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Are men intimidated by highly educated women? Undercover on Tinder

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ABSTRACT

In this study, we examine the impact of an individual's education level on her/his mating success on the mobile dating app Tinder. To do so, we conducted a field experiment on Tinder in which we collected data on 3,600 profile evaluations. In line with previous research on mating preferences from multiple fields, our results indicate a heterogeneous effect of education level by gender: while women strongly prefer a highly educated potential partner, this hypothesis is rejected for men. In contrast with recent influential studies from the field of economics, we do not find any evidence that men would have an aversion to a highly educated potential partner. Additionally, in contrast with most previous research – again from multiple fields – we do not find any evidence for preferences for educational assortative mating, i.e. preferring a partner with a similar education level.

1. Introduction

The way we find our life partner has drastically changed over the last few decades. Indeed, while before the Internet, i.e. around 25 years ago, no one could find their significant other online, 22% of heterosexual couples met each other this way by 2009. As a result, for heterosexuals the Internet has become 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).[1] 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), not in the least due to the recent advent of extremely popular mobile dating apps such as Tinder (Ranzini & Lutz, 2017; Ward, 2016), which is the app we focus on 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, 2019). Therefore not surprisingly, Tinder is currently valued at least $3 billion (Kuchler, 2018). Further, also in terms of 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, also in terms of couple formation Tinder plays a significant role nowadays. For example, as of this writing, Tinder users evaluate 2 billion other users per day, which has already resulted in more than 30 billion matches in total since its launch in 2012, in turn facilitating around 1 million offline dates per week (About Tinder, 2019).

Although for some people Tinder has the connotation of being used mainly to solicit casual and short relationships, multiple independent studies have shown – through (semi-structured) interviews and surveys of Tinder users – that this is not the case (LeFebvre, 2017; Sumter et al., 2017; Timmermans & Courtois, 2018; Timmermans & De Caluwé, 2017). Although these studies rely on self-reported motivations and are therefore prone to socially desirable answers, they are the best indication to date of why individuals use Tinder. Sumter et al. (2017) and Timmermans and De Caluwé (2017) have both shown 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 they reported that one-third of offline Tinder encounters led to casual sex, Timmermans and Courtois (2018) argue that nowadays, casual sex increasingly leads to a

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[1] For same-sex couples, the Internet has even become the most likely way to meet a life partner, with around two in three couples meeting each other this way.

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committed relationship. Nonetheless, even if relationships initiated on Tinder would ultimately be mainly casual, we believe determinants of successfully initiating these casual relationships would still be of high interest, given the indisputable popularity of Tinder and the time investment in this app (*supra*).

Despite its popularity, as of today, no study has examined mating behaviour[2] on mobile dating apps such as Tinder. This allows us to make several unique contributions to two bodies of literature. First, we contribute to the literature on mating success by examining for the first time the impact of an individual's education level on her/his mating success[3] on the mobile dating app Tinder. We link our findings to the important discussion of income inequality that may be facilitated by individuals' partner choice (*infra*, Section 2.2). Second, we add to the literature examining the (non-monetary) returns to education, *in casu* dating market returns. By doing so, we also contribute to the recently growing literature reporting negative dating market returns for women due to men's aversion to highly educated women (*infra*, Section 2.1). This aversion may have substantial consequences for women's progress in the labour market.

Additionally, 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,[4] 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 be substantially different (*infra*, Section 2.3). Second, we examine mate preferences *ex ante* to interactions instead of *ex post*, avoiding bias due to cues of attraction during these interactions. Third, we are able to estimate the impact of education level on mating success without substantial search frictions or 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 literature on both the returns to education and mating behaviour. 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, indicates several limitations of this study, and formulates various directions for future research.

2. Literature review

2.1. Returns to education

As noted above, this study adds to two main bodies of literature. First, it adds to the literature examining the returns to education. On the one hand, most previous studies on this topic examined the impact of education on monetary outcomes such as earnings, finding a positive effect (Card & Krueger, 1992; Jensen, 2010; Leigh & Ryan, 2008; Psacharopoulos & Patrinos, 2004). On the other hand, several other studies examined the impact of education on non-monetary returns, such as, among many others,[5] health (Groot & van den Brink, 2007; Silles, 2009), happiness (Chen, 2012; Cuñado & de Gracia, 2012), and criminal behaviour (Buonanno & Leonida, 2009; Groot & van den Brink, 2010; Machin, Marie & Vujić, 2011), all of which improved with higher education level. The present study adds to this second branch of studies in the returns to education literature by examining the returns to education on the dating market.

In recent years, an increasing number of studies (*infra*) reported negative returns to education on the dating market for women. This finding is often explained by the cost that is accompanied by deviating from social norms (Akerlof & Kranton, 2000), *in casu* gender identity norms. Even today, gender identity norms prescribe that men should be the main breadwinner in a relationship (Bertrand, Kamenica & Pan, 2015; Fortin, 2005). Therefore, given the positive correlation between education and earnings (*supra*), highly educated – and therefore high-earning – women have a disadvantage on the dating market, as it makes them less desirable to (some) men.

Bertrand et al. (2015) and Hwang (2016) indeed found that marriages where the wife earns more than the husband are substantially less common compared to the reversed situation. The former authors also found that when these marriages do occur, they are less happy and more likely to end in divorce. Additionally, Pierce, Dahl and Nielsen (2013) even found that men who are outearned by their partners suffer more sexual health problems. Using data from classic online dating websites and speed-dating, Hitsch, Hortaçsu and Ariely (2010a) and Fisman, Iyengar, Kamenica and Simonson (2006) also found that men are intimidated by highly educated and highly ambitious women, respectively. Finally, Bursztyn, Fujiwara and Pallais (2017) have shown that this aversion of men to highly educated women causes women to shy away from actions that could improve their careers in order to avoid signalling undesirable traits on the marriage market, such as high ambition. As a result, (women's anticipation to) men's aversion to highly educated, high-earning, and/or highly ambitious women may have a detrimental impact on women's progress on the labour market.

2.2. Mating behaviour

Second, this study contributes to the literature examining mating behaviour, which in the past focused on partner choice in an offline setting and on classic online dating websites. In an offline setting, multiple studies from the field of psychology have shown that men (compared to women) state a higher preference for physical attractiveness while women (compared to men) state a higher preference for highly educated partners and partners with a high earnings potential (Buss, 1989; Buss & Barnes, 1986; Buss et al., 1990; Shackelford, Schmitt & Buss, 2005; Wiederman & Allgeier, 1992). Similarly, using data from speed-dating events, Fisman et al. (2006) found that men (compared to women) put greater weight on physical attractiveness while women (compared to men) put greater weight on intelligence and ambition.

