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ABSTRACT

Education Level and Mating Success: Undercover on Tinder*

In this study, we examine the impact of an individual's education level on her/his mating success by means of a field experiment on the mobile dating app Tinder, using a sample of 3,600 profile evaluations. In line with previous studies from the field of evolutionary psychology, our results indicate a heterogeneous effect of education level by gender: while females strongly prefer a highly educated potential partner, we cannot accept this hypothesis for males. Additionally, in contrast with previous literature on partner choice in an offline context and on classic online dating websites, we do not find any evidence for educational assortative mating, i.e. preferring a partner with a similar education level, on mobile dating apps such as Tinder. We argue that this is due to our research design, which allows us to examine actual (instead of stated) mate preferences in a dating market without search frictions and social frictions.

JEL Classification: C93, I26, J12

Keywords: returns to education, mating success, assortative mating, dating apps, Tinder

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1. Introduction

The way we find our life partner has drastically changed over the last few decades. Indeed, before the Internet, i.e. around 25 years ago, no one could find their significant other online; however, 22% of couples met each other this way by 2009, making it the third most likely way of meeting a partner, following closely behind meeting through friends (28%) or at a bar/restaurant (23%) (Rosenfeld & Thomas, 2012). Additionally, one third of marriages initiated between 2005 and 2012 in the US started online, and half of these started through online dating (Cacioppo, Cacioppo, Gonzaga, Ogburn, & VanderWeele, 2013). In the future, these figures are only expected to increase, as online dating has been losing its social stigma (Finkel, Eastwick, Karney, Reis, & Sprecher, 2012; Smith & Duggan, 2013), not in the least due to the recent advent of extremely popular mobile dating apps such as Tinder (Ward, 2016; Ranzini & Lutz, 2017), which is the app we consider in this study.

The popularity of Tinder in the present dating landscape is apparent from the fact that in August 2018 it became the number one app people log into with their Facebook account, beating other apps like YouTube, Spotify, and Candy Crush Saga (Fruhlinger, 2018). Additionally, it is the most popular dating app for iOS and Android, with more than 100 million downloads and more than 10 million daily active users (Sumter, Vandenbosch, & Ligtenberg, 2017) in more than 190 countries (About Tinder, 2018). Therefore not surprisingly, Tinder is currently valued at at least $3 billion (Kuchler, 2018). Further, also in terms of the user's time investment, Tinder is one of the most engaging apps. Indeed, according to an interview with Tinder's executives in The New York Times in 2014, the average Tinder user logs into the app 11 times a day and spends around 1.5 hours on the app daily (Ward, 2016). Finally, in terms of couple formation Tinder also plays a significant role nowadays. For example, as of this writing, Tinder users swipe 1.6 billion times per day, which already has resulted in more than 20 billion matches in total since its launch in 2012, in turn facilitating around 1 million offline dates per week (About Tinder, 2018).

Despite the ubiquitousness of mobile dating apps such as Tinder, no study to date has examined mating behaviour[1] on these apps. The present study contributes to the previous literature on mating behaviour by examining the impact of an individual's education level on

[1] In this study, we define 'mating behaviour' as the behaviour of individuals in any stage of the dating process, ranging from the first contact to the initiation of a casual or committed relationship.

her/his mating success[2] on the mobile dating app Tinder. Simultaneously, we add to the literature examining the (non-monetary) returns to education. In contrast to most other studies examining the impact of education level on mating success in an offline setting and on classic online dating websites,[3] we do this by means of a correspondence experiment, which allows us to estimate causal effects. Apart from this methodological contribution, our study offers several theoretical contributions. First, our unique experimental design allows us to examine actual revealed mate preferences instead of stated mate preferences, which have been shown to exhibit substantial differences (infra, Section 2). Second, we are able to estimate the impact of education level on mating success in the absence of both search frictions and social frictions. While search frictions influence partner choice as a consequence of increased contact opportunities between individuals who are similar on various characteristics (such as education level), social frictions affect mating behaviour through the psychological cost of being rejected.

The remainder of this article is structured as follows. In the next section we summarise the theoretical foundations for this study. In Section 3, we elaborate on the features of our correspondence experiment and in Section 4 we present and discuss the results of our analyses. Section 5 concludes and indicates several limitations of this study and formulates various directions for future research.

2. Theoretical Framework

This study adds to two bodies of literature. First, it adds to the literature examining the returns to education. Previous studies on this topic mainly examined the impact of education on monetary outcomes such as earnings, finding a positive effect (Card & Krueger, 1992; Psacharopoulos & Patrinos, 2004; Jensen, 2010). However, a few other studies examined the impact of education on non-monetary returns, such as, among many others,[4] health behaviour and health status (Cutler & Lleras-Muney, 2006), happiness (Oreopoulos & Salvanes, 2009; Chen, 2012; Cuñado & de Gracia, 2012), and criminal behaviour (Buonanno & Leonida, 2009; Oreopoulos & Salvanes, 2009; Groot & van den Brink, 2010; Machin, Marie,

[2] Similar to the definition of 'mating behaviour' (see footnote 1), in this study we define 'mating success' as the success of individuals in any stage of the dating process, ranging from the first contact to the initiation of a casual or committed relationship.
[3] Such websites include Match.com, PlentyOfFish, and OkCupid.
[4] See Vila (2000), Owens (2004), and Hout (2012) for more extensive reviews on the non-monetary returns to education.

& Vujić, 2011), all of which improved with a higher education level. The present study adds to this second branch of studies in the returns to education literature, examining the returns on the non-monetary outcome mating success.

Second, we add to the literature examining mating behaviour, which in the past focussed on partner choice in an offline setting and on classic online dating websites. In an offline setting, Buss and Barnes (1986) found that males value physical attractiveness more than females when choosing a partner, while females have a higher preference than males for highly educated partners and partners with a high earning potential. Multiple studies have shown this sex difference in mate preferences using different data and different methods (see Shackelford, Schmitt, and Buss (2005) for an overview). Additionally, Buss et al. (1990) have shown this is a universal phenomenon by finding this sex difference in mate preferences with data from 33 countries on six continents. These findings from evolutionary psychology suggest that mate preferences are driven by a potential partner's reproductive capacity. More specifically, on the one hand a woman's reproductive value is signalled by greater physical attractiveness, indicating a higher fertility. On the other hand, a man's reproductive capacity can be evaluated by his potential to provide (financially) for future offspring, which is signalled by (among others) his education level. Also using data from classic online dating websites, previous studies have found evidence for this higher male preference for attractiveness and higher female preference for earning potential and education level (Hitsch, Hortaçsu, & Ariely, 2010a, 2010b; Egebark et al., 2017). Additionally, Whyte, Chan, and Torgler (2018) showed that women (compared with men) are almost twice as likely to state a preference for a certain education level in a potential partner and that women state a higher minimum acceptable education level in a preferred partner. Based on these earlier theoretical reasonings and empirical findings on mating behaviour and assuming that on Tinder this mating behaviour is similar, we formulate the following two hypotheses:

H1a: Male Tinder users do not have a higher preference for highly educated potential partners.

