Panel D: Negative Consequences						
Sexual assault	0.09	0.28	0	0	0	1,093,523
Chlamydia	0.01	0.11	0	0	0	1,077,696
HIV test	0.26	0.44	0	0	1	1,024,991
Panel E: Mental Health Characteristics						
Hopeless (last 30 days)	0.46	0.50	0	0	1	1,098,765
Overwhelmed (last 30 days)	0.68	0.47	1	1	1	1,098,765
Exhausted (not physically, last 30 days)	0.66	0.48	1	1	1	1,068,836
Very lonely (last 30 days)	0.38	0.49	0	1	1	1,098,765
Very sad (last 30 days)	0.40	0.49	0	1	1	1,098,765
Severely depressed (last 30 days)	0.18	0.39	0	0	1	1,098,765
Overwhelming anxiety (last 30 days)	0.35	0.48	0	1	1	1,098,765
Overwhelming anger (last 30 days)	0.21	0.41	0	0	1	1,098,765
Self-harm (last 30 days)	0.03	0.16	0	0	0	1,098,765
Considered suicide (last 30 days)	0.03	0.18	0	0	0	1,098,765

Notes: This table presents the summary statistics for our analytical sample of the NCHA survey between Fall 2008 and Spring 2019. The sample is restricted to undergraduate students. Height is measured in inches. For detailed variable definitions, see Appendix Table A2.

Table 2: Sexual Behavior and Activity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	# of Sex Partners Previous 12 Months		# of Sex Partners (Intensive Margin)		Sex Previous 12 Months		Sex Previous 30 Days	
Fraternity/Sorority × Post	0.219***	0.217***	0.132***	0.156***	0.040***	0.031***	0.039***	0.029***
	(0.029)	(0.028)	(0.031)	(0.030)	(0.005)	(0.004)	(0.005)	(0.004)
College-semester FE	✓	✓	✓	✓	✓	✓	✓	✓
Has controls		✓		✓		✓		✓
Observations	1,017,084	1,017,084	685,070	685,070	1,017,084	1,017,084	1,023,299	1,023,299
Mean of dep. var.	1.492	1.492	2.215	2.215	0.674	0.674	0.520	0.520
SD of dep. var.	2.918	2.918	3.322	3.322	0.469	0.469	0.500	0.500

Notes: This table presents the estimates of the impact of Tinder's introduction on student sexual activity. The outcome variables are the number of sexual partners that a student had within the previous 12 months, the number of sexual partners that a student had within the previous 12 months conditional on having at least one, an indicator for whether a student had sex within the previous 12 months, and an indicator for whether a student had sex in the previous 30 days. The coefficient of interest is the interaction of a student's fraternity or sorority membership and an indicator for semesters post the full-scale launch of Tinder. All columns include college-semester fixed effects. Columns (2), (4), (6), and (8) include controls for age, gender, race, grade, international student status, height, and BMI. For detailed variable definitions, see Appendix Table A2. Standard errors in parentheses are clustered at the college level. * p<0.1, ** p<0.05, *** p<0.01.

Table 3: Relationship Status and Relationship Quality

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Cohabiting	Abusive Relationship	Difficult Relationship	Relationship Problems	Abusive Relationship	Difficult Relationship	Relationship Problems
					Conditional on Being in Cohabitation		
Fraternity/Sorority × Post	-0.003	0.000	-0.000	-0.005*	0.013	-0.011	0.003
	(0.002)	(0.002)	(0.004)	(0.003)	(0.009)	(0.014)	(0.014)
College-semester FE	✓	✓	✓	✓	✓	✓	✓
Has controls	✓	✓	✓	✓	✓	✓	✓
Observations	1,027,344	1,026,570	1,024,314	1,019,315	116,712	116,369	115,826
Mean of dep. var.	0.114	0.105	0.320	0.316	0.125	0.313	0.319
SD of dep. var.	0.318	0.307	0.466	0.465	0.331	0.464	0.466

Notes: This table presents the estimates of the impact of Tinder's introduction on relationship incidence and quality. The outcome variables are whether the student was in a relationship, whether a student had been in an emotionally or physically abusive relationship within the previous 12 months, whether a student had a difficult romantic relationship that was traumatic or very difficult to handle within the previous 12 months, and whether a student experienced any problems in their romantic relationships within the previous 12 months. The coefficient of interest is the interaction of a student's fraternity or sorority membership and an indicator post the full-scale launch of Tinder. All columns include college-semester fixed effects and controls (age, gender, race, grade, international student status, height, and BMI). The last three columns present the regressions for a subset of students who were in a relationship at the moment of the survey. For detailed variable definitions, see Appendix Table A2. Standard errors in parentheses are clustered at the college level. * p<0.1, ** p<0.05, *** p<0.01.

Table 4: Heterogeneity By Predicted Sexual Activity and Respondent Gender

	Number of Partners (Previous 12 Months)		Cohabitation	
Sample:	Male	Female	Male	Female
Fraternity/Sorority × Post	0.195*	0.235***	0.002	-0.005*
	(0.116)	(0.050)	(0.003)	(0.003)
Fraternity/Sorority × Post × 2nd Quartile Predicted Sexual Activity	0.093	-0.020		
	(0.154)	(0.061)		
Fraternity/Sorority × Post × 3rd Quartile Predicted Sexual Activity	0.065	0.020		
	(0.148)	(0.065)		
Fraternity/Sorority × Post × Upper Quartile Predicted Sexual Activity	0.292*	-0.038		
	(0.173)	(0.065)		
Fraternity/Sorority × Post × Above Median Predicted Sexual Activity			0.009*	0.000
			(0.005)	(0.004)
College-Semester FE	✓	✓	✓	✓
Has Controls	✓	✓	✓	✓
Observations	331,701	683,769	335,907	689,778
R^2	0.037	0.029	0.246	0.232
Mean of dep. var.	1.760	1.356	0.100	0.121
SD of dep. var.	3.872	2.241	0.300	0.326

Notes: This table explores the heterogeneity of the baseline estimates for the impact of Tinder's introduction along LASSO-predicted level of sexual activity (which serves as a proxy for baseline dating-market appeal) and gender. Each column presents the results of a triple-difference specification where we interact the *Post Tinder* indicator with the *Greek* indicator and the variable indicated in each column. Columns 1, and 3 present the results for male students; and columns 2 and 4 are for females. For the LASSO prediction, we use age indicators, gender, race indicators, and BMI categories, as well as their square terms and interaction terms, and we train the model using only pre-Tinder data. All columns include college-semester fixed effects and controls (age, gender, race, grade, international student status, height, and BMI). For detailed variable definitions, see Appendix Table A2. Standard errors in parentheses are clustered at the college level. * p<0.1, ** p<0.05, *** p<0.01.

Table 5: Negative Outcomes Related to Sexual Activity

	Sexual Assault		Chlamydia		HIV Test	
	(1)	(2)	(3)	(4)	(5)	(6)
Fraternity/Sorority × Post	0.021***	0.019***	0.006***	0.006***	0.020***	0.015***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.004)	(0.003)
College-semester FE	✓	✓	✓	✓	✓	✓
Has controls		✓		✓		✓
Observations	1,027,277	1,027,277	1,023,250	1,023,250	972,120	972,120
Mean of dep. var.	0.087	0.087	0.013	0.013	0.256	0.256
SD of dep. var.	0.282	0.282	0.113	0.113	0.437	0.437

Notes: This table presents the estimates of the impact of Tinder's introduction on negative outcomes related to sexual activity. The outcome variables are reported experiences of sexual abuse within the previous 12 months, having been diagnosed or treated for chlamydia within the previous 12 months, and having ever tested for HIV. The coefficient of interest is the interaction of a student's fraternity or sorority membership and an indicator post the full-scale launch of Tinder. All columns include college-semester fixed effects and controls (age, gender, race, grade, international student status, height, and BMI). For detailed variable definitions, see Appendix Table A2. Standard errors in parentheses are clustered at the college level. * p<0.1, ** p<0.05, *** p<0.01.

