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JOB PRESTIGE AND MOBILE DATING SUCCESS: A FIELD EXPERIMENT

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Job Prestige and Mobile Dating Success: A Field Experiment*

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Abstract

Research exploiting data on classic (offline) couple formation has confirmed predictions from evolutionary psychology in a sense that males attach more value to attractiveness and women attach more value to earnings potential. We examine whether these human partner preferences survive in a context of fewer search and social frictions. We do this by means of a field experiment on the mobile dating app Tinder, which takes a central place in contemporary couple formation. Thirty-two fictitious Tinder profiles that randomly differ in job status and job prestige are evaluated by 4,800 other, real users. We find that both males and females do not use job status or job prestige as a determinant of whom to show initial interest in on Tinder. However, we do see evidence that, after this initial phase, males less frequently begin a conversation with females when those females are unemployed but also then do not care about the particular job prestige of employed females.

Keywords: job prestige; partner preferences; dating apps; online dating; Tinder.

JEL: J12, J16, J13, C93.

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1 Introduction

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, Iyengar, Kamenica & Simonson, 2006; Geary, Vigil & Byrd-Craven, 2004; Stewart-Williams & Thomas, 2013; Webster, Jonason & Schember, 2009). Because the contribution to 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). Due to the fact 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 who they perceive to be highly fertile). Youth and attractiveness are strong cues for this fertility so that males have, in line with evolutionary psychology, a mate preference for young and attractive females (Buss, 1989; Geary et al., 2004; Hatfield & Sprecher, 1995; Li, Bailey, Kenrick & Linsenmeier, 2002; Miller, 2000). In contrast, whereas the contribution of males to the reproduction of offspring is rather limited, females expect them to compensate for this investment discrepancy by providing resources for offspring during their childhood. Because females gauge males' ability to provide these resources by—among others—males' earnings capacity, they have a mate 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, while they are neutral—or even negative—for women (Bertrand, Kamenica & Pan, 2015; Bursztyn, Fujiwara & Pallais, 2017).

Today, the question presents itself whether these partner preferences 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. Indeed, multiple studies have shown that approximately one in five committed relationships and one in six marriages over the past decade have begun through online dating (Cacioppo, Cacioppo, Gonzaga, Ogburn & VanderWeele, 2013; Chadwick Martin Bailey, 2010; Rosenfeld & Thomas, 2012; Statistic Brain Research Institute, 2017). 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, Baumann, Krasnova and Buxmann (2016) for a structured overview of research on these partner preferences on classic online dating websites. However, to the best of our knowledge, no study to date has examined whether these partner preferences are still present on the increasingly popular mobile dating apps, of which Tinder, with its more than 50 million active users is the most popular (Tinder, 2019).

In this study, we fill this gap within the literature. More specifically, we determine whether on Tinder, males and females differ in the extent to which they attach value to the earnings potential of potential partners. We do this by transposing the golden standard framework used in labour economics to measure hiring discrimination (i.e. the correspondence experimentation framework (Baert, 2018; Bertrand & Mullainathan, 2004; Eriksson & Rooth, 2014; Neumark, 2018)) to the Tinder setting. That is, we conduct a field experiment on Tinder in which we randomly vary both job status (being unemployed or being employed) and job prestige across fictitious (heterosexual) Tinder profiles, which randomly like 4,800 other real Tinder users. By monitoring the subsequent number of matches for our fictitious profiles, we are able to estimate the effect of job status and job prestige on match probability and give this effect a causal interpretation.

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' mate preferences are *not* influenced by the job status or job prestige of female Tinder users.

H2. Female Tinder users' mate preferences are influenced by the job status or job prestige of male Tinder users.

However, there are two main reasons to believe 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 *true* partner preferences through the revealed interest Tinder users show in our fictitious profiles. Because multiple studies have shown that stated partner preferences may differ from true partner preferences (Eastwick & Finkel, 2008; Todd, Penke, Fasolo & Lenton, 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 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, Hortaçsu & Ariely, 2010; Neyt, Vandenbulcke & Baert 2019). However, on Tinder showing interest in another person only takes a few seconds and is done anonymously. As a consequence, both time costs and psychological costs are (nearly) non-existent in the Tinder setting; therefore, true preferences might come to the fore more readily.

The remainder of this article is structured as follows. In Section 2, we elaborate on how Tinder works and how we used this platform to conduct our field experiment. In Section 3, we present the results of this experiment. Section 4 concludes and indicates several limitations of this study as well as interesting directions for future research.

2 Methods

2.1 Tinder

The impact of the online dating app Tinder on the time allocation and couple formation in the OECD world, particularly in the 18-to-35 age range, can hardly be overestimated. Tinder is the most popular dating app for iOS and Android, with more than 100 million downloads and more than 10 million daily active users in more than 190 countries, and in August 2018, Tinder even 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, Vandenbosch & Ligtenberg, 2017; Tinder, 2019). Already in 2014, the average Tinder user logged into the app 11 times a day and spent around 1.5 hours on the app daily. Today, Tinder users evaluate more than 2 billion other users per day, which facilitates more than 1 million offline dates per week (Neyt et al., 2019; Smith, 2016; Tinder, 2019; 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 is not the case. For instance, 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 lead to a committed relationship. Finally, 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. Therefore, even if relationships initiated on Tinder would ultimately be mainly casual, Neyt et al. (2019) argue that investigating the determinants of successfully initiating these casual relationships is still of high interest. Moreover, beyond Tinder's central place in contemporary couple formation, investigating the determinants of Tinder success is relevant given the platform's aforementioned popularity and the worldwide time investment in this app.

