Gender and Academic Hiring: Evidence from a Two-Sided Matching Model[1]

Peter Slade
Ph.D. Candidate
Food, Agricultural and Resource Economics
University of Guelph
pslade@uoguelph.ca

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Females in the North America have long been subject to labour market discrimination (Goldin and Polachek, 1987).[2] While significant gender differences remain in high status positions[3], affirmative action policies have led many to argue that females and minorities are now the recipients of "positive discrimination" (Benatar, 2010). Yet few studies have analyzed the existence or size of gender preferences in hiring. One reason for this gap in the literature is that gender differences in employment can be attributed to either gender discrimination or differences in preferences.

To address this issue this paper develops a model of two-sided matching with non-transferable utility that estimates preferences (utility functions) for both job candidates and employers. The estimator is then employed on a data set of PhD graduates in economics matching into their initial jobs. Identification of the model relies on an identification at infinity argument, similar in spirit to those invoked for discrete games (Tamer, 2003; Bajarai, Hong, and Ryan, 2010). The identification argument is illuminated by the following example: say we observe two PhD graduates who are hired at two different schools in the same year. Allow that the impact factor weighted publications of one of these graduates goes to infinity as the other's remains at some finite level. Then one could safely assume the graduate with the infinitely large publication record was the preferred candidate of both the school where she was hired *and* the school where her peer was hired. Thus her observed choice of departments reveals information about her preferences. A similar argument can be used to identify the preferences of departments over differing candidates. Estimation of the model is done through maximum score estimation which builds upon the strategy of Fox (2010b), who studies matching markets with transferable utility.

Previous work on the hiring of PhD economists found significant gender differences in hiring and promotion. Kolpin and Singell (1996), in a sample of AEA members spanning from 1973 to 1989, find that higher ranked departments are less likely to hire women. McMillen and Singer (1994) find that women are less likely to be found in top 50 economics departments. My data set covers PhD recipients in economics between 1990 and 2004. During this time period most schools enacted employment equity policies that precluded discrimination based on gender. My findings reveal that the hiring decisions of universities are largely consistent with these policies; gender has

[2]There is some argument as to the extent of this discrimination when factors such as unobserved ability (Becker, 1985), and preferences for non-work activities (i.e. child raising) are considered (Waldfogel, 1998).

[3]For example just women comprise just 4% of Fortune 500 CEOs, 17% of congress people, and 22% of federal judges.

a statistically and economically insignificant effect on hiring.

The impact of gender on hiring and promotion has become an increasingly important issue within economics. According to annual surveys of the Committee on the Status of Women in the Economics Profession (CSWEP), females accounted for only 11% of full professors (and 28% of assistant professors) in PhD granting economics departments in 2010, up from 7% (and 21%) in 2000 and 4% (and 17%) in 1990.[4] It has been suggested that the lack of female representation has led to a bias in research[5], lower research productivity[6], and a path dependency whereby a lack of female role models dissuades female students from entering the profession.[7]

Positive steps to redress this bias have been advocated by professional associations[8], prominent members of the profession, and university administrators. Since the 1960s the US government has enacted policies ensuring at least equal treatment of women and minorities. Although the government hasn't extended affirmative action laws to universities (as they have for government contractors), civil rights laws put the burden on the employer to prove the non-existence of discriminatory policies in the face of a gender imbalance in hiring. To avoid this type of legal action, it is in the interest of universities to maintain a gender balance, or at least to maintain policies that ensure no accusation of bias in the hiring process could be levelled (Rai and Critzer, 2000).

Recent literature has raised the possibility of a preference for female candidates in academic hiring. Friedman (1998) suggests that while females were once the subject of discrimination, "the pendulum has probably swung too far so that men are the ones currently being discriminated against" [p. 199]. Ginther and Kahn (2004) explain that the discrepancy between the number of assistant and full professors in economics *may* be the result of affirmative action policies at the time of hiring which are not carried through in the tenure and promotion phase.

Previous research on gender differences in the initial hiring of academic economists is mixed.

[4]These are voluntary surveys and therefore subject to some self-reporting bias.

[5]Ferber (1995) argues the lack of interest in topics such as household economics and the causes and consequences of women's entry into the labour market, are indicative of this bias.

[6]Page (2007) suggests that environments with more diversity result in more effective group decision making and higher creative output.

[7]Evidence for this proposition is mixed. Hale and Regev (2011) shows that women are more likely to enter graduate studies in a department that has a higher proportion of female professors. Dynan and Rouse (1997); Jensen and Owen (2001) both find that having a female instructor for introductory economics courses does not encourage females to major in economics.

[8]As an example, the American Economics Association created CWEP in 1971 with a mission "to eliminate discrimination against women, and to redress the low representation of women, in the economics profession." (http://www.aeaweb.org/committees/cswep/mission.php). Similar committees are supported by the Applied and Agricultural Economics Association and the European Economic Association

McMillen and Singer (1994), use a mutlinomal logit model to estimate the probability of PhD graduates placing in one of five job types: (1) top 50 economics department, (2) non-top 50 economics department, (3) other academic departments, (4) government and (5) private sector (which include not for profit organizations). Using data from the 1989 AEA membership directory, they find gender to have no impact on the total probability of selecting into any of these five categories. Kolpin and Singell (1996), use data from earlier AEA member directories to find that the ranking of an economics department was inversely correlated with the hiring of a female assistant professor. This contradicts descriptive statistics from Ginther and Kahn (2004) whose data, taken from a sample of assistant professors in 1989, show that a higher percentage of female academic economists are in both top 6 and top 15 departments, compared to male counterparts.

While these papers use some form of discrete choice model, they differ significantly in their motivation. McMillen and Singer (1994) motivate their multinomial logit model through a random utility model in which the job candidate chooses their initial placement. Conversely, Kolpin and Singell (1996) seem to suggest that the choice of whether or not to hire a female professor is entirely up to the university. There is good reason for the inelegance with which these discrete choice models are motivated, and their results are interpreted. Simply put, it is the wrong model. The initial placement of a graduate is the result of a discrete choice by both the candidate and the university.

Not only may gender impact the choices of the University, a job candidate's preferences may also be influenced by their gender. Women in patriarchal societies, are relatively more risk averse (Croson and Gneezy, 2009), and tend gravitate to jobs that are less competitive, stress interpersonal skills and offer a greater work-life balance (Konrad et al., 2000). If this generalized to the academic job market, one would expect to see women exhibit a greater preference for positions that offer greater job security (i.e. a higher probability of attaining tenure), greater interaction with students and faculty, and less pressure to compete through publications. In a survey of PhD students near graduation, Barbezat (1992) found that women exhibited a stronger preference for employment in liberal arts colleges, while men exhibited a stronger preference for employment in top economics or business departments.[9] My results however show no significant differences in preferences of women and men.