Additionally, studies using data from classic online dating websites also found similar mate preferences. For example, Whyte, Chan and Torgler (2018) found that women were almost twice as likely than men to state a preference for a certain education level and that women also stated a higher minimum acceptable education level in a preferred partner. Similarly, Hitsch et al. (2010a) and Hitsch, Hortaçsu and Ariely (2010b) found that men value physical attractiveness more than women and that women value education and earnings potential more than men. Finally, using data from a field experiment on a classic, Chinese online dating website, Ong (2016) found that men did not have a higher preference for highly educated women while women did have a higher preference for highly educated men.

All these findings are in line with evolutionary psychology, which suggests that mate preferences are driven by a potential partner's reproductive capacity (Trivers, 1972). More specifically, on the one hand a woman's reproductive value is signalled by greater physical attractiveness, indicating higher fertility. On the other hand, a man's

[2] 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.

[3] Similar to the definition of 'mating behaviour' (*supra*, footnote 2), 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.

[4] Such websites include Match.com, PlentyOfFish, and OkCupid.

[5] See Vila (2000) and Hout (2012) for more extensive reviews of the literature on the non-monetary returns to education.

reproductive capacity can be evaluated by his potential to provide (financially) for future offspring, which is signalled by (among others) his education level.

Many studies examining mating behaviour do not only examine so-called *common preferences*, i.e. preferences that are valued by everyone irrespective of one's own attributes, they also examine *assortative preferences*, i.e. preferences for attributes similar to one's own attributes (Buss, 1985). Multiple studies found evidence for these assortative preferences. For example, previous research on assortative mating in the field of psychology 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]

Additionally, earlier research has examined the presence of educational assortative mating using data from offline dating, i.e. data on marriages and from speed-dating events, as well as using data from classic online dating websites. In an offline setting, many studies – from different fields including psychology, sociology, and economics – have shown that marriages in which the partners have a comparable education level occur significantly more often than would be predicted by chance alone (Blossfeld, 2009; Domingue, Fletcher, Conley & Boardman, 2014; Mare, 1991; Pencavel, 1998; Rockwell, 1976; Watson et al., 2004). Using data from speed-dating events, Belot and Francesconi (2013) found evidence for assortative mating preferences based on education level. 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; Ong, 2016; Skopek, Schulz & Blossfeld, 2010; Whyte & Torgler, 2017a).

These preferences for assortative mating based on education level may have important economic consequences. Indeed, since in a relationship resources are shared, income inequality in a society increases when high-earning (low-earning) men mate with high-earning (low-earning) women. Given the strong link between education level and earnings potential (*supra*, SubSection 2.1), educational assortative mating preferences should thus increase income inequality. Indeed, multiple independent studies – from both sociology and economics – have shown that increased educational assortative mating increases income inequality in society (Blossfeld & Buchholz, 2009; Greenwood, Guner, Kocharkov & Santos, 2014; Hu & Qian, 2015; Mare, 1991).

2.3. Limitations of previous research

Most of the abovementioned studies suffer from various limitations preventing their results to be interpreted as causal effects. First, many studies – especially those in the field of psychology – examined data on *stated* mate preferences (Buss, 1989; Buss & Barnes, 1986; Buss et al., 1990; Shackelford et al., 2005; Whyte et al., 2018; Wiederman & Allgeier, 1992). However, the main issue with *stated* mate preferences is that they do not necessarily coincide with *actual* mate preferences, as it is not (always) the case that individuals pick a partner who satisfies their *a priori* stated preferences for a potential partner (Eastwick & Finkel, 2008; Hitsch et al., 2010b; Todd, Penke, Fasolo & Lenton, 2007; Whyte & Torgler, 2017b). The discrepancy between stated and actual mate preferences may especially be present for preferences for education level, as it may reveal unromantic and possibly mercenary motives as has been suggested by Ong and Wang (2015), who examined mate preferences for income.

Next, although multiple studies mentioned in the previous subsection did examine actual mate preferences, it is still not possible to give a causal interpretation to their results, as they examined dating outcomes *ex post* to interactions. This is the case for studies using marriage data (Bertrand et al., 2015; Hwang, 2016) and studies using speed-dating data (Belot & Francesconi, 2013; Fisman et al., 2006). Ong and Wang (2015) have argued that using such data to examine dating outcomes may lead to biased results due to cues of attraction during interaction. Additionally, it may be the case that individuals connected on factors that were correlated with education, such as beauty (Katz, 1995), intelligence, or income (*supra*, SubSection 2.1). In studies using speed-dating data, this concern is reinforced by the fact that it is uncertain whether individuals explicitly talked about their education in their three- or four-minute dates.

Additionally, although Hitsch et al. (2010a), Hitsch et al. (2010a), 2010b), Skopek et al. (2010), and Whyte and Torgler (2017a) used data from classic online dating websites to examine dating outcomes *ex ante* to interactions, they did not randomly assign different education levels to various profiles. As a result, these studies were unable to rule out that their results were driven by (unobservable) factors correlated with education and were therefore unable to estimate causal relationships. This concern is especially present for studies in which there is no control for beauty and income, such as in the studies by Skopek et al. (2010) and Whyte and Torgler (2017a), although these factors have been shown to have a strong correlation with education (*supra*). Furthermore, given that on several classic online dating websites – such as OKCupid – users are able to create their own idiosyncratic screening mechanisms, these websites could select for rather unconventional daters, causing results to be potentially biased due to this selection effect.

To the extent of our knowledge, only one study to date has examined the impact of education level on actual, revealed mate preferences *ex ante* to interactions and with random assignment of education level. Ong (2016) found that men's visits to women's profiles were unaffected by the profiles' education level, while women's visits to men's profiles were increasing with the profiles' education level. We build on this study by examining the impact of education level on mate preferences by means of a randomised field experiment on Tinder. Our study significantly differs from the study by Ong (2016) in three ways. First, we used a more precise measure of mating success: while Ong (2016) used the number of profile visits as an indicator of mating success, we used an explicit indication of interest by potential partners (*infra*, Section 3.5). Second, we set up our field experiment on a mobile dating app instead of on a classic online dating website. Third, we examined Western singles instead of Chinese singles.

As noted earlier, many studies examining mating behaviour also examine preferences for assortative mating. However, next to the abovementioned methodological challenges when examining mate preferences, examining assortative mate preferences is accompanied by two additional challenges. First, results on assortative mating patterns using marriage data and data from classic online dating websites could be biased due to search frictions. When using marriage data, 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 (Hitsch et al., 2010a; Mare, 1991; Skopek et al., 2010). Blossfeld (2009); Mare (1991), and Shafer and Qian (2010) indeed argue that educational assortative mating in an offline setting is due to increased contact opportunities between men and women with similar education levels. When using data from classic online dating websites, search frictions are caused by the ability of users to filter potential partners based on their education level.

