Hard to get:
The scarcity of women and the competition for high-income men in urban China*

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Reports of the difficulties of elite women in finding suitable mates have been increasing despite the growing scarcity of women in China. We show that this phenomenon can be a consequence of women's preference for men who have higher incomes than themselves. With such a reference-dependent preference, the pool of preferred men shrinks as women's income increases, while the pool of competing poorer women expands. For high-income (h-)women, even when high-income (H-) men are more plentiful and richer (as in China), the direct effect of a greater number of desirable men can be overwhelmed by the indirect effect of the competitive "entry" of low-income (l-)women. We test for these competitive effects using online dating field experimental, Census, and China Family Panel Studies data. Consistent with competitive entry, the search intensity of beautiful l-women for H-men increases with sex ratio and the income of H-men, while that of the plain-looking decreases. The marriage probability of l-women—irrespective of their beauty—increases. Correspondingly, the search intensity of h-women—irrespective of their beauty—for H-men also increases, while the probability of marriage of the plain-looking among them decreases. Our findings can be explained as the comparative statics of intra-female competition for spouses who can cover their labor market opportunity cost of household specialization after marriage and childbirth.

JEL Codes: C93, J01, J12

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I. Introduction

Reports in the popular press (Fincher 2012) and in the academic literature (Qian and Qian 2014) of the difficulties of elite women in finding suitable mates have been increasing, despite the growing scarcity of marriageable women in China (Jiang, Feldman, and Li 2014). This scarcity is partly the consequence of one of the most radical family planning experiments in history. Initiated in 1979, the one-child policy has resulted in hundreds of million fewer births in China. Owing to the traditional Chinese son preference, this decrease in births has not been equally distributed; at least 30 million women are now missing from the prime-age marriage market.

One might have supposed that the surviving women can only benefit from their own scarcity. Indeed, this outcome is predicted by established economic theory; the short side of the mating market should enjoy more surplus from their presumably greater bargaining power (Becker 1973). Moreover, when women are scarce, men should compete harder to increase their mate value. Positive assortative matching predicts that high-income women particularly benefit when the income of high-income men increases. However, we conceptually and empirically show that if women generally prefer men who possess not only a high income, but specifically higher income than themselves, i.e., a reference-dependent preference (RDP) for mate income, as suggested by Ong and Wang (2015), Hitsch, Hortaçsu, and Ariely (2010b), and Bertrand, Kamenica, and Pan (2015), then high-income women can be worse off when there are more men or when men are richer. We outline a neo-classical basis for both the gender difference in preference for mate income and for women’s RDP in the literature review section.

The key insight for the comparative statics implications which we test in this study is that, with an RDP for mate income, increases in a woman’s income reduces the pool of the men she most prefers, while expanding the pool of other women who most prefer these same men.

In the context of an RDP for mate income, the fierceness of the competition a woman faces for the men she most prefers “escalates” as her income increases. The main focus of this present study is how this escalation in competition can, moreover, be exacerbated by increases in the income and availability of high-income men. Either may boost the expected return of pursuing such men: the former increases the value and the latter increases the probability of getting such a man. The *direct effect* of increases in the income and in the availability of high-income men benefit high-income women. In the case of increases in men’s income, men are more desirable. In the case of increases in the local sex ratio (number of men/number of women in a city), more high-income men are available for each woman to desire. In either case, the higher *ex-ante* expected returns for pursuing these high-income men may also increase the number of low-income women (particularly the beautiful among them) who might switch from pursuing low-income men to pursuing these high-income men as well. A greater number of women can therefore desire the same high-income men. Accordingly, an *indirect effect* of both increases in the income and availability of high-income men is the increased “entry” of low-income women into the matching market for high-income men. That makes high-income women, who are averse to matching with low-income men, worse off. The indirect effect is likely to dominate the direct effect for high-income women, whereas the opposite is true for low-income women, who can be satisfied with matching with low-income men. Consequently, high-income women can on-net be worse off when high-income men are even richer or more plentiful due to this ‘competitive entry’ of low-income women into the market for high-income men. Such may be the situation in China, where both the sex ratio and men’s income compared to women’s have been increasing dramatically (Ge and Yang 2014).

We exploit variation in local sex ratio and the incomes of men across Chinese cities to test for our competitive entry hypothesis. We use three data sets: field experimental data with random assignment of income, the China Family Panel Studies (CFPS) household survey data, and the Chinese Census. The local sex ratio of a city within a certain age range can be regarded as representing the *ex-ante* prospects for each side of finding a marriage or remarriage partner, and thus, as a measure of the competitiveness of the mating market (Becker 1973). For the online dating field experiment, we chose 15 major cities for variation in local sex ratios and measured the variation across these different types of women's *relative* search intensities for men of different income levels. In this experiment, we randomly assigned three income levels to 450 artificial male profiles on a large online dating-for-marriage website (with more than 100 million members in 2016) and recorded the incomes and other characteristics of 1,811 "visits" from women to these male profiles. The women visitors were divided into high-, medium-, and low-income levels. Moreover, we also had a random sample of nearly two-thirds of these female visitors' profile photo rated for their beauty.

Consistent with our competitive entry hypothesis, we show that the search intensity of the beautiful low-income women for high-income men increases with the local sex ratio and the income of high-income men. Consistent with exiting in the face of greater competition for high-income men and substitution towards low-income men, the search intensity of the plain-looking among these women for high-income men decreases with the same. Consistent with efforts at entry deterrence on the part of high-income women, the search intensity of high-income women—irrespective of the beauty—for the high-income men increases with the local sex ratio and the income of these high-income men.[1] The lack of exiting on the part of the less beautiful among high-income women is expected if women's RDP for mate income makes them averse to settling for low-income men even when the competition for

[1] These results are robust to the instrumentation of sex ratio following Edlund et al. (2013) and Wei and Zhang (2011).

high-income men increases.

Our analysis of the Chinese Census data finds the expected ultimate consequence of the increased entry of beautiful low-income women into the market for high-income men. Only the marriage probability of high-income women decreases with the local sex ratio and the income of high-income men, notwithstanding our finding of an increase in these women's search intensity. By contrast, low-income women's marriage probability increases with sex ratio and on the income of high-income men, despite their aggregate (irrespective of their beauty) search intensity for these men not increasing with either.[2] Although the negative effect of men's mean income on high-income women's probability of marriage may in part be due also to those men's marginal utility for beauty increasing with their income, we can find no standard explanation for the negative effect of sex ratio on high-income women's probability of marriage. Indeed, consistent with our hypothesis of competitive entry by beautiful low-income women into the market for high-income men, the CFPS data, furthermore, suggests that it is the plain-looking high-income women's probability of marriage which decreases with sex ratio, whereas the probability of marriage of the beautiful high-income women actually increases. These opposing effects on the marriage rates of beautiful and plain-looking high-income women as sex ratio increases is not explained by prior findings that women in general delay marriage as men's income inequality increases (Gould and Paserman 2003).[3]

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[2] Our results with married couples based on the income levels of women can be biased by their decision to participate in the labor market. Although we only included employed wives in our Census data, we do not know if these wives had reduced or planned to reduce their labor market participation prior to marriage. However, we find similar qualitative results when we impute the wages for women using their age, educational attainment, and the number and gender of children based on the methodology in Zhang and Liu (2003). (These results are available on request.)

[3] Despite the novelty of our findings for high-income women, our empirical results support standard theories – when we average across women of all income levels and beauty. Consistent with more outside options from the greater availability of men, the marriage probability

Our findings would be less surprising if the deterioration in the marital prospects of high-income women can be attributed to the cross-border migration of brides from low-income regions (Weiss, Yi, and Zhang 2017). In fact, significant internal migration has occurred within China in recent years. However, because local sex ratio includes the migrant population, the greater influx of low-income women migrants, which *reduces* sex ratio, cannot be the driving factor for the association we find between *higher* sex ratio and the decreased rate of marriage among high-income women. Moreover, sex ratio is controlled for when we find that high-income women are adversely affected by increases in the income of high-income men.

Instead, our online dating evidence suggests a shift in the attention and search efforts of low-income women toward high-income men within cities when these men are richer or more plentiful. In this sense, the topic of our study is also related to migration, but of attention, rather than across borders.[4] This shift in attention in matching markets is itself becoming an area of study in the nascent theoretical matching literature on directed search (Chade, Eeckhout, and Smith 2017). However, to our knowledge, no existing search model captures the rich phenomena documented here. It is beyond the scope of this study to fill in the theoretical gap. Rather, we focus on the effect of sex ratio and men's income on the search *effort* levels of women of different income types and on these women's probability of marriage, rather than the search behavior itself. Such effects are well captured by a simple game theoretical contest example that we provide in Appendix 1 of Ong, Yang, and Zhang (2018). It exhibits a contest game between high- and low-income women for high-income men prizes. The example shows that high-income women can be negatively affected in the marriage market by the increased mate value of high-income men, when low-income women

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of women *on average* increases with sex ratio.

[4] Attention has been shown to be sensitive to the expected surplus in the price dispersion literature (Morgan, Ong, and Zhong 2018).

decide to compete for them instead of settling for their low-income men option. It also shows that low-income women's effort to win over the high-income men is more influenced by their beauty than high-income women's by theirs.

