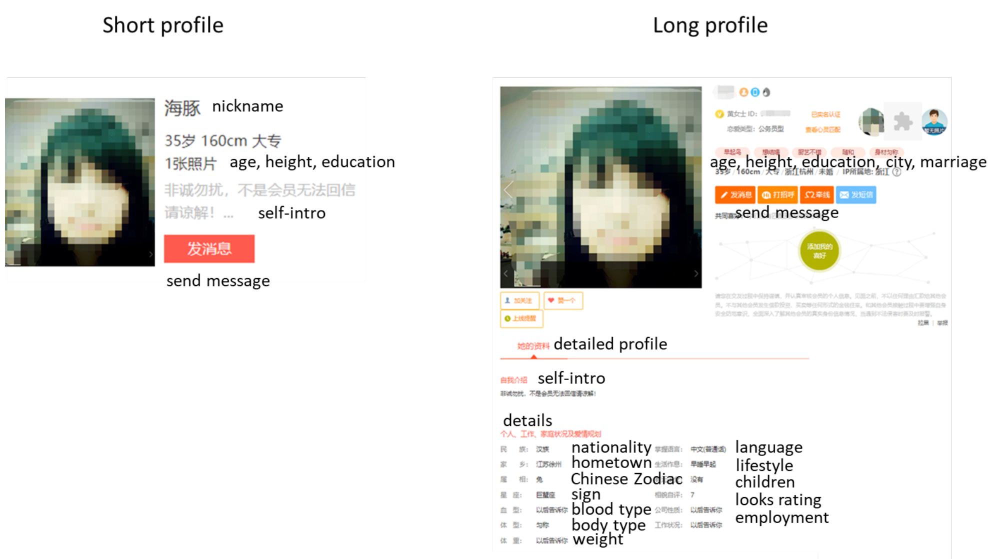
Online Appendix

The Online Appendix is available at https://www.dropbox.com/s/s6g16sbb7y734ln/online_app_ISR-2022-233.pdf?dl=0.

A Example of User Profiles

Figure A.1: Example of A User's Short and Long Profiles



Notes: These are the screenshots of the current website. They show the difference in information amount contained in short and long profiles, though the attributes may not be exactly the same as in the 2011 version.

B Summary Statistics

Table A.1: Summary Statistics of User Attributes

	Male Focal Users		Female Focal Users	
	Mean	SD	Mean	SD
Age	27.95	6.98	29.37	7.88
Height (cm)	173.47	5.17	162.17	4.43
Has looks rating	0.14	0.35	0.17	0.37
Has photo	0.42	0.49	0.55	0.50
# Words in self-intro	59.62	69.19	77.90	81.21
Degree				
Middle school	0.10		0.06	
Technical school	0.19		0.15	
High school	0.14		0.11	
Junior college	0.29		0.35	
Bachelor	0.25		0.29	
Master	0.03		0.04	
Income (CNY)				
Less than ¥2,000	0.10		0.25	
¥2,000-¥3,000	0.29		0.37	
¥3,000-¥4,000	0.22		0.17	
¥4,000-¥5,000	0.14		0.10	
¥5,000-¥7,000	0.10		0.06	
¥7,000-¥10,000	0.06		0.03	
¥10,000-¥15,000	0.03		0.01	
¥15,000-¥20,000	0.02		0.01	
¥20,000-¥25,000	0.01		0.00	
¥25,000-¥30,000	0.01		0.00	
¥30,000-¥50,000	0.01		0.00	
More than ¥50,000	0.01		0.00	
Marriage status				
Single	0.83		0.71	
Divorced	0.16		0.26	
Widowed	0.01		0.03	
If have children				
No	0.84		0.75	
Yes, live with me	0.05		0.09	
Yes, sometimes live with me	0.03		0.05	
Yes, but not live with me	0.08		0.11	
Chinese Zodiac sign				
Rat	0.07		0.08	
Ox	0.08		0.08	
Tiger	0.10		0.10	
Rabbit	0.12		0.12	
Dragon	0.11		0.11	
Snake	0.10		0.10	
Horse	0.10		0.09	
Goat	0.08		0.07	
Monkey	0.08		0.08	
Rooster	0.04		0.05	
Dog	0.06		0.06	
Pig	0.06		0.07	
Religion				
Atheism	0.96		0.95	
Buddhism	0.02		0.03	
Others	0.01		0.01	
Housing status				
Will tell you in future	0.28		0.26	
Live with parents	0.18		0.29	
Renting	0.14		0.21	
Own house (with loan)	0.08		0.04	
Own house (without loan)	0.18		0.08	
House provided by employer	0.06		0.07	
Will buy when need	0.07		0.03	
Lifestyle				
Regular	0.22		0.33	
Irregular	0.09		0.15	
Unknown	0.69		0.53	

C Preference Mismatch at Attribute Level: More Evidences

Table A.2: Preference Mismatch: Height (subsample)

	Propose a match			
	(1) Male Focal		(2) Female Focal/Candidate	
-25	-0.1622***	(0.0396)	0.0070	(0.0116)
-24	-0.1477**	(0.0561)	-0.0009	(0.0108)
-23	-0.0852*	(0.0360)	0.0198*	(0.0085)
-22	-0.0559	(0.0384)	0.0245**	(0.0079)
-21	-0.0646	(0.0406)	0.0314***	(0.0080)
-20	-0.0557	(0.0312)	0.0223***	(0.0055)
-19	-0.0604*	(0.0304)	0.0319***	(0.0062)
-18	-0.0109	(0.0269)	0.0244***	(0.0050)
-17	-0.0271	(0.0217)	0.0215***	(0.0051)
-16	-0.0470	(0.0247)	0.0209***	(0.0049)
-15	-0.0462*	(0.0206)	0.0189***	(0.0045)
-14	-0.0433*	(0.0205)	0.0189***	(0.0046)
-13	-0.0165	(0.0207)	0.0170***	(0.0043)
-12	0.0017	(0.0190)	0.0096*	(0.0043)
-11	-0.0374	(0.0203)	0.0088*	(0.0043)
-9	-0.0484*	(0.0225)	0.0057	(0.0049)
-8	-0.0021	(0.0203)	-0.0087*	(0.0041)
-7	-0.0482*	(0.0204)	-0.0093	(0.0050)
-6	-0.0485*	(0.0245)	-0.0167**	(0.0052)
-5	-0.0122	(0.0237)	-0.0254***	(0.0052)
-4	0.0047	(0.0275)	-0.0368***	(0.0058)
-3	-0.0411	(0.0279)	-0.0319***	(0.0061)
-2	-0.0069	(0.0283)	-0.0351***	(0.0071)
-1	-0.0645*	(0.0286)	-0.0442***	(0.0077)
0	-0.0476*	(0.0217)	-0.0340***	(0.0057)
Candidate attributes	Yes		Yes	
Focal FE	Yes		Yes	
Adjusted R^2	0.010		0.017	
Observations	12354		120126	