Second, 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 (Hitsch et al., 2010a). Consequently, they will only

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

contact potential partners who they perceive to be equally (or less) desirable as them, a perception that may be determined by (among others) one's education level.

To the extent of our knowledge, again only the study by Ong (2016) was able to examine actual, revealed preferences for educational assortative mating *ex ante* to interaction and with random assignment of education level, in a context without substantial search frictions and social frictions. Ong (2016) found that on a classic, Chinese online dating website, women do not mate assortatively based on education level *per se* – i.e. because it may increase relationship public goods such as enlightened conversation. However, he did find that women mate assortatively based on education level for the sake of maximising (future) mate income, which is strongly correlated with education (*supra*, Section 2.1).

Similarly to Ong (2016), we were able to examine assortative mate preferences in the absence of search frictions and social frictions. Indeed, contrary to offline dating, contact opportunities do not differ on Tinder between people with equal education levels and people with unequal education levels, eliminating bias due to search frictions. Similarly, contrary to classic online dating websites, Tinder users cannot filter based on education level (*infra*, Section 3.2). Therefore, 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*), 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. Additionally, on Tinder bias due to social frictions is eliminated as the fear of rejection is less (or even not at all) present because users anonymously show interest in a potential partner. This anonymity is only lifted when both users show interest in each other (*infra*, Section 3.2) and therefore reduces (or even removes altogether) the psychological cost of explicit rejections. Furthermore, the (time) cost of expressing interest in a potential partner on Tinder is low (*infra*, Section 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 causes for unequal treatment that have been identified in previous literature spanned from racial discrimination (Baert, Cockx, Gheyle & Vandamme, 2015; Bertrand & Mullainathan, 2004) 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

In contrast to classic online dating websites, on Tinder users need to fill in only three criteria to get started. More specifically, they fill in (i) their sexual preference, (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 on the main screen of these profiles is the other users' (i) picture(s), (ii) first name, (iii) age, (iv) education, and (v) occupation, although the latter two pieces of information are optional entries. See Fig. A–1 in the Appendix for a fictitious example of a Tinder profile. Additionally, users have the possibility to click on a profile, after which they get shown the other user's distance in kilometres and (if provided by the other user) their bio (a short free text), Instagram photos, and favourite songs on Spotify.

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.[8] 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 indicates they dislike the other person.

3.3. Fictitious 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, which was randomly assigned to the 24 fictitious profiles. Education level was signalled by filling in the line 'education' on the main screen.[9] See Fig. A–1 for an example, in which the profile has the education level 'Master in Economics'. The people in our fictitious profiles all obtained a degree related to the field of study 'business and economics'. Although this limits our external validity (*infra*, Section 5, third paragraph, on the limitations of this study), it ensures internal validity. The four degrees of education level that were used, i.e. the four treatments, were the following, ranked from highest to lowest:

- 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–').[10,11]

In Flanders, Master's degrees are obtained at universities while these Bachelor's degrees are obtained at colleges, which are less prestigious than universities.

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. Given the popularity of the education levels used in our fictitious profiles (see footnote 11), it is likely that this ranking of starting salaries is known to the subjects (*infra*, Section 3.4) of our study. As a consequence, the effect of education level identified in our study may (partly) be due to the signal of a higher earnings potential that often coincides with a higher education level (*supra*, Section 2.1). We therefore interpret our results as the total effect of education level, i.e. encompassing also higher earnings potential, instead of as the direct effect of education level – as examined by Ong (2016) – which for example could be due to a preference for an

[7] See Baert (2018) for an extensive review of correspondence experiments in the labour market since 2005.

[8] This is possible once (five times) a day for non-paying (paying) users.

[9] On Tinder, about two-thirds of users show their education level (see also Subsection 3.4).

[10] Revealing one's education level on this level is not uncommon on Tinder, as 356 of the 2,345 Tinder users in our sample who revealed their education level (*infra*, Subsection 4.3), revealed it on this level.

[11] Table A–1 in the Appendix shows that the four degrees of education levels which we used for the fictitious profiles are fairly (for Ma–) to very (for all other education levels) popular in Flanders. Therefore, no education level was uncommon or distinctive to hold. This is true both in general as well as when considering each gender separately.

enlightened conversation or a desire to go on sophisticated dates.

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 subjects of our study 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, to ensure that the profiles signal that they acquired the degree mentioned in their profiles. As students in Flanders start higher education at the age of 18, and the longest period of study for our profiles was the 'Master in Business Engineering', which spans five years, our profiles would all be perceived as recently graduated. As a consequence of using age 23 for our profiles, our profiles were only shown to subjects who included age 23 in their age range.

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 making them aware of the experiment. 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 different pictures (16 male, 16 female) on Amazon Mechanical Turk (hereafter: 'MTurk'),[12] and selected eight pictures (four male, four female) that 493 workers on MTurk judged to be similar in level of attractiveness. Then, to ensure that the effect of education level was not driven by the picture, we attached to each picture three different education levels in three different cities.[13] Table A–2 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 names 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.). There was no randomisation of the names over the different pictures: each name was mapped one-to-one with the pictures. This could not influence our results, as we randomised our treatment of interest, i.e. education level, over the (fixed) combination of the names and the pictures.

Finally, we did not fill in an occupation and short bio for our Tinder profiles. Additionally, we did not link our profiles to an Instagram or Spotify account. All of this is not unusual on Tinder, as we show in the next subsection.

3.4. Subjects

Our subjects were other, real, Tinder users who fit our three criteria, i.e. (i) sexual preference, (ii) age range, and (iii) distance range. First, in this study we only looked at heterosexual preferences. Therefore, we indicated that we only wanted to see male (female) subjects with our female (male) profiles. Second, for the age range, we chose ages 23 to 27, in order to exclude students from our sample. Third, our distance range we gradually increased per kilometre from the minimum of two kilometres on, in order to find the subjects who 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. Only once we had to increase the range above the minimum of two kilometres and all subjects were found in a range of three kilometres.

With each of our 24 fictitious profiles, between January 2018 and March 2018 we randomly liked 150 of the first Tinder users who were presented to our fictitious profiles, resulting in a sample size of 3600 observations. We did not simply like the very first 150 Tinder users presented to us, as Tinder may then have perceived our fictitious profiles as robots. Therefore, for each Tinder user presented to us, we randomly generated a number between 0 and 1 and liked the Tinder user if the number was above 0.5. For each of our 24 fictitious profiles, all subjects were recruited from the first 325 Tinder users presented to our fictitious profiles.