Related Literature

We build on Hitsch et al.'s (2010a) framework for analyzing first-contact email behavior to reveal user mate preferences. As they point out, the Gale-Shapley model, in particular the deferred-acceptance algorithm, approximates the behavior of online daters in their exchanges of signals of interest and emails if the search frictions they face are negligible. Hitsch et al. show that preferences revealed in the online dating context are correlated with preferences revealed in actual marriages. We focus on the click-throughs of dating profiles on preliminary search results. We argue that such click-throughs, which are prior to and necessary for making first-contact emails, are also reflective of dating preferences.

Our conceptual framework of escalating competition is similar to other theories in predicting that women's marriage rate decreases with their income (Isen and Stevenson 2010) or educational attainment (Boulier and Rosenzweig 1984). Recent research has focused on the potential effect of social norms in the US (Bertrand, Kamenica, and Pan 2015), Asia excluding China (Hwang 2016), and other developed countries (Bertrand et al. 2016). We too do find women's marital prospects decrease with their educational attainment, but not with income, once educational attainment is controlled for. However, entirely different from the prior literature, we examine the comparative statics effect of sex ratio and men's income on the search intensity and the probability of marriage of high- and low-income women.

Our study is closely related to, but still differs significantly from, the burgeoning literature on the effect of sex ratio on the competition for mates, particularly in China. Already, evidence exists for the expected increase in competition among men or their supporting families and the relaxation of competition among women. The rise in local sex ratio (population of men/population of women within a province or city) predicts not only increases men's work hours in dangerous and risky jobs (Wei and Zhang 2011), male criminal activities (Edlund et al. 2013), the savings of families with sons (Wei and Zhang 2011), and women's participation in decision making (Edlund et al. 2013); but also decreases in women's educational attainment and employment (Edlund et al. 2013). These studies about outcomes, which focus primarily on the behavior of men, confirm Becker's (1973) theory that the bargaining position of women improves as sex ratio rises.

The effect of sex ratio on competition for mates has been studied in countries other than China. For example, consistent with Becker, Abramizky et al. (2011) find that the low sex ratio (i.e., shortage of men after World War I) led more men to "marry up". That is, the short side of the market benefited from its shortage. Our contribution to this sex ratio literature is to test for heterogeneity in the effect of sex ratio on subgroups of the mating market. In contrast to previous studies, we demonstrate that a subgroup of the short side of the market (women in our case) was negatively affected by RDP despite their shortage, which is the opposite result and contrary to what one might expect based on Becker's theory.

Women's RDP can be explained as a consequence of the classical assumption that women generally specialize in household production after marriage due to traditional gender roles (Becker 1973).[5] This assumption is fleshed out in, for example, Caucutt et al. (2002), which posits that women take up the bulk of the burden of childcare and will marry only if the utility from pooled consumption and investment in children in the context of marriage is higher than their outside option of being single (consume and/or raise children using their own income). Women's own income is their reference point within our conceptual framework.

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[5] Women's RDP has also been documented in the large sociological literature on female hypergamy.

With regards to women's labor market opportunity cost from specialization in household production, recent evidence supports Becker's (1973) prediction that marriage rates would increase with the gender gap in wages because the gap decreases women's labor market opportunity cost from specialization in household production (Autor, Dorn, and Hanson 2017; Shenhav 2018). Recent evidence also confirms Becker's prediction that marriage and childbirth decrease women's labor market participation. Women in the West (Lundberg and Rose 2000) and in China (Feng, Hu, and Moffitt 2017; Hare 2016) often relinquish full-time work after marriage and childbirth. The more highly educated among these women are relatively more likely to "opt-out" completely (Hersch 2013). Women's decreased labor market participation after marriage, particularly in the high earning professions in the US (Goldin 2014), and childbirth in Denmark (Kleven, Landais, and Søgaard 2018; Lundborg, Plug, and Rasmussen 2017), is the main source of gender differences in wages. Furthermore, women anticipate and report preferring (Parker and Wang 2013) decreased labor market participation after marriage and childbirth in the US, even before they marry or graduate from college. They also anticipate a relatively higher income husband (Wiswall and Zafar 2016), who could potentially support their premarital standard of living. Correspondingly, men anticipate a lower income wife and no change in labor market participation after marriage.

Women's anticipation of lost income after marriage helps explain the asymmetry in preference for mate income found in Ong and Wang (2015). To the extent that woman's income is expected to be forgone after marriage, her income will not benefit her potential husband. Men's apparent lack of income-based attraction to women as marriage partners may reflect their anticipation of the women's loss of income. Given women's likely and anticipated reduction in income after marriage, it is natural for them to seek out a husband whose income would substantially offset the opportunity cost of their *potentially* decreased labor market participation and specialization in household production in order to maintain their standard of living.[6] We provide evidence consistent with the dominance of women's RDP for a higher income mate over a possible men's RDP for a lower income mate.

Our empirical results appear to be novel in the context of standard search and matching theories. Sex ratio within Becker's theory of marriage matching determines who gets married. In particular, if the sex ratio is higher than one, some men are not married. Among married couples, sex ratio also determines who gets the marital surplus in a transferable utility (TU) framework. Within a TU framework, when the sex ratio is higher than one, wives get all the marital surplus.

III. Online Dating Field Experiment

Experimental Design

We outline the design of our experiment as follows. Further details are available in Ong, Yang, and Zhang (2018), particularly in the footnotes. We use the experiment to identify the comparative statistics of women's preferences for mate income as sex ratio and men's mean income vary. The analysis of this experimental data forms the basis of our predictions for marital patterns observed in household survey and Census data in subsequent sections.

We used one of the largest online dating websites in China, with a reported membership of 100 million members in 2016. The website we used (and its competitors) advertises itself as a marriage matching website for white-collar professionals in the 25-45 age group.

[6] Such behavior is in-line with job search behavior in general which has been found to be reference-dependent on the prior job (Dellavigna et al. 2017). In many cases, women literally also do search for jobs with less demanding more flexible hours, travel, and consequently lower pay after marriage and childbirth (Blau and Kahn 2017). Men, in contrast, do not. This notion that a woman may search for a mate with a view to offsetting her opportunity cost is consistent with the long standing theory of habit formation and with the recent behavioral theory of reference-dependent preference in which the reference point is lagged consumption (Kőszegi and Rabin 2012). Regardless of whether RDP has a standard microeconomic basis, we consider RDP as a primitive notion and focus on the potential over-entry/congestion effect of a targeted search for a mate based on income. In particular, we test for the possibility of crowding out of high-income women by the competitive entry of low-income women, when high-income men become more plentiful or richer.

The users of this website can create a profile for free. The profile must include demographic (e.g., age and gender), socioeconomic (e.g., income), and physical characteristic (e.g., height) information, at least one photo, and a free-text personal statement. These requirements are standard to most online dating websites. Users may also add more information, and in particular, verifiable information to increase the "credibility"[7] of their profile. Users can browse, search, and interact with other members after registration. Generally, users start by entering their preferred age range and geographic location of partners into the search engine. The query returns a set of abbreviated profiles which include: ID, picture, nicknames, age, city, marital status, height, the first two lines of a free-text statement, and perhaps uniquely to China: income. Users can then click a link and "visit" the full profile, where they can signal interest for free. Emails, however, require membership. The membership fee was 10 CNY/month at the time of the experiment, when 1 USD was about 6 CNY. We recorded only visits.

We constructed our 450 male profiles on this website by collecting nicknames, pictures, and statements from real profiles from *another* website that would have automatically hidden them after a month of inactivity.[8] These profiles were posted for only 24 hours, after which, the accounts were closed. To further minimize any possibility of being recognized by acquaintances, we ensured that their picture was assigned to a province (city) that was

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[7] The credibility of the profile is indicated by a positive score, which can be increased with additional forms of verification, e.g., government-issued identification. All of our profiles simply display phone verification and one photo, giving them the minimal score. Such scores would not generally affect visit rates because they do not appear in search results.

[8] We are unaware of legal restrictions on the noncommercial use of user created content uploaded to social media websites in China.

Chinese universities like their European counterparts, do not have IRBs to approve the ethics of experiments. However, to the best of our understanding, our design falls under the "minimal risk" exemption from IRB approval. "Minimal risk means that the probability and magnitude of harm or discomfort anticipated in the research are not greater in and of themselves than those ordinarily encountered in daily life or during the performance of routine physical or psychological examinations or tests."

See for example: http://humansubjects.stanford.edu/hrpp/Chapter9.html different from their work area or birthplace.

We assigned 30 profiles of five ages: 25, 28, 31, 34, and 37; three incomes: 3-5, 8-10, and 10-20 (1k CNY) per month, which we will call low-, middle-, and high-income, respectively; and two replicas to each of the 15 major cities (see Appendix 2 of Ong, Yang, and Zhang (2018)), resulting in 450 profile "slots." Then, we randomly assigned 450 pictures, nicknames, and personal statements to these 450 slots. For the profile's fixed traits, we gave all male profiles the height of 175cm. Birthdays were within eight days of each other and of the same zodiac sign. All of our profiles listed college education and the marital status of "single with no children" and "buy a house after marriage" (i.e., did not already own a house).