Table 6: Mental Health

	(1) Hopeless	(2) Over-whelmed	(3) Exhausted (Not Physically)	(4) Very Lonely	(5) Very Sad	(6) Severely Depressed	(7) Over-whelming Anxiety	(8) Over-whelming Anger	(9) Self-Harm	(10) Considered Suicide	(11) Index Poor Mental Health (30 Days)
Panel A: All											
Fraternity/Sorority × Post	-0.008**	-0.013***	-0.012***	-0.010***	-0.007*	-0.010***	-0.010***	-0.008**	-0.002**	-0.004***	-0.035***
	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.008)
College-semester FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Has controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1,029,122	1,029,122	1,029,122	1,029,122	1,029,122	1,029,122	1,029,122	1,029,122	1,029,122	1,029,122	1,029,122
Mean of dep. var.	0.463	0.691	0.666	0.388	0.406	0.186	0.354	0.213	0.027	0.032	0.094
SD of dep. var.	0.499	0.462	0.472	0.487	0.491	0.389	0.478	0.410	0.163	0.177	1.046
Panel B: Males											
Fraternity/Sorority × Post	-0.006	-0.014**	-0.017***	-0.016***	-0.006	-0.005	-0.004	-0.008	0.001	-0.001	-0.027**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.004)	(0.005)	(0.005)	(0.002)	(0.002)	(0.013)
College-Semester FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Has Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	336,565	336,565	336,565	336,565	336,565	336,565	336,565	336,565	336,565	336,565	336,565
Mean of dep. var.	0.412	0.570	0.563	0.323	0.314	0.152	0.255	0.188	0.021	0.031	-0.124
SD of dep. var.	0.492	0.495	0.496	0.468	0.464	0.359	0.436	0.390	0.143	0.174	1.019
Panel C: Females											
Fraternity/Sorority × Post	-0.009**	-0.014***	-0.011***	-0.009**	-0.008*	-0.013***	-0.015***	-0.006*	-0.003**	-0.005***	-0.040***
	(0.005)	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)	(0.003)	(0.001)	(0.002)	(0.009)
College-Semester FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Has Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	690,896	690,896	690,896	690,896	690,896	690,896	690,896	690,896	690,896	690,896	690,896
Mean of dep. var.	0.488	0.750	0.716	0.418	0.450	0.202	0.401	0.226	0.030	0.033	0.198
SD of dep. var.	0.500	0.433	0.451	0.493	0.498	0.401	0.490	0.418	0.172	0.178	1.041

Notes: This table presents the estimates of the impact of Tinder's introduction on student mental health. The outcome variables are feeling hopeless, overwhelmed, exhausted (not from physical activity), very lonely, very sad, severely depressed (such that it was difficult to function), overwhelming anxiety, overwhelming anger, self-harm, and considering suicide within the last 30 days. The index of poor mental health is obtained by adding the standardized versions of all of the variables above and standardizing the resulting variable. The coefficient of interest is the interaction of a student's fraternity or sorority membership and an indicator post the full-scale launch of Tinder. All columns include college-semester fixed effects and controls (age, gender, race, grade, international student status, height, and BMI). For detailed variable definitions, see Appendix Table A2. Standard errors in parentheses are clustered at the college level. * p<0.1, ** p<0.05, *** p<0.01.

Table 7: Academic Performance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Did This Issue Negatively Affect Student's Academic Performance In The Previous Year?							
	Relationship Difficulties	Sexual Assault	STD	Depression	Anxiety	Stress	ADHD	Eating Disorder
Fraternity/Sorority × Post	-0.000	0.003***	0.000	-0.006**	-0.005**	-0.006*	0.000	-0.002*
	(0.002)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)	(0.002)	(0.001)
College-Semester FE	✓	✓	✓	✓	✓	✓	✓	✓
Has Controls	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1,019,315	1,017,737	1,019,094	1,017,427	1,018,808	1,019,695	1,019,127	1,019,413
Mean of dep. var.	0.103	0.012	0.004	0.146	0.227	0.316	0.055	0.013
SD of dep. var.	0.304	0.108	0.065	0.353	0.419	0.465	0.229	0.115

Notes: This table presents the estimates for whether the issues affected by the introduction of Tinder had any meaningful effects on students' academic performance. The outcome variables are indicators for whether a student reported that any of the following issues had negatively affected their academic performance within the previous 12 months: relationship difficulties, sexual assault, STDs, depression, anxiety, stress, ADHD, and eating disorders. The coefficient of interest is the interaction of a student's fraternity or sorority membership and an indicator post the full-scale launch of Tinder. All columns include college-semester fixed effects and controls (age, gender, race, grade, international student status, height, and BMI). For detailed variable definitions, see Appendix Table A2. Standard errors in parentheses are clustered at the college level. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

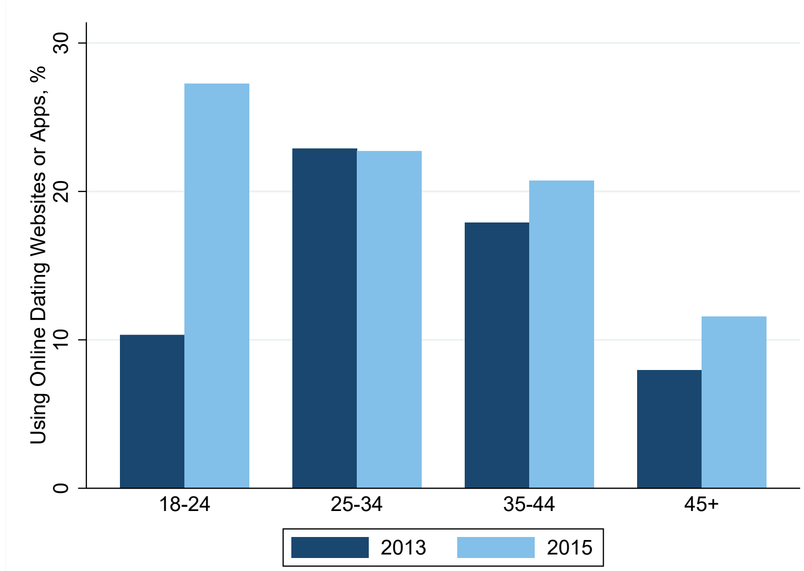
Table 8: Effects of Tinder's Introduction, College Level Treatment

		Share of Students:			Share of Students:		
	Average # of Sex Partners	Sex Previous 30 Days	Cohabiting	Average Index Poor Mental Health	Chlamydia	HIV Test	Sexual Assault
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Greek Share × Post	0.590***	0.073***	0.018	0.028	0.014***	0.036**	0.027*
	(0.110)	(0.019)	(0.012)	(0.062)	(0.004)	(0.017)	(0.014)
College FE	✓	✓	✓	✓	✓	✓	✓
Semester FE	✓	✓	✓	✓	✓	✓	✓
College-Level Controls	✓	✓	✓	✓	✓	✓	✓
Observations	1,644	1,644	1,644	1,644	1,644	1,644	1,644
Mean of dep. var.	1.482	0.512	0.113	0.073	0.013	0.238	0.086
SD of dep. var.	0.341	0.084	0.086	0.169	0.008	0.071	0.033

Notes: This table presents the estimates of the impact of Tinder's introduction on main outcomes using a college-wide share of Greek students as a treatment intensity. Each observation is a college and survey-wave pair. The outcome variables are (1) the average number of sexual partners per student within the previous 12 months, (2) the share of students who had sex within the previous 30 days, (3) the share of students in a relationship, (4) the average value of the index of poor mental health among students, (5) the share of students who have been diagnosed or treated with chlamydia within the last 12 months, (6) the share of students who ever tested for HIV, and (7) the share of students who reported experiencing sexual assault within the previous 12 months. The coefficient of interest is the interaction of the percentage of students who are a part of Greek life organizations and an indicator post the full-scale launch of Tinder. All specifications include college and survey-wave fixed effects. College-level controls are created by taking the median value of individual-level controls. For detailed variable definitions, see Appendix Table A2. Standard errors in parentheses are clustered at the college level. * p<0.1, ** p<0.05, *** p<0.01.

