Labor Market Returns to Personality: A Job Search Approach to Understanding Gender Gaps

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Abstract

This paper investigates the effects of the Big Five personality traits on labor market outcomes and gender disparities within a job search, matching and bargaining model with heterogeneous workers. In the model, parameters pertaining to human capital endowments, job offer arrival rates, job dissolution rates and bargaining powers depend on worker education, cognitive skills, personality traits and other demographic characteristics. The model is estimated using a representative panel dataset, the German Socio-Economic Panel (GSOEP). Results show that both cognitive and noncognitive traits are important determinants of wage and employment outcomes. For both men and women, higher levels of conscientiousness and emotional stability and lower levels of agreeableness increase hourly wages and promote greater job stability. A decomposition analysis shows that gender differences in two personality traits - agreeableness and emotional stability - account for a substantial proportion (10% and 11.8%) of the gender wage gap and that their effect operates largely through reducing women's bargaining power.

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1 Introduction

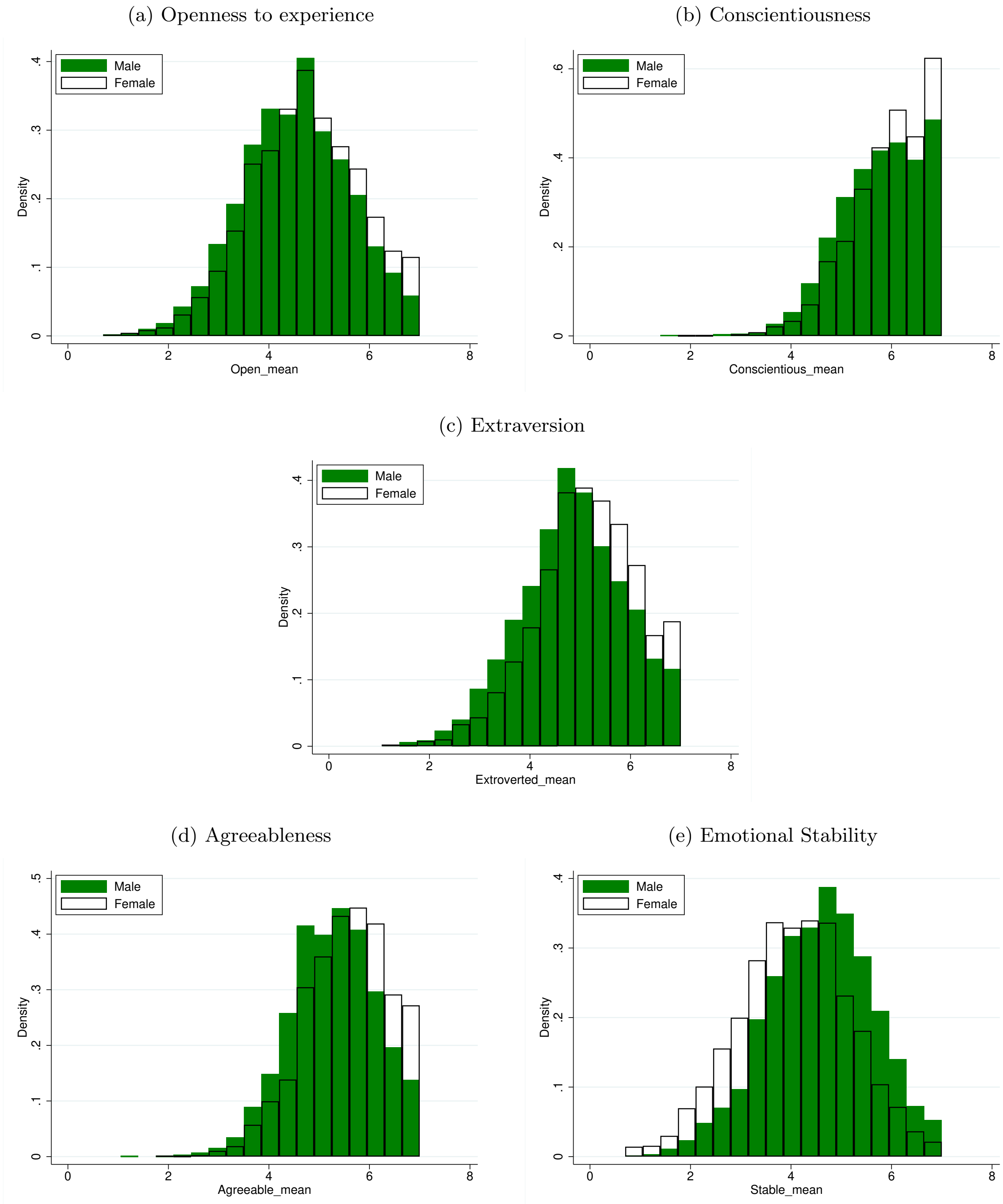
Despite substantial convergence in gender wage and employment differentials over the 1970s and 1980s, significant differences remain with women earning on average 25 percent less than men (Blau and Kahn (2006), Flabbi (2010b)). A large empirical literature uses data from the US and Europe to investigate the reasons for gender disparities. Individual attributes, such as years of education and work experience, account for a portion of gender wage and employment gaps, but a substantial unexplained portion remains. The early gender wage gap literature generally attributed residual gaps to unobserved productivity differences and/or labor market discrimination.

In recent decades, however, there is increasing recognition that noncognitive skills, such as personality traits, are important determinants of worker productivity and may also contribute to gender disparities. The most commonly used noncognitive measurements are the so-called "Big Five" personality traits, which measure an individual's openness to experience, conscientiousness, extraversion, agreeableness and neuroticism (the opposite of emotional stability).[1] Figure 1 compares the distribution of the Big Five personality traits in our data for women and men. Women are more likely to score in the highest categories on openness to experience, conscientiousness, extraversion and agreeableness and in the lowest categories on emotional stability. Similar patterns have been documented for many countries and these trait differences have been shown to be significantly associated with gender wage gaps (e.g. Nyhus and Pons (2005), Heineck (2011), Mueller and Plug (2006), Braakmann (2009), Cattan (2013)). However, the mechanisms through which personality traits affect labor market outcomes have not been much explored.

This paper examines the relationship between personality traits and labor market outcomes within a partial-equilibrium job search model. We develop and estimate a model in which personality traits potentially operate through multiple channels. In the model, workers, who are heterogeneous in their characteristics, stochastically receive employment opportunities from firms characterized in terms of idiosyncratic match productivity values. Workers' human capital accumulates while employed but depreciates when unemployed. Firms and job searchers divide the match surplus using a Nash-bargaining protocol, with the fraction going to the worker determined by a bargaining parameter. We propose a new way of incorporating individual heterogeneity into the search framework by specifying job search parameters as index functions of a possibly high-dimensional set of worker attributes, including both cognitive and noncognitive trait measures. We use the estimated model to explore how cognitive and noncognitive traits affect hourly wages, employment and labor market dynamics and to better understand gender wage gap determinants. The modeling framework that we develop allows examination of gender differences in the *ex ante* and *ex post* value of entire labor market careers, not just in wages at a point in time. Understanding the mechanisms through which gender disparities in labor market outcomes arise is important for designing effective labor market policies.

[1]The measures aim to capture patterns of thoughts, feelings and behavior that correspond to individual differences in how people actually think, feel and act (Borghans et al. (2008), Almlund et al. (2011)).

Figure 1: The distribution of Big Five personality traits by gender



(a) Openness to experience

(b) Conscientiousness

(c) Extraversion

(d) Agreeableness

(e) Emotional Stability

Notes: The measures are based on the scores of individuals aged 25 to 60 who report personality traits in the GSOEP. Each trait measure is defined on a scale of 1 to 7.

Our job search model builds on the traditional Bertrand competition model with bargaining that is used, for example, in Cahuc et al. (2006) and Dey and Flinn (2005). We extend the model by allowing for human capital appreciation and depreciation, following a similar approach to Burdett et al. (2016) and Amano-Patino et al. (2020).[2] The analysis in this paper also contributes to a smaller literature that uses job search models to analyze gender wage gaps (e.g. Bowlus and Grogan (2008), Flabbi (2010a), Liu (2016), Morchio and Moser (2020), Xiao (2020), Amano-Patino et al. (2020)). Our approach differs from prior studies by allowing job search parameters to depend in a flexible way on a larger set of worker characteristics and by incorporating personality traits.[3] We quantify the importance of workers' characteristics operating through four distinct channels: initial human capital levels, job finding rates, job exit rates, and bargaining power.

Model parameters are estimated by maximum likelihood using data from the German Socioeconomic Panel (GSOEP), a large, representative, longitudinal sample of German households. We focus on working age (age 25-60) individuals surveyed in 2013 and followed until 2019 (the most recent year of data available). We use information on their gender, age, education, cognitive skills (measured by a test), work and unemployment experiences, wages, job transitions, and on the Big Five personality trait measurements. We show that personality traits are significantly associated with hourly wages and unemployment/employment spell lengths.

We estimate three different, but nested, job search models that incorporate varying degrees of individual heterogeneity. In the most general specification, initial human capital endowments, job arrival rates, job exit rates, and bargaining parameters all depend, through indices, on a comprehensive set of worker characteristics that include cognitive and noncognitive skill measures. In the less general specification, we allow parameters to vary by the same characteristics but exclude the noncognitive measures (i.e. personality traits). In the most restricted version, we only allow parameters to vary by gender. Likelihood ratio tests overwhelmingly reject the more restrictive specifications in favor of one that allows for the highest degree of heterogeneity, and that model also provides a better visual fit to the data. The specification that incorporates more observable dimensions of individual heterogeneity assigns a lesser role to unobserved model components (e.g. match quality, measurement error) in fitting the model to the data.

Using our estimated heterogeneous job search model, we simulate steady state labor market outcomes for men and women. We analyze how each of the cognitive traits (education, cognitive skills) and each of the personality traits, ceteris paribus, affects labor market outcomes. We find that the effects of personality traits on men's and women's outcomes are qualitatively similar but quantitatively different. For both men and women, conscientiousness and emotional stability

[2] Burdett et al. (2016) and Amano-Patino et al. (2020) assume that human capital can grow during periods of employment, but our model also takes into account the potential human capital depreciation during periods of unemployment.

[3] In the estimation of structural search models, conditioning variables are often used to define labor markets, and then estimation proceeds as if these labor markets are isolated from one another. In our case, the labor market parameters are allowed to depend on a linear index of individual characteristics, which include personality measures and other individual characteristics.

increase hourly wages and shorten unemployment spells, whereas agreeableness leads to worse labor market outcomes. The results indicate that a one standard deviation increase in conscientiousness results in a 2.7 percent and 2.6 percent increase in average wages for men and women. An increase of similar magnitude in emotional stability increases average wages by 4.9 percent for men and 4.1 percent for women. However, a one standard deviation increase in agreeableness decreases average wages by 3.2 percent and 3.3 percent for men and women.

To assess the relative importance of personality traits and other characteristics in explaining gender wage gaps, we perform a decomposition similar in spirit to an Oaxaca-Blinder decomposition but adapted to our nonlinear model setting. Results show that work experience and personality traits are the two main factors contributing to the gender gap, with effects of similar magnitude. Eliminating gender differences in work experience would reduce the wage gap by 22.5 percent. Equalizing average personality traits would reduce the wage gap by 17.6 percent. Detailed investigation of different traits shows that agreeableness and emotional stability contribute the most to the gender wage gap. In particular, women's higher average levels of agreeableness and lower average levels of emotional stability relative to men substantially reduce their bargaining power and lower their initial human capital endowment.

Most personality psychologists believe personality traits are relatively stable after age 25 (e.g. Costa Jr and McCrae (1988); McCrae and Costa Jr (1994)) and are not that responsive to common life events or experiences (e.g. Lüdtke et al. (2011); Cobb-Clark and Schurer (2013, 2012); Bleidorn et al. (2018)), However, there are some recent studies of randomized control trials (RCTs) in clinical psychology that find that some aspects of personality are amenable to change (e.g. Barlow et al. (2014); Bagby et al. (2008); Soskin et al. (2012)). Roberts et al. (2017) report results from a meta-analysis of 207 studies and conclude that personality traits are modifiable with short-term (6-8 weeks) therapeutic mental health treatments, with modest increases in the emotional stability trait being the primary treatment outcome. We use our estimated job search model to evaluate the effects of providing such treatments to individuals (both males and females) with low levels of emotional stability, which is known to be a risk factor for anxiety and depression. We find a modest reduction in overall wage inequality and in the gender wage gap. A cost-benefit analysis indicates that the estimated lifetime benefits of such interventions outweigh the cost, with both males and females benefiting.

Our results contribute both theoretically and empirically to the literature analyzing gender differences in job search behaviors and outcomes. Most prior studies estimate different search parameters by gender and education groups (e.g. Bowlus (1997), Bowlus and Grogan (2008), Flabbi (2010a), Liu (2016), Morchio and Moser (2020), Amano-Patino et al. (2020)). In comparison, we allow job search model parameters to depend on a larger set of worker characteristics to account for both cognitive and noncognitive dimensions of heterogeneity. There are two studies that empirically investigate the association between noncognitive traits and job search, Caliendo et al. (2015) and McGee (2015). The noncognitive measure used in both papers is "locus of control" (LOC), which is a measure of how much individuals think success depends on “internal factors”(i.e. their own actions) versus “external factors.”[4]. To the best of our knowledge, ours is the first study to incorporate the Big Five personality traits into a job search, matching, and bargaining framework.

A few studies further investigate the relationship between personality traits and gender wage gaps using an Oaxaca-Blinder decomposition framework (Mueller and Plug (2006); Braakmann (2009); Nyhus and Pons (2012); Risse et al. (2018); Collischon (2021)). They generally find that endowment difference in agreeableness and emotional stability contribute most to the gender gaps, with differential returns to these traits mattering much less. By incorporating personality traits into a canonical job search and bargaining model, our results not only provide further support for previous findings but also quantify the main mechanisms behind them. In particular, we find that the most important channel through which personality traits affect gender gaps is wage bargaining, rather than human capital or job search behavior. Our paper also contributes to a small literature incorporating personality traits into specific behavioral models (Todd and Zhang (2020); Heckman and Raut (2016); Flinn et al. (2018)).

There are several studies in the workplace bargaining literature showing that women are less likely to ask for fair wages, both in lab experiments (e.g. Stuhlmacher and Walters (1999); Dittrich et al. (2014)) and survey data (e.g. Säve-Söderbergh (2007); Card et al. (2015); Biasi and Sarsons (2022)). However, there is no consensus on the reason for this phenomenon. Possible explanations offered include gender differences in risk preferences (e.g. Croson and Gneezy (2009)), attitudes towards competition (e.g. Lavy (2013); Manning and Saidi (2010)) and negotiation skills (e.g. Babcock et al. (2003); Biasi and Sarsons (2022)). Our results suggest that gender differences in personality traits are a key factor underlying differences in bargaining outcomes. Specifically, we find that women’s higher average levels of agreeableness and lower levels of emotional stability reduce their relative bargaining power. This result is consistent with Evdokimov and Rahman (2014), who design a bargaining experiment and show that an increase in a worker’s agreeableness level leads a manager to allocate less money to the worker.

This paper proceeds as follows. The next section presents our baseline job search model. Section 3 describes the data. Section 4 discusses the model’s econometric implementation. Section 5 presents the parameter estimates of the model. Section 6 interprets the model estimates and presents wage gap decomposition results. Section 7 concludes.

2 Model

We now introduce our job search, matching, and bargaining model, which allows for worker heterogeneity and human capital accumulation. We then discuss how the model is extended to incorporate heterogeneous primitive parameters that are functions of individual attributes.

[4]Previous studies generally indicate that higher internal LOC is positively correlated with earnings. However, LOC is not that relevant for gender wage gaps either in terms of differential endowments or returns (see e.g. Semykina and Linz (2007); Heineck and Anger (2010); Nyhus and Pons (2012))

2.1 Setup and environment

The model is set in continuous time, with a continuum of risk-neutral and infinitely lived agents: firms and workers. Workers are distinguished by different observable "types," represented by the vector pair (z, τ). Here, τ denotes the individual's gender, while the vector z encompasses all other observed individual characteristics, including education level, cognitive skills, birth cohort, and the Big Five personality trait assessments. To simplify the notation, we temporarily suppress the τ notation but will reintroduce it later when discussing individual heterogeneity in subsection 2.3.[5]

Each worker enters the market with an initial human capital level $a_0(z)$, which may vary depending on their observable characteristics. The human capital each worker possesses is one-dimensional and general, in the sense that it generates the same flow productivity at all potential employers. While employed, a worker's human capital grows at rate $\psi(z)$, which can be interpreted as learning by doing. When unemployed, human capital depreciates at rate $\delta(z)$. A type z worker with cumulative employment experience S_E and unemployment experience S_U has a human capital level equal to

$$a(z, S_E, S_U) = a_0(z) \exp(\psi(z) S_E - \delta(z) S_U).^6$$

When a type z worker with human capital a is matched with a firm, their productivity is

$$y(\theta, a(z, S_E, S_U)) = a(z, S_E, S_U) \times \theta$$

where θ captures the match-specific productivity–a random draw from the probability density distribution $g_z(\theta)$, defined on R_+.[7] The flow utility of unemployment to the individual is assumed to be $a \times b$, where b is allowed to differ by gender.[8]

An unemployed worker and an employed worker meet potential employers at predetermined rates, $\lambda_U(z)$ and $\lambda_E(z)$, which may vary with observable worker characteristics.[9] Employment

[5]We separate gender τ from z as an independent state variable because we will incorporate gender in a more flexible way than other observed characters when we estimate the model.

[6]This way of specifying human capital accumulation considerably simplifies the model's solution. However, it has the implication that $\frac{S_E}{S_U} \to \infty \Rightarrow w \to \infty$, which means infinitely-lived individuals who spend more time employed than unemployed will have an unbounded wage. Consequently, the steady-state distribution of wages is not well-defined. Burdett et al. (2016) address this issue by introducing a constant death rate, which maintains stationarity. Their model accommodates both a death rate and an instantaneous discount rate. In our model, the discount rate (ρ) can be interpreted as the sum of a positive constant death rate and a "true" discount rate, which results in a well-defined steady state wage distribution. In our likelihood specification, the steady state distributions that are utilized do not depend on the accumulated experience distribution, so the issue is irrelevant for estimating the model.

[7]This specification of the production technology is commonly used in the search literature, although the interpretation of θ varies. In Postel-Vinay and Robin (2002) and Cahuc et al. (2006), matched worker-firm information is available, enabling the authors to identify distributions of worker and firm types nonparametrically. To the best of our knowledge, there are no such data sets that report worker's personality traits. Therefore, our model's identification and estimation rely only on supply side data. Our model does not incorporate different firm types, but we do allow male and female workers to draw from different match quality distributions.

[8]The assumption that the flow value of being unemployed is proportional to worker's ability a is common in the literature (e.g. Postel-Vinay and Robin (2002); Bartolucci (2013); Flinn and Mullins (2015)) and is made mainly for tractability. This assumption is exploited when making our model identification arguments below.

[9]Different rates might arise, for example, from job application behavior that could depend on worker traits. The exogeneity assumption regarding worker-firm contact rates is what makes our analysis "partial equilibrium." A

matches are dissolved at the exogenous rate $\eta(z)$. The common discount rate of all agents in the model, firms and workers, is ρ, assumed to be independent of z.[10] The worker and the firm bargain over the wage w using a Nash bargaining protocol, with the outside option of the worker dependent upon the assumed protocol (described below). The worker's flow payoff from the match is w and the firm's flow profit is $y(\theta, a) - w$. The bargaining power of the individual is denoted by $\alpha(z)$.

2.2 Job search and wage determination

2.2.1 Worker and firm value functions

A worker receives job offers at the rate $\lambda_U(z)$ when unemployed and $\lambda_E(z)$ when employed. Following Dey and Flinn (2005) and Cahuc et al. (2006), we assume firms are able to observe the worker's productivity at competing firms, either directly or through the process of repeated negotiation. When an employee receives an outside job offer, firms behave as Bertrand competitors, with the culmination of the bidding process resulting in the worker going to the firm where her productivity is greatest. Because the worker's human capital a is the same at all firms, productivity differences across firms are entirely attributable to different match productivities.

When two firms compete for the same worker, their positions are symmetric. This means the incumbent has no advantage or disadvantage in retaining the worker with respect to the potential employer.[11] Let θ and θ' denote the two match productivity draws at the firms, and assume that $\theta > \theta'$. We will refer to θ as the *dominant* match value and θ' as the *dominated* match value. When the firms engage in Bertrand competition in terms of wage negotiations, the firm associated with the dominated match value will attempt to attract the worker by increasing its wage offer to the point where it earns no profit from the employment contract. That is, the firm with match value θ' will offer a maximum wage of $a\theta'$. The value of working in the dominated firm with wage $a\theta'$ (equal to worker's productivity) then serves as the worker's outside option when engaging in Nash bargaining with the firm with the dominant match productivity value θ.

To simplify the model, we assume that workers retain the option to accept any previous job offers received during the current employment spell. For example, let's say an individual leaves unemployment to accept a job at a firm where their match value is θ'. While working at that firm, the worker's productivity continuously grows at the rate $\psi(z)$, and their wage grows at the same rate because the worker renegotiates the wage using the value of unemployment, which is proportional to their human capital, as the outside option. Suppose the worker encounters another firm at which their match productivity is $\theta > \theta'$. Due to efficient mobility, the worker will move to the new firm. The wage there will be negotiated, with the worker's outside option being the

general equilibrium version of the model would endogenize these rates.

[10]There is some evidence that workers with different cognitive and noncognitive ability tend to have different discount rates (Dohmen et al. (2011)). However, we do not allow for such dependence because the (ρ, b) are not individually identified in the canonical search framework (Flinn and Heckman (1982)).

[11]This would not be the case if, for example, there was a finite positive cost associated with changing employer. In this case, there would be a "wedge" between the values associated with the two match productivity values, the size of which would be a function of the size of the mobility cost.

value of employment at the previous firm with wage $a\theta'$. The assumption that individuals can return to their former employer at any time during their subsequent employment implies that their wage at the new firm will grow at a rate of $\psi(z)$, mirroring the increase in their outside option value. This can be seen as a continuous renegotiation process during their employment, which leads to consistent wage growth at a rate $\psi(z)$ across all jobs, as workers acquire more general human capital.

This rationale extends to the case where the worker encounters more than two firms during the employment spell. In this case, if we continue to denote the best match productivity value encountered during the current employment spell by θ and the second-best value encountered by θ', the individual will have a wage determined by the two values (θ, θ') with wage growth given by the exogenous parameter $\psi(z)$.[12]

We now derive the expression for the bargained wage. Let $a = a(z, S_E, S_U)$ denote human capital, as previously defined. First, consider an employed worker with the state variable (θ, θ', z, a). When offered a wage w, the value of employment can be written as

(1)

$$\rho V_E(\theta,\theta',z,a;w) = w + \underbrace{a\psi(z)\frac{\partial V_E(\theta,\theta',z,a)}{\partial a}}_{\text{(1) Human capital accumulation}} + \underbrace{\lambda_E(z)\int_{\theta'}^{\theta}(V_E(\theta,x,z,a)-V_E(\theta,\theta',z,a))dG_z(x)}_{\text{(2) same firm, better outside option}}$$
$$+\underbrace{\lambda_E(z)\int_{\theta}(V_E(x,\theta,z,a)-V_E(\theta,\theta',z,a))dG_z(x)}_{\text{(3) change firm, better match productivity}} + \underbrace{\eta(z)(V_U(z,a)-V_E(\theta,\theta',z,a))}_{\text{(4) job dissolved}}$$

where $V_U(z,a)$ denotes the value of being unemployed. Term (1) reflects the growth in the value of employment value due to human capital accumulation while employed.[13] When human capital increases, the wage will be renegotiated, because the human capital increase applies to all potential employers and the employee still holds her best dominated offer θ'. Term (2) corresponds to the case where the worker encounters a new firm with match productivity x, where $\theta' < x \leq \theta$. The employee will remain at the current firm, but the wage will be renegotiated given the increased value of the worker's outside option (from θ' to x). Term (3) corresponds to the case in which the new match productivity value x exceeds the current match value θ. In this case, the individual moves to the new job, where their match productivity increases to x, and θ becomes the new dominated match value. In cases (1), (2) and (3), the wage offer the individual gets from the dominated firm equals the individual's productivity at that firm. Term (4) corresponds to the case in which the

[12]If firms are forced to offer fixed wage contracts and offers are withdrawn as soon as they are rejected, then wages will only be renegotiated to reflect productivity gains due to human capital accumulation when the worker encounters another firm and a renewed round of bargaining begins. In the Burdett et al. (2016) model of wage posting, upon which our specification of the human capital growth process is based, employers compete on piece rates. In this way productivity gains through human capital accumulation are reflected in continuous increases in the wage at a rate equal to the piece rate offered by the employer.