Users can see our profiles' picture, nickname, age, city, marital status, height, income and the first few lines of a free-text statement in their default search results. They can then click a link and visit the full profile, which contained no additional information. For each of our profiles, we can see the profiles of the visitors by clicking their link in the history of visitors.

In total, our male profiles received 1,811 visits from women. 1,474 of these visits have photos. Among these, 1316 were of a quality useable for ratings purposes, e.g., of high enough resolution, had faces not obscured by sunglasses...etc. We had a random sample of two-thirds or 867 of these women visitor's photos rated for their beauty using a proprietary rating program accessible through a standard web browser. In the rating program, each female visitor's photo (i) is randomly matched with 10 other photos ($j \neq i$) from the pool of all photos. Each photo is selected with replacement from the pool of photos 20 times. Each photo was on average rated 200 times, which is approximately 10 times the frequency of other studies. A total of 692 Chinese raters (326 male) rated these 867 photos. The raters were graduate students from Peking University HSBC Business School recruited through a mass email. We used two rounds for rating (one-third of photos in each round), because of our limited capacity to recruit raters during the first-round.[9]

We asked raters to choose the more physically attractive within each pair of 100 pairs instead of asking for a numerical rating within a certain range of numbers, as is standard in the field (Hamermesh and Biddle 1994). This binary judgement may be easier and more precise than assigning a number to how good-looking someone is based on a numerical scale. The binary decision also avoids potential scale differences across individuals and genders which would add noise to our data. The software then aggregates the ratings for each photo into a continuous number between 0 percent, for the least attractive, and 100 percent, for the most attractive. For each photo, these numbers represent the share of other photos that the raters on average found less attractive.

We also use data from another experiment which was run simultaneously with 390 female profiles in the same 15 cities. These female profiles had ages of 22, 25, 28, 31 and 34, a height of 163 cm, were college educated, and had incomes of 5*k* to 8*k* CNY/month. We utilize the reported incomes of the male visitors attracted by these female profiles to construct the distribution of men's income on the website in the 15 cities of our main experiment.

Overview of the Raw Experimental Data

Before we present our main findings, we first establish the background correlation between sex ratio and men's income across the cities in our experiment. The left side of Figure 1 is based on the reported incomes of 5,535 visits from men aged 18 to 45 to the 390 female profiles in the experiment we conducted simultaneously in the same 15 cities. Based on city-level population data from the 2010 China Census, we grouped these cities by local sex

[9] We paid raters 5 RMB to rate 100 pairs of photos in the first-round (January 4, 2016) and in the second-round (November 23, 2016). Given the few minutes it took to rate all 100 photos, our payment was relatively high for China. We set a high wage to attract sufficient numbers of raters within a short period.

ratio into top-, medium-, and bottom-five-city groups. The graph shows that the distribution of high sex ratio cities (top-five-city group) is more right-skewed than that of those in the medium- and bottom-five-city group. The right side of Figure 1 displays a similar pattern for the top-third of the 243 cities in the China 2005 1 percent Population Survey.[10] This right-skewness finding is supported by regression results in A-Table 4 and A-Table 5 in Appendix 2 of Ong, Yang, and Zhang (2018). This implies that increases in sex ratio are not driven by a disproportionate increase in the share of low-income men with respect to high-income men. Therefore, we can conclude that *there are more rich men and/or men are richer both on the dating website and in the surrounding city in higher sex ratio cities*.

[Insert Figure 1 here]

Recall that we fixed the number of profiles (10 for each of our three income levels) across all cities in our online dating experiment. Thus, our high-income profiles should have received a smaller share (relative to our medium- and low-income profiles) of all visits in the higher sex ratio cities given a constant distribution of visits to the three income levels across all cities, not a larger share, as our main findings indicate below. *Our high-income profiles can only receive a larger share of all of visits to our profiles in higher sex ratio cities if women visit high-income men more than low-income men when men are richer or plentiful.*

This increase in women's visits is already evident in the graphs of our raw data in A-Figure 2 in Appendix 2 of Ong, Yang, and Zhang (2018). The summary statistics of age, income, and education for each gender of our visitors are in A-Table 6 and A-Table 7. We grouped female visitors into three income levels: <3, 3-8, and 8-20 (in 1*k* CNY) in A-Figure 3, which shows that the probability of women's visits to high-income male profiles increases with their own reported incomes.

[10] The 2005 Census is the last available with micro level data.

Regression Analysis

Here follows our formal analysis, which becomes the basis for our predictions for married couples observed in household survey and Census data. We exclude 51 visits without income information from the 1,811 visits we received from women, leaving 1,760 visits for analysis. Each of our 450 male profiles is at one of the three income levels in one of 15 cities. Let the income level of the male profiles that woman i chooses to visit be represented by the latent variable y_i^*. We observed her visits if these were made to one of our three income types of male profiles. We treat each as one of the three choices in an ordered probit model

$$y_i^* = X\beta + \varepsilon_i \qquad \text{Eq.(1)}$$

where X includes *m-women dummy* (medium-income women), *h-women dummy* (high-income women), and *log* sex ratio (the *log* of the number of men/number of women--sex ratio from this point forward) and its interactions with the above two dummies, and individual and city characteristics.[11]

We group visits from women into three income levels: <3, 3-8, and >8 (in 1k CNY), and associate a dummy variable with each level: *l*-, *m*-, and *h-women*, respectively. The low-income level is the omitted benchmark.[12] We calculate the local sex ratio using county-level data based on the full sample of the 2010 Census.[13] The 2010 Census released only the aggregate number of people of each gender in five-year age groups. The local sex ratio is defined as the number of males aged 22-32 over females aged 20-30 at the time of

[11] Note that our treatment variable in the experiment is men’s income type (*H, M, L*). However, this may not be evident in our ordered logit regression because men's income type does not appear on the RHS. Nevertheless, this information is implicit in our dependent variable, that is, the *log* odds of visiting higher income men.

[12] We used absolute cutoffs for incomes in the online dating section of the study because the website aggregates incomes into nine levels.

[13] See the tabulation of the 2010 Population Census at the County Level by the National Bureau of Statistics

experiment in 2014, proxied by males aged 18-28 and females aged 16-26 in the 2010 Census, which allows for the two year age gap observed between married couples in China.[14]

The individual characteristics of our women visitors that we collected include income, age, years of education, and height. We calculate the wage distribution (means and standard deviations of men's and women's incomes) from the incomes of our visitors. We collect city characteristics, namely, GDP per capita, and migration share (the share of the population without local *hukou*[15] of the total population in a city) from the 2010 Census data.

The ordered probit regression models the probability that a woman from a specific level of income visits a male profile of a specific level of income among all income levels of male profiles. We interpret this probability as search intensity for a man of a specific income level, which being a probability, is normalized by the total number of visits per women's income level at the city level. We control for city-level income, and therefore, women's average opportunity costs for presumably specializing in household production after marriage by testing for the change across cities in their search intensities.

[Insert Table 1 here]

Table 1 displays the results of the ordered probit regression of women's visits as a function of their own income and local sex ratio. The positive term for the *h-women dummy* (0.993) in column (1) indicates that high-income women visit high-income male profiles more than low-income women do, thereby confirming our impression from A-Figure 3 in Appendix 2 of

[14] We find similar results when we follow Edlund et al. (2013) in constructing the age-specific sex ratios using data from the 2010 Census. We proxy the sex ratio faced by the husband and the wife at the time of marriage using a five-year window (adjacent two years above and below) with a two-year age gap between men and women. Thus, for example, for a 30-year-old woman, we use the ratio of the number of men 3-34 to the number of women age 28-32. To impute the number of women in each age in the range 28-32, we take 1/5 of the number of women 25-29 for women in this age range, and likewise 1/5 of the number of women 30-34 for women in this age range. Then we sum up the number of women 28-32.

[15] An internal passport system from the command economy era: a *hukou* entitles holders to local benefits and to government social services.

Ong, Yang, and Zhang (2018) and supporting previous findings (Ong and Wang 2015). Column (1) of Table 1 demonstrates not only that the intercept for high-income women (0.208) is higher than that of the benchmark low-income women, but also that the difference increases with sex ratio (3.575). Importantly for our competitive entry hypothesis, the coefficient for *sex ratio* for the benchmark low-income women is small and statistically insignificant (0.418) in column (1).[16] However, the lack of significance can also be due to low-income women enjoying more outside options among low- and medium-income men. We show below that the lack of significance is in fact due to the less attractive among low-income women decreasing their search intensity for high-income men. This decrease exerts an offsetting effect on the increased search intensity of the beautiful low-income women for these same men.

Facial beauty is generally regarded as an important characteristic for females because facial femininity, which adds to female facial beauty, signals high levels of the female hormone estrogen, and therefore, fertility (Rhodes 2006). However, with few exceptions, facial beauty is neglected in the literature on the economics of marriage. We focus on the effect of facial beauty in the mating market in a companion study. In this article, we merely note that beautiful low-income women may still expect good odds of matching with high-income men even when the competition for these men increases (see Appendix 1 of Ong, Yang, and Zhang (2018) for details). Therefore, we control for facial beauty in column (2) of Table 1.

