Directed search on the marriage market

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Abstract

In this study, a static two-sided directed search model is applied to the marriage market to unravel male and female preferences over partner characteristics and terms of marriage given observed matches. The model takes into consideration the trade-off individuals face when searching for a partner, balancing between partner characteristics, terms of marriage, and matching probability. By using data from the ACS 5-year PUMS dataset (2015-2019), the study will estimate this equilibrium search-and-matching model and derive identifying power from variation in gender ratios across US regions. A unique aspect of this study is the incorporation of the collective household model literature by defining the terms of marriage as the distribution of bargaining power in the next relationship. Counterfactual analyses will also be conducted to examine the impact of exogenously changing the gender ratio on individuals' searching behavior.

Keywords: Bargaining power, Directed search, Gender ratio, Marriage, Matching

JEL classification codes: D10, D13, D83, J12, J16, J22

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1. Introduction

In the quest for true love, would you go to great lengths or settle for less? Are you willing to make sacrifices and take the higher risk of ending up alone for the person of your dreams, or would a more achievable partner with a higher chance of success be enough? This paper focuses on this particular behavior where individuals trade-off certain characteristics of potential partners (such as race and education) against specific features of a match (such as bargaining power) while facing a competitive environment.

To unravel this trade-off, this study uses a two-sided directed search model in order to examine the different preferences of men and women in the marriage market for partner characteristics and terms of marriage. The model assumes that individuals derive utility from both the characteristics of their partner and the terms of the marriage, leading them to make a trade-off between these factors and the probability to match when deciding which market they will target to search on. They have the possibility to direct their search toward less preferred type-terms combinations to obtain higher matching probabilities.

At first glance, it might be expected that individuals would always seek out potential partners in the market based on their preferred terms. However, this expectation does not hold true in all cases. Some individuals may willingly accept less-preferred terms for themselves due to two reasons: 1) a desire to attract a more desirable partner, or 2) possessing characteristics perceived as less desirable by potential mates, both observed and unobserved. Remark that searching individuals can target markets with more favorable or less favorable terms of marriage, while they are not able to change their own characteristics. Thus, the terms of marriage are viewed as characteristics of the match rather than either partner.

As already explained, the likelihood of seeking a partner of a specific type depends on the probability of success, i.e., the chance of matching with someone of that type. Notably, this probability is endogenously determined by the search probabilities themselves, and is thus affected by the number of competitors of the same gender and potential partners of the opposite gender in that particular market. As a result, it becomes evident that changes in the supply of males and females of different types, and thus the gender ratios, have a direct impact on the equilibrium distribution of relationships. Interestingly, the identification power of this model will be obtained from existing variation in gender ratios across regions in the United States. For instance, regions with more men than women (i.e., a gender ratio in favor of women) are expected to lead to relationships that align more closely with women's preferences. This idea is supported by studies conducted by McElroy and Horney (1981), McElroy (1990), Angrist (2002), and Chiappori, Fortin and Lacroix (2002), which demonstrate that gender ratios do influence the bargaining power between spouses.

The directed search model offers some modeling advantages compared to the traditional search model. Firstly, the directed version will imply that the terms of marriage are fixed and described in advance of meetings. Thus, it will be assumed that transfers between partners are infeasible after a match is established. The division of the gains is exogenous, and therefore, utility is nontransferable. This allows for separate identification of individual-specific preferences for partner characteristics and terms of marriage. This is in contrast to the traditional search model where search is assumed to be random, where typically the terms of marriage are negotiated after two individuals are matched, and where only the joint gains from matching can be identified. Secondly, market tightness is included in the model by introducing competition among love seekers. Thirdly, the behavior modeled in a directed search model is more time efficient than in the traditional one. As an example, examine the following situation described by Chade, Eeckhout and Smith (2017): "Consider the market for executives. In the random search framework, executives must randomly be paired with janitor jobs, to only reject those." This clearly shows that random search is time inefficient because not all relevant information is used. Consequently, this also shows that the modeled behavior is more realistic in a directed search framework. For example, if you want to buy new shoes, you go to a shoe shop instead of randomly and sequentially entering a shop to see whether they sell shoes (Howitt, 2005).

Next to some modeling advantages, this paper also offers some contributions. Firstly, this paper contributes to the literature applying a directed search model to the marriage market. Only two studies adressed this topic so far, i.e., Arcidiacono, Beauchamp and McElroy (2016) with a static framework applied to a high school setting, and Beauchamp, Calvi and Fulford (2022) taking place in a dynamic setting on the Indian marriage market. Directed search models are more commonly used in applications on the labor and goods markets.

A second contribution of this study is the incorporation of the collective household literature to define the terms of marriage. Within this literature, a central focus lies on examining the distribution of bargaining power between potential partners, which in this context, will also shape the terms of marriage. Examining the bargaining power of household members is important because, e.g., it is related to intra-household inequality. This inequality can have far-reaching consequences for all household members, ranging from issues like the "missing women" phenomenon in India to instances of intra-household violence and poverty. While bargaining power is adopted as a central element defining the terms of marriage, the question arises of how to represent it empirically. In this paper, labor supply division within the household will take on this role and will serve as a reduced form representation of bargaining power.[2] Labor supply division emerges as an appealing concept since it allows individuals to commit to certain terms. For instance, one might commit to either discontinuing work entirely or working full-time, with the expectation that their partner will likewise choose to discontinue work or work full-time. As later elaborated in this text, within the framework of directed search, once individuals target a particular market, predetermined terms on that market are present, allowing no room for

[2] Note that this is just one way of representing intra-household bargaining power. There are many more possibilities.

deviation. For example, one may target a market where they choose to work full-time and anticipate their partner to do the same.

The third key contribution involves a comparative analysis of the model, which is a non-transferable utility framework (NTU) in conjunction with directed search, juxtaposed with two alternative frameworks. On the one hand, it is contrasted with the imperfect transferable utility (ITU) framework in the light of Galichon, Kominers and Weber (2019). On the other hand, it is compared with a transferable utility (TU) model à la Choo and Siow (2006).

To estimate the model, a sample is drawn from the American Community Survey (ACS) 5-year Public Use Microdata Sample (PUMS), covering the period 2015-2019. The ACS is a comprehensive national survey crafted to annually provide communities with reliable and up-to-date information on social, economic, housing, and demographic aspects. The 5-year estimates combine 5 consecutive years of ACS data to produce multiyear estimates. Searching individuals can target their quest towards potential partners (of the opposite sex) with respect to a certain education level and race, as well as to the labor supply division they would prefer. To gather information on gender ratios, the ACS is used as well, which offers detailed data on gender ratios categorized by education level and race for each region.