[13]To see this, note that the dynamic component in the value function is given by $\frac{\partial V_E(\theta,\theta',a,z)}{\partial t_E} = \frac{\partial V_E(\theta,\theta',a,z)}{\partial a}\frac{\partial a}{\partial t_E} = a\psi(z)\frac{\partial V_E(\theta,\theta',a,z)}{\partial a}$. An important feature is that the dynamic component is proportional to the worker's human capital a.

current job is dissolved due to an exogenous shock that occurs at rate $\eta(z)$.

In the special case where the match productivity is the same at both the dominant and dominated firms (i.e. $\theta = \theta'$), equation (1) simplifies to

$$\begin{aligned}(2)\qquad & \rho V_E(\theta', \theta', z, a) = a\theta' + a\psi(z)\frac{\partial V_E(\theta',\theta',z,a)}{\partial a} \\ & +\lambda_E(z)\int_{\theta'}\left(V_E(x, \theta', z, a) - V_E(\theta', \theta', z, a)\right)dG_z(x) + \eta(z)\left(V_U(z, a) - V_E(\theta', \theta', z, a)\right).\end{aligned}$$

The value of the employment match to the firm, given that the state of the worker is (θ, θ', z, a), at wage w, is

(3)

$$\begin{aligned}\rho V_F(\theta, \theta', z, a; w) = a\theta - w + a\psi(z)\frac{\partial V_F(\theta,\theta',z,a)}{\partial a} + \lambda_E(z)\int_{\theta'}^{\theta}\left(V_F(\theta, x, z, a) - V_F(\theta, \theta', z, a)\right)dG_z(x) \\ +\lambda_E(z)\int_{\theta}\left(0 - V_F(\theta, \theta', z, a)\right)dG_z(x) + \eta(z)(0 - V_F(\theta, \theta', z, a))\end{aligned}$$

where $a\theta$ is the flow revenue to the firm and $a\theta - w$ is the firm's flow profit. Note that when the match is exogenously terminated, which occurs at rate $\eta(z)$, the value to the firm is the value of an unfilled vacancy, which equals 0 due to the free entry condition.[14]

A type z worker with human capital a has flow utility when unemployed equal to ab, where b is a fixed constant.[15] The value of unemployment is

$$(4)\quad \rho V_U(z, a) = ab + \underbrace{\lambda_U(z)\int_{\theta^*(z,a)}\left(V_E(x, \theta^*, z, a) - V_U(z, a)\right)dG_z(x)}_{\text{(1) hire out of unemployment}} - \underbrace{a\delta(z)\frac{\partial V_U(z, a)}{\partial a}}_{\text{(2) human capital depreciation}},$$

where $\theta^*(z)$ is the reservation match value, which is the match productivity at which an individual is indifferent between employment and continued search in the unemployment state. Thus θ^* is given by $V_U(z, a) = V_E(\theta^*, \theta^*, z, a)$. Term (1) corresponds to the case where job seekers receive job offers with match equality greater than or equal to the reservation match value. Term (2) captures stochastic human capital depreciation while unemployed.

2.2.2 The bargained wage

The Nash-bargained wage for a worker who is employed is given by

$$(5)\qquad w(\theta, \theta', z, a) = \arg\max_{w}(V_E(\theta, \theta', z, a; w) - V_E(\theta', \theta', z, a))^{\alpha(z)}V_F(\theta, \theta', z, a; w)^{1-\alpha(z)}$$

where the worker's outside option is $V_E(\theta', \theta', z, a)$, given in equation (2). The firm's outside option is assumed to be 0 and the worker's share of the surplus is $\alpha(z)$. The solution to the above

[14] The free entry condition is a common assumption in the literature and is always imposed when solving a general equilibrium version of the model in which the contact rates between searchers and firms are endogenously determined. See Pissarides (1984) and Pissarides (1985) for the first applications of the "zero-profit condition."

[15] This assumption greatly simplifies the solution to the steady state value functions, and is made, for example, in Postel-Vinay and Robin (2002), Cahuc et al. (2006), and Flinn and Mullins (2015).

Nash-bargaining protocol has a closed form expression (see Section A.1.1 for the derivation)
(6)

$$w(\theta,\theta',z,a) = \underbrace{a_0(z)\exp(\psi(z)S_E - \delta(z)S_U)}_{a(z,S_E,S_U)} \underbrace{\left(\theta - (1-\alpha(z))\lambda_E(z)\int_{\theta'}^{\theta} \frac{\rho+\eta(z)-\psi(z)+\alpha(z)\bar{G}_z(x)}{\rho+\eta(z)-\psi(z)+\lambda_E(z)\alpha(z)\bar{G}_z(x)}dx\right)}_{\chi(\theta,\theta',z)}$$

$$= a_0(z)\exp(\psi(z)S_E - \delta(z)S_U)\left(\alpha(z)\theta + (1-\alpha(z))\theta' - (1-\alpha(z))^2\lambda_E(z)\int_{\theta'}^{\theta}\frac{\bar{G}_z(x)}{\rho+\eta(z)-\psi(z)+\lambda_E(z)\alpha(z)\bar{G}_z(x)}dx\right), \theta' < \theta$$

This expression shows that human capital, a, increases wages proportionally. The term labeled $\chi(\theta,\theta',z)$ denotes the wage per unit of human capital, which does not depend on a. Our wage determination expression nests the wage equation in Cahuc et al. (2006), which is a model without changes in human capital, i.e., $\psi(z) = \delta(z) = 0$. The wage also increases in the bargaining power $\alpha(z)$. In the limiting case where $\alpha(z) = 1$, the bargained wage equals the current productivity, that is $w(\theta,\theta',z,a) = a\theta$. In this scenario, new job offers will not affect the wage within the current job. In the opposite scenario, where $\alpha(z) = 0$, the bargained wage $w(\theta,\theta',z,a) = a\theta' - a\lambda_E(z)\int_{\theta'}^{\theta}\frac{\bar{G}_z(x)}{\rho+\eta(z)-\psi(z)+\lambda_E(z)\bar{G}_z(x)}dx$. The first term $a\theta'$ in this expression represents the maximum wage offered by the dominated firm. The second term represents the option value of moving from a job with lower match value θ' to a job with higher match value x. This option value increases with the difference between the two competing offers $(\theta - \theta')$.

Based on equation (6), we can derive the following comparative statics. First, the bargained wage increases with the worker's human capital a. Second, the wage decreases with the offer arrival rate $(\lambda_E(z))$ but increases with the job termination rate $(\eta(z))$. This reflects an option value effect: workers are willing to get paid less today for higher future wage prospects. When this possibility is reduced to 0 (when $\lambda_E(z) = 0$), the bargained wage is simply the weighted average of the productivity in the current job and the productivity in the best other job encountered during the current employment spell. Lastly, the wage also increases with the value of dominated offer θ' and bargaining power $\alpha(z)$, because Bertrand competition and Nash bargaining work both work to increase wages.

The bargained wage for a worker with human capital a hired directly out of unemployment is

$$(7) \qquad w_0(\theta,z,a) = \arg\max_w (V_E(\theta,\theta^*,z,a;w) - V_U(z,a))^{\alpha(z)} V_F(\theta,\theta^*,z,a;w)^{1-\alpha(z)},$$

where $V_E(\theta,\theta^*,z,a)$ denotes the value to an unemployed type z individual at a firm at which their match productivity is θ, and $V_F(\theta,\theta^*,z,a)$ denotes the value to the firm in such a case. Using the definition of the reservation match value $V_E(\theta^*,\theta^*,z,a) = V_U(z,a)$, we have

$$w_0(\theta,z,a) = w(\theta,\theta^*,z,a) = a\left(\theta - (1-\alpha(z))\lambda_E(z)\int_{\theta^*(z,a)}^{\theta}\frac{\rho+\eta(z)-\psi(z)+\alpha(z)\bar{G}_z(x)}{\rho+\eta(z)-\psi(z)+\lambda_E(z)\alpha(z)\bar{G}_z(x)}dx\right)$$

We can uniquely solve for the reservation match value $\theta^*(z,a)$ from the following fixed point problem (see Section A.1.1 for the derivation):

$$\theta^*(z,a) = \frac{\rho+\eta(z)-\psi(z)}{\rho+\eta(z)+\delta(z)}b + \alpha(z)\left(\frac{\rho+\eta(z)-\psi(z)}{\rho+\eta(z)+\delta(z)}\lambda_U(z) - \lambda_E(z)\right) \times \int_{\theta^*(z)} \frac{\bar{G}_z(x)}{\rho+\eta(z)-\psi(z)+\lambda_E(z)\alpha(z)\bar{G}_z(x)}dx \tag{8}$$

The reservation match value solution implies no direct dependence of $\theta^*(\cdot)$ on the level of human capital a.

2.2.3 Household search

Because men and women often inhabit households together, their labor supply decisions can reasonably be thought of as being jointly determined. Gender differences in wages may reflect patterns of assortative mating in the marriage market as well as the manner in which household decisions are made. In Flinn et al. (2018), we develop and estimate a static model of household bargaining over time allocation decisions, using Australian data, and use the model to examine gender wage differences. In this paper, the linear flow utility assumption provides a way to reconcile our model with a household model.[16] Both men and women are assumed to have flow utility functions given by their respective wages w when employed and by the constants ab when unemployed. The linear utility assumption allows the household's maximization problem to be decentralized as the sum of two individual maximization problems, as previously noted in Dey and Flinn (2008). Under this assumption, there is no interdependence in household decision-making.[17]

2.3 Incorporating individual heterogeneity

Thus far, we have described the search and bargaining model given a set of labor market parameters $\Omega(z) = \{\lambda_U(z), \lambda_E(z), \eta(z), \alpha(z), a_0(z), \psi(z), \delta(z), b(z), \sigma_\theta(z)\}$, where the parameter σ_θ denotes the standard deviation of distribution of $\ln\theta$, which is assumed to be normal (so that θ follows a lognormal distribution). We assume that the mean of θ is equal to 1 for all individuals.[18] We now reintroduce individual types (z,τ) and describe how we allow search parameters to depend on worker characteristics. The vector z includes education, cognitive skills, personality traits, and birth cohort and τ denotes gender. For an individual i, we specify gender-specific "link" functions

[16] Another reason that this assumption is made is that it obviates the need to include a specification of the capital markets within which individuals operate, because there is no demand for borrowing or saving under the risk neutrality assumption.

[17] Under the alternative assumption of non-linear utility, bargaining between spouses as well as with firms must be taken into account, which considerably complicates the analysis.

[18] This means that we implicitly assume $\mu_\theta = -0.5\sigma_\theta^2$ so that $E(\theta) = \exp(\mu_\theta + 0.5\sigma_\theta^2) = 1$.

l that map linear index functions into the primitive model parameters as follows:

$$l \equiv \begin{cases} \alpha(z,\tau): & \frac{\exp(z\gamma_\alpha^\tau)}{1+\exp(z\gamma_\alpha^\tau)} \\ \eta(z,\tau): & \exp(z\gamma_\eta^\tau) \\ a_0(z,\tau): & \exp(z\gamma_a^\tau) \\ \lambda_U(z,\tau): & \exp(z\gamma_U^\tau) \\ \lambda_E(z,\tau): & \exp(z\gamma_E^\tau) \\ \psi(\tau), \delta(\tau), b(\tau), \sigma_\theta(\tau): & \text{Only differ by gender} \end{cases} \tag{9}$$

where the vector z that appears in the index functions includes all observable heterogeneity except for gender τ. The γ_j^τ are gender-specific index coefficients, where $\tau \in \{\text{male, female}\}$ and j refers to the different primitive parameters. The gender-specific coefficients γ_j^τ allow for potential asymmetries in how traits of men and women are valued in the labor market.

As indicated above, we assume the parameters $\{\alpha(z,\tau), \eta(z,\tau), a_0(z,\tau), \lambda_U(z,\tau), \lambda_E(z,\tau)\}$ are all functions of z and τ. Recall that our specification of human capital is $a = a_0(z,\tau)\exp(\psi(\tau)S_E - \delta(\tau)S_U)$, where $\psi(\tau)$ is the growth rate during employment and $\delta(\tau)$ is the depreciation rate during unemployment. The initial human capital $(a_0(z,\tau))$ is allowed to be a function of z as well as τ, but we restrict $\psi(\tau)$ and $\delta(\tau)$ to only differ by gender for identification purposes (see below). We also assume that $b(\tau)$ and $\sigma_\theta(\tau)$ differ only by gender.

The "link" functions were chosen to map each of the linear index functions into the appropriate parameter space for the primitive parameter. For example, the $\exp(\cdot)$ function ensures that the job arrival rate parameter is positive $(\lambda_U(z,\tau) \in R_+,)$. The logit transform is used to map $z\gamma_\alpha^\tau$ into the unit interval, which is appropriate given its interpretation as a surplus share parameter. These link functions are commonly used in the estimation of nonlinear models. Although other link functions could be chosen, we have no reason to believe that they would yield substantially different implications regarding the impact of (z,τ) on labor market outcomes.

3 The German socio-economic panel (GSOEP)

Our empirical work uses the German Socio-Economic Panel (GSOEP), which is a large-scale representative longitudinal household survey. Every year, there were nearly 11,000 households surveyed and more than 20,000 persons sampled from the German residential population. We focus on individuals surveyed in 2013 and followed until 2019.[19] We exclude individuals younger than 25 or older than 60, because we do not model schooling decisions or retirement. The GSOEP collects core labor market outcomes in all waves. It also collects individual's personality traits and cognitive abilities in selected years. Below, we describe how we make use of these variables in our

[19] We did not include the most recent year available, 2020, in the empirical analysis because of the effects of Covid-19 on labor market behavior.

analysis. As previously noted, personality traits are usually considered to be fairly stable after age 30. (McCrae et al. (2000)) Some studies find that personality traits change somewhat over the life course but observe that the rate of change is modest, allowing for meaningful comparisons across individuals.[20]

Personality traits. The Big-Five personality traits are measured using a 15-item self-assessment short version of the Big Five Inventory (see Appendix Table A2). Compared to the most widely used revised NEO Personality Inventory (NEO PI-R) with 240 items, the 15-item mini version is more tractable and fits into the time constraints imposed by a general household survey. Respondents were asked to indicate the degree of agreement with each statement on a 7-tier Likert-Scale from "strongly disagree" to "strongly agree." The lowest number '1' denotes a completely opposite description and the highest number '7' denotes a perfectly fitting description. Each personality trait is constructed by the average scores of three items pertaining to that trait, and each trait value has a range between 1 to 7.

Personality traits are collected in waves 2012, 2013, 2017 and 2019 of the GSOEP. Our analysis includes individuals for whom personality traits were measured at least once. When there are multiple measurements, we average the values across the waves.[21] We standardize personality traits and use Z-scores in our empirical analysis.[22]

Cognitive ability. Cognitive skills are measured using a symbol correspondence test in the GSOEP called the SCT, which was modeled after the symbol digit-modalities-test. This test is intended to be a test of "cognitive mechanics," measuring the capacity for information processing (speed, accuracy, processing capacity, coordination and inhibition of cognitive processes).[23] Cognitive ability tests were administered in years 2012 and 2016. We include in our analysis individuals for whom cognitive ability was measured at least once. When there are multiple measures, we use the average value across the waves. We standardize the cognitive ability measure in the same way as for personality traits and use Z-scores.

Hourly wages. The wage is calculated from self-reported gross monthly earnings and weekly working hours. Gross monthly earnings refer to wages from the principal occupation including

[20] A meta-analysis by Fraley and Roberts (2005) reveals a remarkably high rank-order stability: test-retest correlations (unadjusted for measurement error) are about 0.55 at age 30 and then reach a plateau of around 0.70 between ages 50 and 70.

[21] According to Roberts et al. (2008), changes of personality traits in a short course are usually inconsistent and too noisy to be consequential. Therefore, we treat differences observed within a 7-year time frame to likely arise from measurement errors rather than fundamental changes.

[22] Z-scores are calculated by subtracting the overall sample mean (including both men and women) and dividing by the sample standard deviation. The standardized variable has mean 0 and standard deviation 1. This makes it easy to compare magnitudes of estimated model coefficients corresponding to different traits. The coefficients can also be easily interpreted as the effect of a one standard deviation change in the trait.

[23] The test was implemented asking respondents to match as many numbers and symbols as possible within 90 seconds according to a given correspondence list which is visible to the respondents on a screen. Another available test in GSOEP is a word fluency test developed after the animal-naming-task Lindenberger and Baltes (1995): Respondents name as many different animals as possible within 90 seconds. Compared with the symbol correspondence test, this test requires sufficient language skills and therefore could be less accurate for non-native individuals. Therefore, we only use SCT as our primary measure for cognitive ability.

overtime remuneration but not including bonuses. Weekly working hours measures a worker's actual working hours in an average week.[24] The hourly wage is calculated by

$$\text{Hourly wage} = \frac{\text{Monthly gross wages (including overtime pay; without annual bonus)}}{\text{Weekly working hours} * 4.33}$$

We deflate wages using the consumer price index with 2005 serving as the base year.

Job Spells and unemployment spells. Each wave in the panel contains retrospective monthly information about the individual's employment history. The GSOEP distinguishes between several categories of employment status, and we aggregate the information into three distinct categories: unemployed, employed and out of labor force. A person is defined as unemployed (a job searcher) if they are currently not employed and indicate that they are looking for a job. Employment status refers to any kind of working activity: full time, part time, short working hours or mini-jobs. Out of labor force includes retirement, parental leave, school, vocational training and military service. As described below, our model is estimated based on observed employment cycles, which do not include out of labor force spells. If a job A directly follows a job B in the same employment spell, we code such occurrence as a job-to-job transition. If an individual reports any unemployment spells between two jobs, then we consider the previous job to have ended with a transition to unemployment. We drop individuals with missing information on key variables (education, age, gender, personality traits, cognitive ability). We further drop individuals who are out of labor force during the entire survey. The final sample contains data on 6,540 individuals.[25]

As seen in the upper panel of Table 1, men and women have very similar average years of education (12.40 for men and 12.59 for women) and cognitive ability (3.33 for men and 3.30 for women). In terms of demographic characteristics, the women and men in our sample are roughly the same age on average (42). Men are more likely to be married (66 percent versus 59 percent) and to have more dependent children under the age of 18 (1.00 for men in comparison to 0.92 for women).

With regard to the Big Five personality traits, there are significant gender differences for each of the traits.[26] Women have a higher average score for all the traits except for emotional stability, for which the score is lower by 0.49 – the largest gender disparity observed for any of the traits. As previously discussed in the introduction, similar gender differences in traits have been documented for many countries.

The lower panel of Table 1 presents summary statistics for labor market outcomes. As seen in the last column, all of the gender differences are statistically significant at conventional levels. Before entering into the sample period, men have on average 16.98 years full-time experience, compared to

[24] When the actual working hours are not available, we use reported contracted working hours when they are available.

[25] Appendix section A.3.1 discusses the sample selection criteria in greater detail. Table A1 compares the full sample and the final estimation sample.

[26] In Table 1, the traits are measured on a scale of 1 to 7, as reported in the raw data. However, in our empirical analysis we use standardized z-scores for ease of interpreting effect sizes.

Table 1: Summary Statistics by Gender†

	Male			Female			Difference	
	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.	Diff in mean	P-value
Age	41.96	9.94	3218	41.78	9.97	3319	-0.20	0.061
Cohort 1:age $\in [25, 37)$	0.32	0.47	3218	0.33	0.47	3319	-0.02	0.146
Cohort 2:age $\in [37, 49)$	0.39	0.49	3218	0.38	0.48	3319	0.02	0.162
Cohort 3:age $\in [49, 60]$	0.29	0.45	3218	0.29	0.45	3319	0.00	0.999
Years of Education	12.40	2.84	3218	12.59	2.79	3319	-0.19	0.006
Marriage	0.66	0.47	3218	0.59	0.49	3319	0.07	0.000
Number of children (under age 18)	1.00	1.17	3218	0.92	1.06	3319	0.08	0.003
Cognitive ability	3.33	0.93	3218	3.30	0.86	3319	0.03	0.174
Openness to experience	4.53	1.05	3218	4.74	1.07	3319	-0.21	0.000
Conscientiousness	5.77	0.80	3218	5.94	0.76	3319	-0.17	0.000
Extraversion	4.84	1.03	3218	5.12	0.98	3319	-0.28	0.000
Agreeableness	5.24	0.83	3218	5.51	0.82	3319	-0.26	0.000
Emotional stability	4.57	1.03	3218	4.09	1.09	3319	0.49	0.000
Labor market outcomes								
Prior full time experience (years)	16.98	11.01	3218	10.23	9.64	3319	6.75	0.000
Prior part time experience (years)	0.90	2.47	3218	4.97	6.41	3319	-4.07	0.000
Prior unemployment experience (years)	1.03	2.74	3218	1.21	3.08	3319	-0.18	0.013
Employment during sample period (months)	39.33	25.55	6580	34.90	25.09	7239	4.43	0.000
Unemployment during sample period (months)	14.21	16.26	2212	15.50	17.70	2096	-1.29	0.013
Average hourly wages (€/h)	16.65	8.34	6497	14.00	6.95	7116	2.65	0.000

†The p-value is for a two-sided t-test of equality of means. Cognitive ability and personality traits reported in the table are measured on a scale of 1 to 7 but we use their Z-scores in the later empirical analysis. Observations in the upper panel are number of individuals and observations in the lower panel refers to the number of spells. Each individual may have multiple spells. Wages are deflated using the consumer price index with 2005 serving as the base year.

10.23 for women. However, women have more part-time experience (4.97 years versus 0.90). Men also have less unemployment experience than female workers. During the sample period, between 2012 to 2018, men spend more months in employment, 39.33 on average in comparison to 34.90 for women. They also spend less time in unemployment, 14.21 months compared to 15.50 for women.

The dataset contains information on actual wages. Men's average hourly wage is higher, €16.65 on average for men in comparison to €14.00 on average for women. Comparing average hourly wages for men and women, there is a 18.9 percent gender wage gap, which is substantial considering that men and women have nearly the same years of education and cognitive skill levels. In comparison to other estimates in the literature, a study by Blau and Kahn (2000) found a gender hourly gap in West Germany of 32 percent, placing West Germany in position 6 in a ranking of 22 industrialized countries. The gap we find is consistent with reports from the German Federal Statistical Office, which show that the gender wage gap was fairly stable from 2013 to 2019, declining slightly. The gap stood at 22 percent in 2014 and 19 percent in 2019, placing Germany as the European Union country with the second-worst gender pay gap (after Estonia).

3.1 How are personality traits associated with wages and unemployment spells

In this section, we use "reduced-form" regression and hazard models to examine whether cognitive and noncognitive traits are important determinants of hourly wages and employment transitions. In our model, wages are a nonlinear function of individual characteristics z and of employment and unemployment experience as shown in equation (6). The wage regression estimated here can be viewed as a linear approximation to that equation. The hazard model estimates the probability of transiting from unemployment to employment, which corresponds to $h_U(z,\tau) = \lambda_U(z,\tau)[1 - G_\tau(\theta^*(z,\tau))]$ in our model.

Table 2 presents the estimated regression coefficients where the dependent variable is log hourly wages. Columns 1-6 show gender-specific coefficients, while columns 7-9 report coefficients from a pooled sample of men and women, including a male indicator variable. Columns 1, 4, and 7 report coefficients from a regression of log wages on education, labor market experience, unemployment experience, cognitive ability, and cohort dummies. Columns 2, 5, and 8 show the estimated coefficients from the same wage regressions but include the Big-5 personality traits as additional covariates. Columns 3, 6, and 9 include, in addition, marital status and the number of dependent children.

Comparing the coefficients from regressions with and without personality traits (e.g. columns 1 and 2, and columns 4 and 5) shows that including personality traits improves the explanatory power of the regression, especially for men. The estimated returns to work experience are similar for both genders. However, men have a greater wage penalty for unemployment experience compared to women. In terms of personality traits, agreeableness and emotional stability are significantly correlated with hourly wages. Individuals with high scores on agreeableness have lower hourly wages, while individuals with high scores on emotional stability have higher hourly wages. Cognitive abilities are also significantly positively related to wages, with similar estimated coefficients for men and women. When examining the impact of personality traits on the gender wage gap (columns 7 and 8), we find that including personality traits as additional covariates reduces the coefficient on the male indicator variable from 0.173 to 0.156, which indicates that personality traits explain a significant portion of the wage gap. Lastly, both the younger cohort (age 25-37) and older cohort (age 49-60) have lower wages compared with the reference group (age 37-48).