Importantly for our previous finding of an insignificant increase in the search intensity of low-income women for higher income men, column (2) of Table 1 also reveals heterogeneity

[16] This insignificance can be due to our design being naturally biased toward a negative effect for increases in sex ratio. Our fixed number of high-income profiles at fixed income levels should receive fewer visits in cities with higher sex ratio, where men on the website (and in the surrounding city) are richer and more plentiful. Hence, the reader should perhaps interpret the weakly negative coefficients as weakly positive.

in the reactions of women according to their beauty with different income levels to increases with sex ratio. The significantly negative coefficient for *sex ratio* (-4.875) indicates a pronounced decrease in the search intensity among of the benchmark plain-looking low-income women for high-income men when the sex ratio increases. By contrast, the highly significant positive coefficient for *sex ratio*beauty* (10.083) indicates a pronounced increase in the search intensity among the beautiful low-income women for high-income men when the sex ratio increases. Thus, increases in sex ratio induce divergent reactions among beautiful and plain-looking low-income women, which helps to explain the apparent lack of reaction of low-income women in aggregate (when we do not disaggregate by beauty).

The medium- and high-income women show diminishing contrasting reactions by their beauty as sex ratio increases, due to their RDP. The significant positive coefficient (5.923) for the interaction between sex ratio and the medium-income women dummy suggests that the plain-looking among them react less negatively than low-income women to the increase in sex ratio. In contrast, the significant negative coefficient (-7.686) for the interaction among sex ratio, beauty, and the medium-income women dummy suggests that the reaction of the beautiful among medium-income women to the sex ratio is less influenced by their beauty than those among low-income women. The positive and significant coefficient (11.564) for the interaction of sex ratio and the high-income women dummy suggests that the plain-looking among the high-income women search more intensively for high-income men when these men are more plentiful. Similarly, in contrast, the negative coefficient (-17.930) for the high-income women suggests that their reaction to the sex ratio is less positively influenced by their beauty compared to that for low-income women. This pattern of decreasing differentiation in search intensity between women of different income levels by their beauty, as the women’s income level increases, is expected because the lower the women’s income level, the larger their set of options among low-income men, and therefore, the greater their latitude to avoid the increasing competition for high-income men.

We calculate the marginal effects of sex ratio on high-income women's probability of visits based on the coefficients of the ordered probit regression in column (3) of Table 1, where we include more controls than in column (2), keeping all variables at their mean values. A 10 percent increase in the sex ratio decreases the probability of plain-looking low-income women (rank 25th percentile in beauty rank) visiting high-income male profiles by 13.8 percentage points.[17] In contrast, a 10 percent increase in sex ratio increases the plain-looking high-income women visiting high-income male profiles by 10.2 percentage points, which nearly matches the increase of 10.7 percentage points of beautiful low-income women (75th percentile in beauty rank).

To summarize, the reaction to the increase in sex ratio of the plain-looking among medium- and high-income women is less negative than that of the plain-looking among low-income women. The reaction of the beautiful among the medium- and high-income women is less positive than that of the beautiful low-income women. Thus, the greatest contrast between the behaviors of the high- and low-income women when the sex ratio increases is between the plain-looking high-income women and the plain-looking low-income women. The women's own beauty makes less of an impact on their search intensity for high-income men as the women's income increases, because their reluctance to substitute toward low-income men increases with the women's own income. This result is expected if

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[17] In our ordered probit model, the probability of each type of male profile being visited is given by $P(L=1)=\Phi(\kappa_1 - X\beta)$, $P(M=1)=\Phi(\kappa_2 - X\beta)-\Phi(\kappa_1 - X\beta)$, and $P(H=1)=1-\Phi(\kappa_2 - X\beta)$, where κ_1 and κ_2 are the estimated cutoffs, and Φ is the cumulative density function of the standard normal distribution. We calculate the marginal effect on each probability's change as $\frac{\partial P}{\partial X}$, keeping all explanatory variables at their mean values. For a positive coefficient β_i of X_i, the marginal effect $\frac{\partial P(L=1)}{\partial X_i} = -\beta_i \phi(\kappa_1 - X\beta) < 0$, where ϕ is the probability density function of the standard normal distribution, and $\frac{\partial P(H=1)}{\partial X_i} = \beta_i \phi(\kappa_2 - X\beta) > 0$, whereas $\frac{\partial P(M=1)}{\partial X_i} = \beta_i \phi(\kappa_1 - X\beta) - \beta_i \phi(\kappa_2 - X\beta)$ is in general ambiguous.

high-income women are more desperate (less willing to avail themselves of the option of low-income men) to match with a high-income man, when the competition for high-income men increases, due to women's RDP.

Observation 1. Among low-income women, the more beautiful they are, the more they visit high-income men when the sex ratio increases. By contrast, plainer looking low-income women visit high-income men less when the sex ratio increases. Both effects decrease with women's income level.

The website allows for the reporting of only 9 income levels (<1, 1-2, 2-3, 3-5, 5-8, 8-10, 10-20, 20-50, and >50 in 1*k* CNY). We define *h*-, *m*-, and *l*-women by absolute cutoffs: *l*-women: <3*k*/month, *m*-women: 3-8*k*, *h*-women: >8*k* with the shares of *l*-, *m*-, and *h*-women being about 23, 62 and 15 percent of our visits, respectively. Our results are robust if we vary the cutoffs by +/- one level of income. The only case where our results become insignificant occurs when *h*-women are defined as those having incomes above 10*k*. However, that may be because only 4.5 percent of our female visitors fall into that category.

The local sex ratio for each city calculated from the 2010 Census includes migrants; thus, our findings may suffer from endogeneity because of unobserved factors in each city that affect migration decisions and the preference for mate income, even after we control for various characteristics of individuals and cities. Therefore, we use the share of minorities in each city's population as an instrument for local sex ratio (Li and Zhang 2009; Wei and Zhang 2011) in Appendix 3 of Ong, Yang, and Zhang (2018). The skewed distribution of local sex ratios (men outnumber women) in China is the result of traditional son preference, exacerbated by the one-child policy, under which people used ultrasound and other techniques to guarantee sons. Nonetheless, the one-child policy was considerably less strictly applied for minorities than for the *Han* majority. Hence, if a higher proportion of minorities exists in a city, then local sex ratios should be less skewed (i.e., lower). However, the share of minorities should not affect people's preference for mate income, controlling for individual and other characteristics. Column (4) of Table 1 reports results of the instrumental variable ordered probit regression which are consistent with our findings.

After demonstrating that only the search efforts of high-income women increase uniformly, irrespective of their beauty, when men became more plentiful, we now examine the effect of the changes in the incomes of the top-, middle- and bottom-1/3 income men (*H*-, *M*-, and *L*-men) in each city on the probability of these women visiting our high-income male profiles in column (5) of Table 1.[18] We omit discussion of the *M*-men because, being intermediate between *H*-men and *L*-men, the effect of the change in their mean income on high- and low-income women will be ambiguous. We make these results available on request.

In column (5) of Table 1, we include beauty and its interaction with sex ratio and the mean income of men with different income levels. Similar to increases in sex ratio in columns (1)-(3) of Table 1, the influence of beauty on women's response to the increase in the mean income of high-income men diminishes as women's income level rises in column (5), because of women's RDP. As with increases in sex ratio in columns (1)-(3), increases in the income of high-income men induce opposing reactions among the beautiful and the plain-looking low-income women in column (5). When the income of high-income men increases, the significant negative coefficient of *mean income of H-men* (-0.334) indicates that plain-looking low-income women are less likely to pursue (more likely to exit the market for) high-income men. In contrast, the coefficient for *mean income of H-men*beauty* (0.499) suggests that beautiful low-income women are more likely to enter the market for high-income men. The positive coefficient for *mean income of H-men*m-women dummy* (0.288) in column (5) indicates that the plain-looking medium-income women are less likely than low-income

[18] Recall that we gathered this income information from the men visiting our female profiles in another experiment that we conducted simultaneously with this experiment.

women to exit (at least weakly more likely to enter) the market for high-income men. In contrast, the significant negative coefficient for *mean income of H-men*beauty*m-women dummy* (-0.567) indicates that beautiful medium-income women are significantly less likely to enter than beautiful low-income women are when the income of high-income men increases. The significant positive coefficient for *mean income of H-men*h-women dummy* (0.593) indicates that plain-looking high-income women are significantly less likely to exit (at least weakly more likely to enter) the market for high-income men than low-income women. Similarly, in contrast, the insignificant negative coefficient for *mean income of H-men*beauty*h-women dummy* (-0.950) indicates that beautiful high-income women are less likely to enter than beautiful low-income women. Again, this pattern of decreasing differentiation by beauty among women as women's income increase is expected if high-income women are more desperate (less willing to avail themselves of the option of low-income men) to match with a high-income man, due to women's RDP.

These results in **Error! Reference source not found.** are summarized in Observation 2.

Observation 2. Even controlling for the effects of sex ratio, among low-income women, the more beautiful they are, the more they visit high-income men when the latter's mean income increases. By contrast, plainer looking low-income women visit high-income men less when the latter's mean income increases. Both effects decrease with women's income level.