[9] While assumed exogenous in this paper, these preferences may be a function of the current distribution of female faculty, and gender stereotypes within the profession. Konrad et al. (2000, p 594) note that, "Changing one's preferences to conform to alternatives that are realistically available reduces the tension caused by frustrated desires."

The two-sided matching model is able to account for both the preferences of universities and candidates.[10] One can think of matching as the product of a discrete choice made by both the university and the candidate. The choice set that faces each university is the set of all candidates that prefer this university to their current match (the choice set of a candidate can be similarly defined.) Empirically, there is a surprisingly small literature on matching models. Much of the matching literature deals with aggregate matching, based on agent types. Choo and Siow (2006) study marriage in the context of transferable utility. Building on the previous work of Dagsvik (2000), Choo and Siow use a logit specification to transform the matching problem into one of supply and demand for agent types. In a two step procedure they find the transfers between agent types that will clear the market, and then find the parameters that rationalize these transfers. Hsieh (2011) adapts this framework to a non-transferable utility setting. Hsieh defines a modified deferred acceptance algorithm, for aggregate types, then finds preferences that rationalize the male and female optimal stable matching.

Other papers have studied non-transferable utility matching games using micro-data. Boyd et al. (2012) use a simulated method of moments estimator, to study the matching of teachers to schools in New York State. The moment condition is based on minimizing differences between the actual characteristics of matches and the estimated matches based on a school-optimal Gale-Shapley algorithm. Logan, Hoff, and Newton (2008) employ a Bayesian approach to estimation, which is based on estimating the parameters that maximize the probability of a stable matching. Sørensen (2007) also uses a Bayesian approach to estimation, while restricting the payoff function to ease computational burdens. Each of these papers rely on assumptions on the equilibrium selection mechanism: Boyd et al. (2012) assume the equilibrium is the optimal outcome for one side of the market, Logan, Hoff, and Newton (2008) assume the most probable equilibrium will be the result. None study formally study identification of these parameters.

Fox (2010b,a), studies identification and estimation of matching games with transfers. When transfers are introduced to matching games, analysis centres on the joint production of matching. The joint production function can also be thought of as the sum of the utility functions of the man and woman who have matched. Given the ability to transfer, the joint production of a

[10] This being said whether the impact of gender on both sides of the market can be identified is a non-trivial question.

one-to-one matching must maximize social production. This is quite a different assumption than underlies matching with non-transferable utility. While some have argued that transfers are simply a fiction that serve to reduce computational complexity (WHO), the assumption has empirical consequences. Most importantly, assuming transferability precludes identification of parameters that are not match-specific.

The rest of this paper proceeds largely in two parts. The first three sections discuss identification and estimation of matching models with non-transferable utility; the first section introduces a two-sided matching model with non-transferable utility, the second section provides a proof of identification, and the third discusses the estimation procedures. The next three sections pertain to the problem of academic hiring; the fourth section provides information on the academic labour market, the fifth introduces the data and the sixth discusses estimation results. The seventh section concludes the paper.

1 Two-sided matching models

Matching markets can be characterized either by *transferable*, or *non-transferable* utility. In markets with transferable utility, agents can transfer their utility to their match. For example in a supply chain upstream and downstream firms can transfer profit through the price mechanism (see Fox (2010b)). The assumption of transferable utility is less applicable to the present context. Transferable utility would imply that a lower qualified candidate could displace a highly qualified candidate at a top ranked department if they offered to take a lower salary. Universities are unlikely to accept such a proposal. Academics are highly protective of their reputation, which is in turn a function of their department's reputation. Hiring a candidate of lower quality would harm the reputation of the department, thus department members are likely to hire the best candidate they can afford within their budget. According to Ehrenberg, Pieper, and Willis (1998), starting salaries in PhD granting economic departments are fairly homogenous, due perhaps to institutional norms, faculty unions, or collusion by departments.

Matching markets can further be subdivided by the number of agents that form a match. The model developed herein is of one-to-one matching. Alternatively, matching markets could be characterized as one-to-many, such as when many students match to one and only one school, or many-to-many, such as when firms partner in a supply chain. Although some schools hire multiple candidates in some years, I assume that these decisions are independent, and thus no violence is done to the assumption of one-to-one matching. This section serves to define the concept of a one-to-one matching market with non-transferable utility, as first discussed by Gale and Shapley (1962), and neatly overviewed by Roth and Sotomayor (1990).

Let us define the set of departments as $\mathscr{D} = \{d_1, d_2, ..., d_D\}$, and the set of candidates as $\mathscr{C} = \{c_1, c_2, ..., c_C\}$. Departments have observable characteristics $\boldsymbol{X} = \{X_{d_1}, X_{d_2}, ..., X_{d_D}\}$, and candidates have observable characteristics $\boldsymbol{Z} = \{Z_{c_1}, Z_{c_2}, ..., Z_{c_C}\}$. Further, there are match specific characteristics which are specific to a matching of a particular candidate and department that are denoted, $\boldsymbol{\Psi} = \{\Psi_{d_1,c_1}, ..., \Psi_{d_D,c_1}, \Psi_{d_1,c_2}, ..., \Psi_{d_D,c_2}, ..., \Psi_{d_D,c_C}\}$. Subsets of these match specific characteristics, $\boldsymbol{\Xi_{c,d}}$, $\boldsymbol{\Phi_{c,d}} \subset \boldsymbol{\Psi_{c,d}}$, are of importance to departments and candidates respectively. Allow that the ith department, receives utility u_{d_i,c_j} from matching with the jth candidate, and receives utility u_{d_i,d_i} from remaining single, where,

$$u_{d_j,c_i} = \gamma_1 X_{c_i} + \gamma_2 Z_{d_j} + \gamma_3 \Xi_{c_i,d_j} + \eta^1_{ji} \tag{1}$$
$$u_{d_j,d_j} = \gamma_4 Z_{d_j} + \eta^0_j \tag{2}$$

where η^1_{ij}, and η^0_i are drawn independently from F_η, a mean zero distribution. Similarly, we can write the respective utilities the jth candidate receives from matching with the ith department, and remaining single as,

$$u_{c_i,d_j} = \beta_1 Z_{d_j} + \beta_2 X_{c_i} + \beta_3 \Phi_{c_i,d_j} + \epsilon^1_{ij} \tag{3}$$
$$u_{c_i,c_i} = \beta_4 X_{c_i} + \epsilon^0_i \tag{4}$$

where ϵ^1_{ij}, and ϵ^0_i are both drawn independently from F_ϵ, a mean zero error term. To rule out indifference, assume that both departments and candidates have at least one characteristic that is absolutely continuous with no atoms, and an associated coefficient not equal to zero.

The assumption of match-specific errors is potentially restrictive, though it is in keeping with previous work on matching with non-transferable utility (Logan, Hoff, and Newton, 2008; Boyd et al., 2012), and represents a relaxation of the assumptions that are commonly employed in matching games with transfers. In the estimation of matching games with transfers authors who have used aggregate data have assumed that each individual of a certain type has an equivalent unobserved utility for each member of the opposite type (Graham, 2011). Alternatively, Fox (2010b,a) using micro-data, relies on assignment specific errors, where an assignment is a set of two matches.