The remainder of the paper is structured as follows: Section 2 provides background information on relevant literature and concepts used in this paper. Section 3 constructs a theoretical framework of a static nontransferable utility two-sided directed search model. An expression for the search and matching probabilities will be obtained, and it will be shown which fixed point must be solved in order to obtain an equilibrium. Moreover, the identification strategy will be explained. Subsequently, section 4 starts with a description of the sample construction and the data used in this paper, after which the distribution of the realized matches will be analyzed. Section 5 explains the estimation approach, while section 6 will provide the results of the estimation procedure applied to the earlier obtained sample. Section 7 describes the counterfactual analyses, and where section 8 will do a comparison exercise in which the NTU with directed search will be contrasted against an ITU and a TU model. Finally, section 9 concludes the paper.

2. Background

Search and matching models - In contrast to Walrasian markets, trade in matching markets is a decentralized, uncoordinated and time-consuming economic activity. A central theme within this field of literature is the concept of sorting. For instance, one can observe companies investing substantial resources in finding the right employees, or individuals dedicating significant time and effort to search for the right partner. Initially, the theory of frictionless matching emerged, which comprises two distinguishable branches in the literature. On one hand, match payoffs can be nontransferable, a concept originating from Gale and Shapley (1962) under stable matching. In this scenario, transfers between agents are either not possible or the division of the match surplus is exogenously given. On the other hand, the work of Monge (1781), Kantorovic (1942) and Koopmans and Beckmann (1957) laid the foundation for a model that allows for transferable payoffs (i.e., they worked on optimal transportation theory). This model later served as the basis for the seminal paper by Shapley and Shubik (1972). In a transferable utility framework, agents can freely make transfers at a constant rate. Generally, matching models do not account for the cost of acquiring information about potential matches and the role of meeting technologies of all sorts. Therefore, these models assume a frictionless environment, where both men and women have open access to each other, possessing perfect knowledge of the characteristics of all potential mates.

At the same time as the matching literature was developing, search theory also emerged. Search models emphasize the presence of frictions in economic interactions. In contrast, a frictionless matching environment predicts no unmatched agents, except in cases of obvious imbalances. Moreover, a frictionless matching model does not address the issue of mismatch among those who do find matches. Stigler (1961) pioneered the first search optimization model in economics, creating a model of simultaneous search where all options are considered at once, and the best one is chosen. However, his model was quickly abandoned. It was McCall (1965) who introduced sequential search to economics. In sequential search models, individuals typically meet one person of the opposite gender randomly and sequentially. After the meeting, both the man and the woman must decide to start a relationship or to continue his or her search. Continuing the search will entail some costs, e.g., discounting or the risk of never finding a better partner. If both agree to start a relationship, a negotiation is started on how to share the surplus. In essence, search models illustrate the trade-off between the cost of delaying a decision and the potential value of exploring other options. Mathematically, search models can be framed as optimal stopping problems. Some influential papers in the search theory domain include works by Diamond (1982), Mortensen (1982), Pissarides (1984) and Shimer and Smith (2000). The fields of matching and search theory initially developed independently until the early 1990s when frictional matching models were introduced. Since then, these two literatures have become closely interconnected (Chade, Eeckhout and Smith, 2017).

Directed search model - Relatively recent, a subbranch has emerged in which the assumption of random search is replaced by that of directed search. For example, the seminal paper by Moen (1997) is a directed search version of the papers by Diamond - Mortensen - Pissarides. Other examples are Eeckhout and Kircher (2010), Shi (2001), Delacroix and Shi (2006), Engelhardt and Rupert, 2017, ... To explain the assumption of directed search, an analogy is made with the goods market. In a competitive economy, prices serve an informative role as they convey the willingness to buy and sell. In the context of anonymous random search, prices primarily dictate how the surplus is shared between buyers and sellers, without affecting the actual process of finding one another. However, in the case of directed search, it's assumed that prices have a more direct influence on the meeting process, rather than just determining the allocation of surplus. Unlike in the traditional random search model, where trading partners meet first and then negotiate prices, directed search reverses this sequence. Here, sellers establish and publicly declare their prices upfront. Subsequently, buyers, after considering these posted prices, make informed decisions about which sellers they want to engage with. This approach allows buyers to direct their search towards sellers who offer more attractive pricing. In summary, agents must not only consider the terms of trade (e.g., the price), but also the probability of trade.

In the literature, applying a directed search model to the marriage market is relatively new, with only two studies addressing this topic: Arcidiacono, Beauchamp and McElroy (2016) and Beauchamp, Calvi and Fulford (2022). On the one hand, the former paper did a similar exercise as this paper within a static framework applied to a sample of high school relationships. The researchers defined the terms of marriage as the subjective response of individuals on whether sex should be included in someone's ideal relationship. Their findings revealed that some women engage in sexual activities due to concerns related to finding a suitable match, even when they ideally would prefer not to engage in a sexual relationship. The reverse pattern was observed among men. Furthermore, their counterfactual analyses demonstrated that the higher likelihood of sexual activity among black women compared to white women is attributable to the specific matching environment that black women encounter. On the other hand, the latter study extended this framework to a dynamic setting in India. They defined the terms of marriage as post-marriage migration, dowry payments, and women's involvement in the choice of partner.

Collective household model - A unique aspect of this study is the incorporation of the collective household literature to define the terms of marriage. The collective household model, developed by Chiappori (1988, 1992) and Apps and Rees (1988), acknowledges the presence of multiple individuals within a household, each with their own rational preferences. It assumes that an intra-household bargaining process occurs among these individuals, ultimately leading to a Pareto efficient outcome. The focal point of interest in this literature is the distribution of bargaining power between two potential partners, which will also serve as the terms of marriage in this paper. This power division has been extensively explored in existing research and is commonly referred to as the sharing rule.[3] The collective household model enables a comprehensive examination of the intra-household distribution of welfare, going beyond the traditional focus on inter-household welfare distribution (Chiappori, 1992).

As explained before, a proxy for bargaining power in this paper will be the labor supply

[3] The sharing rule is often considered an indicator of the relative bargaining power among household members. The Pareto weight is another frequently employed metric for assessing the intra-household power distribution. However, what makes the sharing rule particularly appealing is its ability to be quantified in monetary terms (Browning, Chiappori and Weiss, 2014).

division within a household. Extensive research has explored labor supply dynamics within households, e.g., investigating how gender ratios and divorce laws affect labor supply (Chiappori, Fortin and Lacroix, 2002), the impact of children on labor supply (Blundell, Chiappori and Meghir, 2005), and how education choices are linked with the marriage and labor market (Chiappori, Costa Dias and Meghir, 2018). For a complete overview, see Chiappori et al. (2022).

