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SUPPLEMENT TO "DYNAMIC MARRIAGE MATCHING: AN EMPIRICAL FRAMEWORK"

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This supplement provides details and extensions omitted from the main paper. I first provide a literature review on closed-form matching functions derived from dynamic equilibrium model of firms-workers matching, and I attempt to draw connections with the dynamic marriage matching function in this paper. Section S.2 relaxes the i.i.d. distributional assumption and considers correlation in the idiosyncratic shocks using the Generalized Extreme Value Distribution. In Section S.3, I propose a bootstrap procedure to derive the standard errors of the marriage gains. Finally, Section S.4 details the estimation results of the logit model used to parameterize the divorce hazard in the dynamic model.

S.1. EXTENDED LITERATURE REVIEW

AGGREGATE MARRIAGE MATCHING DATA strongly suggest that matches occur between individuals of the same age as well as between ages that are far apart. The marriage matching functions developed in CS and this paper emphasize this heterogeneity in matching. The model permits substitution across all age groups of spouse, though with many restrictions. In this paper, the dynamics in marriage decision adds an implicit interdependence across ages. A single individual faced with choices at age i knows his or her type's marriage prospect in the future and internalizes that in his or her decisions. In other words, a high expected value from being single in the future would raise the opportunity cost of being locked in a match today, hence lowering marriage gains and the relative attractiveness of the match.

There is much literature devoted to understanding how frictions in the decentralized labor market affect employment through the use of an aggregate job matching function. Labor markets are characterized by the simultaneous presence of job seekers and job vacancies. Analogously to the marriage matching function, the aggregate job matching function maps the stock of job vacancies and the stock of job seekers to the flow of new jobs (Pissarides (2000)). The job matching function provides a convenient reduced-form way to introduce frictions into conventional models without modeling the complex process that generates job matches.

An extensive empirical literature has largely taken a reduced-form approach and focused on estimating the elasticities with respect to the number of job vacancies and the number of job seekers. There is considerable empirical evidence to support a stable well-behaved aggregate matching function of the Cobb–Douglas form with constant return to scale in vacancies and unemployment (see Petrongolo and Pissarides (2001) for a detailed survey). Other papers have identified heterogeneity in the form of individual characteristics to be important in explaining individual hazard rates. This individual-level

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heterogeneity in the matching function can be rationalized through the job seeker's choice of search intensity or through differences in their reservation wage.[1]

As in the marriage market, many papers have recognized the importance of heterogeneity in workers and jobs in a decentralized labor market. Frictions in job matching arise because of heterogeneities in job quality, worker skill, differences in job and worker locations, and imperfect information about these and other relevant parameters (see Pissarides (2000)). Unlike the match heterogeneity seen in marriage markets (where couples of different types match), heterogeneity in workers and jobs generates unfilled jobs and unemployed workers.[2] That is, heterogeneous unemployed workers (skills, occupations, industries, locations) are seeking employment in sectors different from those where vacancies exist. The literature considering heterogeneity in vacancies and job seekers within a model of employment is extensive.[3] Heterogeneity is usually cast in terms of worker or match productivity and job characteristics. (Lise and Robin (2013), Han and Yamaguchi (2013), and Hagedorny, Manovskii and Stetsenko (2010) are some recent papers that allow for heterogeneity in productivity and job characteristics.) Another unique feature of the marriage matching function that is absent in the macro and labor literature is the implicit interdependence between the number of matches for, say, age (i, j) couples, and the future marriage prospects of these age groups.

S.2. ALLOWING FOR PERSISTENCE IN PREFERENCES—GENERALIZED EXTREME VALUE DISTRIBUTION

The i.i.d. assumption on the unobserved state vectors $\boldsymbol{\varepsilon}_i$ (and $\boldsymbol{\varepsilon}_j$) is not innocuous. It is well known that the static discrete choice model with independent Type I Extreme Value distribution exhibits the I.I.A. property, which imposes proportional substitution across alternatives. McFadden (1978) proposed the Generalized Extreme Value class of distributions that maintains the convenient closed-form representations, such as the Type I Extreme Value, while permitting a variety of less restrictive substitution patterns. Following McFadden (1978), the distribution function for this class of models takes the form

$$F(\varepsilon_1, \varepsilon_2, \dots, \varepsilon_K) = \exp\bigl(-\mathcal{H}\bigl(e^{-\varepsilon_1}, e^{-\varepsilon_2}, \dots, e^{-\varepsilon_K}\bigr)\bigr), \tag{S.1}$$

[1] Merz and Yashiv (2007), Feve and Langot (1996), and Yashiv (2000) are part of the growing number of papers that take a structural approach to estimating the matching function.