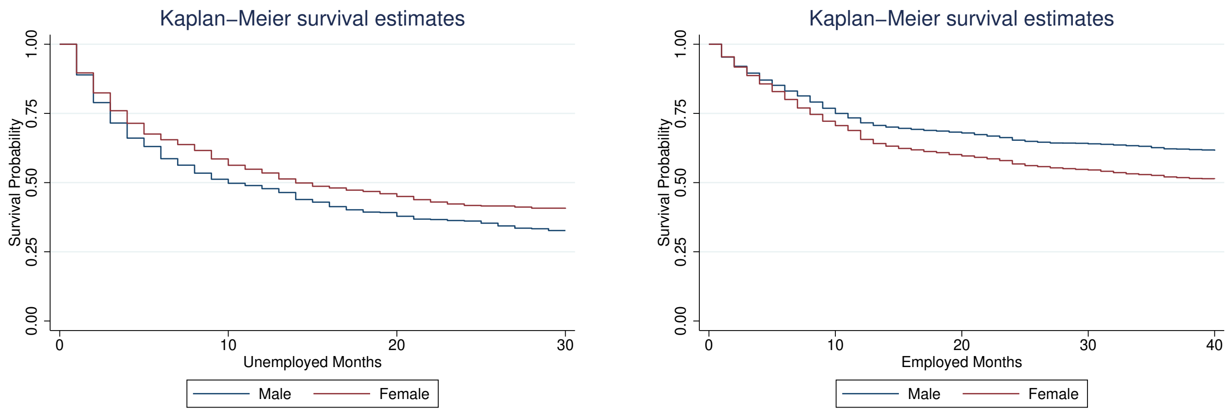
Table 2: The association between individual traits and hourly wages (by gender)†

Outcome variable:		Male			Female			Pooled	
(log) hourly wage	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Years of education	0.072***	0.070***	0.070***	0.080***	0.080***	0.080***	0.075***	0.075***	0.075***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Working experience	0.013***	0.012***	0.012***	0.012***	0.012***	0.013***	0.012***	0.012***	0.013***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Unemployment experience	-0.041***	-0.040***	-0.038***	-0.033***	-0.033***	-0.032***	-0.037***	-0.036***	-0.034***
	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
Cognitive ability	0.054***	0.051***	0.052***	0.052***	0.049***	0.048***	0.053***	0.051***	0.051***
	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)	(0.006)	(0.006)	(0.006)
Openness to experience		-0.008	-0.004		-0.012	-0.010		-0.011*	-0.007
		(0.008)	(0.008)		(0.008)	(0.008)		(0.006)	(0.006)
Conscientiousness		-0.003	-0.006		0.000	-0.001		-0.001	-0.004
		(0.008)	(0.008)		(0.008)	(0.008)		(0.006)	(0.006)
Extraversion		0.005	0.002		0.012	0.011		0.008	0.007
		-0.008	(0.008)		(0.008)	-0.008		(0.006)	(0.006)
Agreeableness		-0.024***	-0.023***		-0.015*	-0.015*		-0.019***	-0.019***
		(0.008)	(0.008)		(0.008)	(0.008)		(0.006)	(0.006)
Emotional stability		0.037***	0.039***		0.022***	0.023***		0.031***	0.032***
		(0.008)	(0.008)		(0.008)	(0.008)		(0.006)	(0.006)
Male indicator							0.173***	0.156***	0.144***
							(0.011)	(0.012)	(0.012)
Cohort (ref group: 37-48)									
Cohort 1 (age $\in [25, 37)$)	-0.087***	-0.092***	-0.057**	-0.086***	-0.085***	-0.072***	-0.089***	-0.090***	-0.065***
	(0.023)	(0.023)	(0.022)	(0.019)	(0.019)	(0.020)	(0.014)	(0.014)	(0.014)
Cohort 3 (age $\in [49, 60]$)	-0.154***	-0.150***	-0.103***	-0.051***	-0.049**	-0.023	-0.100***	-0.096***	-0.062***
	(0.024)	(0.024)	(0.025)	(0.019)	(0.019)	(0.021)	(0.015)	(0.015)	(0.016)
Constant	1.755***	1.765***	1.648***	1.445***	1.460***	1.408***	1.702***	1.707***	1.613***
	(0.057)	(0.057)	(0.057)	(0.042)	(0.043)	(0.045)	(0.034)	(0.035)	(0.036)
Additional control variables									
Marriage indicator			X			X			X
Number of dependent children			X			X			X
Number of Obs	13593	13593	13593	12522	12522	12522	26115	26115	26115
Adjusted R^2	0.277	0.283	0.297	0.283	0.286	0.289	0.310	0.314	0.321

†Standard errors are clustered at the individual level.

Figure 2: Kaplan-Meier survival estimates by gender

(a) Unemployment duration　　　　(b) Employment duration



Source: GSOEP data.

Comparing the coefficients from regressions with and without marital and child status (columns 3 and 4, and columns 5 and 6), we see that the magnitude of the statistically significant personality trait coefficients does not vary much. Marital status and child status are significantly related to wages, but do not significantly affect the explanatory power of personality traits. The wage equation we use in the job search model includes work experience, unemployment experience, cognitive scores, personality traits, and cohort indicator variables. It does not include marital and child status, because these variables could be time-varying and our model is stationary, and because these characteristics are not typically considered direct wage determinants.

Figure 2 displays estimated Kaplan-Meier survival functions for unemployment duration by gender. Women exit unemployment more slowly and exit employment more quickly than men. We also estimated a Cox proportional hazards model, shown in Table 3, to analyze how employment transitions relate to observed individual traits. The results indicate that higher levels of education and cognitive ability lead to a higher exit rate from unemployment for both men and women. Additionally, education appears to improve job stability for men by reducing the hazard of leaving their current jobs.

The results also reveal that all five personality traits (except agreeableness) are related to labor market transitions. For both men and women, higher scores in conscientiousness and emotional stability are associated with lower rates of leaving employment and higher rates of exiting unemployment. This means that these traits are beneficial, because they both improve the chances of finding a job and increase job stability. On the other hand, openness to experience increases the hazard rate of leaving employment for both men and women. For men, agreeableness is also associated to a higher rate of exiting unemployment.

In summary, our analysis of hourly wages and employment transitions using regression and hazard models indicates that both cognitive and noncognitive traits are significant determinants of

Table 3: Estimated unemployment and employment Cox proportional hazard rates†

Outcome variable:	Unemployment		Employment	
	(1) Male	(2) Female	(4) Male	(5) Female
Years of education	0.100***	0.177***	-0.024***	0.001
	(0.016)	(0.013)	(0.008)	(0.007)
Cognitive Ability	0.080**	0.208***	-0.031	0.026
	(0.041)	(0.047)	(0.025)	(0.021)
Openness to experience	0.035	-0.022	0.124***	0.062***
	(0.042)	(0.045)	(0.025)	(0.020)
Conscientiousness	0.111***	0.088**	-0.162***	-0.084***
	(0.041)	(0.043)	(0.022)	(0.021)
Extraversion	-0.048	0.032	0.056**	0.056***
	(0.042)	(0.045)	(0.024)	(0.021)
Agreeableness	0.009	-0.039	0.080***	0.005
	(0.038)	(0.041)	(0.024)	(0.021)
Emotional stability	0.086**	0.086*	-0.111***	-0.067***
	(0.043)	(0.045)	(0.025)	(0.020)
Cohort (ref group: 37-48)				
Cohort 1 (age $\in [25, 37)$)	0.153	-0.191*	0.402***	0.532***
	(0.094)	(0.098)	(0.051)	(0.042)
Cohort 3 (age $\in [49, 60]$)	-0.203*	-0.183*	-0.041	-0.316***
	(0.107)	(0.108)	(0.061)	(0.056)
Number of Obs	1,002	1,015	5,972	6,729

these outcomes. Ignoring personality traits can lead to possibly biased conclusions about the sources of gender wage gaps. Our analysis also suggests that personality traits impact wages through their effects on employment dynamics. To gain a more comprehensive understanding of how personality traits contribute to gender disparities in labor market outcomes, we now turn to the estimation of the job search model presented in section 2.

4 Identification and estimation

In this section, we discuss the model's empirical implementation. We begin by discussing our measurement error assumptions, which are reasonably standard. Subsequently, we examine the identification of the model's primitive parameters and elucidate how our modeling assumptions facilitate identification. The most vital assumptions are those that pertain to the additive separability of individual human capital from the bargaining and matching processes. We will then turn to the specification of our maximum likelihood estimator.

4.1 Measurement error

The endogenous processes of the model are the wages and the timing of labor market state changes. As is virtually always assumed in the literature, we will assume that there is no measurement error in the timing of labor market state changes.[27] In terms of the measurement error in wages, we make a fairly standard assumption that is consistent with most Mincerian wage equations. Specifically, the wage determination equation (equation 6) in our model suggests that the log of the measured wage for an individual with observed characteristics z, τ at a given point in time can be expressed as:

$$\log \tilde{w}_{z,\tau} = z\gamma_a^\tau + (\psi(\tau) S_E - \delta(\tau) S_U) + \ln \chi \left(\theta, \theta', z, \tau; \gamma_{-a}^\tau\right) + \xi_{z,\tau}, \tag{10}$$

where S_E is the accumulated labor market time spent employed, S_U is the accumulated labor market time spent unemployed, and $\xi_{z,\tau}$ is the measurement error in the log wage, which is assumed to be an i.i.d. draw from a normal distribution with mean 0 and variance σ_ξ^2. The term γ_{-a}^τ denotes all of the primitive parameters of the model with the exception of those characterizing the general initial human capital of the individual. Ignoring the term $\ln \chi \left(\theta, \theta', z, \tau; \gamma_{-a}^\tau\right)$ for the moment, this log wage equation includes a vector of individual-specific time-invariant characteristics z reflecting labor market productivity, the total amount of labor market experience, S_E, and the total time spent in unemployment over the labor market career, S_U. To consistently estimate the coefficients $(\gamma_a^\tau, \psi(\tau), \delta(\tau))$ using an ordinary least squares estimator requires that $\xi_{z,\tau}$ is mean independent of the covariates (z, S_E, S_U). Our assumption that $\xi_{z,\tau}$ is normally distributed with mean 0 is a sufficient condition for mean independence to hold.

We include measurement error in wages for multiple reasons. First, survey data on wages typically include measurement error. In a well-known validation study using data from the Panel Study of Income Dynamics (PSID), Bound et al. (1994) find that measurement error is not a major concern in self-reported annual earnings measures. However, they find that reported hourly wage compensation contains a greater degree of measurement error, with the proportion of log wage variation attributable to measurement error as high as 50 to 60 percent. The GSOEP respondents probably report their monthly earnings more accurately than do the PSID respondents, as they are required to have their pay statements on hand at the time of reporting. However, hours worked may be subject to a greater degree of measurement error. In addition, rounding errors, recall bias and social desirability bias may all contribute to measurement error in survey data.

A second reason for incorporating measurement error is to ensure that the model can rationalize all patterns of wage changes observed in the data, which guarantees a well-defined likelihood function. For example, the job search model described previously implies that wages should be strictly increasing over any given job spell. In the data, there are a significant number of violations of this implication during the course of continuous job spells. With two-sided measurement error, the likelihood of observing a wage decrease is strictly positive. It is worth noting that our model can

[27]The one exception known to us is Romeo (2001), who considers the "seam problem" that is well known to exist in the Survey of Income and Program Participation. The main reason that virtually all empirical analyses of duration data assume the correct dating of the beginning and ending of spells is the inevitable mismeasurement of all subsequent spells if an error occurs in dating one spell. Consequently, the measurement error process will be complex and most assuredly not i.i.d., as is typically assumed when allowing for measurement error in wages.

generate a wage decrease even without measurement error when an individual moves from one firm to another. However, wage decreases occur more frequently in the data than implied by the model (given reasonable primitive parameter values) and measurement error in wages helps to account for such outcomes.

In addition, and perhaps more crucially, measurement error can reconcile cases where the model predicts a reservation wage that is higher than we observe a worker hired from unemployment accepting. In our model, every individual inhabits his/her own labor market, because most primitive parameters are a function of a linear index for which the value varies continuously across individuals. As a result, the reservation match value $\theta^*(z,\tau)$ differs across individuals. The lower bound of the theoretical wage distribution for a given individual with state $\{z,\tau\}$, implied by the model is $w_0(\theta^*, z, \tau, a) = a\theta^*(z,\tau)$. However, we occasionally observe a wage below this threshold in the data. Measurement error in wages assigns a positive probability to such occurrences.

As alluded to above, we assume a classical measurement error structure for the observed wages (e.g. Wolpin (1987); Flinn (2006)). In particular, we assume

$$\tilde{w} = w\varepsilon$$

where $\tilde{w}$ is the reported wage and w is the worker's "true" wage. Also, we assume that the measurement error, ε, is independently and identically distributed both within individuals across job spells and across individuals and that it is log-normal. The density of ε is

$$m(\varepsilon) = \phi\left(\frac{\log(\varepsilon) - \mu_\varepsilon}{\sigma_\varepsilon}\right) / (\varepsilon\sigma_\varepsilon) \tag{11}$$

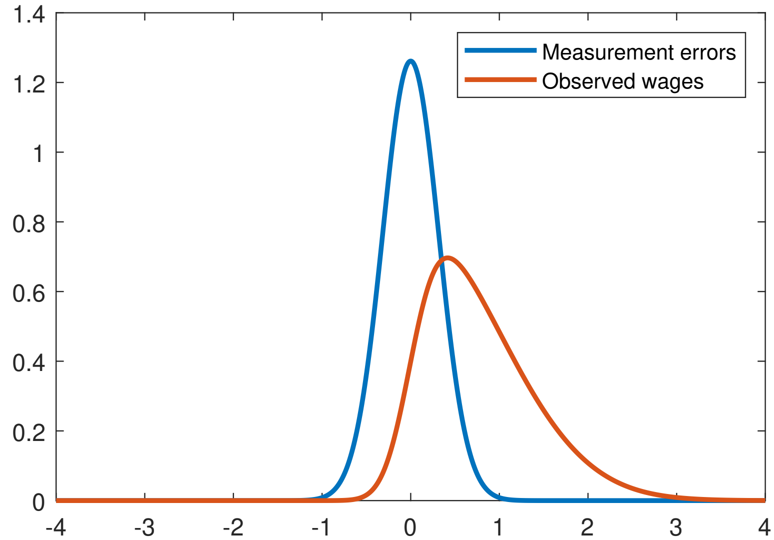
where ϕ denotes the standard normal density and μ_ε and σ_ε are the mean and standard deviation of $\ln\varepsilon$. We impose the restriction $\mu_\varepsilon = -0.5\sigma_\varepsilon^2$, so that $E(\varepsilon|w) = 1$.[28] The expectation of the observed wage is equal to the true wage since

$$E(\tilde{w}|w) = w \times E(\varepsilon|w) = w \ \forall w.$$

The measurement error dispersion parameter, σ_ε, can be identified from multiple wage measures within the same job spell. To see this, let $\tilde{w}_k^{t_1}$ and $\tilde{w}_k^{t_2}$ be two wage measures at two different periods, t_1 and t_2, in the same job k with a match value θ. Denote the "true" wages at these two points by $w(\theta, \theta'_{t_1}, z, \tau, a_{t_1})$ and $w(\theta, \theta'_{t_2}, z, \tau, a_{t_2})$, where θ'_{t_1} and θ'_{t_2} are the best dominated job offers, and a_{t_1} and a_{t_2} are the associated human capital levels at these two times. By definition, we have $\theta'_{t_1} \leq \theta'_{t_2} \leq \theta$ and $a_{t_1} \leq a_{t_2}$. Our wage determination equation (6) implies the following expression

[28] Given that ε follows a lognormal distribution, $E(\varepsilon) = \exp\left(\mu_\varepsilon + 0.5\sigma_\varepsilon^2\right) = 1$ if $\mu_\varepsilon = -0.5\sigma_\varepsilon^2$. Note that there is an apparent discrepancy between our assumptions regarding the properties of the disturbance term ε and the assumption that ξ has mean 0 in (equation 10). In fact, under our measurement error assumption, $E(\xi) \neq 0$. However, this term will only impact the estimate of the constant term in (equation 10) and can easily be recovered. In any event, (10) is not actually used in estimating the model, it is only a device to make our identification arguments more intuitive.

Figure 3: An graphical illustration of how measurement error is identified



for the differences in log wages between t_1 and t_2:

$$\begin{aligned} \log \tilde{w}_k^{t_2} - \log \tilde{w}_k^{t_1} &= \log w(\theta, \theta'_{t_2}, z, \tau, a_{t_2}) - \log w(\theta, \theta'_{t_1}, z, \tau, a_{t_1}) + \log \varepsilon^{t_2} - \log \varepsilon^{t_1} \\ &= \underbrace{\psi(\tau)\,(t_2 - t_1)}_{(1)} + \underbrace{\log \chi(\theta, \theta'_{t_2}, z, \tau) - \log \chi(\theta, \theta'_{t_1}, z, \tau)}_{(2)} + \underbrace{\log \varepsilon^{t_2} - \log \varepsilon^{t_1}}_{(3)} \end{aligned} \tag{12}$$

where the term (1) captures wage changes due to human capital accumulation, term (2) captures wage changes arising from Bertrand competition, and term (3) captures wage changes due to measurement error. Terms (1) and (2) are both non-negative (because of $t_2 \geq t_1$ and $\frac{\partial \chi(\theta, \theta', z, \tau)}{\partial \theta'} \geq 0$), so any negative observed wage changes will occur only due to measurement error. The measurement error variance can be identified from the asymmetry of the distribution of observed wage changes within a job spell, as illustrated in Figure 3. In particular, without the contribution of terms (1) and (2), log wage changes within the same job would arise only from measurement error and be a symmetric normal distribution with mean 0 (the blue curve). Adding terms (1) and (2) skews the distribution to the right and increases its mean as seen in the figure (the orange curve).

Table 4 reports the distribution of wage changes within the same job spell for various time intervals between the two measures. The mean values are positive, indicating wage growth. In a five-year period, for example, the average wage increased by 10.5 percent. However, for lower quantiles the wage changes are negative, consistent with measurement error.

4.2 Identification and Estimation

We now provide a brief discussion of how the primitive parameters characterizing our partial equilibrium model are identified (further details are provided in Appendix A.4). We examine how

Table 4: The distribution of within job spell wage changes by gender and for different time intervals

$\log \tilde{w}_k^{t_2} - \log \tilde{w}_k^{t_1}$	Mean	10%	25%	50%	75%	90%	Obs
One-year gap ($t_2 - t_1 = 12$)							
Male	0.03	-0.19	-0.07	0.02	0.12	0.25	9,189
Female	0.03	-0.23	-0.07	0.02	0.13	0.30	7,888
Three-year gap ($t_2 - t_1 = 36$)							
Male	0.08	-0.15	-0.03	0.07	0.18	0.33	3,975
Female	0.07	-0.21	-0.04	0.06	0.19	0.36	3,087
Five-year gap ($t_2 - t_1 = 60$)							
Male	0.11	-0.13	0.00	0.11	0.23	0.38	1,019
Female	0.12	-0.17	-0.03	0.10	0.25	0.46	750

Note: $\tilde{w}_k^{t_1}$ and $\tilde{w}_k^{t_2}$ are two measures at t_1 and t_2 at the same job spell. The number of observations are reported at the last column of the table.

the following parameters are separately identified, including: (1) Initial human capital endowment: $a_0(z, \tau)$; (2) Bargaining parameter: $\alpha(z, \tau)$; (3) Transition parameters: $\lambda_E(z, \tau), \lambda_U(z, \tau), \eta(z, \tau)$; (4) Human capital growth parameters: $\psi(\tau), \delta(\tau)$; and (5) the variance of match quality distribution $\sigma_\theta^2(\tau)$ and the variance of measurement error $\sigma_\varepsilon^2(\tau)$. As indicated by the notation, all the parameters are allowed to differ by gender τ, while parameters in (1)-(3) are allowed to also vary by the observable individual characteristics.

The analysis in Flinn and Heckman (1982) considers the estimation of a nonequilibrium search model with an exogenous wage offer distribution, which can be thought of as a special case of the model developed in this paper when $\alpha = 1$.[29] They consider the homogeneous case in which all labor market participants have the same primitive parameter values. Furthermore, they assume that wages are measured without error and that there is no on-the-job search. They demonstrate that the parameters λ_U, η, and the parameters characterizing the population wage offer distribution are identified using only monthly Current Population Survey data. These data have information on wages for currently employed individuals and the duration of on-going unemployment spells for those unemployed at the survey date. They further show that the flow utility of unemployment b and the instantaneous discount rate ρ are not point-identified. Assuming a value of one of them, however, enables point identification of the other.

Extending this argument to the case considered here is relatively straightforward. When an individual is employed at a job with match productivity θ, then their reservation value for moving to a new employer is simply θ. Because the distribution of match productivity is assumed to only be gender-specific, the rate at which an individual of type z and gender τ moves directly from one

[29]When $\alpha = 1$, the exogenous wage offer distribution is simply the distribution of θ scaled by the individual's productivity a.

job to another, given our mapping from (z, τ) into $\lambda_E(z, \tau)$, has the following expression:

$$h_{EE}(\theta, z, \tau) = \lambda_E(z, \tau)(1 - G_\tau(\theta)) = \exp(z\gamma_E^\tau)(1 - G_\tau(\theta))$$

These transitions are observed in the data and are included in the likelihood function. Of course, we do not observe θ, but the wage history over the current employment spell provides information regarding this value. This wage history also appears in the likelihood function. By assuming that individuals of gender τ share the same coefficient vectors, job-to-job transitions among same gender individuals are essentially pooled in estimation, making the vector γ_E^τ estimable even in more modest size samples.

The rate at which an employed individual of type z and gender j exits employment and enters unemployment is

$$\eta(z, \tau) = \exp(z\gamma_\eta^\tau)$$

Under our assumption that job dissolution rates are independent of match productivity, this hazard rate does not involve the distribution G_τ.[30] Because we observe these transitions in the data and this rate parameter appears explicitly in the likelihood function, the parameter vector γ_η^τ is easily estimable as well.

Finally, the rate at which an individual of type z and gender τ leaves unemployment for employment is given by

$$h_U(z, \tau) = \lambda_U(z, \tau)(1 - G_\tau(\theta^*(z, \tau))) = \exp(z\gamma_U^\tau)(1 - G_\tau(\theta^*(z, \tau)))$$

The reservation match value for an unemployed individual of type (z, τ) is given in equation (8). It is complex function of all of the parameters characterizing the search environment of the individual, excluding those associated with the constant ability function, γ_a^τ. All of the parameters that determine $\theta^*(z, \tau)$ appear explicitly in the likelihood function, except for (b_τ, ρ). From Flinn and Heckman (1982) we know that these parameters are not separately identified, so that we fix the instantaneous interest rate at $\rho = 0.006$ (where the rate is monthly) and assume that it is the same for all individuals in the sample.

Identification of the bargaining power parameter, α, is difficult without access to information concerning the total size of the surplus to be shared. Although we possess data on the individual's share of the surplus (represented by the wage), we lack measures of the firm's profit linked to a specific job.[31] The identification and estimation of α using only supply-side data was considered in some detail in Flinn (2006). In a homogeneous stationary model without on-the-job search but with bargaining, a sufficient condition for the surplus share parameter α to be identified is that

[30] Positive job dissolution rates are required for the model to be stationary. Although it is theoretically possible to allow these rates not to be independent of the match productivity at the job, to our knowledge no researchers have considered this possibility.

[31] Even when using matched worker-firm data with some measure of total firm profits, assigning the profit associated with a particular job at the firm is not possible without making restrictive assumptions on the production process.

the distribution $G(\theta)$ does not belong to a parametric location-scale family. Under the assumption of lognormality, the wage distribution is not location-scale (although $\ln w$ is), and the nonlinearity enables identification of α.[32]

A key difference between the model estimated in this paper and models developed in the earlier literature (cited in this section) is the inclusion of the human capital parameter a. Our identification argument relies on the additive separability in the term involving γ_a^τ and the term involving the rest of the primitive parameters (denoted γ_{-a}^τ), as implied by the log wage equation (equation 10)

$$\log \tilde{w}_{z,\tau} = \underbrace{z\gamma_a^\tau + (\psi(\tau)S_E - \delta(\tau)S_U)}_{\log a(z,S_E,S_U;\gamma_a^\tau)} + \log\chi\left(\theta,\theta',z,\tau;\gamma_{-a}^\tau\right) + \xi_{z,\tau},$$

where

$$\log\chi(\theta,\theta',z,\tau;\gamma_{-a}^\tau) = \ln\left(\theta - (1-\alpha(z,\tau))\lambda_E(z,\tau)\int_{\theta'}^{\theta}\frac{\rho+\eta(z,\tau)-\psi(\tau)+\alpha(z,\tau)\bar{G}_\tau(x)}{\rho+\eta(z,\tau)-\psi(\tau)+\lambda_E(z,\tau)\alpha(z,\tau)\bar{G}_\tau(x)}dx\right)$$

Having identified the parameters determining $\log\chi(\theta,\theta',z,\tau;\gamma_{-a}^\tau)$, the parameter vector γ_a^τ is identified from the log wage equation (10). The coefficient associated with human capital depreciation during unemployment spells, $\delta(\tau)$, does not appear in the $log\chi$ function, although the parameter associated with human capital appreciation, $\psi(\tau)$ does.