Intrahousehold inequality - Examining the bargaining power of household members is important because, e.g., it is related to intra-household inequality. This inequality can have various implications for every member of the household. For instance, Calvi (2020) demonstrated that the limited bargaining power of women in India contributes significantly to the phenomenon of missing women.[4] The study established a negative causal relationship between women's bargaining power and their mortality risk. Additionally, Thomas (1990) argued that unearned income controlled by mothers has a greater impact on the health of their families compared to income controlled by fathers in Brazil. Similarly, Duflo (2000) evaluated the effects of a large cash transfer program in South Africa on children's nutritional status and explored whether the gender of the recipient influences these effects. The findings of Duflo (2000) aligned with Thomas (1990), supporting the notion that the gender of the recipient plays a role in the program's impact.

Subsequently, some examples from the developed world can be found in Aizer (2010) and Anderberg et al. (2016). Aizer (2010) investigated the relationship between intra-household violence and the male-female wage gap in the United States, and found that it aligned with a typical household bargaining model. According to such a model, an increase in women's relative wages enhances their bargaining power and reduces the likelihood of intra-household violence. The study by Anderberg et al. (2016) was interested in the question whether rising unemployment can cause an increase in domestic violence. Based on a UK dataset, the findings provided compelling evidence supporting the theory that male and female unemployment exert opposite effects on domestic abuse. Specifically, an increase in male unemployment is being associated with a decrease in intimate partner violence, while an increase in female unemployment is linked to a rise in domestic abuse. The underlying rationale for this phenomenon can be attributed to the same logic as explained in the previously described household bargaining model. Finally, it is worth mentioning the studies that explore the concept of hidden poverty, such as the works by Cherchye et al. (2015) and Cherchye et al. (2020). These papers examined the disparity between household poverty rates and individual poverty rates, utilizing a non-parametric method to set-identify the sharing rule. The findings revealed that household poverty rates underestimate the overall poverty level in society and fail to account for the welfare distribution within households. Specifically, a larger proportion of women are found to fall below the poverty line compared to men.

[4] The number of missing women was previously quantified by Anderson and Ray (2010).

3. Model

While searching for a partner, individuals will trade-off the following three sources of expected utility: the characteristics of the partner (i.e., the partner's type), the terms of marriage, and the matching probability. Individuals have the knowledge about what payoff every type-terms combination will yield. Actually, it will be possible that individuals direct their search toward less preferred type-terms combinations in order to obtain higher matching probabilities. Therefore, the risk of not being matched is built into the model. The terms of marriage are determined and fixed once a market is chosen, i.e., it is not possible to negotiate about the terms when searching on a particular market. This implies that on the moment a match is established, a marriage contract is signed of which the conditions are deterministic and constant over the match.

Only monogamous and heterosexual matching is examined in this static nontransferable utility two-sided directed search model, which will be based on the model introduced by Arcidiacono, Beauchamp and McElroy (2016). Each male is characterized by several observed traits (e.g., age, race, education, ...). Those traits can be summarized by a type. Thus, every male will be categorized as a certain type m, where $m \in \{1, 2, ..., M\}$ (i.e., there will be M types of men). This correspondingly holds for women, where each female is characterized by a type f, with $f \in \{1, 2, ..., F\}$ (i.e., there will be F types of women). Overall, males will have F types of female mates, while females will have M types of male mates. Let im stand for the i-th member of type m.

To generalize the model, it will be assumed that there are R possibilities to specify the terms of marriage, where one particular possibility will be $r \in \{1, 2, ..., R\}$. Every individual will make use of both the partner's type and the terms of marriage to direct their search. In summary, every man must make a discrete choice to search in one of the $F \times R$ markets within the region he lives in, while every woman must do the same in one of the $M \times R$ markets within her region of residence.[5] Important to notice is that this is a static framework, resulting in the fact that individuals only have one shot to find a partner while searching.[6]

3.1 Individuals

Three factors will influence the expected utility of an m-type man searching for an f-type woman with marriage terms r. The first factor is the matching probability between those two types, i.e., P_m^{fr}. The second factor is μ_m^{fr}, which is the deterministic part of utility conditional

[5] The US region of residence serves as the primary market in the paper's empirical application.

[6] In this model, the dynamic aspect of marriage is not considered, though acknowledging that incorporating the dynamic nature would create a more realistic representation of the marriage problem. As noted by Beauchamp, Calvi and Fulford (2022), ignoring the dynamic aspect will result in a reduction of the substitution patterns available to future spouses. However, this framework provides an excellent foundation for adding a dynamic component in future research.

on matching. The last factor is the individual-specific preference term ϵ_{im}^{fr}. The same reasoning holds for an f-type woman searching for an m-type man, but where her factors will be P_f^{mr}, μ_f^{mr} and ϵ_{if}^{mr}, respectively.

A few assumptions must be made. Firstly, the individual-specific preference term is assumed to be known by the individual before he/she will make a search decision. Moreover, it is assumed that same m-type men searching on the same $\{f,r\}$-market all have the same matching probability. Lastly, the utility of not matching with someone is put equal to zero.

The expected utility of an individual searching in a market is the multiplication of the matching probability in that market with the utility conditional on matching. As such, the functional form of the utility function will be specified in a way such that the expected utility of an m-type man searching on the $\{f,r\}$-market becomes:

$$E(U_{im}^{fr}) = P_m^{fr} \cdot e^{\mu_m^{fr} + \epsilon_{im}^{fr}}. \tag{1}$$

By taking the logarithm of this expected utility, the following is obtained:

$$\ln(E(U_{im}^{fr})) = \mu_m^{fr} + \ln(P_m^{fr}) + \epsilon_{im}^{fr}. \tag{2}$$

Man i of the m-type men decides to search on the $\{f,r\}$-market when

$$\{f, r\} = \arg\max_{f',r'} \mu_m^{f'r'} + \ln(P_m^{f'r'}) + \epsilon_{im}^{f'r'}. \tag{3}$$

The individual-specific preference terms ϵ_{im}^{fr}'s are assumed to be independent and identically distributed following a type I extreme value distribution. Moreover, these terms are not known by the econometrician. Thus, the probability that an m-type man will be searching a partner on the $\{f,r\}$-market, ϕ_m^{fr}, will be represented by

$$\Pr(f, r|m) = \phi_m^{fr} = \frac{\exp\left(\mu_m^{fr} + \ln\left[P_m^{fr}\right]\right)}{\sum\limits_{f'}\sum\limits_{r'} \exp\left(\mu_m^{f'r'} + \ln\left[P_m^{f'r'}\right]\right)}. \tag{4}$$

