Dating Preferences and Meeting Opportunities in Mate Choice Decisions

Michèle Belot
Marco Francesconi

ABSTRACT

Much empirical evidence shows that female and male partners look alike along a variety of attributes. It is, however, unclear how this positive sorting comes about because marriage is an equilibrium outcome arising from a process that entails searching, meeting, and choosing one another. This study takes advantage of unique data to shed light on the forces driving choices at the earliest stage of a relationship. Both women and men value physical attributes, such as age and weight, and reveal that their dating choices are assortative along several traits. Importantly, meeting opportunities have a substantial role in determining dating proposals.

I. Introduction

A well-established tradition of social science research has documented the strong resemblance of traits and socioeconomic status between husbands and wives. Both men and women tend to choose mates of similar age, race, education, and physical appearance (see, for example, Weiss (1997), Schwartz and Mare (2005), Kurzban and Weeden (2005), Fernandez, Guner, and Knowles (2005), and Choo and Siow (2006) for recent analyses and reviews). But isolating the forces that lie behind

Michèle Belot is at the University of Edinburgh (Michele.Belot@ed.ac.uk). Marco Francesconi is at the University of Essex (mfranc@essex.ac.uk) and research associate at the Institute for Fiscal Studies. *They are grateful to two anonymous referees, Gary Becker, Maristella Botticini, Martin Browning, Ken Burdett, Pierre-André Chiappori, Melvyn Coles, Aureo de Paula, Paul Eastwick, John Ermisch, Eli Finkel, Chris Flinn, James Heckman, Alison Lenton, Shelly Lundberg, Pedro Mira, Michele Pellizzari, Motty Perry, Robert Pollak, Aloysius Siow, and seminar participants at Amsterdam, CEMFI (Madrid), Chicago, Essex, IZA (Bonn), LSE, Milan, Oxford, Southampton, Swansea, Tilburg, Turin, and Warwick for suggestions and comments. The authors would like to thank the speed-dating agency personnel for providing and helping us with the data, and Aikaterini Dimika and Domenico Tabasso for excellent research assistance. Marco Francesconi also thanks the ESRC Centre for the Microeconomic Analysis of Public Policy at IFS and the ESRC Centre for Micro-social Change at Essex. The authors take responsibility for all errors.*
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this pattern of positive marital sorting is challenging because marriage is an equilibrium outcome arising from a process that entails searching, meeting, and choosing one another.

In a frictionless world, positive sorting may arise simply as a result of individual preferences or technological complementarities in the marital production function (Gale and Shapley 1962; Becker 1981). For instance, positive sorting can be consistent with aligned or "agreed-upon" preferences (whereby everyone values the same attributes) as well as with assortative or "likes-attract" preferences (whereby people prefer partners who are similar to themselves).

Search frictions, on the other hand, may lead to positive sorting through alternative mechanisms. In particular, matches could be determined by who meets whom, who proposes to whom, and who searches where. The first force, who meets whom, implies that meeting opportunities play a key role in the matching process. There is evidence that people tend to meet individuals who are like themselves (Kalmijn and Flap 2001) and this alone could lead to positive sorting. Even in an environment where everyone can potentially meet everyone else, search frictions, combined with aligned preferences on the partner's type, give rise to positive sorting. As shown in Burdett and Coles (1997), a class structure will emerge in equilibrium, whereby the optimal strategy is to propose to and accept proposals from potential partners only in a fixed type interval.[1]

Disentangling all such different channels empirically is challenging, as it is to identify whether mating preferences are aligned or assortative. A major problem is that analysts only observe "final matches" (that is, marriages and cohabitations), but seldom observe the whole pool of potential partners, nor do they have information on the process of proposals and rejections that prelude the formation of a relationship. As a result, we are typically unable to unravel the separate influence of the forces that underlie this union formation.[2] A few recent studies, however, shed light on the importance of such mechanisms by examining dating choices (for example, Kurzban and Weeden 2005; Todd et al. 2007).

This paper contributes to that new growing literature by using unique data from a large commercial speed-dating agency in Britain, and makes two substantive contributions. First, we provide direct evidence on the nature of the choices underlying mate selection. Second, we assess the importance of meeting opportunities relative to that of other forces driving dating choices (such as preferences for partners with certain attributes) in explaining the observed patterns in dating behavior. Both contributions rely on the fact that we use a large sample of speed daters who have a more diverse set of attributes than those analyzed in earlier studies. This in itself allows us to focus on an extensive set of dyadic interactions and analyze individual patterns of mate choices over several personal characteristics and over many events with a wide variation in the composition of the pool of participants across events.

As in earlier speed-dating studies, dating preferences can be recovered under the as-

1. If individuals can choose not only who to propose to and whom to accept proposals from, but also where they search (and therefore who they are likely to meet), then segmentation will emerge in equilibrium—that is, the marriage market will be segmented in a number of submarkets organized around classes of types (Jacquet and Tan 2007).

2. At the cost of model-specific functional form identifying restrictions, this has been achieved with the estimation of structural parameters of marriage (final match) models as in Wong (2003) and Bisin, Topa, and Verdier (2004).

sumption that speed daters engage in *straightforward* behavior (Fisman et al. 2006)—that is, if whenever a participant proposes to one individual but does not to another, then the flow utility value that the participant receives from the former is greater than the corresponding value obtained from the latter. Given straightforward dating behavior, the speed-dating protocol offers considerable advantages in comparison to other nonexperimental settings. First, it shares some of the key useful features of an experimental setup. Subjects meet a large number of potential partners in a sequence of short dates that are always organized in the same way: participants meet in pairs (a man and a woman), sit at a table, and chat for three minutes. This is a compelling example of a naturally occurring market as in other field studies (for example, Harrison and List 2004, 2008). Subjects' choices in these speed-dating sessions constitute real behavior with actual consequences.

Second, matches are formed via a fully anonymized central process, whereby participants report who they wish to meet again to the dating agency and have no limit to the number of proposals they can make. The agency, in turn, exchanges contact details only between participants who have proposed to each other. This setting therefore offers us detailed information on the dyadic choices made by each party as well as whether they form a match or not, enabling us to analyze the determinants of mate choices and to underpin the process through which matches are formed. Third, mate choices in this context are made at the earliest stage of a union—that is, after a first meeting. Since social mixing only can be achieved if people choose to engage further with each other after a first encounter, these early choices are crucial for our understanding of the formation of long-term partnerships.

Finally, subjects meet before they choose. This differs from studies of other forms of mediated dating, such as small ads (Lynn and Shurgot 1984) or online dating (Hitsch, Hortaçsu, and Ariely 2010; Finkel et al. 2012), where people choose whom to meet first and, only after, they possibly meet. This process of selection is likely to be driven by the information available to the parties before they meet, which may tend to exaggerate the role of certain attributes in the dating/mating market. Speed daters, in contrast, interact shortly with each other before they decide to propose or not, and have therefore more information at their disposal. There is a bulk of psychological evidence demonstrating that people make sophisticated social judgements (from mate choice to consumer choice) based on "thin slices" of social observations or very short interactions (for example, Ambady and Rosenthal 1992; Miller and Todd 1998; Finkel, Eastwick, and Matthews 2007; Finkel and Eastwick 2008; Iyengar 2009). These short interactions could therefore change the weight given to certain attributes.

We use data from 84 events, and in each of these events, we observe participants (approximately 22 men and 22 women in each event) who face exactly the same pool of potential partners (that is, the same choice set), and we observe their choices within this choice set. In addition, the real-life nature of our data is important for us to identify the role played by socioeconomic attributes: Not only is the sample of participants large, but crucially it is also much more diverse than that used in other speed-dating studies (for example, Fisman et al. 2006 and 2008).

Despite such methodological advantages, there may be questions about the external validity of our results. An argument could be raised on the self-selection of speed daters ("who goes speed dating?"). Although this cannot be summarily dismissed, we should stress the growing popularity of speed-dating events in Britain and elsewhere which gather individuals from all walks of life with ample variation in age, socioeconomic position, and physical attributes. In Section III, we will provide detailed information on our sample and discuss further the issues of its statistical representativeness and misreporting.

Our analysis yields three main findings. First, both women and men value easily observable physical attributes: Women prefer men who are young and tall, while men are more attracted to women who are young and thin. We also find that partner's education and occupation have an impact on desirability, irrespective of gender. Second, there is evidence of mild positive assortative preferences (rather than agreed-upon preferences) along a number of characteristics, with both women and men preferring partners of similar age, height, and education. Third, the impact of dating preferences is limited with meeting opportunities playing a more dominant role. This result emphasizes the notion that mating requires meeting: The pool of potential partners shapes the type of people whom subjects propose to and, ultimately, with whom they form durable relationships.

The rest of the paper is organized as follows. Section II discusses the related literature. Section III introduces the speed-dating protocol and describes our data. In Section IV, we discuss our main findings on attribute demands. The aim is to identify the determinants of mate choice and to establish whether, even at this early stage, a pattern of positive sorting emerges. Section V presents a picture of the patterns of dating proposals observed in the aggregate in each speed-dating session, providing us with evidence on the importance of meeting opportunities. In particular, we analyze how the relative abundance of specific attributes in a given market, as opposed to market homogeneity, affects mate selection. Section VI looks at dating matches — that is, cases in which individuals propose to each other. Section VII discusses our main findings emphasizing caveats and interpretations, and Section VIII concludes.