H1b: Female Tinder users do have a higher preference for highly educated potential partners.

The assumption that mating behaviour on Tinder is similar to that in offline dating and on classic online dating websites would be violated if on Tinder only casual and short relationships are formed in the majority of cases.[5] However, although for some Tinder indeed has the connotation of being used mainly to solicit casual and short relationships (Ward, 2017), multiple independent studies have indicated that this is not the case (LeFebre, 2017; Sumter et al., 2017; Timmermans & De Caluwé, 2017; Timmermans & Courtois, 2018). Indeed, Sumter et al. (2017) and Timmermans and De Caluwé (2017) both showed that the casual sex motive for using Tinder ranks well behind the motive for finding a committed relationship. Further, Timmermans and Courtois (2018) found that more than a quarter of offline Tinder encounters led to a committed relationship. Finally, although Timmermans and Courtois (2018) report that one third of offline Tinder encounters led to casual sex, they argue that casual sex could eventually lead to a committed relationship. This is especially true in today's society in which a relationship is increasingly initiated by a sexual encounter (Bogle, 2008; Wade, 2017).

Many studies examining mating behaviour found evidence for assortative mating, which is defined by Buss (1985, p. 47) as 'the coupling of individuals based on their similarity on one or more characteristics'. Indeed, previous research on assortative mating has identified this sorting behaviour on a large number of characteristics, ranging from age, religion, and political orientation (Watson et al., 2004) to body mass index (Silventoinen, Kaprio, Lahelma, Viken, & Rose, 2003) and even non-obvious physical traits such as nose breadth and earlobe length (Spuhler, 1968).[6] In this study we add to this literature by examining for the first time whether assortative mating based on education level is present on mobile dating apps such as Tinder.

Earlier research has already examined the presence of educational assortative mating using data on marriages and data from classic online dating websites. In an offline setting, many studies have shown that marriages in which the partners have a comparable education level occur significantly more often than would be predicted by chance alone (Rockwell, 1976; Mare, 1991; Pencavel, 1998; Watson et al., 2004; Blossfeld, 2009; Domingue, Fletcher, Conley, & Boardman, 2014). Similarly, using data from classic online dating websites, the preference for a partner with a comparable education level has again been shown by multiple authors (Hitsch et al., 2010a, 2010b; Skopek, Schulz, & Blossfeld, 2010; Whyte &

[5] If this assumption would be violated for this reason (although we argue against it in the present paragraph), our findings can be interpreted as the impact of education level on the probability of initiating a casual and short relationship on Tinder. Given the time investment in Tinder (supra, Section 1), we believe also these findings would be of high interest.

[6] See Buss (1985) for a more extensive review on assortative mating patterns.

Torgler, 2017a). Assuming that sorting behaviour is similar on Tinder, we therefore formulate the following hypothesis:

H2: Tinder users have a higher preference for potential partners with a similar education level.

Based on the literature on mating behaviour from evolutionary psychology and the literature on assortative mating, H1b and H2 may be viewed as rival hypotheses when the female has a low education level. Indeed, based on H1b we hypothesise that this female would prefer a partner with a high education level, while based on H2 we hypothesise that this female would prefer a partner with a similar (i.e. low) education level. In the scenario that a female with a low education level would prefer a partner with a high education level (consistent with H1b) instead of a partner with a low education level (opposing H2), this would be considered as educational hypergamy, i.e. preferring a partner who is higher educated than oneself.

H2 is based on the assumption that sorting behaviour on the marriage market and on classic online dating websites is generalisable to users of mobile dating apps such as Tinder. However, we have several reasons for why this could not be the case. First, in contrast to most studies looking at dating in an offline setting and on classic online dating websites, our experimental design allows us to examine actual, revealed mate preferences, instead of stated mate preferences. Todd, Penke, Fasolo, and Lenton (2007), Eastwick and Finkel (2008), Hitsch et al., (2010b), and Whyte and Torgler (2017b) have shown this is an important distinction when examining mating behaviour, as it is not (always) the case that individuals pick a partner who satisfies their *a priori* stated preferences for a potential partner. Moreover, Todd et al. (2007) found, using data from a speed-dating event, that while stated mate preferences are in line with the literature on assortative mating, actual mate preferences did not exhibit this behaviour.

Second, match formation on Tinder cannot be due to search frictions, which may have potentially driven educational assortative mating in previous research. In offline dating, these search frictions are due to people with a certain education level matching with people with a comparable education level just because they spend a lot of time with these people at school, in college, or at work, rather than because of an actual preference for a partner with this education level (Mare, 1991; Hitsch et al., 2010a; Skopek et al., 2010). Mare (1991), Blossfeld (2009), and Shafer and Qian (2015) indeed argue that educational assortative mating in an offline setting is due to increased contact opportunities between males and females with similar education levels. However, on Tinder, contact opportunities do not differ between people with equal education levels and people with unequal education levels. On classic online dating websites, search frictions are due to the ability of users to filter potential partners based on their education level. As this is not the case on Tinder (infra, Subsection 3.2), the pool of potential partners encountered on this app is both bigger and more diversified in terms of (among others) education level compared to classic online dating websites. As people's actual preferences may differ from their stated preferences (supra, previous paragraph), Tinder users may find themselves attracted to people who they would not have encountered on classic online dating websites, because these people would already have been filtered out based on their (too low) education level.

Finally, mating behaviour in an offline setting and on classic online dating websites is influenced by the psychological cost of being rejected, also denoted as 'social frictions'. Indeed, due to fear of rejection, individuals might not approach potential partners who they perceive to be unattainable. Consequently, they will only contact potential partners who they perceive to be equally desirable as them, a perception that may be determined (among others) by one's education level. On Tinder, this fear of rejection is less (or even not at all) an issue as users anonymously show interest in a potential partner (Jung, Umyarov, Bapna, & Ramaprasad, 2014). This anonymity is only lifted when both users show interest in each other (infra, Subsection 3.2), reducing (or even removing altogether) the psychological cost of explicit rejections. Additionally, the (time) cost of expressing interest in a potential partner on Tinder is low (infra, Subsection 3.2), in turn also reducing the psychological pain of being rejected.

3. Method

3.1 Correspondence Experiment Framework

Correspondence experiments have been used in labour economics to identify causal unequal treatment on the labour market. The reasons for unequal treatment have spanned from racial discrimination (Bertrand & Mullainathan, 2004; Baert, Cockx, Gheyle, & Vandamme, 2015) to discrimination based on a candidate's previous experience in the labour market

(Kroft, Lange, & Notowidigdo, 2013; Eriksson & Rooth; 2014).[7] We extend this correspondence experiment framework to the mobile dating app Tinder.