3.2 Matching

The number of matches in the $\{m,f,r\}$-market will be represented by the matching function $X_{mfr}(\phi_m^{fr} N_m, \phi_f^{mr} N_f)$, which can be interpreted as a function that takes the number of searching men and searching women in every market as inputs and displays the number of matches as output.[7] The overall number of m-type men and f-type women will be set equal to N_m and N_f, respectively. Remember the searching probabilities ϕ_m^{fr} and ϕ_f^{mr}, which stand for the probabilities that m-type men and f-type women will be searching on the $\{m,f,r\}$-market. Now, the ϕ's can be used to express mathematically the total number of searching m-type men on the $\{f,r\}$-market, $\phi_m^{fr} N_m$, and the total number of searching f-type women on the $\{m,r\}$-market, $\phi_f^{mr} N_f$. The functional form of $X_{mfr}(\phi_m^{fr} N_m, \phi_f^{mr} N_f)$ will be of the constant elasticity

[7] Notice that for all m, f and r: $X_{mfr} = X_{fmr}$.

of substitution (CES) type[8], and is given by

$$X_{mfr}(\phi_m^{fr} N_m, \phi_f^{mr} N_f) = A[(\phi_m^{fr} N_m)^\rho + (\phi_f^{mr} N_f)^\rho]^{1/\rho}. \tag{5}$$

The specific elements of this functional form can be interpreted as follows:

- $\phi_m^{fr} N_m$ and $\phi_f^{mr} N_f$ are the inputs of the matching function. Moreover, both are equally important for the determination of the output.

- Within production theory, A can be interpreted as the factor productivity, but here, it will measure the matching efficiency or search frictions. These frictions may occur due to the existence of a costly process of obtaining information about potential spouses. A must be smaller than or equal to 1 because the number of matches cannot exceed the number of searching men or the number of searching women in every market.[9]

- ρ displays the substitution parameter and determines β, i.e., the elasticity of substitution (where $\beta = 1/(1-\rho)$). Within the class of CES functions, the parameter ρ provides insight into the substitutability of the inputs. In production theory, the interpretation of ρ is straightforward, but this is a much harder exercise in a marriage matching setting. In this environment, ρ will be required to be strictly smaller than 0. Firstly, a positive ρ is not considered, since that would entertain the possibility of more "too many" matches (i.e. more matches than available partners), which is not possible. Secondly, the way the matching probability is parameterized (i.e., see Equation 6) means that another extreme case exists, the Cobb-Douglas function (i.e., where ρ tends to 0). In this case, the gender ratio drops out of the equation for the probability of matching. This is not desirable since the whole idea of identification in this paper rests on the assumption that search behavior is impacted by the gender ratio. The convergence of ρ towards 0 will not be ruled out a priori; it will be investigated in the empirical application of this paper whether gender ratios do matter for the search and matching probabilities. Lastly, consider the extreme case where ρ would approach $-\infty$, i.e., the matching function turns into a Leontief function. This implies that the number of matches depends completely on the short side of the market. Consequently, alterations in the gender ratio profoundly impact the majority group in a specific market while leaving the minority group unaffected.

By assuming that all m-type men searching in the same market have the same matching probabilities, P_m^{fr} can be written as

$$\begin{aligned} P_m^{fr} &= \frac{X_{mfr}(\phi_m^{fr} N_m, \phi_f^{mr} N_f)}{\phi_m^{fr} N_m} = \frac{A[(\phi_m^{fr} N_m)^\rho + (\phi_f^{mr} N_f)^\rho]^{1/\rho}}{\phi_m^{fr} N_m} \\ &= A\left[1 + \left(\frac{\phi_f^{mr} N_f}{\phi_m^{fr} N_m}\right)^\rho\right]^{1/\rho}. \end{aligned} \tag{6}$$

[8]The CES function is a convenient, flexible, and often used form in traditional production models.

[9]To meet this requirement, the CES matching function will take the following form when estimating the model: $X_{mfr} = \min\{A[(\phi_m^{fr} N_m)^\rho + (\phi_f^{mr} N_f)^\rho]^{1/\rho}, \phi_m^{fr} N_m, \phi_f^{mr} N_f\}$.

The logarithm of this probability will be inserted into equation 4, i.e., the search probabilities. Thus, this term will contain the influence of the gender ratio on the search decisions.

3.3 Equilibrium

Remember from Equation 4 that the search probabilities depend on the matching probabilities. Nevertheless, it is quite straightforward to see that the matching probabilities, in their turn, also depend on the search probabilities. To make this relationship clear, Equation 4 can be rewritten as

$$\phi_m^{fr} = \frac{\exp\left(\mu_m^{fr} + \ln[P_m^{fr}(\phi_m^{fr}, \phi_f^{mr})]\right)}{\sum\limits_{f'}\sum\limits_{r'} \exp\left(\mu_m^{f'r'} + \ln\left[P_m^{f'r'}(\phi_m^{f'r'}, \phi_{f'}^{mr'})\right]\right)}. \tag{7}$$

It is required for the search probabilities to sum up to 1 for both men and women. Therefore, equilibrium in this model is characterized by stacking the $(M \times R - 1)$ and $(F \times R - 1)$ search probabilities and solving for the fixed point defined by equation 7. The fixed point theorem of Brouwer makes sure of the existence of an equilibrium since ϕ is a continuous mapping on a compact and convex space. Moreover, only one equilibrium exists (and will be played) where positive search probabilities are observed in all the markets (Diamond, 1982).[10]

3.4 Gender ratio

Turning to the question of what the impact is of exogenously changing the gender ratio on individuals' searching behavior. To answer this, consider the following two markets $\{m, f, r\}$ and $\{m, f, r'\}$. The only thing that differs between the two markets are the terms of marriage r and r'. Suppose for a moment that the search probabilities are fixed and that the number of m-type men or f-type women is adjusted upwards or downwards. Doing such an exercise makes it possible to see which of the two types of marriage becomes relatively more interesting for men and women. To obtain an equilibrium, the search probabilities need to be adjusted. In Proposition 1, the relationship between the gender ratio and the individuals' search behavior will be expressed.[11]

Proposition 1 - *Take $G_{mf} = N_m/N_f$. If $\rho < 0$ and $\mu_f^{mr'} - \mu_f^{mr} > \mu_m^{fr'} - \mu_m^{fr}$, it holds that:*

i) $\dfrac{\phi_f^{mr}}{\phi_m^{fr}} < \dfrac{\phi_f^{mr'}}{\phi_m^{fr'}}$,

[10]According to Diamond (1982), a necessary condition to have multiple equilibria in a similar static framework is a matching function that exhibits increasing returns to scale. However, the particular CES function defined in Equation 5 has a degree of homogeneity equal to 1, indicating that the function has constant returns to scale.

