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ORIGINAL PAPER

Job Prestige and Mobile Dating Success: A Field Experiment

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Abstract

Research using data on offline couple formation has confirmed predictions from evolutionary psychology that women (not men) attach value to the earnings potential of a potential partner. In this study, we examine whether the partner preferences with respect to earnings potential survive in an online context with fewer search and social frictions. We did this by means of a field experiment on the popular mobile dating app Tinder. Thirty-two fictitious Tinder profiles that randomly differed in job status and job prestige were evaluated by 4800 other, real Tinder users. We find that both men and women do not use job status or job prestige as a determinant of whom to show initial interest in on Tinder. However, we do find evidence that, after this initial phase, men less frequently start a conversation with women when those women are unemployed. Still, also then men do not care about the particular job prestige of employed women.

Keywords Job prestige · Partner preferences · Online dating · Dating apps · Tinder

JEL Classification J12 · J16 · J13 · C93

1 Introduction

Over the last few decades, key moments in one's dating life increasingly originated in an online setting. Indeed, multiple independent studies using data from the United States have shown that approximately one in five committed relationships and one in six marriages over the past decade have begun through online dating (Cacioppo

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et al., 2013; Chadwick Martin Bailey, 2010; Rosenfeld & Thomas, 2012). The latest development in online dating is the increasing popularity of mobile dating apps, of which Tinder is the most used.[1]

Despite the ubiquity of mobile dating apps, little is known about what drives partner preferences on these apps. Indeed, previous research on partner preferences has mainly examined partner preferences in an offline setting. A first contribution of this study to the existing literature is examining whether job status (being employed or being unemployed) and job prestige have an impact on success on the mobile dating app Tinder. This way, we examine whether earnings potential still plays a substantial role in online dating preferences, as it has been shown in the field of evolutionary psychology to do in offline dating preferences (see also Sect. 2).

A second contribution of the current study to earlier research is that we examine dating preferences by transposing the correspondence experimentation framework used in labour economics to measure hiring discrimination (Baert, 2018; Bertrand & Mullainathan, 2004; Eriksson & Rooth, 2014; Neumark, 2018; Van der Klaauw & Ziegler, 2022) to the Tinder setting. That is, we conduct a field experiment on Tinder in which we randomly vary both job status and job prestige across fictitious (heterosexual) Tinder profiles and then monitor which fictitious profiles are the most successful in a sample of 4800 other, real Tinder users. This way, we are able to estimate *revealed* rather than *stated* partner preferences with respect to earnings potential in a setting with fewer search and social frictions (see also Sect. 2).

The remainder of this study is structured as follows. In Sect. 2, we summarise the literature on partner preferences and formulate our hypotheses. Then, in Sect. 3, we elaborate on how Tinder works and how we used this platform to conduct our field experiment. In Sect. 4, we present the results of this experiment and Sect. 5 concludes and indicates several limitations of this study as well as interesting directions for future research.

2 Literature Review

The field of evolutionary psychology has established that human partner preferences are influenced by the capacity of the partner to reproduce and raise offspring (Bech-Sørensen & Pollet, 2016; Buss, 1989; Fisman et al., 2006; Geary et al., 2004; Stewart-Williams & Thomas, 2013; Webster et al., 2009). Because the contribution to the reproduction and raising of offspring differs by gender, partner preferences also vary between males and females (Bech-Sørensen & Pollet, 2016; Fisman et al., 2006; Geary et al., 2004). Given that females contribute to the reproductive process by bearing offspring, males have a preference for females whom they perceive to have high reproductive capacity (i.e. females whom they perceive to be highly fertile). Youth and attractiveness are strong cues

[1] This can easily be backed by Tinder's statistics: since its launch in 2012, Tinder has been downloaded over 400 million times, currently has more than 10 million daily active users, and is as of today available in 190 countries and in 40 languages (Tinder, 2020).

for this fertility so that males have, in line with evolutionary psychology, a preference for young and attractive females (Buss, 1989; Geary et al., 2004; Hatfield & Sprecher, 1995; Li et al., 2002; Miller, 2000). In contrast, as the contribution of males to the reproduction of offspring is rather limited, females expect them to compensate for this lack of investment by providing resources for offspring during their childhood. Because in recent times females assess males' ability to provide these resources by—among others—males' earnings capacity, they have a preference for males who have high (potential) income (Buss, 1989; Fisman et al., 2006; Geary et al., 2004; Hatfield & Sprecher, 1995; Li et al., 2002). Therefore not surprisingly, recent research in economics found that the returns to labour market status in the marriage market are positive for men, i.e. for men a higher job status or higher job prestige also increases their value as a romantic partner. For women, however, returns to labour market status in the marriage market have been shown to be neutral or even negative, i.e. for women a higher job status or higher job prestige does not increase their value as a romantic partner and could even decrease it as some men have a dispreference for a higher earning partner (Bertrand et al., 2015; Bursztyn et al., 2017).

Today, the question presents itself whether the partner preferences with respect to earnings potential established in the field of evolutionary psychology—which has historically focussed both theoretically and empirically on partner preferences in an offline setting—still hold today in a society where people increasingly find their significant other online (see also Sect. 1). Several studies that assessed partner preferences on 'classic' online dating websites (such as Match.com, eHarmony, and PlentyOfFish) found evidence that partner preferences on such platforms do not differ from those established earlier in the field of evolutionary psychology—see Abramova et al. (2016) for a structured overview of research on these partner preferences on classic online dating websites. Under the assumption that partner preferences on Tinder are equivalent to those established using data from offline dating and classic online dating websites, we formulate the following two hypotheses:

H1 Male Tinder users' *do not* have a preference for female Tinder users with better job status or higher job prestige.

H2 Female Tinder users' *do* have a preference for male Tinder users with better job status or higher job prestige.