Let's now define a matching function, μ, that maps from the set of departments and candidates unto itself, $\mu : \mathscr{D} \cup \mathscr{C} \to \mathscr{D} \cup \mathscr{C}$. The matching function maps from every agent to their mate, or back to itself if the agent is single; $\mu(d_i) \in \mathscr{C} \cup d_i$. Pairwise stability implies that a department chooses its most preferred candidate, from all the candidates that prefer that department to their current mate, or decides to remain single,

$$\mu(d_i) = \arg\max_{x \in \mathscr{E}_{d_i}} u_{d_i,x} \tag{5}$$

where,

$$\mathscr{E}_{d_i} = \{c_j \in \mathscr{C} | u_{c_j,d_i} \geq u_{c_j,\mu(c_j)}\} \cup d_i. \tag{6}$$

where $\mathscr{E}_{d_i}$ represents the choice set that faces the ith department ($\mathscr{E}_{d_i}$ contains the set of all candidates that prefer the department to their equilibrium match and the choice to remain single). Similarly, a candidate chooses the department she prefers from her choice set, which consists of all departments who prefer her to their equilibrium match, and the choice to remain single.

An equilibrium, or stable, matching relies on individual rationality and pairwise stability. Individual rationality implies that in equilibrium no agent would prefer to remain single, then match with their equilibrium mate. Pairwise stability implies that no unmatched agents from opposite sets, would prefer to match together than with their current mates. The literature typically refers to such matchings as pairwise stable.

Gale and Shapley (1962) show that a stable matching always exists, although it is not necessarily unique. Importantly, for identification and estimation, the pairwise stability of a market implies the pairwise stability of every submarket, where a submarket is a some subset of matches from the larger market. In estimation I focus attention on submarkets composed of two matches.

1.1 Multiple equilibria

Matching games with non-transferable utility frequently have a large number of equilibria. In practice it is computationally infeasible to calculate all possible equilibria in large matching games. However, we can use the property that a pairwise stable matching implies stability in all subsets of the market. Particularly, we can focus attention on sets of two different matches - be they matchings of two agents, or one agent's decision to remain single. For expositional purposes the following discussion assumes no agent remains single, though it can be added with little complication, and is formally treated in the identification argument of the following section.

Consider matching market with two departments and two candidates. The ith department-prefers candidate 1 to candidate 2 if,

$$\delta_{d_i,1-2} > \epsilon_{d_i,2-1} \tag{7}$$

where $\delta_{d_i,2-1}$ is the difference in deterministic utility the ith department receives from candidate 1 vis-a-vis candidate 2,

$$\delta_{d_i,1-2} = \beta_1(Z_{c_1} - Z_{c_2}) + \beta_3(\Xi_{d_i,c_1} - \Xi_{d_i,c_2}) \tag{8}$$

and $\epsilon_{d_i,2-1}$ is the difference in the stochastic utility the ith department receives from the two candidates,

$$\epsilon_{d_i,2-1} = \epsilon_{d_i,c_2} - \epsilon_{d_i,c_1}. \tag{9}$$

Similarly the conditions under which jth candidate prefers department 1 to department 2 is given by,

$$\delta_{c_j,1-2} > \eta_{c_j,2-1} \tag{10}$$

where $\delta_{c_j,1-2}$ is the difference in deterministic utility the jth candidate receives from department 1 and department 2 respectively, and $\eta_{c_j,2-1}$ is the difference in stochastic utility she receives from these departments.

Note that only two matchings are possible; $\mu \in (\{(d_1, c_1), (d_2, c_2)\}, \{(d_1, c_2), (d_2, c_1)\})$. For notational simplicity let's denote the matchings as $\mu_1 = \{(d_1, c_1), (d_2, c_2)\}$ and $\mu_2 = \{(d_1, c_2), (d_2, c_1)\}$, and define the set of possible matches as $\Omega = \{\mu_1, \mu_2\}$. The probability of μ_1 being uniquely predicted by the model is,

$$
\begin{aligned}
\Pr\left(\Omega = \mu_1)\right) &= \Pr\big((\delta_{d_1,1-2} > \epsilon_{d_1,2-1} \cap \delta_{c_1,1-2} > \eta_{c_1,2-1}) \cup \\
&\quad (\delta_{d_2,2-1} > \epsilon_{d_2,1-2} \cap \delta_{c_2,2-1} > \eta_{c_2,1-2})\big) \qquad (11)
\end{aligned}
$$

The equilibrium matching of department 1 and candidate 1 is unique only when department 1 and candidate 1 are each others preferred match, or department 2 and candidate 2 are each others preferred match. The probability of the model predicting multiple equilibria as,

$$
\begin{aligned}
\Pr(\Omega = \{\mu_1, \mu_2\}) &= \Pr((\delta_{d_1,1-2} - \epsilon_{d_1,2-1}) * (\delta_{d_2,2-1} - \epsilon_{d_2,2-1}) < 0 \cap \\
&\quad (\delta_{c_1,2-1} - \eta_{c_1,1-2}) * (\delta_{c_2,1-2} - \eta_{c_2,2-1}) < 0). \qquad (12)
\end{aligned}
$$

Multiple equilibria only occur when both men and both women differ in their ranking of their opposites. Therefore the probability of observing the outcome $\mu(m_1) = w_1$, is,