[11]For a proof, see the appendix in Arcidiacono, Beauchamp and McElroy (2016).

ii) $P_f^{mr} > P_f^{mr'}$ *and* $P_m^{fr} < P_m^{fr'}$, *and*

iii) $\dfrac{\partial(\phi_f^{mr'}/\phi_f^{mr})}{\partial G_{mf}} > 0$ *and* $\dfrac{\partial(\phi_m^{fr'}/\phi_m^{fr})}{\partial G_{mf}} > 0.$

It is possible to derive from Proposition 1 that f-type women, when matched with an m-type man, do prefer r' over r relatively more than m-type men matched with an f-type woman. Relationship $i)$ expresses that, in equilibrium, women will search relatively more in r' than men because of their relative preference for r' over r. This difference in search behavior must also be translated into different matching probabilities. This can be seen in relationship $ii)$ where the female matching probabilities need to be lower in r' than in r because women search relatively more than men in r'. In summary, there will be relatively more women than men searching on the $\{m, f, r'\}$-market than on the $\{m, f, r\}$-market. The opposite reasoning holds for men.

Suppose now that G_{mf} increases, i.e., women become relatively more scarce and men become relatively more abundant. Interestingly, according to relationship $iii)$ both genders start searching relatively more in the $\{m, f, r'\}$-market, thus, in the market for which f-type women have a relative preference. This result stems from the lack of substitutability between men and women whenever ρ is less than 0. Due to this partial unsubstitutability, an increase in G_{mf} will decrease the matching probability for men more in the market where they are with relatively more, i.e., the r-market, while the matching probability for women will experience a higher increase in the market where men are relatively less present.[12]

Identification - Proposition 1 shows that you need variation in gender ratios to make sure that identification of the parameters of interest can be obtained. There are a few ways to do so. For example, variation in gender ratios over time within a region is a possible way to go. Another possibility is to use gender ratio variation across regions (at one point in time), which is the option chosen in this paper. To understand this approach, consider the following example. Suppose there are two regions $S1$ and $S2$, and there are two markets $\{m, f, r\}$ and $\{m, f, r'\}$ in every region. The only difference between the two markets is the terms of marriage. Moreover, assume that the gender ratio in region $S1$ is bigger than the gender ratio in region $S2$, i.e., $\frac{N_m^{S1}}{N_f^{S1}} > \frac{N_m^{S2}}{N_f^{S2}}$. The relative preference for r and r' will be revealed based on which market will be relatively more populated. The advantage of following this approach is that only a cross-sectional data set is needed. In summary, it is required to observe couples with similar m-type men and f-type women across regions with different levels of competition in order to uncover the preferences of men and women separately.

[12] A more mathematical explanation, in which the elasticity of the matching probability with respect to the gender ratio is given, can be found in Appendix A.

4. Data

This section will start with a description of the data and the sample used in the empirical application of this paper. Secondly, some distributions of the realized matches will be provided with respect to education and race. Thirdly, the terms of marriage will be under scrutiny. Finally, a look will be taken at the gender ratios across the different states of the US.

4.1 Data description

In this paper, a sample is drawn from the American Community Survey (ACS) 5-year Public Use Microdata Sample (PUMS), covering the period 2015-2019. The ACS is a comprehensive national survey crafted to annually provide communities with reliable and up-to-date information on social, economic, housing, and demographic aspects. The 5-year estimates combine 5 consecutive years of ACS data to produce multiyear estimates.

Table 1: Descriptive statistics

	Mean	SD	MIN	MAX
A. Couples				
Male age	47.59	10.92	25	65
Female age	45.65	10.92	25	65
Male has at least undergraduate degree	0.46	0.50	0	1
Female has at least undergraduate degree	0.52	0.50	0	1
Male work hours	38.24	15.96	0	69
Female work hours	27.68	18.59	0	69
B. Singles				
Male age	47.12	12.05	25	65
Female age	47.72	11.82	25	65
Male has at least undergraduate degree	0.42	0.49	0	1
Female has at least undergraduate degree	0.46	0.50	0	1
Male work hours	33.37	18.77	0	69
Female work hours	29.46	18.44	0	69

Note: The sample consists of 4 063 989 observations, of which 2 288 182 are couples and 1 775 807 are singles. Wages are net hourly wages in dollars. Work hours are hours per week.

To be more specific, the sample drawn had to meet specific sample selection criteria. Specifically, only heterosexual couples were included in the sample, ensuring that both spouses were present and aged between 25 and 65 years. Cohabiting couples were also considered and treated as if they were married. Moreover, the sample encompassed singles as well. By applying the same sample selection rules to singles, a total of 4 063 989 observations were obtained, comprising

2 288 182 couples and 1 775 807 singles. Descriptive statistics for both couples (Panel A) and singles (Panel B) can be found in Table 1.

4.2 Distribution of realized matches

Individuals searching for a partner possess certain inherent traits that cannot be altered. However, they do have control over the terms of marriage, allowing them to seek better conditions for marriage. This behavior becomes particularly apparent when an individual encounters limited competition on the marriage market. This subsection will primarily concentrate on the former aspect, namely the characteristics of the partner. The subsequent subsection will delve into the latter aspect, namely the terms of marriage.

Firstly, consider Table 2 which displays the matching distribution across education of all included couples in the sample. Some findings from the table are as follows. Taking a look at the diagonal elements in the table, it can be seen that the most common matches are those between two partners with a similar education level, i.e., approximately 60% of all the couples are same-education matches. Remarkably, 23% of all matches belong to the category "higher educated wife with lower educated husband", while the opposite category "higher educated husband with lower educated wife" only represents 17% of the matches.

Turning to Table 3 which expresses the matching distribution across race. A similar observation as in the previous table is that the same-race couples make up the majority of the total matches, i.e., more than 90% of the matches. Interracial couples including one white person are most common among all the interracial couples, i.e., approximately 8.5%, while interracial couples where one partner is Black, Hispanic, or from another ethnic minority group (where this latter category is predominantly Asian) take each between 1.5 and 5.5% of the matches. Moreover, men are more likely to be matched with women of a different race. For example, the group of white men are most likely to be with someone of a different race.

Table 2: Matching distribution across education

	Female education			
Male education	≤ High school	Associate or Bachelor	Master ≤	Total
≤ High school	37.07	13.60	3.31	53.97
Associate or Bachelor	8.90	16.17	6.05	31.12
Master ≤	2.05	6.21	6.65	14.91
Total	48.01	35.98	16.01	100.00

Note: The sample consists of 2 288 182 couples. The numbers in this table are displayed as percentages.

