Same-Occupation Spouses: Preferences or Search Costs?

Hani Mansour* Terra McKinnish**

Abstract

Married individuals match with spouses who share their occupation more frequently than should happen by chance if marriage markets are large frictionless search markets covering a particular geographic area. This suggests that either there is a preference for same-occupation matches or that search costs are lower within occupation.

This paper uses 2008-2015 data from the American Community Survey to analyze same-occupation matching among a sample of recently-married couples. Our empirical strategy compares the difference in wages between same-occupation husbands and different-occupation husbands across occupations with different percent male workers. Under a preferences explanation, this difference should become less negative as the share of males in the occupation increases. Under a search cost explanation, this difference should become more negative as the share of males increases.

Our results are consistent with the search cost explanation. Furthermore, using an occupation-specific index of workplace communication, we demonstrate that the results are most consistent with the search cost mechanism for occupations with a greater degree of workplace communication. Finally, we show that matching on field of degree for couples in which both spouses have a college degree is also consistent with the search cost explanation.

JEL Classification: J12, J24

Key words: marital matching, occupation, sex composition, search costs

We gratefully acknowledge helpful comments from Chris Bollinger, Murat Iyigun and Rick Mansfield and two anonymous referees as well as seminar participants at the University of Kentucky, Osaka University, University of Melbourne, University of Sydney, University of New South Wales, UC-Santa Barbara, Deakin University, SEA annual meetings, SOLE/EALE World Congress, and the IZA/SOLE transatlantic meetings.

* University of Colorado Denver and IZA, Department of Economics, University of Colorado Denver, Campus Box 181, Denver, CO 80217-3364, USA, hani.mansour@ucdenver.edu.
** Corresponding author: University of Colorado and IZA, UCB 256, University of Colorado, Boulder, CO 80309-0256, USA, terra.mckinnish@colorado.edu, 303-492-6770, 303-492-8960 (fax)

I. Introduction

Husbands and wives match on many similar characteristics, such as education, religion, and race (Blossfeld, 2009). It has also been documented that married individuals are more likely to share their spouse's occupation even if, in most cases, the opposite-sex members of one's occupation comprise a relatively small fraction of the total number of available spouses in the local marriage market (Hout, 1982; Smits et al., 1999). These matching patterns can reflect an individual's preference to match with a spouse that shares his or her own attributes. Alternatively, it could also be a function of the social environments individuals are exposed to and the lower search costs associated with finding a spouse with similar characteristics (Kalmijn 1998; Nielsen and Svarer, 2009; Hitsch et al., 2010; Belot and Francesconi, 2013; Pestel, 2016).

In this paper, we study the case of same-occupational matches in order to shed light on the relative role played by preferences and search costs. At the surface, both of these mechanisms produce the same pattern of assortative mating by occupation. Distinguishing between them, however, has important implications for our understanding of how marriage markets function. For instance, evidence that individuals match within occupation primarily because it is simply easier to meet people of the same occupation would imply that early educational and career choices can have important consequences for matching by changing the group of people with whom one interacts most easily.

Economic models of marital matching often assume that marital search is costless in order to focus on the role of preferences (e.g. Chiappori et al., 2002; Choo and Siow, 2006). Previous empirical studies on similarities between spouses have emphasized the role of preferences in generating these pairings. Kalmijn (1994) analyzes marital matching patterns using 70 occupational categories in the 1970 and 1980 U.S. censuses, and finds that occupations of husbands and wives are similar in average level of schooling. He argues that this matching is driven by a desire for cultural similarity with one's spouse, which supports a common lifestyle in marriage. Furtado and Theodoropolous (2011) analyze the relationship between ethnic and educational similarities and suggest that individuals with higher levels of schooling are more likely to match across ethnicities because they are better able to adapt culturally compared to lower-educated individuals, and because assortative matching on education facilitates inter-ethnic marriages. Wong (2003) investigates the low rate of intermarriage between black men and white women by estimating a structural model that allows for a "mating taboo." She finds that the taboo, or preferences, explains the majority of the shortfall in this form of intermarriage.[1] These studies, however, do not analyze the importance of differences in interracial meeting opportunities by education and its potential contribution to these matching patterns.

More recently, online dating sites have been used to study the role of preferences. Hitsch et al. (2010) use preferences estimates generated from online dating data to predict marriages under the assumption of frictionless search. Although they find preferences to be an important determinant in contact behavior, they under predict sorting by education and race/ethnicity, which could be explained by search costs. A similar paper by Lee (forthcoming) uses online data from Korea. She finds that there is less marital sorting by hometown and industry in online matching compared to matches in the population as a whole, suggesting that the Internet reduces search costs. Belot and Francesconi (2013) provide some of the most direct evidence to date on the role of search costs using British speed-dating data. They analyze the effects of changes in choice set on dating proposals and find that meeting opportunities play a substantial role in dating choices.

[1] Bruze (2011) show that movie actors, whose job does not require a specific level of education, are more likely to marry spouses with their same level of education. He concludes that preferences play a significant role in explaining educational assortative matching.

Some prior studies highlight the role of search costs in the context of college as a marriage market. Using Danish data, Nielsen and Svarer (2009) show that about half of marital sorting on education is due to individuals marrying spouses who attended the same or nearby educational institutions, suggesting a role for search costs. They also find that the density of women in a man's educational group in his municipality positively predicts sorting on education. Kaufmann et al. (2013) find that the marriage market returns of attending an elite university in Chile are particularly high for women, consistent with a model in which the cost of marital search for high quality spouses is lower within an elite university than outside it. Using German data, Pestel (2016) finds that women studying in a field with a high share of male students have a higher probability of marriage.

This paper's main contribution is to propose and implement an empirical strategy that distinguishes between the preferences and the search costs explanations for same-occupation matches using the 2008-2015 American Community Survey (ACS). Our analysis focuses on a sample of couples ages 25-45, married four years or less, in which the wife is non-Hispanic white and in her first marriage. These restrictions on the wife's characteristics are intended to generate a sample of women who are searching in a more homogenous marriage market.

In order to test whether preferences explain same-occupation matching, we compare, for women working in a given occupation, the wages of same- and different-occupation husbands. We then investigate how this wage difference varies with the sex composition of the woman's occupation. Chiappori et al. (forthcoming) predict that individuals who prefer to match within a certain category (in our case, occupation) and face a shortage of prospective mates within that category, will on average "marry down" on other attributes to accommodate the match. We test empirically for evidence that women marry lower wage husbands when matching within occupation (relative to matching outside occupation) in occupations where men are in short supply. Our empirical results suggest the opposite, that women marry lower wage same-occupation husbands (relative to outside occupation) in occupations where men are plentiful.

We suggest a possible explanation for our empirical results that highlights the role of search costs. Specifically, in the presence of search costs, women in occupations where men are plentiful are more likely to match within occupation and will only incur the larger search cost of searching outside occupation when there is a higher expected return in husband's wage.

Additionally, because the search costs mechanism should be most relevant in occupations with sufficient workplace interaction to facilitate search, we allow our estimates to differ by occupation using an occupation-specific measure of workplace communication. Specifically, we take a measure from the O*Net data base that measures "Communicating with Supervisors, Peers, or Subordinates: Providing information to supervisors, co-workers, and subordinates by telephone, in written form, e-mail, or in person" in the occupation on a scale from 0 to 7. We find, as predicted, the results are most consistent with a search costs mechanism when there is a greater degree of workplace communication.

We also analyze matching on field of study for couples with college degrees. These results are also consistent with the importance of search costs. Among those searching over potential partners in a university setting, field of degree may be an even more relevant search market than the student body as a whole. Of course, couples who match on occupation may have met as students in the same or related field of study and couples who match on field of study may have met in the workplace in the same or related occupations. In this paper we do not attempt to disentangle the relative importance of school-based search and workplace-based search, as our interest is in determining whether search costs in general, as opposed to preferences, is the predominant explanation for observed matching on occupation or field of degree.

The paper proceeds as follows. In the next section we lay out the theoretical predictions underlying our empirical strategy and state our hypotheses. Section three describes our empirical methodology. Section four reports the results and we conclude in section five.

II. Same-Occupation Matching

A. Descriptive Statistics

Table 1 presents descriptive statistics by occupation on sex composition and same-occupation matching using 2008-2015 ACS data. Descriptive statistics are reported for 79 occupational categories based on the 2-digit SOC codes. The table is sorted on the fraction of males in occupation from the most male-dominated to the least male-dominated occupations. The first column reports the percent male using the sample of women and men ages 25-45 who report an occupation for most recent job in the past 5 years. Column 2 reports the fraction of married women in the occupation married to a same-occupation spouse. Column 3 reports the analogous statistic for men.

For column 4 of Table 1, we calculate the fraction of married women in the occupation who would be married to a same-occupation spouse under the assumption of random matching by occupation conditional on non-random matching by education. In column 5 we report the analogous statistic for men.[2]

From the table, it is clear that there is considerable same-occupation matching. 9% of married couples ages 25-45 who both report an occupation match on 2-digit occupation. It is also apparent from the table that same-occupation matching is particularly common for individuals in occupations with a high proportion of workers of the opposite sex. For example, 49% of married women in the military are married to military husbands, 27% of married female engineers are married to male engineers, and 39% of married male schoolteachers are married to

[2] Details on the procedure of calculating random matching by occupation, following the procedure from Fryer (2007), are in the Appendix.

female schoolteachers. In comparison, random matching predicts that only 2% of women in the military would match with military husbands, 4% of married female engineers would match with male engineers, and 18% of married male schoolteachers would be married to female schoolteachers.