So far our results indicate that low-income women's entry into the market for high-income men when the sex ratio or high-income men's income increases with their (the women's) beauty. These results predict that the probability of high-income women (particularly plain-looking) marrying decreases when either sex ratio or high-income men's income increases. We will return to test these predictions after testing for demand side effects of men's search behavior.

We divide men into rich and poor and show the interaction between these men's probability of visits to more beautiful women and sex ratio in Table 2.

[Insert Table 2 here]

Columns (1) and (2) use the level of men's income (0.822 and 0.935, respectively). Columns (3) and (4) use a high-income men dummy. The search intensity of high-income men for beautiful women does not increase with sex ratio in either case. High-income men are not more likely to search for a beautiful girlfriend/wife when they have more potential competition from other men. Column (2) displays this by interacting sex ratio and the level of men's income. Column (4) shows this by interacting sex ratio and the high-income men dummy. Column (4) does, however, show that low-income men are weakly less likely to visit beautiful women where the sex ratio is higher (-8.969).

Observation 3. Men's probability of visits to more beautiful female profiles increases with men's income, but not with sex ratio.

Hence, though richer men search more vigorously for beautiful women, that greater search intensity does not increase with the availability of men. This result suggests high-income men are not more desperate in the face of what *should be* greater competition.

IV. Results from Census and Household Survey Data

Marriage Probability

Here we test for the effects that we have found thus far of the accumulating entry of beautiful low-income women into the mating market for high-income men on the marriage probability of high-income women. These results predict that the marriage probability of high-income women, particularly the plain-looking, decreases with this competitive entry, whereas that of low-income women, including the plain-looking, is not adversely affected. We use the 20 percent random sample of the China 2005 1 percent Population Survey, often called the Mini Census.[19] The entire sample contains 2,585,481 individuals in 31 provinces in China.[20] The median age of first marriage for women in 2005 was 23. 98.5 percent were married by the age of 30.[21] We restrict the sample to women aged 20-30 years and men 22-32 years in Table 3. Males earn a positive income, and both males and females have urban *hukou*. We also excluded cities for which this population of men and women is below 300. Excluding the smaller cities makes our sample of cities here more similar to our sample of large cities in the online dating part of our study. Our findings are only slightly less significant if we exclude cities with less than 250 of the men and women in which we are interested. These results are available on request. We exclude provinces with significant minority populations,[22] which can exhibit unique marriage matching traditions, obtaining a final sample of 20,929 women.

We estimate the following logit model of the probability of being married for woman *i*

$$P(married_i|X) = \frac{\exp(X\beta)}{1+\exp(X\beta)} \qquad \text{Eq.(2)}$$

where the dependent variable is the marital status of female *i* in city *c*. It equals 1 if the woman is married and 0 if she is single. *X* includes woman *i*'s *log* monthly wage, the local sex ratio (the *log* of the number of males over the number of females both aged 22-35 years in each city), and the mean incomes of *H*-, *M*-, and *L*-men (defined as the top-, middle- and bottom-thirds, respectively, of the income distribution of the male populations of each city). The average bounds across cities for men are 1,211-5,978 CNY/month for *H*-men, 757-1,123 CNY/month for *M*-men, and 194-702 CNY/month for *L*-men. The average bounds across cities for women are 1,019-3,197 CNY/month for *h*-women, 610-934 CNY/month for

[19] 2005 is the latest year made available by the Chinese Government which contains micro-level data.

[20] Hong Kong, Macau, and Taiwan were excluded.

[21] The 2010 Census does not have contain micro level data. However, CFPS data for 2010 shows a similar pattern.

[22] The provinces we dropped are Gansu, Guangxi, Guizhou, Inner Mongolia, Ningxia, Qinghai, Tibet, Xinjiang, and Yunnan.

m-women, and 191-547 CNY/month for *l*-women. These ranges are not necessarily contiguous because the average bounds across cities are not the averages of bounds defined within each city.[23] We interact the dummy variables for the different categories of women with sex ratio and the mean income of *H*-, *M*-, and *L*-men. We use the mean income of men of different income categories within a city as the treatment variable because these are exogenous to women's individual income. Again, we omit discussion of the *M*-men because the effect of the change in their mean income on high- and low-income women will be ambiguous. The regression results are presented in Table 3.

[Insert Table 3 here]

The weakly positive coefficient for sex ratio in columns (1)-(4) of Table 3 for the benchmark *l*-women is consistent with our hypothesis that they may merely subsitute towards high-income when more of them are available. Controlling for educational attainment, high-income women are more likely to be married than low-income women. Consistent with our findings of the competitive entry of beautiful low-income women into the market for high-income men when sex ratio increases in columns (2)-(4) in Table 1, the availability of men negatively affects the marriage probability of high-income women (*sex ratio*h-women dummy*) in all specifications in Table 3. Moreover, consistent with our finding in columns (5) and (6) of differentiation by beauty among low-income women when the income of high-income men income increases in Table 1, column (2) in Table 3 shows that the marriage probability of low-income women increases significantly with increases in the mean income of high-income men (1.879). That increase in high-income's income should increase low-income women's probability of marriage because it strictly improves the low-income

[23] Note also that though women earn a lower income, the average bounds of incomes of the men and the women overlap for each income category. In particular, the average lower bound of the income of low-income men (194-702 CNY/month) is not higher than the average upper bound of the income of high-income women (1,019-3,197 CNY/month).

women's options among high-income men and induces not only substation to high-income men from low-income men, but actually more of the low-income women to marry. Consistent with this competitive entry hypothesis, the marriage probability of high-income women decreases relative to low-income women (-2.152) and even absolutely with respect to a zero benchmark with increases in *H*-men's mean income.

Women's marriage probability can decrease with their level of education in the West (Isen and Stevenson 2010) and in China. This is consistent with the possibility that women who have lower marriage market endowments (e.g., attractiveness to men) have better labor market endowments or work harder (Boulier and Rosenzweig 1984). However, this pattern is also consistent with our hypothesis that women's probability of marriage decreases with their own opportunity costs, which may have a purely educational component. High-income women's probability of marriage may decrease because the number of highly educated women rises faster than the number of highly educated men, rather than due to the increase in competition from low-income women. To control for this possibility, columns (3) and (4) additionally control for the effect of the relative supply of men with a college education college or above to women with a college education or above (*Edu ratio*). The coefficient for *Edu ratio* and *Edu ratio*h-women dummy* are significant for columns (4) and (5), suggesting that high-income women do indeed benefit from more educated men. However, column (3) shows a slight increase in the magnitude of the coefficient of the interaction between sex ratio and the high-income women dummy (-2.134) with respect column (2). Column (4) similarly shows a slight decrease in the magnitude of coefficient of the interaction between the mean income of high-income men and the high-income women dummy (-1.904).[24]

[24] We also find that women's probability of marriage decreases when the dispersion in men's income increases, which is consistent with women waiting longer when the inequality of men increases (Gould and Paserman 2003). However, our other coefficients are unchanged in terms of significance. (These results are available on request.)

We also find that women's probability of marriage decreases when the dispersion in men's income increases, which is consistent with women waiting longer when the inequality of men increases (Gould and Paserman 2003). However, our other coefficients are unchanged in terms of significance. (These results are available on request.)

In terms of the magnitude of the marginals evaluated at the mean values of all variables, a 10 percent increase in the mean income of high-income men decreases the probability of marriage for high-income women by 5.4 percentage points compared to low-income women. Women's RDP for a mate with high-income predicts this relative negative effect. When the competition for high-income men escalates, high-income women, unlike low-income women, are less disposed to substitute towards low-income men to avoid this competition.

However, this negative *relative* effect of *H*-men's income on *h*-women's probability of marriage (relative to low-income women) is also consistent with a positive *total* effect of *H*-men's income on *h*-women's probability of marriage. In that case, the marriage probability of women of all income levels increases, but that of high-income women increases less than that of low-income women. Such a positive total effect is also consistent with a possible men's RDP for lower income mates. In the case of men's RDP, we expect that the first-order effect of an increase in the mean income of high-income men is to increase high-income women's marriage probability, because more of these women are of lower income than the high-income men. Instead, we find a weakly *negative* total effect of men's mean income on high-income women's marriage probability, which is the sum of the interaction and the level of the *mean income of H-men* (-2.152+1.879=-0.273). The fact that the total effect is entirely from the significant interaction effect of the mean income of *H*-men with the *h*-women dummy rather than the positive level effect of merely the *h*-women dummy further highlights the importance of competitive entry. This total effect translates into a decrease of 0.681 percentage points in their marriage probability for a 10 percent increase in the mean income of *H*-men. Thus, this evidence with married couples from Census data is consistent with prior results with online dating data that only women have a RDP for mate income (Hitsch, Hortaçsu, and Ariely 2010b; Ong and Wang 2015).[25]

The finding that the probability of marriage of high-income women decreases at all with increases with men's incomes is remarkable because it contradicts an important intuition and an empirical observation of positive assortative matching. When men are richer, more high-income women can match positively with them. However, this intuition/observation for women on average disregards the effect of increased competition from women's RDP for mate income. Further corroboration of women's RDP comes from the fact that the marriage probability of high-income women is also insignificantly affected (0.034) by the incomes of low-income men (*mean income of L-men*h-women dummy*). Despite these counterintuitive results, consistent with standard theory, the average marriage probability at the bottom of Table 3 is always positive; on average, women benefit from higher sex ratio.