[2] See Shimer (2007) and Sahin, Song, Topa, and Violante (2012).

[3] Yashiv (2007) provided a comprehensive recent survey. Part of the literature focuses on explaining the large flow of job-to-job transition seen in the data. Pissarides (1994) allowed for on-the-job search where jobs vary by productivity depending on job-specific human capital which takes time to accumulate. Related contributions include Krause and Lubik (2006), Albrecht and Vroman (2002), Acemoglu (1999), and Moscarini (2001).

where $\mathcal{H}(\cdot)$ is a member of the class of functions from $\Re_+^K \to \Re_+$, with properties outlined in Appendix A.2 in the main paper.

A widely used GEV distribution in the discrete choice literature is the nested logit model. Consider a marriage market where an individual's type is characterized by race and age, where race is either white or black. Let r, i be the index for an aged i male of race $r \in \{w, b\}$ and s, j be the index for an aged j female of race $s \in \{W, B\}$. Suppose choices within each race group are correlated. For a white male choosing a white female, let the statistic $\lambda_{w,W}$ be a measure of correlation between spouses who are white and $\lambda_{w,B}$ be a measure of correlation between spouses who are black. A value of $\lambda_{w,W} = 1$ indicates that the group of spouse choices who are white are also independent.[4] The choice to remain single is contained in its own (single-hood) nest and is uncorrelated with the choice to match with either race. Suppressing the subscript for the (w, i) type men, the function $\mathcal{H}(\cdot)$ becomes

$$\text{(S.2)} \quad \mathcal{H}(Y_0, Y_{W,1}, \ldots, Y_{W,Z}, \ldots, Y_{B,1}, \ldots, Y_{B,Z}) = Y_0 + \left(\sum_{j=1}^{Z} Y_{W,j}^{1/(1-\lambda_{w,W})} \right)^{1-\lambda_{w,W}} + \left(\sum_{j=1}^{Z} Y_{B,j}^{1/(1-\lambda_{w,B})} \right)^{1-\lambda_{w,B}}.$$

I can derive an analogous system of quasi-demand and quasi-supply equations for matches that are consistent with the nested logit error structure. For expositional convenience, I will suppress the race subscript where possible. For (w, i, W, j) matches,

$$\text{(S.3)} \quad \ln \frac{\mathcal{P}_{i,j}^{1/\lambda_{w,W}}}{\mathcal{P}_{i,\cdot}^{1/\lambda_{w,W}-1}} - \sum_{k=0}^{T_{i,j}-1} \big(\beta(1-\delta)\big)^k \ln \mathcal{P}_{i+k,0} = \boldsymbol{\alpha}_i(j) - \boldsymbol{\alpha}_{i,0}(j) - \tau_{i,j} - \kappa,$$

$$\text{(S.4)} \quad \ln \frac{\mathcal{Q}_{i,j}^{1/\lambda_{w,W}}}{\mathcal{Q}_{\cdot,j}^{1/\lambda_{w,W}-1}} - \sum_{k=0}^{T_{i,j}-1} \big(\beta(1-\delta)\big)^k \ln \mathcal{Q}_{0,j+k} = \boldsymbol{\gamma}_j(i) - \boldsymbol{\gamma}_{j,0}(i) + \tau_{i,j} - \kappa.$$