Notes: The proposing decision is conditional on viewing long profiles. The height difference in the table is the height of female minus the height of male. The baseline of the height difference is that the female is 10 cm shorter than the male. The controlled candidate attributes are the same set of attributes as in the mate preference estimation. Standard errors are clustered at the focal user level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.3: Preference Mismatch: Age

	Propose a match			
	(1) Male Focal		(2) Female Focal	
Age difference				
-15	-0.0239***	(0.0069)	0.0251*	(0.0120)
-14	-0.0146*	(0.0067)	0.0025	(0.0111)
-13	-0.0120	(0.0072)	0.0076	(0.0090)
-12	-0.0121*	(0.0056)	0.0073	(0.0075)
-11	-0.0026	(0.0054)	0.0139*	(0.0068)
-10	-0.0048	(0.0048)	0.0023	(0.0059)
-9	-0.0018	(0.0045)	0.0184***	(0.0053)
-8	0.0028	(0.0038)	0.0133**	(0.0051)
-7	0.0029	(0.0033)	0.0202***	(0.0043)
-6	0.0019	(0.0033)	0.0160***	(0.0046)
-5	0.0052	(0.0027)	0.0157***	(0.0038)
-4	0.0066*	(0.0028)	0.0208***	(0.0040)
-3	0.0105***	(0.0025)	0.0183***	(0.0037)
-2	0.0109***	(0.0022)	0.0127***	(0.0034)
-1	0.0091***	(0.0020)	0.0143***	(0.0035)
1	0.0002	(0.0021)	-0.0133**	(0.0041)
2	0.0036	(0.0024)	-0.0178***	(0.0052)
3	-0.0019	(0.0030)	-0.0281***	(0.0063)
4	-0.0119**	(0.0039)	-0.0287***	(0.0075)
5	-0.0089*	(0.0045)	-0.0210*	(0.0096)
6	-0.0127*	(0.0053)	-0.0222	(0.0149)
7	-0.0300***	(0.0058)	-0.0279**	(0.0106)
8	-0.0256***	(0.0069)	-0.0425***	(0.0111)
9	-0.0202**	(0.0076)	-0.0568***	(0.0109)
10	-0.0250**	(0.0081)	-0.0503***	(0.0122)
11	-0.0192	(0.0104)	-0.0538***	(0.0131)
12	-0.0176*	(0.0087)	-0.0569***	(0.0105)
13	-0.0200	(0.0102)	-0.0492***	(0.0116)
14	-0.0060	(0.0113)	-0.0458***	(0.0120)
15	-0.0064	(0.0123)	-0.0470**	(0.0152)
Candidate attributes	Yes		Yes	
Focal FE	Yes		Yes	
Adjusted R^2	0.005		0.017	
Observations	484742		156603	

Notes: The proposing decision is conditional on viewing long profiles. Here the controlled candidate attributes are the same set of attributes as in the mate preference estimation. The baseline of the age difference is 0. Standard errors are clustered at the focal user level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.4: Preference Mismatch: Income

	Propose a match			
	(1) Male Focal		(2) Female Focal	
Income difference (level)				
-11	-0.1015***	(0.0145)	0.0623***	(0.0149)
-10	-0.0856***	(0.0116)	0.0580***	(0.0089)
-9	-0.0839***	(0.0099)	0.0521***	(0.0105)
-8	-0.0642***	(0.0098)	0.0473***	(0.0089)
-7	-0.0562***	(0.0087)	0.0632***	(0.0079)
-6	-0.0374***	(0.0058)	0.0529***	(0.0063)
-5	-0.0310***	(0.0044)	0.0426***	(0.0054)
-4	-0.0189***	(0.0030)	0.0295***	(0.0048)
-3	-0.0136***	(0.0024)	0.0216***	(0.0036)
-2	-0.0065***	(0.0019)	0.0157***	(0.0031)
-1	-0.0019	(0.0015)	0.0076**	(0.0028)
1	-0.0040*	(0.0018)	-0.0180***	(0.0037)
2	0.0033	(0.0024)	-0.0170***	(0.0050)
3	0.0036	(0.0031)	-0.0317***	(0.0074)
4	0.0009	(0.0038)	-0.0293	(0.0171)
5	0.0071	(0.0057)	-0.0147	(0.0201)
6	0.0054	(0.0083)	-0.0323	(0.0175)
7	0.0440***	(0.0133)	-0.0500	(0.0269)
8	0.0084	(0.0140)	-0.0458	(0.0275)
9	0.0392*	(0.0176)	-0.0081	(0.0610)
10	0.0227	(0.0201)	-0.0758*	(0.0323)
11	-0.0015	(0.0377)	0.1396	(0.1139)
Candidate attributes	Yes		Yes	
Focal FE	Yes		Yes	
Adjusted R^2	0.005		0.017	
Observations	484742		156603	

Notes: The proposing decision is conditional on viewing long profiles. Here the controlled candidate attributes are the same set of attributes as in the mate preference estimation. The baseline of the income difference is that the male and female have the same income level. The income level is denoted on a scale of 1 to 12, signifying a range spanning from ”Less than ¥2,000” to ”More than ¥50,000”. Standard errors are clustered at the focal user level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

D Robustness Checks on the Main Regression

Table A.5: The Role of Information on Matching Outcomes: Different Match Cutoffs (Male Focal Users)

	Male Focal					
	Cutoff = 2		Cutoff = 3		Cutoff = 4	
	(1)	(2)	(3)	(4)	(5)	(6)
Obtaining more info	-0.0043***	-0.0046***	-0.0091***	-0.0091***	-0.0229***	-0.0232***
	(0.0003)	(0.0004)	(0.0005)	(0.0006)	(0.0010)	(0.0010)
Candidate FE	No	Yes	No	Yes	No	Yes
Focal FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.000	-0.016	0.001	0.009	0.002	0.081
Observations	479987	340933	479987	340933	479987	340933