Table 3: Matching distribution across race

	Female race				
Male race	White	Black	Hispanic	Other	Total
White	69.94	0.30	2.56	1.71	74.51
Black	0.80	5.13	0.25	0.11	6.29
Hispanic	2.25	0.10	9.89	0.21	12.46
Other	0.78	0.03	0.15	5.80	6.75
Total	73.76	5.55	12.85	7.84	100.00

Note: The sample consists of 2 288 182 couples. The numbers in this table are displayed as percentages.

4.3 Terms of marriage

As said before, the terms of marriage will be defined as the bargaining power within a household. Moreover, it was also argued that labor supply division within the household will serve as a reduced form representation of bargaining power to respresent it empirically. Taking a look at the distribution of people not working, working part time or working full time (see Table 4) reveals that women are still more likely to be unemployed or working part time in comparison to men.[13] Slightly more single women are working full time compared to women in a relationship. Interestingly, nearly 80% of men are working full time, but only 70% of single men do so in comparison to 82% of men in couples. When only looking at couples (see Table 5), it is remarkable that almost 50% of couples have two spouses working full time. Moreover, it can be observed that the majority of couples (i.e., 82%) have a full time working husband.

4.4 Gender ratios

The gender ratios are obtained from the ACS. The 2019 1-year estimates are used since these estimates possess the required level of detail (i.e., at the desired level of race and educational attainment). The level of region is taken at the US state level (i.e., 50 states + District of Columbia). Variation in gender ratios across US states is required to identify the male and female preferences separately.[14] This variation reflects varying levels of competition on the marriage market. Via this way, it is possible to see how m-type men and f-type women trade-off different terms of marriage with partner characteristics while subjected to differing levels of competition.

Table 6 displays in the second and fourth column the gender ratio of the region with the lowest and highest gender ratio per race and education category, respectively. The third column

[13] Working full time is defined as individuals performing at least 35 hours on the labor market, while working part time defines everyone working at least 1 hour and at most 34 hours on the labor market.

[14] The gender ratio is defined as the ratio of total m-type men over total f-type women.

Table 4: Employment status

	Full sample	Couples	Singles
Women			
Unemployed	24.39	25.05	22.94
Part time	17.93	18.91	15.78
Full time	57.68	56.04	61.28
Men			
Unemployed	13.06	10.95	19.66
Part time	7.57	6.94	9.54
Full time	79.37	82.11	70.81

Note: The full sample consists of 4 063 989 observations, of which 2 288 182 are couples and 1 775 807 are singles. The numbers in this table are displayed as percentages.

Table 5: Matching distribution across employment status

	Female employment			
Male employment	Unemployed	Part time	Full time	Total
Unemployed	4.31	1.57	5.07	10.95
Part time	1.70	1.69	3.55	6.94
Full time	19.03	15.65	47.43	82.11
Total	25.05	18.91	56.04	100.00

Note: The sample consists of 2 288 182 couples. The numbers in this table are displayed as percentages.

provides the average gender ratio over all the regions per race and education category. Remark that the gender ratios in this table are counting all individuals that are 25 years or older. It is not possible to exclude the individuals that are +65 years old because of data limitations.

What can be observed from Table 6 is that the average gender ratio across regions is 0.95. Moreover, the region with the lowest overall gender ratio has a ratio of 0.89 and the region with the highest gender ratio has one of 1.09. Furthermore, the interpretation of the other summary statistics is as follows. Within the category of white lower educated individuals, the region with the lowest gender ratio has a ratio of 0.93. Within the same category, alle regions have a gender ratio of 1.02 on average. All these summary statistics show that there is considerable variation in gender ratios across race and education categories and across US states.

Table 6: Gender ratios across race and education categories

Gender ratio (+25 years)	MIN	MEAN	MAX
All regions	0.89	0.95	1.09
White			
$\leq$ High school	0.93	1.02	1.27
Associate or Bachelor	0.77	0.88	1.03
Master $\leq$	0.68	0.89	1.51
Black			
$\leq$ High school	0.80	1.17	2.99
Associate or Bachelor	0.51	1.90	19.63
Master $\leq$	0.33	0.73	1.70
Hispanic			
$\leq$ High school	0.75	1.10	1.30
Associate or Bachelor	0.48	0.86	1.55
Master $\leq$	0.39	0.90	1.60
Other			
$\leq$ High school	0.54	1.28	1.51
Associate or Bachelor	0.32	0.43	1.45
Master $\leq$	0.54	1.22	2.46

Note: The gender ratio is defined as the ratio of total m-type men over total f-type women.

5. Estimation

In this section, the construction of the utility function will be discussed, which will be followed by the formation of the likelihood function. The findings from the previous section shed light on variations in matching patterns among different races and education levels. These findings provide evidence that the types formed based on these two characteristics are credibly constructed. The terms of marriage will be defined as labor supply division. Consequently, within each US region, individuals of each gender can explore a total of 108 distinct markets for a partner. This takes into consideration three levels of education, four racial categories, and nine distinct terms of marriage.

5.1 The utility function

Denote E_m as the education level of an m-type man, where $E_m \in \{1, 2, 3\}$. When a male is searching for an f-type female, the education level of the partner is PE_m. Same reasoning holds for the race of an m-type man, i.e., $R_m \in \{1, 2, 3, 4\}$. Again, PR_m represents the race of the partner. Subsequently, SE_{mf} and SR_{mf} specify whether the potential partner has the same education level and race as the searching individual, respectively. Finally, LSD_{mf} indicates within which range the potential labor supply division will be situated, with $LSD_{mf} \in \{1, 2, ..., 9\}$.

Now, the deterministic part of utility conditional on matching for men and women can be parameterized in the following way[15]:

$$\mu_m^{fr} = \alpha_1^m SE_{mf} + \alpha_2^m PE_m + \alpha_3^m SR_{mf} + \sum_{j=1}^{4} I(PR_m = j)\alpha_{4j}^m + \sum_{j=1}^{9} I(LSD_{mf} = j)\alpha_{5j}^m, \quad (8)$$

$$\mu_f^{mr} = \alpha_1^f SE_{mf} + \alpha_2^f PE_f + \alpha_3^f SR_{mf} + \sum_{j=1}^{4} I(PR_f = j)\alpha_{4j}^f + \sum_{j=1}^{9} I(LSD_{mf} = j)\alpha_{5j}^m. \quad (9)$$

5.2 The likelihood function

Denote θ by the set of parameters that needs to be estimated $\{\alpha, \rho, A\}$. The log-likelihood function for the i-th woman of type f is constructed as follows:

$$\begin{aligned} \mathcal{L}_{if}(\theta) = I(y_{if} = 1) &\left[\sum_m \sum_r I(d_{if} = \{m, r\})(\ln[\phi_f^{mr}(\theta)] + \ln[P_f^{mr}(\theta)])\right] \\ &+ I(y_{if} = 0) \ln\left[\sum_m \sum_r \phi_f^{mr}(\theta) \times (1 - P_f^{mr}(\theta))\right], \end{aligned} \quad (10)$$

where $y_{if} = 1$ indicates that the i-th woman of type f is matched with someone, while $y_{if} = 0$ indicates she is not. Logically, it is only possible to see woman i's search decision d_{if} if she is matched. Therefore, there is the need to integrate out over the (unobserved) search decisions for all the unmatched individuals.