Equations (S.3) and (S.4) maintain a very similar structure to their i.i.d. counterpart in Equations (3.28) and (3.29) in the main paper. The derivation of these two equations is shown in Section S.2.1 of this supplement. The terms $\mathcal{P}_{i\cdot} = \sum_{j=1}^{Z} \mathcal{P}_{w,i,W,j}$ and $\mathcal{Q}_{\cdot j} = \sum_{i=1}^{Z} \mathcal{Q}_{w,i,W,j}$ refer to the probability that a white aged i man marries a white spouse, and a white aged j woman marries a white spouse, respectively. The constant κ is the geometric sum of Euler's constants, $\kappa = c\beta(1-\delta)[1 - (\beta(1-\delta))^{T_{i,j}}]/[1 - \beta(1-\delta)]$. There are a corresponding

[4]More precisely, McFadden (1978) referred to $(1 - 1/\lambda_k)$ as an index of similarity for choices in nest k. McFadden (1978) also pointed out that the actual correlation coefficient is more complicated. See Chapter 4 of Train (1993) for further discussion.

pair of equations for the race pairs (w, B), (b, B), and (b, W). The correlations of marital choices within a race pair are captured by parameters $\lambda_{w,W}$, $\lambda_{w,B}$, $\lambda_{b,B}$, and $\lambda_{b,W}$. Unlike the i.i.d. counterpart, this dynamic model with the nested logit error (without additional structure) is unidentified from a single cross-section of aggregate matching data.

There are other approaches to allowing for heterogeneity and persistence in choices. Galichon and Salanié (2012) generalized the Type I Extreme Value distribution in the static CS model to allow for a wide class of unobserved heterogeneity distributions (of which the Generalized Extreme Value is a subset).

S.2.1. *Derivation of Equations (S.3) and (S.4)*

I first derive the choice probabilities for an (ri) type male. Using Equation (A.2) and for $\mathcal{H}(\cdot)$ given by Equation (S.2),

$$\mathcal{P}_{r,i,0} = \frac{e^{\tilde{v}_{r,i,0}}}{e^{\tilde{v}_{r,i,0}} + \left(\sum_{j=1}^{Z} \exp(\tilde{v}_{r,i,W,j})^{\delta_{w,W}}\right)^{1/\delta_{w,W}} + \left(\sum_{j=1}^{Z} \exp(\tilde{v}_{r,i,B,j})^{\delta_{w,B}}\right)^{1/\delta_{w,B}}}, \tag{S.5}$$

$$\mathcal{P}_{r,i,W,k} = \frac{\exp(\tilde{v}_{r,i,W,k})^{\delta_{w,W}} \left(\sum_{j=1}^{Z} \exp(\tilde{v}_{r,i,W,j})^{\delta_{w,W}}\right)^{1/\delta_{w,W}-1}}{e^{\tilde{v}_{r,i,0}} + \left(\sum_{j=1}^{Z} \exp(\tilde{v}_{r,i,W,j})^{\delta_{w,W}}\right)^{1/\delta_{w,W}} + \left(\sum_{j=1}^{Z} \exp(\tilde{v}_{r,i,B,j})^{\delta_{w,B}}\right)^{1/\delta_{w,B}}}. \tag{S.6}$$

Summing $\mathcal{P}_{r,i,W,k}$,

$$\begin{aligned} \mathcal{P}_{r,i,W,\bullet} &= \sum_{k=1}^{Z} \mathcal{P}_{r,i,W,k} \\ &= \frac{\left(\sum_{j=1}^{Z} \exp(\tilde{v}_{r,i,W,j})^{\delta_{w,W}}\right)^{1/\delta_{w,W}}}{e^{\tilde{v}_{r,i,0}} + \left(\sum_{j=1}^{Z} \exp(\tilde{v}_{r,i,W,j})^{\delta_{w,W}}\right)^{1/\delta_{w,W}} + \left(\sum_{j=1}^{Z} \exp(\tilde{v}_{r,i,B,j})^{\delta_{w,B}}\right)^{1/\delta_{w,B}}}. \end{aligned} \tag{S.7}$$

Substituting Equation (S.7) into Equation (S.6) and taking log-odds ratios,

$$\ln\left(\frac{\mathcal{P}_{r,i,W,k}^{1/\delta_{w,W}}\mathcal{P}_{r,i,W,\bullet}^{1-1/\delta_{w,W}}}{\mathcal{P}_{r,i,0}}\right)=\tilde{v}_{r,i,W,k}-\tilde{v}_{r,i,0}.$$