As a result of randomly liking 150 subjects with each of our fictitious profiles, some subjects were liked by more than one of our fictitious profiles. More specifically, 39 subjects were liked by all four fictitious profiles in the same city, 210 subjects were liked by three profiles in the same city, 604 subjects were liked by two profiles in the same city, and 1606 subjects were liked by one profile. No subjects were liked by profiles in different cities. Therefore, the total number of unique subjects in our sample is 2459. We take this into account in our analyses in Section 4.

Table 1 presents summary statistics on all available information on our subjects.[14] In column (1) the summary statistics are reported for the full sample of subjects. Subjects had on average 4.432 pictures in their Tinder profile and were on average 24.141 years old. A total of 65.1% (26.3%) of individuals revealed their education (occupation). This education level (occupation level) was high in 57.7% (26.3%) of the (revealed) cases.[15] Finally, 57.1% of subjects filled in a short bio and 14.1% (11.3%) of subjects linked their Tinder profile to their Instagram account (Spotify account). Columns (2) to (5) present the summary statistics of the subjects by treatment status, i.e. by the four different education levels of our fictitious profiles. To test whether subjects differed by treatment status, we used the treatment status as a categorical independent variable in (logistic) regressions with the variables in Table 1 as dependent variables. We report the p-values of the coefficients measuring the differences between subjects with different treatment status in Table A–3. We find one significant difference at the 5% confidence level. However, when making 54 comparisons, rejecting one true null hypothesis is to be expected (Type I error). Therefore, we conclude that for all variables reported in Table 1, subjects did not significantly differ from each other by treatment status and that our randomisation process was thus successful.

3.5. Responses

Because with each fictitious profile we liked just the 150 subjects (and no other), if a subject liked or superliked our profile, we would be made aware of this by Tinder, which would indicate that we had a

[12] MTurk is an Internet marketplace on which individuals can hire 'workers' to perform small online 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).

[13] 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), it 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.

[14] Although we also have information on the names of the subjects, quantifying this was not informative. Additionally, we do not report information on the subjects' distance from our fictitious profiles, as this changed when the subjects were physically moving.

[15] Education level was considered high when subjects had a university degree. Occupation level was considered high when subjects had occupations that required a university degree.

Table 1
Summary statistics of the subjects for the full sample and by treatment status.

Variable	Description	(1)	(2)	(3)	(4)	(5)
			By treatment status			
		Full sample mean (SD)	Ma + mean (SD)	Ma- mean (SD)	Ba + mean (SD)	Ba- mean (SD)
Number of profile pictures	Continuous variable.	4.432 (1.411)	4.467 (1.390)	4.433 (1.416)	4.406 (1.412)	4.422 (1.426)
Age	Continuous variable.	24.141 (1.180)	24.140 (1.195)	24.161 (1.218)	24.126 (1.154)	24.138 (1.152)
Education displayed	1 if displayed, 0 otherwise.	0.651 (-)	0.628 (-)	0.648 (-)	0.681 (-)	0.649 (-)
Education level	1 if high, 0 otherwise.	0.577 (-)	0.572 (-)	0.587 (-)	0.582 (-)	0.568 (-)
Occupation displayed	1 if displayed, 0 otherwise.	0.263 (-)	0.249 (-)	0.274 (-)	0.258 (-)	0.272 (-)
Occupation level	1 if high, 0 otherwise.	0.263 (-)	0.268 (-)	0.279 (-)	0.241 (-)	0.261 (-)
Bio displayed	1 if displayed, 0 otherwise.	0.571 (-)	0.560 (-)	0.577 (-)	0.587 (-)	0.562 (-)
Instagram account displayed	1 if displayed, 0 otherwise.	0.141 (-)	0.146 (-)	0.137 (-)	0.129 (-)	0.151 (-)
Spotify account displayed	1 if displayed, 0 otherwise.	0.113 (-)	0.125 (-)	0.109 (-)	0.111 (-)	0.106 (-)
N	Number of observations.	3600	900	900	900	900

Notes. No standard deviations are presented for binary variables. The education levels (Ma + , Ma–, Ba + , and Ba–) are those of the evaluated profiles. See Section 3.3 for definitions of the variables Ma + , Ma–, Ba + , and Ba–.

Table 2
Summary statistics of the outcome variables for the full sample and by gender of the subjects.

	(1) All subjects (N = 3600)	(2) Male subjects (N = 1800)	(3) Female subjects (N = 1800)
No match (proportion of all observations)	2403 (0.668)	684 (0.381)	1719 (0.955)
Match (proportion of all observations)	1197 (0.332)	1116 (0.619)	81 (0.045)
Like (proportion of number of matches)	1180 (0.986)	1100 (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.

match with that subject.[16] 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. Two weeks after liking 150 subjects with a certain fictitious profile, we stopped registering responses by the subjects.

Table 2 gives an overview of the frequencies 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. These findings are in line with previous research on online dating in general (Fiore, Taylor, Zhong, Mendelsohn & Cheshire, 2010; Todd et al., 2007) and on Tinder in particular (Tyson, Perta, 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, these findings are 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. Finally, the fact that the subjects were the same age or older than our profiles, may also have caused female subjects to (super)like our profiles less often than male subjects, given that in heterosexual relationships the male partner is often older (Buss, 1989; Hitsch et al., 2010b). However, the fact that all subjects indicated in their search criteria that they were interested in profiles aged 23 (*supra*, Section 3.3), reduces the likelihood that age preferences are the driver of this selectivity.

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 8). 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 to men) with regard to (super)liking a certain profile.

Fig. 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 that the match probability decreased as the education level of the evaluated profiles also decreased. Similarly, in the centre and the rightmost bar charts, 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.

3.6. Ethical considerations

The creation of fictitious profiles on Facebook – which is a necessary prerequisite to create profiles on Tinder – and on Tinder is against the usage policies of both companies. However, creating fictitious profiles was indispensable for our research design. This research design was approved by the Ethical Committee of the Faculty of Economics and Business Administration of Ghent University. To minimise inconvenience to the subjects in our study, we did not interact with these subjects once a match was obtained. This lack of interaction once a

[16] Recall that a match is only formed when two users both like each other (*supra*, Subsection 3.2).