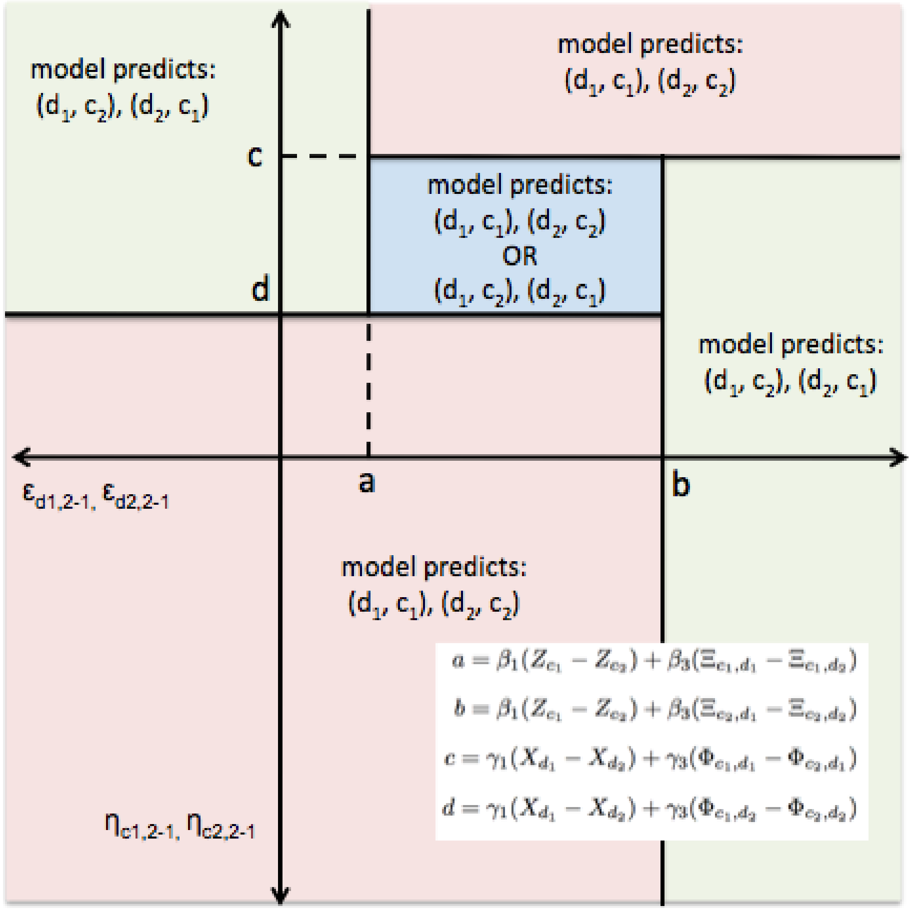
$$
\Pr(\mu_1) = \Pr(\Omega = \mu_1) + \Pr(\Omega = \{\mu_1, \mu_2\})\lambda(\mu_1|\Omega = \{\mu_1, \mu_2\}) \qquad (13)
$$

where $\lambda(\mu_1|\Omega = \{\mu_1, \mu_2\})$ is the probability of μ_1 being selected from the two equilibria. The regions where the model predicts unique and multiple equilibria are outlined in figure 1.

The probability of multiple of equilibria in this four agent matching game is related to the correlation of preferences. By equation 12, multiple equilibria can only exist when both candidates have different rankings of departments, and both departments have different rankings of candidates. Thus if match specific characteristics and stochastic elements, play a small role in the utility functions, then multiple equilibria will be rarely predicted.

A broad literature on estimation of discrete games has employed four broad strategies to deal with the presence of multiple equilibria. First, an *ad hoc* assumption on the selection mechanism can be imposed. For example in the matching literature, Boyd et al. (2012) assume the equilibrium is the result of a Gale-Shapley algorithm. A second approach restrict attention to estimating joint

Figure 1: Diagram of model predictions



probabilities of certain equilibria, as done by Breshnahan and Reiss (1990, 1991) in entry games. A third method is to remain agnostic as to the equilibrium selection mechanism, and estimate bounds on the probability of certain equilibria, which in turn set identifies the parameters of the model (Ciliberto and Tamer, 2009). Finally, when multiple equilibria are present one can estimate the probability of a particular equilibrium being selected (Bajarai, Hong, and Ryan, 2010).

The identification argument of the next section demonstrates that in principle one can identify parameters of the utility function without identifying the equilibrium selection mechanism. In principle, one could also identify parameters of the equilibrium selection mechanism. In matching models it may be of particular interest which side of the market is more powerful. In this particular application I assume that the market follows a form of the deferred acceptance algorithm in which departments make offers to candidates. Thus I assume that school-optimal equilibrium will always be selected (as the deferred acceptance algorithm would predict). In future research this assumption could be tested and relaxed.

2 Identification

No previous paper has examined identification of parameters in matching markets with non-transferable utility with micro-data. In this section I show the parameters $\beta_1, \beta_3, \gamma_1, \gamma_3$ of the utility functions in equations 1-4 are identified. Furthermore, we can identify $\beta_2 - \beta_4, \gamma_2 - \gamma_4$ from these equations.

To summarize the argument of this section, I assume there exists a match-specific characteristic in each department's utility function that is absolutely continuous, with everywhere positive support and an associated coefficient greater than zero. I further assume this characteristic is orthogonal to all errors, and to each characteristic in the candidate utility function. I then focus attention on the covariate values where a set of departments prefer a particular candidate to their observed matches with probability approaching one. This implies that the candidate in question is free to choose any department in this set, as opposed to her actual match. By varying the covariates of the preferred candidate's utility functions (equations 1 and 2) we can identify the parameters of this function. A similar argument can be used to identify the parameters of the department utility function (equation 3 and 4).

The identification results previously summarized rely on certain assumptions common to identification in the discrete choice and discrete game literature.

Assumption 1. An iid random sampling of matches is observed.

Assumption 2. F_η and F_ϵ are absolutely continuous with mean zero, and unknown finite variance.

Assumption 3. There is a special regressor $\xi^*_{d,c}$ in the department utility function that is orthogonal to $\Phi_{d,c}$, Z_d, X_c, and all errors. ξ^* is absolutely continuous, and with positive support on some interval $[a, \infty]$, or $[-\infty, a]$, where a is some constant. Define a $\zeta^*_{d,c}$ in the female utility function with the same type of distribution, orthogonal to $\Xi_{d,c}$, X_d, Z_c and all errors.

Assumptions 1 and 2 are common in discrete choice literature. The third assumption defines a "special regressor" that has a strictly positive probability of taking extreme values, which is crucial to identification at infinity arguments. It is further essential that the special regressor in the department utility function not be included or strongly correlated with a regressor in the candidate utility function. If this were not so, then as the special regressor tended to infinity both utility functions would be driven to infinity, robbing us of identification. We are now ready to prove identification.

Theorem 1. Assumptions 1-3 hold. $(\beta_1, \beta_3, \gamma_1, \gamma_3)$ are identified. We cannot separately identify β_2 and β_4, nor γ_2 and γ_4, however, we can identify $(\beta_2 - \beta_4, \gamma_2 - \gamma_4)$

Proof. With no loss of generality, define our special regressor as $\xi^*_{c,d}$, and the associated coefficient $\beta^*_3 > 0$. Define $(b_1, b_3) \neq (\beta_1, \beta_3)$. As $\xi^*_{c_j,d_i} - \xi^*_{\mu(d_i),d_i}$ goes to infinity, for any i and j, both $u_{d_i,c_j}(\beta_1, \beta_3) - u_{d_i,\mu(d_i)}(\beta_1, \beta_3)$, and $u_{d_i,c_j}(b_1, b_3) - u_{d_i,\mu(d_i)}(b_1, b_3)$ tend to infinity. Which implies that d_i prefers c_j to its current mate, or in probabilistic terms

$$\lim_{\xi^*_{c_j,d_i} \to \infty} Pr(u(d_i, c_j) > u(d_i, \mu(d_i)) = 1. \tag{14}$$

The distributional assumptions on $\xi^*_{c_j,d_i}$, ensures that asymptotically, some set of departments will prefer a candidate to their observed match with probability approaching 1. Let's define this set of departments as,

$$\mathscr{S}^0_{c_j} = \{d_i \in D | \xi^*_{c_j,d_i} - \xi^*_{\mu(d_i),d_i} \to \infty\}. \tag{15}$$

The candidate in question may have other departments that she can choose from (that is to say there are some departments who may prefer this candidate to their equilibrium match, though not *infinitely* more.) Thus $\mathscr{S}^0_{d_j}$ is a subset of the candidates's true choice set.