3.2 How Tinder Works

On Tinder, users need to fill in only three criteria to get started. More specifically, they fill in (i) their sexual preference,[8] (ii) the minimum and maximum age of potential partners (the 'age range'), and (iii) the maximum distance a potential partner can be removed from them (the 'distance range'). Then, users get shown, one by one, all profiles of other users that fit their three criteria. The information provided in these profiles is the other users' (i) picture(s), (ii) name, (iii) age, (iv) education, and (v) occupation on the main screen, although the latter two pieces of information are optional entries.[9] (See Figure A–1 in the Appendix for a fictitious example.) Based on this information, users anonymously decide (i.e. without the other user knowing their decision) whether they dislike (swipe left) or like (swipe right) the other user. Additionally, users can superlike (swipe up) a profile.[10] With a superlike, the other person gets a notification that someone superliked her/him, which is not the case with regular likes. After making a decision on a certain profile, the user immediately gets shown the next profile. In the case that two users (super)like each other, they 'match' and have the possibility to start a conversation, potentially to arrange an offline date. This is not the case if one person indicated they disliked the other person.

3.3 Tinder profiles

For this study, we created 24 fictitious Tinder profiles in multiple cities in Flanders, the Northern, Dutch speaking region of Belgium. We only let these profiles differ on our characteristic of interest, i.e. education level.[11,12] The people in our profiles all obtained a degree related to the field of 'business and economics'. Although this limits our external validity (infra, Section 5, third paragraph on limitations of this study), it ensures internal validity. These were the four degrees (education levels) used, ranked from highest to lowest:

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[7] See Baert (2018) for an extensive review of correspondence experiments in the labour market since 2005.
[8] In this study, we only examine heterosexual preferences.
[9] Users also have the possibility to click on a profile, after which they get shown the other user's distance in kilometres, and (if used by the other user) their bio (a short free text), Instagram photos, and favourite songs on Spotify.
[10] This is possible once (five times) a day for non-paying (paying) users.
[11] On Tinder, about two thirds of users show their education level (see also Subsection 4.3).
[12] The education level was signalled by filling in the line 'education' on the main screen. See Figure A–1 for an example, in which the profile has the education level 'Master in Economics'.

• Master (5 years) in Business Engineering (hereafter: 'Ma+')

• Master (4 years) in Public Administration and Management (hereafter: 'Ma–')

• Bachelor (3 years) in Business Management (hereafter: 'Ba+')

• Bachelor (3 years) in Office Management (hereafter: 'Ba–').

The ranking of these education levels was based on the average starting wage for graduates from each of these studies when leaving school. Graduates with a Master in Business Engineering earn the most, graduates with a Master in Public Administration and Management earn the second most, and so on.

It must be noted that the four education levels are all degrees from higher education. We refrained from using non-higher education degrees for our profiles, as then it may have been unclear for the other, real, Tinder users (hereafter: 'subjects') that that degree was the highest education level our profiles attained. For example, a Tinder profile that reports as degree 'secondary education in the general track', may be thought to have had higher education without mentioning this in their profile. Consequently, our results can be considered as a lower bound for the true effect of education level on mating success. More specifically, the results are expected to be more pronounced when comparing profiles with a tertiary education degree with profiles with a secondary education degree.

Our profiles were all aged 23,[13] to ensure that the profiles signal that they obtained the degree mentioned in their profiles. As students in Flanders start higher education at the age of 18, and the longest study for our profiles was the 'Master in Business Engineering' which spans five years, our profiles would be perceived as recently graduated.

We could not deploy four profiles with four different education levels in the same city using the same picture, as subjects could then encounter the same picture multiple times with different education levels, potentially tipping them off that something is going on. Therefore, we used four different 'looks', i.e. four different pictures, for our profiles, to which we attached the four education levels. To ensure that the pictures we used for the profiles were similar in terms of attractiveness, we scored 32 (16 male, 16 female) different pictures on Amazon Mechanical Turk (hereafter: 'MTurk'),[14] and selected 8 pictures (four male, four female) that 493 workers on MTurk judged to be similar in level of attractiveness. Then, to

[13] Consequently, our profiles are only shown to subjects who included age 23 (the age of our profiles) in their age range.

[14] MTurk is an Internet marketplace on which individuals can hire 'workers' to perform small tasks in return for financial compensation. Multiple independent studies have shown that data gathered on MTurk is of high quality (Buhrmester, Kwang, & Gosling, 2011; Goodman, Cryder, & Cheema, 2013; Paolacci, Chandler, & Ipeirotis, 2010; Rand, 2012).

ensure that the effect of education level is not driven by the picture, we attached to each picture three different education levels in three different cities.[15] Table A–1 in the Appendix shows a schematic overview of our 24 fictitious profiles.

For the names of our profiles, we chose eight (four male, four female) of the most common Dutch names for 23-year-olds, as this was the age of the people in our profiles (supra). More specifically, these were Jens, Simon, Michiel, and Niels for the male profiles (De populairste Vlaamse jongensnamen van 1995, n.d.), and Lisa, Eline, Jana, and Melissa for the female profiles (De populairste Vlaamse meisjesnamen van 1995, n.d.).

Finally, we did not fill in an occupation for our Tinder profiles. This is not unusual on Tinder. Indeed, in our sample the subjects (discussed below) mentioned their occupation in only 26.3% of the cases.[16]

3.4 Subjects

Our subjects were other, real, Tinder users who were within our defined age and distance ranges. For the age range, we chose age 23 to age 27, in order to exclude students from our sample. The average age of our subjects was 24.141 (SD = 1.180). Our distance range we gradually increased per kilometre from the minimum of two kilometres on, in order to find the subjects that were closest to us. We did this to ensure that our profiles were in the distance range of our subjects, so that our profiles would show up in the stack of profiles that our subjects evaluated (swiped). We rarely had to increase the range above the minimum of two kilometres.

3.5 Responses

Using each of our 24 profiles, we liked 150 subjects between January 2018 and March 2018, resulting in a sample size of 3,600 observations. Because we liked just the 150 subjects (and no others) with each profile, if a subject liked or superliked our profile, we would be made aware of that by Tinder, which would indicate that we had a match with that subject.[17]

[15] It was our intention to attach to each picture all four education levels over four cities. However, as Facebook realised we were creating fake Facebook profiles (which is a necessary prerequisite to create a Tinder profile), they started blocking our accounts and we were unable to perform our experiment in the fourth city. However, we are confident that we have enough randomisation left in the three cities to estimate causal effects.
[16] We also did not fill in a bio for our profiles and did not show any Instagram photos or favourite songs on Spotify (see also footnote 8). This is not unusual on Tinder, as in our sample only 57.1%, 14.1%, and 11.3% of the subjects, respectively, used these features.
[17] Recall that a match is only formed when two users both like each other (supra, Subsection 3.2).