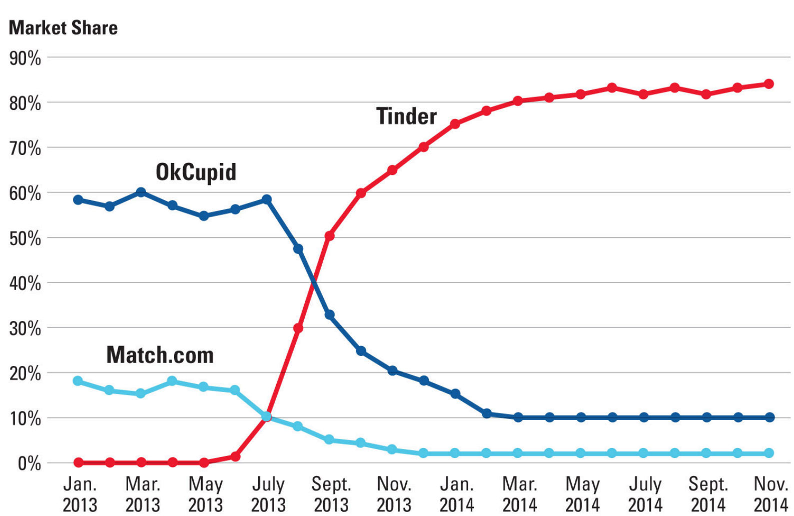
Online Appendix

Figure A1: Online and Mobile Dating by Age Group, 2013 and 2015



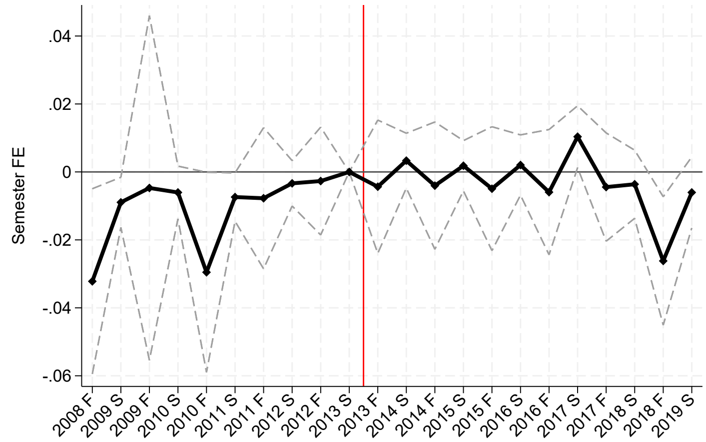
Notes: The figure illustrates the rapid and disproportionate growth in the share of young adults using online dating websites or apps following the rise of Tinder starting in the fall of 2013. The data come from the Pew Internet and American Life Survey conducted April 17 to May 19, 2013, and from the Pew Tracking Survey conducted on June 10 to July 12, 2015.

Figure A2: The Rise of Tinder's Market Share Among Dating Apps in 2013–2014



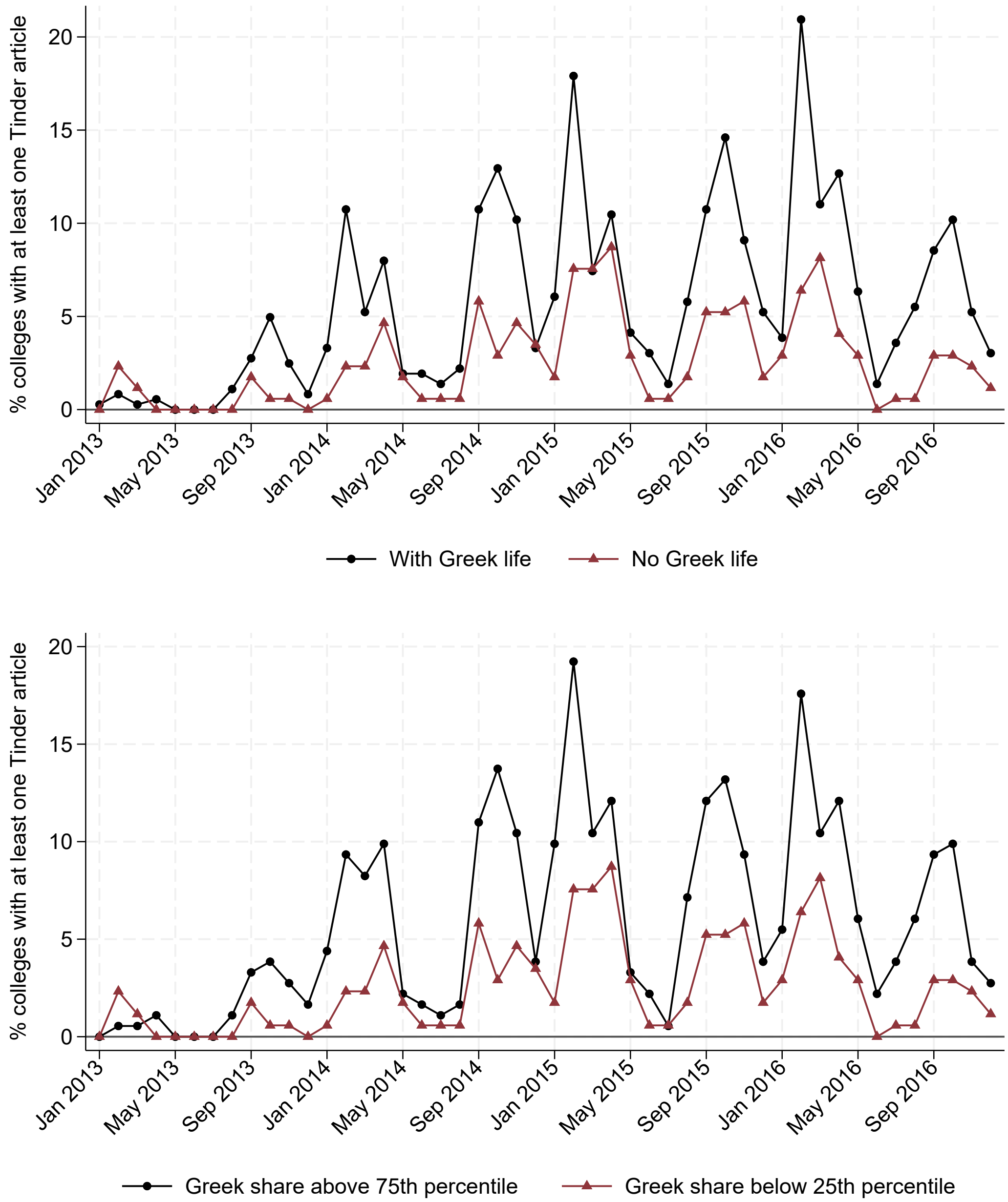
Notes: This figure presents the evolution of the market share of the three most prevalent smartphone-based dating apps in 2013–2014. The aggregate market share is calculated as a percentage of total app sessions by an anonymous panel of millions of U.S. users. Source: Abolfathi and Santamaria (2020).

Figure A3: Evolution of the Share of Undergraduate Students Involved in Greek Life