In most cases, the opposite-sex workers in one's occupation only represent a fraction of one's broader marriage market prospects. Therefore, the frequency of same-occupation matches and their responsiveness to the sex-composition of one's occupation suggest that there is some marriage market feature that give advantage to same-occupation matches over different-occupation matches.[3]

Kalmijn (1998), Blossfeld (2009), and Hitsch et al. (2010) have previously pointed out that similarities between husband and wife in characteristics such as education and race can result from preferences or from search costs. It could be that individuals, all else equal, prefer same-occupation partners. Alternatively, if marital search is costly, this sorting could reflect the fact that individuals often spend a lot of time in the company of individuals with their same occupation, through contact in school, contact in the workplace, and through peer networks (Blossfeld and Timm, 2003).

If search costs are the dominate explanation for same-occupation matching, individuals disproportionately match with individuals who share their occupation because the potential partners they meet, whether through school, workplace or peer networks, are disproportionately in the same occupation or likely to end up in the same occupation (because, for example, of their field of study). In other words, it is not that individuals prefer same-occupation matches

[3] An additional explanation for within-occupation matching is that married individuals might recruit their partners into their own occupations after matching. For example, in Table 1, it might be that the very few women who report being fishers, hunters or trappers are in that category because their husbands brought them into the occupation, generating a very large within-occupation matched rate for women in that occupation (0.60). This explanation is less likely to be relevant for married individuals with college degrees, because entrance into an occupation often requires investment in specialized education and training.

conditional on whom they have met, it is just a matter of the potential partners an individual is most likely to meet.

In contrast, under the preferences mechanism, conditional on meeting opportunities, individuals actually prefer partners who share their occupation or have attributes (such as field of study) that make it likely they will ultimately share the same occupation.

To generate theoretical predictions for our empirical analysis, we first use the results of Chiappori et al. (forthcoming) who develop a bi-dimensional frictionless matching model that allows for sex imbalances. This provides an empirical prediction for the case in which there are preferences for same-occupation matches. We then consider an alternative model without preferences for same-occupation matches that incorporates search costs. This generates a different empirical prediction.

B. Preferences and Spouse Quality

It could be that individuals prefer same-occupation spouses. For example, it is likely that individuals within the same occupation are more homogenous in their preferences compared to the larger marriage market. If individuals experience greater marital surplus by matching with partners with similar preferences for consumption of leisure, investments in children, and so forth, then a preference for partners with similar tastes would generate a higher rate of matching within occupation. If individuals have preferences for same-occupation spouses, then this implies that not only does occupation affect an individual's attractiveness on the marriage market, but that people have heterogeneous preferences regarding the desirability of different occupations. For example, female doctors and female lawyers may both generally find doctors and lawyers attractive as husbands because these occupations are high-earning, but female doctors would disproportionately prefer to match with doctors and female lawyers would disproportionately prefer to match with male lawyers.

If there were equal numbers of men and women within each occupation, and same-occupation matches increased marital surplus, then a simple matching model would predict that all individuals would match with same-occupation spouses and then match assortatively on quality within occupation.

The more realistic case is that there is a sex imbalance in most occupations, some having a surplus of men and some having a surplus of women. A bi-dimensional frictionless matching model with sex imbalances is formally developed in Chiappori et al. (forthcoming). They apply their model to the case in which non-smokers prefer to match with non-smokers, and there is excess supply of female non-smokers (because more men smoke than women). They predict that among the husbands of equal quality non-smoking wives, non-smoking husbands will on average be lower quality than smoking husbands.[4] In other words, among equal quality non-smoking wives, those who match, as desired, with non-smoking husbands will marry on average a lower quality husband.[5]

The case in which workers prefer to match with same-occupation spouses fits nicely into the Chiappori et al. theoretical framework, with the additional beneficial empirical feature that rather than a single category (smoking) with a single sex composition, we are able to compare marital sorting across multiple occupations with very different sex-compositions. This provides an empirical test for a preferences mechanism for same-occupation matching. Specifically, in

[4] This raises the question of how, in this two-sided matching model, the non-smoking women are able to attract higher quality smoking husbands. It is *not* because the smoking men value non-smoking wives (Chiappori et al. assume that smokers, unlike non-smokers, are indifferent to smoking status). Rather, the smoking men face a shortage of smoking wives, and it is this gender imbalance that drives some smoking men to match with non-smoking wives.

[5] Banerjee et al. (2013) analyze an Indian marriage market in which individuals care about caste and other attributes. While matching by caste may seem very applicable to matching by occupation, there is a crucial difference; there is sex balance across castes, but sex imbalance across occupations. A key finding of Banerjee et al (2013) is that, under the assumption of sex balance, sorting on other attributes does not change much in the presence of preferences for same-caste matching. Chiappori et al. (forthcoming) have a similar prediction for the case in which men and women smoke at the same rate. The prediction we are using from Chiappori et al. is driven by the sex-imbalance across groups.

occupations in which men are scarce, women will have to on average marry lower quality men in order to accommodate this preference. Put differently, the average quality of same-occupation husbands should be lower than the average quality of different-occupation husbands for similar quality women working in the same occupation. Importantly, however, we expect this difference in quality between same-occupation and different-occupation husbands to be less negative in occupations in which men are plentiful.

More generally, this approach fits in with a broader literature in which individuals trade off a specific spousal characteristic with other desirable partner qualities. Chiappori et al. (2012), for example, estimate the marriage market trade-off between earnings and Body Mass Index. Angrist (2002) studies marriage among second generation immigrants, who often prefer endogamous (within ethnicity) marriages. Using U.S. Census data from 1910-1940, he documents that, on average, second generation women obtained higher quality husbands when the sex ratio within ethnicity was more favorable. Other studies have also documented that more favorable sex ratios allow individuals to marry higher quality partners (Abramitzky et al., 2011; Charles and Luoh, 2010; Lafortune, 2013).

C. Search Costs and Spouse Quality

In this section, we propose a simple search cost explanation that generates the opposite empirical prediction to that generated by preferences for same-occupation matches. Our focus is therefore on the same comparison discussed above: the comparison of the average quality of same-occupation husbands to the average quality of different-occupation husbands for similar quality women working in the same occupation.

We first note that if there is no difference in search costs between within-occupation and outside-occupation search and no preferences for same-occupation matches, we would expect there to be no difference in average spousal quality when comparing same- and different-occupation spouses of similar quality women in the same occupation. Under these simple assumptions, women in a given occupation should be unwilling to accept lower quality husbands within occupation relative to outside occupation.[6]

In the discussion that follows, we allow for marital search to be costly and assume that the cost of search in an occupation (as measured by sex composition) is uncorrelated with the average quality of workers in the occupation. Clearly, empirically there is a relationship between sex composition of an occupation and the wage distribution in the occupation. Our empirical analysis, however, will use occupation fixed-effects as well as interactions with occupation wage characteristics to control for this empirical relationship. Therefore, the relevant theoretical discussion is one that conditions on average quality in the occupation.

Consider a model in which individuals have two search pools with potentially different search costs: a within-occupation pool and an outside-occupation pool. For a given search pool with search costs c and a distribution of spousal quality F(q), an individual searching in the pool will have a reservation quality w as described by:

$$\int_{w}^{\overline{q}} (q - w) dF(q) = c .$$

Therefore, the reservation quality, w, is the expected value of searching in the pool. Under optimal sequential search, individuals search in the pool with the highest expected value, w, and then search until they find a match with $q > w$ (Weitzman, 1979).[7] It is clear that $\partial w / \partial c < 0$, so that all else equal, the returns to search will be highest in the pool with the lowest search cost.

[6] There is a substantial literature on models of marriage markets with search costs. Unlike the perfect assortative matching predicted in frictionless markets, in the presence of search costs markets will develop a class structure in which individuals match with one of a range of acceptable partners rather than their ideal partner (Burdette and Coles, 1997; Bloch and Ryder, 2000; Smith, 2006; Jacquet and Tan, 2007). These models, however, do not allow search costs to vary across different types of potential partners or across different marriage markets.

[7] It may seem more realistic to have a model in which individuals allocate some effort to within occupation search and some effort to outside occupation search. But in this simple search framework, one search pool will always dominate the other in the marginal return to additional search, so it would never be optimal for an individual to

We assume that individuals in an occupation with a favorable sex composition face lower within occupation search costs relative to outside occupation. In this case, the individual should only search outside their occupation if the expected return from outside occupation dominates the expected within occupation return, that is if F(q) is shifted to the right in the outside occupation pool.

This implies that for females in occupations with a large share of males, within-occupation search costs should be lower and the fraction of women who match within-occupation should be higher. The remaining women who choose to pay the higher search costs and match outside-occupation should be women who expect particularly high realizations of husband quality from search in the outside-occupation pool. Therefore, this simple model provides a prediction for the comparison of same-occupation husbands and different-occupation husbands for similar quality women working in the same occupation. For women in an occupation with a favorable sex composition, those who match outside occupation should on average match with higher quality husbands than those who match within occupation.   The women who match outside occupation are paying a higher search cost, and they should not have been willing to do so just to end up with a husband of the same quality they could have obtained within-occupation.[8]   Put another way, when the share of males in an occupation is high, women

allocate effort to both pools. A potential model extension would be to allow search costs to increase as an individual searches in a given pool, perhaps if the search pool has a limited number of options, so that at some point it becomes optimal for an individual to switch to the other search pool.