In addition to using wage data alone, the separate identification of the human capital term, $a(z,S_E,S_U;\gamma_a^\tau)$, and the Bertrand competition term, $\chi\left(\theta,\theta',z,\tau;\gamma_{-a}^\tau\right)$, can be facilitated by incorporating data on job-to-job transitions. Wage changes within a job spell occur either because of human capital appreciation or as a result of renegotiation in response to outside offers. In contrast, wage changes associated with job-to-job transitions occur solely because of outside offers and Bertrand competition. Thus, differences in the wage variation observed within job spells versus wage variation associated with job-to-job transitions can be used to separately identify the human capital parameters $\{\psi(\tau),\delta(\tau)\}$ from the other model parameters, γ_{-a}^τ.

Multiple wage observations within the same job spell also provide identifying information for the bargaining power parameter $\alpha(z,\tau)$, in addition to that given by the lognormality assumption on the match productivity distribution $G_\tau(\theta)$. Heuristically speaking, the bargaining parameter describes how the flow match quality surplus, θ, is divided between employers and employees. The proportion of flow surplus per unit of human capital that goes to the firm side is given by the expression:

$$\frac{\theta-\chi(\theta,\theta',z,\tau)}{\theta} = (1-\alpha(z,\tau))\lambda_E(z,\tau)\int_{\theta'}^{\theta}\frac{\rho+\eta(z,\tau)-\psi(\tau)+\alpha(z,\tau)\bar{G}_\tau(x)}{\rho+\eta(z,\tau)-\psi(\tau)+\lambda_E(z,\tau)\alpha(z,\tau)\bar{G}_\tau(x)}dx$$

This fraction decreases as the bargaining power parameter $\alpha(z,\tau)$ increases, meaning that a high

[32]In addition to the functional form of $G(\theta)$, the identification argument of the bargaining power parameter is further strengthened by exploiting the variation from multiple wages within the same job spell, as discussed below.

value of $\alpha(z,\tau)$ implies less wage growth within the job spell. The reasoning behind this is that if workers receive a larger share of the surplus at the beginning of their job, they would expect lower wage growth over the spell, as the firm has less surplus to offer to match their outside options. In the limit, as $\alpha \to 1$, the worker receives all of the flow surplus from the match, and the wage is independent of the outside option, θ'. In this case, the only wage growth during a job spell is due to the deterministic increase in general human capital.

As described below, we adopt a maximum likelihood estimation approach. The likelihood efficiently uses the sample information on wages and labor market transitions and provides a straightforward way of establishing the conditions under which model parameters are identified. Appendix A.4 demonstrates identification within our likelihood framework. A key requirement is the usual full rank condition on the Hessian matrix. In the appendix, we also show that the estimation of the index coefficient vectors γ_j^τ associated with the parameters, which depend on z, does not raise additional identification concerns as long as the matrix of covariates, Z, is of full rank, which is the case in our application.

4.3 Constructing the individual likelihood contribution

We estimate the model parameters using maximum likelihood. We first discuss how we construct each individual likelihood conditional on an individual-specific set of parameter values Ω_i and taking into account data censoring. We first consider the problem of right censoring that takes the form of incomplete unemployment or employment spells. Later, we also describe how we address left-censoring (spells in progress at the start of the observation period). After characterizing the individual likelihood, we then show how to construct the overall likelihood function using the mapping between individual characteristics (z_i, τ_i) and Ω_i specified in subsection 2.3. For notational simplicity, our initial discussion of the individual likelihood suppresses the (z_i, τ_i) notation, but the reader should bear in mind that the econometric model allows the search-environment parameters to vary across individuals.

As in Flinn (2002) and Dey and Flinn (2005), the information used to construct the likelihood function is defined in terms of employment cycles (EC). The exact composition of ECs that an individual has will depend on the individual's initial status. If an individual enters into our sample with an existing job, the first EC begins with this job, followed potentially by more jobs, and the cycle ends with any transition into unemployment. If an individual is unemployed at the start of the observation period, then the EC begins with an unemployment spell, followed by one or more jobs, and ending with any transition into unemployment. For computational tractability, we construct the likelihood for an EC using at most two jobs within a single employment spell.[33] That

[33]This simplification resulted in a small decrease in the number of job spell observations used, dropping from 13,411 to 12,313, a decrease of less than 10 percent.

is, an employment cycle can consist of

$$EC = \begin{cases} \underbrace{\left\{\{T_k, q_k, r_k\}, \{\tilde{w}_k^{(j)}, t_k^{(j)}\}_{j=1}^{n}\right\}_{k=1}^{2}} & \text{One employment spell with a pre-existing job} \\ \underbrace{\{T_U, r_U\}}_{\text{Unemployment spell}}, \underbrace{\left\{\{T_k, q_k, r_k\}, \{\tilde{w}_k^{(j)}, t_k^{(j)}\}_{j=1}^{n}\right\}_{k=1}^{2}}_{\text{Up to two consecutive jobs}} & \text{One unemployment spell + one emp spell} \end{cases}$$

In the above definition, t_U is the length of the unemployment spell and r_U is an indicator variable that takes the value 1 if the unemployment spell is right-censored. If we observe a subsequent employment spell, which can consist of up to two jobs, T_k is the length of job k in the employment spell, $k \in \{1, 2\}$. We observe multiple wages $\tilde{w}_k^{(j)}, j \in \{1, 2, ..., n\}$, along with corresponding time intervals $t_k^{(j)}$ when individuals report these wages within each job spell k. There are up to n wage observations in total. The indicator variable $r_k = 1$ indicates that the duration of job k is right-censored. The indicator variable q_k takes the value 1 when the k^{th} job is dissolved at the end of the job spell, with the individual entering the unemployment state, and takes the value 0 when the individual transitions immediately to another job. Each individual may contribute information on multiple ECs to the likelihood.

In describing the individual likelihood contribution, it is useful to distinguish eleven different kinds of ECs that are observed in the data. An employment cycle starting with an unemployment spell can be one of the following six cases:

1. One right-censored unemployment spell ($r_U = 1$)
2. One completed unemployment spell ($r_U = 0$)
   (a) + first right-censored job spell ($r_1 = 1$)
   (b) + first completed job spell ending with unemployment ($r_1 = 0, q_1 = 1$)
3. One completed unemployment spell + first completed job spell ($r_1 = 0, q_1 = 0$)
   (a) + second right-censored job spell ($r_2 = 1$)
   (b) + second completed job spell ending with unemployment ($r_2 = 0, q_2 = 1$)
   (c) + second completed job spell ending with third job ($r_2 = 0, q_2 = 0$)

We will write one likelihood expression that encompasses all of these cases. The likelihood depends on the following components from our job search model: the reservation wage, θ^* (determined by equation (8)), the measurement error p.d.f. denoted by $m(\cdot)$ (defined in equation (11)), and the (gender-specific) match productivity c.d.f. given by $G(\theta)$, and $\bar{G}(\theta) = 1 - G(\theta)$. The hazard rates associated with unemployment and employment transitions are h_U and $h_E(\theta)$, where

$$\begin{aligned} h_U &= \lambda_U \bar{G}(\theta^*) \\ h_E(\theta) &= \eta + \lambda_E \bar{G}(\theta), \end{aligned}$$

The overall likelihood for individuals whose ECs begin with unemployment is given by

$$\begin{aligned}
(13)\quad & l(t_U, r_U, \{\tilde{w}_1^{(j)}, \tilde{t}_1^{(j)}\}_{j=1}^n, T_1, r_1, q_1, \{\tilde{w}_2^{(j)}, \tilde{t}_2^{(j)}\}_{j=1}^n, T_2, r_2, q_2) = \int_{\theta^*} \int_{\theta_1} h_U^{(1-r_U)} \exp(-h_U t_U) \\
& \times \left\{ \exp\left(-h_E(\theta_1)T_1\right) \left[\left(\lambda_E \bar{G}(\theta_1)\right)^{1-q_1} \eta^{q_1} \right]^{1-r_1} f_w(\tilde{w}_1^{(1)}, ..., \tilde{w}_1^{(n)}, \tilde{t}_1^{(1)}, ..., \tilde{t}_1^{(n)}, \theta_1 | \theta^*) \right\}^{1-r_U} \\
& \times \left\{ \exp\left(-h_E(\theta_2)T_2\right) \left[\left(\lambda_E \bar{G}(\theta_2)\right)^{1-q_2} \eta^{q_2} \right]^{1-r_2} f_w(\tilde{w}_2^{(1)}, ..., \tilde{w}_2^{(n)}, \tilde{t}_2^{(1)}, ..., \tilde{t}_2^{(n)}, \theta_2 | \theta_1) \right\}^{1-r_1} \frac{dG(\theta_2)}{\bar{G}(\theta_1)} \frac{dG(\theta_1)}{\bar{G}(\theta^*)}
\end{aligned}$$

An employment cycle that starts with can employment spell can be one of the following five cases:

1. One right-censored job spell ($r_1 = 1$)
2. One completed job spell ending with unemployment ($r_1 = 0, q_1 = 1$)
3. One completed job spell ($r_1 = 0, q_1 = 1$)
    (a) + second right-censored job spell ($r_2 = 1$)
    (b) + second completed job spell ending with unemployment ($r_2 = 0, q_2 = 1$)
    (c) + second completed job spell ending with third job ($r_2 = 0, q_2 = 0$)

The following likelihood expression for individuals whose ECs begin with employment covers the above five cases.

$$\begin{aligned}
& l(\{\tilde{w}_1^{(j)}, \tilde{t}_1^{(j)}\}_{j=1}^n, T_1, r_1, q_1, \{\tilde{w}_2^{(j)}, \tilde{t}_2^{(j)}\}_{j=1}^n, T_2, r_2, q_2, \theta_1 | \theta_0) = \\
& \int_{\theta_1} \left\{ \exp\left(-h_E(\theta_1)t_1\right) \left[\left(\lambda_E \bar{G}(\theta_1)\right)^{1-q_1} \eta^{q_1} \right]^{1-r_1} f_w(\tilde{w}_1^{(1)}, ..., \tilde{w}_1^{(n)}, \tilde{t}_1^{(1)}, ..., \tilde{t}_1^{(n)}, \theta_1 | \theta_0) \right\}^{1-r_U} \\
& \times \left\{ \exp(-h_E(\theta_2)t_2) \left[\left(\lambda_E \bar{G}(\theta_2)\right)^{1-q_2} \eta^{q_2} \right]^{1-r_2} f_w(\tilde{w}_2^{(1)}, ..., \tilde{w}_2^{(n)}, \tilde{t}_2^{(1)}, ..., \tilde{t}_2^{(n)}, \theta_2 | \theta_1) \right\}^{1-r_1} \frac{dG(\theta_2)}{\bar{G}(\theta_1)}
\end{aligned}$$

We now discuss how we deal with left-censoring problem, which arises because some unemployment/employment spells may be in progress at the beginning of a sample period.[34] For those sample members who are unemployed at the beginning of the sampling period the left-censoring can be ignored due to the "memoryless" property of the exponential distribution. That is, if job offer arrival times are generated by a homogeneous Poisson process, the distribution of the duration of further job search time does not depend on the length of the time searching already spent searching.

For workers who enter the sample in an employment spell, their initial job offer and best dominated job offer pair $\{\theta_0, \theta_1\}$ is a sufficient statistic for their job history. Conditioning on $\{\theta_0, \theta_1\}$, the job history has no additional impact on future working decisions. We are not able to observe $\{\theta_0, \theta_1\}$, but we can instead assume that $\{\theta_0, \theta_1\}$ are random draws from the steady-state distribution $SS(\theta_0, \theta_1)$ derived in subsection A.1.2. The likelihood function then "integrates out" (θ_0, θ_1) using $SS(\theta_0, \theta_1)$:

[34] It is worth noting that our general human capital, a, doesn't suffer this left-censoring problem since we have the completed measure of their prior accumulated work experience and unemployment experience. However, as was shown in the identification section, individual heterogeneity in general human capital does not have an impact on job offer choices.

(14)

$$l(\{\tilde{w}_1^{(j)},\tilde{t}_1^{(j)}\}_{j=1}^n,T_1,r_1,q_1,\{\tilde{w}_2^{(j)},\tilde{t}_2^{(j)}\}_{j=1}^n,T_2,r_2,q_2)=$$

$$\int_{\theta^*}\int_{\theta^*}^{\theta_1}\int_{\theta_1}\left\{\exp\left(-h_E(\theta_1)t_1\right)\left[\left(\lambda_E\bar{G}(\theta_1)\right)^{1-q_1}\eta^{q_1}\right]^{1-r_1}f_w(\tilde{w}_1^{(1)},...,\tilde{w}_1^{(n)},\tilde{t}_1^{(1)},...,\tilde{t}_1^{(n)},\theta_1|\theta_0)\right\}^{1-r_U}$$

$$\left\{\exp(-h_E(\theta_2)t_2)\left[\left(\lambda_E\bar{G}(\theta_2)\right)^{1-q_2}\eta^{q_2}\right]^{1-r_2}f_w(\tilde{w}_2^{(1)},...,\tilde{w}_2^{(n)},\tilde{t}_2^{(1)},...,\tilde{t}_2^{(n)},\theta_2|\theta_1)\right\}^{1-r_1}\frac{dG(\theta_2)}{\bar{G}(\theta_1)}dSS(\theta_0,\theta_1)$$

where $SS(\theta_0,\theta_1)$ denotes the cumulative density function for the joint distribution $\{\theta_0,\theta_1\}$ in the steady-state

$$SS(\theta_0,\theta_1)=\frac{G(\theta_1)}{1+\kappa_1\bar{G}(\theta_1)}\left(\frac{1+\kappa_1\bar{G}(\theta_1)}{1+\kappa_1\bar{G}(\theta_0)}\right)^2,\theta^*\leq\theta_0<\theta_1,\kappa_1=\frac{\lambda_E}{\eta}$$

We compute the above individual likelihood function by Monte Carlo integration using importance sampling.[35]

Recall that our model allows the parameter values to differ depending on a vector of observable characteristics, (z_i,τ_i). We now incorporate the mapping into the likelihood and construct the overall log likelihood function $\ln L$ for the entire sample of individuals (of size N). Individual i with individual observable characteristics (z_i,τ_i) has labor market parameters given by

$$\Omega(z_i,\tau_i)=\{\lambda_U(z_i,\tau_i),\lambda_E(z_i,\tau_i),\alpha(z_i,\tau_i),\eta(z_i,\tau_i),a_0(z_i,\tau_i)\psi(\tau_i),\delta(\tau_i),b(\tau_i),\sigma_\theta(\tau_i),\sigma_\varepsilon(\tau_i)\}.$$

Then the log likelihood function $\ln L$ is defined by

$$\ln L=\sum_{i=1}^N\sum_{j=1}^J\ln\ell(\text{Employment cycle}_{ij}|\Omega(z_i,\tau_i))$$

where $\ell(\text{Employment cycle}_{ij}|\Omega(z_i,\tau_i))$ is the likelihood function for the j^{th} employment cycle for individual i defined by either equation (13) or (14). Because individual heterogeneity z_i is (essentially) continuously distributed, computing individual i's log likelihood contribution at each iteration of the estimation algorithm requires solving for each person's reservation strategy $\theta^*(z_i,\tau_i)$.

5 Model estimates

5.1 Estimated model parameters under homogeneous/heterogeneity specifications

Many previous papers have estimated search models that allow parameters to differ by gender (e.g. Bowlus (1997), Bowlus and Grogan (2008), Flabbi (2010a), Liu (2016), Morchio and Moser (2020), Amano-Patino et al. (2020)), but gender is only one of many individual traits relevant to the job search process and in determining labor market outcomes. The index formulation introduced previously allows for more individual heterogeneity, with parameters depending on gender, education level, cognitive skills, birth cohort, work experience, unemployment experience and personality traits. Table 5 presents the estimated coefficients

[35] In practice we generate 2500 repetitions of the match quality trajectory $\{\theta_0,\theta_1,\tilde{\theta}_1^{(1)},,...,\tilde{\theta}_1^{(n)},\theta_2,\tilde{\theta}_2^{(1)},,...,\tilde{\theta}_2^{(n)}\}$ in the 6-year window of observations, using an importance sampling algorithm. We average over these sample trajectories to compute a simulated likelihood value for each sample member.

of the search model under three different specifications: a "homogeneous" specification, in which the model parameters are allowed to differ by gender but are otherwise assumed to be the same; a "full heterogeneous" specification, in which the parameters are allowed to vary by gender and by education, cognitive skills, personality traits, and age cohort; and a "without personality" specification, in which the parameters vary by all observables except for personality traits. Figure 4 shows the distributions of the estimated parameter values for males and females under the "full heterogeneous" model and Table 5 shows the means and standard deviations of the parameter values for the specifications that allow for observed heterogeneity beyond gender (in the last two columns).

A comparison of the estimates for the homogeneous and heterogeneous specifications reveals important gender differences as well as substantial individual heterogeneity. Further comparison between estimates for the "fully heterogeneous" and "without personality" specifications highlight the role of personality traits in the model's ability to match the data. First, the estimated initial human capital endowment parameters (a_0) indicate that males have higher innate human capital endowment on average than females. Average female human capital endowment is 6.01 in comparison to 8.76 for men for the fully heterogeneous model. This 31 percent gap is in line with the findings in other studies. For example, Bowlus (1997) finds women's productivity is 20 to 41 percent lower than men's productivity in similar jobs. As seen in Figure 4, there is substantial variance in the estimated ability parameters and the male-female distributions display non-negligible overlap.

In addition to having higher estimated initial human capital endowment values, men are estimated to have a higher bargaining parameter (α), so that they receive on average a larger initial share of the job surplus than do women.[36] The estimated parameter values range from 0.45-0.53, which is fairly consistent with values reported in the search literature using similar modeling frameworks. For example, Bartolucci (2013) uses German matched employer-employee data and finds female workers have, on average, slightly lower bargaining power than their male counterparts, with an average α of 0.42 (for both genders). Flinn (2006), using CPS data, finds that the overall bargaining power is approximately 0.42 in a sample of young adults. Figure 4 shows substantial heterogeneity in bargaining parameters across individuals, again with substantial overlap in the male and female distributions.

The distribution of job arrival rates during unemployment (denoted λ_U) is similar for men and women and exhibits right skewness (shown in Figure 4), meaning that most people have low probabilities of finding a job, while a small fraction have higher values. Once employed, women tend to receive more job offers than men (with an arrival rate of 0.11) compared to men (with an arrival rate of 0.05). This suggests that women, ceteris paribus, would improve their share of surplus faster than men due to receiving more frequent counter offers during their job spell. The estimated job separation rate (denoted η) is generally small in magnitude and similar for men and women. It's worth noting that jobs may also end due to workers leaving for better wages at other employers. Additionally, men tend to have lower flow utility when unemployed.

The two bottom lines of Table 5 report p-values for likelihood ratio (LR) tests where we test the "without personality" specification against the "homogeneous" and the "fully heterogeneous" specifications. The full heterogeneous model nests the other two specifications. The test results suggest that the more flexible model specifications, which allow for greater parameter heterogeneity, fit the data better. Importantly, there is a statistically significant improvement in the model fit when the personality traits are added. The estimates of the standard deviations of measurement error (denoted as ε) also support this conclusion. In the "full

[36] The fact that men have a higher initial share of the match surplus does not necessarily mean that they will always have a larger share over the course of the job spell. The worker's share of the surplus can increase over time due to counter offers. See the discussion of Table 7.

Figure 4: The distribution of search parameters $\{a_0, \alpha, \lambda_U, \lambda_E, \eta\}$

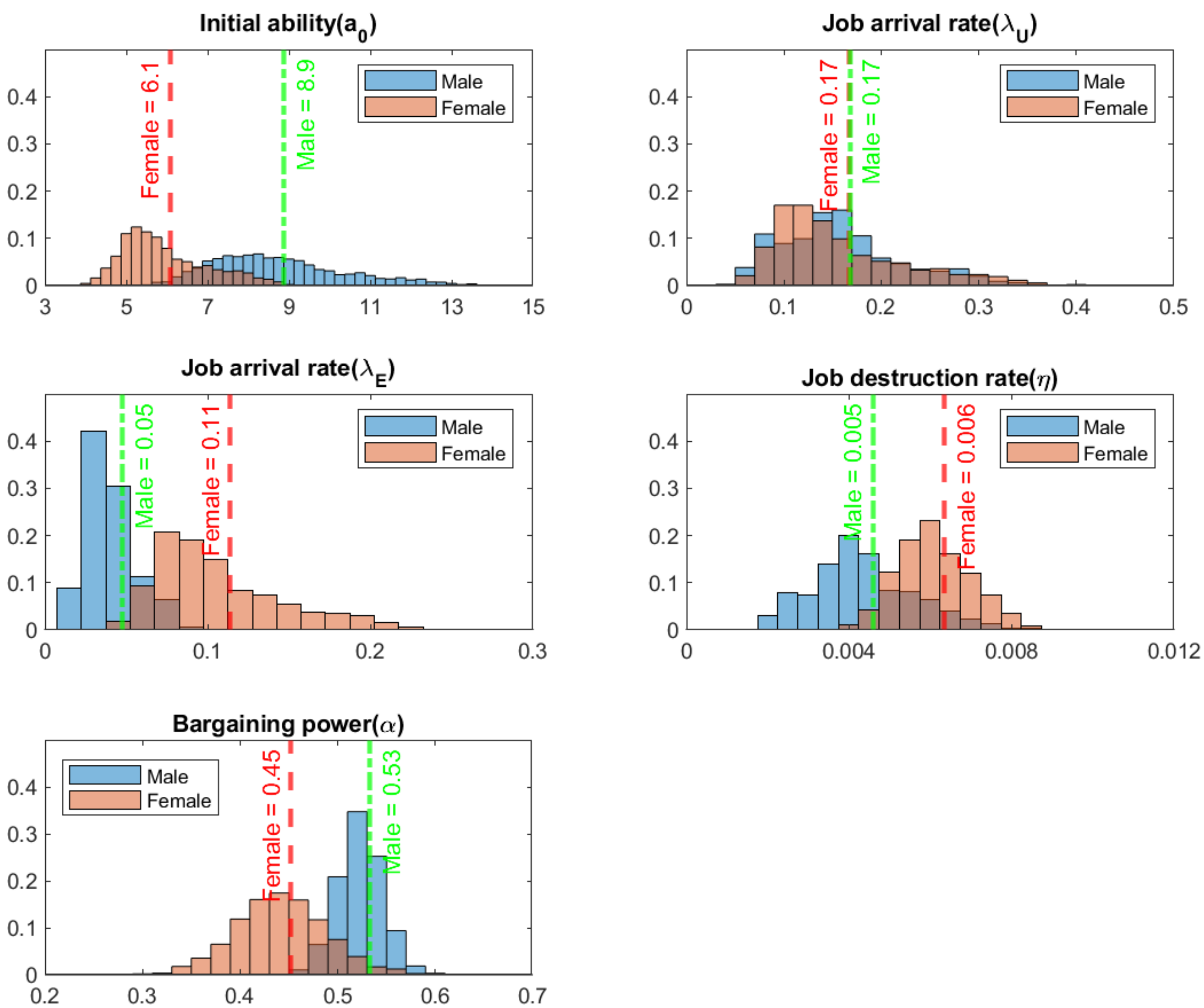


Table 5: Parameter estimates under alternative heterogeneity specifications

	Description	(1) homogeneous		(2) w/o personality†		(3) fully heterogeneous†	
		Male	Female	Male	Female	Male	Female
a_0	initial ability	9.731	5.897	7.993	5.423	8.755	6.013
		(0.042)	(0.042)	[1.008]	[0.560]	[1.623]	[1.064]
α	bargaining	0.531	0.475	0.527	0.467	0.532	0.452
		(0.002)	(0.006)	[0.029]	[0.024]	[0.025]	[0.045]
η	separation rate	0.005	0.006	0.005	0.006	0.005	0.006
		(2.2e-05)	(5.9e-05)	[0.001]	[0.001]	[0.001]	[0.001]
λ_U	offer arrival rate, in unemp.	0.185	0.183	0.175	0.185	0.163	0.163
		(0.0006)	(0.0006)	[0.067]	[0.062]	[0.059]	[0.064]
λ_E	offer arrival rate, in emp.	0.052	0.142	0.061	0.132	0.047	0.112
		(0.0002)	(0.0007)	[0.017]	[0.056]	[0.015]	[0.039]
b	flow utility when unemp.	-0.981	0.921	-0.946	0.396	-0.971	0.395
		(0.010)	(0.010)	(0.014)	(0.011)	(0.012)	(0.010)
ψ	human cap. acc.(monthly)	0.0008	0.0008	0.0009	0.0009	0.0009	0.0009
		(1.43e-5)	(2.81e-5)	(1.53e-5)	(2.97e-5)	(2.00e-5)	(3.25e-5)
δ	human cap. dep.(monthly)	0.0042	0.0035	0.0043	0.0040	0.0043	0.0045
		(0.0001)	(9.47e-5)	(0.0001)	(7.26e-5)	(0.0002)	(6.44e-5)
σ_θ	$\theta \sim \log N\left(-\frac{\sigma_\theta^2}{2}, \sigma_\theta\right)$	0.434	0.605	0.434	0.605	0.403	0.576
		(0.0010)	(0.0016)	(0.0008)	(0.0017)	(0.0011)	(0.0019)
σ_ε	$\varepsilon \sim \log N\left(-\frac{\sigma_\varepsilon^2}{2}, \sigma_\epsilon\right)$	0.233	0.324	0.233	0.324	0.231	0.331
		(0.0005)	(0.0009)	(0.0004)	(0.0009)	(0.0006)	(0.0011)
$\log L$		-62,510		-59,927		-58,242	
LR tests‡				(1) & (2) ($P < 0.001$)		(2) & (3) ($P < 0.001$)	

†In the *without personality* and *fully heterogeneous* specifications, the parameters $\{a_0, \alpha, \lambda_U, \lambda_E, \eta\}$ depend on indices of individual characteristics. For these parameters, we report the standard deviations of the parameter distribution in square brackets. For all other parameters and for all the parameters under the homogeneous specification, we report standard errors in parentheses.