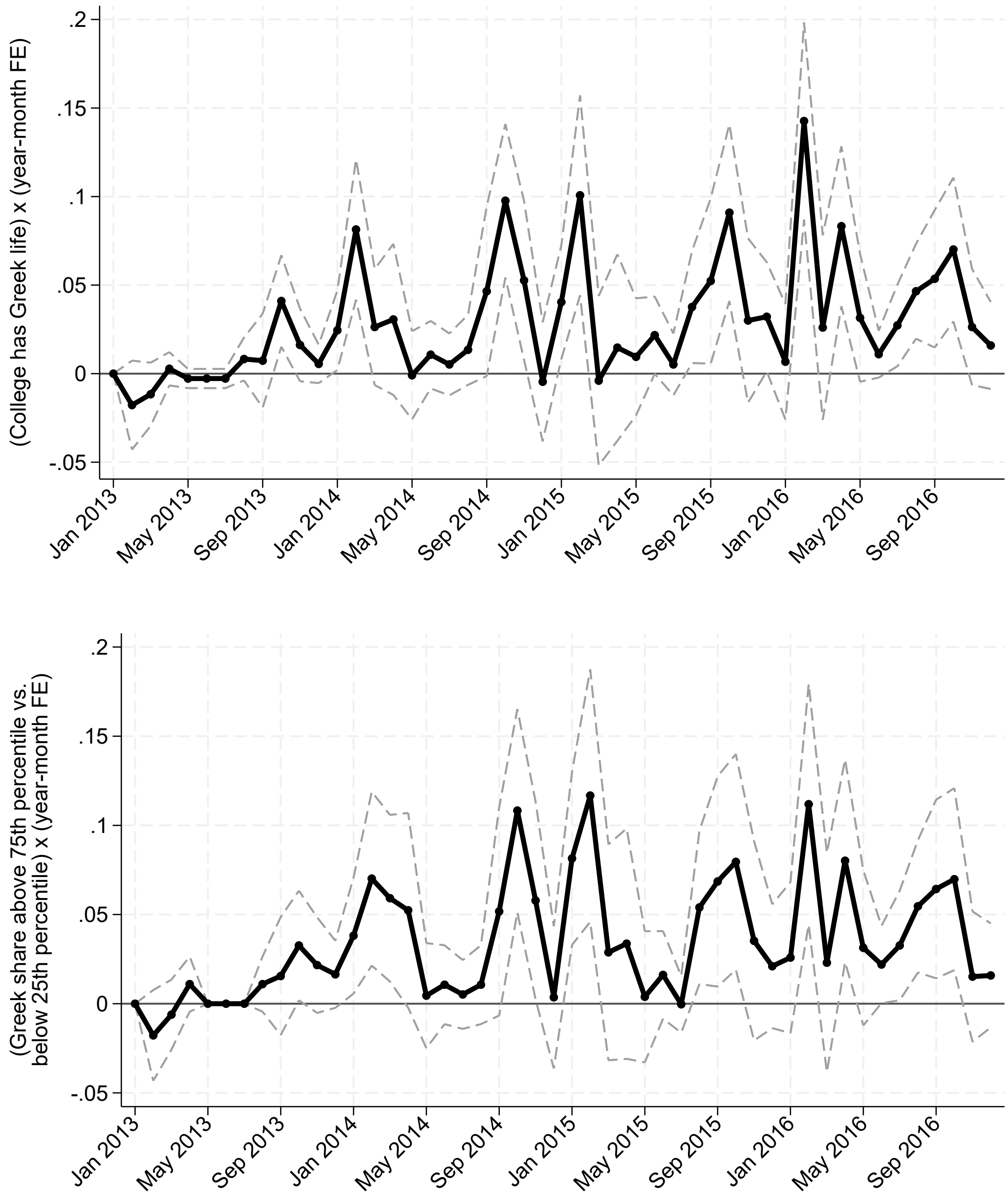
Notes: This figure presents the evolution of the share of undergraduate students who were involved in Greek life. It presents the estimates of a college-semester-level specification, regressing the share of students in Greek organizations on the semester fixed effects. The upper and lower lines represent 95% confidence intervals.

Figure A4: College Newspaper Articles Mentioning Tinder



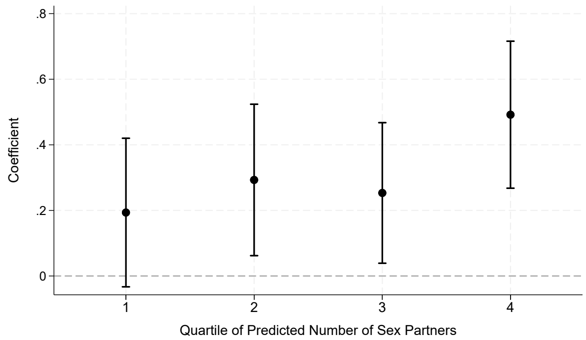
Notes: The top figure illustrates the evolution of the share of colleges with at least one article containing the keyword '*Tinder*' in a given month, separately for colleges with and without Greek life, from January 2013 through December 2016. The bottom figure shows the same trend for colleges in the bottom quartile in terms of Greek life participation versus colleges in the top quartile. Data on the college newspapers come from LexisNexis; data on Greek organizations are from the Common Data Set.

Figure A5: College Newspaper Articles Mentioning Tinder, Difference-in-Differences Estimates

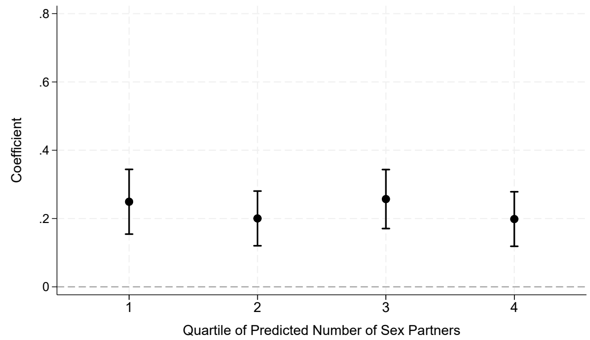


Notes: The figures present the difference-in-differences estimates for the data presented in Figure A4, illustrating that colleges with more active Greek life were more likely to have newspapers publish articles mentioning Tinder. Specifically, we estimate $Y_{ct} = \alpha_c + \sum_{t=Jan2013}^{Dec2016} \beta_t \times Greek_c + \varepsilon_{ict}$ where Y_{ct} stands for the indicator for whether newspapers in college c had at least one article containing the keyword '*Tinder*' in a given month t, and α_c and β_t are the college and year-month fixed effects, respectively. For the top figure, $Greek_c$ takes the value of 1 if college c has Greek life and 0 otherwise. For the bottom figure, $Greek_c$ takes the value of 1 if the share of Greek students at college c is in the top quartile and takes the value of 0 if it is in the bottom quartile. The figures display the coefficients β_t where the omitted period is January 2013. Standard errors are clustered at the college level. Data on the college newspapers come from LexisNexis; data on Greek organizations are from the Common Data Set.

Figure A6: Distributional Effect on Number of Sex Partners By Respondent Gender



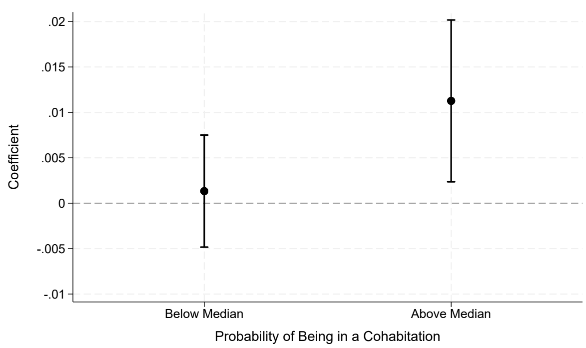
(a) Males



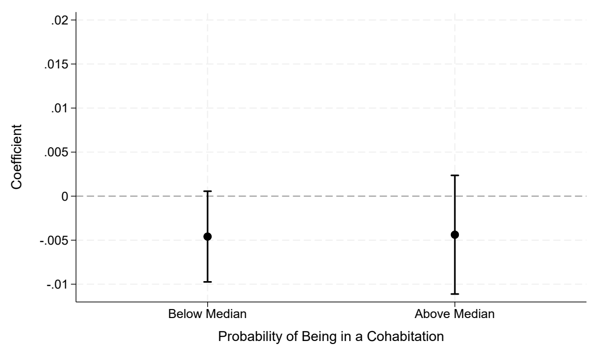
(b) Females

Notes: This figure explores the heterogeneity of the impact of Tinder on student sexual activity depending on students' LASSO-predicted number of sex partners. For prediction, we use age indicators, gender, race indicators, and BMI categories, as well as their square terms and interaction terms, and we train the model only using pre-Tinder data. The upper and lower lines represent 95% confidence intervals. Standard errors are clustered at the college level.

Figure A7: Distributional Effect on Cohabitation Status by Respondent Gender



(a) Males



(b) Females

Notes: This figure explores the heterogeneity of the impact of Tinder on the probability of being a cohabitation depending on students' LASSO-predicted number of sex partners (below/above median). For prediction, we use age indicators, gender, race indicators, and BMI categories, as well as their square terms and interaction terms, and we train the model only using pre-Tinder data. The upper and lower lines represent 95% confidence intervals. Standard errors are clustered at the college level.