II. Related Literature

Early studies on human mating date back to Westermarck (1903) and Hamilton (1912). The economics literature, which has grown out of Becker's (1973; 1974; 1981) seminal work, has produced search and matching models that can generate wide arrays of sorting (for example, Lam 1988; Burdett and Coles 1997; Shimer and Smith 2000; Teulings and Gautier 2004; Choo and Siow 2006; Smith 2006; Chiappori, Iyigun, and Weiss 2009; Gautier, Svarer, and Teulings 2010; Coles and Francesconi 2011). The focus of most of these studies, however, is different from ours, as they characterize the conditions under which positive assortative matching arises and explain *why* matching is assortative. They pursue this goal in a variety of ways by, for example, imposing payoff supermodularity and transferable utilities between partners, or allowing for frictions in the matching process with nontransferable utilities, or modeling a household production function with spousal trait complementarities.

A different issue concerns the *nature* of mating preferences. This has not yet become a central issue in economics, although it is of great salience. Evolutionary psychologists and anthropologists argue that individuals prefer those who are similar to themselves on relevant dimensions (Berscheid et al. 1971). For example, similarity of values and tastes gives partners a better chance to participate in joint activities and leads to mutual confirmation of each other's behavior and lifestyle (Kalmijn 1994). A natural implication of this "likes-attract" mechanism is positive marital sorting. Others claim that mate preferences are shared across all individuals and primarily reflect traits that are evolutionarily advantageous (Trivers 1972; Buss 2003). People compete with others to search for mates with valuable resources. The result of this competition is that the most attractive candidates select amongst themselves while the least attractive must rely on one another. Competition for key resources on the marriage market, therefore, leads again to an aggregate pattern of positive assortative mating.

A small but burgeoning number of recent studies have analyzed mate selection taking advantage of the experimental setting of speed dating. Kurzban and Weeden (2005) use data from HurryDate, a large dating company operating in major metropolitan areas in the United States, to investigate the choices that approximately 2,600 subjects make in dating partners. Their main estimates show that female and male subjects have strong agreed-upon preferences rather than assortative preferences: They are equally attracted by physically observable attributes like weight, height, and age, and much less so by other attributes such as education and religion. They also report evidence of small positive assortative patterns along race and height.[3]

Within the economics literature, Fisman et al. (2006) base their experimental design on the HurryDate format to analyze a sample of about 400 students at Columbia University, with the objective of identifying gender differences in dating preferences. Their results slightly differ from those found by Kurzban and Weeden (2005). Only men exhibit a preference for physical attractiveness while women respond more to intelligence and race. They find some evidence of positive sorting, with male subjects valuing women's intelligence or ambition only if it does not exceed their own. They also document the importance of group size, whereby women (but not men) become more selective in larger meetings.[4]

Hitsch, Hortaçsu, and Ariely (2010) follow a different approach. They use data from a large sample of users of an online dating service in Boston and San Diego to see how individual traits affect the likelihoods of having a personal profile browsed, being contacted, and exchanging contact information via e-mail. Although online daters do not physically meet, this study confirms some of the previous evidence based on speed dating and final match data. For example, in line with the results discussed in Fisman et al. (2006), Hitsch and colleagues find that women put more weight on a partner's income than men do and, consistent with Fisman et al. (2008), women have a more pronounced preference to form a match with men of their own ethnicity. Lee (2009) also uses data from an online dating service in Korea. Her analysis compares sorting as observed in the general population to the simulated sorting that arises among daters. She finds more sorting along age and less sorting along socioeconomic attributes among daters than among individuals in the general population.

Finally, the paper by Nielsen and Svarer (2009) is, to our knowledge, the only study that explicitly examines the extent to which opportunities in the marriage market influence the tendency of individuals to marry someone who went to the same educational

3. Other contributions in the speed-dating literature include Todd et al. (2007) and Eastwick and Finkel (2008).

4. In a subsequent study using the same data, Fisman et al. (2008) investigate racial preferences in dating. Their finding that women have stronger racial preferences than men is not consistent with the results reported in Kurzban and Weeden (2005).

institution or to an institution near them. Using Danish administrative data on final matches, they find that about half of the systematic sorting on education can be explained by that tendency. They attribute this finding to low search frictions or selection of people with similar preferences into the same institutions — that is, proximity to partners, which is arguably an important component of matching opportunities.[5]

III. Data and Selection Issues

A. The Speed-Dating Protocol

Speed dating offers single individuals the opportunity to meet a large number of potential mates over a short predetermined period of time. We use data from one of the biggest U.K. private agencies. Participants register for an event that takes place in a specific location during the evening in a bar or club. Participants pay a fixed fee, which varies with location and occasional discounts. There is no specified maximum number of women and men who can participate in each session, although there are rarely more than 30 women and 30 men. Events are stratified by age (23–35 and 35–50 are typical age ranges) so that individuals of roughly the same ages participate in the same session. Bookings are made on the Internet or, less frequently, by phone. Individuals can book for an event as long as there are enough places available. The agency does not screen participants, nor does it intervene in the allocation of participants across events. Participants simply select a location and time.

In general, participants arrive for the event and, at registration, are given a starting table number, a label tag with a film star alias, and a pen and a card to indicate the alias of the people they wish to meet again (we shall refer to this choice as a *proposal*). The evening proceeds as follows. People sit at the assigned table, with women usually staying seated at the same table and men moving around. Each date lasts for three minutes. After a date, men move to the next table, and a new date begins. After eight individual dates the session stops and participants can move around before another round of eight three-minute dates starts. A typical evening consists of three such rounds, after which participants leave. Speed daters communicate their proposals to the agency after the event. There is no limit to the number of proposals subjects can make from the pool of participants. In fact, each individual can be matched more than once. The agency collects all these proposals and exchanges contact details only between participants who have a *match* — that is, those who propose to each other.

Participants are recommended to create a personal profile on the agency's website reporting information on age, education, occupation, basic physical characteristics (for example, weight and height), interests, smoking habits, and family situation (presence of children). [6] This information is self-reported and is not formally verified by the agency.[7] Profiles are accessible by all participants *after* the event only.

5. Bruze (2011) finds a strong tendency to sort positively on education in marriage among movie stars. Although this result, as Bruze suggests, could be ascribed to preferences, it might be driven instead by the pool of available partners movie stars usually interact with.

6. The profiles, however, do not contain information on race or ethnic origin.

7. Anecdotal evidence obtained from the agency reveals that the information given by speed daters in their profiles is truthful and the extent of lying is minimal.

Our estimating sample uses most of the available data drawn from these profiles. Each profile contains information on variables generally believed to be salient determinants of mate selection (Buss 2003). These include cues that can be apprehended visually, such as age, weight, height, as well as other traits that cannot be easily assessed, for example, educational attainment, occupation, and smoking status.

There are two potential problems with this information. The first is the misrepresentation of attributes and the other is missing information about (or nonreporting of) attributes. Regarding the first issue, we do not know the extent to which participants may have misrepresented their attributes in the online profiles. Using a random sample of daters, Hanckock, Toma, and Ellison (2007) provide direct evidence of the prevalence of misrepresentation in online dating profiles. They directly measure height, weight, and age for 80 online daters and then compare these "ground truth" data to the information provided in online dating profiles. The results suggest that deception is frequently observed, but that the magnitude of the deceptions is usually small. The average discrepancy between reported height and actual height is less than 1 centimeter, that between reported weight and actual weight is about 2.5 kilograms, and the deviation between observed and online age is five months. These findings therefore provide evidence of limited misrepresentation of attributes for online daters. We expect a smaller scope for lying among speed daters. This is because they meet personally even before accessing the online profiles. Arguably, the face-to-face meeting gives all participants an opportunity to assess the truthfulness of the information contained in the online profiles, especially in the case of attributes that are easier to verify. We will come back to the issue of misrepresentation in Section V.

The second problem—nonreporting—is more complex and possibly strategically motivated. Since reporting is not compulsory, participants may strategically abstain from reporting attributes they judge less desirable, rather than lie. As we will see later in this section, this behavior could explain discrepancies between the descriptive statistics of the sample and the general population.

B. Descriptive Statistics

We have data on approximately 1800 women and 1800 men who participated in 84 speed-dating events organized between January 2004 and October 2005. Table 1 presents the summary statistics of these meetings. The average size of an event is approximately 22 men and 22 women. Most events do not have exactly equal numbers of women and men, but the difference in numbers rarely goes beyond three. The median participation fee across all markets is £20 per session and ranges from £10 to £25 (in 2005 prices). About 38 percent of men and 46 percent of women do not propose to anyone, and three-quarters of the nonproposing men and almost half of the nonproposing women in the sample go back another time. Proposers too go back another time, albeit at a smaller rate on average (about 10 and 20 percent for women and men, respectively).

Striking gender differentials in proposal behavior are observed in the data. In line with sexual selection theory (Trivers 1972; Buss 2003), women are much choosier than men. On average, women select 2.6 men and see 45 percent of their proposals matched, while men propose to 5 women and their proposals are matched in only 20 percent of the cases. About 1 in 3 men and 1 in 10 women do not get any proposal.

Table 1
Sample Characteristics of Speed-Dating Events

	Mean	Standard Deviation	Minimum	Maximum
Number of female subjects (N_m = 84)	22.3	3.9	15	31
Number of male subjects (N_m = 84)	22.3	3.9	15	30
Number of proposals made per meeting by:				
Female subjects (N_i = 1,868)	2.6	3.1	0	30
Male subjects (N_i = 1,870)	5.0	5.8	0	30
Number of proposals received per meeting by:				
Male partners (N_j = 1,870)	2.6	3.1	0	18
Female partners (N_j = 1,868)	5.0	4.4	0	22
Number of matches per meeting	22	20	2	117
Share of proposals matched (as a fraction of all proposals) for:				
Female subjects (Obs = 4,119)	0.45			
Male subjects (Obs = 9,467)	0.20			

Note: N_m is the number of events (or markets), N_i is the number of subjects, N_j is the number of partners, and "Obs" refers to the number of subject-partner pairs in which the subject has made a proposal.