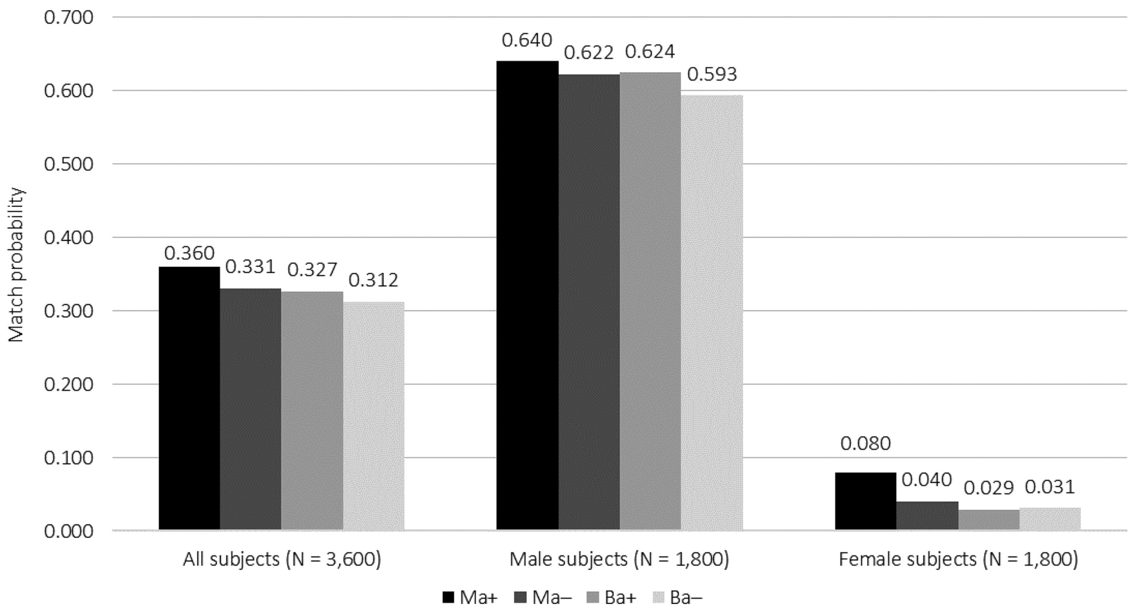

Fig. 1. Match probability by treatment status and by gender of the subjects.

match was obtained is not unusual on Tinder. Indeed, 60.2% of subjects with whom we matched did not start a conversation with our fictitious profiles.

4. Results

4.1. Bivariate analyses

In this subsection we present our bivariate analyses. As in Fig. 1, in Table 3 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 match probability of the evaluated profiles with the highest education level 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.

When considering all subjects in Panel A, we see that evaluated profiles with a higher education level consistently score better compared to 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

Table 3
Match ratios by treatment status.

	(1) Match probability education level (i)	(2) Match probability education level (ii)	(3) Match ratio: (1)/(2) [*t*-test]
A. All subjects			
Ma + (i) versus Ma– (ii)	0.360	0.331	1.087 [1.477]
Ma + (i) versus Ba + (ii)	0.360	0.327	1.102* [1.667]
Ma + (i) versus Ba– (ii)	0.360	0.312	1.153** [2.355]
Ma– (i) versus Ba + (ii)	0.331	0.327	1.014 [0.220]
Ma– (i) versus Ba– (ii)	0.331	0.312	1.060 [0.947]
Ba + (i) versus Ba– (ii)	0.327	0.312	1.046 [0.718]
B. Male subjects			
Ma + (i) versus Ma– (ii)	0.640	0.622	1.029 [0.604]
Ma + (i) versus Ba + (ii)	0.640	0.624	1.025 [0.511]
Ma + (i) versus Ba– (ii)	0.640	0.593	1.079 [1.499]
Ma– (i) versus Ba + (ii)	0.622	0.624	0.996 [0.071]
Ma– (i) versus Ba– (ii)	0.622	0.593	1.049 [0.923]
Ba + (i) versus Ba– (ii)	0.624	0.593	1.052 [0.987]
C. Female subjects			
Ma + (i) versus Ma– (ii)	0.080	0.040	2.000*** [2.650]
Ma + (i) versus Ba + (ii)	0.080	0.029	2.769*** [3.491]
Ma + (i) versus Ba– (ii)	0.080	0.031	2.571*** [3.295]
Ma– (i) versus Ba + (ii)	0.040	0.029	1.385 [0.982]
Ma– (i) versus Ba– (ii)	0.040	0.031	1.286 [0.770]
Ba + (i) versus Ba– (ii)	0.029	0.031	0.929 [0.221]

Notes. The education levels (Ma +, Ma–, Ba +, and Ba–) are those of the evaluated profiles. See Section 3.3 for definitions of the variables Ma +, Ma–, Ba +, and Ba–. The t-tests are corrected for clustering of the observations at the subject level. * (**) ((***)) indicates significance at the 10% (5%) ((1%)) level.

(super)like compared to the latter group.

We show the results for 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 to their counterparts who 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 and the names 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' if 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, dummy variables for the pictures and the names used in the evaluated profiles, and dummy variables 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 4. 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 are 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).

Similar to the results of the bivariate analyses, we find that higher-educated evaluated profiles are more successful on Tinder compared to their lower-educated counterparts. This finding is present in each of our five analyses shown in Table 4 and is driven by the highest education level. Indeed, when considering all subjects, the evaluated profiles with the highest education level have around one-third higher odds of obtaining a match compared to their lower-educated counterparts. When considering the male and female subjects separately, we find that this preference for profiles with the highest education level is driven by the female subjects. Indeed, male subjects do not significantly favour female evaluated profiles with the highest education level (the odds ratios never significantly differ from 1), whereas female subjects have around two times higher odds of (super)liking male evaluated profiles if these profiles had the highest education level.

As a first robustness check, we replicate all these regression analyses with an ordered logistic regression in which our dependent variable is assigned a value of '0' if 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 4
Match probability by treatment status: binary logistic regression results.