Notes: Standard errors are clustered at the focal user level for columns (1), (3), and (5); and at both the focal user and candidate level for the other columns.* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.6: The Role of Information on Matching Outcomes: Different Match Cutoffs (Female Focal Users)

	Female Focal					
	Cutoff = 2		Cutoff = 3		Cutoff = 4	
	(1)	(2)	(3)	(4)	(5)	(6)
Obtaining more info	-0.0071***	-0.0050**	-0.0148***	-0.0135***	-0.0349***	-0.0352***
	(0.0008)	(0.0015)	(0.0013)	(0.0022)	(0.0024)	(0.0035)
Candidate FE	No	Yes	No	Yes	No	Yes
Focal FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.000	0.038	0.001	0.059	0.002	0.118
Observations	144162	73854	144162	73854	144162	73854

Notes: Standard errors are clustered at the focal user level for columns (1), (3), and (5); and at both the focal user and candidate level for the other columns. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.7: The Role of Information on Matching Outcomes (continuous DV)

	Male Focal		Female Focal	
	(1)	(2)	(3)	(4)
Obtaining more info	-0.0975***	-0.0995***	-0.1665***	-0.1608***
	(0.0042)	(0.0041)	(0.0101)	(0.0099)
Candidate attributes	No	Yes	No	Yes
Focal FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.002	0.016	0.003	0.018
Observations	479987	479987	144162	144162

Notes: Standard errors are clustered at the focal user level for columns (1) and (3); and at both the focal user and candidate level for the other columns. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.8: The Role of Information on Matching Outcomes (count DV)

	Male Focal		Female Focal	
	(1)	(2)	(3)	(4)
Obtaining more info	-0.0855***	-0.0868***	-0.1282***	-0.1237***
	(0.0036)	(0.0035)	(0.0079)	(0.0077)
Candidate attributes	No	Yes	No	Yes
Focal FE	Yes	Yes	Yes	Yes
Observations	475725	475725	142660	142660

Notes: Standard errors are clustered at the focal user level for columns (1) and (3); and at both the focal user and candidate level for the other columns. Some observations are dropped by the Poisson FE model because of all zero outcomes. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.9: The Role of Information on Matching Outcomes (demographics)

	Male Focal		Female Focal	
Obtaining more info	-0.0551***	(0.0019)	-0.0902***	(0.0050)
Candidate attributes				
Age: elder	-0.0112***	(0.0017)	-0.0047	(0.0055)
Age difference (+)	-0.0015***	(0.0003)	-0.0044***	(0.0008)
Age difference (-)	-0.0087***	(0.0003)	0.0006	(0.0005)
Degree: higher	-0.0021	(0.0019)	0.0056	(0.0071)
Degree difference (+)	-0.0080***	(0.0010)	0.0029	(0.0045)
Degree difference (-)	0.0015*	(0.0007)	-0.0227***	(0.0020)
From the same city	0.0162***	(0.0024)	0.0309***	(0.0046)
Have photo	0.0058***	(0.0017)	0.0215**	(0.0070)
Height: higher than baseline	-0.0042**	(0.0015)	0.0079	(0.0045)
Height difference (+)	-0.0012***	(0.0002)	0.0022**	(0.0008)
Height difference (-)	0.0014***	(0.0002)	-0.0050***	(0.0004)
Income: higher	0.0058**	(0.0018)	0.0157*	(0.0078)
Income difference (+)	-0.0020**	(0.0006)	0.0024	(0.0037)
Income difference (-)	0.0029***	(0.0007)	-0.0067***	(0.0006)
Marriage: both divorced	0.0511***	(0.0044)	0.0709***	(0.0107)
Marriage: either single	0.0103***	(0.0028)	0.0263***	(0.0076)
Have children: both	0.0152***	(0.0031)	0.0318***	(0.0062)
Have children: neither	0.0016	(0.0029)	-0.0147*	(0.0074)
Zodiac sign: best match	0.0028*	(0.0011)	0.0004	(0.0028)
Zodiac sign: worst match	0.0001	(0.0014)	-0.0059	(0.0033)
Religious: both	0.0017	(0.0077)	0.0088	(0.0137)
Religious: neither	0.0009	(0.0016)	-0.0061	(0.0040)
Own house: both	-0.0102**	(0.0036)	-0.0284***	(0.0070)
Own house: either	-0.0045*	(0.0022)	-0.0172***	(0.0032)
Lifestyle: irregular	-0.0040**	(0.0012)	0.0049	(0.0034)
Lifestyle: unknown	-0.0613***	(0.0016)	-0.1201***	(0.0044)
Provide looks rating	0.0046***	(0.0010)	-0.0028	(0.0025)
Log # words in self-intro	0.0073***	(0.0004)	0.0112***	(0.0010)
Focal FE	Yes		Yes	
Adjusted R^2	0.026		0.034	
Observations	479987		144162	

Notes: The baseline of the height difference is that the female is 10 cm shorter than the male. Other omitted baseline categories are: Marriage: both single; Have children: either; Zodiac sign: others; Religious: either; Own house: either; Lifestyle: regular. Standard errors are clustered at the focal user level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

E Online Experiment

We conducted an experiment to gain further insights. Specifically, we designed two online studies on Prolific to measure heterosexual individuals' dating preferences and to test the matching outcomes with different amounts of information. We utilized online studies to alter the amount of information about the other side. In other words, we randomized short versus long profiles of the candidates while simultaneously controlling for factors such as search costs. To make short profiles and long profiles comparable, we kept the overlapping attributes contained in both profiles the same, and varied the information about additional attributes in the long profile.

We first describe study 1. We recruited a pool of heterosexual participants from Prolific, with ages ranging from 25 to 30. In the beginning, We asked for their gender information. Then we randomly showed them some candidate profiles of the opposite gender. After viewing each profile, we asked participants if they wanted to contact this candidate. These profiles are randomized into *short profiles*(i.e., age and education) and *long profiles* (i.e., age, education, and height). For a given short profile, we created three corresponding long profiles with the same age and education information but different heights.[A.1] Lastly, we collected participants' basic demographics. We did not include photos in the profiles, as tastes over appearance vary significantly, and it is extremely difficult to identify within-user preferences for appearance given the capacity of an online study.