Overall, we observe 22 matches per event, an average of roughly one per participant. To ascertain if participants who do not make any proposal are different from those who do, we checked whether the two groups are balanced in their distributions of observed characteristics for each gender separately. Regardless of subject's gender, we cannot reject the null hypothesis that the two groups are the same along each of the variables used in our empirical analysis. We repeated this exercise for partners, to assess if partners who receive no proposal are different from those who are chosen at least once. Again, balance tests can never be rejected at standard levels of statistical significance, irrespective of partner's gender.[8]

To have a better understanding of speed daters' characteristics, we compare them to a representative sample of singles taken from the British Household Panel Survey (BHPS).[9] For this comparison, we use information from the fourteenth wave (2004) of the BHPS, and restrict the BHPS sample to individuals aged between 20 and 50. Summary statistics by sample are reported in Table 2.[10] Clearly, this exercise and our

8. As already mentioned, our data do not contain information on race or ethnicity. However, given that none of the events was aimed at a specific ethnic/religious group and with anecdotal corroborative evidence from the agency's management, the fraction of nonwhite participants is small (and most certainly below 5 percent).
9. Since 1991, the BHPS has annually interviewed a representative sample of about 5500 households covering more than 10000 individuals. More information on the BHPS can be found at <http://www.iser.essex.ac.uk/ulsc/bhps/doc/>.
10. The categorizations of the variables in Table 2 and used in the analysis below are standard. Some, such as education and occupation, have been motivated by data availability. Redefining, for example, education

Table 2
Summary Statistics of Subjects' Attributes

	Women		Men	
	Speed dating	BHPS	Speed dating	BHPS
Age (years)	34.5 (7.5)	32.7 (9.4)	35.8 (6.9)	30.5 (9.1)
	0.217	*0.287*	*0.193*	*0.298*
	[1,776]	[1,351]	[1,828]	[1,200]
University degree or greater qualification	0.66	0.20	0.65	0.20
	0.322	*0.797*	*0.339*	*0.803*
	[974]	[1,248]	[1,071]	[1,053]
Occupation				
Professional and managerial	0.36	0.33	0.43	0.24
	0.611	*0.672*	*0.521*	*0.755*
Skilled nonmanual	0.50	0.19	0.40	0.16
	0.486	*0.802*	*0.583*	*0.827*
Other occupations[a]	0.14	0.48	0.17	0.60
	0.877	*0.520*	*0.827*	*0.403*
	[1,008]	[862]	[1,110]	[905]
Height (cm)	165.4 (6.7)	163.8 (6.4)	179.1 (6.9)	178.4 (7.4)
	0.041	*0.039*	*0.039*	*0.041*
	[1,008]	[1,270]	[1,139]	[1,095]
Weight (kg)	57.8 (5.9)	66.4 (14.0)	77.6 (10.0)	79.9 (15.5)
	0.102	*0.211*	*0.129*	*0.194*
	[334]	[1,192]	[774]	[1,067]
Share underweight[b]	0.05	0.04	0.00	0.02
Share overweight[c]	0.05	0.38	0.29	0.45
Smoking	0.13	0.38	0.09	0.36
	0.824	*0.619*	*0.886*	*0.636*
	[844]	[1,278]	[1,045]	[1,101]

Note: In each cell, we report the mean, the standard deviation in parentheses, the coefficient of variation (which, in the case of the speed-dating sample is a weighted average by market, with weights given by the number of participants over the total population of speed daters) in italics, and the number of subjects in square brackets. Standard deviations are not reported for dummy variables.
a. Includes workers in manual occupations, self-employed, full-time students, and individuals in other jobs.
b. If BMI<18.5.
c. If BMI>25.

considerations are relevant only for those speed daters and BHPS respondents with nonmissing information in each of the characteristics under analysis. As mentioned, the issue of speed daters lying about their self-reported personal traits is generally

(occupation) so that lower educational qualifications (other occupational groups) are explicitly considered would only lead to small cell size problems without adding new insights into mate choice decisions.

believed to be minimal.[11] The issue of missing information, instead, is more problematic, especially for some variables, such as female weight. Later in this section and in Section IV, we shall come back to this issue.

Bearing these caveats in mind, the differences across samples in Table 2 are notable. Speed-dating participants are more educated (about two thirds of men and women have at least a university degree, against 20 percent of singles in the BHPS) and more concentrated in relatively high-skilled occupations (83 percent of men and 76 percent of women are in "skilled nonmanual" and "professional and managerial" jobs, as opposed to 40 percent in the BHPS). Our sample therefore fits the popular view that speed-dating markets attract a disproportionate fraction of career people (Kurzban and Weeden 2005).

Speed daters (especially men) are also older than their BHPS counterparts. But if we restrict the BHPS sample to individuals with at least a university degree, the age differentials are reversed: Male and female speed daters are 1–4 years *younger*, respectively. The average height is similar in both samples, slightly below 180 centimeters for men and around 165 centimeters for women. The average weight is comparable among men in the two samples, but it is much lower for female speed daters, and this difference does not disappear even if the BHPS sample is restricted to highly educated women. Dividing weight (measured in kilograms) by height squared (measured in meters), we obtain the Body Mass Index (BMI), which we include in our empirical analysis.[12] The shares of overweight men and, in particular, women are substantially larger in the BHPS sample than in the speed-dating sample. The two sets of figures do not get closer even when the BHPS sample is restricted to more educated respondents.

As anticipated, the speed-dating sample is characterized by an issue of item nonresponse. It is possible that participants fail to report because of strategic motives, and this might make the interpretation of our demand analysis more difficult. For this reason, in Section IV we will try to minimize the resulting loss in sample size by assigning participants with missing weight information to the (base) normal weight category and identifying them with a missing weight dummy variable.[13] We shall proceed in a similar fashion for all the variables with missing information (except age, because we restrict the sample to individuals with valid age data). Alternative assignment rules (for example, substituting missing values with market mean or modal values computed on valid cases) have delivered exactly identical results to those discussed below and are, therefore, not reported.

Finally, smoking is more prevalent among BHPS respondents, with 36 percent of men and 38 percent of women smoking against 9 and 13 percent respectively in the speed-dating sample. Limiting the BHPS sample to highly educated individuals does not eliminate the differences but reduces them by more than half. Speed daters without missing information are therefore healthier than their BHPS counterparts. But participants in general could believe that smoking reduces their overall desirability and, consequently, may be more likely to fail to report smoking information.

11. In fact the reliability of the BHPS, our comparator data set, is also hard to establish (Lynn, 2006).

12. General health guidelines associate "normal" weight with a BMI between 18.5 and 25, and define "underweight" when BMI is below 18.5, and "overweight" when BMI is above 25.

13. There might be a concern that those not reporting their weight information are overweight or obese. Thus, we also reclassified participants with missing information into the overweight (rather than the normal weight) category. This alternative classification did not alter any of the results shown in the next sections.

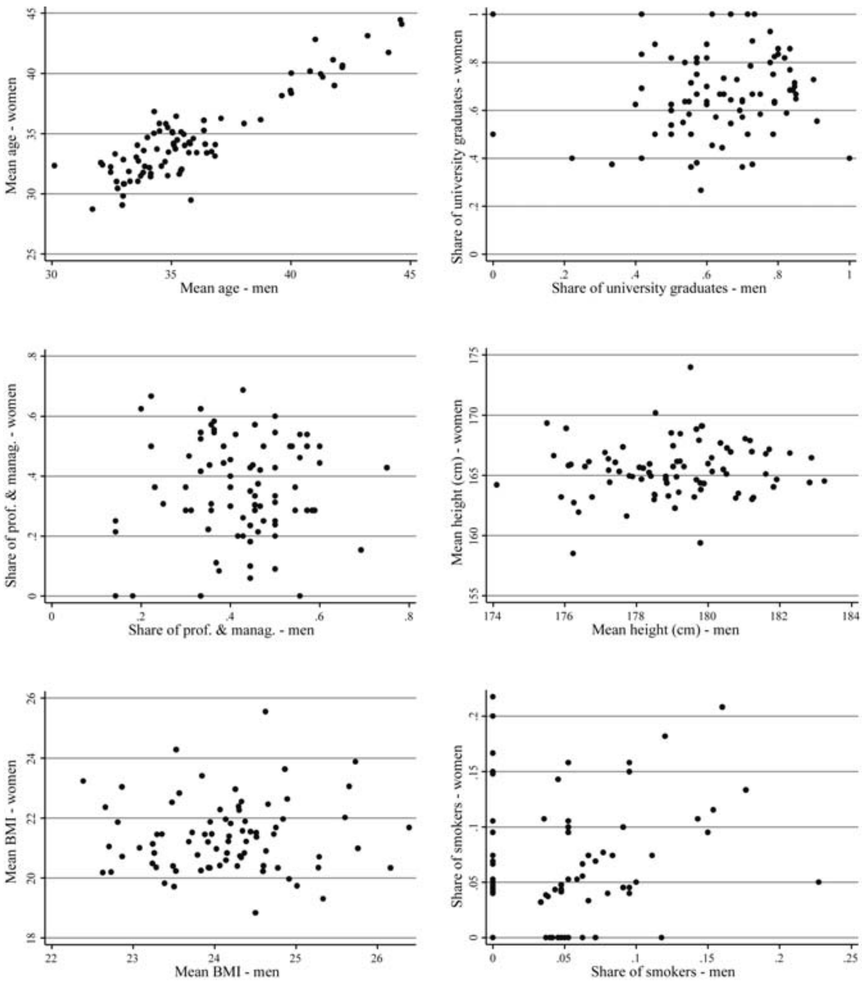

Figure 1
Joint (Female and Male) Average Distribution of Attributes

An attractive feature of the speed-dating protocol is the diversity of attributes of the participants attending the same event. Becausee events are stratified by age and location, however, it is plausible that they attract people with similar attributes. To gauge the degree of sorting ex ante, we plot the distribution of female and male characteristics (means for age and height, and shares for the other attributes) across sessions (Figure 1). It shows a widespread distribution of participants along all traits, except age (which is not surprising). This is broadly confirmed by the correlation estimates reported in the first column of Table 3. Apart from age and smoking, the correlation between female and male attributes is close to zero and not significant. In addition,