However, there are three main reasons why partner preferences on Tinder as measured in the present study may differ from results found by studies based on data concerning offline dating and dating via classic online websites. First, most studies examining partner preferences in offline dating and on classic online dating websites have relied on survey data. In these studies, individuals *stated* which characteristics they found most desirable in a partner. In our field experiment, however, we were able to examine *revealed* partner preferences through the interest Tinder users show in our fictitious profiles. Because multiple studies have shown that *stated* partner preferences may differ from *revealed* partner preferences (Eastwick & Finkel, 2008; Todd et al., 2007), our findings may deviate from those presented in previous studies on human partner preferences.

Second, offline dating and dating on classic online dating websites may be accompanied by social frictions, such as the time cost of showing interest in another person and the psychological cost in the case of rejection. If these costs are high, people may want to avoid them by not showing interest in a highly desirable person, although they would ideally like to match with them. In this scenario, preferences not only reflect individuals' true preferences but also their expectations for obtaining a match with the person they evaluate (Hitsch et al., 2010; Neyt et al., 2019). However, on Tinder showing interest in another person only takes a few seconds and is done without the other person necessarily knowing you showed interest in them—this is only the case if this interest is mutual (see also Subsect. 3.1). As a consequence, both time costs and psychological costs are (nearly) non-existent in the Tinder setting; therefore, true preferences come to the fore more readily.

Third, dating in an offline context and on classical online dating websites may also be accompanied by search frictions. Search frictions influence partner choice as a consequence of increased contact opportunities between individuals who are similar on various characteristics (such as job status and job prestige). In offline dating, search frictions are a result of people with a certain job (status and prestige) being more likely to meet—and therefore more likely to match—people with a similar job (status and prestige), for example at work but also in one's circle of friends. On classical online dating websites, search friction are due to the ability of users to filter potential partners based on their job (status and prestige), which is not possible on Tinder (see also Subsect. 3.1). However, search frictions may lead to a suboptimal partner choice as only a fraction of potential partners are met.

However, the fact that social frictions and search frictions on Tinder are lower compared to offline dating and dating on classic online dating websites does not mean Tinder is strictly superior for finding a partner compared to these channels. Indeed, offline dating, for example, may be more informative about personal characteristics compared to dating in an online environment. Additionally, search filters on classic online dating websites, for example, may cause this channel to be more efficient compared to dating on Tinder, as there is no need to evaluate profiles that one would be completely uninterested in, such as females who are only interested in males who are strictly taller than them.

Finally, due to the abovementioned differences between online dating on Tinder on the one hand and offline dating and dating on classic online dating websites on the other hand, we do not wish to claim findings from this study can be extrapolated to offline dating or dating on classic online dating websites. However, given the ubiquitousness of Tinder in the current landscape, we believe findings from this study are nonetheless valuable in itself.

3 Methods

3.1 Tinder

The impact of the online dating app Tinder on couple formation and time allocation in OECD countries, particularly in the 18–35 age range, can hardly be overestimated. Tinder is the most popular dating app for iOS and Android with its users evaluating more than 2 billion other users per day, facilitating over 55 billion matches since its launch in 2012, and therefore being at the root of over 1.5 million offline dates per week (Tinder, 2020). Additionally, in August 2018, Tinder became the number one app people log into with their Facebook account, beating other apps such as YouTube and Spotify (Neyt et al., 2019; Sumter et al., 2017). Already in 2014, the average Tinder user logged into the app 11 times a day and spent around 1.5 h on the app daily (Ward, 2016).

Although for some people Tinder has the connotation of being used mainly to solicit casual or short relationships, multiple independent studies have shown that this view is unjustified. Indeed, survey research among Tinder users by Sumter et al. (2017) and Timmermans and De Caluwé (2017) indicates that the casual sex motive for using Tinder ranks well behind the motive for finding a committed relationship. Moreover, Timmermans and Courtois (2018) report that more than a quarter of offline Tinder encounters led to a committed relationship. Next, although they reported that one-third of offline Tinder encounters led to casual sex, Timmermans and Courtois (2018) argue that today, casual sex increasingly leads to a committed relationship. Consequently, even Tinder users who initially use the app in search of casual sex may eventually end up finding a committed relationship.

Additionally, we conducted an ex-post survey among a representative sample of 218 respondents (104 male and 114 female respondents) in their twenties in Flanders, i.e. the region of Belgium where we conducted our experiment (see also Subsect. 3.2). 73 respondents (36 male; 37 female) indicated they were currently using Tinder. We asked these 73 respondents whether they were currently using Tinder mainly for (i) finding a short-term relationship/casual sex, (ii) finding a long-term relationship, or (iii) another reason. 10 respondents (13.7%) indicated they used Tinder mainly for finding a short-term relationship/casual sex; 50 respondents (68.5%) indicated they used Tinder mainly for finding a committed relationship; and 13 respondents (17.8%) indicated they used Tinder mainly for another reason, among which (i) fighting boredom, (ii) finding friends, and (iii) for fun. This confirms the findings from previous literature that Tinder is used to find long-term relationships also in the context in which we conducted our experiment (i.e. among people in their twenties in Flanders).

Finally, even though some Tinder users may ultimately use the app solely for finding casual sex, this should not substantially bias our results, as also these users may still be selective in who to have casual sex with, a selection that may be influenced by—among other factors—the potential partner's job status and job prestige.

To use Tinder, users first need to create a Tinder profile. This profile is based on the Facebook account of the user, from which the name and age of that user are imported. Although it is also possible to create a Tinder profile through a mobile phone number, this option is rarely chosen. After a profile is created, users can complete their profile with (at the time of the experiment) up to six pictures, a short bio, their education level, and their job title. It is also possible to link this Tinder profile to one's Spotify and Instagram account, upon which the Tinder profile also shows songs and Instagram pictures selected by the Tinder user.

Next, users fill in three criteria with which they narrow down the number of other users whom they will encounter on the application. First, they indicate whether they want to see only male, only female, or both male and female users. Second, they indicate the minimum and maximum age of the people they want to encounter. Third, because Tinder is a location-based application, they indicate the maximum distance other users can be removed from them.