We collected 197 valid surveys, with 73 female participants and 124 male participants. Based on their contact decisions, we manually matched these participants. For example, if a participant decided to contact a candidate who is 26 years old but not a candidate who is 29 years old, then she was matched with males aged 25 to 27 years old. Similar logic applies to other attributes. In this way, we identified all the male participants whom a female participant would contact, and

[A.1] In study 1, we used 2 age values (26 and 29), 3 education levels (high school, associate degree, and bachelor degree), and 3 height values (5′2″, 5′5″ and 5′8″ for female candidates, and 5′8″, 5′11″ and 6′2″ for male candidates). In total, we had 6 short profiles and 18 long profiles.

similarly, all the female participants whom a male participant would contact. If a female and a male contacted each other, they were matched. Using the short profile answers, we obtained the matching outcomes that were based on *partial* information. Similarly, we also had the matching outcomes of *complete* information using the long profile answers.

To better reveal user preferences in a larger attribute space, we added more attributes and attribute values in study 2.[A.2] The survey flow is the same as that in study 1. Since there are 225 long profiles, it is not practical to show all of them to a participant. We randomly showed 2 long profiles for a given short profile (i.e., each age-education combination). As a result, each participant was shown 15 short profiles and 30 long profiles in study 2. We collected 493 valid surveys with 237 female and 256 male participants.

Table A.10: The Role of Information on Matching Outcomes: Experiment Results

	Study 1		Study 2	
	(1) Male Focal	(2) Female Focal	(3) Male Focal	(4) Female Focal
If more info	-0.0509***	-0.0466***	-0.0814***	-0.0331***
	(0.0076)	(0.0111)	(0.0027)	(0.0024)
Candidate FE	Yes	Yes	Yes	Yes
Focal FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.610	0.668	0.507	0.664
Observations	3360	2613	70511	62361

Notes: Robust standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

We present the results in Table A.10. The regression models follow the main test of the information role (Table 5). We regress the matching outcomes on whether the participants saw more information about the candidates. Both experiments replicate the "less information is more" effect: more information about the candidates makes the matching outcomes worse. This is true for both the male participants (columns 1 and 3) and the female participants (columns 2 and 4).

[A.2]In study 2, we used 5 age values (20, 23, 26, 29, 32) and three education levels (high school, associate degree, and bachelor degree) in short profiles. We also added height and income level in long profiles. For height, we have 5′3″, 5′5″, 5′7″, 5′9″ and 5′11″ for female candidates, and 5′8″, 5′10″, 6′, 6′2″ and 6′4″ for male candidates. For income level, we have three options, i.e., below $25000, $25,000 - $50,000 and $50,000 - $75,000. So there are 15 short profiles and 225 long profiles.

F A Stylized Model of Preference Mismatch

In this section, we build a stylized model to help understand why, with preference mismatch, seeking more (vs. less) information about the other side makes matching outcomes worse. For simplicity, we first derive the matching outcomes in two cases, where both a focal user and candidates know the same attributes of the other side. Then we show the results of all the cases that allow the focal user and candidates to have different amounts of information about the other side.

F.1 Matching Outcomes When Partial (vs. Complete) Information Is Observed

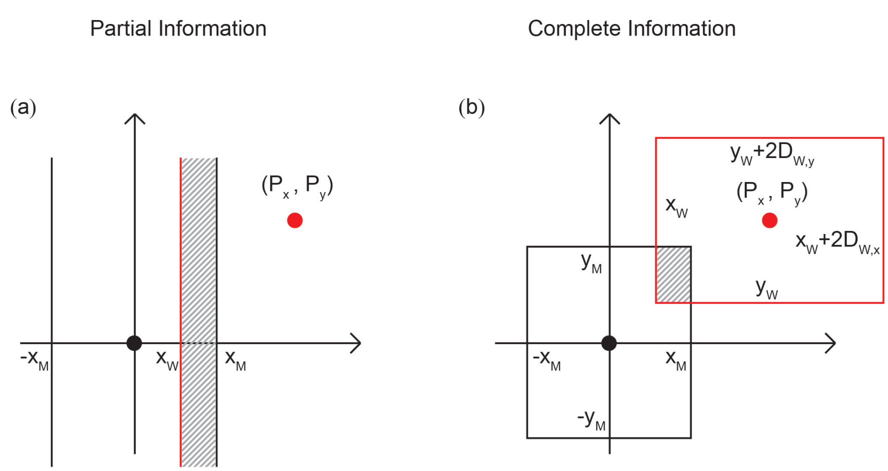
Setup. Without loss of generality, we consider a man (i.e., the focal user) coming to a dating website searching for women candidates. He can click on the profiles of the candidates, with each profile showing the candidate's attribute information x_W.[A.3] We denote the focal user's attribute(s) as x_M, and the difference between the attributes can be denoted as $x = x_M - x_W$. We denote the focal user's utility as $u_M(|x - P_{M,x}|)$ which is a monotonic decreasing function of the distance between the relative user attribute x and the focal user's ideal relative attribute point $P_{M,x}$. That is, when $x = P_{M,x}$, the focal user gets the highest utility and the further away x is from $P_{M,x}$, the lower the utility. The focal user makes a matching proposal to a candidate when $u_M(|x - P_{M,x}|) \geq \bar{u}_M$, where $\bar{u}_M$ is the utility threshold of proposing. When a candidate receives the match proposal, she also observes the attribute of the focal user. She will accept the proposal if her utility satisfies $u_W(|x - P_{W,x}|) \geq \bar{u}_W$; otherwise she will decline the proposal. Here $P_{W,x}$ is her ideal value of the attribute(s) and $\bar{u}_W$ is her accepting threshold. A match is realized if the candidate accepts the match proposal.

With this basic setup, let's illustrate our model. In the following discussion, we will assume each user has two attributes x and y. The setup is similar to the one-dimensional case. First, we

[A.3] Here x_W can be either a scalar or a vector depending on the number of attributes on the profile.

will discuss how preference mismatch impacts the matching outcomes (measured by the matching rate) under two cases: (A) when only one attribute x is observed (i.e., when *partial* information is observed); and (B) when both attributes x and y are observed (i.e., when *complete* information is observed). We show this in a two-dimensional Euclidean space (Figure A.2). Without loss of generality, in this coordinate system, the origin $(0,0)$ is the focal user's ideal preference for attributes x and y. The closer (x,y) is to the origin, the higher the utility of the focal user. We use (P_x, P_y) to denote women candidates' ideal preference for the two attributes. Similarly, the closer (x,y) is to (P_x, P_y), the higher the utility of the candidate.

Figure A.2: Model Illustration



Then we will compare the matching outcomes across the two cases to illustrate the role of information under preference mismatch, paving the way for our empirical analysis, which is the main focus of this paper. In Section F.2, we discuss the other two cases where the candidates and the focal user observe different amounts of information. The conclusions are consistent with our findings.