An analogous log-odds ratio equation can be derived for the female side of the market:

$$\ln\left(\frac{\mathcal{Q}_{w,k,r,j}^{1/\delta_{w,W}}\mathcal{Q}_{\bullet w,r,j}^{1-1/\delta_{w,W}}}{\mathcal{Q}_{r,j,0}}\right)=\tilde{w}_{w,k,r,j}-\tilde{w}_{r,j,0}.$$

The following steps mirror closely the arguments used in the derivation of Equation (3.20) in Appendix A.3 of the main paper. Using the definition in Equation (3.13),

$$\begin{aligned}\tilde{v}_{r,i,W,j}&=\boldsymbol{\alpha}_{r,i}(W,j)-\tau_{r,i,W,j}+\beta\delta\mathbf{V}_{r,i+1}+\beta^2\delta(1-\delta)\mathbf{V}_{r,i+2}+\cdots\\&\quad+\beta^{T_{i,j}-2}\delta(1-\delta)^{T_{i,j}-3}\mathbf{V}_{r,i+T_{i,j}-2}\\&\quad+\beta^{T_{i,j}-1}\delta(1-\delta)^{T_{i,j}-2}\mathbf{V}_{r,i+T_{i,j}-1}.\end{aligned}$$

Since only marital choices within each race group are correlated and marital decisions are uncorrelated with the decision to remain single, the recursive structure of Equations (3.18) and (3.19) hold. After repeated substitution of Equation (3.18) and some algebra,

$$\begin{aligned}\tilde{v}_{r,i,W,j}&=\boldsymbol{\alpha}_{r,i}(W,j)-\tau_{r,i,W,j}\\&\quad+\sum_{k=1}^{T_{i,j}-1}\beta^k\big(1-(1-\delta)^k\big)(\alpha_{r,i+k,0}-\ln\mathcal{P}_{r,i+k,0}+c),\\\tilde{v}_{r,i,0}&=\alpha_{r,i,0}+\sum_{k=1}^{T_{i,j}-1}\beta^k(\alpha_{r,i+k,0}-\ln\mathcal{P}_{r,i+k,0}+c).\end{aligned}$$

Hence

$$\begin{aligned}&\ln\left(\frac{\mathcal{P}_{r,i,W,k}^{1/\delta_{w,W}}\mathcal{P}_{r,i,W,\bullet}^{1-1/\delta_{w,W}}}{\mathcal{P}_{r,i,0}}\right)\\&\quad=\boldsymbol{\alpha}_{r,i}(W,j)-\tau_{r,i,W,j}-\alpha_{r,i,0}\\&\qquad-\sum_{k=1}^{T_{i,j}-1}\beta^k(1-\delta)^k(\alpha_{r,i+k,0}-\ln\mathcal{P}_{r,i+k,0}+c)\end{aligned}$$

$$\Rightarrow \quad \ln\left(\mathcal{P}_{r,i,W,k}^{1/\delta_{w,W}} \mathcal{P}_{r,i,W,\bullet}^{1-1/\delta_{w,W}}\right) - \sum_{k=0}^{T_{i,j}-1} \beta^k (1-\delta)^k \ln \mathcal{P}_{r,i+k,0}$$
$$= \boldsymbol{\alpha}_{r,i}(W, j) - \tau_{r,i,W,j} - \boldsymbol{\alpha}_{r,i,0}.$$

The arguments for Equation (S.4) are similar.