Let us define two other choice sets, which we can use for identification. The first choice set, $\mathscr{S}^1_{d_j}$, applies only to candidates who are not single in equilibrium, and will allow us to identify γ_1 and γ_3. The second choice set, $\mathscr{S}^2_{d_j}$, applies to all candidates, and allows us to identify $\gamma_2 - \gamma_4$. The choice sets are defined as,

$$\mathscr{S}^1_{c_j} = \mathscr{S}^0_{c_j} \cup \mu(c_j) \text{ where } \mu(c_j) \neq c_j \tag{16}$$

and

$$\mathscr{S}_{c_j}^2 = \mathscr{S}_{c_j}^0 \cup \mu(c_j) \cup c_j. \tag{17}$$

Both sets contain the subset $\mathscr{S}_{c_j}^0$, and the candidates match $\mu(c_j)$ provided the candidate is not single. The set $\mathscr{S}_{c_j}^2$, also contains the choice of remaining single. Again, both sets are subsets of the actual choice set that a candidate faces, $\mathscr{S}_{c_j}^i \subseteq \mathscr{E}_{c_j}$. Nonetheless, we can use these subset of choices to identify the parameters of the candidate's utility function. Identification when observing a subset of actual choices was demonstrated by McFadden (1978), who assumed errors follow an extreme value type 1 distribution. More recently, Fox (2007) proved this result for semi-parametric functions, with minimal assumptions on the error term.

Consider first the identification of γ_1 and γ_3. Using the choice set $\mathscr{S}_{c_j}^1$, it is easy to see that for $c_i, c_k \in \mathscr{S}_{c_j}^1$,

$$\beta_1 Z_{d_i} + \beta_3 \Phi_{c_j,d_i} > \beta_1 Z_{d_k} + \beta_3 \Phi_{c_j,d_k} \rightarrow P(d_i = \mu(c_j)) > P(d_k = \mu(c_j)) \tag{18}$$

That is to say, that if the deterministic utility that candidate j derives from department i is greater than that she derives from department k, then conditional on both departments being in her choice set there is a higher probability of her choosing department i. Identification of parameters then follows from Manski (1975) (see Fox (2007) for a discussion of identification when only a subset of choices are observed.)

Having identified γ_1 and γ_3, we can then turn attention to $\gamma_2 - \gamma_4$. To do so we consider the choice set $\mathscr{S}_{d_j}^2$, and in particular compare the choice of whether to remain single, against the choice of matching with any particular man,

$$\beta_1 Z_{d_i} + (\gamma_2 - \gamma_4) X_{c_j} + \gamma_3 \Phi_{c_j,d_i} > 0 \rightarrow P(d_i = \mu(c_j)) > P(c_j = \mu(c_j)). \tag{19}$$

Again, if the deterministic utility from matching outweighs the deterministic utility from remaining single, than we should observe a higher probability of matching in the data (and vice-versa). Once again identification follows relatively standard discrete choice arguments. Using identical arguments we can identify parameters of the male utility function $(\beta_1, \beta_3, \beta_2 - \beta_4)$. $\square$

The above proof is quite similar to the analysis of simultaneous discrete response models in Tamer (2003). It differs from previous identification arguments in matching and network formation games (Hsieh, 2011; Sheng, 2012), in that it sidesteps the problem of multiple equilibria by focusing on regions where certain actors face a discrete choice. Thus in theory multiple equilibria is not a problem for identification. With limited data however, point identification of the parameters may be infeasible.

The following example clarifies the identification argument. Assume there is a matching market of only two candidates and two departments. As the impact factor weighted publications of one candidate goes to infinity it is clear that she will be preferred by both departments, and thus her choice conveys information regarding her preferences. Conversely, as the ranking of one department increases vis-a-vis the other, it becomes clear that both candidates would prefer the higher ranked department. The highly ranked department therefore has its choice of candidates, which will reveal information about its preferences.

One could also in principle identify parameters governing the equilibrium selection mechanism. Let us define the mechanism as $\lambda = \lambda(W, \alpha)$, where W is some equilibrium feature, for example W may include such information as whether the equilibrium is department or candidate optimal, or the proximity of departments (which might influence their ability to collude), and α is a set of parameters. Identification of equations 1 - 4 do not rely on identification of the selection mechanism, and thus our problem becomes distinguishing the true value of α from some alternate value (say a), given identification of the previous parameters. Following Bajarai, Hong, and Ryan (2010), this could be done using a minimum distance procedure with slightly stronger assumptions on the error term.

Instead of estimating the selection mechanism one could treat λ as an unknown nuisance parameter, and pursue set identification using a non-parametric sieve to estimate λ. Alternatively, one could employ an *ad hoc* assumption on the equilibrium selection mechanism. In my empirical application I employ such an assumption, by assuming that the department optimal equilibrium is always played.

3 Estimation

Suppose that we observed a series of independent matching markets, each with two men and two women and no singletons. Adopting the notation of section 1.1, let the observed matching be $\mu_1 = \{m_1, w_1\}, \{m_2, w_2\}$. Further let us define ρ_i as the probability that agent i prefers their mate to the alternative. For example, $\rho_{m_1}(\gamma_1, \gamma_3)$ denotes the probability that m_1 prefers w_1 to w_2, conditional on the parameters γ_1 and γ_3. Suppressing dependence on γ, β, the probability of μ_i being observed in the data is,

$$\begin{aligned} Pr(\mu_i) &= \rho_{d_1}\rho_{c_1} + (1 - \rho_{d_1}\rho_{c_1})\rho_{d_2}\rho_{c_2} \\ &+ \int \lambda(W)\{\rho_{d_1}\rho_{d_2}(1 - \rho_{c_1})(1 - \rho_{c_2}) + (1 - \rho_{m_1})(1 - \rho_{m_1})\rho_{w_1}\rho_{w_2}\}dg(y), \end{aligned} \tag{20}$$

where λ is the equilibrium selection mechanism, that is conditioned on W, where W represents characteristics of the equilibrium

Equation 20, gives rise to an extremum estimator that aggregates across markets. If one were willing to impose distributional assumptions on the error terms, ρ_i could be estimated using a binomial logit or probit estimator, and the probabilities aggregated to achieve a likelihood score. In contrast, I chose to impose minimal distributional assumptions on the error term using a two-step maximum score estimator. In the first step I estimate $\beta_1, \beta_3, \gamma_1, \gamma_3$, and in the second step I estimate β_4, γ_4 (normalizing β_2, γ_2 to zero).[11]

Of course we do not observe independent two by two matching markets but several large markets. Nonetheless the pairwise stability of the larger markets implies that each submarket, composed of any two matches, will also be pairwise stable. Thus we can treat these markets as if they were independent matching markets. The estimation algorithm is as follows:

- Select a set of submarkets involving only agents that are not single (I use all possible submarkets, but in principle a random subset could be used).