Table 3
Correlation Coefficients and Odds Ratios in Female and Male Attributes

	Female-male correlation (all speed daters)	Odds ratios		
		All speed daters	Matched pairs	Test of equality (p-value)
Age[a]	0.904**	2.39**	11.01**	0.000
	(0.002)	(0.003)	(0.97)	
University degree or greater qualification	0.091	1.10**	1.54**	0.004
	(0.413)	(0.002)	(0.13)	
Professional and managerial occupations	0.052	1.01	1.25*	0.013
	(0.652)	(0.02)	(0.12)	
Height[a]	0.103	1.04*	1.08	0.933
	(0.389)	(0.05)	(0.09)	
Overweight	0.031	1.00	0.69	0.421
	(0.780)	(0.16)	(0.76)	
Smoking	0.232**	1.18**	1.81*	0.059
	(0.030)	(0.01)	(0.41)	

Note: The figures in the first column are correlation coefficients between male and female attributes. Their standard errors (in parentheses) are bootstrapped from 100 replications. The figures in the second and third columns are odds ratios obtained from logistic regressions. Standard errors are in parentheses. In the column labelled "Test of equality" we report the p-value of the test that the odds ratio in the second column equals the corresponding odds ratio in the third column.
a. Odds ratios for this attribute are computed using two distinct groups—that is, individuals who are above the average age or height, and individuals who are at the average or below.
The double asterisks ** in the first column indicate that a correlation is significantly different from zero at the 1 percent level. The asterisk * and double asterisks ** in the second and third columns respectively indicate that an odds ratio is significantly different from one at the 5 and 1 percent level, respectively.

the second column of Table 3 reports odds ratios for all the female-male pairs in our sample. The odds of meeting a similar partner are slightly (but significantly) greater than those of meeting a nonsimilar partner for almost all attributes, with the exception of occupation and weight. Despite this, such odd ratios are much lower than those generally found for women and men in final matches (for example, Mare 1991; Kalmijn 1994). We, therefore, take these results as evidence of only mild sorting ex ante. We shall return to the potential of nonrandom selection in the next sections.

IV. Individual Dating Proposals

We now estimate attribute demands looking at the whole set of proposals a subject can make in a given market and examining which of the potential partner's observed attributes trigger a proposal. At this stage, we remain agnostic on the mechanisms that might drive such proposals, in particular whether they reveal specific mating preferences or strategic considerations. Later in the section, we will come back to this issue.

We use a simple discrete choice framework to analyse proposal behaviour. In each market (or event) m, we observe whether a subject i proposes to partner j or not. We assume the utility U of subject i in event m depends on a vector of attributes Z of both individuals involved (for example, sociodemographic characteristics, personality traits, and physical attractiveness)—that is, $U_{im}(Z_{jm}, Z_{im})$. Each subject i proposes if $U_{im} \geq R_{im}$, where R_{im} is the unobserved reservation utility of individual i in market m. Only a subset of cues Z, labelled X, is observed and we estimate a model of attribute demand which depends on such attributes.

The main question of the paper is to identify whether or not proposals are systematically associated with specific cues of individuals on either side of the dating market. Are some attributes valued by everyone irrespectively of their own attributes (what we call *agreed-upon* or *common* preferences)? Or are people more likely to value attributes similar to theirs (what we refer to as *assortative* preferences)? The identification relies on the fact that we observe subjects with different attributes meeting potential partners with different attributes. If choices are unrelated to attributes, this would not mean that choices are random, but rather that the specific attributes we observe are not relevant to individual decisions. In that case, subjects' choice will entirely depend on the pool of available partners—that is, on meeting opportunities.

A. Baseline Estimates

We begin by investigating the simple association of partner's attributes with the probability of making a proposal, not controlling for the proposer's characteristics. Our basic regression specification is of the form

$$(1) \quad d_{ijm} = \mathbf{X}'_{jm}\beta + \mu_i + \varepsilon_{ijm},$$

where d_{ijm} is the proposal decision that subject i takes with respect to partner j in market m. This is equal to one if i proposes to j, and zero otherwise. The vector $\mathbf{X}_{jm}$ contains sociodemographic characteristics of potential partners in market m, μ_i is a subject-specific permanent fixed effect, and ε_{ijm} is an idiosyncratic shock. As in other standard discrete choice problems, Equation 1 has a direct mapping to the underlying utility from partner's attributes. Of course, it is possible that observable attributes are correlated with unobservable (to us) attributes, such as personality traits or physical attractiveness. Since we cannot identify those cues separately, the patterns we describe are associations between observable attributes and proposals. For ease of interpretation, we estimate Equation 1 using linear probability models with subject fixed effects. Qualitatively similar results were obtained using least squares regression and random effects models, which are therefore not reported.

The estimates by subject's gender are shown in the first two columns of Table 4.[14]

14. In the analysis below, we enter age (in years), height and weight linearly. Height and weight are normalized by subtracting the corresponding sample mean and dividing by the corresponding standard deviation. In addition, Table 4 distinguishes individuals with degree or higher qualifications, includes three occupational dummies and a dummy for smoking status. We experimented with several other specifications (for example, polynomials in age, height, and weight, and different dummy variables for education and occupation) and also included measures of BMI. All our main results remained unchanged.

Table 4
Demand for Partner's Attributes

	Subject's gender		Test equality of coefficients	Subject's gender	
	Female (1)	Male (2)	(*p*-value) (3)	Female (4)	Male (5)
Age (years)	–0.005	–0.011	0.000	–0.005	–0.011
	(0.000)***	(0.000)***		(0.000)***	(0.000)***
University degree or greater qualification	–0.001	0.018	0.002	–0.002	0.017
	(0.004)	(0.005)***		(0.004)	(0.005)***
Professional and managerial	0.063	–0.070	0.000	0.060	–0.066
	(0.024)**	(0.025)***		(0.024)**	(0.025)***
Skilled nonmanual	0.068	–0.074	0.000	0.064	–0.070
	(0.024)***	(0.025)***		(0.024)***	(0.025)***
Other occupations	0.052	–0.096	0.000	0.048	–0.092
	(0.025)**	(0.025)***		(0.025)*	(0.025)***
Smoking	–0.016	–0.040	0.014	0.010	–0.028
	(0.006)**	(0.008)***		(0.012)	(0.015)*
Height (normalized)	0.004	0.008	0.084	0.005	0.007
	(0.001)***	(0.002)***		(0.001)***	(0.002)***
Weight (normalized)	0.009	–0.009	0.000	0.009	–0.009
	(0.001)***	(0.002)***		(0.001)***	(0.002)***
Missing education	–0.016	0.022	0.001	–0.018	0.020
	(0.007)**	(0.009)**		(0.007)***	(0.009)**

(*continued*)

Table 4 (*continued*)

	Subject's gender		Test equality of coefficients	Subject's gender	
	Female (1)	Male (2)	(p-value) (3)	Female (4)	Male (5)
Missing occupation	0.047	–0.122	0.000	0.044	–0.122
	(0.025)*	(0.026)***		(0.025)*	(0.026)***
Missing smoking status	0.014	0.003	0.228	0.014	0.002
	(0.006)**	(0.006)		(0.006)**	(0.006)
Missing height	–0.033	0.000	0.000	–0.035	0.000
	(0.009)***	(0.000)		(0.009)***	(0.000)
Missing weight	0.010	–0.041	0.000	0.011	–0.036
	(0.004)***	(0.005)***		(0.004)***	(0.006)***
Constant	0.235	0.724	0.000	0.189	0.662
	(0.026)***	(0.027)***		(0.028)***	(0.031)***
Observations	41,767	40,544		41,767	40,544
R^2	0.03	0.07		0.03	0.08

Note: Estimates are obtained from linear probability models including subject fixed effects. The variables "height" and "weight" have been normalized by subtracting the corresponding sample mean and dividing by the sample standard deviation. Observations are at the subject-partner meeting level. The regressions in Columns 4 and 5 include similarity variables (see Table 5, Columns 1 and 2).

* significant at 5 percent; ** significant at 1 percent.

The third column reports the results on the test of equal coefficients by gender. All attributes, except height and missing smoking status, appear to affect desirability differently for men and women. A notable result is that partner's attributes explain relatively little (between 3 and 7 percent) of the overall variation in proposals. This does not mean that preferences can have only a minor effect on mate selection: It is well established, in fact, that even mild preferences for certain attributes may lead to high levels of segregation (Schelling 1971).

On average, more educated women are two percentage points more likely to receive a proposal than less educated women. There is no evidence, however, of a similar pattern on the other side of the market—that is, in the case of women's demand. This result does not imply, however, that education is unimportant to their mate selection. For instance, educated men may be more likely to choose educated women, while less educated men may rather choose less educated women, with educational heterogamy being negligible. The next section will examine this possibility.