Table A1: Top 30 Cities in Terms of Google Search Intensity for Tinder: 2013 and 2014

2013				2014			
City	Nearby Colleges	Student Pop.	Total Pop.	City	Nearby Colleges	Student Pop.	Total Pop.
Provo, UT	BYU	35k	116k	Brookline, MA	Northeastern, BU, BC	62k	63k
Somerville, MA	Tufts, Harvard	31k	81k	Santa Monica, CA	UCLA, LMU	56k	93k
Amherst, MA	UMass Amherst	32k	39k	Berkeley, CA	UC Berkeley	45k	124k
Boulder, CO	CU Boulder	36k	108k	Somerville, MA	Tufts, Harvard	31k	81k
Beverly Hills, CA	UCLA	46k	33k	Morro Bay, CA	–	–	11k
Brookline, MA	Northeastern, BU, BC	62k	63k	Bloomington, IN	IU Bloomington	45k	88k
Superior, WI	UW-Superior	3k	26k	Hoboken, NJ	Stevens IT	8k	60k
Santa Monica, CA	UCLA, LMU	56k	93k	East Lansing, MI	MSU	50k	49k
East Lansing, MI	MSU	50k	49k	State College, PA	Penn State	47k	42k
Stanford, CA	Stanford	19k	21k	Mount Pleasant, MI	Central Michigan	12k	89k
Wellesley, MA	Wellesley College	2k	29k	Provo, UT	BYU	35k	116k
Athens, GA	U of Georgia	40k	215k	Cheswold, DE	–	–	1k
Blacksburg, VA	Virginia Tech	37k	45k	Santa Barbara, CA	UCSB	26k	90k
Cambridge, MA	Harvard, MIT	31k	117k	Wilmington, NC	UNC Wilmington	19k	116k
State College, PA	Penn State	47k	42k	Davis, CA	UC Davis	39k	69k
Harrisonburg, VA	James Madison	22k	52k	Carrboro, NC	UNC Chapel Hill	32k	21k
Fairfield, CT	Fairfield	6k	62k	Iowa City, IA	U of Iowa	28k	75k
Waltham, MA	Brandeis	6k	65k	Arlington, TX	UT Arlington	46k	401k
College Park, MD	U of Maryland	41k	35k	Gainesville, FL	U of Florida	54k	135k
Hoboken, NJ	Stevens IT	8k	60k	Troy, MI	–	–	84k
Annapolis, MD	Naval Academy	5k	41k	Superior, WI	UW-Superior	3k	26k
Bloomington, IN	IU Bloomington	45k	88k	SeaTac, WA	–	–	29k
Columbia, MO	U of Missouri	31k	126k	Cambridge, MA	Harvard, MIT	31k	117k
College Station, TX	Texas A&M	73k	124k	Goldsby, OK	–	–	3k
Evanston, IL	Northwestern	22k	75k	Brighton, MI	–	–	8k
Burlington, VT	U of Vermont	13k	45k	Ann Arbor, MI	UMich	47k	124k
Boston, MA	Northeastern, BU	50k	676k	Boston, MA	Northeastern, BU	50k	676k
Fort Collins, CO	Colorado State	33k	176k	Fullerton, CA	CSU Fullerton	40k	141k
Tempe, AZ	ASU	135k	192k	Carlsbad, CA	–	–	115k
Arlington, TX	UT Arlington	46k	401k	Roseville, CA	–	–	149k

Notes: This table lists the 30 cities with the highest Google search intensity for the app Tinder in 2013 and 2014. The data source is Google Trends. The student population and total population columns are in thousands. The cities that don't have colleges nearby are denoted with "–".

Table A2: Variables: Definitions, Constructions, and Associated NCHA Survey Questions

Variable	Description
Treatment Variables	
Post Tinder introduction	Coding: 1 = Tinder had already been introduced by the time the respondent took the survey (after Spring 2013); 0 = Tinder had not been introduced by the time the respondent took the survey.
Greek-life involvement (individual)	Question: "Are you a member of a social fraternity or sorority?"; Coding: 1 = Yes; 0 = No.
Greek-life involvement (college-level)	The share is the ratio of students who are part of Greek life over all students.
Sexual Outcomes	
Number of sex partners	Question: "Within the last 12 months, with how many partners have you had oral sex/vaginal intercourse/anal intercourse?"; Numeric open response.
Number of sex partners (intensive margin)	Question: "Within the last 12 months, with how many partners have you had oral sex/vaginal intercourse/anal intercourse?"; Numeric open response. Coding: replace zeroes with missing values.
Sex previous 12 months	Question: "Within the last 12 months, with how many partners have you had oral sex/vaginal intercourse/anal intercourse?"; Numeric open response. Coding: 1 = {any number above zero}; 0 = {zero}.
Sex previous 30 days	Question: "Within the last 30 days, did you have: Oral sex/Vaginal intercourse/Anal intercourse?" Scale: 1 = No, never done; 2 = Have done, not last 30 days; 3 = Yes. Coding: 1 = {3}; 0 = {1,2}.
Relationship-Quality Outcomes	
Cohabiting	Question: "What is your relationship status?"; Scale: 1 = Not in a relationship; 2 = In a relationship but not living together; 3 = In a relationship and living together. Coding: 1 = {3}; 0 = {1,2}.
Abusive relationship	Question: "Within the last 12 months, have you been in an intimate (coupled/partnered) relationship that was emotionally/physically or sexually abusive?"; Coding: 1 = Yes; 0 = No.
Difficult relationship	Question: "Within the last 12 months, have any of the following been traumatic or very difficult for you to handle?: Intimate Relationships"; Coding: 1 = Yes; 0 = No.
Relationship problems	Question: "Within the last 12 months, have any of the following affected your academic performance? Scale: 1 = Not happened to me, not applicable; 2 = Experienced but academics not negatively affected; 3 = Lower grade on exam/project; 4 = Lower grade in course; 5 = Incomplete or dropped course; 6 = Significant disruption in thesis, dissertation, research, or practicum work. Coding: 1 = {2,3,4,5,6}; 0 = {1}.
Negative Sex-Related Outcomes	
Sexual assault	Question: "Within the last 12 months, have you been subject to sexual abuse (sexually touched without consent/sexual penetration attempted without consent/sexually penetrated without consent)?"; Coding: 1 = Yes; 0 = No.
Chlamydia	Question: "Within the 12 months, have you been diagnosed or treated by any professional for Chlamydia?"; Coding: 1 = Yes; 0 = No.
HIV test	Question: "Have you ever been tested for Human Immunodeficiency Virus (HIV) infection?"; Scale: 1 = No; 2 = Yes; 3 = Don't know. Coding: 1 = {2}; 0 = {1,3}.

Table A1: Variables: Definitions, Constructions, and Associated NCHA Survey Questions (cont.)

Variable	Description
Poor Mental Health Symptoms	
Hopeless	Question: "Have you ever: Felt things were hopeless?"; Scale: 1 = Never; 2 = No, not in last 12 months; 3 = In the last 2 weeks; 4 = In the last 30 days; 5 = In the last 12 months. Coding: 1 = {3,4}; 0 = {1,2,5}
Overwhelmed	Question: "Have you ever: Felt overwhelmed by all you had to do?"; Scale and coding: same as above.
Exhausted (not physically)	Question: "Have you ever: Felt exhausted (not from physical activity)?"; Scale and coding: same as above.
Very lonely	Question: "Have you ever: Felt very lonely?"; Scale and coding: same as above.
Very sad	Question: "Have you ever: Felt very sad?"; Scale and coding: same as above.
Severely depressed	Question: "Have you ever: Felt so depressed that it was difficult to function?"; Scale and coding: same as above.
Overwhelming anxiety	Question: "Have you ever: Felt overwhelming anxiety?"; Scale and coding: same as above.
Overwhelming anger	Question: "Have you ever: Felt overwhelming anger?"; Scale and coding: same as above.
Self-harm	Question: "Have you ever: Intentionally cut, burned, bruised or otherwise injured yourself?"; Scale and coding: same as above.
Considered suicide	Question: "Have you ever: Seriously considered suicide?"; Scale and coding: same as above.
Index for Mental Health Variables	
Index poor mental health	The index is constructed in the following way: (i) For the pretreatment period, all *symptoms of poor mental health* variables have been standardized to have a mean equal to 0 and a standard deviation equal to 1; (ii) An equally weighted average of the standardized variables has been derived; (iii) For the pretreatment period, the equally-weighted average is standardized again to have a mean equal to 0 and a standard deviation equal to 1.
Downstream Academic Performance	
Relationship difficulties (academic)	Question: "Within the last 12 months, have any of the following affected your academic performance?: Relationship Difficulties"; Scale: 1 = Not happened to me, 2 = Experienced but academics not negatively affected, 3 = Lower grade on exam/project, 4 = Lower grade in course, 5 = Incomplete or dropped course, 6 = Significant disruption in thesis, dissertation, research, or practicum work; Coding: 1 = {3,4,5,6}; 0 = {1,2}.
Sexual assault (academic)	Question: "Within the last 12 months, have any of the following affected your academic performance?: Assault (sexual)." Scale and coding as above.
STD (academic)	Question: "Within the last 12 months, have any of the following affected your academic performance?: Sexually transmitted disease/infection (STD/I)." Scale and coding as above.
Depression (academic)	Question: "Within the last 12 months, have any of the following affected your academic performance?: Depression." Scale and coding as above.
Anxiety (academic)	Question: "Within the last 12 months, have any of the following affected your academic performance?: Anxiety." Scale and coding as above.
Stress (academic)	Question: "Within the last 12 months, have any of the following affected your academic performance?: Stress." Scale and coding as above.
ADHD (academic)	Question: "Within the last 12 months, have any of the following affected your academic performance?: Attention Deficit and Hyperactivity Disorder (ADHD)." Scale and coding as above.
Eating disorder (academic)	Question: "Within the last 12 months, have any of the following affected your academic performance?: Eating disorder/problem." Scale and coding as above.