Therefore, we were able to distinguish between four different possible outcomes: the subject (i) disliked, (ii) liked, or (iii) superliked our profile. Additionally, if there was a match (because the subject (super)liked our profile), we also recorded (iv) whether the subject started a conversation with our profile.[18]

Table 1 gives an overview of the frequency of the different outcomes. When considering all subjects, about one third (33.2%) of our profiles (hereafter: 'the evaluated profiles') received a (super)like. However, this conceals remarkable differences between the male subjects and female subjects. Indeed, male subjects (super)liked 61.9% of the female evaluated profiles, while female subjects (super)liked only 4.5% of the male evaluated profiles. This finding is in line with previous research on online dating in general (Todd et al., 2007; Fiore, Taylor, Zhong, Mendelsohn, & Cheshire, 2010) and on Tinder in particular (Tyson, Pera, Haddadi, & Seto, 2016). Indeed, Tyson et al. (2016, p. 1) argue that this is due to a feedback loop: 'men are driven to be less selective in the hope of attaining a match, whilst women are increasingly driven to be more selective, safe in the knowledge that any profiles they like will probably result in a match'. Additionally, this finding is in line with previous research in evolutionary psychology, and more specifically with parental investment theory (Trivers, 1972). This theory argues that women have a greater parental investment and are therefore looking for the most high-quality partner possible, in order to obtain high-quality offspring, therefore being more selective. Conversely, men have a smaller parental investment and are looking to maximise the quantity of offspring, resulting in them being less selective.

<Table 1 about here>

Very few subjects used the superlike option, i.e. only 1.4% of all matches came about in this way. This finding is in line with the limited amount of superlikes available to Tinder users (see footnote 10). Finally, we note that male subjects started a conversation with the female evaluated profiles much more often (42.3%) than the other way around (6.2%). The explanation for this finding is similar to the explanation in the previous paragraph for the higher selectiveness of women (compared with men) with regard to (super)liking a certain profile.

Figure 1 shows the fractions of matches (hereafter: 'match probability') by the education level of the evaluated profiles. The leftmost bar chart shows this for all subjects. Here we see

[18] In agreement with the Ethical Committee of the Faculty of Economics and Business Administration of Ghent University, we did not respond to these messages.

that the match probability decreased as the education level of the evaluated profiles also decreased. Similarly, in the middle and rightmost bar chart, we can see that this is broadly speaking also the case for both the male subjects and female subjects, respectively. This is an indication that highly educated people are more successful on mobile dating apps such as Tinder. In the next section, we examine the statistical significance of these findings.

<Figure 1 about here>

4. Results

4.1 Bivariate analyses

In this subsection we present our bivariate analyses. As in Figure 1, in Table 2 we show for each education level of the evaluated profiles the match probability in columns (1) and (2). Next, we verify in column (3) whether the ratio of pairs of these match probabilities (hereafter: 'match ratios') significantly differs from 1, and therefore whether the match probabilities significantly differ from each other. The higher education level of the evaluated profiles is always in the numerator, so that a match ratio above (below) 1 means there is a positive (negative) effect of a higher education level on the number of matches obtained.

<Table 2 about here>

When considering all subjects in Panel A, we see that evaluated profiles with a higher education level consistently score better compared with their counterparts with a lower education level: all match ratios are above 1. The match ratio is significantly different from 1 when comparing evaluated profiles with a Ma+ degree with those with a Ba– degree. The former group is 15.3% more likely to receive a (super)like compared with the latter.

We consider male and female subjects separately in Panels B and C, respectively. For the male subjects, the match ratios are practically all (slightly) above 1, but they never significantly differ from 1. In contrast, for the female subjects the match ratios are substantially higher and differ significantly from 1. More specifically, we find that male evaluated profiles with a Ma+ degree secure at least twice as many matches compared with their counterparts which were lower educated.

4.2 Multivariate analyses

In addition to our bivariate analyses in the previous subsection, we also conduct multivariate analyses to control for the gender of the subjects, the pictures we used for the evaluated profiles, and the cities in which we conducted our experiment. More specifically, we run a logistic regression in which the dependent variable is assigned a value of '0' when there was no match (subjects disliked the evaluated profile) and '1' if there was a match (subjects (super)liked the evaluated profile). Our independent variables of interest are dummy variables for the different education levels of the evaluated profiles. Additionally, we include the gender of the subject, as well as dummy variables for the pictures used in the evaluated profiles and for the cities in which we deployed the evaluated profiles as control variables. The results from this regression analysis can be found in column (1) of Table 3. Panel A shows the estimates for all subjects, while Panels B and C show the estimates for the male and female subjects, respectively. As a first robustness check, we replicate these analyses while combining education levels of the evaluated profiles that were next to each other in columns (2), (3), (4), and (5). Throughout all these analyses, we use the lowest (combination of) education level(s) as a reference category for the higher (combination of) education level(s).

<Table 3 about here>

Similar to the results of the bivariate analyses, we find that higher-educated evaluated profiles are more successful on Tinder compared with their lower-educated counterparts, and that this result is driven by the female subjects. This finding is present in each of our five analyses in Table 3. When focussing on the analyses which compare evaluated profiles with a Master's degree with their counterparts without a Master's degree in column (5), we find that when considering all subjects, the former group has a 24.7% higher odds of getting a match compared with the latter group. When considering the male and female subjects separately, we find that this result is driven by the female subjects. Indeed, male subjects do not significantly favour the female evaluated profiles who had a Master's degree when making their swipe decision (the odds ratio does not significantly differ from 1), whereas female subjects have a 91.4% higher odds of (super)liking the male evaluated profiles if these profiles had a Master's degree.

As a robustness check, we replicate all these regression analyses with an ordered logistic regression in which our dependent variable is assigned a value of '0' when there was no match (subjects disliked the evaluated profile), '1' if there was a match (subjects (super)liked the evaluated profile), and '2' if the subjects started a conversation with the evaluated profile. This does not substantially change our findings. See Table A–2 in the Appendix for the regression results.

The findings in both our bivariate and multivariate analyses that education level matters significantly only for our female subjects, is in line with previous research on mate preferences both in an offline setting and on classic online dating websites (supra, Section 2) and therefore confirm H1a and H1b. Apparently, these mate preferences are still present on the recently popular mobile dating apps such as Tinder. Additionally, these findings are in line with the previously identified higher selectivity of women (compared with men) when evaluating potential partners, which we discussed in Subsection 3.5.

4.3 Homogamy, hypergamy, and hypogamy

In this subsection we examine whether the findings in the previous subsection are (in part) driven by a preference for a partner with a similar education level, i.e. educational assortative mating. For 2,345 subjects (i.e. 65.1% of all subjects) we have information on whether they attended university.[19] This is the case for 1,354 subjects (57.7%). With this information, we create three new variables. The variable *homogamy* is '1' if the evaluated profile and the subject have the same education level, i.e. they both did or both did not attend university, 0 otherwise.[20,21] The variable *hypergamy* is '1' if the evaluated profile has a higher education level than the subject, i.e. the evaluated profile attended university, but the subject did not, 0 otherwise. The variable *hypogamy* is '1' if the evaluated profile has a lower education level than the subject, i.e. the evaluated profile did not attend university, but the subject did, 0 otherwise.