[8] A similar empirical prediction is generated by the two-sided search market with frictions in Moen (1997). In his model, submarkets vary by wage and search costs (workers per vacancy). Submarkets with higher wages attract more workers per vacancy and therefore have greater search costs. A comparison of identical workers who matched in different submarkets will find that the worker who matched in the market with greater search costs is receiving a higher wage.

may accept lower quality husbands within-occupation than they could obtain outside-occupation in order to avoid the greater search costs of outside-occupation search.[9]

D. Comparing Preferences and Search Costs Predictions

Both the preferences and the search costs mechanisms predict that there are occupations in which, for women of equal quality in a given occupation, same-occupation husbands have lower average quality compared to different-occupation husbands. The difference between the two mechanisms is for which occupations this quality difference will be most negative. With the preferences mechanism, the difference in quality between same-occupation and different-occupation husbands should be most negative for women in occupations where men are scarce, because women have to sacrifice more on quality in order to match with a same-occupation husband. With the search cost mechanism, the difference in quality between same-occupation and different-occupation husbands should be most negative for women in occupations where men are plentiful, because women in these occupations experience the largest difference in search costs between within-occupation and outside-occupation search.

In our empirical analysis, we test whether the difference in husband's quality between same-occupation husbands and different-occupation husbands is more negative or more positive when percent male in wife's occupation is high. Our empirical analysis uses husband's wage as the measure of quality. As we will discuss in more detail below, our empirical analysis controls for occupation fixed-effects and interactions with occupational wage characteristics. Therefore, our analysis is not biased by the fact that, for example, female-dominated occupations pay lower average wages, or the gender wage gap is larger in male-dominated occupations.

[9] This may at first seem counter-intuitive because we expect lower search costs to generate matches with higher quality husbands. But in the analysis, we are not comparing women across occupations facing different search costs. If we were, then we would predict that women in occupations with lower search costs should on average match with higher quality husbands. Instead, we are comparing women in the same occupation, facing the same within-occupation search costs, who match either with same-occupation husbands or different occupation husbands.

Our empirical analysis focuses on the difference in average wage between same-occupation husbands and different-occupation husbands, calculated for women in the same occupation. With preferences for same-occupation spouses, using the Chiappori et al. (forthcoming) results, the difference in husband's wage between same-occupation husbands and different-occupation husbands should be the most negative when men are scarce in the wife's occupation (percent male is low), and the difference should be less negative in occupations where men are more plentiful.

In the case with no preferences for same-occupation spouses, a simple sequential search model can generate the opposite empirical prediction: that the difference in husband's wage between same-occupation husbands and different-occupation husbands should be the most negative when men are plentiful in the wife's occupation (percent male is high). This is because the search cost differential between within-occupation search and outside-occupation search should be greatest when percent male is high.

This suggests that the parameter of interest in our empirical analysis will be an interaction effect. Specifically, we estimate how the difference in average wages between same- and different-occupation husbands, for women in the same occupation, varies with the percent male in the occupation.

It is important to point out that it is likely that both preferences and search costs play a role in generating the observed level of same-occupation matching. We wish, however, to understand whether or not there is empirical evidence that preferences play a large role in generating same-occupation matches. Predominantly negative estimates for the interaction effect would be inconsistent with the preferences explanation. Instead, such results would lead us to believe that search costs may be the more important explanation for same-occupation matching.

It is also important to point out that the timing of the match does not help distinguish between the preferences and search costs explanations. Same-occupation matches can occur due to preferences whether individuals are matching before or after the occupation is known (as long as individuals have preferences for partners with similar fields of study or interests that determine occupation). Same-occupation matches can occur due to search costs whether matching before or after occupation is known (as long as matches are influenced by the fact that the individual disproportionately meets individuals who are likely to share the same occupation due to disproportionate contact with potential partners with similar fields of study or interests).

III. Data and Methods

The empirical analysis makes use of two samples from the 2008-2015 ACS data: the occupation sample of all workers ages 25-45, which is used to calculate occupation-level characteristics at the 3-digit SOC level, and the analysis sample of recently-married couples ages 25-45.

A. Occupation Sample

We use the sample of workers ages 25-45 from the 2008-2015 data to calculate occupation-level characteristics at the 3-digit SOC level. There are a total of 333 3-digit SOC level occupations. Occupation-level characteristics used in the analysis include the percent male, average male wage, average female wage, male wage variance and female wage variance.

In order to calculate the occupation-level wage characteristics, the hourly wage is first calculated for each worker by dividing annual earnings by annual hours. Annual hours are calculated by multiplying weeks worked last year times usual hours per week. Since 2008, the ACS has reported weeks of work in intervals. We impute actual weeks of work using individuals from the 2004-2007 ACS of the same gender and 10-year age category who reported weeks of work in the same interval.[10]

B. Analysis Sample

Data from the 2008-2015 American Community Survey (ACS) are used because year of marriage is not available in the ACS prior to 2008. This allows the analysis to be conducted on the sample of couples who have been married 4 years or less. This sample restriction has two benefits. First, an individual's current reported occupation should be similar to his/her occupation at the time he/she matched with a spouse. Second, we reduce sample selection bias that could occur if same-occupation couples divorce at different rates than those who are not matched on occupation.[11]

The analysis sample includes married couples who a) have been married for 4 years or less, b) are ages 25-45, and c) the wife is native-born, non-Hispanic white and in her first marriage. This restricts the sample to women who faced more homogenous marriage markets.

We additionally restrict our sample to eliminate the smaller 3-digit SOC occupations. Because the analysis makes comparisons of same-occupation and different-occupation husbands for women who share the same occupation, small occupations will generate noisy estimates of within-occupation difference in husband quality. We therefore restrict our sample to occupations which include at least 100 wives in the analysis sample. Removing these occupations reduces the number of wife's occupations to 139 but, because the eliminated occupations were quite small, this only reduces the sample size by 3.1% from 122,028 to 118,223. To be clear, husbands in the

---

[10] Our results are very similar if we instead just use the midpoint of the reported hours interval when calculating the hourly wage. Specifically, if we use hours values of 7, 20, 33, 43.5, 48.5 and 51, respectively, for the reported intervals 1-13, 14-26, 27-39, 40-47, 48-49, and 50-52.

[11] Stevenson and Wolfers (2011), in calculations with SIPP data, find that 91% of women married in the late 1990s were married at their 5th anniversary and 77% were married at their 10th anniversary. Kreider and Ellis (2011) report similar marriage survival statistics. Our findings are similar if we restrict the sample to couples who have been married for 2 years or less. Van Kammen and Adams (2014) show that spouses with similar occupational characteristics are more likely to divorce.

analysis sample may work in any of the 333 3-digit detailed occupations reported in the ACS data. The sample is only restricted with regard to wife's occupation to ensure that there is sufficient data to make within-wife's occupation comparisons of same-occupation and different-occupation husbands.

Finally, to ensure that our occupation-level sex-composition and wage variables are well-measured, we further require that there were at least 500 male and 500 female observations in the occupation sample used to calculate the occupation-level characteristics. This only reduces the number of wife's occupations by 3 and the sample size by 1.5% for a final sample of 116,439 observations and 136 wife's occupations.[12] 6.36% of couples in the analysis sample match on detailed 3-digit occupation.

Table 2 reports descriptive statistics for the main analaysis sample, and for the sample of couples with different and same occupations. The descriptive statistics indicate that women married to same-occupation husbands tend to be more highly educated, earn higher wages and are married to higher-wage husbands. Women who match with same-occupation husbands may be more attached to the labor force and spend more hours at work, increasing the amount of search conducted within occupation. Our analysis, however, does not rest on the comparison of the same-occupation husbands to different-occupation husbands, but rather how this difference between same-occupation and different-occupation husbands varies with percent male in wife's occupation.

C. Spouse quality

[12] Because the eliminated occupations are small, results using the full sample in which the small occupations are retained are quite similar to those in which they are eliminated. Because there may be a concern that the military operates as a somewhat distinct marriage market, we also confirmed that results are robust to excluding couples in which either or both of the husband and wife work in the military.

Our analysis focuses on husband's quality, specifically husband's wage, as the outcome variable. The empirical literature has established that husband's wage is an important determinant of marital surplus for the wife. We eliminate observations in which husband's hourly wage is less than one dollar or greater than 500 dollars.

In some specifications, the outcome variable is instead the ratio of husband's wage to wife's wage. In other words, the dependent variable measures the extent to which the woman is marrying up or down in terms of wage. We acknowledge that this outcome variable is potentially problematic, both because of evidence that the labor market effort of wives is endogenous to partner characteristics, and also because men place less weight on women's potential earnings in mate selection (Fisman et al, 2006; Oreffice and Quinta-Domeque, 2010).[13] However, we still consider the wage ratio a worthwhile outcome for analysis, because it is important that the analysis compares husbands of similar-quality wives. It is therefore useful to have an outcome variable that measures the quality of the husband *relative* to the wife.

In order to maintain a consistent sample across outcome variables, we therefore restrict the analysis sample to only include couples with working wives, so that we can calculate the wife's wage. As with the husband's wage, we eliminate observations in which wife's wage is less than one dollar or greater than 500 dollars.[14]

Our conceptual discussion in Section II abstracted from the fact that male-dominated occupations tend to have higher average wages (England et al. 2007; Levanon et al. 2009; Blau et al., 2013). Therefore, men in these occupations will typically be higher earners and are likely considered more attractive spouses than those in female-dominated occupations. Our empirical

[13] Other papers have used both husband's education and wife's education as measures of quality. We do not use this approach here, because it is important to control for education on the right-hand side of the equation in order to avoid bias due to unobserved heterogeneity in wife's quality.

[14] The results for husband's wage are robust to including non-working wives in the sample. We cannot estimate results for the wage ratio if the sample includes non-working wives.

specification includes occupation fixed-effects for the husband, which control for the average earnings and quality of men in a given occupation, in order to discern whether these men are *differentially* attractive as spouses for the women who share their occupation.