Occupational status has a considerable influence on partner's demand, and affects desirability in opposite directions for men and women. Women in skilled and managerial or professional occupations are less likely to receive a proposal than others, while the opposite pattern emerges for men. Physically observable attributes also have an effect. Both men and women are more likely to receive proposals if they are young and tall. Weight, on the other hand, has differential impacts by gender: It is a disadvantage for women but an advantage for men (see, among others, Tovée et al. 1998; Buss 2003). If a woman smokes, her likelihood of receiving a proposal is reduced by four percentage points, and, if a man does, his likelihood goes down by about 1.5 percentage points.

The analysis also includes indicator variables for missing information on partner's characteristics. Their bivariate correlations are weakly positive and small, indicating that information is not systematically missing among a specific subgroup of participants. Since speed daters create and post their own profiles online, it can be argued that those with missing data might seek not to disclose less desirable attributes. For example, on the basis of our previous results, overweight women and unskilled men could have an incentive not to report. The estimates in Table 4 show mixed evidence that participants who do not report information are less desirable. Women with missing weight information are indeed four percentage points less likely to receive a proposal, but missing occupation information increases men's desirability by almost five percentage points. Regardless of subject's gender, this pattern of association extends to other missing data indicators, with four out of 10 being negatively correlated to proposals and the other six having either positive or zero correlation.

It is worth stressing that socioeconomic status and physical attributes are correlated in our sample. For male subjects, education and occupation are strongly positively associated with both own age and height. For female subjects, instead, height and weight are correlated with neither own education nor occupation, but age is negatively related to higher educational attainment.[15] When formulating their proposals, therefore, individuals may be using partners' desirable physical attributes, such as height and age, as strong predictors of socioeconomic position, as suggested by the matching theory based on costly signals developed by Hoppe, Moldovanu, and Sela (2009).

15. Similar correlation patterns are also found in the BHPS sample used in Section III, especially when it is restricted to more educated individuals.

B. Common Preferences or Sorting?

The estimates so far do not take subjects' own traits into account. It could be that the desirability of certain attributes is due to the composition of the pool of participants. For example, we do not know whether the desirability of higher educated women reflects a true commonly shared preference for education among men or whether it reflects a preference for a partner with similar education, since our sample is relatively highly educated.

We extend our analysis by taking into account the subject's own attributes. We augment the model with concordance variables,[16] and examine if subjects propose to partners who are *similar* to themselves rather than to partners with different attributes. Our analysis is theoretically motivated by many of the studies that show striking similarities between mates along several dimensions, such as age, education and physical appearance (for example, Schwartz and Mare 2005; Kurzban and Weeden 2005). The demand framework analysis used in the previous subsection still yields an appropriate interpretation of the relationships of interest, provided the assumption of straightforward behavior continues to hold.

We begin with a discussion of the estimates on partner variables as in the previous section, but controlling for similarity variables, which account for composition effects. This permits us to assess the extent to which subjects value partner attributes conditional on their own attributes. The results are in Columns 4 and 5 of Table 4. The estimates are essentially the same as those shown in the first two columns.[17] Thus, the pattern of choice we have identified so far is commonly shared across individuals with different attributes. It could still be the case, however, that speed daters attach an additional value to attributes that are similar to theirs.

We therefore augment Model 1 with partner's fixed effects and with concordance variables—that is, we identify the effects of concordance variables controlling for subject and partner's individual attributes. The results by subject's gender are reported in Table 5.[18] The first two columns present a specification with concordance variables indicating whether subject and potential partner share similar or identical cues. The last two columns show the results from a more flexible specification, which allows for differences in the way heterogamy may affect mate choice (for example, whether the subject is more or less educated than the partner) and breaks down different types of concordance (for example, both subject and partner smoke or both do not smoke). Compared to the results of Table 4, we obtain a considerably greater R^2 in all speci-

16. For this analysis, we use differences in age and height between men and women. In particular, we distinguish pairs in which the man is seven centimeters taller from other pairs. Although this cutoff is arbitrary, seven centimeters correspond to one standard deviation in the height distribution of married men and women aged 20–50 in the 2004 BHPS. Seven centimeters are also about half of the gender height difference among married couples. Similar considerations apply to the case of age, for which we distinguish men who are five or more years older than women. Therefore, although the construction of such concordance measures is primarily based on the empirical distributions of male-female attribute differences within our sample, their interpretation is meaningful and justifiable within both the mate selection literature more generally (Trivers 1972; 1998; Buss 2003) and the assortative mating literature more specifically (Kurzban and Weeden 2005; Nielsen and Svarer 2009). Several robustness checks of such measures have yielded comparable results to those reported here.

17. The results on the tests of equal coefficients by gender (not reported) are also the same.

18. The results on the tests of equal coefficients by gender are not reported due to space concerns. But as before, we reject equality for all concordance variables, except for occupation and weight.

Table 5
The Role of Assortative Preferences

	Subject's gender			
	Female (1)	Male (2)	Female (3)	Male (4)
Age				
Man is between zero and five years older	0.039	0.061		
	(0.003)***	(0.004)***		
Man is five years older or more			–0.054	–0.040
			(0.005)***	(0.006)***
Woman is older			–0.022	–0.081
			(0.005)***	(0.006)***
Education				
Similar education level	0.017	0.022		
	(0.003)***	(0.004)***		
Man is more educated			–0.022	–0.088
			(0.086)	(0.083)
Woman is more educated			–0.000	0.051
			(0.086)	(0.083)

(*continued*)

Table 5 (*continued*)

	Subject's gender			
	Female (1)	Male (2)	Female (3)	Male (4)
Occupation				
Similar occupation	0.007	0.006		
	(0.005)	(0.006)		
Both students			–0.010	–0.241
			(0.100)	(0.125)*
Both self-employed			0.106	–0.309
			(0.131)	(0.163)*
Both manual			–0.012	0.001
			(0.023)	(0.028)
Both skilled/nonmanual			0.001	0.002
			(0.007)	(0.008)
Both professional/manual			0.010	0.012
			(0.007)	(0.009)
Smoking				
Similar smoking status	0.025	0.014		
	(0.012)**	(0.014)		
Both smoke			0.045	0.068
			(0.089)	(0.088)
Both do not smoke			0.003	–0.040
			(0.086)	(0.084)

Height				
Man is between zero and seven centimeters taller	0.006	0.028		
	(0.005)	(0.006)***		
Man is more than seven centimeters taller			0.021	–0.009
			(0.007)***	(0.008)
Woman is taller			–0.032	–0.046
			(0.006)***	(0.008)***
Weight				
Similar BMI	0.000	0.012		
	(0.007)	(0.009)		
Woman overweight and man not overweight			0.109	0.047
			(0.121)	(0.087)
Man overweight and woman not overweight			–0.119	0.014
			(0.125)	(0.071)
Observations	46,065	46,065	46,065	46,065
R^2	0.32	0.34	0.32	0.18

Note: Estimates are obtained from linear probability models including subject and partner fixed effects. The similarity variables are defined as follows: Education: both no degree or both with university degree, Occupation: both students, both self-employed, both skilled nonmanual, both manual, both professional/managerial; Smoking status: Both smoking, both not smoking; BMI: Both underweight, both normal weight, both overweight. Observations are at the subject-partner meeting level.
* significant at 5 percent; ** significant at 1 percent.

fications, suggesting that the inclusion of partner-specific fixed effects enhances the model's ability to capture the overall variation in proposals.

We find evidence of positive sorting along age. Both men and women prefer dates where he is up to five years older rather than dates where he is more than five years older or where the man is younger than the woman. Mate desirability is also influenced by educational homogamy (Nielsen and Svarer 2009): Partners with similar educational levels are two percentage points more likely to receive a proposal than partners with different qualifications. Women reveal positive assortative preferences on smoking and men on height, with both men and women disliking dates in which the woman is taller. There is instead no evidence of concordance on occupation or BMI. In fact, a man is substantially less likely to propose to a woman if both of them are students or self-employed.

An important determinant of mate choice decisions, which we have ignored so far, is the variation in the choice set faced by subjects *within* each session. This will be the focus of the next section. A related determinant is the choice set variation *across* sections, as given by event size. Including event size (number of partners) as an additional regressor in Equation 1 does not change any of our results, with the event size estimates being always small and statistically insignificant.

In Section III, we pointed out that speed daters differ from singles from the general population along a number of salient characteristics. We also mentioned the possibility that the decision to speed date might signal a desire to meet people with such traits and individuals might self-select on the basis of these attributes. Consider the case of education, for which we observe speed daters are more educated than individuals from the general population. If speed daters know they are likely to meet highly educated participants and have a penchant for education, then it is possible that preferences play a role that we have not accounted for. Interestingly, we find evidence of only mild preferences for higher educated partners on either side of the market. This observation could be extended to all other cues considered in the analysis.

C. Preferences or Strategic Concerns?

An important question arising from the previous analysis regards the interpretation of the mechanisms driving dating proposals. Proposals might be driven not just by *preferences* but also by *strategic considerations* (for example, anticipation of rejection). Choices, in fact, could be assortative either because speed daters have preferences for partners with similar attributes or because they have strategic concerns. For example, a low-education woman may be more likely to propose to a low-education man not because she prefers a partner with similar education to hers, but because she anticipates that she will not be chosen by a better educated man.