‡The likelihood ratio (LR) test tests the current specification against the previous one. The monthly discount rate is set at 0.006.

heterogeneous" specification, the estimated variance of measurement error is smaller than in the other two specifications, so allowing for heterogeneous parameters reduces the reliance on measurement error to fit the data. There is no presumption that allowing heterogeneity in primitive parameters should reduce the dispersion in ε, because the estimated model is required to fit the turnover patterns observed in the data along with the wage distributions.

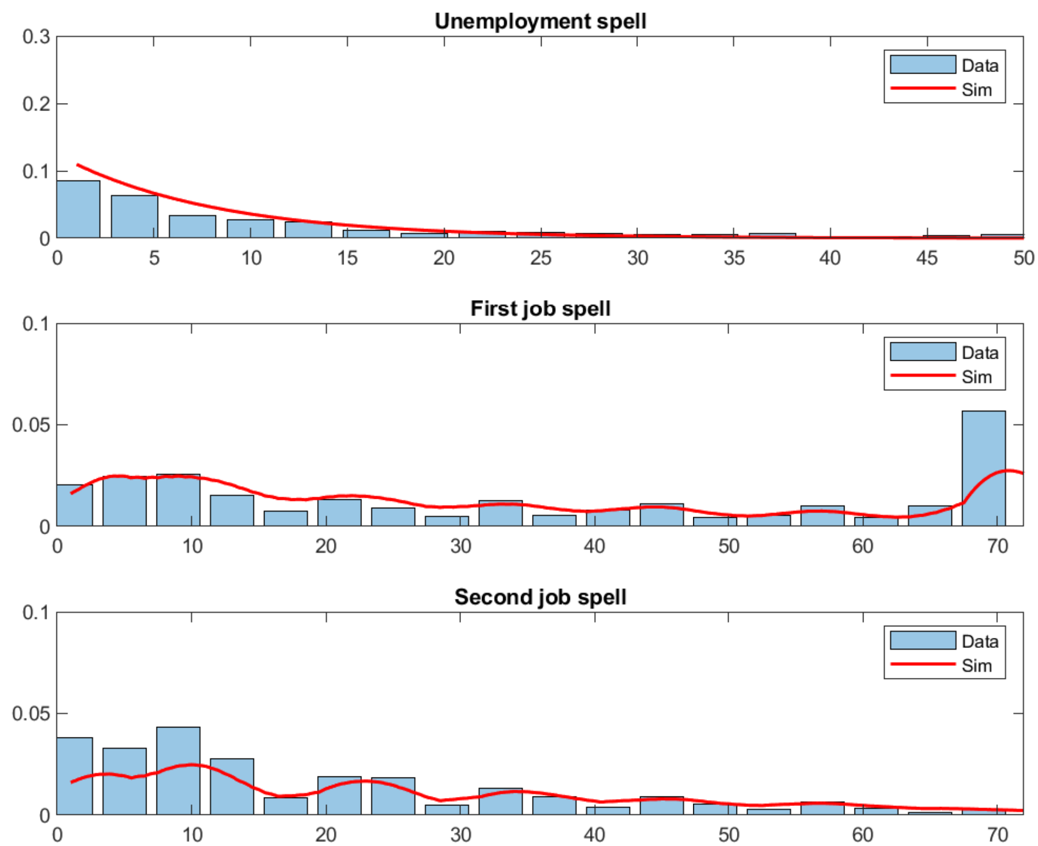
In addition to performing the formal test, we also graphically examine the model goodness of fit by comparing the distributions of wages and of unemployment/employment spell durations from the data and from model simulations. Figure 5 presents the distribution of first and last wages for employment spells of junior workers with work experience ≤ 12 years and senior workers with work experience > 12 years. The estimated model fits the pattern seen in the data of lower wages and less wage growth over the course of the job spell for junior workers compared to senior workers. In Figure 6, we plot the distributions of unemployment spell length, as well as the duration of the first and second jobs, both in the data and for simulations based on the "fully heterogeneous" model. The simulation largely replicates the data patterns, with the exception of a spike in the data at the right end of the first job spell, likely due to right-censoring resulting from the limited 6-year sample observation period.[37]

[37]We fully account for this right-censoring in implementing the maximum likelihood estimator.

Figure 5: Model goodness of fit to wage distributions

Note: The junior workers are those whose prior working experience is below the median level ($\leq$ 12 years), while the senior workers are those whose working experience $>$ 12 years. The blue histograms show the distribution of first observed wages in each employment spell, while the brown histograms show the distribution of last observed wages. The red solid curve and green dashed curve represent the fitted distributions for the simulated first wages and last wages, respectively. These fitted distributions are specified as gamma distributions.

Figure 6: Model goodness of model fit to spell length distributions



Note: the blue histograms show the distribution of unemployment spell lengths, as well as the spell lengths of the first and second jobs in the data. The red curve represents the fitted distributions from the simulations, which are specified as exponential distributions for unemployment spell lengths and Epanechnikov kernel distributions (with a width of 2 months) for employment spell lengths.

5.2 Understanding the role of personality traits and other individual characteristics in a job search model

We next examine how personality traits and other individual characteristics affect job search parameters $\{\lambda_U, \lambda_E, \eta, \alpha, a_0\}$. Table 6 reports the heterogenous model parameter estimates that provide information about the channels through which education, cognitive skills, birth cohort, and personality traits influence wage and employment outcomes. For men and women, education increases the job offer arrival rate in unemployment (λ_U) and lowers the job separation rate (η). Education also increases initial human capital endowment (a_0) and increases bargaining power (α). Conditional on education, the cognitive ability measure significantly increases ability and increases job offer arrival rates for both men and women. Thus, education and cognitive ability enter through multiple model channels, which combine to increase wages and promote employment stability.

As seen in Table 6, personality traits are statistically significant determinants of job search parameters, and, for the most part, affect parameters of men and women in similar ways. As previously noted, conscientiousness and emotional stability have been emphasized in prior literature as two traits most strongly associated with superior labor market outcomes. Consistent with these findings, our estimates indicate that conscientiousness increases job offer arrival rates and decreases job separation rates. It also increases ability and bargaining power for both men and women. All of these effects contribute to higher wage levels and more stable employment for both men and women.

Emotional stability also increases the initial human capital endowment and bargaining power of both men and women, and increases the unemployment job arrival rate for women. The remaining three traits - openness to experience, extroversion and agreeableness - are not necessarily desirable characteristics from a labor market perspective. Openness to experience increases the job separation rate and decreases bargaining power for both men and women. It also increases the job offer rate for men regardless of employment status but only increases the job offer rate for women when employed. The extroversion trait appears to be a more important trait for men. It increases initial human capital endowment, increases the job offer arrival rate when employed, increases the job separation rate, and decreases bargaining power. For women, it increases the job separation rate. Lastly, agreeableness has a uniformly negative effect on labor market parameters, decreasing job offer arrival rates, bargaining power, and initial human capital endowment for both genders, and reducing the on-the-job offer arrival rate for all workers, as well as the unemployed job offer arrival rate for women.

In our model, work experience and unemployment experience affect wages through their effects on human capital accumulation and depreciation. They are endogenous and time-varying and therefore are not components of the z characteristics. However, we do allow there to be differences in the labor market parameters for different age workers by including birth cohort indicators in z. As shown in the bottom rows of Table 6, younger workers generally have lower ability and higher job separation rates compared to middle-aged workers (the reference cohort is age 37-48). For men, young workers have significantly higher job offer arrival rates both on and off the job, while for women, young workers experience lower job offer rates when they are unemployed. Older workers (age 49-60) are found to have lower initial human capital endowment and job offer rates, as well as lower job separation rates. Additionally, older age negatively impacts the bargaining power of women but not men.

Table 6: Estimated index coefficients associated with characteristics (education, cognitive ability, personality traits, cohort) by gender†

	$\log \lambda_{a_0}$		$\log \lambda_U$		$\log \lambda_E$		$\log \eta$		$\log \left(\frac{\alpha}{1-\alpha}\right)$	
	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
Constant	2.241	1.850	-1.723	-1.753	-3.029	-2.193	-5.468	-5.081	0.130	-0.119
	(0.006)	(0.009)	(0.006)	(0.006)	(0.007)	(0.005)	(0.011)	(0.018)	(0.023)	(0.027)
Education	0.125	0.143	0.226	0.306	0.199	0.248	-0.232	-0.104	0.063	0.046
	(0.003)	(0.004)	(0.001)	(0.005)	(0.006)	(0.006)	(0.009)	(0.010)	(0.018)	(0.015)
Cognitive ability	0.056	0.038	0.040	0.105	0.061	0.119	0.020	0.042	-0.025	-0.018
	(0.003)	(0.005)	(0.003)	(0.004)	(0.006)	(0.006)	(0.009)	(0.009)	(0.015)	(0.018)
Openness	-0.006	-0.006	0.063	0.040	0.057	0.048	0.026	0.058	-0.060	-0.089
	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.009)	(0.010)	(0.012)	(0.015)
Conscientiousness	0.018	0.008	0.063	0.049	-0.029	0.011	-0.031	-0.026	0.035	0.051
	(0.003)	(0.004)	(0.006)	(0.004)	(0.006)	(0.003)	(0.008)	(0.007)	(0.014)	(0.012)
Extraversion	0.007	0.011	0.002	0.009	0.020	-0.003	0.007	0.016	0.023	-0.032
	(0.003)	(0.004)	(0.006)	(0.004)	(0.006)	(0.003)	(0.009)	(0.006)	(0.012)	(0.006)
Agreeableness	0.026	-0.018	-0.010	-0.023	-0.005	-0.002	0.008	0.008	-0.027	-0.134
	(0.003)	(0.004)	(0.006)	(0.003)	(0.007)	(0.004)	(0.006)	(0.008)	(0.014)	(0.010)
Emotional stability	0.037	0.021	0.025	0.036	0.012	0.025	-0.024	0.013	0.027	0.113
	(0.003)	(0.004)	(0.006)	(0.006)	(0.006)	(0.003)	(0.008)	(0.008)	(0.014)	(0.012)
Cohort (ref group: 37-48)										
25-36	-0.098	-0.085	0.091	-0.144	0.072	-0.008	0.261	0.121	-0.031	-0.020
	(0.006)	(0.009)	(0.011)	(0.007)	(0.010)	(0.005)	(0.022)	(0.021)	(0.020)	(0.037)
49-60	-0.169	-0.106	-0.501	-0.248	-0.279	-0.126	-0.130	-0.092	0.016	-0.059
	(0.006)	(0.009)	(0.007)	(0.010)	(0.004)	(0.007)	(0.023)	(0.017)	(0.026)	(0.026)

†This table reports estimated parameter coefficients for the fully heterogeneous specification. Asymptotic standard errors are reported in parentheses.

6 Interpreting the model estimates

We now use the estimated model to analyze how different cognitive and noncognitive traits affect labor market outcomes and the implications for gender disparities. We base this analysis on steady-state model simulations. Note that our model becomes a steady state model only after we factor out the human capital term, a. The human capital level for each individual is calculated based on their working and unemployment experience in the year 2013, the first year of our sample period. We assume that the matching offer pair (both the current offer and the best dominated offer), $\{\theta', \theta\}$, are drawn from the steady-state distribution defined in equation (22).

6.1 Effects of cognitive and noncognitive traits on wage and employment outcomes

The results displayed in Table 7 pertain to the effects of a ceteris paribus change in each of the individual traits on labor market outcomes. The first row calculates the average labor market outcomes by gender in the baseline case, where all the traits are set at their mean values in the data. The model simulations reveal significant gender gaps in both wages and working opportunities. Men tend to have higher wages, shorter periods of unemployment, and longer job spells compared to women.

We also calculate the average share of surplus by gender, following a definition given in Cahuc et al.

(2006)

$$\beta(\tau) = \frac{E_{\theta,\theta'} w(\theta, \theta', z, \tau, a) - a\theta^*(z, \tau)}{a\,(E(\theta) - \theta^*(z, \tau))}$$

where θ denotes the match offer and θ' denotes the best dominated offer, which equals θ^* if the worker is hired directly from unemployment. The average share tends to be higher than the share indicated by the bargaining parameter due to the Bertrand competition between firms for workers. The results indicate that women receive significantly more counteroffers and have a similar share of the job surplus compared to men. Between-firm competition has a greater impact on the share of surplus received by women, increasing it by 68 percent (from 0.452 to 0.755), compared to the impact on the share of surplus received by men, which increased by 47 percent (from 0.532 to 0.788).

We also calculate the ex-ante welfare for each gender, which is the expected lifetime welfare when individuals initially enter the labor market with no experience, $V_U(z, a_0)$. As seen in the last columns of Table 7, there is a large gender gap in ex-ante welfare, with women having 68 percent of the welfare of men $\left(\frac{444-264}{264}\right)$. This is a summary measure of gender inequality in both wages and working opportunities and is a more inclusive measure of gender differences in labor market outcomes than are measures solely based on wage distributions.

Rows (2)-(8) report the effect of a ceteris paribus change in each of the individual traits on labor market outcomes. Specifically, we increase each trait by one standard deviation for all individuals (holding other traits constant) and re-simulate their labor market outcomes. The results show that increasing education by one standard deviation (approximately 2.8 years) increases wages by 25-28 percent for both men and women, reduces unemployment, and increases job spell length, particularly for men. It also increases the average share of surplus and improves ex-ante welfare by 42 percent for men and 35 percent for women. Increasing cognitive ability has similar, but smaller, effects on wages and unemployment. It also reduces average job spell lengths, which is not necessarily a negative labor market outcome if job changes occur because of the arrival of superior outside offers.

Conscientiousness and emotional stability both contribute to better labor market outcomes. Increasing conscientiousness increases wages and job spell lengths, and reduces unemployment spell lengths for both men and women, leading to an increase in ex-ante welfare by 27.5 percent for men and 15.4 percent for women. Increasing emotional stability increases wages, increases the share of surplus, and decreases the duration of unemployment. It also increases ex-ante welfare by 8-10 percent for both men and women. Emotional stability has mixed effects on job spell length, increasing it for men but decreasing it for women. Increasing openness to experience has little impact on wages and the share of surplus, but it decreases unemployment and job spell length for both men and women. Increasing extroversion increases men's wages but has little impact on women's wages. It decreases the duration of unemployment and job spell length, with larger effects for women. It decreases men's ex-ante welfare but increases women's. Agreeableness has a negative impact on wages, the share of surplus, unemployment, and job spell length for both men and women, leading to a reduction in ex-ante welfare by 5.3 percent for men and 9.7 percent for women.

In summary, our results show that both cognitive and noncognitive traits are important determinants of wages and labor market dynamics. Among the Big Five personality traits, conscientiousness has the largest positive impact on welfare through higher wages, a higher job finding rate, and more stable employment. Emotional stability has similar positive benefits, although the overall impact on welfare is smaller in magnitude. Agreeableness significantly lowers welfare for both men and women due to lower wages and lower job finding rates.

Table 7: Effects of 1SD changes in cognitive and noncognitive traits on labor market outcomes†

	Average wage		Unemp. spell		Job spell		Surplus division		Ex-ante Welfare	
	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
Baseline	14.9	12.2	6.9	7.1	127.2	84.9	0.788	0.755	444	264
Education (+1SD)	24.9%	27.6%	-19.1%	-25.0%	22.7%	9.3%	3.6%	2.5%	41.7%	35.2%
Cognitive ability (+1SD)	6.2%	5.9%	-4.0%	-10.0%	-2.2%	-4.5%	-0.1%	0.4%	3.2%	1.1%
Openness (+1 SD)	-0.6%	-1.8%	-6.0%	-3.8%	-2.8%	-5.5%	-1.1%	-0.8%	3.0%	1.7%
Conscientiousness (+1 SD)	2.7%	2.6%	-4.9%	-3.6%	3.2%	2.5%	-0.2%	-0.1%	27.5%	15.4%
Extraversion (+1 SD)	1.2%	0.1%	-0.2%	-0.4%	-0.8%	-1.5%	0.6%	-0.7%	-2.3%	7.9%
Agreeableness (+1 SD)	-3.2%	-3.3%	0.9%	1.7%	-0.7%	-0.7%	-0.5%	-0.8%	-5.3%	-9.7%
Emotional stability (+1 SD)	4.9%	4.1%	-2.2%	-3.0%	2.2%	-1.3%	0.6%	0.5%	9.6%	7.8%
Work exp (+1 SD)	12.2%	11.5%	-	-	-	-	-	-	12.2%	11.5%
Unemp. exp (+1 SD)	-14.2%	-14.7%	-	-	-	-	-	-	-14.2%	-14.7%

†The first row shows labor market outcome values in steady-state under the baseline model. Rows (2)-(8) show the deviation from baseline outcomes implied by a ceteris paribus one standard deviation increase in each of the characteristics. The welfare is evaluated ex-ante when workers initially enter into the labor market $V_U(z, a_0)$.

The last two rows of the table report the impact of changes in human capital on labor market outcomes. Increasing work experience by one standard deviation (approximately 11 years) increases wages by 11-12 percent, while increasing unemployment experience by one standard deviation (approximately 3 years) decreases wages by 14 percent for both men and women.[38]

There are various reasons why personality traits could be important determinants of labor market outcomes. As seen in Table 7, some traits directly enhance worker's initial human capital endowment. People who are more conscientious tend to be well-organized, dependable and hard-working, which are all characteristics associated with more productive workers (Barrick and Mount (1991); Salgado (1997); Hurtz and Donovan (2000); Cubel et al. (2016)). Other traits operate through different channels. For example, individuals with higher emotional stability and lower agreeableness may be more willing and able to negotiate pay raises. Evdokimov and Rahman (2014) provide experimental evidence that managers allocate less money to more agreeable workers.

Although previous papers also find associations between personality traits and wages (Mueller and Plug (2006); Heineck and Anger (2010); Risse et al. (2018)), the mechanisms through which they operate have not been explored.[39] Table 8 displays the contribution of each observed trait to wages through the various model channels. Education increases wages through all channels, with initial human capital endowment being the most important. Cognitive ability primarily affects wages through its impact on initial human capital endowment (a_0). The Big Five personality traits operate through multiple channels. Emotional stability and conscientiousness have a large positive effect on wages, while agreeableness has a large negative impact. The overall effects on wages are similar for men and women, but the primary model channels differ. For men, the primary channel through which personality traits impact wages is initial human capital endowment (a_0). For women, along with initial human capital endowment (a_0), the bargaining parameter (α) is important. The effects of extroversion and openness to experience on wages are fairly small, with openness having a small

[38]The effect on ex-ante welfare is identical to the effect on wages, because an implication of our model specification (previously discussed) is that human capital does not impact labor market dynamics beyond the effect of the initial endowment.

[39]Our estimates are mostly consistent with the literature exploring the gender-specific association between wages and personality traits. For example, Nyhus and Pons (2005) note that emotional stability is positively associated with wages for both women and men, while agreeableness is associated with lower wages for women. Using GSOEP data, Braakmann (2009) finds agreeableness, conscientiousness and neuroticism matter for both wages and employment.

Table 8: Decomposing the effects of observed traits on wages by model channel†

		All channels	Ability a_0	Bargaining α	Arrival (U) λ_U	Arrival (E) λ_E	Destruction η
Education (+1SD)	M	24.9%	13.2%	0.7%	1.2%	3.6%	5.1%
	F	27.6%	15.3%	0.6%	1.3%	8.9%	3.1%
Cognitive ability (+1SD)	M	6.2%	5.7%	-0.3%	0.2%	1.0%	-0.4%
	F	5.9%	3.9%	-0.2%	0.3%	4.1%	-1.2%
Openness (+1 SD)	M	-0.6%	-0.6%	-0.7%	0.3%	1.0%	-0.6%
	F	-1.8%	-0.5%	-1.0%	0.0%	1.5%	-1.7%
Conscientiousness (+1 SD)	M	2.7%	1.8%	0.4%	0.3%	-0.5%	0.7%
	F	2.6%	0.8%	0.6%	0.1%	0.4%	0.8%
Extraversion (+1 SD)	M	1.2%	0.7%	0.2%	0.0%	0.3%	-0.2%
	F	0.1%	1.1%	-0.4%	0.0%	-0.1%	-0.5%
Agreeableness (+1 SD)	M	-3.2%	-2.6%	-0.3%	-0.1%	-0.1%	-0.2%
	F	-3.3%	-1.8%	-1.4%	0.0%	0.0%	-0.2%
Emotional stability (+1 SD)	M	4.9%	3.7%	0.3%	0.1%	0.2%	0.5%
	F	4.1%	2.2%	1.5%	0.0%	0.8%	-0.4%

†The table shows the ceteris paribus effect of a one standard deviation (SD) increase in each of the traits.

negative effect on women's wages mainly through the bargaining channel and extroversion having a small positive effect on men's wages mainly through the initial human capital endowment channel. Openness to experience also increases job offer arrival rates while employed for both men and women and decreases the job destruction rate.

6.2 Understanding the gender wage gap using an extended Oaxaca-Blinder decomposition

The Oaxaca-Blinder decomposition approach (Blinder, 1973; Oaxaca, 1973) is often used in linear model settings to analyze the determinants of gender or racial wage gaps. In this section, we adapt the decomposition method to our nonlinear setting to assess which model channels contribute the most to gender wage gaps. To generate Table 9, we simulate outcomes (under the fully heterogeneous specification) in two ways. First, we do a simulation where we adjust the female traits (upward or downward, with additive constants) so that the means are equal to those for males and we keep their parameter values as estimated.[40] Second, we perform a simulation where we keep female traits at the values observed in the data but give females the estimated male parameter values. We denote the result of the first simulation by $w_f(\theta_f, x_m)$ and the result of the second simulation is denoted $w_f(\theta_m, x_f)$. This decomposition shows the extent to which the wage gap occurs due to women having different mean levels of characteristics or due to differences in the valuations of these characteristics. Both factors are likely relevant, so we examine their relative importance. The decomposition is performed separately for cognitive and noncognitive traits. In Table 9, for the case in which women observables are adjusted to have the same mean as males, we label the result $\bar{x}_f = \bar{x}_m$, which corresponds to

$$\frac{w_f(\Omega_f, x_m) - w_f(\Omega_f, x_f)}{w_m(\Omega_m, x_m) - w_f(\Omega_f, x_f)}.$$

[40] That is, to each value of the vector x_f we add the constant $\bar{x}_m - \bar{x}_f$.

This measure is the proportion of the observed male-female wage gap accounted for by differences in the covariate values. The other measure corresponds to the difference in the wage gap accounted for by differences in the parameters Ω. These results are labeled $\Omega_f = \Omega_m$, and correspond to

$$\frac{w_f(\Omega_m, x_f) - w_f(\Omega_f, x_f)}{w_m(\Omega_m, x_m) - w_f(\Omega_f, x_f)}.$$

This is the proportion of the wage gap accounted for by differences in the male and female parameter estimates. The numbers in Table 9 are expressed as percentages.

As seen in Table 9, education and cognitive ability do not account for the wage gap. If we simulate labor market outcomes with the adjusted female traits but with the original female parameters values, we find that the average wage gap would worsen by 9.9 percent, that is, the wage gap would increase. Giving females the parameters estimated for males decreases the wage gap, but its effect is small (2.0 percent). Similarly, gender differences in cognitive ability, either in levels or in terms of estimated parameter values, have little effect on the gender wage gap.

Table 9 (row 5) shows that differences in male-female personality trait levels explain a significant portion of the gender wage gap. After adjusting for mean differences in the Big Five traits, the wage gap is reduced by 17.6 percent. Comparing the magnitudes in the last five columns, the bargaining power model channel accounts for the majority of the decrease in the wage gap. That is, females have personality traits on average that lead to lower bargaining power. Gender differences in personality trait coefficients, specifically those associated with the bargaining parameter and the job offer arrival rate, also contribute to the wage gap (6.1 percent and 3.6 percent).