Furthermore, our empirical analysis also controls for wife's occupation fixed-effects. These controls are necessary because average wages and average quality for both men and women vary by occupation, and in particular, also vary with percent male in occupation. For instance, these occupation fixed-effects control for the fact that women in male-dominated occupations are higher skilled than women in female-dominated occupations and through assortative matching tend to match with higher earning men.[15] The focus of our analysis is whether individuals value potential spouses within their own occupation differently than they do spouses of similar quality outside their occupation, after conditioning on the average characteristics of individuals in each occupation.

D. Baseline Regression Specification

Our primary regression specification is:

$$\begin{aligned} HusbandWage_{ijk} = {} & \beta_o + \beta_1 Same\_Occ_i + \beta_2 Same\_Occ_i * \%Male_j + X_i \beta_3 \\ & + \sum_{m=1}^{4} \theta_m * Same\_Occ_i * Occ\_WageVar_{mj} + \sum_{j=1}^{J} \lambda_j * Occ_j + \sum_{k=1}^{K} \phi_k * Occ_k \\ & + \sum_{s=1}^{S} \delta_s * State_i + \sum_{s=1}^{S} \gamma_s * State_i * Urban_i + \sum_{t=1}^{T} \eta_t * Year_i + \varepsilon_{ijk} \end{aligned} \tag{1}$$

For couple *i* with wife's occupation *j* and husband's occupation *k*, *HusbandWage* is the husband's calculated hourly wage. *Same_Occ* is an indicator that equals 1 if husband and wife share the same occupation. $\%Male_j$ is percent male in wife's occupation (divided by 100 so the

[15] It is likely that, even in the absence of preferences for same-occupation spouses, individuals prefer spouses from high-wage occupations. A certain amount of same-occupation matching will occur just from individuals in high-wage occupations assortatively matching with spouses in high-wage occupations. But this form of sorting will be picked up by the occupation fixed-effects. If both female doctors and female lawyers agree that male doctors are the most desirable spouses, there is no reason for female doctors to *disproportionately* sacrifice to marry a male doctor. The focus of our analysis is whether the male doctor is *disproportionately* attractive to female doctors compared to women from other occupations.

maximum value is 1). $Occ\_WageVar_1$-$Occ\_WageVar_4$ are four occupation-level wage characteristics for occupation *j*: the average male wage, the average female wage, the male wage variance, and the female wage variance. *X* is a vector of controls for husband's and wife's age and age-squared, husband's and wife's education (indicators for high school degree, college degree, and advanced degree), an indicator for whether husband and wife have the same educational attainment (using the categories already described), husband's race/ethnicity (indicators for non-Hispanic white, non-Hispanic black, Hispanic), and the wife's age of marriage and its square. The model also contains fixed-effects for wife's 3-digit occupation, husband's 3-digit occupation, state, state interacted with urban status, and year. Standard errors are corrected for clustering by wife's occupation.

By controlling for wife's occupation fixed-effects, we are comparing the difference in wages between same-occupation husbands and different-occupation husbands across wives in the same occupation. As discussed above, the husband's and wife's occupation fixed-effects control for the overall attractiveness of women and men in any given occupation to isolate the effects of a same-occupation match. For example, we want to control for the fact that male doctors and lawyers are generally considered attractive husbands, and conditional on that, estimate whether male doctors and lawyers are particularly attractive to women who share their occupation.

Occupation fixed-effects control for any main effects of occupation-level wage characteristics, but because our parameter of interest is the interaction of percent male in occupation with the *Same_Occ* indicator, it is important that we also control for interactions of *Same_Occ* with the occupation-level wage characteristics listed above. Therefore, the coefficient estimate for the interaction term of interest is not driven by differences in average wages, the gender wage gap or the wage distribution across occupations with different sex compositions.

If same-occupation matching is predominantly generated by preferences for same-occupation spouses, the prediction is that the coefficient on *Same_Occ*%Male* is positive. If the coefficient on *Same_Occ*%Male* is negative, this is not consistent with preferences driving the observed level of same-occupation matching, but is potentially consistent with a role for search costs in generating same-occupation matching.

The preferences and search costs mechanisms also generate some predictions for the main effects of *Same_Occ* and *%Male*, but these main effects are more susceptible to omitted variable bias than the interaction term. For example, the search costs mechanism predicts that the main effect of *%Male* should be positive, that women in occupations with a higher male percentage (lower search costs) should have higher quality husbands. But the main effect of percent male is not estimated, due to the inclusion of wife's occupation fixed-effects. Furthermore, a comparison of husband's wages across wives in different occupations would be rather suspect. The preferences mechanism predicts that the main effect of *Same_Occ* is negative, that women take lower earning husbands in order to match within occupation. But it could be that women who match within occupation are different in unobserved ways from those who do not. For example, perhaps women who work more hours are more likely to match within occupation.

The coefficient on the interaction term provides a much more compelling test, as it is much less likely that omitted variable bias affects the differences-in-differences estimate. For the interaction term to be biased, there would have to be an omitted variable that not only affects the difference in husband's wages between women within the same occupation who match with same-occupation husbands versus different-occupation husbands, but also causes that difference to be correlated with sex composition of the occupation.

A key concern in equation (1) is that in order to have the desired interpretation, the specification must include adequate controls for wife's quality. It is therefore desirable to control for woman's quality in more detail than the current controls for education, age, location and detailed occupation fixed-effects. To that end, we consider an alternative specification for equation (1) that uses the relative wages of husband and wife as the outcome variable. In other words, the dependent variable measures the extent to which the woman is marrying up or down in terms of wage.

(2)

$$
\begin{aligned}
(HusbandWage/WifeWage)_{ijk} = \beta_o + \beta_1 Same\_Occ_i + \beta_2 Same\_Occ_i * \%Male_j + X_i \beta_3 \\
+\sum_{m=1}^{4} \theta_m * Same\_Occ_i * Occ\_WageVar_{mj} + \sum_{j=1}^{J} \lambda_j * Occ_j + \sum_{k=1}^{K} \phi_k * Occ_k \\
+\sum_{s=1}^{S} \delta_s * State_i + \sum_{s=1}^{S} \gamma_s * State_i * Urban_i + \sum_{t=1}^{T} \eta_t * Year_i + \varepsilon_{ijk}
\end{aligned}
$$

An additional benefit of the specification in equation (2) is that it is symmetric between husbands and wives.[16] This specification could, therefore, just as easily be interpreted as estimating changes in the wife's relative wage for same-occupation matches relative to different-occupation matches as women become less plentiful in husband's occupation. There remain, however, the caveats discussed earlier that a wife's wage could be endogenous to her marriage market match and that wife's wage is not necessarily as strong a proxy for partner quality as husband's wage.

E. Interaction Effects with Workplace Communication

Search costs should be most relevant in explaining same-occupation matching for occupations in which there is sufficient workplace interaction with co-workers to facilitate marital search. To test whether this is true, we obtained a measure of communication with co-

[16] Because the interaction term is zero unless husband and wife share the same occupation, it is equivalent to the interaction of Same_Occ with the percent male in husband's occupation.

workers from the O*Net database (version 18), containing a rich set of occupational characteristics describing the different combinations of skills, abilities, and work contexts required in each occupation (O*Net Research Center). Specifically, the workplace communication index is obtained from the "Generalized Work Activities" descriptors and it measures the extent of "Communicating with Supervisors, Peers, or Subordinates: Providing information to supervisors, co-workers, and subordinates by telephone, in written form, e-mail, or in person" on a scale from 0 to 7. Interactions with this occupation-level measure of workplace communication are added to equation (1):

(3)

$$\begin{aligned} HusbandWage_{ijk} = {} & \beta_o + \beta_1 Same\_Occ_i + \beta_2 Same\_Occ_i * \%Male_j \\ & + \beta_3 Same\_Occ_i * WorkplaceComm_j + \beta_4 Same\_Occ_i * \%Male_j * WorkplaceComm_j \\ & + X_i \beta_5 + \sum_{m=1}^{4} \theta_m * Same\_Occ_i * Occ\_WageVar_{mj} + \sum_{j=1}^{J} \lambda_j * Occ_j + \sum_{k=1}^{K} \phi_k * Occ_k \\ & + \sum_{s=1}^{S} \delta_s * State_i + \sum_{s=1}^{S} \gamma_s * State_i * Urban_i + \sum_{t=1}^{T} \eta_t * Year_i + \varepsilon_{ijk} \end{aligned}$$

In equation (3), the β_2 coefficient estimates the *Same_Occ*%Male* effect for occupations with very limited interaction with coworkers. In these occupations, we would expect same-occupation matches to be driven by preferences as opposed to search costs. A positive estimate for β_2 would be consistent with this prediction.

The estimate of β_4 indicates how the coefficient on *Same_Occ*%Male* changes when estimated for workers in occupations with higher levels of workplace interaction. If the search cost mechanism becomes more relevant in occupations with higher levels of workplace interaction, then we would expect to obtain a negative estimate for β_4.[17]

[17] It could be the case the individuals who select into low communication workplaces are particularly adverse to social interaction and therefore consider search outside the workplace disproportionately difficult. If that were so, then individuals in low-communication workplaces should be even more willing to accept a low-quality match

F. Matching on Field of Degree

Individuals who share the same occupation may meet through shared classes in college and graduate school, through the workplace or work activities, or through common peer networks. It is not possible to separately identify these pathways, all of which may reduce the cost of search among same-occupation partners. It is, however, possible to analyze matching on field of bachelor's degree, which is available in the ACS starting in 2009. A key benefit of analyzing matching on field of degree instead of occupation is that while current occupation can differ from occupation at time of matching and is potentially endogenous to partner characteristics, field of degree is time constant and much less likely to reflect an endogenous response to partner characteristics. For this reason, it is arguable that for couples in which both spouses have a bachelor degree, analyzing matching on field of degree is in fact preferable to analyzing matching on current occupation. To be clear, however, couples who share the same field of degree may meet through school, through the workplace or through common peer networks. Our interest is in testing whether matching on field of degree or occupation primarily occurs due to shared preferences or due to reduced search costs, not in separating out the relative importance of meeting through school or through the workplace.