Then, users get shown, one by one, every Tinder user that fits their three criteria. Through swiping, they indicate—without the other users knowing unless there is a match—whether they dislike (swipe left) or like (swipe right) the users that they encounter. No new users can be reviewed before making a decision about the presented profile. Only if both users indicate that they like each other they match and have the possibility to start a conversation with each other (Ward, 2016).

3.2 Experiment

Our experiment is inspired by the many so-called correspondence experiments to measure (and explain) hiring discrimination conducted in the fields of labour economics, sociology of work, and organisational psychology. In this literature, recently reviewed by Baert (2018) and Neumark (2018), fictitious job applications to which a treatment—such as a foreign sounding name—is assigned in a random way are sent to real vacancies. By monitoring the subsequent call-backs from employers, the effect of the treatment of interest on the probability of a job interview invitation can be identified. Moreover, this effect can be given a causal interpretation because, by design of the experiment, the treatment is not correlated to any other (observed or unobserved) candidate characteristic.

In the present study, we transpose this method from the labour field setting to the Tinder field setting. That is, we randomly assign job status and job prestige to fictitious Tinder profiles while keeping other factors such as attractiveness constant to investigate the revealed partner preferences with respect to these characteristics among other, real Tinder users. Thus, our study is close to that of Neyt et al. (2019), who conducted a field experiment with 3600 fictitious profile evaluations to investigate the returns to education on Tinder.

More concretely, we created 32 fictitious Tinder profiles—16 male and 16 female. Each fictitious profile comprised a set of three pictures of the same person. In four cities in Flanders (Belgium), the same four sets of male pictures and four sets of female pictures were used to construct these fictitious profiles. City by city, four levels of job status and job prestige were randomised over these four sets of pictures. Table 1 features a schematic overview of the randomisation procedure discussed in the following paragraphs.

Table 1 Overview of the 32 fictitious profiles used in the experiment

City 1: Antwerp	City 2: Bruges	City 3: Ghent	City 4: Leuven	City 1: Antwerp	City 2: Bruges	City 3: Ghent	City 4: Leuven
High job prestige	Medium job prestige	Low job prestige	Unemployed	High job prestige	Medium job prestige	Low job prestige	Unemployed
Unemployed	High job prestige	Medium job prestige	Low job prestige	Unemployed	High job prestige	Medium job prestige	Low job prestige
Low job prestige	Unemployed	High job prestige	Medium job prestige	Low job prestige	Unemployed	High job prestige	Medium job prestige
Medium job prestige	Low job prestige	Unemployed	High job prestige	Medium job prestige	Low job prestige	Unemployed	High job prestige

The different shades of grey indicate different sets of pictures (with four sets of male pictures to the left and four sets of female pictures to the right)

Our fictitious profiles were all aged 23 because this was the actual age of all people in the pictures. We chose this age so that our profiles embodied people at the start of their professional career. We decided to not differ the age between the male and the female fictitious profiles, to be able to compare the effect of job status and job prestige for male and female fictitious profiles at the same phase in their lives, i.e. the start of their professional careers. Further, for the names of the people in our profiles, we used four of the most popular Flemish names for 23 year olds (per gender). More specifically, we used the names Jeroen, Thomas, Dennis, and Tim for the male profiles and Lisa, Laura, Anne, and Michelle for the female profiles (De populairste Vlaamse jongensnamen van 1995, n.d.; De populairste Vlaamse meisjesnamen van 1995, n.d.). Finally, we did not fill in the education level for our profiles. This is not unusual on Tinder. For example, in our sample, 47.5% of the real Tinder users did not mention their education level.

The cities in which we set up our fictitious Tinder profiles were the four biggest cities—in terms of population—in Flanders. In particular, the cities were Antwerp, Bruges, Ghent, and Leuven. For each of the aforementioned four male and female fictitious names, we employed one of four sets of three pictures (per gender) so that no set of pictures (and related names) was used twice in the same city, which could have led to the experiment being detected. Additionally, we ensured that the people in the different sets of pictures were similar in attractiveness. We did this by first conducting a pre-experiment on Amazon Mechanical Turk in which 32 people—16 male and 16 female—were rated for attractiveness. This was done by 493 Amazon Mechanical Turk users. More specifically, the profiles' attractiveness was measured using the physical attractiveness scale (McCroskey & McCain, 1974). This scale comprises six items to be rated on a 7-point Likert scale and had good reliability

(Cronbach's α = 0.95). Then, we chose eight people—four male and four female—who were similar in attractiveness to use in our fictitious profiles. For the male profiles, the attractiveness of the four profiles was (on a total of 42) 27.46, 28.16, 28.38, and 29.17. For the female profiles, the attractiveness of the four profiles was (on a total of 42) 32.37, 32.40, 33.28, and 33.92.

With respect to the job status and job prestige of the fictitious profiles, we first make a distinction between profiles that indicated they were employed and profiles that indicated they were unemployed. Per city and per gender, three profiles were employed and one profile was unemployed. This is hereafter referred to as the difference in *job status* within our experiment. Unemployment was indicated via the word group 'in between two jobs' (but in Dutch), which was the most common way to signal unemployment within a random sample of 250 Flemish Tinder users in the 23–27 age range in November 2017.

Next, among the profiles that were employed, we varied between three different jobs differing in *job prestige*. This job prestige was based on the average starting wage and required education level in three different jobs, with higher paying jobs and jobs which require a higher education level representing more prestigious jobs. We chose to signal job prestige through job title instead of through wages, as it is not possible on Tinder to directly report one's wage. Although one could mention this in her/his bio, this never happens in practice. The job titles, 'supply chain consultant', 'management assistant', and 'salesperson' were used to indicate high, medium, and low job prestige, respectively. Following glassdoor.be, where current and former employees anonymously review companies, the average salary in these functions is 2150 euro, 2069 euro, and 1522 euro per month, respectively. Additionally, while vacancies for supply chain consultants in the database of the Public Employment Service of Flanders are heavily dominated by vacancies at the Master's level (ISCED 2011 level 7), management assistants are most often hired at the Bachelor's level (ISCED 2011 level 6), and salespersons are most often hired at the upper secondary education level (ISCED 2011 level 4). Finally, we opted for jobs in business based on the balanced gender representation there. That is, the fraction of female workers in these occupations is between 25.0 and 75.0% following the Flemish indicators used in Baert et al. (2016). We did this in order to not choose a particularly 'feminine' or particularly 'masculine' field.