Table A1: Variables: Definitions, Constructions, and Associated NCHA Survey Questions (cont.)

Variable	Description
Control Variables	
Nonmale	Question: "What is your gender?"; Coding: 1 = female, transgender; 0 = male.
Height	Question: "What is your height in feet and inches?". This variable has been winsorized by cutting off 0.5%
Weight	Question: "What is your weight in pounds?". This variable has been winsorized by cutting off 0.5%.
Body Mass Index (BMI)	Question: "What is your body mass index (BMI)?"; Constructed by the ACHA as BMI = kg/m^2;
White	Question: "How do you usually describe yourself? (Mark all that apply)"; Coding: 1 if chose "White"; 0 otherwise.
Black	Question: "How do you usually describe yourself? (Mark all that apply)"; Coding: 1 if chose "Black or African American"; 0 otherwise.
Hispanic	Question: "How do you usually describe yourself? (Mark all that apply)"; Coding: 1 if chose "Hispanic or Latino/a"; 0 otherwise.
Asian	Question: "How do you usually describe yourself? (Mark all that apply)"; Coding: 1 if chose "Asian or Pacific Islander"; 0 otherwise.
Native American	Question: "How do you usually describe yourself? (Mark all that apply)"; Coding: 1 if chose "American Indian, Alaskan Native, or Native Hawaiian"; 0 otherwise.
Other race	Question: "How do you usually describe yourself? (Mark all that apply)"; Coding: 1 if chose "Other"; 0 otherwise.
International	Question: "Are you an international student?"; Scale: 1 = Yes; 0 = No.
Age	Question: "How old are you?" This variable has been winsorized by cutting off 0.5% at the right tail. This has been used within regressions as separate indicators.
College grade	Question: "What is your year in school?"; Scale: 1 = 1st year undergraduate; 2 = 2nd year undergraduate; 3 = 3rd year undergraduate; 4 = 4th year undergraduate; 5 = 5th year or more undergraduate. We keep only undergraduate students in our sample.
Gay/Lesbian	Question: "What is your sexual orientation?;" Scale: 1 = Asexual; 2 = Bisexual; 3 = Gay; 4 = Lesbian; 5 = Pansexual; 6 = Queer; 7 = Questioning; 8 = Same-Gender Loving; 9 = Straight/Heterosexual; 10= Another identity (please specify). Coding: 1 = {2,3,4}; 0 otherwise . We use this variable and coding as opposed to broader categories due to the inconsistency of the available answer options across years.
Grade point average (GPA)	Question: "What is your approximate cumulative grade average?" Scale: 1 = A, 2 = B, 3 = C; 4 = D/F; 5 = N/A.
Financial Difficulties	Question: "Did you have any financial difficulties in the last 12 months?; Scale: 1 = Yes; 0 = No.
Working hours per week	Question: "How many hours a week do you work for pay?;" Scale: 0 hours; 1-9 hours; 10-19 hours; 20-29 hours; 30-39 hours; 40 hours; More than 40 hours.
Working (volunteer) hours per week	Question: "How many hours a week do you volunteer?;" Scale: 0 hours; 1-9 hours; 10-19 hours; 20-29 hours; 30-39 hours; 40 hours; More than 40 hours.
Other Variables	
Campus size	Size of campus; Scale: 1 = Less than 2,500 students, 2 = 2,500–4,999 students, 3 = 5,000–9,999 students, 4 = 10,000–19,999 students, 5 = 20,000 or more students.
Region	The region where the campus is located; 1 = Northeast, 2 = Midwest, 3 = South, 4 = West.

Table A3: Online Dating Patterns Among College-Student Population

Survey	Year(s)	Question	Relevant Respondents	Sample Size	Response
Pew Internet and American Life Project Polls[1]	2005 and 2009	Do you ever use an online dating website? (Yes)	Full-time students aged 18–24	33	3.1%
Pew Research Center Poll: Generation Next[2]	2006	Have you ever gone on a date with someone you met online? (Yes)	College undergraduates aged 18–24	24	8.3%
Online College Social Life Survey[3]	2005–2011	Where did you first meet your last (romance, hookup, date)? (Personal ad/dating service or "Other response" mentions the internet)	College Undergraduates from 22 different US colleges/universities	24,131	3.58%
Pew Internet & American Life Poll[4]	2013	Have you ever used an online dating site or a dating app on your cell phone? (Yes)	Adults with a high school or college degree aged 18–24	211	9.5%
Pew Research Center: Tracking[5]	2015	Have you ever used an online dating site or a dating app on your cell phone? (Yes)	College undergraduates aged 18–24	55	29%
Pew Research Center: American Trends Panel[6]	2019	Have you ever used an online dating site or dating app? (Yes)	Adults with some college or a college degree aged 18–29	731	49.7%

Notes: This table presents the shares of college-educated young adults who reported using online dating websites or apps from 2005 through 2019. The surveys were identified by searching the Roper Center iPoll database for surveys from the years 2000–2020 containing the keyword "online dating." Surveys that had questions related to the use of online dating, as well as questions on education level and age, were kept.
1: Only internet users were surveyed. The 2009 survey only has only nine respondents who fit the age and education criteria, so their responses are merged with the 2005 survey.
2: Only internet users were surveyed.
3: The indicator for meeting via the internet is equal to one if an individual indicated that they met their most recent romance, hookup, or date through a personal ad/dating service or if they chose the "other" category and their response contains one or more of the following strings: "internet, online, Facebook, Myspace, Craigslist, eHarmony, .com"; otherwise, their indicator is equal to zero.
4: The variable is constructed as equal to one if an individual answered yes to ever using a dating website or app. The former question was put to internet users, and the latter question was asked to users of cellphone apps.
5: The variable is constructed in the same way as for the 2013 survey.
6: The sample is restricted to individuals aged 18–29 (finer age categories are not available) and with the highest education level being either a bachelor's degree or one or more years of college.

Table A4: Changes in Composition of Greek Students Relative to Overall Student Population