A. When users only observe *partial* information

We first illustrate how preference mismatch between the focal user and the candidates influences the reply decisions of the users when only one attribute x is observed. In this case, we assume only one attribute x (i.e., partial information) is observed on both sides (Figure A.2(a)). Therefore both the focal user and the candidates will make their decisions based on this attribute.

Focal user's proposing decision. Upon observing candidates' x attribute, the focal user will propose to candidates with $|x| \leq x_M$. x_M is the attribute value when utility $u_M(|x - P_{M,x}|)$ is equal to the proposing threshold $\bar{u}_M$. So candidates in the region between $-x_M$ and x_M will receive match proposals. The fraction of candidates being proposed is equal to $F_x(x_M) - F_x(-x_M)$, where $F_x(x) = \int_{-\infty}^{x} f_x(u)du$ is the cumulative distribution function of x.

Candidates' accepting decision. Due to preference mismatch, the candidates have a different preference over attribute x. They are only interested in men with x which satisfies $|x - P_x| \leq D_{W,x}$, and the closer x is to P_x, the higher the utility of the candidates. As shown in Figure A.2(a), $x_W = P_x - D_{W,x}$ is the lower bound that satisfies this condition. To be specific, x_W is the attribute value when the candidates' utility is equal to the accepting threshold $\bar{u}_W$. Upon receiving the match proposal from the focal user, only candidates with $x \in (x_W, x_M)$ will accept the proposal. This mutual preference is indicated by the shaded area in Figure A.2(a). The matching rate is therefore the fraction of candidates who accept the proposal among all the candidates who receive the proposal: $r = \frac{F_x(x_M) - F_x(x_W)}{F_x(x_M) - F_x(-x_M)}$.

B. When users observe *complete* information

Now we discuss the matching outcome when both x and y are observed. The decision rules are similar to the partial information case, but this time the decision criterion is based on the values of two attributes.

Focal user's proposing decision. Upon observing the value of candidates' x and y attributes, the focal user will propose to candidates with $|x| \leq x_M$ and $|y| \leq y_M$, which translates to $(F_x(x_M) - F_x(-x_M)) * (F_y(y_M) - F_y(-y_M))$ candidates being proposed by the focal user (i.e., the black rectangle in Figure A.2(b)).

Candidates' accepting decision. Similar to the partial information case, given preference mismatch, candidates prefer a focal user with $x \in (x_W, x_W + 2D_{W,x})$ and $y \in (y_W, y_W + 2D_{W,y})$ (i.e., the red rectangle in Figure A.2(b)). Candidates who lie in the intersection (i.e., the shaded area in Figure A.2(b)) of the two rectangles will accept the match proposal. Therefore the matching rate is $r' = \frac{(F_x(x_M)-F_x(x_W))*(F_y(y_M)-F_y(y_W))}{(F_x(x_M)-F_x(-x_M))*(F_y(y_M)-F_y(-y_M))}$.

Now we have derived the matching rates when partial and complete information is observed. Comparing these two matching rates (Figure A.2(a) and (b)), we have $\frac{r}{r'} = \frac{F_y(y_M)-F_y(-y_M)}{F_y(y_M)-F_y(y_W)} > 1$. This means, with partial information (i.e., one attribute) revealed to the focal user, he will receive more replies from the candidates to whom he proposes. Proposition 1 is based on this result.

Proposition 1. *With the existence of preference mismatch, knowing less information about the other side will result in a higher matching rate. That is, $r > r'$.*

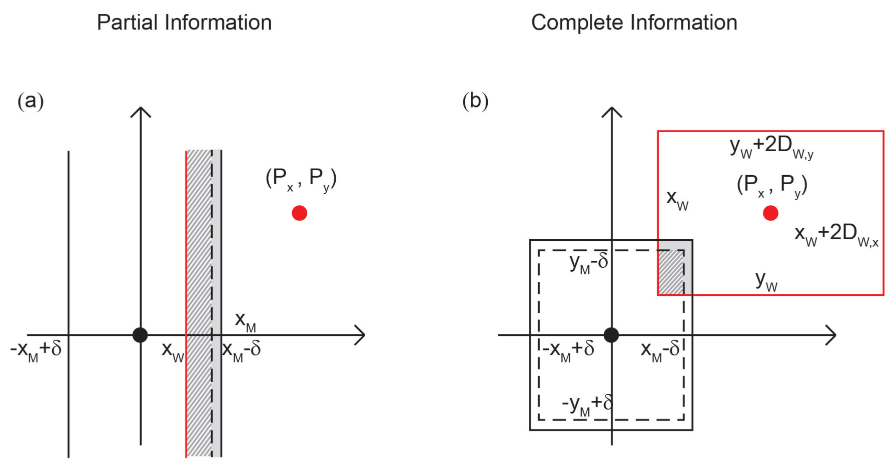
Benefiting from the unique information structure of the dating website we studied, we tested the proposition in our empirical analysis in the main text.

When partial information is observed. Following the setting in Section F.1, we now consider a focal user's reply decision upon receiving the reply message from a candidate. When the focal user receives the replies, additional information about the candidates can be observed. [A.4] Based on this additional information, the focal user updates the candidates' attribute values x. As a result,

[A.4] This also reflects the real-world scenario that message communication usually reveals supplementary/additional information of an attribute that was previously unobserved.

some candidates whose updated x may fall beyond the boundary x_M, whom the focal user is no longer interested in. Formally, we assume candidates who are originally in the region $(x_M - \delta, x_M]$ are now out of the boundary x_M after the first message communication.[A.5] These candidates are ruled out by the focal user after one mutual communication (grey area between $x_M - \delta$ and x_M in Figure A.3 (a)). We denote the focal user's reply rate at this stage as r_M. It is equal to the fraction of candidates the focal user replies to upon receiving the candidates' replies divided by all the candidates who reply to the focal user: $r_M = \frac{F_x(x_M - \delta) - F_x(x_W)}{F_x(x_M) - F_x(x_W)}$.

Figure A.3: Focal User's 1st Reply Decision



When complete information is observed. When both attributes x and y are observed, similar to the partial information case, based on the candidates' replies, the focal user updates the evaluation of the candidates' attributes x and y. We assume the candidates who are originally in the region $(x_M - \delta, x_M]$ or $(y_M - \delta, y_M]$ are no longer qualified for the focal user's further consideration therefore the focal user stops replying to these candidates (i.e., the grey area between the dotted line and the black line in Figure A.3(b)). The reply rate of the focal user can be calculated as $r'_M = \frac{(F_x(x_M - \delta) - F_x(x_W)) * (F_y(y_M - \delta) - F_y(y_W))}{(F_x(x_M) - F_x(x_W)) * (F_y(y_M) - F_y(y_W))}$.