S.3. BOOTSTRAP STANDARD ERRORS

Any inference using the estimates of marriage gains $\boldsymbol{\Pi}$ would necessitate the computation of its standard error. Since the estimator in Equation (3.36) is a function of multinomial probabilities, one approach would be to derive the limiting distribution of $\widehat{\boldsymbol{\Pi}}$ using the delta method applied to multinomial random vectors. The heuristics of that approach go as follows: Consider a universe where the unit of observations are households. There are $(Z^2 + 2Z) \times 1$ possible types of households. A household could be composed of a married couple of age pair (i, j) or an unmarried male or female of age i and j, respectively. Let the $(Z^2 + 2Z) \times 1$ vector $\boldsymbol{\theta}_0$ denote the true probability that we observe a particular type of household.[5] Given a random sample of N households (from which $\boldsymbol{\mu}$, $\mathbf{m}$, $\mathbf{f}$ are constructed), the ML estimator for $\theta_{i,j}$ is $\widehat{\theta}_{i,j} = \mu_{i,j}/N$ where $N = \sum_{i=1}^{Z} \sum_{j=1}^{Z} \mu_{i,j} + \sum_{i=1}^{Z} \mu_{i,0} + \sum_{j=1}^{Z} \mu_{0,j}$. $\widehat{\boldsymbol{\theta}}_N$ denotes the $(Z^2 + 2Z) \times 1$ random vector of ML estimators. Applying the Central Limit Theorem for multinomial random vectors, the limiting distribution is

$$\sqrt{N}(\widehat{\boldsymbol{\theta}}_N - \boldsymbol{\theta}_0) \rightsquigarrow N(0, \Omega), \tag{S.8}$$

where $\Omega = \operatorname{diag}(\boldsymbol{\theta}) - \boldsymbol{\theta}\boldsymbol{\theta}'$. Suppose the vector valued function $\chi(\cdot)$ is continuous and once differentiable in $\boldsymbol{\theta}$. The $Z^2 \times 1$ parameter vector of interest $\boldsymbol{\Pi} = \chi(\boldsymbol{\theta})$, and its corresponding estimator $\widehat{\boldsymbol{\Pi}} = \chi(\widehat{\boldsymbol{\theta}})$. By the continuous mapping theorem, consistency in $\widehat{\boldsymbol{\theta}}_N$ implies that $\widehat{\boldsymbol{\Pi}}$ is a consistent estimator of $\boldsymbol{\Pi}$. Applying the delta methods (see Theorem 3.1 of van der Vaart (2000)), the limiting distribution is as follows:

$$\sqrt{N}\left(\chi(\widehat{\boldsymbol{\theta}}_N) - \chi(\boldsymbol{\theta}_0)\right) \rightsquigarrow N\left(0, \nabla_\theta \chi(\boldsymbol{\theta}_0) \Omega \nabla_\theta \chi(\boldsymbol{\theta}_0)'\right), \tag{S.9}$$

where $\nabla_\theta \chi(\boldsymbol{\theta}_0)$ is the $Z^2 \times (Z^2 + 2Z)$ matrix of first derivatives with respect to $\boldsymbol{\theta}$. The structure of Equation (3.36) suggests that computing the closed form of $\nabla_\theta \chi(\boldsymbol{\theta}_0)$ is algebraically tedious and complicated.

[5]For example, $\theta_{i,j}$ denotes the probability that we observe a household of (i, j) married couple, $\theta_{i,0}$ denotes the probability that we observe a household of a single i age male, and so on.

The empirical application instead uses the bootstrap method to compute the standard errors of the marriage gains. I propose the following bootstrapping algorithm to compute the variance of the limiting distribution. Consider a sample of N observations composed of matches and single individuals by age. The quantities $\mu_{i,j}$, $\mu_{i,0}$, and $\mu_{0,j}$ are simply count frequencies of (i, j) matches, single age i men and age j women observed in the sample of N. Let this empirical distribution be denoted by $\widehat{\mathbb{F}}$. The vector of probabilities $\boldsymbol{\theta}_0$ can be estimated by its ML estimate $\widehat{\boldsymbol{\theta}} = (\mu_{1,1}/N, \dots, \mu_{1,0}/N, \dots, \mu_{0,Z}/N)$. Consider re-sampling with replacement B times, drawing N observations each time from the distribution $\widehat{\mathbb{F}}$. Let b index the bth bootstrap sample and $\boldsymbol{\mu}_b^* = (\mu_{0,1,b}^*, \mu_{0,2,b}^*, \dots, \mu_{1,1,b}^*, \mu_{1,2,b}^*, \dots, \mu_{Z,Z,b}^*)$ denote the vector of count frequencies in the bth bootstrap sample. Accordingly, we can compute $\widehat{\boldsymbol{\theta}}_b^* = (\mu_{1,1,b}^*/N, \dots, \mu_{1,0,b}^*/N, \dots, \mu_{0,Z,b}^*/N)$ and the corresponding structural parameters $\widehat{\boldsymbol{\Pi}}_b^* = \chi(\widehat{\boldsymbol{\theta}}_b^*)$. The variance of the (i, j)th marriage gain $\widehat{\Pi}_{i,j}$ can computed by