	(1)	(2)	(3)	(4)	(5)
A. All subjects					
Ma+	1.360** (0.174)	1.361** (0.174)	/	1.323** (0.150)	/
Ma+ or Ma–	/	/	1.282** (0.144)	/	1.247** (0.117)
Ma–	1.202 (0.157)	/	/	1.169 (0.135)	/
Ma– or Ba+	/	1.126 (0.123)	/	/	/
Ba+	1.059 (0.131)	/	1.058 (0.131)	/	/
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 and name	Yes	Yes	Yes	Yes	Yes
Control for city	Yes	Yes	Yes	Yes	Yes
N	3600	3600	3600	3600	3600
B. Male subjects					
Ma+	1.153 (0.161)	1.153 (0.161)	/	1.110 (0.134)	/
Ma+ or Ma–	/	/	1.123 (0.136)	/	1.082 (0.108)
Ma–	1.095 (0.153)	/	/	1.055 (0.129)	/
Ma– or Ba+	/	1.087 (0.132)	/	/	/
Ba+	1.078 (0.153)	/	1.078 (0.153)	/	/
Ba+ or Ba–	/	/	/	Ref.	Ref.
Ba–	Ref.	Ref.	Ref.	/	/
Control for picture and name	Yes	Yes	Yes	Yes	Yes
Control for city	Yes	Yes	Yes	Yes	Yes
N	1800	1800	1800	1800	1800
C. Female subjects					
Ma+	1.986** (0.691)	1.953** (0.661)	/	2.061** (0.628)	/
Ma+ or Ma–	/	/	1.863* (0.619)	/	1.914** (0.517)
Ma–	1.626 (0.667)	/	/	1.698 (0.580)	/
Ma– or Ba+	/	1.216 (0.420)	/	/	/
Ba+	0.927 (0.385)	/	0.949 (0.401)	/	/
Ba+ or Ba–	/	/	/	Ref.	Ref.
Ba–	Ref.	Ref.	Ref.	/	/
Control for picture and name	Yes	Yes	Yes	Yes	Yes
Control for city	Yes	Yes	Yes	Yes	Yes
N	1800	1800	1800	1800	1800

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

Table A–4 in the Appendix for the regression results. Additionally, as some subjects were recruited into the experiment by multiple fictitious profiles (*supra*, Section 3.4), in a second robustness check we replicated our multivariate analyses correcting for random effects on the subject level. This too does not substantially change our findings.

On the one hand, the finding in both our bivariate and multivariate analyses that education level – potentially signalling earnings potential (*supra*, Section 3.3) – matters significantly only for female subjects, is in line with previous research on mate preferences (*supra*, Section 2.2). More specifically, it is in line with previous studies examining stated mate preferences (Buss, 1989; Buss & Barnes, 1986; Buss et al., 1990; Shackelford et al., 2005; Whyte et al., 2018; Wiederman & Allgeier, 1992) and previous studies examining actual mate preferences in speed-dating events (Fisman et al., 2006) and on classic online dating websites (Hitsch et al., 2010a, 2010b; Ong, 2016). Apparently, women's preference for highly educated – and therefore indirectly potentially high-earning partners – is 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 to men) when evaluating potential partners, which we discussed in Section 3.5.

On the other hand, the finding that men on Tinder do not seem to be intimidated by highly educated – and therefore potentially high-earning – women is in contrast with multiple studies that did find evidence for men's aversion to highly educated women (*supra*, Section 2.1). More specifically, this is in contrast with Bertrand et al. (2015) and Hwang (2016), who found that marriages where the wife earns more than the husband are less common, as well as in contrast with both Hitsch et al. (2010a) and Fisman et al. (2006), who found that men disfavour highly educated and highly ambitious women, respectively. It is also in contrast with the study by Hitsch et al. (2010b), although this study found that men have a preference for a high-income partner compared to a low-income partner.

We suggest three possible explanations for this contrasting finding for male subjects. First, as our results are in line with those of Ong (2016), who also obtained his results by setting up a field experiment, we argue that this research design, i.e. random assignment of education level, is crucial for identifying unbiased mate preferences. Indeed, such a research design is able to estimate the effect of education level on mate preferences separate from the effect of (unobservable) factors correlated with education level (*supra*, Section 2.3). Second, Sumter et al. (2017) found that men more often than women state casual sex as a motivation for using Tinder and that men also have more one night stands through Tinder compared to women. Men's higher focus on casual relationships may be another driver of our result. Still, the fact that men are not intimidated by highly educated women even for short, casual relationships is remarkable and inconsistent with earlier studies that did suggest this aversion (Fisman et al., 2006; Pierce et al., 2013). Third, our study focuses on relatively young people (aged between 23 and 27, *supra* SubSection 3.4), who have to a great extent been raised by working mothers. Multiple studies have shown that women's increasing presence on the labour market is weakening traditional gender identity roles: Fernández Fogli and Olivetti (2004) have shown this change in attitudes for men and Olivetti, Patacchini and Zenou (2018) have shown this change in attitudes for women. This weakening of gender identity roles causes the cost for men from deviating from these gender identity roles – i.e. when mating with a highly educated or high-earning partner – to decrease, in turn causing them to be less intimidated by highly educated women.

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. a preference for educational assortative mating (also 'homogamy based on education level'). For 2345 subjects (65.1%), we have information on whether or not they attended university.[17] A total of 1354 of these subjects (57.7%) attended university while the other 991 subjects (42.3%) did not. Also for the evaluated profiles we know – by design – that some attended university (those with education levels 'Ma + ' and 'Ma–'), while others did not (those with education levels 'Ba + ' and 'Ba–') (*supra*, Section 3.3) – they attended the less-prestigious colleges.[18] Based on 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. 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. In our sample, there was a situation of homogamy, hypergamy, or hypogamy in 1173, 483, and 689 cases, respectively.

Similar to our bivariate analyses in Section 4.1, in Table 5 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.

We do not find any evidence for a specific preference for homogamy based on education level. Indeed, when we compare the situation of homogamy with the situation of no homogamy, the match ratios never significantly differ from 1, neither in the full sample nor in the subsamples of male and female subjects. These findings are not in line with most studies examining mating preferences in an offline setting and on classic online dating websites that found evidence for educational assortative mating (*supra*, Section 2.2).

We suggest that the lack of evidence for educational assortative mating on mobile dating apps such as Tinder is 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 2.2). Second, as already mentioned in Section 2.3, search frictions, which may have driven educational assortative mating in previous research on offline dating and 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 2.3, social frictions influence mating behaviour less (or even not at all) on Tinder compared to offline dating or classic online dating websites, as the anonymity within which Tinder users express interest in another user reduces (or even eliminates) the psychological cost of being rejected.

While we find no evidence for a specific preference for homogamy, we do find that Tinder users favour (disfavour) a situation of homogamy compared to a situation of hypogamy (hypergamy). Indeed, in the full sample the match ratio is significantly above (below) 1 when comparing the situation of homogamy with the situation of hypogamy (hypergamy). Although the results seem to be driven by the female subsample, the match ratios are, however, insignificant for both the male and female subsamples.

[17] We cannot rule out that the results in this subsection are driven by a selection bias introduced by only considering subjects who reported their own education level. However, as the results from the previous paragraphs are unchanged when considering only these subjects (see Table A–5 in the Appendix for a replication of Table 3 for these subjects), we are confident that the results in this subsection are not driven by a selection bias.

[18] As the education level of the 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 5
Match ratios by homogamy, hypergamy, and hypogamy.