As already emphasized, the room for strategic incentives in the way in which speed daters express their preferences is likely to be limited in our setting. First, proposals are made online and require only a tick of an anonymous (alias) name. Second, there is no limit to the number of proposals that can be made. Third, if a proposal is not reciprocated, the rejection goes through a third party (the speed-dating agency) rather than on a face-to-face basis, and participants are unlikely to meet again. Thus, both the cost of proposing and the fear of rejection are arguably small at this early stage of the process, and these in turn should reduce the scope for strategic considerations.

If variation in the quality of subjects in a given market leads them to make different choices, then this may be indicative of strategic choice behavior. For instance, participants with relative attractiveness concerns may anticipate to be rejected in markets where they are relatively less attractive than their competitors. To test for this possibility, we augmented Equation 1 with the vector $(\mathbf{X}_i - \bar{\mathbf{X}}_i^{(s)})$, where each $\bar{X}_i^{(s)}$ denotes the mean of attribute X computed over all subjects in a given market. If there is no strategic behavior of this kind, we expect the new estimated coefficients on all differences to be zero. All such estimates (not shown for convenience) are indeed not statistically different from zero, with the lowest p-values on age being equal to 0.174 for female subjects and 0.143 for male subjects, and with p-values of the F-test of joint significance being 0.448 and 0.403 for women and men, respectively. These results suggest, at best, a limited role for strategic choice behavior among subjects, in the sense that proposal decisions do not seem to be driven by subjects' relative attractiveness concerns.

Another way of gauging the salience of strategic incentives is by looking at unmatched proposals.[19] By definition, a proposal is successful only if it is matched. If speed daters are strategic and their proposal behavior is driven by the anticipation of who will reject them, we should find that the correlation between proposals is positive and large, and that the proportion of proposals being matched is substantial. In events with a large fraction of "reject-averse" individuals, therefore, participants may be reluctant to propose to partners who are believed to be less likely to reciprocate their proposal, simply because they do not wish to be turned down and not because such partners are not desirable. As documented in Section III, men propose to an average of five women per session and women propose to an average of two men; the small number of male proposals is matched in only 20 percent of the cases, while the even smaller number of female proposals is matched in 38 percent of the cases. As a result, the overall correlation between proposals is positive but small (less than 0.15). This evidence supports the notion of straightforward behavior formalized by Fisman et al. (2006), on which the identification of preferences in a speed-dating setup rests.

V. Aggregate Pattern of Dating Proposals

The estimates of the previous section offer evidence in favor of positive sorting along a number of individual attributes. The goal of this section is to describe the aggregate patterns of proposals arising at the event (or "market") level. As mentioned already, an important advantage of our data is that they have information on several events and, for each event, on *both* sides of the market in which individuals propose to each other.

In what follows we analyze two salient dimensions along which markets may vary: The first is the abundance (or scarcity) of desirable attributes, and the second is the degree of homogeneity among potential partners. In some markets there may be an abundance of university graduates on both sides, while in others university graduates might be short in numbers. Alternatively, some sessions could be highly heteroge-

19. It is worth reminding that, on the basis of the homogeneity tests discussed in the previous section, speed daters who do not make or receive proposals are *not* statistically different from those who do.

neous, with participants being evenly distributed across educational groups on either side of the market. Although both dimensions could have a significant impact on dating proposal behavior, we know little about their influences.

A. Relative Abundance of Attributes and Aggregate Proposals

We start by presenting a simple conceptual framework that guides our empirical analysis and the interpretation of the results. We have information on 84 events, each of them involving two pools of potential partners, one on each side of the market. Consider a specific speed-dating event, m (m=1, …, 84). Although, the full choice set is the product of distributions of all the observable attributes of all potential partners in m, we focus for simplicity on one attribute at the time, denoted by X, and represent the distribution of X over partners by its mean, $\bar{X}_m^{(p)}$. For each m, we also observe the mean attribute of all partners who have been proposed to, which we refer to as the *proposal set* $\bar{X}_m^{(c)}$.[20]

Suppose dating proposals are exclusively formulated on the basis of meeting opportunities—that is, subjects have no intrinsic preferences for X. In this environment, the mean attribute of partners who have been proposed to in market m will have to be equal to the mean attribute of all potential partners in m—that is, $\bar{X}_m^{(c)} = \bar{X}_m^{(p)}$. For instance, the share of highly educated women who have been proposed to in a given event should be equal to the share of highly educated women in that same event. Put differently, in a scatter plot of $\bar{X}_m^{(c)}$ against $\bar{X}_m^{(p)}$, we would expect the data points to be scattered along the 45-degree line. This is what we refer to as the "opportunity-only" (O-O) model, whose empirical counterpart corresponds to the following constrained regression:

$$(2)\quad \bar{X}_m^{(c)} = \bar{X}_m^{(p)} + u_m,$$

where u_m is an idiosyncratic shock to market m. If there is a commonly shared preference for X, then we will observe $\bar{X}_m^{(c)} > \bar{X}_m^{(p)}$ (that is, in the scatter plot, $\bar{X}_m^{(c)}$ will lie above the 45-degree line), and if there is a commonly shared distaste, $\bar{X}_m^{(c)} < \bar{X}_m^{(p)}$ (that is, $\bar{X}_m^{(c)}$ will lie below the 45-degree line). Such possibilities imply that Equation 2 becomes:

$$(3)\quad \bar{X}_m^{(c)} = \alpha_0 + \alpha_1 \bar{X}_m^{(p)} + u_m,$$

with the O-O model corresponding to the constrained version of Equation 3 in which

$$(4)\quad \alpha_0 = 0 \text{ and } \alpha_1 = 1.$$

The equalities in Equation 4 provide the necessary and sufficient statistical conditions under which meeting opportunities determine sorting. That is, if both equalities in Equation 4 cannot be statistically rejected, we say that meeting circumstances, as defined by the dating event, determine mate selection. When instead either or both equalities do not hold, the O-O hypothesis is violated. If both preferences and oppor-

20. By definition, and regardless of whether X is binary or continuous, $\bar{X}_m = (\sum_{j=1}^{J_m} X_{jm})/J_m$ and $\bar{X}_m^{(c)} = (\sum_{j=1}^{J_m^{(c)}} X_{jm}^{(c)})/J_m^{(c)}$ where j ind. exes partners, J_m is the. . total number of potential (other-sex) partners in market m, and $J_m^{(c)}$ the number. of partners who receive a proposal in market m.

tunities play a role, the O-O model is rejected, but we expect α_1 to be significantly positive. If instead opportunities do not play a role at all, α_1 should be equal to zero.

For each of the attributes used so far, Panel A of Table 6 reports the results from the regressions in Equation 3 by subject's gender. To ease interpretation, the estimates are complemented by Figures 2 and 3, which plot $\bar{X}_m^{(c)}$ against $\bar{X}_m^{(p)}$ for male and female subjects respectively. The O-O model cannot be rejected in eight out of the 12 attribute-proposal patterns analyzed here, while it can be rejected in the case of age (for both male and female proposals), smoking (female proposals) and education (male proposals). All estimates are robust to the inclusion of event size in Equation 3.

Consider the four cases in which the O-O model is rejected. In line with our earlier analysis, younger partners (regardless of gender), more educated women, and men who do not smoke tend to receive more proposals on average. Interestingly, in each of these cases, there is a switch in the aggregate proposal pattern depending on whether the attribute is abundant or not at the market level. The tendency to propose to participants who are younger than the average in a given session is weaker in events in which there is an abundance of older-than-average partners, despite the fact that speed daters generally prefer younger partners. Similarly, the propensity to propose to men who do not smoke decreases when there are more male smokers present in the market. The scarcity of a desirable attribute (young age and nonsmoking) reduces its desirability, rather than heightening its demand. This cannot be easily interpreted on the basis of preferences only without resorting to opportunities. The opposite pattern is observed in the case of female education. Although women who are highly educated tend to be less popular than the average woman in sessions where there are only few of them, they become more desirable in markets where there are more of them.

The education estimates allow us to reconsider the issue of sample selection which was previously discussed in Sections III and IV. Speed daters are more educated than individuals from the population at large. If they know this and they wish to date highly educated people, the matching process we estimate at the event level should be driven by preferences to a large extent. If this is the mechanism underlying the proposal behavior under study, then the slope parameter for education should be greater than unity. In Table 6, this emerges only for female subjects, although α_1 is not statistically significantly different from one. In the case of male subjects, instead, we find exactly the opposite. Like in the analysis of individual demands, this evidence is hard to reconcile with the notion of a greater role for preferences in matching.

Dating proposals, therefore, cannot be assumed to be just a function of potential partners' characteristics. The environment in which potential partners meet matters and may shape proposal behavior, albeit the O-O model is statistically rejected in such cases. It is worth stressing this point because market information is generally unavailable, even when online dating data are used, and, by leaving the market out of the analysis, we are likely to obtain an incomplete picture of mate choice decisions.

Along the other attribute-proposal combinations, the O-O model cannot be rejected. Such combinations refer to occupation, height, and weight for both women and men, education in the case of female proposals, and smoking in the case of male proposals. In these instances, the intercept α_0 is always equal to zero, and the slope parameter α_1 is never statistically different from 1. These results, even accounting for the identification caveat raised earlier, suggest that meeting opportunities are likely to play an important role in shaping the observed pattern of mate choice in our sample.