$$\operatorname{Var}(\widehat{\Pi}_{i,j}) = \frac{1}{B-1} \sum_{b=1}^{B} \left(\widehat{\Pi}_{i,j,b}^* - \widehat{\Pi}_{i,j}\right)^2.$$

S.4. ESTIMATION OF THE DIVORCE HAZARDS

The divorce hazard is estimated using divorce records in the Divorce Public-Use Tape Files published by the National Center of Health Statistics. Data from 1968 to 1995 are available from the data link on the National Bureau of Economic Research website (http://www.nber.org/data/marrdivo.html). The divorce records provide information on the state of divorce registration, the date of birth, marriage, and divorce for couples. Using this information, I construct for each divorced couple the age of marriage (i, j), the duration of the match d, the year of marriage t, and the share of marriages that dissolve after d years of marriage, $\delta_{i,j,d,t}$. The marriage records from the Vital Statistics for year t provide the flow of new marriages for age pairs (i, j). The states of divorce registration are chosen to match the reporting states in the Vital Statistic record. The following simple logit regression was used to fit the share data:

$$\ln\left(\delta_{i,j,d,t}/(1 - \delta_{i,j,d,t})\right) = g(i, j) + \theta_d + \psi_t + \varepsilon_{i,j,d,t}, \qquad \text{(S.10)}$$

where $g(i, j)$ is a fourth order polynomial of the couple's age, θ_d are coefficients on duration dummy variables, and ψ_t are coefficients on year of marriage dummy variables. The coefficient estimates are used to construct the predicted probability of divorce used in the empirical application of the model. The parameter estimates are presented in Table S-I(i), (ii), and (iii).

TABLE S-I
PARAMETER ESTIMATES

Parameters	Estimates	Std. Error
	(i) Estimates of Polynomial $g(i, j)$	
Constant	0.8941	0.1723
i	−0.3194	0.1636
j	−3.5168	0.1493
i^2	0.0007	0.0615
j^2	1.1594	0.0599
$i^2 \times j$	−0.2260	0.0234
$j^2 \times i$	0.0660	0.0268
i^3	0.1214	0.0125
j^3	−0.1126	0.0150
$i^2 \times j^2$	−0.1298	0.0040
i^4	−0.0270	0.0010
j^4	−0.0152	0.0019
$i^3 \times j$	0.0954	0.0027
$j^3 \times i$	0.0839	0.0042
	(ii) Estimates on Duration Dummies, θ_d	
θ_2	0.3088	0.0121
θ_3	0.2576	0.0123
θ_4	0.1696	0.0124
θ_5	0.0733	0.0125
θ_6	−0.0005	0.0127
θ_7	−0.0820	0.0129
θ_8	−0.1518	0.0131
θ_9	−0.2256	0.0132
θ_{10}	−0.3162	0.0135
θ_{11}	−0.3512	0.0138
θ_{12}	−0.4253	0.0143
θ_{13}	−0.4875	0.0151
θ_{14}	−0.5564	0.0159
θ_{15}	−0.5946	0.0169
θ_{16}	−0.6586	0.0180
θ_{17}	−0.6272	0.0194
θ_{18}	−0.6627	0.0212
θ_{19}	−0.6394	0.0235
θ_{20}	−0.7073	0.0256
θ_{21}	−0.7241	0.0288
θ_{22}	−0.7771	0.0328
θ_{23}	−0.9049	0.0391
θ_{24}	−0.9113	0.0487
θ_{25}	−1.0090	0.0723

(*Continues*)