	(1) Match probability situation (i)	(2) Match probability situation (ii)	(3) Match ratio: (1)/(2) [*t*-test]
A. All subjects			
Homogamy (i) versus no homogamy (ii)	0.321	0.322	0.996 [0.064]
Homogamy (i) versus hypergamy (ii)	0.321	0.385	0.833** [2.485]
Homogamy (i) versus hypogamy (ii)	0.321	0.277	1.156** [2.067]
Hypergamy (i) versus no hypergamy (ii)	0.385	0.305	1.265*** [3.113]
Hypogamy (i) versus no hypogamy (ii)	0.277	0.339	0.817*** [2.953]
Hypergamy (i) versus hypogamy (ii)	0.385	0.277	1.389*** [3.528]
B. Male subjects			
Homogamy (i) versus no homogamy (ii)	0.638	0.623	1.024 [0.539]
Homogamy (i) versus hypergamy (ii)	0.638	0.672	0.950 [0.916]
Homogamy (i) versus hypogamy (ii)	0.638	0.583	1.094 [1.622]
Hypergamy (i) versus no hypergamy (ii)	0.672	0.618	1.086 [1.508]
Hypogamy (i) versus no hypogamy (ii)	0.583	0.649	0.899** [2.001]
Hypergamy (i) versus hypogamy (ii)	0.672	0.583	1.152** [2.068]
C. Female subjects			
Homogamy (i) versus no homogamy (ii)	0.037	0.038	0.974 [0.095]
Homogamy (i) versus hypergamy (ii)	0.037	0.062	0.601 [1.422]
Homogamy (i) versus hypogamy (ii)	0.037	0.024	1.554 [1.124]
Hypergamy (i) versus no hypergamy (ii)	0.062	0.032	1.922* [1.750]
Hypogamy (i) versus no hypogamy (ii)	0.024	0.044	0.546* [1.821]
Hypergamy (i) versus hypogamy (ii)	0.062	0.024	2.583** [2.058]

Notes. See Section 4.3 for definitions of the variables homogamy, hypergamy, and hypogamy. The *t*-tests are corrected for clustering of the observations at the subject level. * (**) ((***)) indicates significance at the 10% (5%) ((1%)) level.

The preference for hypergamy is confirmed when comparing the situation of hypergamy directly to the situation of no hypergamy. Indeed, when considering all subjects, they are 26.5% more likely to (super)like an evaluated profile that is higher educated than themselves, compared to when that is not the case. This effect is driven by the female subjects, who (super)like higher educated profiles 92.2% more often, while this effect is not significant for the male subjects. These findings are in line with those of Whyte and Torgler (2017a), who found, using data from a classic online dating website, that women are more likely than men to contact a potential partner with a higher education level.

Additionally, the aversion to hypogamy is confirmed when comparing the situation of hypogamy to the situation of no hypogamy. When considering all subjects, they are 18.3% less likely to (super)like an evaluated profile that is lower educated than themselves, compared to when that is not the case. This effect is present for both male and female subjects. More specifically, compared to a situation of no hypogamy, male and female subjects (super)like lower-educated evaluated profiles 10.1% and 45.4% less often, respectively – although for the female subjects this result is only significant at the 10% confidence level. The finding that this match ratio is substantially lower for the female subjects compared to 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.

Finally, when directly comparing a situation of hypergamy to a situation of hypogamy we find – naturally – that in this scenario there exists a strong preference for hypergamy. Taking into account the discussion in the previous paragraph, in the female subsample this result is driven by both a preference for hypergamy and an aversion to hypogamy, while in the male subsample this result is driven solely by an aversion to hypogamy.

Combining these findings with our findings from the previous subsection, we can conclude that for women on Tinder the preference for a highly educated partner is not only absolute but also relative to their own education level. Contrarily, men on Tinder do not have a preference for a potential partner with a higher education level than themselves. However, the fact that they also do not have an aversion to this situation again confirms that they are not intimidated by highly educated women, even if a woman's education level would exceed their own. Moreover, they even disfavour women who have a lower education level than themselves. Three possible explanations for these findings for men are similar to those raised in Section 4.2 when discussing the absence of men's aversion to highly educated women.

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 the (non-monetary) returns to education and the literature on mating behaviour. 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 substantial search frictions and social frictions. Based on a sample of 3600 Tinder profile evaluations, 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 multiple fields that found that women have a higher preference for a highly educated partner who in turn has a higher earnings potential. Additionally, in contrast to earlier studies from the field of economics we found no evidence that men are intimidated by highly educated – and therefore potentially high-earning – women. This may have important, positive consequences for women on the labour market, who have been shown in the past to shy away from behaviour that may improve their careers in order to avoid signalling undesirable traits on the dating market, such as ambition.

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 most studies examining this sorting behaviour in an offline setting and on classic online dating websites. We argue 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 (Blossfeld & Buchholz, 2009; Greenwood et al., 2014; Hu & Qian, 2015; Mare, 1991), 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 could not be 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 because it is to a great extent only populated by female students (74,21%). Therefore, a logical way for future research to build on this study would be to verify 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 that each individual using mobile dating apps needs to get through in order to advance to the later stages of a relationship. It is in this sense comparable to previous studies conducting field experiments on the labour market that 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 the 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 women favoured potential partners who were highly educated, we were unable to deduce *why* this was the case. More specifically, we do not know if this effect was driven by a preference for (i) an intelligent partner, (ii) a partner with high status, (iii) a partner with a high earnings potential, or (iv) something else. Future research could complement this study by identifying the main driver(s) of this preference of women for a highly educated potential partner.

Similarly, we argue that the lack of evidence for preferences 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.

Declaration of interest

None.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.econedurev.2019.101914.