Despite the abovementioned objective underpinnings for job prestige—average starting wage and required education level—it remains the subjects' *perception* of job prestige that will drive results. Therefore, the effects identified in this study should be interpreted as the effects of *perceived* job prestige. To validate whether the objective ranking of treatment statuses indeed corresponded to the perceived ranking of treatment statuses, we conducted an ex-post survey among a representative sample of 218 respondents (104 male and 114 female respondents) in their twenties in Flanders, i.e. the region of Belgium where the cities that were used in our study (Kortrijk, Ghent, Antwerp, and Leuven) were located. More specifically, they were asked to "Rank the [following] jobs […] from most prestigious (1) to least prestigious (4): 'In between jobs', 'Salesperson', 'Management assistant', and 'Supply chain consultant'". Column (i) of Table 2 shows the results for this question. In line with what we expected, 'in between jobs' is perceived as the

Table 2 Validation of treatment status

	(i)	(ii)	(iii)	(iv)	(v)
		Supply chain consultant	Management assistant	Salesperson	In between jobs
	Mean (SD)	z (p)	z (p)	z (p)	z (p)
Supply chain consultant	1.761 (0.046)	–	–	–	–
Management assistant	1.560 (0.051)	2.545*** (0.011)	–	–	–
Salesperson	2.890 (0.037)	− 10.802*** (0.000)	− 10.875*** (0.000)	–	–
In between jobs	3.789 (0.045)	− 12.164*** (0.000)	− 12.079*** (0.000)	− 10.633*** (0.000)	–

Column (i) shows the mean and standard deviation (SD) for each treatment. Columns (ii)–(v) show results from Wilcoxon matched-pairs signed-rank test. A positive (negative) z-value indicates that the treatment status in the row is more (less) prestigious compared to the treatment status in the column. * (**) ((***)) indicates significance at the 10% (5%) ((1%)) level

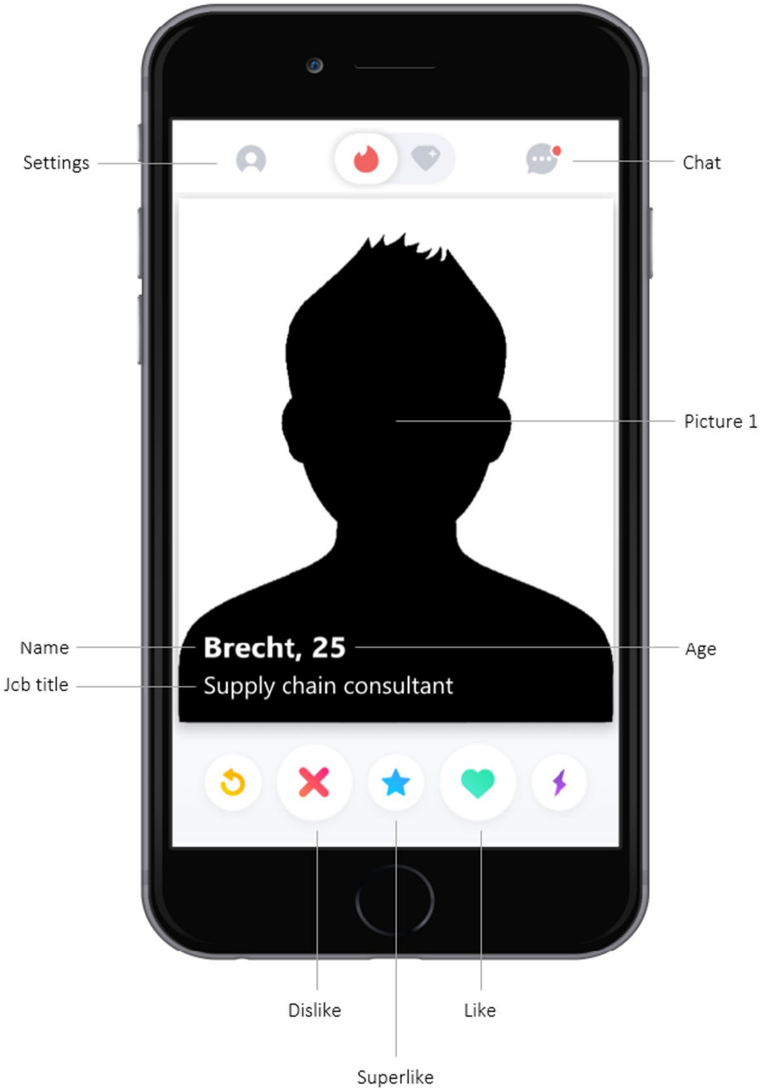

Fig. 1 Anonymous example of a fictitious profile

fourth most (i.e. least) prestigious ‘job’ and salesperson is perceived as the third most (i.e. second least) prestigious job. However, contrary to what we expected, management assistant is perceived as more prestigious compared to supply chain consultant. Therefore, we consider management assistant as the most prestigious job and supply chain consultant as the second most prestigious job. Additionally, column (ii) to column (v) of Table 2 reports Wilcoxon matched-pairs signed-rank tests that show that treatment statuses are perceived as statistically significantly different from each other.

The four experimental identities (i.e. unemployed, low-prestige job, medium-prestige job, and high-prestige job) were, city by city, randomly assigned to the aforementioned combinations of picture sets and names. Given this random assignment, small differences in attractiveness and other perceptions related to the pictures and names used could not bias our results (because correlation with job status and job prestige is ruled out by design). Additionally, we control by means of dummy variables for the pictures, names, and locations used in the field experiment.