The log-likelihood function just described was for the i-th woman of type f, and moreover, it was for a general region. Denote the regions in the data by $s \in \{1, ..., 51\}$. Now, the summation of the log-likelihoods will be taken over all the female types at each region in the first term on the right-hand side of Equation 11, and the same will be done for all the male types at each region in the second term on the right-hand side of the same equation. Thus, the parameters of interested can be estimated by

$$\hat{\theta} = \arg\max_{\theta} \left(\sum_s \sum_f \sum_{i=1}^{N_f^s} \mathcal{L}_{if}^s(\theta) + \sum_s \sum_m \sum_{i=1}^{N_m^s} \mathcal{L}_{im}^s(\theta) \right). \quad (11)$$

[15] Function I is an idicator function.

6. Results

Table 7: Structural model estimates

A. Matching parameters		
ρ	-9.1472	
	(0.5496)	
A	0.9127	
	(0.0064)	
Preferences	**B. Men**	**C. Women**
Same education (α_1^m)	0.5946	0.8589
	(0.0045)	(0.0131)
Partner's education (α_2^m)	0.0690	-0.1824
	(0.0093)	(0.0191)
Same race (α_3^m)	2.3406	2.1509
	(0.0228)	(0.1066)
Partner White (α_{41}^m)	-1.2006	-1.1927
	(0.5004)	(0.5016)
Partner Black (α_{42}^m)	-4.1403	-3.8536
	(0.5066)	(0.5093)
Partner Hispanic (α_{43}^m)	-2.1641	-2.0503
	(0.5026)	(0.5106)
Partner Other (α_{44}^m)	-0.5040	-0.9055
	(0.5193)	(0.5446)
NE,NE (α_{51}^m)	-2.0965	-2.4517
	(0.3365)	(0.3337)
NE,PT (α_{52}^m)	-2.9926	-3.4310
	(0.3964)	(0.3649)
NE,FT (α_{53}^m)	-0.5277	-1.0127
	(0.3352)	(0.3343)
PT,NE (α_{54}^m)	-3.2394	-3.3588
	(0.4675)	(0.4945)
PT,PT (α_{55}^m)	-3.2006	-3.2581
	(0.5988)	(0.6806)
PT,FT (α_{56}^m)	-0.9136	-1.0804
	(0.3351)	(0.3364)
FT,NE (α_{57}^m)	-2.2968	-1.8106
	(0.3348)	(0.3414)
FT,PT (α_{58}^m)	-2.7004	-2.0388
	(0.3335)	(0.3347)
FT,FT (α_{59}^m)	-0.0550	0.4358
	(0.3347)	(0.3336)
-log($\mathcal{L}$)	16462200	
Time	+/- 27 days	

The structural model estimates are displayed in Table 7. As stated in Section 3.2, crucial to unravel male and female preferences given observed matches is considering the influence of varying gender ratios on individuals' search decisions. The impact of these gender ratios becomes apparent through their effect on the probability of matching. Panel A of Table 7 shows the estimate of ρ (i.e., ρ measures the extent to which the decision to seek a specific partner is correlated with the gender ratio), which is significantly negative. This confirms the identifying assumption that gender ratios do matter for the search and matching probabilities.[16] Furthermore, the estimate of A is significant and smaller than 1, indicating the presence of search frictions.

The preferences of men and women are presented in Panel B and Panel C of Table 7, respectively. With respect to education, both men and women have a (significant) preference for

[16] Moreover, this also confirms that the matching function does not take the Cobb-Douglas form.

a partner with a similar education level as themselves. Moreover, men do like on average higher educated women, while women do prefer lower educated men, which does not coincide with the literature (where typically women do prefer men that are higher educated than themselves). Nevertheless, it does reflect the fact that in our data set, there are more couples belonging to the category where the wife is higher educated than the husband in comparison to the opposite category.

Looking at race, a much stronger homogamy preference is present for both sexes compared to the preference of homogamy in education.

Work in progress.

7. Counterfactual analyses

Work in progress.

8. Conclusion

In conclusion, this paper delves into the intricate dynamics of individuals navigating the marriage market, exploring the profound trade-offs they make between partner characteristics (i.e., race and education) and terms of marriage (i.e., bargaining power). The study employs a two-sided directed search model to disentangle male and female preferences in their pursuit of love, acknowledging the competitive environment that shapes their decisions.

Contrary to the initial expectation that individuals would exclusively seek partners aligning with their preferred terms, there might be some instances where individuals willingly accept less-favorable conditions. This readiness stems from a desire to attract a more desirable partner or, in some cases, from possessing characteristics perceived as less desirable. Notably, the model emphasizes that individuals can strategically direct their search toward markets with either favorable or less favorable terms of marriage.

The study further underscores the interplay between gender ratios and relationship dynamics, showing that variations in the supply of males and females across different types have a direct impact on the equilibrium distribution of relationships. The identification power of the model comes from existing variation in gender ratios across regions in the US, aligning with previous research indicating the influence of gender ratios on bargaining power between spouses.

The directed search model, with its fixed terms of marriage and inclusion of market competition, presents several modeling advantages over the traditional random search framework. Notably, it allows for the separate identification of individual-specific preferences for partner characteristics and terms of marriage. Additionally, the paper is bridging the gap in existing research, where little work is done in which a directed search model is applied to the marriage market. A novel aspect of this study is the incorporation of the collective household literature to define the terms of marriage. By examining the distribution of bargaining power within households, the research sheds light on the far-reaching consequences of intra-household inequality, emphasizing the importance of understanding and representing bargaining power empirically.

The empirical estimation of the model relies on a sample drawn from the American Community Survey, providing a comprehensive exploration of the marriage market dynamics based on real-world data from 2015 to 2019. Through this thorough investigation, the paper contributes valuable insights to the ongoing discourse on marriage market behavior and preferences, enriching our understanding of the complexities involved in the pursuit of true love.