[A.5] This is equivalent to the situation when the focal user tightens his criterion on the selection of x.

Comparing these two reply rates we have: $\frac{r_M}{r'_M} = \frac{F_y(y_M)-F_y(y_W)}{F_y(y_M-\delta)-F_y(y_W)} > 1$. Again, the ratio is greater than one, which implies that the focal user also has a higher reply rate when only *partial* information is revealed about the candidates as compared to the *complete info* case. We document this result as follows.

Proposition 2. *Conditional on the first-round message replies from the candidates, a focal user has a higher reply rate for candidates with partial rather than complete information in the beginning.*

In reality, both the focal user and the candidates can have many message communications. Our model setup can be easily extended to multi-round replying decisions. We have the following corollary.

Corollary 1. *When the focal user and the candidates make their second-round or later-round reply decisions, the reply rates of the focal user and the candidates are higher if partial instead of complete information is revealed in the beginning.*

This corollary implies that if partial information is observed, there will be more message communication on both sides, hence a higher matching rate. Our empirical results (Table 5) support all the propositions and the corollary.

F.2 A More Comprehensive Discussion

When there are two attributes x and y of each user, there are a few possibilities regarding the amount of information each side knows about the other side. Since we are interested in the role of information under preference mismatch, we will *not* consider the case when the two sides have completely different types of information[A.6] since preference mismatch happens when the two sides have at least some common type of information. In sum, there are four cases that we will consider (Figure A.4):

[A.6] E.g., the focal user has information about x only, and the candidates have information about y only.

- Case 1: Both sides know partial information about the other side. That is, both the focal user and the candidates know about one attribute x. This is one of the cases we discussed in the previous subsection.

- Case 2: Candidates have complete information (both attributes x and y) about the focal user, and the focal user has partial information about the candidates (only attribute x).

- Case 3: The focal user has complete information (both attribute x and y) about the candidates while the candidates only have partial information about the focal user (only attribute x).

- Case 4: Both sides have complete information about the other side. That is, both sides know about both attributes x and y. This is the other case we discussed in the previous subsection.

Similar to the calculation of reply rate before, we will first calculate the message reply rates of these cases and then compare them.

Case 1. We have calculated the reply rate of candidates' first reply, that is, $r_{1c} = \frac{F_x(x_M)-F_x(x_W)}{F_x(x_M)-F_x(-x_M)}$ (Figure A.4(a)), and the reply rate of the focal user's first reply is $r_{1f} = \frac{F_x(x_M-\delta)-F_x(x_W)}{F_x(x_M)-F_x(x_W)}$ (Figure A.4(b)).

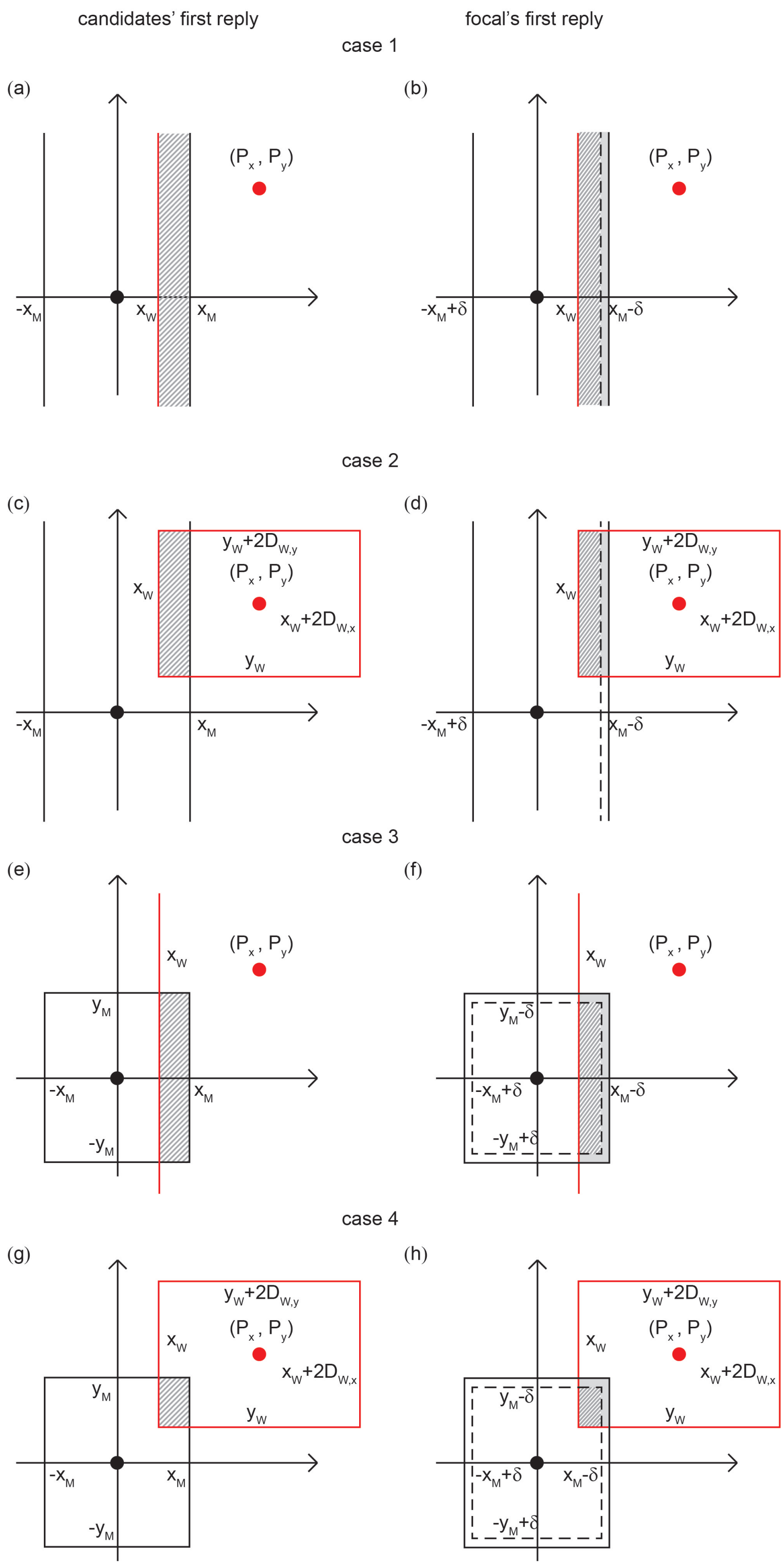
Case 2. Candidates that are proposed by the focal user are the same as in case 1 (the area between $-x_M$ and x_M in Figure A.4(c)). Next, the candidates make their reply decisions based on both x and y. They prefer a potential mate with (x, y) which falls in the area within the red rectangular in Figure A.4(c). Therefore the candidates in the shaded area will reply to the focal user. The reply rate is calculated as $r_{2c} = \frac{(F_x(x_M)-F_x(x_W))*(F_y(y_W+2D_{W,y})-F_y(y_W))}{F_x(x_M)-F_x(-x_M)}$. After updating their information about the candidates based on the candidates' first message replies, the focal user will reply to candidates who are located in the area between x_W and $x_M - \delta$, that is, the shaded area in Figure A.4(d): $(F_x(x_M-\delta)-F_x(x_W))*(F_y(y_W+2D_{W,y})-F_y(y_W))$. Therefore the focal user's first reply rate is $r_{2f} = \frac{(F_x(x_M-\delta)-F_x(x_W))*(F_y(y_W+2D_{W,y})-F_y(y_W))}{(F_x(x_M)-F_x(x_W))*(F_y(y_W+2D_{W,y})-F_y(y_W))} = \frac{F_x(x_M-\delta)-F_x(x_W)}{F_x(x_M)-F_x(x_W)}$.