Similar to our bivariate analyses in Subsection 4.1, in Table 4 we show for each situation (homogamy and no homogamy, hypergamy and no hypergamy, and hypogamy and no hypogamy) the match probability in columns (1) and (2). Next, we show in column (3) whether the ratio of pairs of these match probabilities (again denoted as 'match ratios') significantly differs from 1, and therefore whether the match probabilities significantly differ from each other.

[19] We cannot rule out that the results in this subsection are due to a selection bias introduced by only considering subjects who reported their own education level. However, as the answers to H1a and H1b are unchanged when considering only these subjects (see Table A–3 in the Appendix for a replication of Table 2 for these subjects), we are confident that the results in this section are not driven by a selection bias.
[20] Profiles with education levels 'Ma+' and 'Ma–' attended university, while profiles with education levels 'Ba+' and 'Ba–' did not.
[21] As the education level of subjects consisted of two levels, i.e. attended university or not, we limited the four education levels of the evaluated profiles also to two levels, again attended university or not.

<Table 4 about here>

We do not find any evidence for homogamy based on education level (also 'educational assortative mating'), either in the full sample or in the subsamples of male and female subjects, as the match ratios never significantly differ from 1. This is not in line with previous literature that found evidence for educational assortative mating both in an offline setting and on classic online dating websites (supra, Section 2), and therefore opposes H2.

We suggest that the lack of evidence for educational assortative mating on mobile dating apps such as Tinder is likely due to three reasons. First, compared to most previous studies in an offline setting and on classic online dating websites, our experimental design allows us to examine actual mate preferences instead of stated mate preferences, which have been shown to differ substantially (supra, Section 2). Our lack of evidence for educational assortative mating is in line with the findings by Todd et al. (2007), who examined actual mate preferences using data from a speed-dating event. Second, as already mentioned in Section 2, search frictions, which may have driven educational assortative mating in previous research in offline dating and on classic online dating websites, are non-existent on Tinder. Ortega and Hergovich (2017) already suggested that Tinder's ability to eliminate search frictions has decreased racial homogamy, illustrated by the jump in interracial marriages following the launch of Tinder in 2012. Third, as introduced in Section 2, on Tinder social frictions influence mating behaviour less (or even not at all) compared with offline dating and dating on classic online dating websites, as the anonymity in which a Tinder user can express interest in another user reduces (or even eliminates) the psychological cost of being rejected.

Next, we find evidence for a preference for hypergamy when considering all subjects: the subjects are 26.5% more likely to like an evaluated profile that is higher educated than themselves, compared with when that is not the case. Again, this effect is driven by the female subjects, who like higher educated profiles 92.2% more often, whereas this effect is not significant for the male subjects. These findings are in line with those of Whyte and Torgler (2017a), who used data from a classic online dating website.

Finally, we find that both male and female subjects disfavour the evaluated profiles who have a lower education level than themselves. More specifically, male and female subjects like these profiles 10.1% and 45.4% less often, respectively. The finding that this match ratio is way lower for the female subjects compared with the male subjects, confirms the findings of both Skopek et al. (2010) and Whyte and Torgler (2017a), who found that women are more reluctant than men to contact lower-educated potential partners.

Combining these findings with our findings from the previous subsection, we can conclude that for females on Tinder the preference for a highly educated partner is not only absolute but also relative to their own education level. Additionally, whereas males on Tinder do not seem to care about the absolute education level of females, they disfavour potential partners that have a lower education level than themselves.

5. Conclusion

In this study, we examined by means of a field experiment the impact of an individual's education level on her/his success on mobile dating apps such as Tinder, thereby contributing to both the literature on mating behaviour and the literature on the (non-monetary) returns to education. Our unique experimental design allowed us to examine the causal effect of education on actual, revealed (instead of stated) mate preferences in a dating market without search frictions and social frictions. Based on a sample of 3,600 'swipe decisions' we found that education level matters only substantially when female Tinder users evaluate male Tinder profiles, and not vice versa. This finding is in line with previous literature from evolutionary psychology that found that females have a higher preference for a highly educated partner who in turn has a higher earning potential (Buss & Barnes, 1986).

Additionally, we examined whether these mate preferences were driven by a preference to find a partner with a similar education level, also denoted as educational assortative mating. We found that this was not the case on Tinder, in contrast to findings in an offline setting and on classic online dating websites (supra, Section 2). We argued that the lack of evidence for educational assortative mating on Tinder was due to our experimental design which allowed us to (i) examine actual (instead of stated) mate preferences, (ii) eliminate search frictions, and (iii) eliminate social frictions. As previous studies have shown that educational assortative mating enforces income inequality (Mare, 1991; Blossfeld & Buchholz, 2009; Eika, Mogstad, & Zafar, 2014; Greenwood, Guner, Kocharkov, & Santos, 2014; Hu & Qian, 2015), the decrease in assortative mating due to the recently popular mobile dating apps such as Tinder may have important implications for the income distribution across households in today's society.

We end this study by summing up several limitations of our research design. First, the main limitation of this study is that using education levels from one field of study limits the generalisability of our results. For both practical and ethical reasons, we were only able and allowed to create a certain number of fictitious profiles and perform a certain number of swipes with each of these profiles, which limited the amount of variation we could introduce in our experiment. In order to maximise internal validity, we did not vary the field of study of our profiles' education level, so that this was not the driver of our results instead of our independent variable of interest, i.e. our profiles' education level. Our choice for the field of study 'economics and business' was driven by the fact that this is the second largest field of study in the region in which we gathered our data, after the field of study 'health sciences', which we did not use as it is to a great extent only populated by female students. Therefore, a logical way for future research to build on this study would be by verifying whether the mating behaviour identified here is also present when examining other fields of study.

Second, we only looked at the first stage of a relationship, i.e. showing interest in another person on a mobile dating app. Therefore, our results cannot be generalised to mating behaviour in later stages of a relationship. Nonetheless, we believe the findings with regard to this first stage are interesting, as it is a necessary stage each individual using mobile dating apps needs to get through in order to advance to the later stages of a relationship. It is in that sense comparable to previous studies that conducted field experiments on the labour market which looked at whether an applicant receives an invitation to a job interview. Here too, the job interview is a necessary first stage applicants need to get through in order to advance to further stages of the job application process and to potentially secure the job. Still, future research can complement this study by examining whether mate preferences in later stages of relationships that started on mobile dating apps are comparable to the mate preferences in the initial phase of the relationship identified here.

Third, our experimental design did not allow us to disentangle which mechanisms drove our results. More specifically, although we established that females favoured potential partners who are highly educated, we were unable to deduce *why* this is the case. More specifically, we do not know if this effect is driven by a preference for (i) an intelligent partner, (ii) a partner with high status, (iii) a partner with a high earning potential, or (iv) something else. Future research could complement this study by identifying the main driver(s) of this female preference for a highly educated potential partner.