We summarize our findings with the Census data as follows.

Observation 4. The marriage probability of high-income women decreases with the local sex ratio and the incomes of high-income men, whereas that of low-income women increases significantly on local sex ratio and weakly on the income of high-income men.

We can gain further insight into which high-income women are losing ground to the competitive entry of beautiful low-income women with the China Family Panel Studies (CFPS) 2010 baseline dataset, which has beauty ratings of surveyed subjects. The CFPS is a

[25] Our finding that high-income women's probability of marriage decreases weakly with high-income men's income is consistent with decreasing marginal utility of income relative to the marginal utility of beauty as these men's income increases. We provide evidence for this in Observation 3. In that case, high-income men will prefer beautiful low-income women as their income increases. However, while men's relative decreasing marginal utility of mate income compared to mate beauty may explain why plain-looking low-income women decrease their search intensity for high-income men when these men's income increases, but it does not explain why plain-looking high-income women do not decrease their search intensity for the same men.

comprehensive survey of individual-, family-, and community-level data across China, covering various aspects of economic and non-economic issues. It includes 16,000 households in 25 provinces and is representative for the whole population of China. We restricted the sample to married couples living in urban areas with local *hukou*. We dropped the couples in which the husband does not earn a positive income. Again, we constructed sex ratio using data from the 2010 Census, which only reports ages at five-year intervals: 20-24, 25-29, 30-34, 35-39, and 40-44. We restrict women to those aged 20-30 and men to those aged 22-32 in the regressions below, leaving us a sample of size of 965. We find quantitatively and qualitatively similar results when we restrict the sex ratio to men and women age 20-29, and test for the probability of women age 20-30 married to men to age 20-30 or men age 20-32, or when we restrict sex ratio to men and women age 20-34 and test for the probability of women age 20-30 married to men age 20-30. We use surveyor's 0-7 scale rating of the beauty of those they surveyed.[26]

We define the beautiful dummy =1 for the top-20 percent of all women (rated 7 on the 1-7 scale). We again estimate the logit model of the probability of being married for woman *i* in Equation (2). Again, we define the mean income of *h*-, *m*-, and *l*-*wo*men to be the top-, middle- and bottom-third, respectively, of the income distribution of the female populations of each city. Table 4 shows the logit regression for marriage probability for women of different income and beauty levels interacted with the local sex ratio and men's mean income in a city.

[Insert Table 4 here]

Column (1) of Table 4 shows that sex ratio has no effect on the marriage probability of either the plain-looking low-income women benchmark (2.298) or the beautiful-looking

[26] Again, as in the online dating section, we also find similar results when we follow Edlund et al. (2013) in constructing the age-specific sex ratios using data from the 2010 Census.

low-income women (-2.774). Column (1) also shows, however, that sex ratio does exert a significantly negative effect on plain-looking high-income women (-6.034), but a weakly positive effect on beautiful high-income women (10.234). This weakly positive effect of sex ratio on beautiful high-income women's probabilty of marriage becomes strongly positive (18.987) in column (2), when we include interactions between women's income type and men's mean income. This suggests that the decline in the high-income women's probability of marriage as sex ratio increases observed in the interaction of sex ratio and the *h*-women dummy in all columns of Table 3 may be limited to the plain-looking among high-income women.

We cannot study the interaction of the mean income of men of different income types with CFPS data because many provinces have zero men in the high-income categories because of the limited sample size. We are, however, able to show that the mean income of men has a positive effect on the marriage probability of beautiful low-income women (1.899), but not of beautiful high-income women (-2.404). This result suggests that the decline in the high-income women's probability of marriage as high-income men's mean income increased in columns (3) and (5) of Table 3, again, may be limited to plain-looking among high-income women.

Beautiful women seem less likely to be married when we introduce interactions between sex ratio, beauty, and men's mean income (-18.043) in column (2). But, this coefficient is difficult to interpret given that the coefficient for this interaction must be interpreted for men's mean income held at zero.

We checked whether the beauty of the wife of high-income men increases also with sex ratio. As might be expected from the increased entry of beautiful low-income women into the market for high-income men, we find that the wife of the high-income man is more attractive than that of the low-income man. Importantly, consistent with the predictable consequences of our result that a greater share of beautiful women competes for high-income men when these men become more plentiful, the beauty of the wife of high-income men increases with sex ratio. These results are consistent with high-income men enjoying a larger pool of more attractive women to choose from when the competition for them increases. Observation 3 suggests that the increase in the beauty of the wife of high-income men with sex ratio is due to the demand side (high-income men's increased search effort for beautiful wife). These findings (available on request) provide further evidence of our competitive entry hypothesis derived from our analysis of online dating data.

V. Conclusions

We use variations in men's incomes and local sex ratio to explore the increasing burdens on high-income women from the competitive entry of low-income women into the market for high-income men due to women's RDP. When the local sex ratio or the income of high-income men increases so that there are more high-income men or high-income men are richer, there is an increase in the search intensity of beautiful low-income women and that of the high-income women (irrespective of their beauty) for high-income men (Observation 1 and Observation 2). In contrast, only plain-looking low-income women decrease their search intensity for high-income men, when the local sex ratio or the income of high-income men increases (Observation 1 and Observation 2).

The consequence of the competitive entry of beautiful low-income women into the mating market for high-income men is evident in the marriage probability of high-income women. Despite the greater search intensity of high-income women, their marriage probability decreases when there are more high-income men or when high-income men are richer (Observation 4). Analysis of the CPFS data further reveals that it is specifically the plain-looking among high-income women whose marriage probability decreases, while the beautiful among them experience an increased marriage probability. We moreover find that the beauty of the wife of high-income men increases with sex ratio. The fact that we did not find that high-income men's search for beautiful women increasing with sex ratio (Observation 3) is consistent with the interpretation that these findings are the consequences of low-income women searching more intensively for high-income men when the sex ratio increases. These findings from an online dating field experiment, CFPS, and Census data demonstrate the novel comparative statics effects of women's RDP for mate income, which we suggest is the consequence of women's attempt to cover their labor market opportunity cost of household specialization after marriage and childbirth with the shared income of who they marry.

References

Abramitzky, Ran, Adeline Delavande, and Luis Vasconcelos. 2011. “Marrying up: The Role of Sex Ratio in Assortative Matching.” *American Economic Journal: Applied Economics* 3(July): 124–57.

Autor, D, D Dorn, and G Hanson. 2017. “When Work Disappears: Manufacturing Decline and the Falling Marriage-Market Value of Men.” *Working Paper*.

Becker, Gary S. 1973. “A Theory of Marriage: Part I.” *Journal of Political Economy* 81(4): 813–46.

Bertrand, Marianne, Emir Kamenica, and Jessica Pan. 2015. “Gender Identity and Relative Income within Households.” *Quarterly Journal of Economics* 130(2): 571–614.

Blau, Francine D, and Lawrence M Kahn. 2017. “The Gender Wage Gap: Extent, Trends, and Explanations.” *Journal of Economic Literature* 55(3): 789–865.

Boulier, Bryan L., and Mark R. Rosenzweig. 1984. “Schooling, Search, and Spouse Selection: Testing Economic Theories of Marriage and Household Behavior.” *Journal of Political Economy* 92(4): 712.

Caucutt, Elizabeth M., Nezih Guner, and John Knowles. 2002. “Why Do Women Wait? Matching, Wage Inequality, and the Incentives for Fertility Delay.” *Review of Economic Dynamics* 5(4): 815–55.

Chade, Hector, Jan Eeckhout, and Lones Smith. 2017. “Sorting through Search and Matching Models in Economics.” *Journal of Economic Literature* 55(2): 493–544.

Dellavigna, Stefano, Attila Lindner, Balázs Reizer, and Johannes F. Schmieder. 2017. “Reference-Dependent Job Search: Evidence from Hungary.” *Quarterly Journal of Economics* 132(4): 1969–2018.

Edlund, Lena, Hongbing Li, Junjian Yi, and Junsen Zhang. 2013. “Sex Ratios and Crime: Evidence from China.” *Review of Economics and Statistics* 95(5): 1520–34.

Feng, Shuaizhang, Yingyao Hu, and Robert Moffitt. 2017. “Long Run Trends in Unemployment and Labor Force Participation in Urban China.” *Journal of Comparative Economics* 45(2): 304–24.

Fincher, Leta H. 2012. “China’s ‘Leftover’women.” *The New York Times*.

Ge, Suqin, and Dennis Tao Yang. 2014. “Changes in China’s Wage Structure.” *Journal of the European Economic Association* 12(2): 300–336.

Goldin, Claudia. 2014. “A Grand Gender Convergence: Its Last Chapter.” *American Economic Review* 104(4): 1091–1119.

Gould, Eric D, and M Daniele Paserman. 2003. “Waiting for Mr. Right: Rising Inequality and Declining Marriage Rates.” *Journal of Urban Economics* 53(2): 257–81.

Hamermesh, Daniel S., and Jeff E. Biddle. 1994. “Beauty and the Labor Market.” *American Economic Review* 84(5): 1174–94.