The disadvantage of using field of degree is that the analysis is limited to couples in which both spouses have a bachelor's degree and that we do not have information by field of degree analogous to the workplace communication index used in equation 3. The ACS provides detailed field of degree codes for 181 fields. Imposing the same sample limitations used in our analysis of occupation, we end up with a sample size of 46,007 and 83 wife's degree fields. 8.47% of couples in the analysis sample match on detailed field of degree.

---

within occupation rather than engage in wider search. This would work against our finding a negative estimate for the coefficient on *Same_Occ*%Male*Comm*.

The specification is the same as in equation (1), but replacing occupation variables with field of degree variables:[18]

$$\begin{aligned}
HusbandWage_{ijk} &= \beta_o + \beta_1 Same_\text{Field}_i + \beta_2 Same_\text{Field}_i * \%MaleField_j + X_i\beta_3 \\
&+\sum_{m=1}^{4}\theta_m * Same_\text{Field}_i * \text{Field_}WageVar_{mj} + \sum_{j=1}^{J}\lambda_j * \text{Field}_j + \sum_{k=1}^{K}\phi_k * \text{Field}_k \\
&+\sum_{s=1}^{S}\delta_s * State_i + \sum_{s=1}^{S}\gamma_s * State_i * Urban_i + \sum_{t=1}^{T}\eta_t * Year_i + \varepsilon_{ijk}
\end{aligned} \tag{4}$$

IV. Results

A. Baseline Results

Panel A of Table 3 reports the estimates from equations (1) and (2) for the full sample. The first two columns report estimates from equation (1) using linear and logged husband's wage as the outcome variables. In both cases, the *Same_Occ*%Male* interaction is negative though insignificant.[19] While imprecisely estimated, these negative coefficient estimates for the *Same_Occ*%Male* interaction are inconsistent with a model in which preference for shared occupation is the main mechanism generating same-occupation matches.

These estimates would, however, be subject to negative bias if women who match with same-occupation husbands within male-dominated fields are relatively more negatively selected than women who match with same-occupation husbands in female-dominated fields. In this case, the negative coefficient estimate indicating the relatively lower quality of same-occupation husbands in male-dominated fields would simply reflect the fact that they are married to particularly negatively-selected wives. In results not reported in the table, we checked whether

[18] As was the case with the occupation-level characteristics in equations (1)-(3), field of degree characteristics are calculated on the larger sample of men and women ages 25-45 who report a field of degree in the 2008-2015 ACS, unconditional on marital status.

[19] We do not report the coefficient estimate for the main effect of the same-occupation variable, because this coefficient is only interpretable in combination with the coefficients on the interaction of the same-occupation variable with the four occupation-level wage characteristics.

we obtain a negative coefficient estimate on the *Same_Occ*%Male* interaction when the outcome variable is wife's wage (linear or logged) instead of husband's wage. In fact, both coefficient estimates are positive, though insignificant, suggesting that if anything, same-occupation wives are somewhat more *positively* selected within male-dominated occupation than female-dominated occupations. [20] This suggests that if anything, omitted measures of wife's quality bias us *against* obtaining negative coefficient estimates in Table 3.

Columns 3 and 4 of Table 3 explicitly condition on wife's wage, as a measure of wife's quality, by using the wage ratio and logged wage ratio as the outcome variable. In both cases, the coefficient estimate is negative, and, for logged wage ratio, is statistically significant.

The estimates in Table 3 could still be subject to negative bias if women who marry same-occupation husbands are negatively-selected on some other characteristic, besides wages, that we do not observe. An example would be if women who marry same-occupation husbands in male-dominated fields are relatively more negatively selected on physical appearance than women who marry same-occupation husbands in female-dominated fields. Because less attractive women on average have to accept lower earning husbands, this pattern of negative selection would also generate negative coefficient estimates for the interaction term. A key limitation of this study, and indeed of most marriage market studies, is that we do not observe all characteristics that men and women value when choosing spouses.

Panel B of Table 3 explores the sensitivity of the estimates in Panel A to the set of occupations used in the analysis. The first row restricts the sample to wives who work in male-dominated occupations where at least 50% of workers are male.[21] Because only a minority of

[20] Specifically, the coefficient (standard error) on *Same_Occ*%Male* is 0.185 (1.50) using wife's wage and 0.038 (0.043) using logged wife's wage.

[21] Percent male in wife's occupations included in the sample ranges from a maximum of 93.5% to a minimum of 2.0%.

women in the sample work in male-dominated occupations, this restricts the sample to only 25,629 observations and 44 wife's occupations. The estimates using this restricted sample are all negative and larger in magnitude than the baseline results in Panel A. However, given the reduction in sample and number of occupations, the standard errors are larger, so most of the estimates remain statistically insignificant. In the second row, the sample is expanded to include wife's occupations with percent male ranging from 0.4 to 1, which increases the sample size to 40,623 and the number of wife's occupations to 64. This brings down the standard errors considerably and increases the statistical significance of the negative estimates.

The next rows of Table 3 report results using wife's occupations with percent male 0.2-0.8 and then 0.1-0.7. The estimates remain negative, and several are statistically significant. However, when in the remaining rows of Panel B, the sample range is restricted to primarily women in female-dominated occupations, the estimates become small and insignificant and even positive. The Table 3 estimates do appear to be sensitive to whether the occupations included in the sample are primarily male-dominated, female-dominated or from the middle of the distribution.

In Panel C of Table 3, the sample is split by wife's education into women with college degrees and women without college degrees. The estimates for both samples are mostly negative, but imprecisely estimated, with the estimates for the non-college sample more negative than the college sample.

Finally, in Panel D of Table 3, we make use of the fact that we know whether the husband and wife share the same industry in addition to the same occupation. We split the indicator for same occupation into two separate indicators, one for same occupation and different industry and a second for same occupation and same industry.

Husbands and wives in both the same occupation and same industry are even more likely to have met through workplace contacts compared to those who are in the same occupation but not in the same industry. Therefore, we would expect that the interaction term on the same occupation and same industry interaction to be more negative than the one on the same occupation and different industry interaction. This is exactly what we find in Panel D of Table 3. In all cases, the interaction of percent male with the indicator for same occupation and same industry is more negative than the interaction of percent male with same occupation and different industry. The same occupation and same industry interaction is statistically significant for three of the four outcome variables.

B. Results for Interactions with Workplace Communication

Table 4 reports the results when interactions with occupation-level measures of workplace communication are added to the specification as described in equation (3). The workplace communication index is not available for 27 of the occupations in the sample, reducing the sample size to 81,909 observations and 109 occupations for the results reported in Panel A.

Column 1 reports the results when husband's wage is the dependent variable. As predicted, the coefficient on *Same_Occ*%Male* is positive, indicating that when workplace communication is very low, the coefficient on the interaction term is more consistent with a preferences explanation for same-occupation matching. Also as predicted, the coefficient on the triple interaction, *Same_Occ*%Male*WorkplaceComm*, is negative and significant, indicating that as the level of workplace communication increases, there is greater support for the search costs mechanism for same-occupation matching. The total effect of *Same_Occ*%Male* becomes negative once the *WorkplaceComm* index is greater than 4.1 (about the 33rd percentile of our analysis sample).

In the remaining columns, the interactions with workplace communication are also all negative and with the exception of the logged wage ratio, are also statistically significant. The calculated "crossing points" where the total effect of *Same_Occ*%Male* becomes negative range from a workplace communication level of 2.4 to 4.3. These results indicate that our main results in Table 3 are likely downward biased because we were estimating the interaction effect across all occupations, some of which do not have sufficient workplace interaction to facilitate within-occupation search.

Similar to Table 3, Panel B of Table 4 repeats the estimation for different ranges of percent male in wife's occupation. The estimates reported in Panel B are mostly negative, but the standard errors are considerably larger and the estimates noisier when the sample is restricted to male-dominated occupations, which results in fewer observations and occupations in the sample. The statistically significant negative estimates all occur in samples with more observations and more occupations, where more female-dominated occupations are included.

Notice that the statistically significant negative coefficients obtained for women working in female-dominated occupations in Panel B of Table 4 are in direct contrast to those in Panel B of Table 3, in which many of the estimates obtained using female-dominated occupations were positive. Likewise, in Panel C, the strongest negative estimates are found for the sample of college women, in direct contrast to the prior results in Panel C of Table 3. Incorporating into the analysis the fact that occupations differ in the degree of workplace communication strengthens the evidence for the search cost mechanism.

C. Results for Matching on Field of Degree

Table 5 reports results for matching on field of degree using equation (4). The sample is restricted to couples in which both the husband and wife have a college degree. The coefficients on the *Same_Field*%Male* interactions are negative for all husband's wage and wage ratio outcome variables and are statistically significant for all but the linear wage ratio outcome.