Figure 1 portraits an anonymous example of one of our fictitious profiles. It shows that the treatment (job status or job prestige) is immediately (i.e. without the need to click through to the bio) and prominently visible on the first picture of the profile. Because of this prominence of the job status or job prestige, we assume that subjects will have seen it. However, as we could not verify with 100% certainty whether subjects indeed looked at the treatment given to each one or our fictitious profiles, throughout the manuscript treatment should be interpreted as an *intent* to treat.

Finally, we ensured a similar activity on Tinder with all of our fictitious profiles. We received no messages that indicated that the subjects (see also Subsect. 3.3) were aware of the field experiment, nor were our profiles reported to Tinder.

3.3 Subjects

In February and March 2018, with each one of our 32 fictitious profiles, we liked the first 150 other real Tinder users (hereafter: 'subjects') that fit our three criteria and were therefore presented to our fictitious profiles. This resulted in a sample size of 4800 subjects. Because in this study we focus on heterosexual dating outcomes, we indicated that we only wanted to see male (female) Tinder users with our female (male) fictitious profiles. As a result, the gender of the fictitious profiles automatically determines the gender of the subjects who will evaluate these fictitious profiles, preventing a direct comparison between male and female subjects, as they evaluate different fictitious profiles (i.e. female fictitious profiles and male fictitious profiles, respectively). However, we are able to estimate causal effects *within* (but not *between*) gender. Additionally, given that examining the evaluation of female (male) fictitious profiles by female (male) subjects is nonsensical in examining heterosexual partner preferences, we measure everything we want to measure. Also examining homosexual partner preferences would not solve this problem, as dynamics in homosexual dating can be expected to be different compared to dynamics in heterosexual dating. Although results from such analyses would be interesting, they are beyond the scope of this study.

Next, we indicated that we only wanted to see subjects between the ages of 23 and 27. We decided to not differ the age between the male and the female subjects, to be able to compare the evaluation of the fictitious profiles by male and female subjects at the same phase in their lives, i.e. the start of their professional careers.

Finally, we used the lowest possible distance (i.e. two kilometres) to ensure our fictitious profiles would show up in the stack of profiles evaluated by our subjects.

Table 3 presents summary statistics on all available information on our subjects. Column (1) shows that our subjects have on average 4.44 pictures in their profiles

Table 3 Summary statistics of the subjects for the full sample and by treatment status

Variable	Description	(1)	(2)	(3)	(4)	(5)
			By treatment status			
		Full sample	High JP	Medium JP	Low JP	Unemployed
		Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
Number of profile pictures	Continuous variable	4.436 (1.418)	4.442 (1.440)	4.373 (1.452)	4.431 (1.412)	4.498 (1.365)
Age	Continuous variable	24.657 (1.335)	24.642 (1.340)	24.661 (1.330)	24.656 (1.341)	24.667 (1.328)
Education displayed	1 if displayed, 0 otherwise	0.525 (–)	0.515 (–)	0.511 (–)	0.548 (–)	0.527 (–)
Education level	1 if high, 0 otherwise	0.589 (–)	0.621 (–)	0.582 (–)	0.574 (–)	0.581 (–)
Occupation displayed	1 if displayed, 0 otherwise	0.271 (–)	0.265 (–)	0.248 (–)	0.291 (–)	0.282 (–)
Occupation level	1 if high, 0 otherwise	0.337 (–)	0.368 (–)	0.329 (–)	0.330 (–)	0.322 (–)
Instagram account displayed	1 if displayed, 0 otherwise	0.189 (–)	0.194 (–)	0.193 (–)	0.183 (–)	0.184 (–)
Spotify account displayed	1 if displayed, 0 otherwise	0.197 (–)	0.212 (–)	0.200 (–)	0.184 (–)	0.193 (–)
N	Number of observations	4800	1200	1200	1200	1200

No standard deviations are presented for binary variables. The following abbreviation is used: JP (Job Prestige). Based on Bonferroni-corrected *p*-values on the differences between subjects by treatment status for each variable, we find no significant differences at the 10% confidence level (see also Table 8)

Table 4 Descriptive statistics

	(1) All subjects (N = 4800)	(2) Male subjects (N = 2400)	(3) Female subjects (N = 2400)
No match (proportion of all observations)	3188 (0.664)	939 (0.391)	2249 (0.937)
Match (proportion of all observations)	1612 (0.336)	1461 (0.609)	151 (0.063)
Conversation started (proportion of number of matches)	644 (0.400)	632 (0.433)	12 (0.079)

Absolute numbers are reported with the corresponding proportion of all observations in parentheses

and are on average 24.66 years old. Additionally, 52.5% (27.2%) of subjects report their education (occupation). Finally, 18.9% (19.7%) of subjects show their favourite photos on Instagram (favourite songs on Spotify). Column (2) to column (5) show that these summary statistics are very comparable across treatment status—job status and job prestige. To provide statistical evidence on this, we conducted t-tests with Bonferroni corrections for multiple testing to examine whether subjects differed on any variable that we had information on. In Table 8 we report the Bonferroni-corrected *p*-values on the differences between subjects with different treatment status for each variable. We find no significant differences at the 10% confidence level. Consequently, we are highly confident that subjects did not vary significantly across treatment status and that our randomisation procedure was therefore successful.

3.4 Outcomes

As with each one of our 32 profiles we only liked 150 subjects (and no others), we know whether or not these subjects liked our profiles because our profiles then had a match with these subjects or not. This—having a match or not—is our first outcome of interest. Consequently, our sample size consists of 4800 evaluations of our fictitious profiles by the subjects.[2] Additionally, as a second outcome of interest, we registered whether the subjects started a conversation with our profiles (conditional upon having a match with our profiles, which is a necessary prerequisite to start a conversation, see also Sect. 3.1).