- Select a trial set of parameters for $\hat{\theta}^1 = \hat{\beta}_1, \hat{\beta}_3, \hat{\gamma}_1, \hat{\gamma}_3$. For each set of trial parameters:

[11] The maximum score estimator requires the error term to be median independent. In my example, if candidate i faces the choice of departments 1 and 2 then ϵ must be distributed such that $P(\epsilon^1_{i1} - \epsilon^1_{i2} = 0) = 1/2$.

– For each submarket calculate,

$$Q^1_{sm} = \rho_{d_1}\rho_{c_1} + (1-\rho_{d_1}\rho_{c_1})\rho_{d_2}\rho_{c_2} + \rho_{d_1}\rho_{d_2}(1-\rho_{c_1})(1-\rho_{c_2}) \tag{21}$$

where ρ_{d_1} is set equal to 1 if the deterministic utility that department 1 receives from candidate 1 (its observed match) is higher than the deterministic utility it receives from candidate 2: $\rho_{d_1} = 1\{\gamma_1 X_{c_1} + \gamma_3 \Phi_{c_1,d_1} > \gamma_1 X_{c_2} + \gamma_3 \Phi_{c_2,d_1}\}$. Similarly, $\rho_{d_2}, \rho_{c_1}, \rho_{c_2}$, are set equal to one if the agent in question derives a higher deterministic utility from their match than the alternative. Note that $Q_{sm} \in \{0,1\}$.

– Aggregate the scores across the submarkets $Q_{iter} = \sum Q_{sm}$

- Find the trial parameters that maximize Q_{iter}.
- Select a set of submarkets involving both agents that are single and those who are not.
- Select a set of trial parameters $\hat{\theta}^2 = \{\beta_4, \gamma_4\}$. For each set of trial parameters,

– Calculate Q^2_{sm} as,

$$Q^2_{sm} = \rho^s_{c_1}\rho^s_{c_2}Q^1_{sm} \tag{22}$$

where $\rho^s_{c_i}$ is set equal to 1 if the ith candidate is single, or if the ith candidate is matched and the deterministic utility received from matching is greater than the deterministic utility she receives from remaining single. ρ_{c_i} is set equal to one if $\rho_{c_{-i}}$ is single.

– Aggregate the scores across the submarkets $Q^2_{iter} = \sum Q^2_{sm}$

– Find the trial parameters that maximize Q^2_{iter}.

4 The academic labour market

The vast majority of academic hiring within economics occurs in one brief window, that centres around the meeting of the American Economic Association in January. In the months previous to the "winter meetings", jobs are advertised in *Job Openings for Economists*[12], with a deadline for

[12]Since ???? *Job Openings for Economists* has been available for free online, previous to this there was a nominal charge for paper copies.

applications typically a month before the winter meetings. Preliminary interviews are conducted during the meetings, and select candidates (typically 3-5) are invited for campus visits between January and March. Job offers are typically made between February and March.

The outcome of this process is quite likely to approximate a pairwise stable equilibrium. Information on all advertised jobs is freely available to all interested candidates, and candidates have a low cost of applying. Further, departments can easily gain more information through a brief preliminary interview during the winter meetings. In a survey of job candidates in 1995-1996, Stock, Alston, and Milkman (2000) found that the applicants sent out on average 76 applications, and received an average of 9 interviews. In a sample of job seekers from 1996-1997, List (2000) found the mean number of applications to be 41, with a standard deviation of 32, and the mean number of interviews per job seeker was 6 with a standard deviation of 6.6.

Typically when an offer is made to a candidate, they are given ten to fourteen days to respond. One would expect that if the candidate had a reasonable expectation of a job from a preferred department, they could communicate their offer and ensure the preferred department had the opportunity to also offer a position.

While economics has traditionally been a male dominated field, recent decades have seen a concerted effort to increase the number of women in academia. Such policies are typically termed affirmative action or employment equity. Federal laws prevent discrimination based upon gender, thus Universities do not set quotas for the number of women that must be hired nor give overt preference to female candidates. Typically, hiring committees are tasked with seeking out female candidates for initial interviews to ensure some gender balance in the list of candidates that are interviewed. List (2000) shows that female PhD graduates have significantly more initial interviews than their male counterparts. Thus while hiring policies typically allow for a gender bias in initial recruitment and interviewing, the final decision on hiring is not allowed to be influenced by gender.

5 Data and preliminary analysis

The universe of job candidates was taken from the list of PhD graduates published annually in the *Journal of Economic Literature* between 1991 and 2004. To focus attention on graduates who sought out a career in research, a search was done for the publications of each graduate using EconLit.

Graduates with fewer than four publications where considered to be uninterested in a research career. An exhaustive search was made to find the educational and job history of each candidate that had four or more publications. This information was typically found in the graduate's CV, their web bio or a departmental website. ProQuest's dissertation database contained information on the PhD advisor, while the Journal of Economic Literature listed the subject area of the graduate's dissertation.

The web search was typically revealed the graduate's gender. If the web search did not yield information on their gender, a determination was made based on the graduates first or second name. Unfortunately, the gender of 10% of graduates is unknown. Following Hilmer and Hilmer (2012), I assume that a paper published less than a year after a candidate is hired is observable before they were hired, thus the quality of these publications (as revealed by an impact factor weighted count of publications) would impact a department's propensity to hire. Similarly, I derive an index of adviser quality by examining the impact factor adjusted publications of an advisor at the time of the advisee's graduation.[13]

The list of schools active in the market is taken as the set of schools to which a candidate matched (based on their job history). For each school a ranking was developed based on the number of publications the school had in top 30 journals during the period 1990-2000. The top 30 journals are the Diamond list which is commonly used in rankings of economic departments Kalaitzidakis, Mamuneas, and Stengos (2003). Schools were then ranked based on the impact factor weighted publications. Rankings were calculated based on overall publications and publications within a each specific JEL subject code.

Most graduates that entered academia were hired within economic departments, though some were employed in other academic departments, such as business, public policy, and health policy. The main analysis does not differentiate between departments at schools as there is typically a high correlation in the ranking of economics and other departments within the schools. Considering the subset of candidates that match only into economics departments does not change the qualitative results.

I assume that each year represents an independent market. The candidates in each year include those who were hired in that year, and those who did not enter academia but were listed in the

[13]For simplicity I use impact factor's from 2000 for all publications.

Journal of Economic Literature annual list, which covers the period of July of the previous year to June of the current year. Using this procedure, I define fourteen markets, from 1991 to 2004.