Comparing these results to those for college educated women in Panel C of Table 3, the magnitudes on the interaction terms are noticeably larger using field of degree compared to occupation. This difference in magnitude could indicate that field of degree better represents the set of potential partners among whom college women search at lowest cost than current occupation. It could also be that the weaker results for college educated women in Table 3 resulted from endogenous sorting into current occupation in response to partner's characteristics.

Panel B of Table 5 reports field of degree results using restricted ranges of percent male in wife's field of degree. The estimates are largely negative throughout the distribution of percent male, but the results are weaker in the tails of the distribution.

D. Summary of evidence on matching mechanism

Our empirical results are overwhelmingly inconsistent with a model in which same-occupation matches are largely generated by individual preferences for spouses who share own occupation. While it is true that a few estimates in Tables 3-5 are occasionally positive, all but one of the statistically significant coefficient estimates are negative. Thus, we conclude that the results are more consistent with a larger role for search costs in generating same-occupation matches.

Furthermore, the negative coefficient estimates are particularly large in magnitude and statistically significant for the specifications that are arguably the most convincing. This is especially apparent when we distinguish between same occupation-same industry matches and same occupation-different industry matches (Panel D of Table 3), when we add interactions with the workplace communication measure (Panel A of Table 4) and when we use field of degree, which is immutable, instead of current occupation (Panel A of Table 5). While Panel C of Table

3 reports particularly weak results for the sub-sample of college-educated wives, the results using interactions with workplace communication (Panel C of Table 4) and the results for field of degree (Panel A of Table 5) indicate that the results for college-educated wives are consistent with the search cost mechanism.

To give an idea of magnitudes, the coefficient estimate in column 1 of Panel D of Table 3 indicates that the difference in average hourly wages between same-occupation same-industry husbands and different-occupations husbands for wives in a 75% male occupation is predicted to be 1.89(0.5)=0.945 dollars more negative than the same wage comparison for wives in a 25% male occupation. The coefficient estimate in column 1 of Panel A of Table 5 indicates that the difference in average hourly wages between same-degree field husbands and different-degree field husbands for wives who graduated in a 75% male degree field is predicted to be 5.55 (0.5)=2.775 dollars more negative than the same wage comparison for wives who graduated in a 25% male degree field.

V. Conclusions

There is a growing literature that indicates the potential importance of schools and workplaces as local marriage markets. Previous research has found that workplace sex composition affects divorce rates (McKinnish, 2007; Svarer 2007). Kaufman et al. (2013) use regression discontinuity analysis to document the large marriage market return for women attending an elite university. Mansour and McKinnish (2014) find that individuals with large marital age gaps tend to be lower quality in terms of cognitive ability, educational attainment, earnings and appearance. Their explanation is that high skilled individuals interact more heavily with similarly-aged peers in school and the workplace while low-skilled individuals spend more time in age-heterogeneous settings.

The implication of our analysis that individuals often match within occupation because it is simply easier to meet potential partners who share their occupation (whether through schooling or workplace), suggests that marriage markets are much more local than is typically modeled in the literature. As a result, early education and career decisions can change the group of people with whom one interacts most easily and affects spousal matching. In marriage models without search costs, characteristics such as education and occupational wage have traditionally affected matching through the marital surplus. Our findings suggest they also affect matching by changing the set of prospective mates with whom one interacts at lowest cost.

Compliance with Ethical Standards:
The authors declare that they have no conflict of interest.

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(3):124-56.

Angrist, Josh. 2002. "How do sex ratios affect marriage and labor markets? Evidence from America's second generation." *Quarterly Journal of Economics* 117(3): 997-1038.

Banerjee, Abhijit, Esther Duflo, Maitreesh Ghatak and Jeanne Lafortune. 2013. "Marry for What? Caste and Mate Selection in Modern India." *American Economic Journal:Microeconomics* 5(2): 33-72.

Belot, Michele and Marco Francesconi. 2013. "Dating Preferences and Meeting Opportunities in Mate Choice Decisions." *Journal of Human Resources* 48(2): 474-508.

Blau, Francine, Peter Brummund and Albert Yung-Hsu Liu. 2013. "Trends in occupational segregation by gender 1970-2009: Adjusting for the impact of changes in the occupational coding system." *Demography* 50(2): 471-492.

Bloch, Francis and Harl Ryder. 2000. "Two-Sided Search, Marriage and Matchmakers." *International Economic Review*. 41(1): 93-115.

Blossfeld, Hans-Peter. 2009. "Educational Assortative Marriage in Comparative Perspective." *Annual Review of Sociology.* 35: 513-530.

Blossfeld, Hans-Peter, and Andreas Timm, ed. 2003. Who Marries Whom? Educational Systems as Marriage Markets in Modern Scoeities. Dordrecht: Kluwer Acad.

Bruze, Gustaf. "Marriage Choices of Movie Stars: Does Spouse's Education Matter?" *Journal of Human Capital* 5(1): 1-28.

Burdett, Ken and Melvyn Coles. 1997. "Marriage and Class." *Quarterly Journal of Economics* 112(1): 141-68.

Charles, Kerwin and Ming Luoh. 2010. "Male Incarceration, the Marriage Market, and Female Outcomes." *Review of Economics and Statistics* 92(3): 614-27.

Chiappori, Pierre-Andre, Bernard Fortin, Guy Lacroix. 2002. "Marriage Markets, Divorce, Legislation and Household Labor Supply." *Journal of Political Economy* 110(1): 37-72.

Chiappori, Pierre-Andre, Sonia Oreffice and Climent Quintana-Domeque. Forthcoming. "Bidimensional Matching with Heterogenous Preferences: Education and Smoking in the Marriage Market." *Journal of the European Economic Association*.

Chiappori, Pierre-Andre, Sonia Oreffice and Climent Quintana-Domeque. 2012. "Fatter Attraction: Anthropometric and Socioeconomic Characteristics in the Marriage Market."

Journal of Political Economy 120(4): 659-695.

Choo, Eugene and Aloysius Siow. 2006. "Who Marries Whom and Why." *Journal of Political Economy* 114(1): 175-201.

England, Paula, Paul Allison and Yuxiao Wu. 2007. "Does bad pay cause occupations to feminize, does feminization reduce pay, and how can we tell from longitudinal data?" *Social Science Research* 36(3): 1237-1256.

Fisman, Raymond, Sheena Iyengar, Emir Kamenica, and Itamar Simonson. 2006. "Gender Differences in Mate Selection: Evidence from a Speed Dating Experiment." *Quarterly Journal of Economics* 121(2): 673-97.

Fryer, Roland G. Jr. 2007. "Guess Who's Been Coming to Dinner? Trends in Interracial Marriage over the 20th Century." Journal of Economic Perspectives 21(2): 71-90.

Furtado, Delia and Nikolaos Theodoropolous. 2011. "Interethnic Marriage: A Choice between Ethnic and Educational Similarities." *Journal of Population Economics* 24: 1257-1279.

Hitsch, Guner, Ali Hortascsu and Dan Ariely. 2010. "Matching and Sorting in Online Dating." *American Economic Review* 100(1): 130-63.

Hout, Michael. 1982 "The Association Between Husbands' and Wives' Occupations in Two-Earner Families." *American Journal of Sociology* 87 (September): 397-409.

Jacquet, Nicholas and Serene Tan. 2007. "On the Segmentation of Markets." *Journal of Political Economy* 115(4) 639:64.

Kalmijn, Matthijs. 1994. "Assortative Mating by cultural and economic occupational status." *American Journal of Sociology* 100: 422-52.

Kalmijn, Matthijs. 1998. "Intermarriage and Homogamy: Causes, Patterns, Trends." *American Review of Sociology* 24: 395-421.

Kaufman, Katja, Matthias Messner and Alex Solis. 2013. "Returns to Elite Higher Education in the Marriage Market: Evidence from Chile." Working Paper. Available at: http://kaufmann.vwl.uni-mannheim.de/fileadmin/user_upload/kaufmann/Paper_Chile_MarriageMarket-SSRN.pdf

Kreider, Rose M. and Renee Ellis. 2011. "Number, Timing, and Duration of Marriages and Divorces : 2009." *Current Population Reports*, P70-125, U.S. Census Bureau, Washington, DC.

Lafortune, Jeanne. 2013. "Making Yourself Attractive: Pre-Marital Investments and Returns to Education in the Marriage Market." *American Economic Journal: Applied Economics* 5(2): 151-78.

Lee, Soohyung. Forthcoming. "Effect of Online Dating on Marital Sorting." *Journal of Applied Econometrics*.

Levanon, Asaf, Paula England and Paul Allison. 2009. "Occupational feminization and pay: Assessing causal dynamics using 1950-2000 Census data." *Social Forces* 88(2): 865-981.

Mansour, Hani and Terra McKinnish. 2014. "Who Marries Differently-Aged Spouses? Ability, Education, Occupation, Earnings and Appearance." *Review of Economics and Statistics* 96(3): 577-80.

McKinnish, Terra. 2007. "Sexually-Integrated Workplaces and Divorce: Another Form of On-the-Job Search." *Journal of Human Resources* 42(2): 331-352.

Moen, Espen. 1997. "Competitive Search Equilibrium." *Journal of Political Economy* 105(2): 385-411.

Nielsen, Helena and Michael Svarer. 2009. "Educational Homogamy: How Much is Opportunity?" *Journal of Human Resources* 44(4): 1066-86.

Oreffice, Sonia and Climent Quintana-Domeque. 2010. "Anthropometry and socioeconomics in ' the couple: evidence in the United States." *Economics and Human Biology* 8(3): 373-384.

Pestel, Nico. 2016. "Searching on the Campus? Marriage Market Effects of the Student Gender Composition by Field of Study." Working Paper. Available at: https://ideas.repec.org/p/zbw/vfsc16/145510.html

Smith, Lones. 2006. "The Marriage Model with Search Frictions." *Journal of Political Economy* 114(6): 1124-1144.