Table 4 lists the descriptive statistics for these two outcome variables. First, when considering the number of matches for the full sample of male and female subjects, we see that our profiles received a like—and therefore matched with the subjects—in 33.6% of the cases. However, this overall statistic conceals remarkable differences

[2] It could be that subjects did not encounter our fictitious profiles because they – for example – were not active on Tinder anymore (without deleting their profile) or because they swiped too little so that they did not encounter our fictitious profiles. However, this should not bias results due to the randomisation strategy outlined in Sect. 3.2.

between the subsamples of male and female subjects: whereas male subjects liked our female profiles in 60.9% of the cases, female subjects liked our male profiles in only 6.3% of the cases. In addition, when examining whether subjects started a conversation with our profiles after obtaining a match, the results are similar: male subjects started a conversation with our female profiles in 26.3% of the cases (i.e. 43.3% of their matches), whereas female subjects only did so with our male profiles in 0.5% of the cases (i.e. 7.9% of their matches). This finding of more selectivity by the female subjects with respect to both outcome variables is in line with earlier evidence examining Tinder usage (Neyt et al., 2019; Tyson et al., 2016).

4 Results

In this section, we present the results of our field experiment. In Subsect. 4.1, we examine the impact of job status and job prestige on the probability of obtaining a match, our first outcome of interest. Next, in Subsect. 4.2, we investigate whether job status and job prestige are determinants of the probability that subjects start a conversation with our profiles (conditional on a match), our second outcome of interest.

4.1 Match Probability

Table 5 presents the results of bivariate analyses assessing the probability that our profiles obtain a match. More concretely, the first row of each panel compares the match probability of our profiles that were employed (column 1) with the match probability of our profiles that were unemployed (column 2). Column 3 features the ratio of these match probabilities with, in the numerator (denominator), the match probability of the employed profiles (unemployed profiles). Therefore, if the ratio of these two match probabilities (hereafter: 'match ratio') is above (below) 1, it means there exists a positive (negative) effect of being employed on the probability of obtaining a match. Similarly, the three subsequent rows of each panel compare the match probability of the profiles by job prestige. The profiles in the numerator (column 1) always have higher job prestige than the profiles in the denominator (column 2). Consequently, here too, a match ratio (column 3) above (below) 1 means there exists a positive (negative) effect of job prestige on the probability of obtaining a match.

None of the match ratios differ substantially or significantly from 1—neither for the full sample nor for the subsamples of male and female subjects. Hence, profiles that are employed do not have higher (or lower) chances of obtaining a match than profiles that are not employed. Additionally, the job prestige of our profiles does also not influence the chance of matching with another user.

Given the randomisation procedure outlined in Subsect. 3.2, the job status and job prestige of the profiles is orthogonal to the set of pictures used for each profile across cities. An implicit, but plausible, assumption for the measures in Table 5 to be unbiased is therefore that the dynamics in liking other profiles are comparable

Table 5 Match ratios by job status and job prestige of our profiles and by gender of the subjects

	(1) Match probability by job status/job prestige of our profiles (i)	(2) Match probability by job status/job prestige of our profiles (ii)	(3) Match ratio: (1)/(2) [χ^2]	(4) N
Panel A. All subjects				
Employed (i) vs. unemployed (ii)	0.336	0.336	1.000 [0.000]	4800
High (i) vs. medium (ii)	0.341	0.322	1.059 [0.995]	2400
High (i) vs. low (ii)	0.341	0.345	0.988 [0.046]	2400
Medium (i) vs. low (ii)	0.322	0.345	0.933 [1.470]	2400
Panel B. Male subjects				
Employed (i) vs. unemployed (ii)	0.610	0.605	1.008 [0.047]	2400
High (i) vs. medium (ii)	0.625	0.583	1.072 [2.178]	1200
High (i) vs. low (ii)	0.625	0.622	1.005 [0.014]	1200
Medium (i) vs. low (ii)	0.583	0.622	0.937 [1.841]	1200
Panel C. Female subjects				
Employed (i) vs. unemployed (ii)	0.062	0.067	0.925 [0.191]	2400
High (i) vs. medium (ii)	0.057	0.060	0.950 [0.061]	1200
High (i) vs. low (ii)	0.057	0.068	0.838 [0.697]	1200
Medium (i) vs. low (ii)	0.060	0.068	0.882 [0.347]	1200

See also Subsect. 3.2 for a description of the profiles in the 'unemployed' versus 'employed' (with 'high'-, 'medium'- or 'low'- prestige jobs) conditions. The χ^2-values are based on Chi-square tests. * (**) ((***)) indicates significance at the 10% (5%) ((1%)) confidence level between the subjects of the four Flemish cities. To relax this assumption, we present multivariate analyses with picture and city fixed effects.[3] We opt to use linear probability models with heteroscedasticity-robust standard errors instead of probit or logit models because including fixed effects in a probit or logit model may cause an incidental parameters problem (Greene, 2002). Additionally, the results of linear probability models are easier to interpret than probit or logit models. The findings from these multivariate analyses with respect to match probability are located in the first two columns of Table 6. In these analyses, the results from the bivariate analyses are confirmed: job status and job prestige do not determine success in the first stage of the dating process on Tinder, i.e. matching with another user.

The findings from our analyses examining the chances of obtaining a match are in agreement with H1: male subjects do not have a higher preference for female Tinder users with a (prestigious) job. However, our findings are not in accordance with H2 as female subjects also do not have a higher preference for male Tinder users if these users have a (prestigious) job. However, it could be that (female) subjects make their decision on whom to date later in the dating process. We examine this suggestion in the next subsection, where we look at the probability that subjects start a conversation with our profiles.

4.2 Conversation Probability

In this subsection, we determine whether job status and job prestige impact the probability that the subjects start a conversation with our profiles conditional on an established match (see also Subsect. 4.1). We do this again by discussing results from bivariate analyses complemented with results from multivariate analyses. The results from the bivariate analyses can be found in Table 7. Similar to Table 5, column 3 presents 'conversation ratios': the ratio between the probabilities that the subjects start a conversation with our profiles with diverging job status and job prestige levels (conditional on having a match with these profiles).