Table 1 contains descriptive statistics from the entire data set, and a subset of the data set comprised of graduates from top thirty economic programs. Women represent 17% of graduates and 19% of those who select into academia. We can say with statistical significance that women, on average, have fewer quality adjusted publications then men and are less likely to have graduated from a US undergraduate program. No other variables show statistically significant differences between genders. Unsurprisingly, graduates of top 30 programs have stronger publication records, fewer post-doc positions, and higher initial placements than the overall sample.

6 Results

Before reporting the results of the matching model, two preliminary regressions are run using traditional methods. The first regression is a censored regression of the log rank of the hiring school on various explanatory variables. The results of this regression are displayed in table 2. Given that departments are ranked in ascending order a negative coefficient implies a positive relationship between the variable and the rank of the hiring school.

Unsurprisingly, the rank of the candidate's PhD school is strongly related to the rank of the hiring school. The impact factor weighted publications of the candidate (one year after hiring), and the impact factor weighted publications of their advisor in the past ten years is associated with sorting into higher ranked departments, while having a previous post-doc position was associated with sorting into a lower ranked school. The coefficient attached to the female dummy variable implies that women sort into higher ranked departments, though the coefficient is not statistically significant at standard levels. Candidates who completed their dissertations in quantitative methods, financial economics, industrial organization and business administration, are all able to sort into higher ranked departments than the control group which is candidates who completed their dissertation in the history of economic thought.

The previous regression does not discriminate between candidates who match into domestic or foreign departments, nor those who match into economics versus other departments. To make these

Table 1: Descriptive statistics of PhD graduates from economic departments between 1991 and 2004, with a minimum of four lifetime publications. The mean value of each variable is reported with the standard deviation in parenthesis. The gender of 360 graduates could not be determined. A Wilcoxon test was used to determine if significant differences were found in the average values by gender. Differences at the .1, .05, and .01 levels are denoted in the third column by one, two, and three asterisks, respectively.

	All	Men	Women
All			
Observations	3870	2838	672
Rank of PhD program	62.68 (111.53)	62.75 (112.42)	54.17 (88.9)
Advisor publictions	4.57 (4.93)	4.59 (4.97)	4.72 (4.92)
Own publications	1.8 (4.44)	1.96 (4.58)	1.56 (4.35)***
All academic			
Observations	2501	1962	474
Rank of PhD program	57.06 (106.68)	59.56 (112.84)	48.71 (78.82)
Advisor publictions	4.98 (5.15)	4.95 (5.17)	5.02 (5.14)
Own publications	2.08 (4.9)	2.16 (4.92)	1.77 (4.83)***
Post-doc dummy	0.14 (0.34)	0.14 (0.34)	0.14 (0.35)
US undergraduate degree	0.46 (0.5)	0.47 (0.5)	0.4 (0.49)**
Rank of hiring school	340.54 (460.85)	343.77 (466.15)	328.14 (442.8)
Top 30			
Observations	2267	1670	407
Rank of PhD program	11.26 (8.33)	10.97 (8.29)	11.7 (8.38)*
Advisor publictions	6.09 (5.43)	6.16 (5.47)	6.01 (5.4)
Own publications	2.22 (5.21)	2.39 (5.34)	1.87 (5.1)***
Top 30 academic			
Observations	1531	1190	294
Rank of PhD program	10.74 (8.19)	10.66 (8.17)	11.09 (8.33)
Advisor publictions	6.47 (5.61)	6.51 (5.63)	6.29 (5.65)
Own publications	2.52 (5.75)	2.65 (5.8)	2.1 (5.58)**
Post-doc dummy	0.12 (0.32)	0.11 (0.32)	0.14 (0.34)
US undergraduate degree	0.48 (0.5)	0.49 (0.5)	0.38 (0.49)***
Rank of hiring school	198.34 (343.69)	196.66 (343.95)	198.8 (340.44)

Table 2: Censored regression of the log of the hiring school rank on dependent variables. Significance at the .1, .05 and .01 levels is denoted by one, two and three asterisks, respectively.

	Full	Top 30
Intercept	4.094 (1.333)***	3.793 (0.772)***
Log PhD Rank	0.588 (0.055)***	0.575 (0.027)***
Female (dummy)	-0.146 (0.121)	-0.095 (0.088)
US undergraduate degree (dummy)	0.209 (0.099)**	0.099 (0.071)
Publication one year post hire	-0.058 (0.009)***	-0.053 (0.008)***
Advisor publications	-0.002 (0)***	-0.002 (0)***
Post-doc (dummy)	0.438 (0.168)***	0.234 (0.113)**
Dissertation Subject Codes		
General Economics and Teaching	-1.4 (0.999)	-0.456 (0.542)
Mathematical and Quantitative Methods	-2.201 (0.964)**	-1.445 (0.485)***
Microeconomics	-1.855 (0.958)*	-1.164 (0.478)**
Macroeconomics and Monetary Economics	-1.553 (0.963)	-0.855 (0.484)*
International Economics	-1.583 (0.961)*	-0.753 (0.481)
Financial Economics	-1.86 (0.963)*	-1.075 (0.483)**
Public Economics	-1.321 (0.983)	-0.758 (0.5)
Health, Education, and Welfare	-1.563 (0.971)	-1.024 (0.492)**
Labor and Demographic Economics	-1.632 (0.963)*	-0.844 (0.482)*
Law and Economics	-0.668 (1.06)	-0.226 (0.596)
Industrial Organization	-1.892 (0.966)*	-0.956 (0.487)**
Business Administration and Business Economics	-2.626 (1.055)**	-1.53 (0.573)***
Economic History	-1.018 (0.993)	-0.556 (0.508)
Economic Development, Technological Change, and Growth	-1.329 (0.965)	-0.611 (0.487)
Economic Systems	-0.483 (1.057)	-0.167 (0.569)
Agricultural and Natural Resource Economics	-1.575 (0.975)	-0.9 (0.487)*
Urban, Rural, Regional, Real Estate, and Transportation Economics	-1.664 (1.027)	-0.526 (0.528)
Other Special Topics	1.678 (1.881)	2.369 (1.545)
log σ	0.476 (0.021)***	0.382 (0.017)***

Table 3: Total probability of selecting into five employment categories, based on a multinomial logit regression evaluated at the mean values of other covariates. The five employment categories are 1) Not academic, 2) a top 50 economics department within North America, 3) a non-top 50 economics department within North America, 4) a foreign university, 5) a non-economics department within North America

	Not Academic	Top 50 econ	Other econ	Foreign dept	Other academic dept
All					
Average man	0.3642	0.07224	0.2845	0.2190	0.06009
Average woman	0.2785	0.08043	0.3907	0.1708	0.07953
Top 30					
Average man	0.3179	0.14869	0.2291	0.2323	0.07208
Average woman	0.2588	0.16212	0.3218	0.1541	0.10306

distinctions a multinomial logit regression is run to determine the probabilities of sorting into one of five categories: 1) a non-academic position, 2) a top 50 economics department in North America, 3) a non-top 50 economics department in North America, 4) a non-economics department in North America, or 5) a foreign university.