Table 6
Opportunities and Preferences in the Speed-Dating Market—Relative Abundance of Attributes

	Age (mean) (1)	University degree or greater qualification (2)	Professional and managerial occupations (3)	Height (mean) (4)	Overweight (5)	Smoking (6)
A. Partner's attributes						
Female subject						
α_0	–8.75**	–0.06	–0.02	–8.32	–0.05	–0.02*
	(1.87)	(0.06)	(0.06)	(17.63)	(0.04)	(0.01)
α_1	1.18**	1.11**	1.03**	1.05**	1.19**	1.30**
	(0.05)	(0.09)	(0.13)	(0.10)	(0.13)	(0.10)
F test ($\alpha_1 = 1$)	0.001†	0.268	0.806	0.636	0.122	0.005†
F test ($\alpha_0 = 0, \alpha_1 = 1$)	0.000	0.399	0.896	0.130	0.297	0.018
R^2	0.864	0.633	0.433	0.585	0.538	0.657
Observations	84	81	81	82	81	84
Male subject						
α_0	–7.34**	0.10*	0.03	7.18	0.00	–0.01
	(1.56)	(0.04)	(0.02)	(10.47)	(0.02)	(0.01)
α_1	1.13**	0.90**	0.94**	0.96**	0.86**	1.09**
	(0.04)	(0.06)	(0.07)	(0.06)	(0.04)	(0.07)
F test ($\alpha_1 = 1$)	0.005†	0.085	0.388	0.509	0.140	0.202
F test ($\alpha_0 = 0, \alpha_1 = 1$)	0.000†	0.000	0.465	0.229	0.194	0.263
R^2	0.886	0.762	0.717	0.737	0.787	0.729
Observations	84	84	78	84	80	84

B. Subject's attributes						
Female subject						
η_1	0.88**	0.10	–0.09	0.11	0.09	0.10*
	(0.07)	(0.14)	(0.10)	(0.12)	(0.05)	(0.05)
R^2	0.647	0.012	0.009	0.010	0.042	0.042
Observations	84	83	82	82	79	82
Male subject						
η_1	1.13**	0.001	0.02	0.10	–0.002	0.04
	(0.08)	(0.12)	(0.11)	(0.15)	(0.008)	(0.08)
R^2	0.704	0.001	0.003	0.005	0.001	0.003
Observations	84	83	82	82	79	82

Note: Ordinary least squares estimates; standard errors in parentheses. Figures in panel A are obtained from the estimation of Equation 3; those in panel B are from Equation 5 which includes a constant (see text). Observations are at the meeting level. In the rows labelled "*F* test," we report the *p*-value of the test that α_1=1 or of the test that α_0=0 and α_1=1.

* significant at 5 percent; ** significant at 1 percent.

† indicates that equality is rejected (at 5 percent).

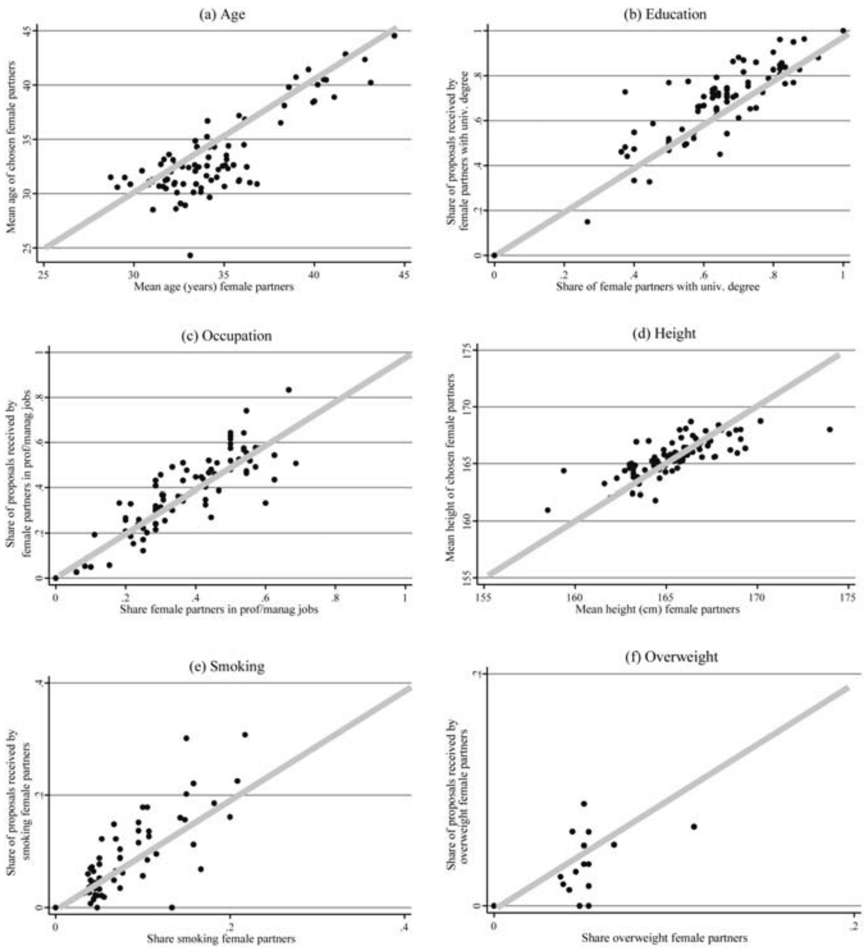

Figure 2
Selection and Partners' Supply—Male Subjects

Note: Each dot represents means or shares of characteristics of partners in a specific meeting. The straight line is the 45 degree line.

In the previous section, we mentioned the potential issues raised by individuals who participate to more than one event. To assess the influence of"returning" speed daters on our results more formally, we recomputed the statistics needed to test the O-O model after excluding individuals who were observed in more than one event. The estimates from this new exercise were very close to those shown in Table 6 and are thus not reported.

Our analysis so far has assumed that proposals are determined only by partners' characteristics and attribute distributions. Of course, they may be influenced also by subjects' characteristics and distributions. For example, highly educated women may

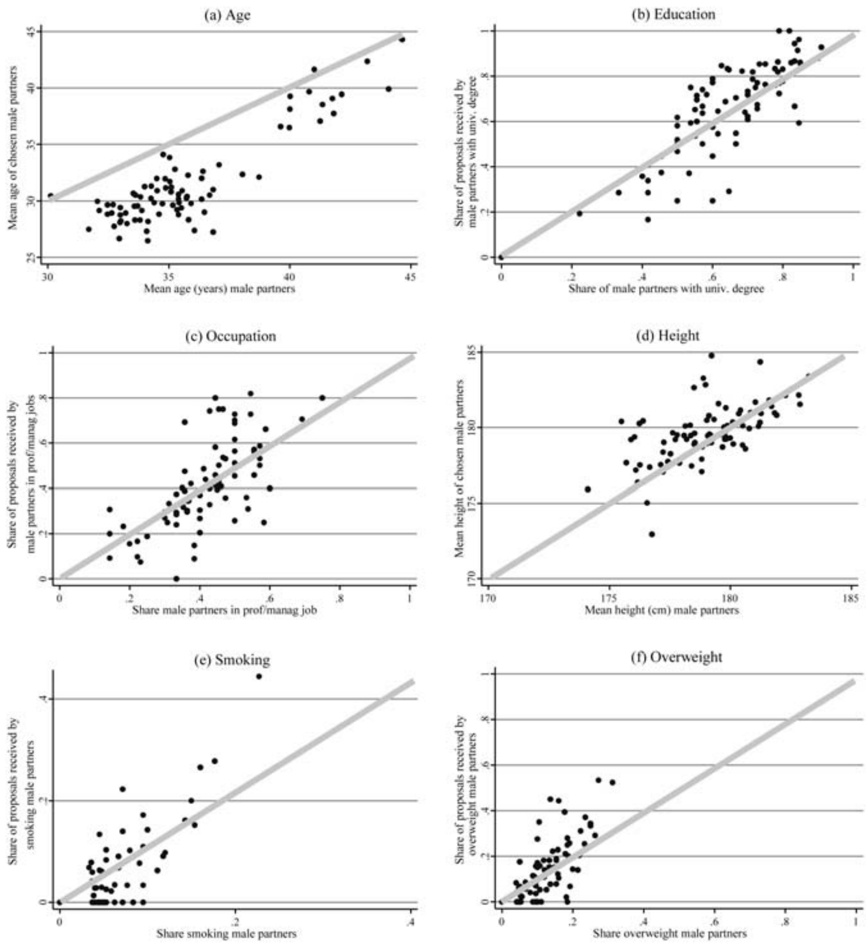

Figure 3
Selection and Partners' Supply—Female Subjects

Note: Each dot represents means or shares of characteristics of partners in a specific meeting. The straight line is the 45 degree line.

receive a larger share of proposals in sessions with a greater concentration of highly educated male subjects; and, conversely, they may receive a smaller share of proposals when the pool of subjects is relatively less educated. To explore this possibility and provide a further robustness check of our results, we analyze a relationship similar to Equation 3 in which, on the righthand side, $\bar{X}_m^{(p)}$ is replaced with the observed mean of X computed over all *subjects* in m, $\bar{X}_m^{(s)}$, that is:

(5) $\bar{X}_m^{(c)} = \eta_0 + \eta_1 \bar{X}_m^{(p)} + \nu_m.$

The idea here is that if, given m and X, subjects' proposal behavior, summarized by $\bar{X}_m^{(c)}$, is independent of subjects' own attribute distribution, captured by $\bar{X}_m^{(s)}$, (or, in other words, $\eta_1 = 0$), then dating proposals are expected to be shaped mainly by market conditions.[21]

The results are in Panel B of Table 6. Except for the cases of age and smoking, the distribution of subjects' attributes turns out to be uncorrelated to subjects' demands. This means that, in our speed-dating context, subjects' characteristics do not influence subjects' proposals (to whom they propose). Proposals, therefore, continue to be largely determined by the opportunities of meeting specific partners with specific attributes.