From the bivariate analyses, we see that male subjects more often start a conversation with our female profiles when these females are employed compared to when they are unemployed—21.9% more often to be precise.[4] This difference is statistically significant at the 5% confidence level. However, conditional upon our female profiles being employed, males still do not have a significant preference for our female profiles that have more prestigious jobs.

For our female subjects, the conversation ratio for profiles with different job status (job prestige) is below (above) 1, but does not significantly differ from 1 because of—very—high standard errors. These high standard errors are due to the very

[3] Some estimates for these fixed effects are statistically significantly different from zero. This is probably due to preferences of our (mainly Flemish) subjects to be different from preferences of the (mainly American) respondents who rated the pictures (see also Subsect. 3.2) or due to the variation in attractiveness that is left between the pictures used for the fictitious profiles. However, this does not bias results due to our randomisation strategy also outlined in Subsect. 3.2.

[4] These analyses survive a correction for multiple hypotheses testing.

Table 6 Outcome probability by job status and job prestige of our profiles and by gender of the subjects: linear probability models

	(1)	(2)	(3)	(4)
Outcome variable	Match probability		Conversation probability	
Explanatory variable of interest	Job status	Job prestige	Job status	Job prestige
Panel A. All subjects				
Employed	0.000 (0.013)	–	0.052* (0.027)	–
Unemployed	Ref	–	Ref	–
High	–	−0.004 (0.015)	–	0.003 (0.034)
Medium	–	−0.023 (0.016)	–	0.019 (0.034)
Low	–	Ref	–	Ref
Dummy for female respondent	−0.612*** (0.022)	−0.627*** (0.025)	−0.428*** (0.054)	−0.411*** (0.068)
Picture set fixed effects	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes
N	4800	3600	1612	1209
Panel B. Male subjects				
Employed	0.005 (0.023)	–	0.064** (0.029)	–
Unemployed	Ref	–	Ref	–
High	–	0.003 (0.028)	–	−0.004 (0.037)
Medium	–	−0.038 (0.028)	–	0.008 (0.037)
Low	–	Ref	–	Ref
Picture set fixed effects	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes
N	2400	1800	1461	1098
Panel C. Female subjects				
Employed	−0.005 (0.012)	–	−0.057 (0.056)	–
Unemployed	Ref	–	Ref	–
High	–	−0.012 (0.014)	–	0.009 (0.041)
Medium	–	−0.008 (0.014)	–	0.083 (0.075)
Low	–	Ref	–	Ref
Picture set fixed effects	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes
N	2400	1800	151	111

The dependent variable in columns 1 and 2 (columns 3 and 4) is 0 if there is no match (no conversation) and 1 if there is a match (a conversation). See also Subsect. 3.2 for a description of the profiles in the 'unemployed' versus 'employed' (with 'high'-, 'medium'- or 'low'- prestige jobs) conditions. Statistics are coefficients with robust standard errors between parentheses. * (**) ((***)) indicates significance at the 10% (5%) ((1%)) confidence level. The following abbreviation was used: Ref. (Reference)

Table 7 Conversation ratios by job status and job prestige of our profiles and by gender of the subjects

	(1) Conversation probability by job status/job prestige of our profiles (i)	(2) Conversation probability by job status/job prestige of our profiles (ii)	(3) Conversation ratio (1)/(2) [χ^2]	(4) N
Panel A. All subjects with a match				
Employed (i) vs. unemployed (ii)	0.417	0.347	1.202** [6.082]	1612
High (i) vs. medium (ii)	0.408	0.438	0.932 [0.709]	795
High (i) vs. low (ii)	0.408	0.405	1.007 [0.005]	800
Medium (i) vs. low (ii)	0.438	0.405	1.081 [0.840]	823
Panel B. Male subjects with a match				
Employed (i) vs. unemployed (ii)	0.452	0.375	1.219** [6.603]	1461
High (i) vs. medium (ii)	0.440	0.469	0.938 [0.596]	725
High (i) vs. low (ii)	0.440	0.448	0.982 [0.045]	723
Medium (i) vs. low (ii)	0.469	0.448	1.047 [0.316]	748
Panel C. Female subjects with a match				
Employed (i) vs. unemployed (ii)	0.072	0.100	0.720 [0.314]	151
High (i) vs. medium (ii)	0.059	0.139	0.424 [1.246]	70
High (i) vs. low (ii)	0.059	0.024	2.458 [0.574]	77
Medium (i) vs. low (ii)	0.139	0.024	5.792* [3.498]	75

See also Subsect. 3.2 for a description of the profiles in the 'unemployed' versus 'employed' (with 'high'-, 'medium'- or 'low'- prestige jobs) conditions. The χ^2-values are based on Chi-square tests. * (**) indicates significance at the 10% (5%) confidence level limited variation in this subsample because of the high selectivity of females in the dating process, in general, and on Tinder, in particular (see also Subsect. 3.4). Indeed, only very few female subjects start a conversation with our male profiles—12 to be precise—and therefore no precise conversation ratios could be calculated for this subsample.

The results from the multivariate analyses are presented in the last two columns of Table 6. For our male subjects, these regression analyses confirm our bivariate analyses. The probability with which male subjects start a conversation after liking our female profiles decreases by 6.4 percentage points when these females are unemployed, but these male subjects do not care about the job prestige of the female profiles if these females are employed. Again, because of the more passive role of females in (mobile) dating, for the subsample of female subjects, we could not precisely estimate the impact of job status or job prestige of our male profiles on the probability that female subjects start a conversation with them because there was too little variation in the data.