Appendix A

Fig. A-1

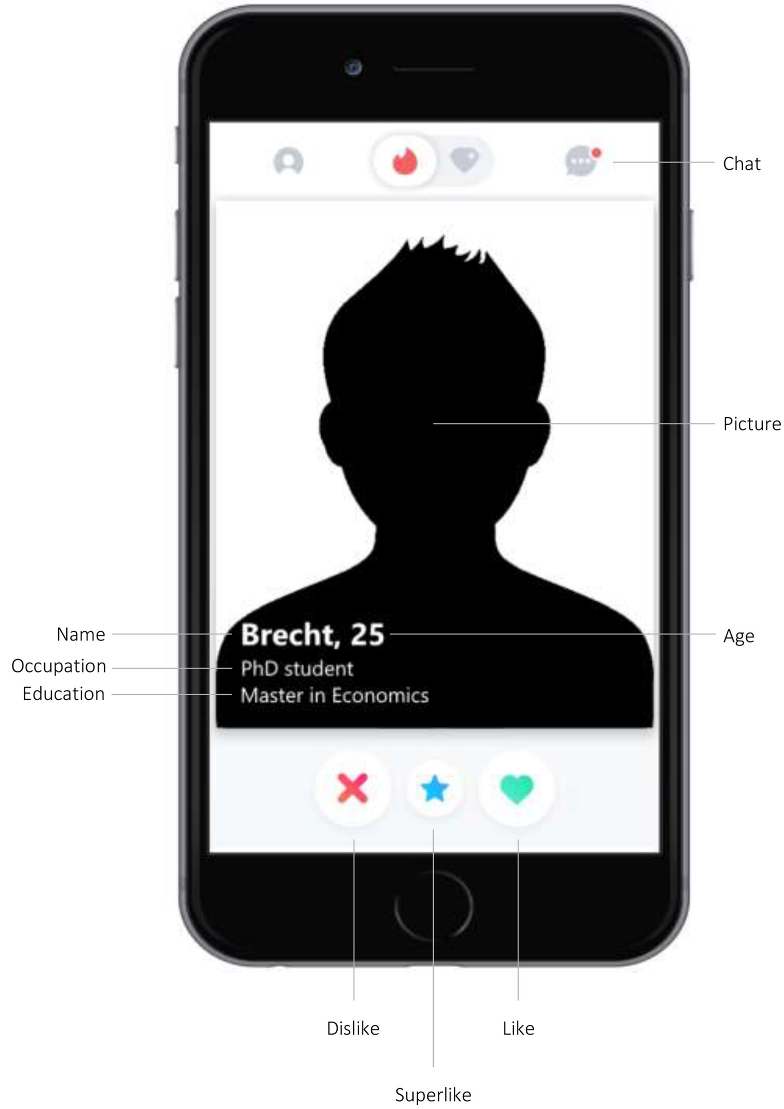

Fig. A-1. Example profile.
Note. As mentioned in Section 3.2, occupation and education are optional entries for one's Tinder profile.

Table A-1

Table A-1
Student enrolment in each subfield of the education levels of the fictitious profiles in the academic year 2017–2018.
Source: Agentschap voor Hoger Onderwijs, Volwassenenonderwijs, Kwalificaties en Studietoelagen.

	Total	Males	Females
Master in Business Engineering (Ma+)	3739	2445 (65.39%)	1294 (34.61%)
Master in Public Administration and Management (Ma–)	506	226 (44.66%)	280 (55.34%)
Bachelor in Business Management (Ba+)	18,775	10,917 (58.15%)	7858 (41.85%)
Bachelor in Office Management (Ba–)	4140	1215 (29.35%)	2925 (70.65%)
Total	27,160	14,803 (54.50%)	12,357 (45.50%)

Table A-2

Table A-2
Representation of the randomisation process.

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

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

Table A-3

Table A-3
P-values for the coefficients measuring the difference between subjects by treatment status.

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Ma + vs. Ma–	Ma + vs. Ba +	Ma + vs. Ba–	Ma– vs. Ba +	Ma– vs. Ba–	Ba + vs. Ba–
Number of profile pictures	0.710	0.810	0.977	0.541	0.689	0.832
Age	0.604	0.363	0.494	0.695	0.869	0.820
Education displayed	0.377	0.017**	0.351	0.134	0.961	0.148
Education level	0.608	0.710	0.913	0.882	0.531	0.627
Occupation displayed	0.218	0.665	0.260	0.424	0.916	0.488
Occupation level	0.780	0.517	0.871	0.345	0.651	0.618
Bio displayed	0.575	0.296	0.755	0.627	0.383	0.175
Instagram account displayed	0.296	0.371	0.203	0.880	0.819	0.705
Spotify account displayed	0.475	0.253	0.924	0.667	0.536	0.294

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

Table A-4

Table A-4
Match/conversation probability by treatment status: ordered logistic regression results.

	(1)	(2)	(3)	(4)	(5)
A. All subjects					
Ma +	1.385*** (0.160)	1.385*** (0.160)	/	1.293** (0.130)	/
Ma + or Ma–	/	/	1.288** (0.131)	/	1.201** (0.101)
Ma–	1.190 (0.142)	/	/	1.109 (0.116)	/
Ma– or Ba +	/	1.170 (0.119)	/	/	/
Ba +	1.151 (0.134)	/	1.152 (0.135)	/	/
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 and name	Yes	Yes	Yes	Yes	Yes
Control for city	Yes	Yes	Yes	Yes	Yes
N	3600	3600	3600	3600	3600
B. Male subjects					
Ma +	1.220 (0.149)	1.219 (0.149)	/	1.124 (0.118)	/
Ma + or Ma–	/	/	1.161 (0.124)	/	1.069 (0.093)
Ma–	1.105 (0.137)	/	/	1.017 (0.110)	/
Ma– or Ba +	/	1.142 (0.124)	/	/	/
Ba +	1.182 (0.151)	/	1.183 (0.151)	/	/
Ba + or Ba–	/	/	/	Ref.	Ref.
Ba–	Ref.	Ref.	Ref.	/	/
Control for picture and name	Yes	Yes	Yes	Yes	Yes
Control for city	Yes	Yes	Yes	Yes	Yes
N	1800	1800	1800	1800	1800
C. Female subjects					
Ma +	1.976** (0.687)	1.944** (0.658)	/	2.052** (0.625)	/
Ma + or Ma–	/	/	1.856* (0.617)	/	1.909** (0.516)
Ma–	1.623 (0.667)	/	/	1.697 (0.580)	/
Ma– or Ba +	/	1.214 (0.420)	/	/	/
Ba +	0.925 (0.385)	/	0.947 (0.400)	/	/
Ba + or Ba–	/	/	/	Ref.	Ref.
Ba–	Ref.	Ref.	Ref.	/	/
Control for picture and name	Yes	Yes	Yes	Yes	Yes
Control for city	Yes	Yes	Yes	Yes	Yes
N	1800	1800	1800	1800	1800

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 Section 3.3 for definitions of the variables Ma +, Ma–, Ba +, and Ba–. Coefficients are odds ratios. Standard errors are corrected for clustering of the observations at the subject level and are reported between parentheses. * (**) ((***)) indicates significance at the 10% (5%) ((1%)) level.

Table A-5

Table A-5
Match ratios by treatment status, 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) [*t*-test]
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 Section 3.3 for definitions of the variables Ma+, Ma–, Ba+, and Ba–. The *t*-tests are corrected for clustering of the observations at the subject level. * (**) ((***)) indicates significance at the 10% (5%) ((1%)) level.

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