Case 3. The focal user makes the proposal decision based on both attributes x and y of the candidates. The fraction of candidates that the focal user proposes to is $(F_x(x_M) - F_x(-x_M)) * (F_y(y_M) - F_y(-y_M))$. Since the candidates only know the attribute x of the focal user, they will make their reply decisions based on this attribute only. The fraction of candidates who reply back is $(F_x(x_M) - F_x(x_W)) * (F_y(y_M) - F_y(-y_M))$ (shaded area in Figure A.4(e)). The reply rate of the candidates is $r_{3c} = \frac{(F_x(x_M)-F_x(x_W))*(F_y(y_M)-F_y(-y_M))}{(F_x(x_M)-F_x(-x_M))*(F_y(y_M)-F_y(-y_M))} = \frac{F_x(x_M)-F_x(x_W)}{F_x(x_M)-F_x(-x_M)}$. After updating the candidates' attribute information, the focal user replies to those who still qualify his requirement on x and y. The fraction of candidates the focal user replies back is $(F_x(x_M - \delta) - F_x(x_W)) * (F_y(y_M - \delta) - F_y(-y_M + \delta))$ (the shaded area in Figure A.4(f)). Therefore the reply rate of the focal user is $r_{3f} = \frac{(F_x(x_M-\delta)-F_x(x_W))*(F_y(y_M-\delta)-F_y(-y_M+\delta))}{(F_x(x_M)-F_x(x_W))*(F_y(y_M)-F_y(-y_M))}$.

Case 4. This is Case B in the previous section. We already derived the message reply rate of both the candidates and the focal user, with the former equal to $r_{4c} = \frac{(F_x(x_M)-F_x(x_W))*(F_y(y_M)-F_y(y_W))}{(F_x(x_M)-F_x(-x_M))*(F_y(y_M)-F_y(-y_M))}$ and the latter equal to $r_{4f} = \frac{(F_x(x_M-\delta)-F_x(x_W))*(F_y(y_M-\delta)-F_y(y_W))}{(F_x(x_M)-F_x(x_W))*(F_y(y_M)-F_y(y_W))}$.

Given the cumulative distribution function $F_x(y)$ is monotonically increasing with y, and $x_W > 0, y_W > 0$, it is straightforward to prove that $r_{1c} = r_{3c} > max(r_{2c}, r_{4c})$ and $r_{1f} = r_{2f} > r_{3f} > r_{4f}$. Among all the cases, the reply rates in Case 1 are always the largest. This implies less information about the other side benefits both sides since they enjoy a higher reply rate—that is, a higher chance of getting matched with each other. The ratio of r_{2c} and r_{4c} ($\frac{r_{2c}}{r_{4c}} = \frac{(F_y(y_W+2D_{W,y})-F_y(y_W))*(F_y(y_M)-F_y(-y_M))}{F_y(y_M)-F_y(y_W)}$) depends on the functional form distribution function F and the degree of preference mismatch. If preference mismatch is stronger, which implies $F_y(y_M) - F_y(y_W)$ is smaller, then r_{2c} is more likely to be larger than r_{4c}.

Figure A.4: A More Complete Discussion of the Stylized Model



F.3 Empirical Evidence of the Model Results

We have derived that obtaining less information about the other side leads to a better reply rate, that is, the reply rate in Case 1 is the highest, while the reply rate in Case 4 is the lowest. Now we show evidence supporting the results with our empirical data.

We empirically compare different cases in Table A.11. This is a similar analysis to our main regression Table 5 in the main text. In column 1, we include samples where both focal users and candidates only know partial information about the other side (Case 1), and samples where focal users know partial information about the candidates and candidates know complete information about the focal users (Case 2). Here, the variations in information acquisition amount come from the candidate side, so we test whether more information acquired by the candidates leads to worse matching outcomes. The results indeed show the ”less information is more” effect. Column 4 shows a similar effect when we include samples of Case 3 and Case 4 where focal users always have complete information about the candidates while candidates have either partial or complete information about the focal users. Columns 2 and 3 again replicate the ”less information is more” effect when variations in information acquisition amount come from the focal user side, while candidates either always only know partial information about the focal users (column 2) or always know complete information about the focal users (column 3). Moreover, if we compare across the four columns, as expected, the matching outcome of Case 1 is the best (i.e., both sides with the least information), and Case 4 is the worst (both sides with the most information). One thing worth noting is that, here the variations in information acquisition amount of the candidates from our data are not exogenously given, which may cause a potential selection problem—similar to what we discussed in the main text for the focal users. Detailed discussions can be found in Section 5.1.1.