Similarly, we argued that the lack of evidence for educational assortative mating on mobile dating apps such as Tinder was due to our research design, which allowed us to (i) investigate actual (instead of stated) mate preferences, (ii) eliminate search frictions, and (iii) eliminate social frictions. However, here too we were unable to disentangle which one of these three elements (or potentially another) was the main driver of this lack of evidence for educational assortative mating. Future research could contribute to the literature on assortative mating by examining the importance of each of these three elements in explaining our findings.

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Appendix A

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Table 1. Descriptive statistics.

	(1) All subjects (N = 3,600)	(2) Male subjects (N = 1,800)	(3) Female subjects (N = 1,800)
No match (proportion of all observations)	2,403 (0.668)	684 (0.381)	1,719 (0.955)
Match (proportion of all observations)	1,197 (0.332)	1,116 (0.619)	81 (0.045)
Like (proportion of number of matches)	1,180 (0.986)	1,100 (0.986)	80 (0.988)
Superlike (proportion of number of matches)	17 (0.014)	16 (0.014)	1 (0.012)
Conversation started (proportion of number of matches)	477 (0.398)	472 (0.423)	5 (0.062)

Note. Absolute numbers are reported with proportion of all observations or matches in parentheses.

Table 2. Match ratios by education level of the evaluated profiles.

	(1) Match probability education level (i)	(2) Match probability education level (ii)	(3) Match ratio: (1)/(2) [Chi square]
A. All subjects			
Ma+ (i) versus Ma– (ii)	0.360	0.331	1.087 [1.661]
Ma+ (i) versus Ba+ (ii)	0.360	0.327	1.102 [2.218]
Ma+ (i) versus Ba– (ii)	0.360	0.312	1.153** [4.604]
Ma– (i) versus Ba+ (ii)	0.331	0.327	1.014 [0.040]
Ma– (i) versus Ba– (ii)	0.331	0.312	1.060 [0.736]
Ba+ (i) versus Ba– (ii)	0.327	0.312	1.046 [0.432]
B. Male subjects			
Ma+ (i) versus Ma– (ii)	0.640	0.622	1.029 [0.305]
Ma+ (i) versus Ba+ (ii)	0.640	0.624	1.025 [0.234]
Ma+ (i) versus Ba– (ii)	0.640	0.593	1.079 [2.073]
Ma– (i) versus Ba+ (ii)	0.622	0.624	0.996 [0.005]
Ma– (i) versus Ba– (ii)	0.622	0.593	1.049 [0.788]
Ba+ (i) versus Ba– (ii)	0.624	0.593	1.052 [0.915]
C. Female subjects			
Ma+ (i) versus Ma– (ii)	0.080	0.040	2.000** [6.383]
Ma+ (i) versus Ba+ (ii)	0.080	0.029	2.769*** [11.418]
Ma+ (i) versus Ba– (ii)	0.080	0.031	2.571*** [10.249]
Ma– (i) versus Ba+ (ii)	0.040	0.029	1.385 [0.835]
Ma– (i) versus Ba– (ii)	0.040	0.031	1.286 [0.518]
Ba+ (i) versus Ba– (ii)	0.029	0.031	0.929 [0.038]

Notes. The education levels (Ma+, Ma–, Ba+, and Ba–) are those of the evaluated profiles. See Subsection 3.3 for definitions of the variables Ma+, Ma–, Ba+, and Ba–. * (**) ((***)) indicates significance at the 10% (5%) ((1%)) level.

Table 3. Match probability by education level of the evaluated profiles: binary logistic regression results.

	(1)	(2)	(3)	(4)	(5)
A. All subjects					
Ma+	1.360** (0.181)	1.361** (0.181)	/	1.323** (0.153)	/
Ma+ or Ma–	/	/	1.282** (0.149)	/	1.247** (0.119)
Ma–	1.202 (0.163)	/	/	1.169 (0.138)	/
Ma– or Ba+	/	1.126 (0.131)	/	/	/
Ba+	1.059 (0.141)	/	1.058 (0.141)	/	/
Ba+ or Ba–	/	/	/	Ref.	Ref.
Ba–	Ref.	Ref.	Ref.	/	/
Female subject	0.054*** (0.011)	0.054*** (0.011)	0.054*** (0.011)	0.054*** (0.011)	0.054*** (0.011)
Control for picture	Yes	Yes	Yes	Yes	Yes
Control for city	Yes	Yes	Yes	Yes	Yes
N	3,600	3,600	3,600	3,600	3,600
B. Male subjects					
Ma+	1.153 (0.170)	1.153 (0.170)	/	1.110 (0.142)	/
Ma+ or Ma–	/	/	1.123 (0.142)	/	1.082 (0.112)
Ma–	1.095 (0.160)	/	/	1.055 (0.134)	/
Ma– or Ba+	/	1.087 (0.138)	/	/	/
Ba+	1.078 (0.158)	/	1.078 (0.159)	/	/
Ba+ or Ba–	/	/	/	Ref.	Ref.
Ba–	Ref.	Ref.	Ref.	/	/
Control for picture	Yes	Yes	Yes	Yes	Yes
Control for city	Yes	Yes	Yes	Yes	Yes
N	1,800	1,800	1,800	1,800	1,800
C. Female subjects					
Ma+	1.986* (0.757)	1.953* (0.729)	/	2.061** (0.641)	/
Ma+ or Ma–	/	/	1.863* (0.676)	/	1.914** (0.530)
Ma–	1.626 (0.724)	/	/	1.698 (0.617)	/
Ma– or Ba+	/	1.216 (0.477)	/	/	/
Ba+	0.927 (0.424)	/	0.949 (0.435)	/	/
Ba+ or Ba–	/	/	/	Ref.	Ref.
Ba–	Ref.	Ref.	Ref.	/	/
Control for picture	Yes	Yes	Yes	Yes	Yes
Control for city	Yes	Yes	Yes	Yes	Yes
N	1,800	1,800	1,800	1,800	1,800

Notes. The dependent variable is '0' when there is no match and '1' when there is a match. See Subsection 3.3 for definitions of the variables Ma+, Ma–, Ba+, and Ba–. Coefficients are odds ratios. Standard errors are reported between parentheses. * (**) ((***)) indicates significance at the 10% (5%) ((1%)) level.

Table 4. Match ratios by homogamy, hypergamy, and hypogamy.