TABLE S-I—*Continued*

Parameters	Estimates	Std. Error
(iii) Estimates on Year of Marriage Dummies, ψ_d		
ψ_{71}	0.0379	0.0128
ψ_{72}	0.0432	0.0128
ψ_{73}	0.0300	0.0128
ψ_{74}	0.0525	0.0128
ψ_{75}	0.0854	0.0129
ψ_{76}	0.1469	0.0129
ψ_{77}	0.1435	0.0130
ψ_{78}	0.1858	0.0131
ψ_{79}	0.2208	0.0132
ψ_{80}	0.2451	0.0134
ψ_{81}	0.2013	0.0136
ψ_{82}	0.1397	0.0138
ψ_{83}	0.1799	0.0140
ψ_{84}	0.1733	0.0144

REFERENCES

ACEMOGLU, D. (1999): "Changes in Unemployment and Wage Inequality: An Alternative Theory and Some Evidence," *American Economic Review*, 89, 1259–1278. [2]

ALBRECHT, J., AND S. VROMAN (2002): "A Matching Model With Endogenous Skill Requirements," *International Economic Review*, 43 (1), 283–305. [2]

FEVE, P., AND F. LANGOT (1996): "Unemployment and the Business Cycle in a Small Open Economy: G.M.M. Estimation and Testing With French Data," *Journal of Economic Dynamics and Control*, 20 (9–10), 1609–1639. [2]

GALICHON, A., AND B. SALANIÉ (2012): "Cupid's Invisible Hands: Social Surplus and Identification in Matching Models," Report, Columbia University. [4]

HAGEDORNY, M., I. MANOVSKII, AND S. STETSENKO (2010): "Taxation and Unemployment in Models With Heterogeneous Workers," Report, University of Pennsylvania. [2]

HAN, S., AND S. YAMAGUCHI (2013): "Compensating Wage Differentials in Stable Job Matching Equilibrium," Report, McMasters University. [2]

KRAUSE, M. U., AND T. LUBIK (2006): "The Cyclical Upgrading of Labor and On-the-Job Search," *Labour Economics*, 13 (4), 459–477. [2]

LISE, J., AND J.-M. ROBIN (2013): "The Macro-Dynamics of Sorting Between Workers and Firms," Report, University College, London. [2]

MCFADDEN, D. (1978): "Modelling the Choice of Residential Location," in *Spatial Interaction and Planning Models*, ed. by F. Snickars and J. Weibull. Amsterdam: North-Holland. [2,3]

MERZ, M., AND E. YASHIV (2007): "Labor and the Market Value of the Firm," *American Economic Review*, 97 (4), 1419–1431. [2]

MOSCARINI, G. (2001): "Excess Worker Reallocation," *Review of Economic Studies*, 68 (3), 593–612. [2]

PETRONGOLO, B., AND C. A. PISSARIDES (2001): "Looking Into the Black Box: A Survey of the Matching Function," *Journal of Economic Literature*, 39 (2), 390–431. [1]

PISSARIDES, C. A. (1994): "Search Unemployment With On-the-Job Search," *Review of Economic Studies*, 61, 457–475. [2]

——— (2000): *Equilibrium Unemployment Theory* (Second Ed.). Cambridge, MA: MIT Press. [1,2]

SAHIN, A., J. SONG, G. TOPA, AND G. L. VIOLANTE (2012): "Mismatch Unemployment," Working Paper 18265, NBER. [2]

SHIMER, R. (2007): "Mismatch," *American Economic Review*, 97 (4), 1074–1101. [2]

TRAIN, K. (1993): *Qualitative Choice Analysis: Theory Econometrics, and an Application to Automobile Demand*. Cambridge, MA: MIT Press. [3]

VAN DER VAART, A. W. (2000): *Asymptotic Statistics*. Cambridge Series in Statistical and Probabilistic Mathematics. Cambridge: Cambridge University Press. [6]

YASHIV, E. (2000): "The Determinants of Equilibrium Unemployment," *American Economic Review*, 90 (5), 1297–1322. [2]

——— (2007): "Labor Search and Matching in Macroeconomics," *European Economic Review*, 51 (8), 1859–1895. [2]

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