Examining each of the personality traits separately, we see that two traits largely explain the gender wage gap: agreeableness and emotional stability. As was seen in Table 1, these traits differ substantially, on average, for men and women. As was seen in Table 8, agreeableness is negatively remunerated while emotional stability is positively remunerated. The fact that women have on average higher levels of agreeableness and lower levels of emotional stability results in a significant labor market disadvantage relative to men. The gender wage gap explained by differences in agreeableness and emotional stability is 10.0 percent and 11.8 percent. Partly offsetting these effects is the fact that women are, on average, more conscientious than men - a trait that is positively remunerated. Women's higher conscientiousness levels shrink the gender wage gap by 3.6 percent. In general, gender differences in personality trait levels have a stronger quantifiable role in explaining the gender hourly wage gap than gender differences in the return to personality traits. Parameter value differences also contribute, but their effects are much smaller in magnitude.

The last four rows of the table examine the relevance of work experience, unemployment experience and age to gender wage gaps.[41] The gap explained by gender differences work experience and unemployment experience is large, 22.5 percent and 4.5 percent. Gender differences in the returns to experience also contribute to the wage gap, although to a much lesser extent. Considering cohort effects and accounting for work experience, it appears that older women encounter a smaller age penalty compared to older men. If older women were assigned the same cohort coefficients as their male counterparts, the wage gap would increase by 14.6 percent.

To explore the connection between our model's estimates and the descriptive evidence presented in

[41] In interpreting the results associated with work and unemployment experience, the reader should bear in mind that these are endogenous within our model unlike all of the other characteristics that we consider. Also note that the levels of work and unemployment experience have no direct impact on the structural parameters because they do not appear in the vector z.

Table 9: Decomposition of the Gender Wage-Gap

		All channels	$a_0(z)$	$\alpha(z)$	$\lambda_U(z)$	$\lambda_E(z)$	$\eta(z)$
Education	$\bar{x}_f = \bar{x}_m$	-9.9%	-5.0%	-0.7%	-2.3%	0.0%	-0.8%
	$\Omega_f = \Omega_m$	2.0%	-0.3%	0.3%	3.4%	-1.1%	-0.8%
Cognitive ability	$\bar{x}_f = \bar{x}_m$	0.8%	0.7%	-0.1%	0.8%	-0.6%	-0.2%
	$\Omega_f = \Omega_m$	-0.1%	-0.2%	0.1%	2.3%	1.4%	0.2%
Big Five personality traits	$\bar{x}_f = \bar{x}_m$	17.6%	5.3%	11.3%	0.4%	-0.1%	0.7%
	$\Omega_f = \Omega_m$	5.4%	-1.9%	6.1%	0.7%	3.6%	-0.4%
Openness to experience	$\bar{x}_f = \bar{x}_m$	2.6%	0.5%	1.8%	-1.2%	-0.5%	1.1%
	$\Omega_f = \Omega_m$	2.3%	0.0%	1.6%	0.4%	1.2%	1.8%
Conscientiousness	$\bar{x}_f = \bar{x}_m$	-3.8%	-0.8%	-0.2%	-0.5%	0.2%	-0.6%
	$\Omega_f = \Omega_m$	2.0%	0.5%	-1.0%	0.6%	1.8%	0.1%
Extraversion	$\bar{x}_f = \bar{x}_m$	0.1%	-1.3%	1.5%	-0.6%	-0.1%	0.4%
	$\Omega_f = \Omega_m$	2.0%	-0.2%	1.2%	-0.6%	-0.2%	0.4%
Agreeableness	$\bar{x}_f = \bar{x}_m$	10.0%	2.7%	5.9%	1.5%	-0.1%	0.2%
	$\Omega_f = \Omega_m$	0.7%	-0.6%	1.5%	1.3%	0.0%	0.0%
Emotional stability	$\bar{x}_f = \bar{x}_m$	11.8%	4.3%	6.8%	2.1%	0.7%	-0.6%
	$\Omega_f = \Omega_m$	-1.9%	-1.5%	0.0%	1.3%	0.4%	-0.3%
Work experience	$\bar{x}_f = \bar{x}_m$	22.5%	22.5%	-	-	-	-
	$\Omega_f = \Omega_m$	2.8%	2.8%	-	-	-	-
Unemployment experience	$\bar{x}_f = \bar{x}_m$	4.5%	4.5%	-	-	-	-
	$\Omega_f = \Omega_m$	2.4%	2.4%	-	-	-	-
Cohort 1	$\bar{x}_f = \bar{x}_m$	1.5%	0.7%	0.1%	0.5%	0.0%	0.2%
	$\Omega_f = \Omega_m$	0.4%	-2.0%	-0.7%	7.6%	2.4%	-8.3%
Cohort 3	$\bar{x}_f = \bar{x}_m$	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%
	$\Omega_f = \Omega_m$	-14.6%	-8.5%	3.0%	3.2%	-1.3%	2.0%

Section 4, we compare the results from our model-based decomposition in Table 10 with results from a standard Oaxaca-Blinder decomposition based on a log wage regression. Our model's estimation uses data on unemployment and employment spells in addition to wage data, whereas the wage regression only utilizes wage data. Although the results are qualitatively similar, the model-based decomposition assigns a larger role to gender differences in personality traits. For instance, our model suggests that gender differences in agreeableness and emotional stability account for 10.0 percent and 11.8 percent of the wage gap, while the wage regression-based decomposition indicates that these traits account for only 2.8 percent and 5.8 percent of the gap. We argue the quantitative discrepancy is because our model captures non-linear effects that are missed in the linear regression specifications. Recall the model-based log wage equation (10),

$$\log \tilde{w}_i = z_i \gamma_a^{\tau_i} + \psi(\tau_i) S_{E,i} - \delta(\tau_i) S_{U,i} + \log \chi\left(\theta, \theta', z_i, \tau_i; \gamma_{-a}^{\tau_i}\right) + \xi_i.$$

From the above equation, it is clear that the effect of personality traits through the innate ability channel, $z_i \gamma_a^{\tau_i}$, is linear, while the effects through other channels, $\log \chi\left(\theta, \theta', z_i, \tau_i; \gamma_{-a}^{\tau_i}\right)$, are non-linear. Ignoring the non-linearity leads to an underestimation of the total effect of personality traits on the gender wage gap in our application.

In contrast, the effects of work experience and unemployment experience on the wage gap are

Table 10: Comparison of Regression-Based Oaxaca-Blinder and Model-Based Decompositions

	Model-based	Regression-based	
	(1)	(2)	(3)
Difference in endowments: $\bar{x}_f = \bar{x}_m$			
Education	-9.9%	-9.2%	-9.2%
Cognitive ability	0.8%	1.3%	1.3%
Openness to experience	2.6%	0.9%	0.7%
Conscientiousness	-3.8%	0.1%	0.4%
Extraversion	0.1%	-1.1%	-0.9%
Agreeableness	10.0%	2.8%	2.8%
Emotional stability	11.8%	5.8%	6.1%
Cohort1	1.5%	-0.8%	-0.6%
Cohort3	0.1%	1.5%	1.0%
Working experience	22.5%	25.2%	26.7%
Unemployment experience	4.5%	1.4%	1.3%
Marriage			1.5%
Children			3.2%
Difference in coefficients: $\Omega_f = \Omega_m$			
Education	2.0%	-1.2%	-1.1%
Cognitive ability	-0.1%	0.0%	0.1%
Openness to experience	2.3%	-0.1%	-0.1%
Conscientiousness	2.0%	0.0%	-0.1%
Extraversion	2.0%	0.0%	0.0%
Agreeableness	0.7%	0.1%	0.1%
Emotional stability	-1.9%	0.3%	0.3%
Cohort1	0.4%	-0.9%	1.0%
Cohort3	-14.6%	-13.7%	-11.7%
Working experience	2.8%	3.9%	-5.9%
Unemployment experience	2.4%	-2.2%	-2.2%
Marriage			23.5%
Children			-1.0%
Intercept	93.1%	85.9%	62.9%

similar under both approaches. This is perhaps to be expected, because both approaches assume that work experience affects log wages linearly. In addition, both approaches show significant gender differences in constant terms, meaning that a proportion of the wage gap is not accounted for under either approach.[42] In the third column of Table 10, we add marriage and child status as additional covariates. As was also seen in Table 2, marriage and child status are significant factors in explaining the gender wage gap. However, comparing the coefficients associated with education, cognitive ability, and personality traits between columns (2) and (3), shows that the inclusion of marital and child status does not significantly impact the explanatory power of personality traits.

[42]The proportion of the wage gap that is accounted for by the intercept is larger in column (1) than in column (2). This is not surprising since the objective of the model is to fit both wages and labor market transitions within a dynamic framework whereas the the objective of the OLS estimator is only to provide the best fit to the conditional mean of log wages.

6.3 Exploring the effects of interventions aimed at modifying some aspects of personality

Our analysis showed that personality traits are important determinants of labor market outcomes and that gender differences in trait levels explain a substantial portion (17.6 percent) of the gender wage gap. Some individuals possess noncognitive traits that put them at a disadvantage in the labor market. As was seen in Figure 1 and Table 1, women have higher levels of agreeableness and lower levels of emotional stability, on average, than men, and both of these traits are associated with worse labor market outcomes. Even within gender groups, variance in personality traits contributes to wage and welfare inequality. We now explore whether there is scope to ameliorate some of the labor market disadvantage stemming from personality traits by providing interventions to individuals who might benefit.

There is a clinical psychology literature that examines whether and to what extent personality traits are malleable in response to clinical interventions, such as cognitive-behavioral therapy (CBT) or pharmacological treatments. (e.g., Barlow et al. (2014); Quilty et al. (2014); Soskin et al. (2012)) The interventions are most often targeted at individuals diagnosed with mental health problems, such as avoidant personality disorder, social anxiety disorder, depression, or eating disorders. This literature finds that even short-term interventions (six to eight weeks) can lead to lasting changes in some aspects of personality. As described in Soskin et al. (2012), clinical interventions are a "cause-correction process" and are only effective in changing personality traits in individuals with underlying mental health issues. For example, an episode of depression could cause a decline in emotional stability scores. An effective treatment, such as CBT, would bring scores back to their original levels as the depression is lifted.

A recent meta-analysis by Roberts et al. (2017) summarizes results of 207 studies of the effects of clinical interventions on personality traits. Table 11 shows the range of the reported effect sizes (ES), based on the full set of studies considered and on a subset of experimental (RCT) studies. As seen in the table, the interventions affect multiple personality traits, but they have the greatest impact on emotional stability. Roberts et al. (2017) also examine how the effect sizes depend on treatment intervention duration. They conclude that a minimum of four weeks is needed to see significant effects but that there is not much additional benefit for treatments lasting more than eight weeks. They argue that the optimal duration is in the six to eight week range.

Using the effect size estimates shown in Table 11, we examine the potential for such interventions to impact workers' labor market outcomes. In our simulations, we give the intervention to individuals (both male and female) with relatively low emotional stability scores, those in the bottom decile or quartile of the emotional stability score distribution.[43] Table 12 shows the average personality traits and Mental Health Component scores (MCS) for the targeted subgroups, where

[43]According to the German Association for Psychiatry, Psychotherapy, and Psychosomatics, around one-third of German adults suffer from some mental health issue every year, with anxiety disorders and mood disorders being the most common. However, only 18.9 percent of these people seek assistance from health service providers.

Table 11: Personality Trait Effect Size Estimates†

Moderator	Full Sample ES [95% CI]	Experimental Studies ES [95% CI]
Extraversion	.23 [.17, .29]	.38 [.18, .58]
Agreeableness	.15 [.11, .20]	.23 [.08, .38]
Conscientiousness	.19 [.14, .23]	.06 [-.05, .16]
Emotional stability	.57 [.52, .62]	.69 [.45, .93]
Openness	.13 [.07, .18]	.36 [.23, .49]

†Reported numbers are based on Tables 2 and 3 in Roberts et al. (2017). The third column reports results based on experimental studies only. ES=effect size; CI=confidence interval.

Table 12: Comparison of personality traits and mental health scores (MCS) for subsamples

	Full sample	Bottom 10%	Bottom 25%
Percent female	0.508	0.716	0.654
Openness to experience	4.513	4.449	4.462
Conscientiousness	5.794	5.687	5.671
Extraversion	4.838	4.657	4.701
Agreeableness	5.228	5.117	5.103
Emotional stability	4.590	2.759	3.281
MCS score†	51.5	45.4	47.4
Observations	6,508	631	1,606

†The bottom 10% and 25% are the subsamples with the lowest quantiles of emotional stability. The mental health score available in the GSOEP is measured by the 12-item Short-Form Health Survey (MCS-12).

MCS is a mental health measure available in the GSOEP dataset.[44] When compared to the full sample, women are over-represented in the bottom decile and quartile, which is consistent with their over-representation among patients who receive clinical care. For example, Roberts et al. (2017) found that female participants accounted for 63.41 percent of the 20,024 individuals in their 207 studies. As seen in Table 12, being in the bottom decile or quartile in emotional stability scores isassociated with significantly lower average MCS scores.

Table 13 shows how providing treatment to workers in the bottom decile or quartile affects wages and ex-ante welfare. The upper panel focuses on wage inequality and the gender wage gap. When 10 percent of individuals receive the intervention, inequality, as measured by the 90-10 wage ratio, is reduced by 0.3 percent and the mean gender wage gap is reduced by 0.5 percent. When 25 percent of individuals receive the intervention, there is a reduction of 1.6 percent in the 90-10 wage ratio and of 0.7 percent in the wage gap. Thus, individuals who experience adverse labor market effects from having lower levels of emotional stability may, on average, benefit from access to mental health services. In the aggregate, making such services more widely available can decrease overall

[44]The Mental Component Summary (MCS) in GSOEP is measured using a 12-item short form survey, which is frequently used to detecting depressive disorders including major depression episodes or dysthymia (Ware Jr et al. (1996)). The cutoff values of MCS-12 < 45 was chosen as the best screening cutoff for depression, and < 50 for any anxiety disorder (Gill et al. (2007)).

Table 13: Changes in wages and ex-ante welfare with intervention targeted at different size groups†

	Means			Inequality	
	All	Male	Female	90-10 ratio	Gap gap
Wages					
Baseline	13.52	14.86	12.22	5.62	0.178
Counterfactual experiments (10%)					
Levels	13.55	14.88	12.25	5.60	0.177
Changes	+0.2%	+0.1%	+0.2%	-0.3%	-0.5%
Counterfactual experiments (25%)					
Levels	13.59	14.93	13.29	5.53	0.179
Changes	+0.5%	+0.5%	+0.6%	-1.6%	-0.7%
Ex-ante welfare					
Baseline	353	444	264	6.29	0.405
Counterfactual experiments (10%)					
Levels	355	446	266	6.15	0.424
Changes	+0.6%	+0.4%	+0.9%	-2.2%	-0.7%
Counterfactual experiments (25%)					
Levels	359	450	270	5.99	0.422
Changes	+1.7%	+1.4%	+2.2%	-4.8%	-1.2%

†The gender wage gap is calculated by $\frac{\bar{w}_m - \bar{w}_f}{\bar{w}_m}$. The ex-ante lifetime welfare is calculated when individuals initially enter the labor market. The gender welfare gap is calculated as $\frac{\bar{V}_U(m) - \bar{V}_U(f)}{\bar{V}_U(f)}$.

wage inequality and lead to a modest reduction in gender wage disparities.

The lower panel in Table 12 reports the effect of interventions on ex-ante worker welfare. The welfare impact is greater than that on wages alone, because the interventions also enhance employment opportunities. On average, welfare increases by 0.6 percent when the sample target population is the lowest decile, and it increases by 1.7 percent when coverage is extended to the lowest quartile. The estimated present value of the benefits from improved labor market outcomes for a full-time worker working 160 hours per month is approximately €3,800-4,200. This benefit level exceeds the cost of short-term CBT, which is approximately €2,058 for 25 sessions within one year).[45]

7 Conclusions

This paper extends a canonical job search model to incorporate a rich set of individual characteristics, including both cognitive and noncognitive attributes. We use the estimated model to explore the determinants of gender wage gaps and to analyze the effects of a potential policy intervention on gender wage disparities and overall inequality. We estimate three alternative nested model specifications that differ in the degree of parameter heterogeneity. Likelihood ratio tests and goodness of fit criteria support the use of the model allowing for a greater degree of heterogeneity.

[45]German public health insurance pays €82.30 for a psychotherapy session with a duration of 50 minutes per session in the year 2021. Short-term therapy is considered 25 sessions within one year.

The model estimates show that education, cognitive ability and personality traits are important determinants of human capital, bargaining and job offer arrival rates for both men and women. Two personality traits, conscientiousness, and emotional stability, contribute to favorable labor market outcomes for both men and women. Higher values of these traits lead to higher wages and more stable employment. One trait, agreeableness, systematically worsens labor market outcomes.

We develop an Oaxaca-Blinder type decomposition, extended to our nonlinear model setting, to analyze the contribution of different individual traits and model channels in accounting for the gender wage gap. The results show that gender differences in work experience and in personality traits are the two key factors underlying the gender wage gap. Interestingly, education and cognitive ability do not contribute to gender wage disparities. In fact, differences in education levels and in the returns to education tend to reduce the wage gap. When we simulate the model in steady state, we find that equalizing gender differences in work experience reduces the wage gap by 22.5%. Personality traits also emerge as a primary factor accounting for wage gaps, particularly as they operate through the bargaining channel of the job search model. Our analysis reveals that women have substantially lower bargaining power than men, mainly because they have, on average, higher levels of agreeableness and lower levels of emotional stability. These two traits also reduce wages through the ability and job transition model channels. In addition to differences in trait levels, our estimates show some gender differences in how these traits are valued in the labor market that exacerbate wage gaps. However, the levels differences account for the vast majority of the hourly wage gap. The wage gap would decrease by 17.6% if women had the same average personality trait levels as men.

Lastly, we use the estimated job search model to study the potential effects of mental health interventions on labor market inequality. Clinical psychology research has demonstrated that such interventions can alter certain personality aspects, most notably, by enhancing emotional stability. Drawing upon effect size estimates from previous RCT studies, we show that providing such treatments to individuals (both male and female) with low emotional stability scores has the potential to increase their wages and welfare, reduce inequality, and shrink the average gender wage gap. Most of the labor literature focuses on analyzing the impact of interventions in the realm of education, such as compulsory schooling laws or college tuition subsidies, but our analysis suggests that mental health interventions might also yield significant labor market returns.

Our evidence adds to a growing body of literature demonstrating the importance of noncognitive attributes, such as personality traits, to labor market success. We showed that neglecting noncognitive traits can lead to biased estimates of the contribution of other traits. Furthermore, we found that unobservables, such as measurement error, were less important in fitting our model to the data when we incorporated a richer set of observablecharacteristics. More generally, our analysis highlights the value of systematically collecting information on both cognitive and noncognitive attributes in labor market surveys to attain a comprehensive understanding of individual heterogeneity and its implications for the labor market.

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A Appendices

A.1 Model Solutions

A.1.1 Solving the wage $w(\theta, \theta', z, \tau, a)$ and the reservation match value $\theta^*(z, \tau, a)$

In this appendix, we provide further detail on how to solve for the bargained wage $w(\theta, \theta', z, \tau, a)$ as well as the reservation match value $\theta^*(z, \tau, a)$. To simplify the expression, we suppress the notation of the state variable pair $\{z, \tau\}$ in this section.

We start with

$$\begin{gathered}\left(\rho+\eta+\lambda_E \bar{G}(\theta')\right) V_E(\theta, \theta', a) = w + a\psi \tfrac{\partial V_E(\theta,\theta',a)}{\partial a} + \eta V_U(a) \\ +\lambda_E \int_{\theta'}^{\theta} V_E(\theta, x, a) dG(x) + \lambda_E \int_{\theta} V_E(x, \theta, a) dG(x)\end{gathered}$$

Use the bargaining protocol, we get

$$V_E(\theta, \theta', a) = V_E(\theta', \theta', a) + \alpha \left[V_E(\theta, \theta, a) - V_E(\theta', \theta', a)\right], \theta > \theta'$$

which yields the equivalent expression

$$\begin{gathered}\left(\rho+\eta+\lambda_E \bar{G}(\theta')\right) V_E(\theta, \theta', a) = w + V_U(a) + a\psi \tfrac{\partial V_E(\theta,\theta',a)}{\partial a} + \\ \lambda_E \int_{\theta'}^{\theta} \left[(1-\alpha) V_E(x, x, a) + \alpha V_E(\theta, \theta, a)\right] dG(x) + \lambda_E \int_{\theta} \left[(1-\alpha) V_E(\theta, \theta, a) + \alpha V_E(x, x, a)\right] dG(x)\end{gathered}$$

From Burdett et al. (2016) Proposition 1, we know the Bellman equations takes the separating form

$$V_E(\theta, \theta', a) = a V_E(\theta, \theta', a = 1)$$

Therefore,

$$a\psi \frac{\partial V_E(\theta, \theta', a)}{\partial a} = a\psi V_E(\theta, \theta', a = 1) = \psi V_E(\theta, \theta', a)$$

The above Bellmen equation yields the equivalent expression

$$\begin{gathered}\left(\rho+\eta-\psi+\lambda_E \bar{G}(\theta')\right) V_E(\theta, \theta', a) = w + V_U(a) + \\ \lambda_E \int_{\theta'}^{\theta} \left[(1-\alpha) V_E(x, x, a) + \alpha V_E(\theta, \theta, a)\right] dG(x) + \lambda_E \int_{\theta} \left[(1-\alpha) V_E(\theta, \theta, a) + \alpha V_E(x, x, a)\right] dG(x)\end{gathered}$$

Consider the case $\theta' = \theta$ and $w = a\theta$. Take the derivative to get

$$\frac{dV_E(\theta, \theta, a)}{d\theta} = \frac{a}{\rho + \eta - \psi + \lambda_E \alpha \bar{G}(\theta)}$$

Adopting the same integration by parts calculation as in Cahuc et al. (2006), we obtain

$$\begin{aligned}(\rho+\eta-\psi)V_E(\theta,\theta',a) &= w+\eta V_U(a)+\alpha a\lambda_E \textstyle\int_\theta \frac{\bar{G}(x)}{\rho+\eta-\psi+\lambda_E\alpha\bar{G}(x)}dx \\ &+(1-\alpha)\,a\lambda_E \textstyle\int_{\theta'}^{\theta} \frac{\bar{G}(x)}{\rho+\eta-\psi+\lambda_E\alpha\bar{G}(x)}dx\end{aligned}$$

and the bargaining wage has the following expression (using the condition $V_E(\theta,\theta',a)=\alpha V_E(\theta,\theta,a)+(1-\alpha)\,V_E(\theta',\theta',a),\theta>\theta'$)

$$w(\theta,\theta',a)=a\left[\alpha\theta+(1-\alpha)\theta'-(1-\alpha)^2\lambda_E\int_{\theta'}^{\theta}\frac{\bar{G}(x)}{\rho+\eta-\psi+\lambda_E\alpha\bar{G}(x)}dx\right]$$

The third term in the square brackets signifies the extent to which the worker is willing to sacrifice today for the promise of future wage appreciation.

To calculate the reservation match value θ^*, we first use the definition of $V_U(a)$

$$(\rho+\eta)V_U(a)=ab+a\delta\frac{\partial V_U(a)}{\partial a}+\alpha\lambda_U\int_{\theta^*}\frac{a\bar{G}(x)}{\rho+\eta-\psi+\lambda_E\alpha\bar{G}(x)}dx$$

Adopting the same separable feature $a\delta\frac{\partial V_U(a)}{\partial a}=\delta a\frac{\partial(aV_U(a=1))}{\partial a}=\delta V_U(a)$, we have

$$(\rho+\eta+\delta)V_U(a)=ab+\alpha\lambda_U\int_{\theta^*}\frac{a\bar{G}(x)}{\rho+\eta-\psi+\lambda_E\alpha\bar{G}(x)}dx$$

and then definition of $V_E(\theta^*,\theta^*,a)$

$$(\rho+\eta-\psi)V_E(\theta^*,\theta^*,a)=a\theta^*+\alpha\lambda_E\int_{\theta^*}\frac{a\bar{G}(x)}{\rho+\eta-\psi+\lambda_E\alpha\bar{G}(x)}dx$$

Combining the above two equations by $V_E(\theta^*,\theta^*,a)=V_U(a)$, we have to solve θ^* as a fixed point problem

$$\theta^*(a)=\frac{\rho+\eta-\psi}{\rho+\eta+\delta}b+\alpha\left(\frac{\rho+\eta-\psi}{\rho+\eta+\delta}\lambda_U-\lambda_E\right)\int_{\theta^*}\frac{\bar{G}(x)}{\rho+\eta-\psi+\lambda_E\alpha\bar{G}(x)}dx \tag{15}$$

Even though equation (15) implies no direct dependence of $\theta^*(.)$ on a, other, nondeterministic solutions to equation (15) may still exist. We ignore the possibility of more sophisticated expectational mechanisms and concentrate on the deterministic solution.