Smits, Jeroen, Wout Ultee, and Jan Lammers. 1999. "Occupational Homogamy in Eight Countries of the European Union." *Acta Sociologia* 42(1): 55-68.

Stevenson, Betsey and Justin Wolfers. 2011. "Trends in Marital Stability." *Research Handbook in the Law and Economics of the Family*, Edward Elgar Press.

Svarer, Michael. 2007. "Working Late: Do Workplace Sex Ratios Affect Partnership Formation and Dissolution?" *Journal of Human Resources* 42(3): 583-595.

Van Kammen, Ben and Scott J. Adams. 2014. "Dissimilar Occupations and Marital Stability." IZA Journal of Labor Economics 3(9).

Weitzman, Martin. 1979. "Optimal Search for the Best Alternative." *Econometrica* 47(3): 641-54.

Wong, Linda. 2003. "Why do only 5.5% of black men marry white women?" *International Economic Review* 44(3): 803-26.

Table 1: Fraction Female and Same-Occupation Matching by Occupation Category

Occupation	% Male[(a)]	% Married Females with same occupation husbands[(b)]	% Married Males with same occupation wives[(b)]	% Married Females w/same occupation husbands random matching	% Married Males w/same occupation wives random matching
Vehicle and Mobile Equipment Mechanics and Repairers	0.98	0.20	0.00	0.04	0.00
Extractive Occupations	0.98	0.21	0.00	0.00	0.00
Material Moving Equipment Operators	0.97	0.12	0.00	0.02	0.00
Construction Trades, Except Supervisors	0.97	0.33	0.01	0.07	0.00
Supervisors, Construction Occupations	0.97	0.12	0.00	0.01	0.00
Helpers, Construction and Extractive Occupations	0.96	0.16	0.01	0.03	0.00
Firefighting and Fire Prevention Occupations	0.95	0.36	0.01	0.01	0.00
Plant and System Operators	0.95	0.06	0.00	0.01	0.00
Precision Metal Working Occupations	0.95	0.11	0.00	0.00	0.00
Rail Transportation Occupations	0.95	0.17	0.00	0.00	0.00
Water Transportation Occupations	0.94	0.11	0.00	0.02	0.00
Electrical and Electronic Equipment Repairers	0.94	0.10	0.01	0.01	0.00
Miscellaneous Mechanics and Repairers	0.94	0.09	0.00	0.00	0.00
Fishers, Hunters, and Trappers	0.93	0.60	0.04	0.00	0.00
Supervisors of mechanics and repairers	0.91	0.03	0.00	0.00	0.00
Forestry and Logging Occupations	0.91	0.09	0.01	0.00	0.00
Precision Woodworking Occupations	0.90	0.09	0.01	0.00	0.00
Motor Vehicle Operators	0.87	0.21	0.02	0.06	0.01
Military	0.86	0.49	0.06	0.02	0.00
Farm Operators and Managers	0.84	0.52	0.09	0.01	0.00
Metal and Plastic Processing Machine Operators	0.84	0.04	0.01	0.00	0.00
Metal Working and Plastic Working Machine Operators	0.84	0.10	0.02	0.00	0.00
Engineers	0.83	0.27	0.05	0.04	0.01
Related Agricultural Occupations	0.83	0.12	0.03	0.02	0.00

Production supervisors or foremen	0.81	0.06	0.01	0.01	0.00
Woodworking Machine Operators	0.80	0.10	0.02	0.01	0.00
Police and Detectives	0.79	0.33	0.05	0.03	0.00
Freight, Stock, and Material Handlers	0.75	0.11	0.05	0.02	0.01
Fabricators, Assemblers, and Hand Working Occupations	0.74	0.14	0.04	0.01	0.00
Printing Machine Operators	0.74	0.06	0.02	0.00	0.00
Engineering and Related Technologists and Technicians	0.74	0.05	0.02	0.02	0.01
Farm Occupations, Except Managerial	0.72	0.41	0.21	0.01	0.00
Supervisors of guards	0.71	0.06	0.01	0.03	0.01
Mathematical and Computer Scientists	0.71	0.13	0.05	0.00	0.00
Guards	0.71	0.07	0.02	0.01	0.00
Machine Operators, Assorted Materials	0.70	0.12	0.04	0.02	0.01
Architects	0.67	0.15	0.07	0.00	0.00
Technicians, Except Health, Engineering, and Science	0.66	0.19	0.10	0.03	0.02
Cleaning and Building Service Occupations, Except Households	0.65	0.12	0.06	0.00	0.00
Science Technicians	0.65	0.03	0.01	0.02	0.01
Mail and Message Distributing Occupations	0.62	0.07	0.04	0.01	0.00
Production Inspectors, Testers, Samplers, and Weighers	0.60	0.03	0.02	0.01	0.00
Material Recording, Scheduling, and Distributing Clerks	0.59	0.05	0.04	0.02	0.02
Supervisors and proprietors of sales jobs	0.56	0.11	0.07	0.14	0.10
Precision Food Production Occupations	0.56	0.07	0.07	0.04	0.02
Executive, Administrative, and Managerial Occupations	0.56	0.22	0.15	0.00	0.00
Natural Scientists	0.55	0.16	0.12	0.01	0.01
Lawyers and Judges	0.54	0.24	0.19	0.02	0.01
Computer and peripheral equipment operators	0.53	0.02	0.02	0.02	0.02
Health Diagnosing Occupations	0.53	0.31	0.27	0.00	0.00
Sales Representatives, Finance and Business Services	0.50	0.08	0.07	0.01	0.01
Writers, Artists, Entertainers, and Athletes	0.49	0.10	0.12	0.02	0.02
Precision Textile, Apparel, and Furnishings Machine Workers	0.47	0.06	0.09	0.00	0.00
Teachers, Postsecondary	0.46	0.18	0.22	0.02	0.02
Sales Representatives, Commodities	0.44	0.09	0.10	0.05	0.05

Food Preparation and Service Occupations	0.44	0.11	0.21	0.02	0.04
Duplicating, Mail, and Other Office Machine Operators	0.42	0.03	0.04	0.00	0.00
Management Related Occupations:	0.41	0.09	0.13	0.05	0.07
Textile, Apparel, and Furnishings Machine Operators	0.37	0.07	0.15	0.00	0.00
Office supervisors	0.36	0.02	0.03	0.01	0.01
Social Scientists and Urban Planners	0.36	0.04	0.07	0.01	0.01
Social, Recreation, and Religious Workers	0.34	0.06	0.10	0.01	0.02
Adjusters and Investigators	0.29	0.04	0.10	0.01	0.03
Sales demonstrators / promoters / models	0.27	0.00	0.01	0.00	0.00
Precision Workers, Assorted Materials	0.25	0.02	0.05	0.00	0.01
Communications Equipment Operators	0.24	0.01	0.03	0.01	0.03
Records Processing Occupations, Except Financial	0.24	0.01	0.03	0.00	0.01
Health Technologists and Technicians	0.24	0.04	0.11	0.00	0.00
Librarians, Archivists, and Curators	0.22	0.02	0.09	0.00	0.00
Teachers, Except Postsecondary	0.21	0.10	0.39	0.04	0.18
Therapists	0.20	0.05	0.21	0.01	0.02
Personal Service Occupations	0.19	0.03	0.20	0.01	0.03
Miscellaneous Administrative Support Occupations	0.19	0.01	0.07	0.01	0.05
Information Clerks	0.15	0.01	0.06	0.00	0.02
Health Assessment and Treating Occupations	0.12	0.05	0.35	0.01	0.06
Health Service Occupations	0.12	0.02	0.18	0.01	0.05
Financial Records Processing Occupations	0.11	0.00	0.04	0.00	0.02
Private Household Occupations	0.09	0.02	0.29	0.00	0.02
Secretaries, Stenographers, and Typists	0.05	0.00	0.10	0.00	0.05

(a) Sample of men and women aged 25-45 who reported an occupation in the 2008-2015 ACS.

(b) Sample of married women (or men) aged 25-45 who reported an occupation in the 2008-2015 ACS.

Table 2: Descriptive Statistics for Sample of Married Couples

	Full sample	Spouses with different occupations	Spouses with same occupation
Wife's characteristics			
Age	29.81	29.79	30.14
	(3.98)	(3.98)	(3.89)
High school degree	33%	34%	19%
College degree	42%	42%	39%
Advanced degree	24%	23%	41%
Age of marriage	27.48	27.45	27.82
	(4.06)	(4.06)	(3.93)
Wage	21.95	21.59	27.27
	(17.53)	(17.07)	(22.62)
Husband's characteristics			
Age	31.62	31.59	31.97
	(4.62)	(4.62)	(4.64)
High school degree	46%	50%	24%
College degree	35%	48%	37%
Advanced degree	16%	36%	38%
Black	1%	1%	1%
Hispanic	4%	4%	5%
Wage	25.27	24.99	29.40
	(20.43)	(19.98)	(25.75)
Sample size	116,439	109,032	7,407

Notes: Sample of married couples in the 2008-2015 ACS ages 25-45, married 4 years or less, with a white non-Hispanic wife in her first marriage. For other sample selections see discussion on p15. Standard errors are in parentheses.