	(1) Match probability scenario (i)	(2) Match probability scenario (ii)	(3) Match ratio: (1)/(2) [Chi square]
A. All subjects			
Homogamy (i) versus no homogamy (ii)	0.321	0.322	0.996 [0.003]
Hypergamy (i) versus no hypergamy (ii)	0.385	0.305	1.265*** [11.424]
Hypogamy (i) versus no hypogamy (ii)	0.277	0.339	0.817*** [8.624]
B. Male subjects			
Homogamy (i) versus no homogamy (ii)	0.638	0.623	1.024 [0.274]
Hypergamy (i) versus no hypergamy (ii)	0.672	0.618	1.086 [2.416]
Hypogamy (i) versus no hypogamy (ii)	0.583	0.649	0.899** [4.162]
C. Female subjects			
Homogamy (i) versus no homogamy (ii)	0.037	0.038	0.974 [0.008]
Hypergamy (i) versus no hypergamy (ii)	0.062	0.032	1.922** [4.472]
Hypogamy (i) versus no hypogamy (ii)	0.024	0.044	0.546* [2.831]

Notes. See Subsection 4.3 for definitions of the variables homogamy, hypergamy, and hypogamy. * (**) ((***)) indicates significance at the 10% (5%) ((1%)) level.

Figure 1. Match probability by education level of the evaluated profiles and by gender of the subjects.

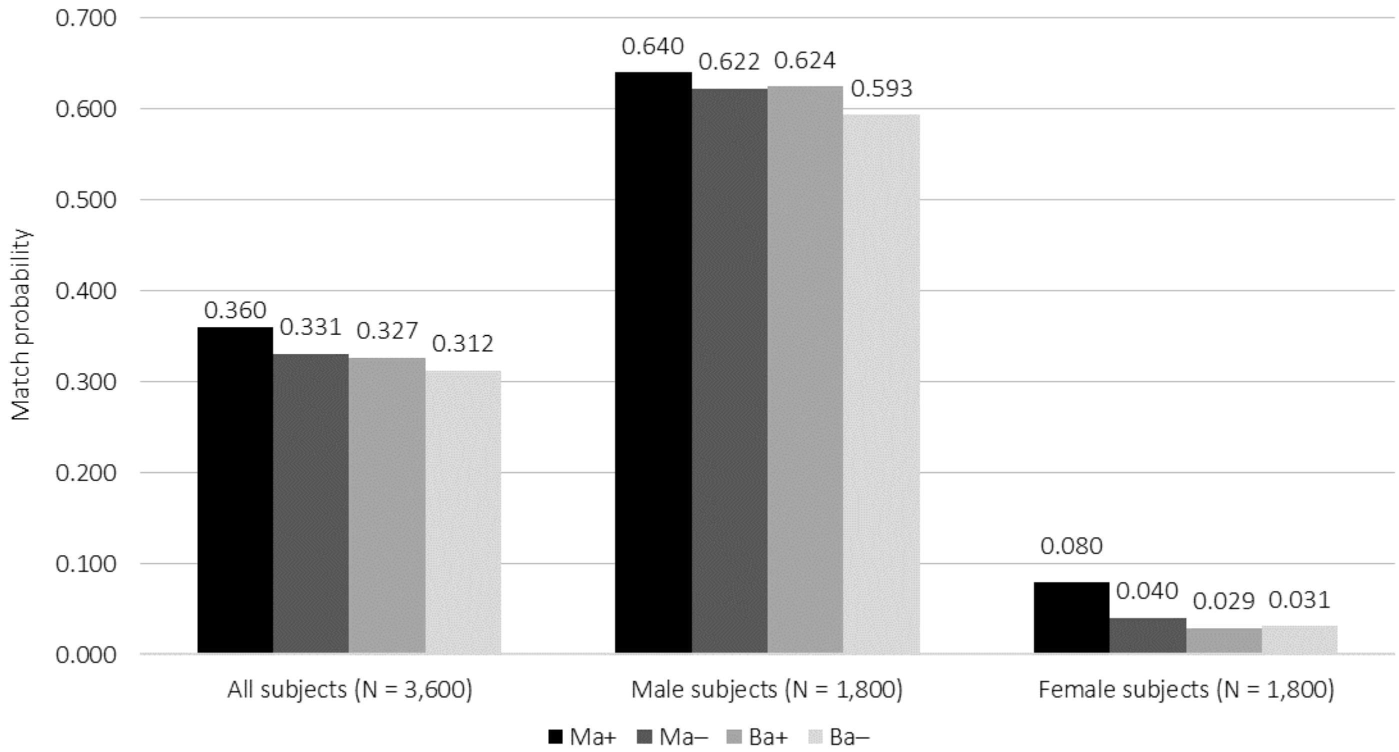


Table A–1. Representation of the randomisation process.

Ghent	Leuven	Bruges
Ma+ degree	Ba+ degree	Ba– degree
Ba– degree	Ma– degree	Ba+ degree
Ba+ degree	Ma+ degree	Ma– degree
Ma– degree	Ba– degree	Ma+ degree

Ghent	Leuven	Bruges
Ma+ degree	Ba+ degree	Ba– degree
Ba– degree	Ma– degree	Ba+ degree
Ba+ degree	Ma+ degree	Ma– degree
Ma– degree	Ba– degree	Ma+ degree

Note. The different shades of grey indicate different ‘looks’, i.e. different pictures.

Table A–2. Match/conversation probability by education level of the evaluated profiles: ordered logistic regression results.

	(1)	(2)	(3)	(4)	(5)
A. All subjects					
Ma+	1.385*** (0.168)	1.385*** (0.168)	/	1.293** (0.135)	/
Ma+ or Ma–	/	/	1.288** (0.136)	/	1.201** (0.104)
Ma–	1.190 (0.147)	/	/	1.109 (0.119)	/
Ma– or Ba+	/	1.170 (0.125)	/	/	/
Ba+	1.151 (0.142)	/	1.152 (0.142)	/	/
Ba+ or Ba–	/	/	/	Ref.	Ref.
Ba–	Ref.	Ref.	Ref.	/	/
Female subject	0.052*** (0.010)	0.052*** (0.010)	0.052*** (0.010)	0.052*** (0.010)	0.052*** (0.010)
Control for picture	Yes	Yes	Yes	Yes	Yes
Control for city	Yes	Yes	Yes	Yes	Yes
N	3,600	3,600	3,600	3,600	3,600
B. Male subjects					
Ma+	1.220 (0.159)	1.219 (0.159)	/	1.124 (0.127)	/
Ma+ or Ma–	/	/	1.161 (0.131)	/	1.069 (0.098)
Ma–	1.105 (0.144)	/	/	1.017 (0.115)	/
Ma– or Ba+	/	1.142 (0.130)	/	/	/
Ba+	1.182 (0.156)	/	1.183 (0.156)	/	/
Ba+ or Ba–	/	/	/	Ref.	Ref.
Ba–	Ref.	Ref.	Ref.	/	/
Control for picture	Yes	Yes	Yes	Yes	Yes
Control for city	Yes	Yes	Yes	Yes	Yes
N	1,800	1,800	1,800	1,800	1,800
C. Female subjects					
Ma+	1.976* (0.753)	1.944* (0.725)	/	2.052** (0.638)	/
Ma+ or Ma–	/	/	1.856* (0.674)	/	1.909** (0.528)
Ma–	1.623 (0.722)	/	/	1.697 (0.616)	/
Ma– or Ba+	/	1.214 (0.476)	/	/	/
Ba+	0.925 (0.424)	/	0.947 (0.434)	/	/
Ba+ or Ba–	/	/	/	Ref.	Ref.
Ba–	Ref.	Ref.	Ref.	/	/
Control for picture	Yes	Yes	Yes	Yes	Yes
Control for city	Yes	Yes	Yes	Yes	Yes
N	1,800	1,800	1,800	1,800	1,800