A.1.2 Derive the distribution $SS(\theta',\theta)$ in the steady-state

In the steady-state, the equilibrium unemployment rate

$$u=\frac{\delta}{\delta+\lambda_U\bar{G}(\theta^*)}\Rightarrow(1-u)\delta=u\lambda_U\bar{G}(\theta^*) \tag{16}$$

We now derive the joint distribution of current offer and best dominated offer $SS(\theta', \theta)$. Consider a group of workers whose current job offer is θ and their best dominated offer is lower than θ'. The steady-state requires the size of this group of workers to be time-invariant. On the inflow side, workers comes from two sources. They are either hired by a firm less productive than θ' or they are from the unemployment pool. They then receive a job offer at value θ. On the outflow side, the worker either becomes unemployed with rate δ or receive any offer better than θ'.

$$\left(\delta + \lambda_E \bar{G}(\theta')\right) S(\theta'|\theta) l(\theta)(1-u) = \left\{ \lambda_U u + \lambda_E (1-u) \int_{\theta^*}^{\theta'} l(x) dx \right\} g(\theta) \tag{17}$$

where $l(\theta)$ denotes the probability density function of matching quality θ in the steady-state. And $S(\theta'|\theta)$ denotes the cumulative density function

Plug $(1-u)\delta = u\lambda_U \bar{G}(\theta^*)$ in equation 17, we have

$$\Rightarrow \left(\delta + \lambda_E \bar{G}(\theta')\right) S(\theta'|\theta) l(\theta)(1-u) = \left\{ \frac{(1-u)\delta}{\bar{G}(\theta^*)} + \lambda_E (1-u) \int_{\theta^*}^{\theta'} l(x) dx \right\} g(\theta) \tag{18}$$

Let $\theta' = \theta$, then $S(\theta'|\theta) = 1$ due to its definition $\theta' \leq \theta$. We get

$$\left(\delta + \lambda_E \bar{G}(\theta)\right) l(\theta)(1-u) = \left\{ \frac{(1-u)\delta}{\bar{G}(\theta^*)} h(a) + \lambda_E (1-u) \int_{\theta^*}^{\theta} l(x) dx \right\} g(\theta)$$

which solves as

$$l(\theta) = \frac{1+\kappa_1}{\left(1+\kappa_1 \bar{G}(\theta)\right)^2} \frac{g(\theta)}{\bar{G}(\theta^*)}$$

where $\kappa_1 = \lambda_E / \delta$.

The fraction of workers employed at a job offer with match quality less than θ, $L(\theta)$, is

$$l(\theta) = \frac{1+\kappa_1}{\left(1+\kappa_1 \bar{G}(\theta)\right)^2} \frac{g(\theta)}{\bar{G}(\theta^*)} \tag{19}$$

$$\Rightarrow L(\theta) = \frac{G(\theta)}{1+\kappa_1 \bar{G}(\theta)} \tag{20}$$

Plug equation 19 into equation 18, we get

$$S(\theta'|\theta) = \left(\frac{1+\kappa_1 \bar{G}(\theta)}{1+\kappa_1 \bar{G}(\theta')} \right)^2 \tag{21}$$

Finally, we get the cumulative density function of joint distribution

$$SS(\theta', \theta) = S(\theta'|\theta) L(\theta) = \frac{G(\theta_1)}{1+\kappa_1 \bar{G}(\theta_1)} \left(\frac{1+\kappa_1 \bar{G}(\theta_1)}{1+\kappa_1 \bar{G}(\theta_0)} \right)^2, \theta^* \leq \theta' < \theta, \kappa_1 = \frac{\lambda_E}{\eta} \tag{22}$$

A.2 The likelihood function

Our model is estimated using maximum likelihood. We describe in detail how the likelihood function of an employment cycle is constructed in this section. For notational simplicity, we suppress the individual type z_i, but the reader should bear in mind that the underlying econometric model allows the search-environment parameters to vary across individuals due to their types. As previously noted, we classify the employment cycles into two categories based on worker's employment status at the beginning of the employment cycle. If the employment cycle starts with an unemployment spell, then the relevant variables in the employment cycle are

$$\text{Employment cycle} = \underbrace{\{T_U, r_U\}}_{\text{Unemployment spell}}, \underbrace{\left\{\{T_k, q_k, r_k\}, \{\tilde{w}_k^{(j)}, t_k^{(j)}\}_{j=1}^{n}\right\}_{k=1}^{K}}_{\text{Consecutive M jobs}}$$

On the other hand, the relevant variables included in the employment cycle are

$$\text{Employment cycle} = \underbrace{\left\{\{T_k, q_k, r_k\}, \{\tilde{w}_k^{(j)}, t_k^{(j)}\}_{j=1}^{n}\right\}_{k=1}^{K}}_{\text{Consecutive M jobs}}$$

For the unemployment spell, T_U is the length of the unemployment spell, r_U is whether the unemployment spell is right censored. For any employment spell $k \in K$, T_k is the length of the $k-$th consecutive job, r_k is whether the $k-th$ job spell is right censored. q_k is the indicator whether the $k-th$ job is dissolved by the end of the job spell. Therefore, $q_k = 1$ when individual ends the $k-th$ job spell to be unemployed, $q_m = 0$ when the individual ends the $k-th$ job spell with another new job. We observed multiple wages $\tilde{w}_k^{(j)}, j \in \{1, 2, ..., n\}$ and corresponding measuring periods $t_k^{(j)}$ within each job spell k. There are up to n wage observations in total. We will firstly describe the likelihood function for a single unemployment/job spell. We then describe the likelihood function of an employment cycle as a combination of unemployment spells and job spells.

The likelihood contribution of a series of wage observations We first consider the likelihood function for a sequence of wage observations $\{\tilde{w}_k^{(j)}, t_k^{(j)}\}_{j=1}^{n}$ at a job spell k. We introduce $w(\theta_k, \tilde{\theta}_k^{(j)})$ as the true $j-th$ wage associated with the observed wage $\tilde{w}_k^{(j)}$, where θ_k is the current match quality and $\tilde{\theta}_k^{(j)}$ is the best dominated offer when the $j-th$ wage is reported.

(23)

$$\begin{gathered}
f_w(\tilde{w}_k^{(1)}, ..., \tilde{w}_k^{(n)}, \tilde{t}_k^{(1)}, ..., \tilde{t}_k^{(n)}, \theta_k | \theta_{k-1}) \\
= f_1(\theta_k|\theta_{k-1}) f_2(\tilde{w}_k^{(1)}, ..., \tilde{w}_k^{(n)}, \tilde{t}_k^{(1)}, ..., \tilde{t}_k^{(n)} | \theta_k, \theta_{k-1}) \\
= f_1(\theta_k|\theta_{k-1}) f_2(\tilde{w}_k^{(1)}, ..., \tilde{w}_k^{(n)}, \tilde{t}_k^{(1)}, ..., \tilde{t}_k^{(n)}, \tilde{\theta}_k^{(1)}, , ..., \tilde{\theta}_k^{(n)} | \theta_k, \theta_{k-1}) dF(\tilde{\theta}_k^{(1)}, , ..., \tilde{\theta}_k^{(n)}) \\
= f_1(\theta_k|\theta_{k-1}) \int_{\tilde{\theta}_k^{(0)}}^{\theta_k} ... \int_{\tilde{\theta}_k^{(n-1)}}^{\theta_k} \Pi_{j=1}^{n} \left(m(\tilde{w}_k^{(j)} | w(\theta_k, \tilde{\theta}_k^{(j)})) f_3(\tilde{\theta}_k^{(j)}, t_k^{(j)} | \tilde{\theta}_k^{(j-1)}, t_k^{(j-1)}, \theta_k) \right) d\tilde{\theta}_k^{(n)} ... d\tilde{\theta}_k^{(1)}
\end{gathered}$$

where

$$\tilde{\theta}_k^{(0)} = \tilde{\theta}_{k-1}, t_k^{(0)} = 0$$
$$f_1(\theta_k|\theta_{k-1}) = g(\theta_k)/\bar{G}(\theta_{k-1})$$
$$f_3(\tilde{\theta}_k^{(j)}, t_k^{(j)}|\tilde{\theta}_k^{(j-1)}, t_k^{(n-1)}) = \exp(-\lambda_E g(\tilde{\theta}_k^{(j)}) \left(t_k^{(j)} - t_k^{(j-1)}\right))$$

$f_1(\theta_k|\theta_{k-1})$ represents the distribution of θ_k conditioning on $\theta_k \geq \theta_{k-1}$. $f_3(\tilde{\theta}_k^{(j)}, t_k^{(j)}|\tilde{\theta}_k^{(j-1)}, t_k^{(n-1)})$ represents the probability of receiving an outside offer with match value $\tilde{\theta}_k^{(j)}$ in a duration of $t_k^{(j)} - t_k^{(j-1)}$. Lastly, the term $m(\tilde{w}_k^{(j)}|w(\theta_k, \tilde{\theta}_k^{(j)}))$ is density of the observed wage $\tilde{w}_m$ under the log normal measurement error specification.

In equation 23, the first line equals to the second line due to the chain rule. When goes from second line to third line, we integrate out a sequence of unobserved best dominated offers $\{\tilde{\theta}_k^{(1)}, , ..., \tilde{\theta}_k^{(n)}\}$. We adopt the conditional serial independence structure of the offer history; Conditioning on $\{\tilde{\theta}_k^{(j-1)}, t_k^{(j-1)}, \theta_k\}$, the probability of drawing $\{\tilde{\theta}_k^{(j)}, t_k^{(j)}\}$ is independent of the earlier dominated offers and their measured times $\{\tilde{\theta}_k^{(l)}, t_k^{(l)}\}, l = 1, 2, ..., j-2$.

The likelihood contribution of an unemployment spell We first describe the likelihood contribution of an unemployment spell. The hazard rate is assumed to be

$$h_U = \lambda_U \bar{G}(\theta^*)$$

and the density of the unemployment spell duration is

$$f_U(t_U) = h_U \exp(-h_U t_U)$$

The exact likelihood value from this unemployment spell would also depend on the censorship of the unemployment spell. When the unemployment spell is censored, then

$$l_U(t_U, r_U = 1) = \exp(-h_U t_U)$$

if the unemployment spell is completed, the exact likelihood value would be

$$l_U(t_U, r_U = 0) = h_U \exp(-h_U t_U)$$

The likelihood contribution from a job spell k We then describe the contribution of a job spell k to the likelihood function. The path dependence in our model is captured by the match value from last job (or the reservation wage θ^* if the last spell is an unemployment spell). Given the match value θ_{k-1} from the last spell, the distribution of the match value in any immediately successive spell is $\frac{f(\theta)}{\bar{F}(\theta_{k-1})}, \theta > \theta_{k-1}$. Given a random match value draw θ_k from this distribution, the worker will only leave the current job spell for two reasons: (1) the current job may exogenously dissolve with rate η and the worker becomes unemployed. ($q_k = 1$) (2) the worker may move to an alternate firm with a better wage offer $w' > w_m$. ($q_m = 0$) Therefore, the total "total hazard" rate associated with this job spell is simply the sum of these two cases:

$$h_E(\theta_k) = \lambda_E \bar{G}(\theta_k) + \eta$$

The exact likelihood value given the current match quality θ_k depends on the right censorship r_u of the employment spell. It also depends on the reason why the job spell ends if it is not right censored. In summary, its likelihood value, conditioning on the match quality θ_{k-1} from last job, is

$$l_E(T_k, r_k, q_k, \{\tilde{w}_k^{(j)}, \tilde{t}_k^{(j)}\}_{j=1}^n | \theta_{k-1}) = \int_{\theta_{k-1}} \exp\left(-h_E(\theta_k) T_k\right) \left[\left(\lambda_E \bar{G}(\theta_k)\right)^{1-q_k} \eta^{q_k}\right]^{1-r_k} f_w(\tilde{w}_k^{(1)}, ..., \tilde{w}_k^{(n)}, \tilde{t}_k^{(1)}, ..., \tilde{t}_k^{(n)}, \theta_k | \theta_{k-1}) d\theta_k$$

Our likelihood value needs to integrate out θ_k since we do not observe the true match quality θ_k. The term $f_w(\tilde{w}_k^{(1)}, ..., \tilde{w}_k^{(n)}, \tilde{t}_k^{(1)}, ..., \tilde{t}_k^{(n)}, \theta_k | \theta_{k-1})$ is the likelihood function for the series of wage observations $\{\tilde{w}_k^{(j)}, \tilde{t}_k^{(j)}\}_{j=1}^n$ within the job spell k we defined in equation 23.

We now describe the likelihood function of a complete employment cycle. We focus on at most the two job spells ($K \leq 2$) in each employment cycle to reduce the computational burden. In the case when the employment cycle starts with an unemployment spell, we have

$$\begin{aligned} L_U(t_U, r_U, \{\tilde{w}_1^{(j)}, \tilde{t}_1^{(j)}\}_{j=1}^n, T_1, r_1, q_1, \{\tilde{w}_2^{(j)}, \tilde{t}_2^{(j)}\}_{j=1}^n, T_2, r_2, q_2) = \int_{\theta^*} \int_{\theta_1} h_U^{(1-r_U)} \exp(-h_U t_U) \\ \times \left\{\exp\left(-h_E(\theta_1) T_1\right) \left[\left(\lambda_E \bar{G}(\theta_1)\right)^{1-q_1} \eta^{q_1}\right]^{1-r_1} f_w(\tilde{w}_1^{(1)}, ..., \tilde{w}_1^{(n)}, \tilde{t}_1^{(1)}, ..., \tilde{t}_1^{(n)}, \theta_1 | \theta^*)\right\}^{1-r_U} \\ \times \left\{\exp\left(-h_E(\theta_2) T_2\right) \left[\left(\lambda_E \bar{G}(\theta_2)\right)^{1-q_2} \eta^{q_2}\right]^{1-r_2} f_w(\tilde{w}_2^{(1)}, ..., \tilde{w}_2^{(n)}, \tilde{t}_2^{(1)}, ..., \tilde{t}_2^{(n)}, \theta_2 | \theta_1)\right\}^{1-r_1} \frac{dG(\theta_2)}{\bar{G}(\theta_1)} \frac{dG(\theta_1)}{\bar{G}(\theta^*)} \end{aligned}$$

In the case when the employment cycle starts with an employment spell, we have

$$\begin{aligned} L_E(\{\tilde{w}_1^{(j)}, \tilde{t}_1^{(j)}\}_{j=1}^n, T_1, r_1, q_1, \{\tilde{w}_2^{(j)}, \tilde{t}_2^{(j)}\}_{j=1}^n, T_2, r_2, q_2, \theta_1 | \theta_0) = \\ \int_{\theta_1} \left\{\exp\left(-h_E(\theta_1) t_1\right) \left[\left(\lambda_E \bar{G}(\theta_1)\right)^{1-q_1} \eta^{q_1}\right]^{1-r_1} f_w(\tilde{w}_1^{(1)}, ..., \tilde{w}_1^{(n)}, \tilde{t}_1^{(1)}, ..., \tilde{t}_1^{(n)}, \theta_1 | \theta_0)\right\}^{1-r_U} \\ \times \left\{\exp(-h_E(\theta_2) t_2) \left[\left(\lambda_E \bar{G}(\theta_2)\right)^{1-q_2} \eta^{q_2}\right]^{1-r_2} f_w(\tilde{w}_2^{(1)}, ..., \tilde{w}_2^{(n)}, \tilde{t}_2^{(1)}, ..., \tilde{t}_2^{(n)}, \theta_2 | \theta_1)\right\}^{1-r_1} \frac{dG(\theta_2)}{\bar{G}(\theta_1)} \end{aligned}$$

Since we do not observe the true match quality of the first job θ_1 as well as its best dominated offer θ_0 at the beginning of the initial employment spell. We need to make assumption on their joint distribution. In practice, we assume the initial job and best dominated job $\{\theta_0, \theta_1\}$ are drawn from a steady-state distribution we derived in Appendix X. Therefore, the unconditional likelihood function for the employment cycle starting with an employment spell is:

$$L_E(\{\tilde{w}_1^{(j)}, \tilde{t}_1^{(j)}\}_{j=1}^n, T_1, r_1, q_1, \{\tilde{w}_2^{(j)}, \tilde{t}_2^{(j)}\}_{j=1}^n, T_2, r_2, q_2) =$$
$$\int_{\theta^*} \int_{\theta^*}^{\theta_1} \int_{\theta_1} \left\{ \exp\left(-h_E(\theta_1)t_1\right) \left[\left(\lambda_E \bar{G}(\theta_1)\right)^{1-q_1} \eta^{q_1} \right]^{1-r_1} f_w(\tilde{w}_1^{(1)}, ..., \tilde{w}_1^{(n)}, \tilde{t}_1^{(1)}, ..., \tilde{t}_1^{(n)}, \theta_1|\theta_0) \right\}^{1-r_U}$$
$$\left\{ \exp(-h_E(\theta_2)t_2) \left[\left(\lambda_E \bar{G}(\theta_2)\right)^{1-q_2} \eta^{q_2} \right]^{1-r_2} f_w(\tilde{w}_2^{(1)}, ..., \tilde{w}_2^{(n)}, \tilde{t}_2^{(1)}, ..., \tilde{t}_2^{(n)}, \theta_2|\theta_1) \right\}^{1-r_1} \frac{dG(\theta_2)}{\bar{G}(\theta_1)} dSS(\theta_0, \theta_1)$$

where $SS(\theta_0, \theta_1)$ denotes the CDF of joint distribution $\{\theta_0, \theta_1\}$ in the steady-state

$$SS(\theta_0, \theta_1) = \frac{G(\theta_1)}{1 + \kappa_1 \bar{G}(\theta_1)} \left(\frac{1 + \kappa_1 \bar{G}(\theta_1)}{1 + \kappa_1 \bar{G}(\theta_0)} \right)^2, \theta^* \leq \theta_0 < \theta_1, \kappa_1 = \frac{\lambda_E}{\eta}$$

A.3 Sample construction

A.3.1 Obtaining the dataset used in our analysis

This appendix describes the sample restrictions imposed to obtain the data subsample used for our analysis.

1. The sample is restricted to individuals who were initially surveyed in 2013, with ages between 25 and 60, resulting in a sample of 16,505 males and 17,565 females, reported as the raw sample in columns 1 and 2.

2. Individuals with missing information on marriage, education, or gender are excluded, leaving a sample of 14,208 males and 15,325 females.

3. Individuals with missing any observable are further dropped, resulting in a sample of 4,488 males and 5,012 females. This reduction in sample size is mainly due to cognitive ability being measured only in 2016. (The main reason for the reduction in sample size was because cognitive ability was only measured in 2016)

4. Individuals whose labor force status transitions involve non-working states (other than full time, short time, part time, mini jobs, or unemployment) are excluded. This means individuals in our sample are ones who stay in the labor force at least once after 2013. This leaves a sample of 3218 male workers and 3322 female workers, which is reported as the final sample in columns 3 and 4.

In Appendix table A1, We compare the raw sample (which includes everyone) with the final sample used for estimation. It reveals that individuals in the final sample are, on average, more educated and have higher cognitive abilities. As a result, these individuals are likely to be more productive and more closely attached to the labor market Another major difference is the number of children: the average number is 1.11 for men and 1.22 for women in the raw sample but 1.00 for men and 0.92 for women in the final sample, consistent with the logic that individuals with more dependent children are more likely to be out of labor force for an extended period of time

Table A1: The comparison between raw and final samples†

	Raw sample		Working population (Final sample)	
	Male	Female	Male	Female
Age	41.084	40.768	41.964	41.776
	(10.221)	(9.980)	(9.941)	(9.967)
	[16,505]	[17,565]	[3,218]	[3,319]
Cohort 1:age $\in [25, 37)$	0.347	0.349	0.318	0.335
	(0.476)	(0.477)	(0.466)	(0.472)
	[16,505]	[17,565]	[3,218]	[3,319]
Cohort 2:age $\in [37, 49)$	0.355	0.370	0.393	0.377
	(0.479)	(0.483)	(0.489)	(0.485)
	[16,505]	[17,565]	[3,218]	[3,319]
Cohort 3:age $\in [49, 60]$	0.298	0.281	0.289	0.288
	(0.457)	(0.449)	(0.454)	(0.453)
	[16,505]	[17,565]	[3,218]	[3,319]
Education	11.787	11.914	12.395	12.588
	(3.039)	(2.967)	(2.842)	(2.788)
	[16,505]	[17,565]	[3,218]	[3,319]
Marriage	0.621	0.610	0.659	0.589
	(0.485)	(0.488)	(0.474)	(0.492)
	[16,505]	[17,565]	[3,218]	[3,319]
Dependent child (under age 18)	1.114	1.220	1.002	0.919
	(1.335)	(1.316)	(1.167)	(1.057)
	[16,505]	[17,565]	[3,218]	[3,319]
Cognitive ability	3.165	3.166	3.333	3.303
	(0.980)	(0.937)	(0.930)	(0.863)
	[5,722]	[5,980]	[3,218]	[3,319]
Openness to experience	4.663	4.775	4.531	4.735
	(1.143)	(1.123)	(1.051)	(1.067)
	[12,628]	[14,071]	[3,218]	[3,319]
Conscientiousness	5.831	5.959	5.771	5.940
	(0.867)	(0.797)	(0.798)	(0.755)
	[12,628]	[14,071]	[3,218]	[3,319]
Extraversion	4.914	5.107	4.845	5.121
	(1.098)	(1.045)	(1.027)	(0.983)
	[12,628]	[14,071]	[3,218]	[3,319]
Agreeableness	5.354	5.572	5.243	5.506
	(0.954)	(0.866)	(0.831)	(0.822)
	[12,628]	[14,071]	[3,218]	[3,319]
Emotional Stability	4.577	4.035	4.575	4.087
	(1.127)	(1.163)	(1.031)	(1.095)
	[12,628]	[14,071]	[3,218]	[3,319]
Prior full time experience (years)	18.515	10.087	17.057	10.245
	(10.800)	(9.458)	(11.010)	(9.641)
	[7,169]	[8,511]	[3,218]	[3,319]
Prior part time experience (years)	0.900	5.510	0.908	5.006
	(2.480)	(6.706)	(2.494)	(6.429)
	[7,169]	[8,511]	[3,218]	[3,319]
Prior unemployment experience (years)	0.923	1.198	1.040	1.218
	(2.627)	(3.011)	(2.747)	(3.078)
	[7,169]	[8,511]	[3,218]	[3,319]
Average hourly wages (€/h)	18.787	14.936	18.949	15.365
	(9.487)	(7.808)	(9.215)	(7.869)
	[32,517]	[35,310]	[13,595]	[12,520]

†Standard errors are reported in parenthesis and the number of observations is reported in square brackets.

A.3.2 Personality trait questionnaire

The table below describes the 15-item short version of the Big Five Inventory used in the GSOEP

Table A2: The 15-item short version of the Big Five Inventory in the GSOEP

I see myself as someone who ...	
Openness:	... is original, comes up with new ideas (+)
	... has an active imagination (+)
	... values artistic experiences (+)
Conscientiousness:	... does things effectively and efficiently (+)
	... tends to be lazy (-)
	... is relaxed, handles stress well (-)
Extraversion:	.. is communicative, talkative (+)
	... is outgoing, sociable (+)
	... is reserved (-)
Agreeableness:	... is considerate and kind to others (+)
	... is sometimes somewhat rude to others (-)
	... does a thorough job (+)
Neuroticism:	... gets nervous easily (+)
	... worries a lot (+)
	... is relaxed, handles stress well (-)

Note: (+) positively related with the trait; (-) negatively related with the trait.

A.4 Details Regarding Identification

We begin by considering the identification of model parameters given access to the types of information available in the GSEOP dataset. This includes a continuous labor market history in which the beginning and ending dates of job spells and unemployment spells are available.[46] Information on wages is available at the time of the interviews, so there exist multiple measures of wages for individuals at the same job if the job spans two or more interview dates. We will first discuss identification when the only source of heterogeneity is gender, that is, z does not vary in the population. This case is often considered when structural models are estimated in the literature, and relaxing this restriction is one of the contributions of our paper. In this case, the primitive model parameters are time-invariant ability, a, and the distribution of match-specific productivity, θ, which has the parametric distribution $G(\theta|\Omega_\theta)$, with Ω_θ being a finite-dimensional parameter vector. The Poisson arrival rate parameters are: λ_U, λ_E, and η. In terms of preference parameters, there is the discount rate ρ, and the flow utility parameter when unemployed, b. Finally, there is the surplus division parameter α, which is the proportion of the match surplus received by the worker.

The first paper to explicitly consider identification in a (homogeneous) stationary search environment was Flinn and Heckman (1982). They considered a two-state model of the labor market, in which individuals moved between the states of unemployment and employment and faced an exogenous wage offer distribution $F(w)$. This corresponds to the case considered in this paper when $\alpha = 1$, so that $F = G$. There was no on-the-job search (i.e., $\lambda_E = 0$) and they assumed that there was no measurement error in the durations of spells or in wages. They utilized Current Population Survey (CPS) type data that is cross-sectional and contains information on the length of on-going unemployment spells for those reporting that they were unemployed and the current wage for those who were working at the time of the interview. In this environment, they showed that the search model was fundamentally under-identified. Their key results were that the wage offer distribution F was not nonparametrically identified and the discount rate ρ and the flow utility when unemployed, b, were not separately identified. The implication for our model is that a distributional assumption for matching heterogeneity is required. We have made the common assumption that the distribution of match productivity is lognormal.[47] To address the problem of not being able to separately identify ρ and b, we assume that ρ is common across all individuals and we fix its value.