	Pre-Non-Greek		Pre-Greek		Post-Non-Greek		Post-Greek		P-value for (Pre-/Post-Greek - Pre-/Post-Non-Greek)
Variable	N	Mean/SD	N	Mean/SD	N	Mean/SD	N	Mean/SD	N
Male	506	0.33	503	0.33	538	0.30	527	0.30	0.979
		(0.00)		(0.01)		(0.00)		(0.01)	
Age	506	21.57	503	21.77	538	21.42	527	21.83	0.402
		(0.10)		(0.14)		(0.09)		(0.16)	
White	506	0.72	503	0.73	538	0.71	527	0.73	0.528
		(0.01)		(0.01)		(0.01)		(0.01)	
Black	506	0.08	503	0.09	538	0.08	527	0.07	0.152
		(0.01)		(0.01)		(0.00)		(0.01)	
Hispanic	506	0.10	503	0.10	538	0.12	527	0.12	0.409
		(0.01)		(0.01)		(0.01)		(0.01)	
Asian	506	0.10	503	0.08	538	0.11	527	0.09	0.992
		(0.01)		(0.01)		(0.01)		(0.01)	
Native American	506	0.02	503	0.03	538	0.02	527	0.03	0.694
		(0.00)		(0.00)		(0.00)		(0.00)	
Other Race	506	0.03	503	0.03	538	0.02	527	0.03	0.705
		(0.00)		(0.00)		(0.00)		(0.00)	
International	506	0.07	503	0.17	538	0.05	527	0.09	0.000***
		(0.00)		(0.01)		(0.00)		(0.01)	
GPA	506	1.87	503	1.85	538	1.79	527	1.77	0.935
		(0.01)		(0.01)		(0.01)		(0.01)	
Freshman	506	0.30	503	0.22	538	0.30	527	0.22	0.694
		(0.01)		(0.01)		(0.01)		(0.01)	
Sophomore	506	0.24	503	0.26	538	0.24	527	0.24	0.118
		(0.00)		(0.01)		(0.00)		(0.01)	
Junior	506	0.22	503	0.24	538	0.22	527	0.25	0.308
		(0.00)		(0.01)		(0.00)		(0.01)	
Height	506	66.79	503	66.79	538	66.48	527	66.59	0.328
		(0.04)		(0.06)		(0.03)		(0.07)	
Weight	506	156.28	503	158.45	538	157.60	527	160.51	0.550
		(0.41)		(0.64)		(0.41)		(0.86)	
BMI	506	24.56	503	24.88	538	25.04	527	25.54	0.386
		(0.06)		(0.10)		(0.07)		(0.15)	
Lesbian/Gay	506	0.03	503	0.02	538	0.03	527	0.02	0.372
		(0.00)		(0.00)		(0.00)		(0.00)	

Notes: This table presents the average characteristics of Greek and non-Greek students across colleges before and after the introduction of Tinder. The p-values in the last column correspond to the difference-in-differences regressions of each characteristic on Post×Greek using aggregate college-by-post-by-Greek data. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table A5: Newspaper Articles—First-Stage Results

	College Has Article on Tinder, 2013–2016			Number of Articles on Tinder, 2013–2016		
	(1)	(2)	(3)	(4)	(5)	(6)
College Has Greek Life	0.145***			1.048***		
	(0.046)			(0.378)		
Share of Students in Fraternities Above Median		0.119***			1.257**	
		(0.045)			(0.579)	
Share of Students in Sororities Above Median			0.117***			1.497***
			(0.045)			(0.565)
Total articles	✓	✓	✓	✓	✓	✓
Observations	540	530	530	540	530	530

Notes: This table presents the relationship between the presence of Greek life and the intensity of the use of Tinder at a college. The outcome variables in columns (1)–(3) are indicators for whether a college had at least one article mentioning Tinder published in any of its newspapers from 2013 through 2016; the outcome variables in columns (4)–(6) are the numbers of articles mentioning Tinder in any newspaper at a given college from 2013 through 2016. All estimates control for the total number of articles published by newspapers from 2013 through 2016. Data on the college newspapers come from LexisNexis; data on Greek organizations are from the Common Data Set. Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table A6: Google Trends—First Stage Results

	Google Top 100 "Tinder" Search Intensity		
	(1)	(2)	(3)
College Has Greek Life	0.052**		
	(0.021)		
Share of Students in Fraternities Above Median		0.042*	
		(0.022)	
Share of Students in Sororities Above Median			0.060***
			(0.022)
Observations	540	530	530
Mean of dep. var.	0.070	0.072	0.072
SD of dep. var.	0.256	0.258	0.258

Notes: This table presents the relationship between the presence of Greek life at a college and an indicator for whether a city or town that the college is located in ranks in the top 100 in terms of Google search intensity for Tinder in 2013–2014. Each observation is a college. Data on search intensity come from Google Trends; data on Greek organizations are from the Common Data Set. Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table A7: App Use Data—First Stage Results

	Fraction of Devices Using Tinder During Fall 2017		
	(1)	(2)	(3)
College Has Greek Life	0.003**		
	(0.001)		
Share of Students in Fraternities Above Median		0.004***	
		(0.001)	
Share of Students in Sororities Above Median			0.004***
			(0.001)
Observations	454	447	447
Mean of dep. var.	0.017	0.017	0.017
SD of dep. var.	0.022	0.022	0.022

Notes: This table presents the relationship between the presence of Greek life at a college and and the usage rate of Tinder within the college's main zipcode. The usage rate is calculated as the total number of devices using Tinder divided by the total number of devices for which college's main zipcode is the most frequently appearing location. We analyze this relationship for the earliest semester that the data on Tinder use becomes available, from September 21, 2017, through December 31, 2017. Each observation is a college. Data on app usage and device location come from Tapestri.io; data on Greek organizations are from the Common Data Set. Observations are weighted by the logarithm of the total number of devices most frequently appearing in the college's main zipcode. Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table A8: Mental Health (Excluding Sexually Abused Individuals)

	(1) Hopeless	(2) Over-whelmed	(3) Exhausted (Not Physically)	(4) Very Lonely	(5) Very Sad	(6) Severely Depressed	(7) Over-whelming Anxiety	(8) Over-whelming Anger	(9) Self-Harm	(10) Considered Suicide	(11) Index Poor Mental Health (Last 30 Days)
Fraternity/Sorority × Post	-0.010***	-0.015***	-0.013***	-0.012***	-0.009**	-0.012***	-0.013***	-0.011***	-0.002***	-0.005***	-0.043***
	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.007)
College-semester FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Has controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	937,888	937,888	937,888	937,888	937,888	937,888	937,888	937,888	937,888	937,888	937,888
Mean of dep. var.	0.453	0.682	0.655	0.370	0.388	0.171	0.338	0.202	0.023	0.028	0.045
SD of dep. var.	0.498	0.466	0.475	0.483	0.487	0.377	0.473	0.401	0.150	0.164	1.015

Notes: This table presents the estimates of the impact of Tinder's introduction on student mental health, excluding individuals who reported being victims of sexual assault in the previous year. The outcome variables are feeling hopeless, overwhelmed, exhausted (not from physical activity), very lonely, very sad, severely depressed (that it was difficult to function), overwhelming anxiety, overwhelming anger, self-harm, and considering suicide in the previous 12 months. The index of poor mental health is obtained by adding the standardized versions of all of the variables above and standardizing the resulting variable. The coefficient of interest is the interaction of a student's fraternity or sorority membership and an indicator post the full-scale launch of Tinder. All columns include college-semester fixed effects and controls (age, gender, race, grade, international student status, height, and BMI). For detailed variable definitions, see Appendix Table A2. Standard errors in parentheses are clustered at the college level. * p<0.1, ** p<0.05, *** p<0.01.

Table A9: Mental Health (Controlling for Sexual Activity)

	(1) Hopeless	(2) Over-whelmed	(3) Exhausted (Not Physically)	(4) Very Lonely	(5) Very Sad	(6) Severely Depressed	(7) Over-whelming Anxiety	(8) Over-whelming Anger	(9) Self-Harm	(10) Considered Suicide	(11) Index Poor Mental Health (Last 30 Days)
Fraternity/Sorority × Post	-0.011***	-0.015***	-0.013***	-0.012***	-0.011***	-0.014***	-0.014***	-0.012***	-0.003***	-0.005***	-0.046***
	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.008)
College-semester FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Baseline controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sexual-activity controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	924,060	924,060	924,060	924,060	924,060	924,060	924,060	924,060	924,060	924,060	924,060
Mean of dep. var.	0.454	0.683	0.657	0.371	0.389	0.171	0.338	0.202	0.023	0.028	0.046
SD of dep. var.	0.498	0.465	0.475	0.483	0.488	0.377	0.473	0.401	0.150	0.164	1.014

Notes: This table investigates whether the average positive impact of Tinder's introduction on mental health is driven by increased sexual activity. Specifically, it displays the estimates of the impact of Tinder on mental health controlling for students' number of sexual partners in the previous 12 months and for whether they had sex in the previous 30 days. The outcome variables are feeling hopeless, overwhelmed, exhausted (not from physical activity), very lonely, very sad, severely depressed (that it was difficult to function), overwhelming anxiety, overwhelming anger, self-harm, and considering suicide in the previous 12 months. The index of poor mental health is obtained by adding the standardized versions of all of the variables above and standardizing the resulting variable. The coefficient of interest is the interaction of a student's fraternity or sorority membership and an indicator post the full-scale launch of Tinder. All columns include college-semester fixed effects and controls (age, gender, race, grade, international student status, height, and BMI). For detailed variable definitions, see Appendix Table A2. Standard errors in parentheses are clustered at the college level. * p<0.1, ** p<0.05, *** p<0.01.