Table A.11: The Role of Information on Matching Outcomes: Compare Different Cases

	(1) Case 1 VS Case 2	(2) Case 1 VS Case 3	(3) Case 2 VS Case 4	(4) Case 3 VS Case 4
Candidates have more info	-0.0993***			-0.0535**
	(0.0036)			(0.0169)
Focal users have more info		-0.0443***	-0.0553***	
		(0.0020)	(0.0119)	
Candidate FE	Yes	Yes	Yes	Yes
Focal FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.339	0.372	0.212	0.271
Observations	296607	302436	12414	7974

Notes: Standard errors are clustered at both focal user and candidate level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

G Simulation

We ran a simple simulation based on our model and demonstrated the "less information is more" effect in equilibrium. In the simulation, we exogenously provide information to users. The simulation procedure goes as follows. First, we generate 1000 male users and 1000 female users. Everyone has two attributes: age and height. Consistent with our empirical data, we use the Gama distribution to randomly generate the age for each user and the normal distribution to randomly generate the height for each user.[A.7] Also, we generate selection criteria for each user. That is, the upper and lower bounds of each attribute difference of the other side that a user can accept. If the attributes of the candidates fall within the interval, the focal user will propose, similar to the model setup. We randomly generate the upper and lower bounds for the two attributes of each user using uniform distribution.[A.8]

Given that our model has four cases, we ran four simulations with these users: Case 1, both sides only have age information; Case 2, the male side has age information about females, the female side has both age and height information about males; Case 3, the female side has age

[A.7] We generate integer numbers for these two attributes.

[A.8] In particular, in our data, a typical male's ideal age difference for a female is -2 (i.e., 2 years younger than him), so we generate a male's upper bar for age difference from [1, 3], and the lower bar from [-7, -5]. Similarly, the upper and lower bars of females are generated from [-4, -2] and [-12, -10] respectively, given the females' ideal age difference of -7. In our data, the males' and females' ideal height differences of the partner are -10 cm and -20 cm respectively. So we generate the upper and lower bounds of height difference preference from [-5, 0] and [-20, -15] for the male users. The upper and lower bounds of females are generated from [-15, -10] and [-30, -25].

information about males, the male side has both age and height information about females; Case 4, Both sides have both attributes' information about the other side.

In each case, male users are the focal users who make initial match proposals. They are allowed to search all the female candidates and propose to those whose observed attribute(s) fall within their selection criteria.[A.9] There is no limit to how many candidates they can propose, similar to the online dating context we study. The candidates make their reply decisions based on the proposals they receive. This is the first round of message communication between the focal user and the candidates. Now we describe the second and later rounds of communication. Following the setting in the model (Online Appendix F), when the focal user receives the replies, additional information about the candidates can be observed. [A.10] Based on this additional information, the focal user updates the evaluation values of the candidates. As a result, the focal user is not interested in some candidates whose updated utility of the attribute difference falls beyond the focal user's selection criteria.[A.11] For simplicity, we assume the focal user is not interested in the candidates whose attribute difference is just 1 distance away from the boundary. This is equivalent to the dashed line we draw in the model ($\delta = 1$). A similar process applies to the later rounds of communications.

Now we show the simulation results. This is an equilibrium result because all users search in the entire user space, and in the end, they communicate with candidates they are interested in, and they have no better options left. In Table A.12, we compare matching outcomes after the third round of communication across the four cases in our model. The regression model follows the main information role test in the paper (Table 5 in the main text). The DVs are matching outcomes

[A.9]This corresponds to the following model description: Upon observing candidates' x attribute, the focal user will propose to candidates with $|x| \leq x_M$. x_M is the attribute value when utility $u_M(|x - P_{M,x}|)$ is equal to the proposing threshold $\bar{u}_M$. So candidates in the region between $-x_M$ and x_M will receive match proposals.

[A.10]This also reflects the real-world scenario that message communication usually reveals supplementary/additional information of an attribute that was previously unobserved.

[A.11]Though the values of age and height do not change, the utility is a function of both the observed attributes and unobserved characteristics, which will be updated through communications.

after the third round of communication, with successful third-round communication equal to one, and zero otherwise. In Column 1 of Table A.12, we compare the matching outcomes of Case 1 and Case 2, where candidates in Case 1 have less information than those in Case 2, while focal users have a similar amount of information. The results show that the matching outcome in Case 1 is better—i.e., the ”less info” case is better than the ”more info” case. When we make the pairwise comparison among other cases (Column 2 to 5, Table A.12), the ”less information is more” effect is consistently true—that is, the ”less info” case is always better than the ”more info” case. We obtain similar results for other rounds of communications.

For robustness checks, we also use Poisson distribution or binomial distribution to generate users' ages. In addition, we tried to generate different amounts of users, such as 2000, 5000, and 10000. In total, we ran 50 simulation tests. All the results consistently show the ”less information is more” effect in equilibrium.

Table A.12: Matching Outcome After Third-Round Communication

	(1) Case 1 VS Case 2	(2) Case 1 VS Case 3	(3) Case 1 VS Case 4	(4) Case 2 VS Case 3	(5) Case 2 VS Case 4
if_case1	0.0250***	0.0078***	0.0287***		
	(0.0016)	(0.0006)	(0.0017)		
if_case2				-0.0191***	0.0017*
				(0.0014)	(0.0008)
Candidate FE	Yes	Yes	Yes	Yes	Yes
Focal FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.102	0.125	0.100	0.084	0.057
Observations	1044760	904098	904098	904098	904098

Notes: Standard errors are clustered at both focal user and candidate level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

H Consumer Learning as an Alternative explanation

Since all the focal users are newly registered users, consumer learning may play a role. In the beginning, users check long profiles to learn about the candidates. When they are more experienced on the platform, they may be capable of knowing who is more likely to be matched with them just based on the short profile information. Therefore the observed ”less information is more”

Table A.13: Learning About Profiles

	Propose based on short profile			
	(1)		(2)	
Time lapse since registration	0.0001	(0.0001)	0.0001	(0.0001)
Candidate attributes	No		Yes	
Focal FE	Yes		Yes	
Adjusted R^2	0.000		0.001	
Observations	479958		479958	

Notes: Here the controlled candidate attributes are the same set of attributes as in the mate preference estimation. Standard errors are clustered at the focal user level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

effect may be driven by the effect of learning about profiles. If this is true, we should observe an increasing proportion of proposals sent by the focal users after they view candidates' short profiles without checking their long profiles. To test this, we regress the probability of sending a match proposal based on short profiles on their tenure with the platform, with one model controlling for focal user fixed effects (column 1, Table A.13) and another model controlling for both focal user fixed effects and candidate attributes (column 2, Table A.13). We find no evidence of consumer learning about profiles.