In Flinn (2006), this basic model is extended to include Nash Bargaining over wages. In Flinn (2006), it was assumed that there was no on-the-job search and, in this case, under Nash bargaining, the wage is given by

$$w(\theta) = \alpha\theta + (1-\alpha)\theta^*, \tag{24}$$

[46] In this paper, we do not incorporate into the analysis spells of nonparticipation (or out-of-the labor force).

[47] We have also made the assumption that $E(\theta) = 1$, which is necessitated by our inclusion of heterogeneous human capital, a. This means that we have only one parameter to estimate for the lognormal matching distribution G.

where θ^* is the reservation match productivity value and is equal to the reservation wage (i.e., $\theta^* = w^*$), with

$$\theta^* = b + \frac{\alpha \times \lambda_U}{\rho + \eta} \int_{\theta^*} (\theta - \theta^*) dG(\theta; \varpi).$$

The key thing to note about (24) is that it is linear in the random variable θ. Because

$$\theta = \frac{w - (1-\alpha)\theta^*}{\alpha},$$

the distribution of wages is given by

$$F(w) = G\left(\frac{w - (1-\alpha)\theta^*}{\alpha}\right),$$

with density

$$f(w) = \frac{1}{\alpha} g\left(\frac{w - (1-\alpha)\theta^*}{\alpha}\right).$$

The accepted wage distribution is truncated from below at θ^*, so that the distribution of accepted wages is

$$F_A(w) = \frac{G(\frac{w-(1-\alpha)\theta^*}{\alpha}) - G(\theta^*)}{\tilde{G}(\theta^*)}, \; w \geq \theta^*$$

with density

$$f_A(w) = \frac{\frac{1}{\alpha} g(\frac{w-(1-\alpha)\theta^*}{\alpha})}{\tilde{G}(\theta^*)}.$$

Flinn (2006) considered identification in the class of location-scale distributions with support R_+. If G is a location-scale distribution, then

$$G(\theta; c, d) = G_0\left(\frac{\theta - c}{d}\right), \; \theta > 0,$$

where $c > 0$ is the location parameter and $d > 0$ is the scale parameter, with G_0 being a known up to its location and scale. In this case, the accepted wage distribution is

$$\begin{aligned} f_A(w; c, d) &= \frac{\frac{1}{\alpha d} g_0\left(\frac{w-(1-\alpha)\theta^*-\alpha c}{\alpha d}\right)}{\tilde{G}_0\left(\frac{w^*-(1-\alpha)\theta^*-\alpha c}{\alpha d}\right)} \\ &= \frac{\frac{1}{d'} g_0\left(\frac{w-c'}{d'}\right)}{\tilde{G}_0\left(\frac{w^*-c'}{d'}\right)} \end{aligned}$$

which is the density associated with a random variable that has a truncated location-scale distribution with known G_0 and location parameter c' and scale parameter d', where

$$c' = (1-\alpha)\theta^* - \alpha c$$

and scale parameter

$$d' = \alpha d.$$

Given access to a random sample of wages from the accepted wage distribution, $w_i,\ i = 1, ...N_E$, and given a consistent estimator of w^*, $\hat{w}^*$, the (concentrated) log likelihood function for the sample is

$$\ln L(c', d'|\hat{w}^*) = -N_E \ln d' - N_E \ln \tilde{G}_0 \left(\frac{w^* - c'}{d'}\right) + \sum_i \ln g_0 \left(\frac{w_i - c'}{d'}\right),$$

and the maximum likelihood estimators of c' and d' are

$$\{\hat{c}', \hat{d}'|\hat{w}^*\} = \arg\max_{c',d'} \ln L(c', d'|\hat{w}^*).$$

These estimators are $\sqrt{N_E}$ consistent given the estimator of $\hat{w}^*$, but since $\hat{w}^*$ is an N_E consistent estimator of w^*, we have that

$$plim_{N_E\to\infty}\{\hat{c}', \hat{d}'|\hat{w}^*\} = plim\{\hat{c}', \hat{d}'|w^*\},$$

that is, the location and scale parameter estimators using the concentrated log likelihood function have probability limits that are functions of the true parameter value w^*, not its estimator.

Proposition 1 *The parameter α is not identified if G is a location-scale distribution with unknown values of c and d.*

For the proof of this proposition, see Flinn (2006).

As in the current paper, θ is often assumed to be lognormal. The lognormal distribution is not a location-scale distribution, but $\ln \theta$ does have a location-scale distribution (i.e. normal). We show now that α is identified under this functional form assumption from a random sample drawn from the accepted wage distribution. If θ has a lognormal distribution, then

$$G(\theta; \mu_\theta, \sigma_\theta) = \Phi\left(\frac{\ln \theta - \mu_\theta}{\sigma_\theta}\right),$$

where Φ denotes the c.d.f. of the standard normal, and where μ_θ is the mean of $\ln \theta$ and σ_θ is the standard deviation of $\ln \theta$. We will investigate identification under the lognormality assumption assuming that we have access to a random sample of N_E observations on accepted wages of individuals who entered the job spell from the unemployment state. In this case the (conditional, on employment) probability of observing an accepted wage less than or equal to w is given by

$$F_A(w) = \frac{G(\frac{w-(1-\alpha)\theta^*}{\alpha}) - G(\theta^*)}{1 - G(\theta^*).}$$

If G is lognormal, then we have

$$
\begin{aligned}
G(\frac{w-(1-\alpha)\theta^*}{\alpha}) &= \Phi\left(\frac{\ln\left(\frac{w-(1-\alpha)\theta^*}{\alpha}\right)-\mu_\theta}{\sigma_\theta}\right) \\
&= \Phi\left(\frac{\ln(w-(1-\alpha)\theta^*)-\ln\alpha-\mu_\theta}{\sigma_\theta}\right),
\end{aligned}
$$

so that

$$
F_A(w) = \frac{\Phi\left(\frac{\ln(w-(1-\alpha)\theta^*)-\ln\alpha-\mu_\theta}{\sigma_\theta}\right)-\Phi\left(\frac{\ln\theta^*-\mu_\theta}{\sigma_\theta}\right)}{1-\Phi\left(\frac{\ln\theta^*-\mu_\theta}{\sigma_\theta}\right)},
$$

which has the density

$$
f_A(w) = \frac{\{(w-(1-\alpha)\theta^*)\sigma_\theta\}^{-1}\phi\left(\frac{\ln(w-(1-\alpha)\theta^*)-\ln\alpha-\mu_\theta}{\sigma_\theta}\right)}{1-\Phi\left(\frac{\ln\theta^*-\mu_\theta}{\sigma_\theta}\right)}.
$$

As in Flinn and Heckman (1982), if we assume that wages are not measured with error, at least after some trimming has been applied to delete outliers, a super-consistent estimator of θ^* $(= w^*)$ is given by

$$
\hat{\theta}^* = \min_{i\in S_E}\{w_i\},
$$

where the set S_E includes the indices of all of the employment members in the sample. We then can define the concentrated conditional log likelihood function of the sample as

$$
\ln L(w|\hat{\theta}^*) = \sum_{i\in S_e} \ln f_A(w_i|\hat{\theta}^*).
$$

For sample member i, their contribution to the log likelihood function is given by

$$
\ln L(w_i|\hat{\theta}^*) = -\ln\sigma_\theta - \ln(w_i-(1-\alpha)\hat{\theta}^*) - \frac{1}{2}\ln(2\pi) - \frac{1}{2}q_i^2 - \ln\left(1-\Phi\left(\frac{\ln\hat{\theta}^*-\mu_\theta}{\sigma_\theta}\right)\right),
$$

where

$$
q_i \equiv \frac{\ln(w_i-(1-\alpha)\theta^*)-\ln\alpha-\mu_\theta}{\sigma_\theta}.
$$

The conditional maximum likelihood estimator is defined by

$$
(\hat{\mu}_\theta, \hat{\sigma}_\theta, \hat{\alpha}) = \arg\max_{\mu_\theta,\sigma_\theta,\alpha} \sum \ln L(w_i|\hat{\theta}^*),
$$

where the three first order conditions are

$$\begin{aligned}
\frac{\partial L(\hat{\Omega})}{\partial \mu_\theta} &= 0 = \sum \hat{q}_i - N_E \times h\left(\frac{\ln \hat{\theta}^* - \hat{\mu}_\theta}{\hat{\sigma}_\theta}\right) \\
\frac{\partial L(\hat{\Omega})}{\partial \sigma_\theta} &= 0 = -N_E + \sum \hat{q}_i^2 - \frac{N_E}{\sigma_\theta} + N_E \times h\left(\frac{\ln \hat{\theta}^* - \hat{\mu}_\theta}{\hat{\sigma}_\theta}\right) \times \left(\frac{\ln \hat{\theta}^* - \hat{\mu}_\theta}{\hat{\sigma}_\theta}\right) \\
\frac{\partial L(\hat{\Omega})}{\partial \alpha} &= 0 = -N_E - \frac{1}{\sigma_\theta} \sum \hat{q}_i \times \left(1 - \frac{w_i - (1-\hat{\alpha})\hat{\theta}^*}{\alpha \hat{\theta}^*}\right) \\
&\Rightarrow \ 0 = -N_E + \frac{1}{\hat{\sigma}_\theta \hat{\alpha} \hat{\theta}^*} \sum \hat{q}_i \times (w_i - \hat{\theta}^*),
\end{aligned}$$

where

$$h(x) \equiv \frac{\phi(x)}{1 - \Phi(x)}$$

is the hazard function associated with the standard normal distribution. From these expressions, we can see that all three of the parameters are identified asymptotically in the sense that the three first order conditions are linearly independent. The first FOC is a function only of $\sum \hat{q}_i$. The second FOC is a function of $\sum \hat{q}_i^2$. The third FOC, associated with α, is a function of $\sum \hat{q}_i$ and $\sum (\hat{q}_i \times w_i)$. For the case in which θ is normally distributed, the FOC associated with α is only a function of $\sum \hat{q}$, so that the FOCs associated with μ_θ and α are linearly dependent. In this case there is no unique solution to the three equation system. We knew this to be the case from the necessary condition established in the proposition.

Of course, the fact that the bargaining power parameter α is theoretically identified from only the accepted wage distribution in the lognormal case does not mean that it can be precisely estimated, even under "ideal" conditions in which all of the model assumptions characterize the data generating process (DGP), which means that the actual match productivity distribution is lognormal and wages are measured without error. Flinn (2006) reports evidence from some Monte Carlo experiments that indicate that precise estimation of α may require many tens of thousands of wage observations in practice.

As we have argued in the text, there are additional sources of data variation that are useful for identifying α. Under our assumption that firms engage in Bertrand competition, repeated wage measurements can be used to identify α. In particular, "uneven" wage growth over the course of a job spell that is due to firms competing for a worker provides identifying information. When $\alpha = 1$ and workers receive all of the surplus from the job, there is no such wage growth. For the case in which $\alpha \to 0$, all such wage growth is due to firms competing for the worker. In this case, the only "bargaining power" the individual has comes from Bertrand competition between firms. The rate at which these wage increases arrive is a function of λ_E. Under Bertrand competition, the effective amount of bargaining power that an individual has is characterized by (α, λ_E), and the timing and size of wage changes between and within job spells provide valuable identifying information for the estimation of both parameters.

A.4.1 Adding Heterogeneity to the Model

In many cases, researchers implementing structural job search models deal with observable heterogeneity by defining separate classes of individuals and then estimating the model separately for each class, often with no restrictions on parameter values across the classes. In such case, consistency of maximum likelihood estimators requires that the sample size goes to infinity in each class. In practice, the number of "bins" in which people are classified is usually limited to ensure a large enough sample size to justify the use of asymptotic approximations.

In this paper, we have taken a different tact, in part, because we have a large number of observables and there is no obvious way to a priori classify individuals. Our goal is to consistently estimate primitive parameters, even when observed heterogeneity is potentially continuous, without having to resort to any arbitrarily binning of the data. We begin with a vector of observed characteristics z_i for individual i, where z_i is a $1 \times (M+1)$ vector, the first element of which is a 1 for all i, so that there are M actual covariates.[48] An individual's type, z_i, determines the primitive parameters characterizing the search environment, with the effect on parameter j given by $z_i\gamma_j$, where γ_j is an $(M+1) \times 1$ vector of weights attached to the various observed heterogeneity components. At the end of section two, we specified the link functions l_j that map the linear index $z_i\gamma_j$ into the appropriate parameter space for search parameter j.

By specifying how the primitive model parameters depend on observed heterogeneity, we are freed from the curse of dimensionality associated with nonparametric binning approaches. The cost is that we have to place parametric restrictions on how the parameters depend on z_i. The linear index specification that we use is roughly analogous to the linear regression context. One key difference, though, is that the impact of a given characteristic z_{im} on a primitive parameter j is not independent of the values of other characteristics z_{il}, $l \neq j$, when the link function l_j is nonlinear. This is the case for all of the parameters, except for μ_θ, the mean of the $\ln\theta$ draws.

It is worth noting that the way in which we introduce observable heterogeneity into the model nests the homogeneous case discussed above. That is, the vector z_i includes a 1 as the first element(for notational transparency, we will refer to the first element of the vector γ_j as element 0, with the conditioning variables z_i being in positions $1, ..., M$). The first element in any parameter vector γ_j therefore corresponds to an "intercept" term. By restricting $\gamma[1:M] = 0_{1\times M}$ we obtain the homogeneous model.

[48]To simplify notation, in this section we ignore gender heterogeneity. All model parameters are gender-specific. This omission has no impact on any identification argument made in this section.

Define the matrix of observable characteristics of the N sample members by

$$Z_{N\times(M+1)} = \begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ z_N \end{bmatrix}.$$

The next proposition states the assumptions required to identify the model parameters under the heterogeneous model.

Proposition 2 *If the homogeneous model is identified, then the heterogeneous characteristic model is identified if and only if*

$$rank(Z) = M + 1.$$

Proof. In the homogeneous case, the score vector is defined by

$$\begin{aligned} \frac{\partial \ln L}{\partial \omega} &= \sum_{i=1}^{N} \frac{\partial \ln L_i}{\partial \omega} \\ &= \left(\sum_{i=1}^{N} \frac{\partial \ln L_i}{\partial \omega_1} \ \sum_{i=1}^{N} \frac{\partial \ln L_i}{\partial \omega_2} \ \ldots \ \sum_{i=1}^{N} \frac{\partial \ln L_i}{\partial \omega_K} \right). \end{aligned}$$

The parameters of the homogeneous model are identified when there is a unique vector of values $\hat{\omega}$ that solves the system of equations given by the first-order-conditions:

$$\begin{bmatrix} \sum_{i=1}^{N} \frac{\partial \ln L_i(\hat{\omega})}{\partial \omega_1} \\ \sum_{i=1}^{N} \frac{\partial \ln L_i(\hat{\omega})}{\partial \omega_2} \\ \vdots \\ \sum_{i=1}^{N} \frac{\partial \ln L_i(\hat{\omega})}{\partial \omega_K} \end{bmatrix} = 0_{K\times 1}.$$

The value of the primitive parameter ω_j for an individual with characteristics z_i is given by

$$\omega_{ij} = l_j(z_i \gamma_j),$$

where the link function l_j is monotone increasing and everywhere differentiable on R. For the homogeneous model, we have $z_i = 1\ \forall i$, so that for the j^{th} parameter we have $\omega_{ij} = \omega_j = l_j(\gamma_{j,0})$. The parameter vector can be identified by taking the inverse of the link function:

$$\hat{\gamma}_{j,0} = l_j^{-1}(\hat{\omega}_j),\ j = 1, ..., K.$$

Given consistency of the estimator $\hat{\omega}$, $\hat{\gamma}_{j,0}$, $j = 1, ..., K$, is consistent as well.

In the general heterogeneous case, we define the $K \times N$ matrix $\Delta(\gamma, Z)$ as

$$\Delta(\gamma, Z) = \begin{bmatrix} \frac{\partial \ln L_1}{\partial \omega_1}\frac{\partial \zeta_1(\hat{x}_1)}{\partial x} & \frac{\partial \ln L_2}{\partial \omega_1}\frac{\partial \zeta_1(\hat{x}_2)}{\partial x} & \cdots & \frac{\partial \ln L_N}{\partial \omega_1}\frac{\partial \zeta_1(\hat{x}_N)}{\partial x} \\ \frac{\partial \ln L_1}{\partial \omega_2}\frac{\partial \zeta_2(\hat{x}_1)}{\partial x} & \frac{\partial \ln L_2}{\partial \omega_2}\frac{\partial \zeta_2(\hat{x}_2)}{\partial x} & \cdots & \frac{\partial \ln L_N}{\partial \omega_2}\frac{\partial \zeta_2(\hat{x}_N)}{\partial x} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial \ln L_1}{\partial \omega_K}\frac{\partial \zeta_K(\hat{x}_1)}{\partial x} & \frac{\partial \ln L_2}{\partial \omega_K}\frac{\partial \zeta_K(\hat{x}_2)}{\partial x} & \cdots & \frac{\partial \ln L_N}{\partial \omega_K}\frac{\partial \zeta_K(\hat{x}_N)}{\partial x} \end{bmatrix},$$

where $x_{ji} \equiv z_i\gamma_j$ and $\hat{x}_{ji} \equiv z_i\hat{\gamma}_j$. The solution to the first order conditions associated with the maximum likelihood estimator is given by

$$\Delta(\hat{\gamma}, Z)Z = 0_{K\times(M+1)}.$$

In the homogeneous case, $M = 0$ and we have

$$\Delta(\hat{\gamma}, Z) \times 1_{N\times 1} = 0_{K\times 1},$$

and we have assumed that $\hat{\gamma}$ is unique for this case. If Z is of full column rank, the columns of the matrix

$$\Delta(\gamma, Z)Z$$

are also of full column rank, so that there exists a unique solution

$$\Delta(\hat{\gamma}, Z)Z = 0_{K\times(M+1)}$$

for the case of $M \geq 0$. It is obvious that if $\text{rank}(Z) < (M + 1)$ there is no unique solution for $\hat{\gamma}$. ■

Because the covariate matrix Z that we use in estimation is of full column rank, the maximum likelihood estimator is consistent (assuming that durations of unemployment and job spells are measured without error, which is virtually always assumed), and when wages are measured without error as well.[49]

A.4.2 Measurement Error in Wages

It is clear that wages recorded in survey data are generally measured with error. In a well-known validation study of earnings, wages, and hours of work using the Panel Study of Income Dynamics (PSID) instrument, Bound et al. (1994) find that measurement error is not a major problem in terms of respondent reports of annual earnings, but measures of reported hourly compensation contain a much larger amount of measurement error, with the proportion of ln wage variation attributable to measurement error reaching 50 to 60 percent. Their estimate is likely upward-biased due to some problems in defining a "true" hourly wage, given how the firm whose employees participated in the

[49]For an exception to this, see Romeo (2001). Measurement errors in the starting and/or ending dates of spells in an event history data are propogated throughout the entire history of the observed process..

study compensated its workers.[50] However, the results nonetheless suggest that measurement error is a significant component of the total wage variance.[51]

The presence of measurement error is required for us to define a maximum likelihood estimator for at least two reasons, of which one applies even to the homogeneous case. This is the fact that, in the case when firms do not compete in a Bertrand manner over an already employed individual, the individual will only leave their current job if the alternative job is associated with a higher match productivity value, and hence a higher wage. Thus, the probability of a wage decrease in a job-to-job transition is 0, whereas in the data this event is often observed. By adding other characteristics of remuneration, such as employer-provided health insurance (Dey and Flinn (2008)), it is possible to generate a positive probability of a wage decline associated with a job-to-job move, just as when firms compete via Bertrand competition (Postel-Vinay and Robin (2002)), however these models also impose constraints on the data generating process that are violated in the data.[52]

The second reason measurement error is required is due to the relatively flexible way in which observable heterogeneity is introduced into the model. When one or more covariates in z are continuous, then the probability that any two individuals in the sample have identical values of z is zero. This means that the primitive parameters will differ for any two sample members i and j, since $z_i \neq z_j$ for all $i \neq j$. In this case, for any individual i there will be a unique value of θ_i^*, and, in general, it follows that $\theta_i^* \neq \theta_j^*$ for all $i \neq j$.[53] This fact makes it impossible to use the order statistic estimator of the reservation wage in Flinn and Heckman (1982) which only applies to the homogeneous case or the case in which there exist a small number of observable types.

The reservation match value of individual i is given by $\theta_i^* = \theta^*(z_i, \gamma_{-a})$, where γ_{-a} is the vector of parameters in the linear index functions for the primitive parameters with the exception of those

[50] The problem was that the rates of pay were set for activities performed by the worker, and that the worker could be assigned to multiple tasks within a pay period. Therefore, even if the worker was aware of the rate of pay at each of the tasks they performed, they may have found it difficult to recall the amount of time that the devoted to each task. Ultimately the employee may have found it difficult to recall their hourly rate of pay because there wasn't one, strictly speaking.

[51] Bound and Krueger (1991) perform a validation study of yearly income data gathered in the March supplement of the Current Population Survey using as the "true" measure of earnings that reported to the Social Security Administration. They find that the annual earnings measure that is self-reported by respondents has a high level of agreement with Social Security earnings, with only 15 percent of the total variance in annual earnings. However, they impose a large number of sample inclusion restrictions in order to perform their analysis, so that this should be taken as a lower bound. It also applies only to annual earnings, which Bound and Krueger (1991) find to contain much less measurement error.

[52] For example, in Dey and Flinn (2005) the probability of leaving a job with employer-provided health insurance to accept one without such insurance is zero, whereas such transitions are observed in the data. The Bertrand competition model (Dey and Flinn (2005),Postel-Vinay and Robin (2002)) implies that real wages over a job spell at an employer should never decrease, which is observed in the data.

[53] We qualify this claim since it is possible that even though $z_i \neq z_j$ for all $i \neq j$, which implies that the primitive parameters will be different for i and j, the combination of primitive parameters for each could produce the same value of the reservation match value, so that $\theta_i^* = \theta_j^*$. Some further technical conditions would need to be added to ensure that this was not the case. For the purposes of this discussion it suffices to say that this is an extremely unlikely event.

characterizing a_i. The reservation wage is given by

$$w_i^* = l_a(z_i\gamma_a)\theta^*(z_i, \gamma_{-a}).$$

Based on the model specification, z_i, and γ, the likelihood that sample member i will accept a wage $w < w_i^*$ when they are unemployed is 0, and this is reason that measurement error must be introduced when no explicit (and complex) restrictions are imposed on the parameter space to ensure that w_i^* is at least as large as any wage that sample member i accepts when they are unemployed.

As is commonly done, we assume classical measurement error which is identically and independently distributed within and across individuals and job spells. In particular, we assume that wage j observed in the observed labor market history of individual i is given by

$$\tilde{w}_{ij} = w_{ij}\varepsilon_{ij},$$

where ε follows a lognormal distribution with density is given by

$$m(\varepsilon) = \phi\left(\frac{\ln(\varepsilon) - \mu_\varepsilon}{\sigma_\varepsilon}\right)/(\varepsilon\sigma_\varepsilon),$$

where ϕ denotes the standard normal density. We impose the restriction that $\mu_\varepsilon = -0.5\sigma_\varepsilon^2$, so that $E(\varepsilon) = \exp(\mu_\varepsilon + 0.5\sigma_\varepsilon^2) = \exp(0) = 1$, and

$$\begin{aligned} E\tilde{w}_{ij} &= w_{ij}E(\varepsilon_{ij}) \\ &= w_{ij} \ \forall(i,j). \end{aligned}$$

The primitive parameters of the model are included in the matrix Γ which contains all of the parameters of the index functions. In addition, we must estimate the standard deviation of measurement error σ_ε. Wolpin (1987) was the first to estimate a search model that allowed for measurement error in wages, although the search framework he considered was substantially different than ours. He modeled only the first search spell after graduating from high school and estimated a nonstationary finite-horizon model in discrete time. He allowed the probability of receiving an offer in each period to be variable. The fact that there were a sequence of wage offer probabilities that changed as the unemployment spell progressed combined with the finite-horizon assumption implied a sequence of reservation wages that varied over the unemployment spell. Measurement error was a necessary addition in the homogeneous environment he considered due to the time-varying reservation wages and the fact that the minimum accepted wage in period t would often be less than the reservation wage (from the model) for that period, w_t^*.

He estimated the model under lognormality assumptions on both the wage offer distribution and the measurement error distribution, just as we do here. Even though measured wages were equal to the product of the actual wage offer distribution and the measurement error distribution, the observed wage distribution was not lognormal since the lognormal distribution of accepted wages in period t is a truncated lognormal, the lower bound of which is w_t^*. It is the fact that the accepted wage distribution is truncated from below that allows the measurement error distribution and the wage offer distribution to be separately identified.

The truncation argument also aids in identification in our model, but the fact that we have repeated wage measurements at the same job and when moving across jobs is an even more important source of identifying information, as we discuss and illustrate in Section 4.1.