The results of this regression are held in appendix 1. Table 3 contains the estimated probability that a man and woman would sort into each of the five categories, with all other explanatory variables are set to their average values.[14]

The results show that men are more likely to sort into non-academic and foreign economic departments, while woman are more likely to sort into North American economic departments with the gap being especially large for departments outside of the top 50.

These results can be explained be competing narratives. It is possible that females simply prefer to remain within academia, and are therefore willing to take employment in a lower ranked department, whereas men would prefer to seek employment in the private sector rather than employment in a lower ranked department. Conversely, positions within North American academe may be easier, or more lucrative, for women than men, inducing larger numbers to enter. Fortunately, these questions can be answered using a two-sided matching model.

Table 4 contains the results from the matching model. Two basic models are considered. In

[14]Note that average values of the explanatory variables are the overall averages, not gender specific averages. Though the use of gender specific averages results in very minor changes in the predicted probabilities.

Table 4: Results from the two-sided matching model. 90% confidence interval are presented in parenthesis for model 2.

	Model 1			Model 2	
	Full data set	Top 30		Full data set	Top 30
Department preferences (equation 1)					
Log PhD rank	-1	-1		-1	-1
Female (dummy)	-0.088	0.047		-0.088	0.045 (-0.116, 0.127)
Publications one year post hire	0.093	0.093		0.093	0.085 (0.07, 0.103)
Advisor publications	0.00183	0.002		0.00183	0.00076 (0.00041, 0.00194)
Country match	-			0.543	0.322 (0.243, 0.547)
Candidate match perferences (equation 3)					
Log hiring school rank	-1	-1		-1	-1
Female * log hiring school rank	0.198	-0.546		0.198	0.311 (-0.784, 1.244)
Log hiring school rank in subject of dissertation	-0.644	-1.876		-0.644	-1.079 (-1.82, -0.832)
Log distance from PhD school	-0.012	-0.12		-0.012	0.053 (0.006, 0.33)
Log distance from undergraduate school	-	-		-0.787	-1.593 (-1.936, -1.393)
Country match	-	-		4.382	3.99 (3.806, 3.999)
Candidate single preferences (equation 4)					
Intercept	$-\infty$	$-\infty$	-	-	
Female (dummy)	Included	Included	-	-	
Log PhD rank	Included	Included	-	-	
Controls for JEL subject of dissertation?	Included	Included	-	-	

the first model I attempt to calculate equations 1, 3 and 4 - note that it is implicitly assumed that schools have no "outside option" and must match. Data on the undergraduate country is however, only available for graduates who have matched into academia, thus we must exclude certain variables from this model. The model provides no information on differential utilities that different candidates receive from the outside option. Regardless of the values of the explanatory variables, on average candidates receive more utility from matching within academia, then from their outside option. Thus the intercept of equation 4 is predicted to be a large negative number, and the other explanatory variables cannot be identified. Essentially the model ensures all candidates receive less utility from remaining outside academia, than they receive from matching within academia. The lack of information derived from the first model on the value of the outside option, makes the second model preferred. As with non-parametric discrete choice models, a normalization of one coefficient in both utility functions required. The utility a department receives from the log rank of the graduate's PhD school is normalized to -1, as is the utility the graduate receives from the log rank of the hiring school. We can interpret the magnitude of the coefficient in relation to the normalized value of the rank of the hiring school. As per table 4 two different sets of data are used in estimation, one which contains the full data set and the other that contains only graduates from schools ranked in the top 30. There is substantial agreement on the signs and significance of parameters between these two data sets.

Gender entered both the department's and the candidate's utility function where it was interacted with the log rank of the hiring school. Gender was found to be both economically and significantly insignificant in the department's utility function. Similarly, the interaction of gender and rank of the hiring school was statistically insignificant in the candidate's utility function. A fuller discussion of these findings is reserved for the subsequent section.

The impact factor weighted publications were found to have a significant impact on department utility. Increasing the impact factor weighted publications of a candidate by a single unit is akin to an 8% increase in the rank of the PhD school from which they graduate. For example a publication in the *Quarterly Journal of Economics* with an impact factor of 4.775 would have the same impact as an increasing the rank of the PhD school by 35.2%, while a publication in the *American Journal of Agricultural Economics* with an impact factor of 1.034 would have the same effect as an increase in the rank of the PhD school of 8%.

The impact factor weighted publications of the advisor in the previous ten years is also positive and significant. This is consistent with Hilmer and Hilmer (2012) who find the ranking of a graduate's advisor to be a significant determinant of early career success, and List (2000) who found that having a well known advisor resulted in a candidate receiving more interviews during the AEA winter meetings. Geography plays an important role for both departments and graduates. Graduates have a strong preference for departments close to, and in the same country, where they completed their undergraduate degree. The distance from the PhD degree had little significance in the utility of the graduate. Departments prefer candidates who completed their undergraduate degrees within the country.

Finally, we can see that candidates have a strong preference for departments that are highly ranked in their own field of study. The schools ranking within their field of study has roughly the same importance as the overall ranking of the school.

7 Discussion and conclusion

This paper used a two-sided matching model to investigate the preferences of employers and job candidates in the job market for new PhD graduates in economics. Using a two sided matching model, the preferences of both sides of the market were uncovered. The matching model allowed for important match specific characteristics, such as geography, country matches and subject matches, which proved important in the market.

The identification of and estimation procedures for matching markets with non-transferable utility, have a myriad of other applications. The estimator is quite simple to implement and tractable even in large matching markets. Although this application employed an assumption on the equilibrium selection mechanism, future research could allow for this mechanism to be estimated, or partial identification arguments could be used treating the mechanism as a nuisance parameter. Further research in matching models should endeavour to reduce the independence assumptions made on the error terms in equations 1-4. In principle one may wish to allow for individual specific, as opposed to match specific errors, or allow some type of correlation between the error terms.

The estimation results show a structural change in the impact of gender on hiring. Previous research which employed data sets from previous decades had found gender to be a significant factor in attainment of academic positions. Kolpin and Singell (1996), using data from 1973-1987 found that higher ranked departments were less likely to hire women, and that women who were hired into academia outperformed men in the same department - suggesting a gender bias within hiring. Further, McMillen and Singer (1994) using data on PhD graduates between 1960 and 1989, find men more likely to be hired into top 50 economics departments. In contrast this paper shows that for the academic markets between 1991 and 2004 gender did not play a large role in the matching of job candidates and employers. These results suggest that employment equity policies, which typically preclude discrimination based on gender, but allow departments to seek out underrepresented candidates (such as females), have had the desired effect. The reverse discrimination that some feared has not been found.

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