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. It is also possible to create a Tinder profile through a mobile phone number, but this option is not often chosen because in that case users also have to input their name and age manually. After a profile is created, users can complete their profile with up to six pictures, a short bio, their education level and their job. 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 (in kilometres).

Then, users get shown, one by one, every Tinder user that fits their three criteria. Through swiping, they indicate anonymously 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 will they match and have the possibility to start a conversation with each other (Tinder, 2019; Ward, 2016).

2.2 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 and sent to genuine 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 aspects of job status or job prestige to fictitious Tinder profiles to investigate the causal impact of these aspects on their popularity with other genuine Tinder users. Thus, our study is close to that of Neyt et al. (2019), who conducted a field experiment with 3,600 fictitious profile evaluations to investigate the returns to education on

Tinder.

More concretely, we created 32 fictitious Tinder profiles—16 with a male gender and 16 with a female gender. 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 level 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 about here >

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. 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 genuine 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. Then, we chose eight people—four male and four female—who were similar in attractiveness to use in our fictitious profiles.

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', which was the most common way to signal unemployment within a random sample of 250 Flemish Tinder users in the 23-to-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 in the three different jobs, with higher paying jobs representing more prestigious jobs. The job titles, 'supply chain consultant', 'management assistant' and 'salesperson' were used to indicate high, medium and low job prestige, respectively. We opted for jobs in commerce 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, De Pauw and Deschacht (2016). 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). Following glassdoor.be, where current and former employees anonymously review companies, the average salary in these functions is 1522 euro, 2069 and

2150 euro per month, respectively.

The four experimental identities (i.e. unemployed, low-prestige job, medium-prestige job and low-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).

2.3 Subjects

With each one of our 32 fictitious profiles, we liked 150 other real Tinder users (hereafter: 'subjects') that fit our three criteria in February and March 2018. This resulted in a sample size of 4,800 evaluations of our profiles by the subjects.

Because in this study, we focus on heterosexual relationships, we indicated that we only wanted to see male (female) Tinder users with our female (male) profiles. Second, we indicated that we only wanted to see subjects between the ages of 23 and 27—the average age of our subjects was 24.657 (SD = 1.335). Third, we used the lowest possible distance (i.e. two kilometres).

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

2.4 Outcomes

As with each one of our 32 profiles we only liked 150 subjects (and no others), we know whether these subjects liked our profiles because our profiles then had a match with these subjects. This—having a match or not—is our first outcome of interest. 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 earlier).

Table 2 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 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).

< Table 2 about here >

This finding of more selectivity by the female subjects with respect to both outcome variables is in line both with earlier evidence examining Tinder usage (Neyt et al., 2019; Tyson, Perta, Haddadi & Seto, 2016) and with parental investment theory (Geary, 2000; Trivers, 1972). This theory argues that because the parental investment is much larger for females than for males—the reproductive process requires little male investment, whereas a female invests nine months' worth of time, energy and resources (Buss, 1989). As a consequence, females become an important reproductive resource for males. Therefore, on the one hand, males have to compete with other males for the females, in turn being less selective to secure a partner. On the other hand, owing to being in high demand, females can be picky and will choose the male with the best reproductive capacities and (potential) resources to maximise the quality and survival chances of potential future offspring.

3 Results

In this section, we present the results of our field experiment. In Subsection 3.1, we examine the impact of job status and job prestige on the probability of obtaining a match. Next, in Subsection 3.2, we investigate whether job status and/or job prestige are determinants of the probability that subjects start a conversation with our profiles (conditional on a match).

3.1 Match probability

Table 3 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.

< Table 3 about here >

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 not influence the chance of matching with another user.

Given the randomisation procedure outlined in Subsection 2.2, 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 3 to be unbiased is therefore that the dynamics in liking other profiles are comparable between the subjects of the four Flemish cities. To relax this assumption, we present multivariate analyses with picture and city fixed effects. 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 Panel I of Table 4. 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).

< Table 4 about here >

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 subjects make their decision on whom to date later in the dating process on Tinder. We examine this suggestion in the next subsection, where we look at the probability that subjects start a conversation with our profiles.

3.2 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 Subsection 3.1). 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 5. Similar to Table 3, 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 liked these profiles).

< Table 5 about here >

From the bivariate analyses, we see that male subjects more often start a conversation with our female profiles when these females are employed compared with when they are unemployed—21.9% more often to be precise. This difference is statistically significant at the 5% significance 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 based on the limited variation in this subsample because of the high selectivity of females in the dating process, in general, and on Tinder, in particular (see Subsection 2.4). 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 Panel II of Table 4. 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 Subsection 3.1), indicates that males are not yet selective when *swiping* but start being selective when deciding with whom to start a conversation. 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.