Table A10: Robustness: Student Characteristics Interacted with Post-Tinder Indicator

	(1) # of Sex Partners	(2) Sex Previous 30 Days	(3) Cohabiting	(4) Index Poor Mental Health (Last 30 Days)	(5) Chlamydia	(6) HIV Test	(7) Sexual Assault
Fraternity/Sorority × Post	0.210***	0.029***	-0.004*	-0.041***	0.006***	0.013***	0.016***
	(0.029)	(0.004)	(0.002)	(0.008)	(0.001)	(0.003)	(0.002)
College-Semester FE	✓	✓	✓	✓	✓	✓	✓
Has Controls	✓	✓	✓	✓	✓	✓	✓
Controls × Post	✓	✓	✓	✓	✓	✓	✓
Observations	1,017,084	1,023,299	1,027,344	1,029,122	1,023,250	972,120	1,027,277
Mean of dep. var.	1.492	0.520	0.114	0.094	0.013	0.256	0.087
SD of dep. var.	2.918	0.500	0.318	1.046	0.113	0.437	0.282

Notes: This table presents the results of a robustness check for whether the baseline results remain stable after the inclusion of the interactions of all controls (age, gender, race, grade, international student status, height, and BMI) with the post indicator for periods after the full-scale launch of Tinder. All columns include college-semester fixed effects. For detailed variable definitions, see Appendix Table A2. Standard errors in parentheses are clustered at the college level. * p<0.1, ** p<0.05, *** p<0.01.

Table A11: Robustness: LASSO-Predicted Sexual Activity Interacted with Post-Tinder Indicator

	(1) # of Sex Partners	(2) Sex Previous 30 Days	(3) Cohabiting	(4) Index Poor Mental Health (Last 30 Days)	(5) Chlamydia	(6) HIV Test	(7) Sexual Assault
Fraternity/Sorority × Post	0.220***	0.029***	-0.003	-0.034***	0.006***	0.015***	0.020***
	(0.028)	(0.004)	(0.002)	(0.008)	(0.001)	(0.003)	(0.002)
College-semester FE	✓	✓	✓	✓	✓	✓	✓
Has controls	✓	✓	✓	✓	✓	✓	✓
LASSO # of Sex Partners × Post	✓	✓	✓	✓	✓	✓	✓
Observations	1,017,084	1,023,299	1,027,344	1,029,122	1,023,250	972,120	1,027,277
Mean of dep. var.	1.492	0.520	0.114	0.094	0.013	0.256	0.087
SD of dep. var.	2.918	0.500	0.318	1.046	0.113	0.437	0.282

Notes: This table presents the results of a robustness check for whether the baseline results remain stable after the inclusion of the interactions of the LASSO-predicted sexual activity of a respondent with the post indicator for periods after the full-scale launch of Tinder. For prediction, we use age indicators, gender, race indicators, and BMI categories, as well as their square terms and interaction terms. All columns include baseline controls and college-semester fixed effects. For detailed variable definitions, see Appendix Table A2. Standard errors in parentheses are clustered at the college level. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table A12: Robustness: Survey Nonresponse

	Missing Response Rate For:						
	(1) # of Sex Partners	(2) Sex Previous 30 Days	(3) Cohabiting	(4) Index Poor Mental Health (Last 30 Days)	(5) Chlamydia	(6) HIV Test	(7) Sexual Assault
Fraternity/Sorority × Post	0.001	0.001	-0.000	0.000	0.001**	-0.001	-0.000*
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)
College-Semester FE	✓	✓	✓	✓	✓	✓	✓
Has Controls	✓	✓	✓	✓	✓	✓	✓
Observations	1,029,122	1,029,122	1,029,122	1,029,122	1,029,122	1,029,122	1,029,122
Mean of dep. var.	0.012	0.006	0.002	0.001	0.004	0.055	0.002
SD of dep. var.	0.108	0.075	0.042	0.030	0.065	0.229	0.042

Notes: This table examines the possible differential changes in misreporting after the introduction of Tinder by estimating whether nonresponse rates for our main outcomes change differentially for Greek students and non-Greek students before and after the full-scale launch of Tinder. All columns include baseline controls and college-semester fixed effects. For detailed variable definitions, see Appendix Table A2. Standard errors in parentheses are clustered at the college level. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table A13: Robustness: Financial Issues

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	# of Sex Partners	Sex Previous 30 Days	Cohabiting	Index Poor Mental Health (Last 30 Days)	Chlamydia	HIV Test	Sexual Assault
Fraternity/Sorority × Post	0.222***	0.028***	-0.002	-0.030***	0.006***	0.015***	0.019***
	(0.027)	(0.004)	(0.002)	(0.007)	(0.001)	(0.003)	(0.002)
College-Semester FE	✓	✓	✓	✓	✓	✓	✓
Has Controls	✓	✓	✓	✓	✓	✓	✓
Financial Controls × Post	✓	✓	✓	✓	✓	✓	✓
Observations	1,001,782	1,007,979	1,011,177	1,012,830	1,009,013	958,346	1,011,238
Mean of dep. var.	1.490	0.520	0.114	0.096	0.013	0.256	0.087
SD of dep. var.	2.901	0.500	0.318	1.045	0.113	0.437	0.282

Notes: This table presents the results of a robustness check for whether the baseline results remain stable after omitting colleges for which the share of Greek-affiliated students has declined. All columns include baseline controls and college-semester fixed effects. Additional controls include whether the student had financial difficulties in the last 12 months and their working hours per week (paid or voluntarily). For detailed variable definitions, see Appendix Table A2. Standard errors in parentheses are clustered at the college level. * p<0.1, ** p<0.05, *** p<0.01.

Table A14: Robustness: Crackdown on Greek Organizations

	(1) # of Sex Partners	(2) Sex Previous 30 Days	(3) Cohabiting	(4) Index Poor Mental Health (Last 30 Days)	(5) Chlamydia	(6) HIV Test	(7) Sexual Assault
Panel A: Omit Colleges With Large Decline in Greek Share Pre/Post Fall 2013							
Fraternity/Sorority × Post	0.213***	0.033***	-0.002	-0.039***	0.006***	0.016***	0.019***
	(0.033)	(0.005)	(0.002)	(0.008)	(0.001)	(0.004)	(0.002)
College-Semester FE	✓	✓	✓	✓	✓	✓	✓
Has Controls	✓	✓	✓	✓	✓	✓	✓
Observations	764,310	768,873	771,885	773,166	768,831	731,181	771,835
Mean of dep. var.	1.506	0.521	0.114	0.091	0.013	0.256	0.086
SD of dep. var.	2.955	0.500	0.318	1.043	0.113	0.436	0.281
Panel B: Omit Colleges With Any Decline in Greek Share Pre/Post Fall 2013							
Fraternity/Sorority × Post	0.207***	0.030***	-0.003	-0.041***	0.007***	0.016***	0.018***
	(0.039)	(0.006)	(0.003)	(0.009)	(0.001)	(0.004)	(0.003)
College-Semester FE	✓	✓	✓	✓	✓	✓	✓
Has Controls	✓	✓	✓	✓	✓	✓	✓
Observations	396,775	398,822	400,331	400,974	398,718	378,904	400,295
Mean of dep. var.	1.576	0.520	0.092	0.078	0.013	0.241	0.090
SD of dep. var.	3.013	0.500	0.290	1.026	0.111	0.428	0.287

Notes: This table presents the results of a robustness check for whether the baseline results remain stable after omitting colleges for which the share of Greek-affiliated students has declined. This addresses a potential concern about concurrent crackdown on Greek life by certain colleges. The estimates in Panel A omit colleges for which the share of Greek students has declined by more than 2.8 percentage points before and after the Fall 2013 semester, which is the 5th percentile of the change in Greek student share. The estimates in Panel B omit colleges for which the share of Greek students has declined by any amount. All columns include baseline controls and college-semester fixed effects. For detailed variable definitions, see Appendix Table A2. Standard errors in parentheses are clustered at the college level. * p<0.1, ** p<0.05, *** p<0.01.