Hare, Denise. 2016. “What Accounts for the Decline in Labor Force Participation among Married Women in Urban China, 1991-2011?” *China Economic Review* 38: 251–66.

Hersch, Joni. 2013. “Opting out among Women with Elite Education.” *Review of Economics of the Household* 11(4): 469–506.

Hitsch, Günter J., Ali Hortaçsu, and Dan Ariely. 2010a. “Matching and Sorting in Online Dating.” *American Economic Review* 100(1): 130–63.

———. 2010b. “What Makes You Click ? — Mate Preferences and Matching Outcomes in Online Dating.” *Quantitative Marketing and Economics* 449625(4): 1–37.

Hoppe, Heidrun C, Benny Moldovanu, and Aner Sela. 2009. “The Theory of Assortative Matching Based on Costly Signals.” *Review of Economic Studies* 76(1): 253–81.

Isen, Adam, and Betsey Stevenson. 2010. “Women’s Education and Family Behavior: Trends in Marriage, Divorce and Fertility.” *Demgraphy and Economy*: 107–40.

Jiang, Quanbao, Marcus W Feldman, and Shuzhuo Li. 2014. “Marriage Squeeze, Never-Married Proportion, and Mean Age at First Marriage in China." *Population Research and Policy Review* 33: 189–204.

Kleven, Henrik Jacobsen, Camille Landais, and Jakob Egholt Søgaard. 2018. "Children and Gender Inequality: Evidence from Denmark." *NBER Working Papers Series*.

Kőszegi, Botond, and Matthew Rabin. 2012. "Reference-Dependent Consumption Plans." *American Economic Review* 99(3): 909–36.

Li, Hongbin, and Junsen Zhang. 2009. "Testing the External Effect of Household Behavior." *Journal of Human Resources* 44(4): 890–915.

Lundberg, Shelly, and Elaina Rose. 2000. "Parenthood and the Earnings of Married Men and Women." *Labour Economics* 7(June): 689–710.

Lundborg, Petter, Erik Plug, and Astrid Würtz Rasmussen. 2017. "Can Women Have Children and a Career?" *American Economic Review* 107(6): 1611–37.

Morgan, John, David Ong, and Zemin (Zachary) Zhong. 2018. "Location Still Matters: Evidence from an Online Shopping Field Experiment." *Journal of Economic Behavior and Organization* 146: 43–54.

Ong, David, and Jue Wang. 2015. "Income Attraction: An Online Dating Field Experiment." *Journal of Economic Behavior and Organization* 111(March): 13–22.

Ong, David, Yu Yang, and Junsen Zhang. 2018. "Hard to Get: The Scarcity of Women and the Competition for High-Income Men in Urban China." *See http://www.cuhk.edu.hk/eco/staff/jszhang/jzhang.htm*.

Parker, Kim, and Wendy Wang. 2013. *Modern Parenthood: Roles of Moms and Dads Converge as They Balance Work and Family*. Pew Research Center.

Qian, Yue, and Zhenchao Qian. 2014. "The Gender Divide in Urban China: Singlehood and Assortative Mating by Age and Education." *Demographic Research* 31: 1337–64.

Rhodes, Gillian. 2006. "The Evolutionary Psychology of Facial Beauty." *Annual Review of*

Psychology 57(1): 199–226.

Shenhav, Na'ama. 2018. "Lowering Standards to Wed? Spouse Quality, Marriage, and Labor Market Responses to the Gender Wage Gap." *Working Paper*.

Wei, Shang-Jin, and Xiaobo Zhang. 2011. "The Competitive Saving Motive: Evidence from Rising Sex Ratios and Savings Rates in China." *Journal of Political Economy* 119(3): 511–64.

Weiss, Yoram, Junjian Yi, and Junsen Zhang. 2017. "Hypergamy, Cross-Boundary Marriages, and Family Behavior." *Forthcoming International Economic Review*.

Wiswall, Matthew, and Basit Zafar. 2016. "Human Capital Investments and Expectations about Career and Family." *NBER Working Papers Series*.

Zhang, Junsen, and Pak-wai Liu. 2003. "Testing Becker's Prediction on Assortative Mating on Spouses' Wages." *Journal of Human Resources* 38(1): 99–110.

Tables and Figures

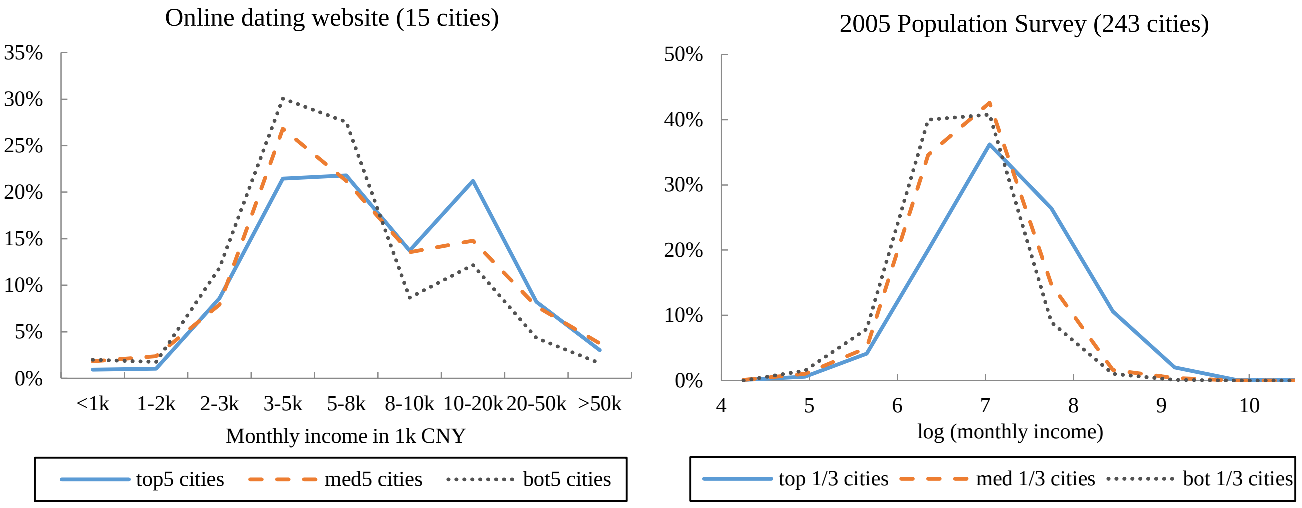

Figure 1: Men's Income Distributions on Online Dating Website and Census Data

Notes: The left panel displays the distribution of men's income for the 15 cities used in the online dating experiment divided into top-5 (top5 cities), middle-5 (mid5 cities) and bottom-5 (bot5 cities) 5-city groups in terms of the size of the local sex ratio. Local sex ratio is defined as the number of males/number of females ages 20-29 in the 2010 Census (which are ages 24-33 at the time of the experiments). The right panel displays the distribution of men's income in 243 cities ranked by local sex ratios, defined as the number of males/number of females ages 22-35 in the 2005 Census, and divided into top-1/3, medium-1/3 and bottom-1/3 local sex ratio city groups. The website only provides nine income categories, with the higher income categories encompassing a larger range of incomes (left panel), similar in scale to the *log* of income in 2005 Population Survey (right panel).

Table 1: Ordered probit Regression of Women's Visits on Male Profile Income

Dependent variable:	Income level of male profile visited (low (3-5*k*), middle (8-10*k*), high (10-20*k*))					
	Ordered Probit	Ordered Probit	Ordered Probit	IV-Ordered Probit	Ordered Probit	IV-Ordered Probit
	(1)	(2)	(3)	(4)	(5)	(6)
m-women dummy	0.208*	-0.558	-0.681	-0.753	-0.478	-0.585
	(0.108)	(0.453)	(0.474)	(0.481)	(0.612)	(0.583)
h-women dummy	0.609**	-0.368	-0.565	-0.611	1.057	0.560
	(0.297)	(0.935)	(0.909)	(0.910)	(0.950)	(1.036)
Sex ratio	**0.418**	**-4.875****	**-6.594*****	**-4.048**	**-2.758**	**2.670**
	(0.614)	(2.332)	(2.506)	(3.734)	(1.936)	(6.108)
Sex ratio*m-women dummy	**1.289**	**5.923****	**6.905****	**6.985****	1.089	1.042
	(0.837)	(2.359)	(2.896)	(2.998)	(0.940)	(0.927)
Sex ratio*h-women dummy	**3.575****	**11.564***	**12.213***	**12.271***	1.906	1.703
	(1.779)	(6.582)	(6.562)	(6.387)	(2.414)	(2.390)
Beauty ranking		-1.190	-1.336	-1.325	0.578	1.151
		(0.772)	(0.826)	(0.813)	(0.740)	(0.862)
Sex ratio*beauty		**10.083****	**12.379*****	**12.499*****	**5.758***	**5.718****
		(4.093)	(4.424)	(4.275)	(3.099)	(2.784)
Beauty*m-women dummy		1.122	1.421	1.527*		
		(0.799)	(0.917)	(0.926)		
Beauty*h-women dummy		2.056	2.441	2.441		
		(1.723)	(1.622)	(1.591)		
Sex ratio*beauty*m-women dummy		**-7.686***	**-11.781****	**-11.869****		
		(4.262)	(5.860)	(5.989)		
Sex ratio*beauty*h-women dummy		**-17.930**	**-21.439**	**-21.619***		
		(13.647)	(13.275)	(13.073)		
Mean income of H-men					**-0.334****	**-0.384*****
					(0.135)	(0.142)
Mean income of H-men*beauty					**0.499****	**0.558*****
					(0.214)	(0.200)
Mean income of H-men*m-women dummy					**0.288***	**0.246**
					(0.155)	(0.150)
Mean income of H-men*h-women dummy					**0.593****	**0.622*****
					(0.259)	(0.231)
Mean income of H-men*beauty*m-women dummy					**-0.567*****	**-0.535*****
					(0.211)	(0.205)
Mean income of H-men*beauty*h-women dummy					**-0.950****	**-1.046*****
					(0.418)	(0.372)
Additional controls:						
Age and education dummies of female visitors	Y	Y	Y	Y	Y	Y
Mean and standard deviation of men's and women's incomes in each city			Y	Y	Y	Y
Observations	1,760	867	867	867	867	867
Pseudo R^2	0.051	0.062	0.073	0.073	0.084	0.084