B. Market Homogeneity and Sorting

Other than with respect to the relative abundance of attributes, markets may also vary in their degree of homogeneity, whereby sessions could comprise more or fewer individuals with similar attributes. To gauge how market homogeneity influences the distribution of proposals, our analysis here follows that just performed, although now it focuses on changes in the degree of partner homogeneity across markets, which is defined as the fraction of pairs of potential partners in a given session who share a specific attribute. If dating proposals are exclusively formulated on the basis of meeting opportunities—that is, subjects have no intrinsic preferences for partners with a similar attribute, the share of partners who have been proposed to in market m will have to be equal to the share of potential partners in the same market. We keep the same notation as before, but now $\tilde{X}$ refers to the fraction of partners sharing an identical attribute. In such an environment, the O-O model corresponds to the following constrained regression:

$$(6) \quad \tilde{X}_m^{(c)} = \tilde{X}_m^{(p)} + \xi_m,$$

where ξ_m is an idiosyncratic shock to market m. Again, if there is a commonly shared preference for similarity along X or if there is a commonly shared distaste, we will observe $\tilde{X}_m^{(c)}$ to be either greater or smaller than $\tilde{X}_m$, respectively. To allow for this possibility, we then estimate

$$(7) \quad \tilde{X}_m^{(c)} = \gamma_0 + \gamma_1 \tilde{X}_m^{(p)} + \xi_m,$$

with the O-O model corresponding to the constrained version of Equation 7 in which $\gamma_0 = 0$ and $\gamma_1 = 1$. The same caveat about this test as the one raised earlier—that is, that it amounts to testing a mixture of preferences and opportunities rather than the O-O model per se, applies again.

For each attribute, Table 7 reports the results from Regression 7 by subject's gender. The O-O model is rejected in six out of the 12 cases at standard levels of statistical significance. These are age and height regardless of the subject's gender, BMI for

21. In Section IVC, we examined subjects' relative attractiveness concerns in standard attribute demands by including the difference between a subject's attribute and the market level mean of the same attribute computed over all subjects. The exercise here is different, not only because it focuses on market level (rather than individual level) behavior, but also because it considers the effect of subjects' average traits on subjects' choice set rather than the effect of deviations from subjects' mean characteristics on the individual likelihood of making a proposal.

Table 7
Opportunities and Preferences in the Speed-Dating Market—Market Homogeneity

	Age	Education	Occupation	Height	BMI	Smoking
Female subject						
γ_0	0.15**	0.03	0.03	–0.16**	–0.25	0.69**
	(0.03)	(0.05)	(0.05)	(0.04)	(0.13)	(0.12)
γ_1	0.75	0.96**	0.87**	0.88**	1.35**	0.28**
	(0.12)	(0.10)	(0.11)	(0.09)	(0.18)	(0.10)
$H_0 : \gamma_0 = 0, \gamma_1 = 1$ (p-value)	0.00†	0.76	0.19	0.00†	0.16	0.01†
Observations	84	84	84	84	84	84
Male subject						
γ_0	0.09**	0.02	–0.06	–0.07	–0.23**	–0.07
	(0.02)	(0.04)	(0.03)	(0.04)	(0.07)	(0.07)
γ_1	0.92**	0.98	1.16**	0.76**	1.27**	1.11**
	(0.07)	(0.09)	(0.08)	(0.07)	(0.09)	(0.08)
$H_0 : \gamma_0 = 0, \gamma_1 = 1$ (p-value)	0.00†	0.71	0.12	0.00†	0.00†	0.06
Observations	84	84	84	84	84	84

Note: Ordinary least squares estimates; standard errors in parentheses. Figures are obtained from the estimation of Equation 7. Observations are at the meeting level. Homogeneity in attributes is defined as follows: Age: Man is at most five years older than the woman; Education: Both with less than A-level qualifications, or both with A-level (or equivalent) qualifications, or both with university degree; Occupation: Both in professional-managerial occupations, or both in skilled nonmanual occupations, or both in manual occupations or both students; Height: Man at most seven centimetres taller than the woman; BMI: Both overweight, or both normal, or both underweight; Smoking: Both smoking, or both not smoking.
** significant at 1 percent.
† indicates that equality is rejected (at 5 percent).

male subjects, and smoking for female subjects. The fact that Equation 6 cannot be rejected in the case of education and occupation indicates that sorting along such characteristics is likely to be mild. But we find evidence of negative sorting along height (especially among women) and BMI (especially among men), while positive sorting emerges in the case of age and smoking. This evidence is indicative of the importance of assortative preferences in mate choice decisions.

VI. From Proposals to Matches

Because our data contain information on proposals made from both sides of the market, we can gain further insights on the nature of the matches arising after a first encounter. A natural question, in fact, is to ask whether greater positive sorting is found when we observe a match—that is, when two people propose to each other.

Repeating the analysis reported in Section III, we compute attribute odds ratios for the female-male pairs for which there is a match. To ease our exposition, these estimates are presented in Table 3, close to the corresponding odds ratios computed on all female-male meetings. The odds of getting matched to a partner of similar age are 11 times greater than those of getting matched to a partner of different age, which represents an almost fivefold statistically significant increase with respect to the corresponding odds ratio computed on all speed daters. The odds ratios for matched pairs on the other attributes increase too, and, as indicated by the last column of the table, this increase is significant in the cases of education and occupation. But the magnitude of such odds ratios is always modest, especially if compared to the estimates found with final match data (Mare 1991; Kalmjin 1994; Schwartz and Mare 2005). Thus, preferences (in particular, on age and education) influence match formation in this environment, but much less than what we observe amongst partners in cohabiting or marital unions in standard survey or census data.

VII. Discussion

The previous two sections document one important new result: Not only are *dating* proposals and matches determined by individual preferences over partner's attributes but they also are shaped by meeting opportunities in the dating market. This indicates that dating and mating require meeting: The pool of available interaction partners is shaped by various institutionally organized arrangements (for example, schools, work places, neighborhoods, family networks, voluntary associations, bars, and clubs) and these constrain the type of people with whom we form personal relationships and eventually durable unions.

The importance of the environment in which individuals choose their partners has been already stressed in earlier studies (for example, Kalmijn and Flap 2001; Nielsen and Svarer 2009). Our results add to such contributions and have ramifications for our understanding of social structure and socioeconomic mobility. Even in settings in which the amount of positive assortative matching is considerable (such as in final matches), the pool of available partners is likely to be salient. This suggests an emphasis not only on assortment, but also on identifying institutional and social milieux where people meet and mate as well as formulating a more precise definition of marriage markets. Put differently, our result calls us to pay attention to the "how"—and not just the "who"—of mate selection (Miller and Todd 1998).

We have long known that the chances to marry endogamously are higher the more often one meets people within the "group" (however this is defined) and the more often one interacts with group members on a day-to-day basis. Stone (1977) offers a fascinating account of the development of a series of county marriage markets, centered on the facilities of county towns (such as balls, card parties, annual fairs, and horse-racing events), and a national marriage market, centered on London and Bath, for the British aristocracy during the first half of the eighteenth century. Despite this, our knowledge of marriage markets is rather patchy and anecdotal. In fact, the operationalization of the very notion of marriage markets is challenging.

Economists have typically studied specific aspects of the number of women and men in a reference population, such as sex ratios among immigrants or ethnic groups or after events (such as wars) that lead to exogenous sex ratio changes (for example, Chiappori, Fortin, and Lacroix 2002; Acemoglu, Autor, and Lyle 2004; Abramitzky, Delavande, and Vasconcelos 2011). But this can offer only a coarse view of the institutional and cultural mechanisms by which the courting process comes about. A well-established strand of sociological research has focused on the geographic distribution of ethnic groups, such as Asian-Americans in California or Jewish-Americans in New York City (Bills 2005). Others have examined local marriage markets such as schools or workplaces (Kalmijn and Flap 2001; Nielsen and Svarer 2009). But the demographic (including gender) composition of a specific population cannot be seen separately from the regional distribution of groups. If people base their decision to live in a given area on factors that are not independent of in-group preferences, then mating preferences cannot be distinguished from partners' availability in standard observational data. Here is where the speed-dating setup of our study turns out to be very important. Despite this, a more precise definition and a better measurement of the concept of marriage market are needed.

VIII. Conclusion

This paper analyzes dating behavior using new data from a large U.K. speed-dating agency. It pursues two primary goals. The first is to shed light on the nature of people's preferences when selecting mates. We find that speed daters' proposals are primarily driven by assortative preferences and less so by generally agreed-upon mate values, with both women and men preferring partners of similar age and education. We also find that women and men equally value observable physical attributes, such as height and weight. The second goal of the paper is to provide empirical evidence on the importance of meeting opportunities in explaining patterns of dating proposals and matches. Our results indicate that the role of meeting opportunities is essential to understand mate selection. This finding stresses the need to gain deeper insights and a better measurement on the wide variety of formal and informal institutions that give rise to what we call marriage markets and that shape mate choice, dating behavior, courtship, and matchmaking.

A number of extensions would be desirable. First, incorporating how speed daters learn about their potential partners' characteristics (either during the meeting or browsing their profiles) would give us a deeper understanding of dating preferences, which may also have ramifications for theory. Second, a methodology similar to that applied here could be used to analyze different substantive issues (such as the extent to which dating preferences differ by ethnicity), different rules of the game (for example, letting them know they have received a proposal even if they do not reciprocate), different agencies that target specific populations (in terms of age, occupation, race, or religion), and speed daters in different countries. Finally, an ambitious extension is to follow speed daters over time and observe how their matches evolve. This will allow us to see whether and how speed dating leads to durable long-term relationships.

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