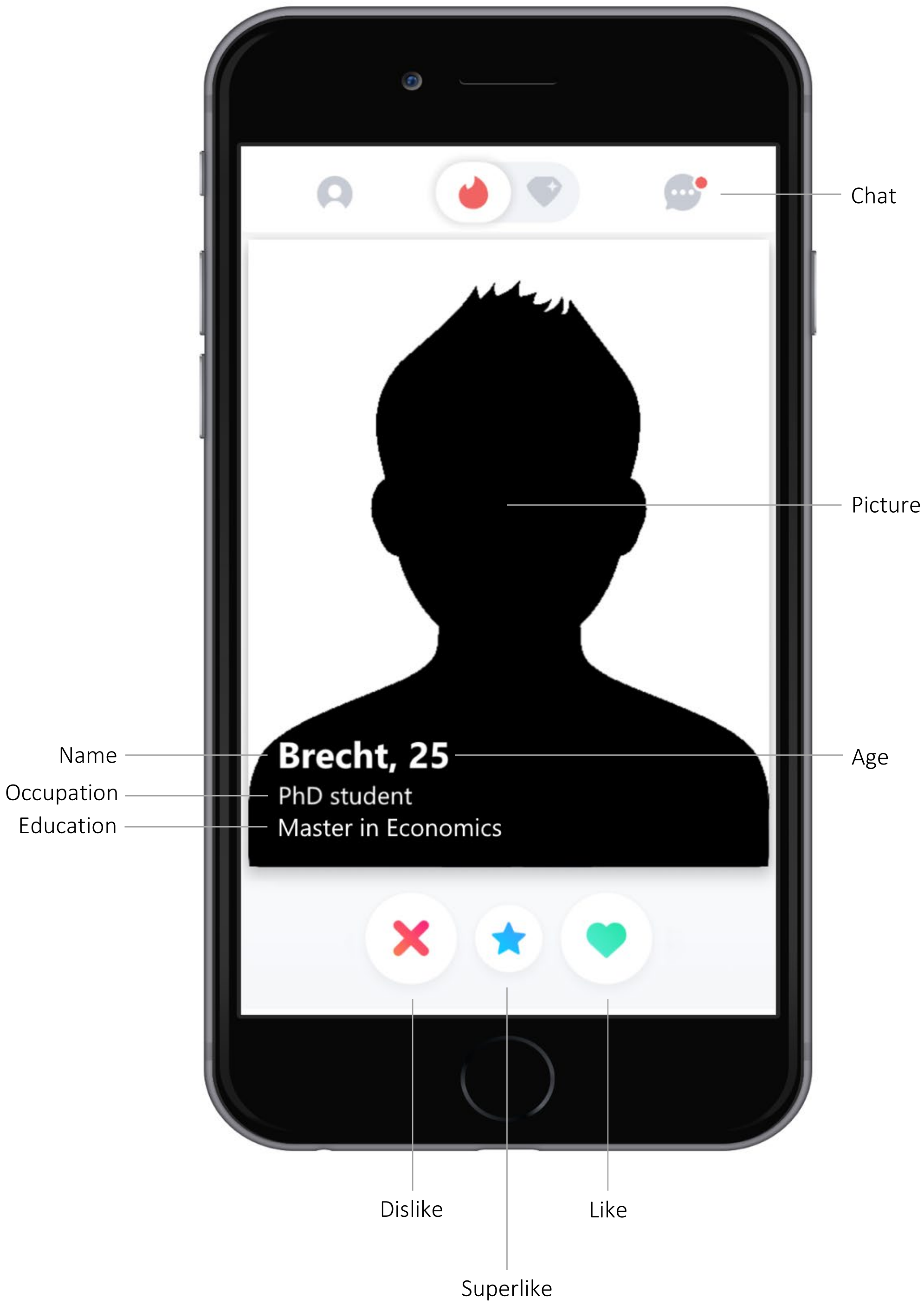
Notes. The dependent variable is '0' when there is no match, '1' when there is a match, and '2' if the subject started a conversation with the evaluated profile. See Subsection 3.3 for definitions of the variables Ma+, Ma–, Ba+, and Ba–. Coefficients are odds ratios. Standard errors are reported between parentheses. * (**) ((***)) indicates significance at the 10% (5%) ((1%)) level.

Table A–3. Match ratios by education level of the evaluated profiles, using the sample of subjects who reported their own education level.

	(1) Match probability education level (i)	(2) Match probability education level (ii)	(3) Match ratio: (1)/(2) [Chi square]
A. All subjects			
Ma+ (i) versus Ma– (ii)	0.347	0.319	1.088 [1.003]
Ma+ (i) versus Ba+ (ii)	0.347	0.321	1.081 [0.862]
Ma+ (i) versus Ba– (ii)	0.347	0.298	1.164* [3.153]
Ma– (i) versus Ba+ (ii)	0.319	0.321	0.994 [0.008]
Ma– (i) versus Ba– (ii)	0.319	0.298	1.070 [0.609]
Ba+ (i) versus Ba– (ii)	0.321	0.298	1.077 [0.767]
B. Male subjects			
Ma+ (i) versus Ma– (ii)	0.652	0.631	1.033 [0.253]
Ma+ (i) versus Ba+ (ii)	0.652	0.640	1.019 [0.094]
Ma+ (i) versus Ba– (ii)	0.652	0.599	1.088 [1.632]
Ma– (i) versus Ba+ (ii)	0.631	0.640	0.986 [0.043]
Ma– (i) versus Ba– (ii)	0.631	0.599	1.053 [0.600]
Ba+ (i) versus Ba– (ii)	0.640	0.599	1.068 [0.996]
C. Female subjects			
Ma+ (i) versus Ma– (ii)	0.062	0.042	1.476 [1.176]
Ma+ (i) versus Ba+ (ii)	0.062	0.022	2.818** [6.003]
Ma+ (i) versus Ba– (ii)	0.062	0.026	2.385** [4.564]
Ma– (i) versus Ba+ (ii)	0.042	0.022	1.909 [2.001]
Ma– (i) versus Ba– (ii)	0.042	0.026	1.615 [1.199]
Ba+ (i) versus Ba– (ii)	0.022	0.026	0.846 [0.101]

Notes. The education levels (Ma+, Ma–, Ba+, and Ba–) are those of the evaluated profiles. See Subsection 3.3 for definitions of the variables Ma+, Ma–, Ba+, and Ba–. * (**) ((***)) indicates significance at the 10% (5%) ((1%)) level.

Figure A–1. Example profile.



Note. As mentioned in Subsection 3.2, occupation and education are optional entries for one's Tinder profile.