Notes: Data from the online dating experiment. Each observation is a visit (click) from a woman visitor. The local sex ratio is defined as the number of males aged 22-32 over females aged 20-30 at the time of experiment in 2014, proxied by males aged 18-28 and females aged 16-26 in the 2010 Census. *l*-women is the omitted benchmark with income less than 3*k* CNY/month. *m*-women dummy = 1 if woman's income is between 3k and 8k CNY/month. *h*-women dummy = 1 if woman's income is more than 8k CNY/month. *H*-, *M*-, and *L*-men = top-, middle- and bottom-1/3 men by monthly income in each city, respectively. Results for *M*-and *L*-men are suppressed and available on request. Beauty is the beauty percentile ranking of female visitors which we acquired for a random sample of 2/3 of visits. Columns (4) and (6) are the second stage of the IV regression results for columns (3) and (5), respectively. The first stage using minority share in each city as the instrument for local sex ratio is in Appendix 3. Mean and standard deviation of men's and women's income are based on online dating users and defined in 1k CNY at the city level. Robust standard errors clustered at the city level in parentheses. *** p<0.01, ** p<0.05, and * p<0.1.

Table 2: OLS Regression of Men's Visits on Female Profile's Beauty

Dependent variable	Beauty ranking (0-100) of female profile visited			
	(1)	(2)	(3)	(4)
Income of men	0.822***	0.935**		
	(0.267)	(0.343)		
Sex ratio		-3.131		-8.969
		(21.026)		(5.638)
Income of men*sex ratio		-0.909		
		(2.568)		
H-men dummy			1.341**	1.739**
			(0.584)	(0.790)
Sex ratio**H*-men dummy				-3.416
				(5.762)
Additional controls:				
Age and education dummies of male visitors	Y	Y	Y	Y
Mean and standard deviation of men's and women's incomes in each city	Y	Y	Y	Y
Constant	43.543*	31.034	50.095**	37.538
	(22.873)	(24.894)	(21.643)	(23.678)
Observations	5,288	5,288	5,288	5,288
R^2	0.043	0.044	0.042	0.044

Notes: Data from another experiment which was run simultaneously with 390 female profiles in the same 15 cities. These female profiles had ages of 22, 25, 28, 31 and 34, a height of 163 cm, were college educated, and had incomes of 5-8k CNY/month. The local sex ratio is calculated in same was as in Table 1. *L*-men is the omitted benchmark in column (3) and (4) with income less than 5*k* CNY/month. *M*-men = 1 if men's income is between 5k and 10k CNY/month. Results for *M*-men are suppressed and available on request. *H*-men = 1 if men's income is more than 10k CNY/month. Robust standard errors clustered at the city level in parentheses. *** p<0.01, ** p<0.05, and * p<0.1.

Table 3: Logit Regression of Women's Marriage Probability (Census data)

Dependent variable	Logit: 1 = married, 0 = single			
	(1)	(2)	(3)	(4)
Sex ratio	**1.541**	**1.448**	**1.894***	**1.669**
	(1.011)	(1.013)	(1.019)	(1.037)
h-women dummy	1.675*	3.148*	1.869**	3.127*
	(0.917)	(1.871)	(0.949)	(1.897)
Sex ratio*h-women dummy	**-1.779***	**-1.990****	**-2.134****	**-2.144****
	(0.908)	(0.981)	(0.951)	(0.976)
Edu ratio (men BA+/women BA+)			-0.457*	-0.275
			(0.240)	(0.183)
Edu ratio*h-women dummy			0.498**	0.266*
			(0.208)	(0.157)
Mean income of H-men		**1.879****		**1.729***
		(0.939)		(0.895)
Mean income of *L*-men		0.034		0.081
		(1.621)		(1.619)
Mean income of H-men*h-women dummy		**-2.152*****		**-1.904*****
		(0.719)		(0.721)
Mean income of L-men*h-women dummy		-1.587*		-1.351
		(0.923)		(0.929)
Additional controls:				
Age and education dummies of women	Y	Y	Y	Y
Mean and standard deviation of men's and women's incomes in each city	Y	Y	Y	Y
Constant	-0.473	-0.764	-0.506	-0.777
	(1.359)	(2.117)	(1.388)	(2.162)
Observations	20,929	20,929	20,929	20,929
Pseudo R^2	0.298	0.299	0.298	0.299
	Average effect of sex ratio			
	1.541 + (-0.466)/3 + (-1.779)/3 =0.793	1.448 + (-0.311)/3 + (-1.990)/3 =0.681	1.894 + (-0.579)/3 + (-2.134)/3 =0.990	1.669 + (-0.298)/3 + (-2.144)/3 =0.855

Notes: Data are from China 2005 1 percent Population Survey (mini-census), restricted to men aged 22-32 and women aged 20-30, with urban *hukou*, and positive monthly income. Local sex ratio is defined as the number of men aged 22-32 over number of women age 20-30 in 2005 mini-census in each city. *H*- (*h*-), *M*- (*m*-), and *L*-(*l*-) men (women) are defined as top-, middle- and bottom-1/3 men (women) by monthly income in each city, respectively. *l*-income women is the omitted benchmark. Results for *M*-men and *m*-women are suppressed and available on request. *Edu ratio* is defined as the number of males with bachelor degree and above over the number of females with bachelor degree and above in the city. *Sex ratio, edu ratio*, and all incomes are in *log* form. To calculate the average effect of sex ratio, denote the coefficients for *sex ratio*, *sex ratio*m-women dummy*, *sex ratio*h-women dummy* by *a*, *b*, and *c*. The marginal effect of sex ratio on *l*-women is *a*, on *m*-women is *(a+b)*, and on *h*-women is *(a+c)*. Given that women are divided into three groups equally, the average effect is a/3 + (a+b)/3 + (a+c)/3 = a + b/3 + c/3. Robust standard errors clustered at city level are in parentheses. *** p<0.01, ** p<0.05, and * p<0.1

Table 4: Logit Regression of Women's Probability of Marriage by Beauty (CFPS data)

Dependent variable	Logit: 1 = married, 0 = single	
	(1)	(2)
Sex ratio	2.298	3.280
	(2.630)	(3.404)
h-women dummy	-0.392*	-1.400
	(0.235)	(6.406)
Sex ratio*h-women dummy	**-6.034****	**-6.498**
	(2.664)	(4.537)
Beautiful dummy	0.735	-18.043*
	(0.471)	(10.611)
Beautiful dummy*h-women dummy	-0.293	23.505*
	(0.387)	(12.107)
Sex ratio*beautiful dummy	**-2.744**	**-9.534**
	(4.719)	(6.319)
Sex ratio*beautiful dummy*beautiful dummy	**10.234**	**18.987****
	(6.677)	(8.572)
Mean income of men	0.105	-0.144
	(0.416)	(0.545)
Mean income of men*h-women dummy		0.101
		(0.645)
Mean income of men*beautiful dummy		**1.899***
		(1.064)
Mean income of men*beautiful *h-women dummy		**-2.404***
		(1.230)
Additional controls:		
Age and education dummies of women	Y	Y
Mean and standard deviation of men's and women's incomes in each province	Y	Y
Constant	0.295	2.480
	(2.354)	(3.249)
Observations	965	965
Pseudo R2	0.332	0.337

Notes: Data are from China Family Panel Studies (CFPS) 2010. CFPS provides residence of each individual and household only at the provincial level. Sample is restricted to men aged 22-32 and women aged 20-30, with urban *hukou*, and positive monthly income. The local sex ratio defined as the number of males aged 22-32 over number of females aged 20-30 in each province is calculated using the 2010 Census. Sex ratio and all incomes are in *log* form. *h*-, *m*-, and *l*-women are defined as top-, middle- and bottom-1/3 women by monthly income in each province, respectively. *l*-women is the omitted benchmark. Results for *m*-women are suppressed and available on request. Beautiful dummy = 1 if a woman has a beauty rating of 7 out of 1-7 in CFPS.Robust standard errors clustered at province level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.