Work in progress.

Appendix

A. Elasticity of the probability of matching wrt the gender ratio

In this part of the appendix, the elasticity of the probability of matching with respect to the gender ratio G_{mf} will be derived for men and women in the $\{m, f, r\}$-market, with $G_{mf} = N_m/N_f$, in order to enhance the intuition of relationship *iii*) of Proposition 1. To reach this goal, take first the logarithm of the matching probability P_m^{fr} as defined in equation 6, as it is easier to work with (similar reasoning will hold for P_f^{mr}). Doing so, the following is obtained:

$$
\begin{aligned}
\ln P_m^{fr} &= \ln\left(\frac{A[(\phi_m^{fr}N_m)^\rho + (\phi_f^{mr}N_f)^\rho]^{1/\rho}}{\phi_m^{fr}N_m}\right)\\
&= \ln\left(A[(\phi_m^{fr}N_m)^\rho + (\phi_f^{mr}N_f)^\rho]^{1/\rho}\right) - \ln\left(\phi_m^{fr}N_m\right)\\
&= \ln A + \frac{1}{\rho}\ln\left((\phi_m^{fr}N_m)^\rho + (\phi_f^{mr}N_f)^\rho\right) - \ln\left(\phi_m^{fr}N_m\right)\\
&= \ln A + \frac{1}{\rho}\ln\left((\phi_m^{fr}N_m)^\rho\right) + \frac{1}{\rho}\ln\left(1 + \frac{(\phi_f^{mr}N_f)^\rho}{(\phi_m^{fr}N_m)^\rho}\right) - \ln\left(\phi_m^{fr}N_m\right)\\
&= \ln A + \frac{1}{\rho}\ln\left(1 + \left(\frac{\phi_f^{mr}}{\phi_m^{fr}}\right)^\rho G_{mf}^{-\rho}\right).
\end{aligned}
$$

Subsequently, take the derivative of the logarithm of the matching probability with respect to the gender ratio for men in the $\{m, f, r\}$-market to reach the following:

$$
\begin{aligned}
\frac{\partial \ln P_m^{fr}}{\partial G_{mf}} &= \frac{1}{\rho}\frac{1}{1 + \left(\frac{\phi_f^{mr}}{\phi_m^{fr}}\right)^\rho G_{mf}^{-\rho}}\left(\frac{\phi_f^{mr}}{\phi_m^{fr}}\right)^\rho (-\rho)G_{mf}^{-\rho-1}\\
&= -\left[\frac{\left(\frac{\phi_f^{mr}}{\phi_m^{fr}}\right)^\rho G_{mf}^{-\rho-1}}{1 + \left(\frac{\phi_f^{mr}}{\phi_m^{fr}}\right)^\rho G_{mf}^{-\rho}}\right]\\
&= -\left[\frac{1}{\left(\frac{\phi_f^{mr}}{\phi_m^{fr}}\right)^\rho G_{mf}^{-\rho-1}} + \frac{\left(\frac{\phi_f^{mr}}{\phi_m^{fr}}\right)^\rho G_{mf}^{-\rho}}{\left(\frac{\phi_f^{mr}}{\phi_m^{fr}}\right)^\rho G_{mf}^{-\rho-1}}\right]^{-1}\\
&= -\left[\left(\frac{\phi_f^{mr}}{\phi_m^{fr}}\right)^{-\rho} G_{mf}^{\rho+1} + G_{mf}^{-\rho+\rho+1}\right]^{-1}\\
&= -\left[\left(\frac{\phi_m^{fr}}{\phi_f^{mr}}\right)^{\rho} G_{mf}^{\rho+1} + G_{mf}\right]^{-1}
\end{aligned}
$$

In doing a similar exercise to obtain the elasticity of the matching probability with respect to the gender ratio for women in the $\{m, f, r\}$-market, the following is obtained:

$$\frac{\partial \ln P_f^{mr}}{\partial G_{mf}} = \left[\left(\frac{\phi_f^{mr}}{\phi_m^{fr}} \right)^{\rho} G_{mf}^{-\rho+1} + G_{mf} \right]^{-1}.$$

Simple numerical example - Let's examine the case in which the gender ratio G_{mf} is equal to 1. In this scenario, the search probabilities for an m-type man searching on the $\{f, r\}$-market and $\{f, r'\}$-market are both 0.5. Similarly, the search probabilities for an f-type woman on the $\{m, r\}$-market and $\{m, r'\}$-market are 0.5 and 0.6, respectively. Lastly, assume ρ is equal to -2. In this example, $\phi_f^{mr}/\phi_m^{fr} = 1 < 1.2 = \phi_f^{mr'}/\phi_m^{fr'}$, indicating that women of an $\{m, f\}$-pair do prefer r' over r relatively more than men of the same pair. The following is obtained for the m-type men of the $\{m, f\}$-pair:

$$\frac{\partial \ln P_m^{fr}}{\partial G_{mf}} = -\left[\left(\frac{\phi_m^{fr}}{\phi_f^{mr}} \right)^{\rho} G_{mf}^{\rho+1} + G_{mf} \right]^{-1} = -0.5 < -0.41 = -\left[\left(\frac{\phi_m^{fr'}}{\phi_f^{mr'}} \right)^{\rho} G_{mf}^{\rho+1} + G_{mf} \right]^{-1} = \frac{\partial \ln P_m^{fr'}}{\partial G_{mf}},$$

while the following is obtained for f-type women of the $\{m, f\}$-pair:

$$\frac{\partial \ln P_f^{mr}}{\partial G_{mf}} = \left[\left(\frac{\phi_f^{mr}}{\phi_m^{fr}} \right)^{\rho} G_{mf}^{-\rho+1} + G_{mf} \right]^{-1} = 0.5 < 0.59 = \left[\left(\frac{\phi_f^{mr'}}{\phi_m^{fr'}} \right)^{\rho} G_{mf}^{-\rho+1} + G_{mf} \right]^{-1} = \frac{\partial \ln P_f^{mr'}}{\partial G_{mf}}.$$

This result provides the intuition of relationship $iii)$ of Proposition 1. For $\rho < 0$, if G_{mf} increases, the decrease in matching probability for men will be smaller in the r'-market compared to the r-market, while the increase in matching probability for women will be larger in the r'-market compared to the r-market. Thus, for any values for G_{mf}, ϕ_m^{fr}, ϕ_f^{mr}, $\phi_m^{fr'}$, and $\phi_f^{mr'}$, and as long as $\rho < 0$, increasing the relative number of men compared to women makes the market where women hold a relative preference more appealing to both genders. Consequently, both sexes shift towards that market in equilibrium.

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