Table 3: Husband’s wage by occupation matching with wife

	Husband’s Wage	Log(Husb’s Wage)	Husb’s Wage/ Wife’s Wage	Log Wage Ratio
A. Full Sample (N=116,439, 136 occupations)				
Same Occ* % Male	-1.17 (0.932)	-0.022 (0.036)	-0.122 (0.112)	-.077 (0.039)**
B. Restrict Range of %Male in Wife’s Occupation				
0.5≤%Male≤1 (N=25,629, 44 occupations)				
Same Occ* % Male	-6.05 (5.35)	-0.108 (0.158)	-1.09 (0.593)*	-0.257 (0.292)
0.4≤%Male≤1 (N= 40,623, 64 occupations)				
Same Occ* % Male	-2.61 (2.90)	-0.059 (0.080)	-0.826 (.318)**	-0.378 (0.142)***
0.3≤%Male≤0.9 (N=50,060, 81 occupations)				
Same Occ* % Male	-4.73 (2.48)*	-0.138 (.067)**	-0.487 (0.344)	-0.285 (0.092)***
0.2≤%Male≤0.8 (N= 70,659, 103 occupations)				
Same Occ* % Male	-1.77 (2.15)	-0.123 (.058)**	-0.114 (0.250)	-0.161 (0.073)**
0.1≤%Male≤0.7 (N= 98,919, 110 occupations)				
Same Occ* % Male	-0.877 (1.45)	-0.006 (0.049)	0.041 (0.135)	-0.008 (0.048)
0<%Male≤0.6 (N= 100,341, 109 occupations)				
Same Occ* % Male	-1.49 (2.31)	0.027 (0.066)	0.022 (0.233)	0.083 (0.078)
0<%Male<0.5 (N= 90,810, 92 occupations)				
Same Occ* % Male	-3.36 (3.15)	0.089 (0.086)	0.384 (0.290)	0.272 (0.104)***
C. By Wife’s Education				
Wife with College (N= 76,330, 136 occupations)				
Same Occ* % Male	-0.764 (1.20)	-0.019 (0.044)	0.006 (0.124)	-0.035 (0.041)
Wife w/o College (N= 39,609, 135 occupations)				
Same Occ* % Male	-2.05 (1.76)	-0.056 (0.050)	-0.280 (0.267)	-0.119 (0.099)
D. Same Occupation and Same Industry, Full Sample				
Same Occ Diff Ind* * %Male	-0.374 (2.27)	-0.004 (0.060)	0.107 (0.180)	-0.077 (0.080)
Same Occ Same Ind *%Male	-1.89 (1.15)*	-0.036 (0.049)	-0.253 (.104)**	-0.083 (0.038)**

Notes: Sample of married couples in the 2008-2015 ages 25-45, married 4 years or less, with a white non-Hispanic wife in her first marriage. For other sample selections see discussion on p15. Table reports estimates from equations (1) and (2). All regressions control for interactions of same-occupation indicator with four occupation wage characteristics: male and female average wage and male and female wage variance. Also included are fixed-effects for husband’s occupation, wife’s occupation, state, state*urban residence, and year. Additional controls include husband’s and wife’s education, age and its squared, husband’s race/ethnicity, wife’s age of marriage and its square, indicator for whether husband and wife share same level of education. Standard errors (in parentheses) clustered by wife’s occupation. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Interaction with Workplace Communication

	Husband's Wage	Log(Husb's Wage)	Husb's Wage/ Wife's Wage	Log Wage Ratio
A. Full Sample (N=81,909, 109 occupations)				
Same Occ* % Male	23.4 (6.8)***	1.85 (1.07)*	0.372 (0.265)	0.122 (0.440)
Same*%Male*Comm	-5.72 (1.54)***	-0.428 (0.232)*	-0.099 (0.059)*	-0.050 (0.094)
B. Restrict Range of %Male in Wife's Occupation				
0.5≤%Male≤1 (N=22,980, 34 occupations)				
Same*% Male*Comm	-5.13 (8.28)	-0.480 (0.368)	-1.16 (1.41)	-0.641 (0.510)
0.4≤%Male<1 (N= 32,980, 51 occupations)				
Same*% Male*Comm	-10.74 (7.20)	-0.217 (0.210)	0.183 (0.799)	0.203 (0.363)
0.3≤%Male≤0.9 (N=40,594, 64 occupations)				
Same*% Male*Comm	-5.12 (5.16)	-0.104 (0.167)	-0.908 (0.868)	0.250 (0.251)
0.2≤%Male≤0.8 (N=57,066, 82 occupations)				
Same*% Male*Comm	-6.10 (2.58)**	-0.062 (0.103)	-0.922 (.394)**	-0.025 (0.150)
0.1≤%Male≤0.7 (N= 71,018, 88 occupations)				
Same*% Male*Comm	-5.61 (1.94)***	-0.038 (0.048)	-0.553 (.261)**	-0.012 (0.090)
0<%Male≤0.6 (N= 69,525, 87 occupations)				
Same*% Male*Comm	-4.76 (3.97)	-0.036 (0.125)	-0.925 (0.502)*	-0.335 (0.168)**
0<%Male<0.5 (N= 58,929, 75 occupations)				
Same*% Male*Comm	-6.41 (5.31)	-0.110 (0.131)	-0.096 (0.572)	-0.304 (0.173)*
C. By Wife's Education				
Wife with College (N= 48,517, 109 occupations)				
Same*%Male*Comm	-10.0 (2.89)***	-0.168 (0.095)*	-0.808 (.325)**	-0.163 (0.134)
Wife w/o College (N= 33,392, 109 occupations)				
Same*% Male*Comm	-3.30 (2.31)	-0.038 (0.064)	-0.372 (0.417)	0.061 (0.129)

Notes: Sample is the same used in Table 2, further limited to observations for which Workplace Communication index is available. Table reports estimates from equation (3). Additional controls are as described in notes of Table 2. Workplace communication is an occupation-level index ranging from 0 to 7 measuring degree of communication with supervisors, co-workers and subordinates. Standard errors (in parentheses) clustered by wife's occupation. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Husband's Wage by Matching on Field of Degree, College-Educated Couples

	Husband's Wage	Log(Husb's Wage)	Husb's Wage/ Wife's Wage	Log Wage Ratio
A. Full Sample (N=46,007, 83 degree fields)				
Same Field * % Male	-5.55 (2.65)**	-0.146 (0.075)*	-0.055 (0.197)	-0.275 (0.071)***
B. Restrict Range of %Male in Wife's Field of Degree				
0.5≤%Male<1 (N=11,080, 26 degree fields)				
Same Field*% Male	1.79 (8.06)	-0.578(.181)***	0.053 (0.837)	-0.455 (0.292)
0.4≤%Male<1 (N= 18,877, 43 degree fields)				
Same Field*% Male	-7.78 (6.21)	-0.384 (.157)**	-0.291 (0.532)	-0.433 (0.152)***
0.3≤%Male≤0.9 (N=28,792, 60 degree fields)				
Same Field*% Male	-7.25 (4.01)*	-0.222 (0.114)*	-0.270 (0.375)	-0.377 (0.131)***
0.2≤%Male≤0.8 (N=36,317, 68 degree fields)				
Same Field*% Male	-2.89 (3.83)	-0.094 (0.093)	-0.256 (.293)	-0.335 (0.110)***
0.1≤%Male≤0.7 (N= 38,000, 73 degree fields)				
Same Field*% Male	-4.43 (3.67)	-0.088 (0.101)	-0.507(.189)***	-0.326 (0.107)***
0<%Male≤0.6 (N= 43,026, 71 degree fields)				
Same Field*% Male	-1.23 (2.39)	0.042 (0.085)	-0.049 (0.235)	-0.137 (0.088)
0<%Male<0.5 (N= 34,927, 57 degree fields)				
Same Field*% Male	-5.82 (5.12)	0.095 (0.154)	0.314 (0.475)	-0.160 (0.131)

Notes: Sample is same as in Table 2, further limited to couples in which both husband and wife have college degrees. Field of degree is not available prior to 2009. Table reports estimates from equation (4). Standard errors (in parentheses) clustered by wife's field of degree. *** p<0.01, ** p<0.05, * p<0.1.

Appendix: Random Matching

In table 2, we report the probability a married man (woman) in occupation k is married to a woman (man) who also works in occupation k under random matching by occupation (conditional on non-random matching by education).

We calculate these random matching probabilities adapting Fryer (2007)'s approach for random matching by race.

There are seven steps to the calculation:

Step 1: Restrict the sample to married mixed-sex couples. Divide married men and women into two education categories based on college degree completion. Calculate for men (women) in each education category the proportion whose spouse is in each education category (e.g., the proportion of male college graduates married to female college graduates)

Step 2: For men (women) in each education category, calculate the number in each occupation category.

Step 3: Multiply the numbers from step 2 (e.g. the number of male college graduates in occupation 1) by the proportions from step 1 (e.g. the proportion of male college graduates married to female college graduates) to calculate the expected number of pairings between men (women) in each education/occupation group and women (men) in each education group (e.g. the expected number of pairings between male college graduates in occupation 1 and female college graduates).

Step 4: Using the numbers from step 2, calculate for men (women) in each education category the share in each occupation category.

Step 5: Multiply the expected number of pairings from step 3 by the shares from step 4 to calculate expected pairings by education/occupation group (e.g. Multiply the expected number of pairings between male college graduates in occupation 1 and female college graduates times the share of female college graduates in occupation 1. This produces the expected number of pairings between male college graduates in occupation 1 and female college graduates in occupation 1).

Step 6: Find the total expected number of same-occupation pairings in each occupation group by summing over the relevant pairings in step 5 (e.g. For men in occupation 1, calculate the total number of expected pairings with women in occupation 1).

Step 7: Convert the expected number of same-occupation pairings to probabilities by dividing by the number of men (women) in the occupation from step 2.