The finding that job status influences males' decision to start a conversation with a female Tinder user, whereas this is not the case when deciding whom to like (see also Subsect. 4.1), indicates that males are not yet selective when swiping but start being selective when deciding whom to start a conversation with. Further, this finding provides evidence that males only take into account job status but not job prestige. Indeed, although they more often start a conversation with female Tinder users in cases these females were employed, they do not care how prestigious the job was that these females held. This suggests that males do not want their potential future partner to be (completely) dependent on them financially, although they do not care how high the earnings potential of that partner is. An alternative explanation is that under the assumption that being on the receiving end of a started conversation is more comfortable than starting a conversation oneself, males may anticipate unemployed females to start the conversation more often because these females might have a greater need to find a potential partner.

5 Conclusion

In this study, we examined whether partner preferences identified in offline dating survive on the increasingly popular mobile dating apps. More specifically, we analysed whether earnings potential—signalled through one's job—determines success on the mobile dating app Tinder. We did this by means of a field experiment on Tinder in which we randomly assigned job status and job prestige to fictitious Tinder profiles and monitored their match success with real Tinder users by these two dimensions. Thereby, we contributed to the literature in two important ways. First, we shed light on the returns to job status and job prestige in a setting that takes a central position in contemporary pastime, in general, and couple formation, in particular. Second, from a broader perspective, we investigated human partner preferences in a framework with fewer search or social frictions than in offline dating and on classic online dating websites; thus, the preferences measured in this study can be seen as revealing more genuine preferences compared to the stated preferences measured in former studies relying on data from offline dating behaviour.

We found that in the first stage of the dating process on Tinder (i.e. when deciding on whether to like another user), both males and females do not care whether other users have a job, nor do they care about their job prestige if those other users are employed. However, during the second stage (i.e. when deciding whether to start a conversation with a Tinder match and potentially organise a date), we established that males less often start a conversation when the female user does not have a job. Again, conditional on females having a job, differences between females in job prestige did not influence males' decision to start a conversation with these females. These findings suggest that males do not want females to be (completely) financially dependent on them but do not care about the particular earnings potential of females. An alternative explanation is that males expect unemployed females to start the conversation more often as these females may have a greater need to find a potential partner. Overall, our results diverge from those in peer-reviewed literature on human partner preferences in classic (offline) dating contexts and on the historical returns to labour market status (by gender) in the marriage market.

We end this study by acknowledging the main limitations of our research design. First, owing to the high(er) threshold for women to like another Tinder user, a phenomenon that is concordant with females' higher selectivity in other forms of (online) dating, we could not estimate precise results for the drivers of the probability that females start a conversation with males on Tinder. Future research should attempt to also present results with respect to this outcome by setting up an even larger field experiment than ours, or, given the ethical concerns imposing restrictions to this scale, opt for overall more attractive male potential dating partners. The latter option will, however, decrease comparability with the current study as it would—by design—differ with respect to the overall attractiveness of the male fictitious profiles.

Second, we only examined the first stages of the dating process (i.e. showing interest in someone and starting a conversation on a mobile dating app). We could not analyse whether the partner preferences identified in these first stages are also valid in the later phases of dating. However, we argue that findings about partner preferences in the first stages of the dating process are interesting because each mobile dating app user needs to pass these first stages in order to progress to the next phases of dating. Still, we are in favour of future research that adds to the literature on partner preferences by examining whether job status and/or job prestige causally impact the long-term success of relationships initiated on mobile dating apps.

Third, in this study we examine one of the two components of parental investment theory, i.e. whether earnings potential is a driver of success on mobile dating apps. It would be equally interesting to explicitly examine the impact of the other component of parental investment theory, i.e. physical attractiveness, on success on mobile dating apps. We suggest examining the impact of this characteristic—and of course of others—as a potential avenue for future research.

Fourth, we were not able to analyse whether partner preferences on Tinder were driven by assortative mating. Such mating involves the pairing of individuals who are similar to each other according to one or more characteristics (Buss, 1985). In the context of our study, it would mean that individuals with similar job status or job prestige would significantly more often show interest in each other than individuals who differed in these characteristics. In our dataset, for 27.2% of the subjects we could allocate their employment to either low or high job prestige. This reduced our sample size by too much to estimate precise results regarding assortative mating based on job status or job prestige. However, we encourage future studies to assess whether the assortative mating found in offline contexts is also a driver of dating success in present-day online settings with fewer search and social frictions.

Finally, this study examines *whether* job status and job prestige are determinants of success on the mobile dating app Tinder. Future research should build on this study by also examining *when* (i.e. what are moderating characteristics) and *why* (i.e. what are mediating characteristics) this is the case. This was not possible given the research design of the current study but could be examined by—for example—lab experiments and vignette studies.

Appendix

See Table 8.

Table 8 Bonferroni-corrected p-values for t-tests measuring the difference between subjects by treatment status

Variable	(1) H JP vs. M JP	(2) H JP vs. L JP	(3) H JP vs. Unem	(4) M JP vs. L JP	(5) M JP vs. Unem	(6) L JP vs. Unem
Number of profile pictures	1.000	1.000	0.184	1.000	1.000	1.000
Age	1.000	1.000	1.000	1.000	1.000	1.000
Education displayed	1.000	0.395	1.000	0.613	1.000	1.000
Education level	0.988	1.000	1.000	0.534	0.865	1.000
Occupation displayed	1.000	0.115	0.398	0.928	1.000	1.000
Occupation level	1.000	1.000	1.000	1.000	1.000	1.000
Instagram account displayed	1.000	1.000	1.000	1.000	1.000	1.000
Spotify account displayed	1.000	1.000	1.000	0.543	1.000	1.000

The following abbreviations are used: H (High), M (Medium), L (Low), Unem. (Unemployed), JP (Job Prestige). * (**) ((***)) indicates significance at the 10% (5%) ((1%)) confidence level

Declarations

Conflict of interest The authors have no conflict of interest to declare that are relevant to the content of this article. No funding was received for conducting this study.

Ethical approval The present research was approved by the Ethical Committee of the Faculty of Economics and Business Administration of Ghent University.

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