4 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 genuine 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, and gender differences therein, 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 eventually organise a date), we established that males do so less often 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. 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 our male profiles. 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.

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 a relationship. However, we argue that findings about partner preferences in the first stages of a relationship are interesting because each mobile dating app user needs to pass these first stages in order to progress to the next phases of a relationship. 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.

Finally, 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, 39.9% of subjects reported their employment and in 27.1% of the cases, we could allocate this 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.

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

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

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

Notes. 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).

Table 2. Descriptive statistics.

	(1) **All subjects** **(N = 4,800)**	(2) **Male subjects** **(N = 2,400)**	(3) **Female subjects** **(N = 2,400)**
No match (proportion of all observations)	3,188 (0.664)	939 (0.391)	2,249 (0.937)
Match (proportion of all observations)	1,612 (0.336)	1,461 (0.609)	151 (0.063)
Conversation started (proportion of number of matches)	644 (0.134)	632 (0.263)	12 (0.005)

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

Table 3. 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
A. All subjects				
Employed (i) vs. unemployed (ii)	0.336	0.336	1.000 [0.000]	4,800
High (i) vs. medium (ii)	0.322	0.341	0.944 [0.995]	2,400
High (i) vs. low (ii)	0.322	0.345	0.933 [1.470]	2,400
Medium (i) vs. low (ii)	0.341	0.345	0.988 [0.046]	2,400
B. Male subjects				
Employed (i) vs. unemployed (ii)	0.610	0.605	1.008 [0.047]	2,400
High (i) vs. medium (ii)	0.583	0.625	0.933 [2.178]	1,200
High (i) vs. low (ii)	0.583	0.622	0.937 [1.841]	1,200
Medium (i) vs. low (ii)	0.625	0.622	1.005 [0.014]	1,200
C. Female subjects				
Employed (i) vs. unemployed (ii)	0.062	0.067	0.925 [0.191]	2,400
High (i) vs. medium (ii)	0.060	0.057	1.053 [0.061]	1,200
High (i) vs. low (ii)	0.060	0.068	0.882 [0.347]	1,200
Medium (i) vs. low (ii)	0.057	0.068	0.838 [0.697]	1,200

Notes. See Subsection 2.2 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.

Table 4. Outcome probability by job status and job prestige of our profiles and by gender of the subjects: linear probability models.

	Panel I: Match probability		Panel II: Conversation probability	
	(1)	(2)	(3)	(4)
A. All subjects				
Employed	0.000 (0.013)	-	0.052* (0.027)	-
Unemployed	Ref.	-	Ref.	-
High	-	-0.023 (0.016)	-	0.019 (0.034)
Medium	-	-0.004 (0.015)	-	0.003 (0.034)
Low	-	Ref.	-	Ref.
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	4,800	3,600	1,612	1,209
B. Male subjects				
Employed	0.005 (0.023)	-	0.064** (0.029)	-
Unemployed	Ref.	-	Ref.	-
High	-	-0.038 (0.028)	-	0.008 (0.037)
Medium	-	0.003 (0.028)	-	-0.004 (0.037)
Low	-	Ref.	-	Ref.
Picture set fixed effects	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes
N	2,400	1,800	1,461	1,098
C. Female subjects				
Employed	-0.005 (0.012)	-	-0.057 (0.056)	-
Unemployed	Ref.	-	Ref.	-
High	-	-0.008 (0.014)	-	0.083 (0.075)
Medium	-	-0.012 (0.014)	-	0.009 (0.041)
Low	-	Ref.	-	Ref.
Picture set fixed effects	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes
N	2,400	1,800	151	111

Notes. The dependent variable in Panel I (Panel II) is 0 if there is no match (no conversation) and 1 if there is a match (a conversation). See Subsection 2.2 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%)) level.

Table 5. 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
A. All subjects with a match				
Employed (i) vs. unemployed (ii)	0.417	0.347	1.202** [6.082]	1,612
High (i) vs. medium (ii)	0.438	0.408	1.074 [0.709]	795
High (i) vs. low (ii)	0.438	0.405	1.081 [0.840]	800
Medium (i) vs. low (ii)	0.408	0.405	1.007 [0.005]	823
B. Male subjects with a match				
Employed (i) vs. unemployed (ii)	0.452	0.375	1.219** [6.603]	1,461
High (i) vs. medium (ii)	0.469	0.440	1.066 [0.596]	725
High (i) vs. low (ii)	0.469	0.448	1.047 [0.316]	723
Medium (i) vs. low (ii)	0.440	0.448	0.982 [0.045]	748
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)	0.139	0.059	2.356 [1.246]	70
High (i) vs. low (ii)	0.139	0.024	5.792* [3.498]	77
Medium (i) vs. low (ii)	0.059	0.024	2.458 [0.574]	75

Notes. See Subsection 2.2 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%) level.